Understanding the Evolution of Momentum Effects in China's Stock Market

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Abstract

This paper studies the evolution of momentum effects in China's A-share market. Momentum strategies that buy past winners and sell past losers yield significant profits in the period before 2005, but they dissipate in the later period. We find that measures of noise trading are markedly higher in the later sample, and there is also significantly more informed trading proxied by major shareholder transactions. These findings are consistent with a model that features overconfident investors being skeptical about private signals. Overall, our analysis points to the changing investor composition as the driver of the disappearing momentum effects.

KEYWORDS: Momentum effect, Noise trading, Major shareholder transactions, Split-Share Structure Reform

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1 Introduction

This paper documents a salient pattern in the evolution of momentum effects in China's A-share market, and we develop a model to explain it. The model features investor under-reaction and noise trading, as well as the constitution of investors, and generates several empirical predictions for which we find support in the data.

We begin our analysis by building momentum portfolios using China's A-share stocks. Following Jegadeesh and Titman (1993), we sort stocks into decile portfolios each month based on their last six-month returns, classifying the top decile as winners and the bottom decile as losers. After a one-month gap to mitigate short-term price frictions, the strategy buys the winners and sells the losers with equal weighting and holds the positions for six months. This approach results in overlapping portfolios, as positions initiated in previous months remain active until the end of their respective holding periods. The average return of all active portfolios in a given month represents the return of the momentum strategy for that month.

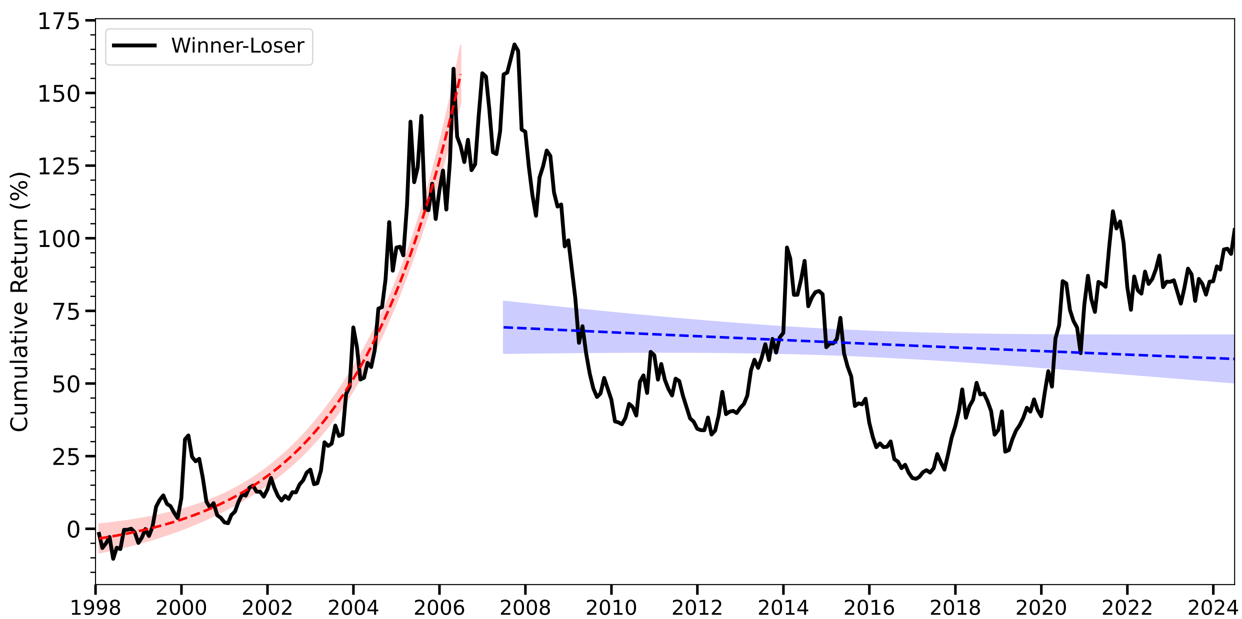

Figure 1: Cumulative return of the 6-6 momentum strategy. This figure illustrates the cumulative return of the 6-6 momentum strategy. The black solid line represents the the percentage return accumulated from the base period. The red and blue dashed lines represent fitted trends for the early and later periods. The sample period spans from January 1998 to June 2024.

Figure 1 shows the cumulative returns of the momentum portfolio with a six-month formation period and a six-month holding period (6-6). As evident in the figure, the 6-6 momentum strategy generated steady returns in the early period, averaging 11.5% per year from January 1998 to September 2005. However, starting in the fourth quarter of 2005, the cumulative return of the momentum strategy began to decline sharply. During the next two and a half years, it dropped by approximately 78.4% from peak to trough, reaching its lowest point at the end of the first quarter of 2010. After that, the performance of the 6-6 momentum portfolio remained weak, with no clear trend. In light of this observation, one might naturally ask, What is the underlying driver? Why do momentum effects seem to exist in the early period, but become insignificant later? [1]

In an attempt to answer these questions, we develop a model that features three types of investors: informed and uninformed investors, as well as noise traders. They trade (at Date 1) a risky stock that pays off only at Date 2. The informed investors observe a private signal about the stock's final payoff, based on which they decide how much to buy or sell. The uninformed investors infer the private signal from the stock price, and make their trading decisions accordingly. Following Luo, Subrahmanyam, and Titman (2021), we assume that the uninformed investors are skeptical about the precision of the private signal. So they end up providing to much liquidity to the informed investors. The equilibrium price at Date 1 hence represents an underreaction to the private signal. At Date 2 when all information is revealed, this underreaction would be corrected, leading to momentum in the stock price.

The model generates several empirical predictions, which we test using data. First, it suggests that, when the intensity of noise trading is sufficiently high, momentum effects may disappear or even reverse. We proxy noise trading using volatility, turnover rate, standard deviation of turnover rate, and maximum daily return, finding that in the later period, these indicators increase significantly, ranging from 24% to 95% market-wide, coinciding with the disappearance of momentum effects. Furthermore, when we exclude stocks with high levels of these characteristics from the momentum portfolio ex ante, we recover an annualized momentum return of 8.2%.

Additionally, the model indicates that as the proportion of informed investors in the market increases, momentum effects should weaken. We proxy the extent of insider trading in a stock using major shareholder transaction events and whether the actual controller of the company simultaneously controls multiple firms. Due to policy changes, many previously non-tradable shares became tradable in the later period, leading to a substantial increase in major shareholder transactions.

We find that major shareholder trades are concentrated in stocks with more extreme past performance, aligning closely with the stocks in momentum portfolios. Further, after conducting the event study, we find that major shareholders tend to buy underperforming stocks and sell outperforming ones. Specifically, stocks sold by major shareholders exhibit a consistent negative abnormal return of -0.6% per month over the following six months, while

[1] Naughton, Truong, and Veeraraghavan (2008) and Cheema and Nartea (2014) also find this pattern.

stocks purchased show abnormal returns of 0.3%, 0.1%, and 0.1% in the first three months after the purchase. This is consistent with the prediction of our model, which suggests that trades by informed insiders weaken momentum effects.

Moreover, within the subsample of firms where the actual controller controls multiple companies, typically those controlled by State-Owned Assets Supervision and Administration Commissions (SASACs), we find that after the Split-Share Structure Reform, the momentum effect in shares of these companies reversed. Based on these subsample, the momentum strategy yields a negative annualized return of 6.3% in the post reform period.

The paper proceeds as follows. Section 2 reviews the relevant literature on momentum effects and regulatory impacts. Section 3 develops a framework to explain the observed dynamics of momentum. Section 4 outlines the methodology used to construct momentum strategies and details the data sources in the Chinese market. In Section 5, we present our primary findings on the momentum effect and its evolution post-reform. Section 6 offers a supplementary analysis, further exploring the factors that shape momentum in the Chinese stock market. Section 7 summarizes the key findings and concludes.

2 Literature Review

Momentum-based investment strategies, where stocks with high past returns ("winners") are bought and those with low past returns ("losers") are sold, have been extensively studied across global markets. Foundational work by Jegadeesh and Titman (1993) demonstrates the profitability of these strategies, attributing the returns to delayed price reactions to firm-specific information rather than systematic risk. Building on this foundation, Jegadeesh and Titman (2001) show that momentum strategies consistently yield approximately 1% per month in returns. While the profitability of momentum strategies is well-established, the mechanisms behind these returns remain a subject of considerable debate. The diverse explanations reflect the complexity of the momentum phenomenon and underscore the need for further exploration, particularly in emerging markets like China.

2.1 Rational explanations

The mechanisms underlying momentum effects have been a key area of research, with several scholars proposing rational explanations based on risk and market dynamics. For instance, Johnson (2002) suggests that momentum arises from positive correlations between past and current returns driven by stochastic dividend growth. Li (2018) propose a unified model where firm-level productivity shocks and associated investment risks contribute to momentum, with firms experiencing positive shocks showing increased momentum. Extending this view, Kelly, Moskowitz, and Pruitt (2021) argue that momentum reflects conditional risk exposure, where returns align with time-varying factor betas based on firm characteristics. Lewellen (2002) further find that momentum can emerge from excess covariance, where stocks move together more closely than fundamentals justify.

Other rational models focus on information-based mechanisms and reversal dynamics. For example, Andrei and Cujean (2017) propose that increasing rates of information flow and word-of-mouth communication propagate momentum effects, while Johnson (2016) show that short-horizon reversals in S&P 500 returns result from relative performance concerns, inducing counter-movements in risk premiums. Daniel and Moskowitz (2016) highlight how momentum is vulnerable to "crashes" in high-volatility markets, with past losers often outperforming winners during market recoveries. These studies underscore the conditional nature of momentum returns, driven by information diffusion, investor awareness, and changing market conditions.

2.2 Behavioral explanations

Behavioral perspectives emphasize investor biases and heuristics in explaining momentum. For example, Grinblatt and Han (2005) examine momentum through the lens of prospect theory, noting that investor disposition effects—where losers are held and winners are sold—lead to predictable price underreactions. An (2016) further explore the "V-shaped disposition effect," where investors are more likely to sell stocks with extreme unrealized gains or losses, depressing prices and fueling momentum. Kandel, Massa, and Simonov (2011) show that shareholder homogeneity can influence managerial behavior, contributing to performance variations linked to momentum effects.

2.3 Momentum in emerging Markets

Momentum dynamics in emerging markets, such as China, are influenced by structural reforms, ownership structures, and investor heterogeneity. The Split-Share Structure Reform (SSSR), which converted non-tradable state shares into tradable assets, significantly impacted liquidity, ownership, and governance (Liao, Liu, and Wang, 2014). This reform allowed large shareholders to reduce holdings, particularly in firms with strong recent performance, suppressing prices and reducing momentum returns (Zhang et al., 2024). Additionally, the reform led to synchronized liquidity fluctuations across firms, especially during downturns, without a corresponding increase in market liquidity (Qian, Tam, and Zhang, 2014).

Ownership and governance changes further influenced corporate behaviors. Megginson, Ullah, and Wei (2014) and Chen et al. (2012) find that reduced state ownership and improved governance after the SSSR led to lower corporate cash holdings, promoting greater financial discipline. Liu, Wang, and Zhu (2021) notes that the SSSR reduced credit discrimination, enabling more equitable lending, which shifted firms towards market-driven behaviors, affecting momentum as state-owned firms adapted to increased market exposure.

2.4 Investor composition

Investor composition plays a critical role in shaping momentum and reversal effects. Du et al. (2022a) and Du et al. (2022b) highlight how retail investor constraints and concept momentum, such as in high-priced or "concept" stocks (e.g., e-commerce, AI), drive stronger momentum. Chui, Subrahmanyam, and Titman (2022) finds that markets with high institutional investor participation, like China's B-share market, exhibit stronger momentum effects, while retail-dominated markets see more reversals. Xiong and Wang (2023) further shows that high institutional ownership boosts momentum profitability, while retail-driven noise trading obscures trends. Additionally, Vayanos and Woolley (2013) suggests that institutional fund flows contribute to momentum as prices adjust to anticipated reallocations.

2.5 Cross-sectional studies

Cross-sectional studies reveal how firm characteristics amplify or dampen momentum. Baltzer, Jank, and Smajlbegovic (2019) and Avramov et al. (2007) show that momentum strategies are more profitable in high-credit-risk or financially distressed firms, where behavioral biases are more prominent. Garlappi and Yan (2011) links financial distress with concentrated momentum profits, especially when shareholder recovery potential is high. Medhat and Schmeling (2022) finds stronger short-term momentum in high-turnover stocks, while low-turnover stocks exhibit reversals, a pattern observed in both U.S. and international markets. Yan and Yu (2023) distinguishes cross-stock momentum, showing unique lead-lag relationships within industries or supply chains. Finally, Kandel, Massa, and Simonov (2011) demonstrates that shareholder homogeneity, such as age similarity, influences managerial behavior, potentially contributing to variations in firm performance tied to momentum effects.

3 Model and Hypotheses

This study develops a theoretical framework inspired by Luo, Subrahmanyam, and Titman (2021) to investigate mid-term momentum in financial markets. While simplifying their model, we retain the key elements of investor skepticism and noise trading in the market to explain observed price dynamics.

Asset Supply and Payoffs

The model considers a single risky stock traded at Dates 0, 1, with its liquidation value at Date 2 denoted by θ. This liquidation value is normally distributed with a mean of zero and variance ν_θ. The supply of the risky stock is fixed and normalized to zero under initial conditions. On date 1, noise trading influences the supply of the risky stock, causing a random deviation represented by z. This random variable z follows a normal distribution with a mean of zero and a variance of v_z. Additionally, a risk-free asset is included, offering a constant price and a fixed return of 1. Unless explicitly stated otherwise, all random variables in this framework are assumed to follow a normal distribution with a mean of zero, and the variance of any generic random variable χ is represented by ν_χ.

Information Structure and Investor Beliefs

On date 1, a mass $m \in (0, 1)$ of informed investors receives a private signal $\gamma = \theta + \mu$, where μ is a noise term independent of θ, normally distributed with zero means and variances ν_μ. Informed investors have unbiased perceptions of the precision of their own signal γ. The remaining proportion $1 - m$ of skeptical, uninformed investors underestimates the precision of the signal γ, believing its precision to be $\omega_\gamma = \nu_\theta + \omega_\mu$, where $\omega_\mu > \nu_\mu$. A constant mass λ of rational, uninformed investors acts as market makers, providing liquidity and maintaining market stability.

Preferences

The utility function of the i-th informed or skeptical uninformed investor is characterized by a standard exponential form:

$$U(W_{i2}) = -\exp(-AW_{i2}),$$

where W_{i2} denotes the investor's final wealth at date 2, and A is a positive constant representing their absolute risk aversion. For the i-th rational uninformed investor, the utility function is expressed similarly as:

$$U_N(W_{i2}) = -\exp(-A_N W_{i2}),$$

where A_N captures the absolute risk aversion specific to rational uninformed investors. At the start date 0, each uninformed investor i holds $\tilde{W}_{i0}$ units of the risk-free asset.

Market Equilibrium and Price Dynamics

To identify the equilibrium, we start with the conjecture that the equilibrium prices of the risky stock at Date 1 take a linear form:

$$P_1 = B\tau, \tag{1}$$

where $\tau \equiv \gamma - \delta z$ with variance $\nu_\tau = \nu_\gamma + \delta^2 \nu_z$, and δ and B are constant parameters.

On date 2, the uncertainty regarding θ is fully resolved, so the price at this date is $P_2 = \theta$. We denote the belief of skeptical uninformed investors about the total variance of the signal τ as $\omega_\tau = \omega_\gamma + \delta^2 \nu_z$.

Define a function:

$$H(x, y) \equiv [x(1 - x/y)]^{-1} \tag{2}$$

where the $H(\cdot)$ function can be interpreted as the conditional precision of a signal based on the investor's biased or rational beliefs. For example, $H(\nu_\theta, \omega_\gamma)$ is the precision of θ conditional on γ, given the belief of skeptical, uninformed investors in the variances of ν_θ and ω_γ. Further, let $\lambda_N = \lambda(A/A_N)$.

Proposition 1. The parameters δ and B, in the equilibrium prices of the risky stock in (1) are specified by:

$$\delta = \frac{A\nu_\gamma}{mH(\nu_\theta, \nu_\gamma)\nu_\theta},$$

and

$$B = \frac{mH(\nu_\theta, \nu_\gamma)\nu_\theta \nu_\gamma^{-1} + (1-m)H(\nu_\theta, \omega_\tau)\nu_\theta \omega_\tau^{-1} + \lambda_N H(\nu_\theta, \nu_\tau)\nu_\theta \nu_\tau^{-1}}{mH(\nu_\theta, \nu_\gamma) + (1-m)H(\nu_\theta, \omega_\tau) + \lambda_N H(\nu_\theta, \nu_\tau)}.$$

From equation (1), we can observe that the price of the risky stock is a linear function of a combination of informed traders' signals and noise trading. The combination coefficient δ depends solely on the level of skepticism among uninformed traders about the signals from informed traders, while the parameter B depends both on the level of skepticism and the intensity of noise in the market. In the following subsections, we introduce the corollaries derived from Proposition 1, which describe the implications for revealing mid-term momentum.

3.1 Momentum profit modeling

We define the mid-term momentum parameter as the of the covariance between the price changes:

$$\overline{MOM} = \text{Cov}(P_2 - P_1, P_1 - P_0),$$

and based on Proposition 1, we can express this covariance as:

$$\text{Cov}(P_2 - P_1, P_1 - P_0) = B\nu_\theta - B^2\left(\nu_\gamma + \delta^2 \nu_z\right).$$

With appropriately chosen parameters, the model can replicate momentum profits that are consistent with empirical studies. The momentum parameter $\overline{MOM}$ represents the return from a momentum trading strategy. At Date 1, the strategy involves buying $P_1 - P_0$ shares of the stock if $P_1 > P_0$, or selling $P_0 - P_1$ shares if $P_1 \leq P_0$, and holding this position until Date 2. Letting ΔP_1 represent the price changes at Dates 1, the expected returns from these mid-term momentum trades are given as:

$$E\left[(P_1 - P_0)(P_2 - P_1)\right] = \mathrm{Cov}(P_1 - P_0, P_2 - P_1), \tag{3}$$

The average number of shares held in long or short positions during this strategy, denoted as $|Z|$, can be expressed as:

$$|Z| = E[\Delta P_1 | \Delta P_1 > 0],$$
$$= [\mathrm{std}(\Delta P_1)](2\pi)^{-0.5}.$$

The final equality holds because ΔP_1 is normally distributed with a mean of zero. The per-share payoff for this momentum strategy is therefore approximately $\overline{MOM}/|Z|$.

In order to study the mid-term momentum effct, we assume each model period represents six months. To convert the momentum payoff into annualized percentage terms, we normalize the payoff variance ν_θ to one in the baseline parameters and assume an annual return standard deviation of 25%. Since θ corresponds to an 12-month period, the equivalent return standard deviation scales the annual 25% value by $(2/2)^{0.5}$. This adjustment is applied to the six-month per-share momentum payoff. Consequently, the scaling factor applied to $\overline{MOM}/|Z|$ becomes 25%.

3.2 Skepticism and noise trading

In this section, we provide an intuitive economic analysis to explain the role of skepticism and noise trading in momentum.

If uninformed investors are skeptical about the signal γ from informed traders (i.e., $\omega_\gamma > \nu_\gamma$), they tend to provide more counterparty trades relative to the informed traders. As a result, the price P_1 does not adjust sufficiently according to the signal. We can verify that $B < \nu_\theta {\nu_s}^{-1}$ in this case, assuming no noise trading supply z. Then, in the second period, as the price is revealed, the price reaction continues, and we observe a positive mid-term momentum driven by skepticism.

If noise trading becomes substantial in the market, the inferred signal τ, which is a combination of the private signal γ from informed traders and the noise trading supply z, will have an increased variance ν_τ. The remaining uninformed traders, who base their buy and sell decisions on the inferred signal, see their trading direction become almost random as their decisions are heavily influenced by the noise component. Consequently, on date 1, the price will deviate significantly from its fundamental value due to the large influence of noise trading. However, after the price is revealed on date 2, the price will eventually revert to its reasonable level, leading to a significant reversal effect.

We can summarize the above analysis with the following corollaries.

Corollary 1. If the skepticism ω_μ of skeptical uninformed investors increases, then an increase in skepticism increases $\overline{MOM}$, but the effect is capped by an upper bound.

Corollary 2. If noise trades are sufficiently intense (i.e., $\nu_z \to \infty$), then we obtain mid-term reversals, that is, $\overline{MOM} \to -\infty$.

Figure 2 illustrates how momentum returns vary with investor skepticism ω_μ and noise trading intensity ν_z. We assume the parameter values $m = 0.5$, $\lambda = 0.1$, $A = A_N = 2$, $\nu_\theta = 1$, $\nu_\mu = 0.4$, and $\nu_\epsilon = 0.3$. Initially, the momentum effect strengthens significantly with increasing skepticism, but the growth rate slows down and eventually plateaus. Regarding noise trading, we observe that even a relatively small scale of noise trading can significantly reduce the magnitude of the momentum effect, and this reduction occurs linearly across different momentum levels. Furthermore, in our parameter settings, after scaling adjustments, the momentum returns can range from an annualized 8% to a negative 4% reversal. This shows that our model has the potential to effectively capture the transition from momentum to reversal in the market.

3.3 Proportion of informed trader

Before the split-share structure reform, a significant portion of restricted shares was held by insiders, such as state-owned entities or concentrated legal entities, but these shares were not tradable. After the reform, these previously restricted shares were unlocked and became tradable, significantly increasing the proportion of informed investors in the market. This increase in the proportion of informed investors in the tradable stock market could play a key role in explaining the disappearance of momentum effects.

At the same time, the model setup suggests that as informed investors gain a larger share of the market, the momentum effects weaken.

Corollary 3. If the proportion of informed investors trading the risky asset increases (i.e. $m \to 1$), then the momentum effects weaken, that is, $\overline{MOM} \to 0$.

Figure 3 presents a series of plots with the same parameter setting with Figure 2, but with different values of m, where m represents the proportion of informed investors in the market. A higher m indicates a higher share of informed investors, while the proportion of skeptical uninformed investors is given by $1 - m$. The figure shows that, while the overall shape of each subplot remains the same, the magnitude of the momentum returns systematically decreases as m increases. This suggests that as the proportion of informed investors increases, momentum effects weaken. The intuition behind this result is that informed investors process information more efficiently, reducing the underreaction that drives momentum. In addition, they are not susceptible to noise trading, which further diminishes the impact of irrational price movements.

4 Data and Methodology

4.1 Data

We focus on all the listed shares in the A-share market. Additionally, monthly stock returns are winsorized at the top and bottom 0.5% to reduce the impact of extreme values on momentum strategies. Momentum portfolios are constructed starting in January 1998, ensuring that the formation period returns reflect the structured market environment shaped by the daily price limit regulatory changes in 1997.

Stock prices, returns, turnover rates, and accounting data used to calculate firm characteristics are sourced from the CSMAR database. The data on the Split-Share Structure Reform and actual controllers is obtained from the Wind database under "AShareEquityDivision" and "AShareEquityRelationships." Information on major shareholder trades in China's A-share market is also sourced from the Wind database under "AShareMjrHolderTrade.' The "AShareMjrHolderTrade" database records changes in shareholdings by company shareholders, including the start and end dates of each transaction. For monthly aggregation, if a transaction spans multiple months, it is allocated proportionally based on the number of days in each month to ensure accurate distribution of trade volumes.

We use semiannual and annual reports from the CSAMR database's classification report for institutional holdings on stocks, since the quarterly reports only disclose the top ten holdings of institutional investors. The construction of all other variables will be detailed in the main text or in the corresponding figure and table captions.

4.2 Methodology

We build momentum portfolios based on the framework of Jegadeesh and Titman (1993). The strategies we analyze incorporate portfolios with overlapping holding periods. In any given month t, the strategy holds a sequence of portfolios that includes both stocks selected in the current month and stocks formed during the previous months $K-1$, where K represents the holding period. Specifically, each month, the strategy ranks the stocks based on their cumulative returns over the J months ending one month before the date of portfolio formation, skips the most recent month, and then holds the selected stocks for the following K months. We refer to this approach as a J-month/K-month strategy and construct it as follows: At the beginning of each month t, we rank stocks in ascending order according to their returns over the past J months. We use these rankings to create ten equally weighted decile portfolios, with the top decile representing the "winners" and the bottom decile representing the "losers."

In each month t, the strategy involves purchasing the winner portfolio and selling the loser portfolio, maintaining this position for K months. Furthermore, the strategy closes any positions that were initiated in month $t-K$. In this approach, we rebalance the portfolio each month by reassessing the weights of $\frac{1}{K}$ of the securities, while carrying over the remaining securities of the previous month. Additionally, to address bid-ask spreads, price pressure, and delayed reactions, we follow the literature to introduce a one-month delay between the formation and holding periods. The monthly return of the strategy is the return of the momentum portfolio.

5 Main Empirical Results

5.1 The absence of momentum

The momentum effect describes the tendency of stock returns to persist in the same direction, where stocks with higher past returns typically continue to outperform those with lower past returns. Building on the Jegadeesh and Titman (1993) framework, we construct momentum portfolios with different formation and holding periods to investigate medium-term momentum effects in the A-share stock market of China. We analyze strategies that select stocks based on their returns over the past 1 to 4 quarters, and combine these stock selection strategies with holding periods of 1 to 4 quarters to obtain 16 distinct momentum strategies.

Table 1 presents the mean returns and t-statistics for momentum portfolios constructed with various combinations of the formation (J) and holding (K) periods from January 1998 to June 2024. Panel A shows that no combination of formation and holding periods achieves statistical significance at the confidence level 90% in the Chinese A share market, with the highest mean return observed in the combination of formation of 6 months and holding period of 6 months, which yields a return of 0.32% per month (t = 1.32). Panel B reveals that when there is no one-month gap between the formation and holding periods, the momentum returns are notably lower. This observation aligns with the literature, which suggests introducing a one-month delay between the formation and holding periods to address issues such as bid-ask spreads, price pressure, and delayed reactions, thus avoiding short-term reversals.

Based on these observations, we adopt a one-month gap in all subsequent momentum strategies to ensure a clearer capture of medium-term momentum and improve the reliability of the strategies. To directly observe the variation of momentum effects over time, we plot the cumulative returns of momentum portfolios.

Figure 4 illustrates the cumulative returns of momentum portfolios with different combinations of formation periods (FP) and holding periods (HP) in each subplot. The data spans from January 1998 to June 2024, providing insight into the dynamics of momentum returns in the China A-share market over time. The plots on cumulative returns from the pre-2007 period confirmed that a six-month medium-term formation period is most effective in capturing momentum in the Chinese market. Additionally, as the holding period increases too long, the momentum effect weakens.

Notably, across most formation and holding period combinations, cumulative returns peak around mid-2006, reflecting a strong momentum effect leading up to that point, with consistent increases in returns before mid-2006. However, after this peak, returns sharply decline and continue to diminish over the following two years, with the momentum effect virtually disappearing in the years that follow.

The momentum effect remains subdued following the 2008 financial crisis, with cumulative returns flattening after 2010. Although Daniel and Moskowitz (2016) argue that momentum declines often stem from "panic states" following market downturns and high volatility periods, in the China A-share market, momentum underperformance extends beyond the crisis period. Another prolonged downturn in momentum from 2014 to 2017, which includes both the 2015 stock market boom and the bust, indicates that shifts in momentum returns may not be fully related to broad market conditions alone. This pattern, evident through different market phases and extending over periods of strong rebounds and volatility, underscores the potential influence of structural factors specific to the Chinese stock market on the decline of momentum effects.

5.1.1 Split-share structure reform

Given the notable shifts in momentum returns observed around 2006, it is essential to examine the market reforms during this period that could have contributed to these changes. This section delves into the significant regulatory transformation in China's capital market, known as the Split-Share Structure Reform, which fundamentally altered the trading dynamics and ownership structures of publicly listed firms.

Before the reform, approximately two-thirds of the shares in listed companies were non-tradable. This issue was historically embedded in the development of China's capital market, as initial regulations were designed to prevent the loss of public shares by prohibiting them from being traded publicly. Particularly in state-owned enterprises (SOEs), which made up 928 out of 1,422 listed firms before the reform, most of the shares were non-tradable.

To address the challenges posed by the split-share structure, the China Securities Regulatory Commission (CSRC) initiated the split-share structure reform on 30 April 2005. Before the reform, 1,335 out of 1,422 listed firms in the Chinese stock market were required to undergo restructuring. At the end of 2006, 1,301 listed companies had completed or entered the reform process, accounting for 97% of the companies that needed to undergo reform and 98% of the market capitalization. Only 40 companies had not yet entered the reform process. At the end of 2007, more than 95% listed companies had completed the reform.

This structure led to significant price manipulation and misaligned interests between shareholders, as the small proportion of tradable shares allowed speculators to distort prices. The reform aimed to increase the volume of tradable shares, allowing for a more equitable distribution of ownership and improved price discovery. However, the substantial increase in the supply of tradable shares resulted in greater market liquidity, attracting more investors, most of whom were unsophisticated retail investors. This influx of retail investors significantly increased volatility and turnover in the market. These shifts laid the groundwork for the subsequent analysis of market fluctuations post-reform, which are reflected in heightened volatility and turnover, setting the stage for the following discussion of market dynamics.

Table 2 presents the monthly returns of momentum strategies for the Pre-Reform (January 1998 to April 2005) and Post-Reform (January 2008 to June 2024) periods. In the Pre-Reform period (Panel A), the 6-month formation period (J = 6) strategies generate the strongest momentum effect, with the 3-month holding (K = 3) combination yielding a monthly return of 1.24% (t = 2.34), significant at the 95% level. Other combinations with formation periods shorter than 12 months and holding periods shorter than 9 months also produce annualized returns around 10%, with statistical significance at the 90% confidence level or higher.

In contrast, the Post-Reform period (Panel B) reveals a significant decline in momentum profitability across all combinations of formation and holding periods, with consistently low and statistically insignificant t-values. The previously most effective strategy, the formation of 6 months with a 3-month hold, now results in a return of -0 16% (t = -0.50), while all other combinations produce negative returns. This sharp decline suggests that momentum strategies have become largely ineffective in the post-reform market environment.

In table 3, we examine whether the momentum profit compensates for systematic risk by presenting the risk-adjusted returns of the 6-6 momentum portfolio, calculated as the alphas of the market model (CAPM) and the Fama-French three-factor and five-factor regressions (FF3 and FF5). The "Raw" model in the table reports the average returns of the raw portfolio, without any adjustment for risk. The momentum portfolios are ranked according to the returns of the last six months, with P1 representing the losers (bottom 10%) and P10 representing the winners (top 10%). The results show that in the post-reform period, the alphas increase monotonically from P1 to P10, with alphas ranging from 1.09% to 1.61%, compared to the profits of the raw momentum of 1.10%. In contrast, the pre-reform period shows a hump-shaped pattern, with raw return and alphas all near zero. These findings suggest a noticeable shift in the return patterns of portfolios based on past returns before and after the split-share structure reform, and that momentum profits do not compensate for systematic risk.

These stark contrasts presented in table 2 and table 3 underscore the profound change in market dynamics after reform, which has significantly reduced the viability of momentum strategies in the Chinese A-share market. In the following sections, we explore the potential mechanisms behind the relationship between the Split-Share Structure Reform and the disappearance of momentum.

5.2 Noise trading

Following the reform of the split-share structure, the increase in tradable shares led to increased market liquidity and trading activity. This surge attracted a significant number of retail investors, many of whom engaged in speculative trading, contributing to the prevalence of noise trading in the market. The high turnover rates and increased volatility observed in the Chinese stock market are indicative of this speculative environment.

Figure 5 compares the characteristics of the stock market before and after the reform of the split-share structure between the past performance decile groups. The figure reports four key trading characteristics measured during the six-month formation period: overall volatility (Vol), turnover (Turn), standard deviation of turnover (Stdtn), and maximum daily return (Max).

The results show significant increases in all four trading characteristics after the reform. On average in all decile groups, volatility rose from 2.40 to 2.98 (+24.0%), turnover nearly doubled from 14.31 to 27.91 (+95.0%), the standard deviation of turnover increased by 33.8% (from 14.67 to 19.63), and the maximum daily return increased by 15.7% (from 7.89 to 9.13). These shifts suggest that post-reform stocks experienced higher price fluctuations and greater trading intensity, likely reflecting changes in market liquidity and investor composition following the reform.

A notable trend across all four metrics is their U-shaped pattern, with both losers and winners exhibiting the highest levels of volatility and turnover, and winners showing the most pronounced increases. Specifically, in the winner group, volatility increased from 2.55 to 3.73 (+46.3%), turnover increased from 19.15 to 41.89 (+118.8%), the standard deviation of turnover increased from 18.67 to 28.39 (+52.0%) and the maximum daily return increased from 8.35 to 11.35 (+35.9%). These changes indicate that post-reform stocks, particularly winners, experienced more frequent trading and larger price fluctuations. These findings suggest that the structural shift induced by the reform fundamentally altered the risk-return dynamics of momentum strategies.

Building on these findings, we next examine whether excluding stocks with extreme trading characteristics can restore the momentum effect. Excessive volatility and turnover may reflect speculative activity or short-term price fluctuations rather than fundamental trends. By removing these stocks, we aim to isolate the true momentum effect and determine if it is driven by more stable, fundamental factors, or distorted by market inefficiencies post-reform.

Table 4 examines the impact of refining the construction of momentum portfolios by excluding stocks from the winners' portfolio that fall into the top 10% to 50% of the market in terms of the trading characteristics of the previous month, including overall volatility (Vol), turnover (Turn), standard deviation of turnover (Stdtn) and maximum daily return (Max). The column "All" represents the exclusion of stocks based on all four characteristics simultaneously.

In the baseline strategy ("None" row), the monthly momentum return is only 0.22% with a t-value of 0.80, indicating an insignificant momentum effect. However, as progressively stricter exclusion criteria are applied, momentum returns and their statistical significance improve across all filtering methods. When the top 50% of stocks in terms of any single trading characteristic (Vol, Turn, Stdtn, or Max) is excluded, the monthly momentum return increases to approximately 0.58%, all of which are statistically significant at the confidence level 90%. The most pronounced effect occurs when stocks are excluded based on all four characteristics simultaneously, with the momentum return increasing to 0.68% and a t-value of 2.24, marking a significant improvement in momentum profitability.

These results suggest that high-turnover and high-volatility stocks disproportionately contribute to momentum attenuation, likely due to noise trading. Additionally, unreported tests show that similar adjustments to the losers' portfolio did not result in significant improvements, reinforcing the idea that the primary distortion of momentum originates from high-risk stocks within the winners' portfolio.

5.3 Major shareholder trading

After the implementation of the split-share structure reform, the unlocking of previously restricted shares triggered significant trading activity by major shareholders, especially in stocks with more extreme past performance. A plausible hypothesis is that the unlocking of previously restricted shares prompted informed major shareholders to trade these holdings—either by selling to lock in gains or buying when they observed undervalued prices. We believe this trading behavior have played a significant role in suppressing the continuation of price trends. To gain a deeper understanding of this phenomenon, it is crucial to first examine the regulatory policies governing major shareholder trades.

5.3.1 Trading policies

The "Administrative Measures for the Split-Share Structure Reform of Listed Companies"", issued by the China Securities Regulatory Commission (CSRC) on September 4, 2005, established specific restrictions on previously non-tradable shares. Under these regulations, such shares could not be listed for trading or transferred within 12 months of the date of implementation of the reform plan. Furthermore, non-tradable original shareholders holding more than 5% of the total shares of a listed company faced further restrictions: after the initial 12 month period, they were restricted to selling no more than 5% of the total shares of the company through stock exchange transactions within the next 12 months and no more than 10% within the following 24 months. These previously non-tradable shares, which gained trading rights but remained subject to holding period and trading ratio restrictions, are referred to as restricted shares or restricted A-shares.

Figure 6 presents a time series trend of the major shareholder trades in the Chinese A-share market from May 1997 to June 2024. The figure is divided into three panels, each capturing a different measure of trading activity. In each panel, the left-hand graph classifies trades by whether the shares traded were previously restricted or non-restricted, while the right-hand graph categorizes trades by shareholder type: individuals, companies, or executives. The red dashed vertical line in June 2006 marks the beginning of full circulation of previously restricted shares under the Split-Share Structure Reform. The blue dashed vertical lines indicate key event dates after which trading activity declined significantly, highlighting major policy interventions.

In panel A, the y-axis represents the fraction of listed stocks experiencing major shareholder trades, calculated as the number of stocks with at least one trade divided by the total number of listed stocks in that month. Panel B captures the average number of trades per stock, calculated as the total number of transactions in the market divided by the number of listed stocks. This measure accounts for instances where a single stock is traded multiple times. Panel C reports the average percentage of shares traded per stock. For each stock, the traded amount in shares is first expressed as a fraction of its tradable shares. This fraction is then averaged across all listed stocks, with stocks that have no reductions assigned a value of zero.

The trends across all three panels exhibit similar patterns in response to key policy changes and market events. Following the Split-Share Structure Reform, which had been gradually implemented, June 2006 marked the official beginning of full circulation for previously restricted shares in the Shanghai and Shenzhen stock markets. This shift significantly increased the supply of tradable shares and lead to a sharp rise in major shareholder trading activities.

In January 2010, trading drop sharply following the introduction of a new tax policy in December 2009, which imposed a 20% personal income tax on gains from the transfer of restricted shares, effective from January 1, 2010. Another turning point occurs in July 2015, when the China Securities Regulatory Commission (CSRC) introduced emergency measures to curb market volatility. The policy temporarily prohibited controlling shareholders, shareholders holding more than 5% of shares, directors, supervisors, and senior executives from selling shares on the secondary market for six months.

The December 2019 revision of the Securities Law of the People's Republic of China introduced key changes to disclosure requirements for major shareholders. The law reduced the threshold for reporting equity changes from 5% to 1%. Additionally, shareholders must disclose the source of funds used for share purchases, as well as the timing and method of any changes in voting shares. Failure to comply with these disclosure requirements now carries a maximum fine of ¥10 million, a significant increase from the previous cap of ¥600,000. The final major drop occurs in August 2023, following the implementation of the "827 New Regulation" by the CSRC. This rule restricted reductions by controlling shareholders and actual controllers under specific conditions, including when the stock price was below the IPO price or net asset value, or when dividend requirements were not met.

Across all panels, restricted shares constitute a substantial portion of reduction trades, particularly after the implementation of the Split-Share Structure Reform in June 2006. As previously restricted shares became tradable, their share in total reductions surged, whereas non-restricted shares played a relatively minor role but gained importance over time. From a shareholder-type perspective, company shareholders account for the majority of reductions immediately after the Split-Share Structure Reform. However, over time, individual and executive reductions have gradually increased, indicating a growing tendency among these groups to liquidate their holdings. This shift suggests that over time the ability to sell shares has expanded beyond large controlling entities, affecting a broader set of market participants.

5.3.2 Pre-trade performance

To understand which types of stocks attract more attention from major shareholders in terms of trading, we examine their past performance prior to trade. The box plots in Figure 7 reveal that major shareholder trades are concentrated in stocks with more extreme past performance, either winners or losers.

Figure 7 shows the distribution of major shareholder reductions in portfolios sorted by cumulative past returns. The red dots represent the mean values, while the upper and lower bounds of the boxes indicate the 25th and 75th percentiles, and the black line in the center of each box represents the median. Panel (a) shows that the proportion of stocks with trades is higher in the extreme deciles of past returns. Panels (b) and (c) reflect similar trends, with a greater number of trades per stock and a higher percentage of shares traded for stocks with more extreme past returns. The trend line connecting the mean values clearly illustrates a U-shaped pattern.

This pattern aligns with the construction of our momentum portfolios, which also consist of stocks with more extreme past performance. Therefore, major shareholder trades tend to focus on the same stocks that are part of the momentum strategy, supporting the idea that these trades are more impactful on the stocks forming momentum portfolios.

5.3.3 Post-trade impact

To understand the impact of major shareholder trades on stock returns over time, we conduct an event studie around these trading events. We examine the month-by-month effects on returns before and after the event by estimating the following panel regression:

$$Ret_{i,t} = \alpha + \sum_{k=-5}^{6} \beta_k \mathbf{1}(EventMonth_{i,t} = k) + \tau_t + \nu_i + \epsilon_{i,t}, \tag{4}$$

where $Ret_{i,t}$ is the stock return of stock i in month t, $\mathbf{1}(EventMonth_{i,t} = k)$ is a Indicator variable that equals one if month t is k months before or after a month with major shareholder trade for stock i , τ_t is the time fixed effect, ν_i is the stock fixed effect, and $\epsilon_{i,t}$ is the error term.

Figure 8 presents the regression coefficients from the event study. The points represent the estimated coefficients, and the upper and lower bounds of the bars indicate the 95% confidence intervals. Panel A examines the performance of stocks sold by major shareholders before and after the sale. The coefficients reveal that as the sale date approaches, stock performance improves, with significant positive abnormal returns of 0.2% observed one month prior. This suggests that major shareholders tend to sell better-performing stocks. However, in the six months following the sale, these stocks consistently underperform by 0.6% per month, indicating that shareholder sales exert continued downward pressure on stock prices.

Panel B, on the other hand, tracks the performance of stocks purchased by major shareholders around the purchase event. The data shows that, on average, these stocks experience negative abnormal returns of about -0.3% each month during the six months leading up to the purchase, reflecting underperformance. After the purchase, there is a short-term boost, with a 0.3% positive abnormal return in the first month. This positive impact diminishes over the next two months, with abnormal returns around 0.1%. This positive effect diminishes quickly over the next two months, with abnormal returns around 0.1%, and becomes insignificant thereafter. Compared to the persistent negative effect following the sale, the positive effect from the purchase fades more rapidly.

Based on the two panels above, it is clear that both purchases and sales have opposing effects on stock abnormal returns before and after the transaction. This strongly supports the notion that major shareholder trades exert a counteracting influence on stock price trends. In other words, major shareholder transactions serve as a reverse or obstructive force to the momentum of individual stocks. This is consistent with the prediction of our model, which suggests that insider trading can lead to the disappearance of momentum effects.

5.4 Controller structure

This section investigates how the structure of corporate ownership, particularly the role of diversified controllers, influences momentum effects. The study draws on the insights of Li et al. (2011), who examine the impact of the Split-Share Structure Reform in China, suggesting that the compensation to tradable shareholders correlates with risk-sharing, especially in firms with undiversified controllers. Their findings indicate that ownership structures influence investors' valuation of a firm's shares, and we hypothesize that diversified controllers may alter momentum dynamics post-reform by facilitating more informed trading.

Table 5 provides a detailed breakdown of diversified actual controllers in Chinese listed companies before the Split-Share Structure Reform, along with key associated metrics. The study focuses on 1,249 companies that had completed the reform by the end of 2007. A listed firm's controller is classified as diversified if it exercised control over more than five listed firms as of April 2005. In the sample, 398 out of 1,249 firms, approximately 31.9%, fall into this category. Diversified actual controllers are primarily state-owned entities, with the SASAC (State-Owned Assets Supervision and Administration Commission) of the State Council and its provincial and municipal counterparts dominating this group. The SASAC of the State Council is the most diversified controller, overseeing 148 listed firms, with an average firm size of 1.30 billion yuan and a beta of 1.14. The second to seventh ranked diversified controllers are SASAC entities from major cities such as Shanghai, Beijing, and Shenzhen, and each oversee more than 10 companies. The remaining diversified actual controllers typically manage an average of around 7 firms. On average, these controllers' firms are smaller in market capitalization and more sensitive to market fluctuations as reflected in their beta.

The distinction between diversified and non-diversified controllers is not merely a matter of ownership concentration but reflects fundamental differences in information environments and trading behaviors. Firms controlled by diversified entities are embedded within a broader network of affiliated companies, creating a unique setting where insiders across multiple firms may have access to shared non-public information and the ability to coordinate their trading activities.

Table 6 presents the regression results examining the relationship between past and future returns, both pre and post the Split-Share Structure Reform, across different controller structures. Panel A (Pre-Reform) shows that for firms with diversified controllers, the coefficient on past returns (α_1) is significantly positive (0.0173, t = 6.73), indicating that before the reform, stocks with higher past returns continued to generate higher future returns. However, in Panel B (Post-Reform), the momentum coefficient for the same group becomes significantly negative (-0.0058, t = -2.72), suggesting that momentum has shifted to a reversal effect within the diversified controller group after the reform. For firms with non-diversified controllers, the results show a weaker momentum effect before the reform (0.0094, t = 4.22) and an insignificant coefficient after the reform (0.0014, t = 0.77), likely because these firms had fewer insiders who could influence price dynamics.

The disappearance of momentum, and even its reversal, particularly in the diversified controller group, can be explained by the changes in insider trading constraints before and after the Split-Share Structure Reform. Prior to the reform, diversified controllers, typically associated with firms having multiple insiders, were restricted in their ability to trade freely, which prevented their private information from being fully incorporated into market prices. As a result, past price trends persisted, contributing to the momentum effect.

However, after the reform, these restrictions were lifted, allowing insiders to trade more freely. In the diversified controller group, this change led to more efficient price corrections, as insiders could now act on private information more quickly. In some cases, this resulted in excessive sell-offs as insiders sought to lock in past gains, causing overcorrections and even shifting the momentum effect into a stronger reversal. Thus, the more pronounced reversal effect observed in this group post-reform reflects the greater price adjustments that followed the removal of insider trading constraints.

Based on the previous mechanism and results, we extend the regression analysis to the portfolio level to examine how ownership structure influences return dynamics. Table 7 presents the results using a modified 6-6 long-short momentum strategy, where past performance rankings are determined at the market level, but buy and sell decisions are restricted to stocks within each ownership category. Before the reform (Panel A), the momentum effect is pronounced among firms with diversified controllers. The "Div" portfolio exhibits a W-L return of 1.16 (t = 2.27), higher than the non-diversified firms (0.75, t = 1.59). This aligns with the hypothesis that momentum effects were more persistent in firms where insider trading was constrained. After the reform (Panel B), momentum disappears across all groups, with diversified firms experiencing a clear reversal. The W-L return for "Div" turns negative at -0.53 (t = -1.80), while the "All" and "Ndiv" portfolios show no significant effect.

This pattern is consistent with the regression results in Table 6, which show a stronger momentum effect before the reform and a more pronounced correction, even turning into a reversal, among diversified firms post-reform. These findings further support the argument that once insiders in diversified firms were able to trade freely, they corrected mispricings more efficiently, eliminating momentum and, in some cases, leading to overcorrections that induced reversal.

6 Additional Evidence

6.1 Risk-return patterns

Understanding how past returns relate to future performance is essential to distinguish between risk-driven return compensation and behavioral anomalies in asset pricing. If past winners continue to outperform, this persistence could reflect exposure to systematic risk factors that reward investors with a risk premium. Conversely, if extreme past returns reverse, it may indicate that such stocks carry temporary mispricing or idiosyncratic risk that is not compensated in the long run. In this context, we explore the basic return patterns of momentum effects and investigate how returns relate to overall volatility. This sets the stage for further analysis of the impact of risk factors on returns.

To examine these dynamics, Figure 9 presents the relationship between past performance and future returns over the next six months. The x-axis represents either the percentile rank of past six-month cumulative returns (left panel) or the logarithm of past cumulative returns (right panel). The y-axis represents the average monthly return for the following six months, with the standard deviation shown by the red bars.

The left panel illustrates a positive correlation between past returns and future returns in the middle of the distribution, reflecting the momentum effect. This aligns with the idea that higher past returns are often associated with higher future returns, which may be attributed to systematic risk factors that reward persistent trends in the market. However, at the extremes, the worst and best past performers, we observe reversal effects: stocks with poor past performance tend to experience strong future returns, while highly performing stocks show weaker future returns. This reversal pattern suggests that extreme past returns may reflect temporary mispricing or idiosyncratic risk, which are not compensated over the long run, as indicated by risk-return theory.

The right panel, which uses the logarithmic transformation of past cumulative returns, makes the extreme values more apparent, emphasizing the reversal effect at both ends of the performance spectrum. This transformation enhances the visibility of the tail behavior, highlighting the dominance of mean reversion for extreme performers. As extreme performance generally indicates either undervaluation or overvaluation, mean reversion can be seen as a corrective force that brings prices back to their equilibrium levels over time.

In the context of momentum, the persistence of returns suggests that such stocks may reflect either exposure to persistent risk factors or mispricing. As shown by figure 9, the risk-return trade-off in the main return intervals implies a positive relationship, meaning there may be a specific risk compensation for stocks with higher past returns. To fully grasp the dynamics of momentum in the Chinese A-share market, we look beyond the return patterns and explore the underlying firm characteristics that may drive or weaken these effects.

Table 8 examines the anomalies in firm characteristics identified in Liu, Stambaugh, and Yuan (2019) by separating stocks into decile portfolios based on past performance. Winner portfolios tend to have higher earnings, cash flow, and market capitalization, along with higher volatility and turnover. In contrast, loser portfolios generally exhibit lower earnings and cash flow, but experience stronger short-term reversals. Profitability (ROE) follows a nonmonotonic pattern, with higher values observed in the extreme deciles. In terms of systematic risk (Beta), better performing stocks tend to have slightly lower systematic risk.

6.2 Institutional ownership and momentum

Given the relatively low institutional participation and trading activity in the Chinese stock market compared to developed markets, where higher institutional participation is often linked to the persistence of the momentum effect, our objective is to investigate the role of institutional investors in China's stock performance. By analyzing how institutional participation affects stock performance, we seek to uncover possible reasons behind the disappearance of the momentum effect in China, particularly in contrast to the dynamics observed in more developed markets.

To address this, we first examine the patterns in institutional investors' holdings across stocks sorted by past performance. By analyzing shifts in institutional holdings, particularly among various types of institutions, our objective is to identify systematic preferences for stocks based on past performance and explore whether institutional strategies align with or diverge from typical momentum-based approaches. We measure position changes in institutional holdings using semiannual and annual reports since institutions only disclose their top ten holdings in the first and third quarters.

Table 9 presents the semiannual changes in institutional investor holdings across stock groups sorted by one-month lagged six-month cumulative returns, with each value representing a percentage change in holdings. For institutional investors overall, holdings show a monotonic increase from "Losers" to "Winners", with a 2.85% increase in the "Winners" group and a -0.95% decrease in the "Losers" group, resulting in a substantial W-L difference of 3.80% and a highly significant t-value of 9.61. This trend is primarily driven by Funds, which show the largest increase, with a W-L difference of 4.48% (t = 8.32). This indicates that funds are actively reallocating their portfolios in favor of stocks that have recently performed well, reflecting a momentum-driven approach. These findings align with Baltzer, Jank, and Smajlbegovic (2019), who also highlight how institutional investors, especially funds, tend to increase their holdings in stocks with stronger past performance while reducing positions in underperforming stocks.

In contrast, certain institutional types, notably Non-Financial Listed Companies (Non-Fin) and Banks, exhibit a tendency to reduce their holdings in well-performed stocks. Non-Financial Listed Companies have a W-L difference of -0.54% (t = -2.27), while Banks show a W-L difference of -0.84% (t = -1.98). These results suggest a contrarian approach among these institutions, as they appear to reduce their stakes in high-performing stocks, possibly due to differing risk preferences or liquidity constraints that make them less likely to follow momentum. Additionally, several other institutional types, such as entrust, broker, and finance, along with non-financial Listed Companies, consistently show negative values across all performance quintiles. This indicates a steady exit from the stock market, regardless of the past performance of the stocks, which may reflect a more general reduction in market exposure rather than any specific reaction to momentum.

Next, we assess whether the strength of momentum effects varies between different levels of institutional participation. Table 10 examines the relationship between institutional ownership and momentum effects using a two-way portfolio sorting approach. Stocks are first sorted according to institutional ownership and within each institutional ownership group, they are further sorted according to past cumulative returns to construct a 6-6 long-short momentum portfolio.

The results indicate that momentum effects are concentrated in stocks with relatively high institutional ownership. Specifically, in the two top institutional ownership quintiles, the 5-1 momentum return is 0.49% (t = 2.21) for the fourth quintile and 0.63% (t = 2.17) for the highest quintile, both of which are statistically significant. In contrast, stocks in the three lowest institutional ownership quintiles do not show significant momentum profitability, with 5-1 returns ranging from 0.02% to 0.20%, none of which are statistically significant. These findings suggest that institutional ownership is an important determinant of momentum profitability.

To futher investigate how institutional ownership interacts with past performance in shaping momentum effects, we modify the standard 6-6 momentum sorting procedure by incorporating institutional ownership into the ranking process. The detection method follows the Z-Score approach proposed by Altman (1968). Instead of sorting stocks solely on the basis of past cumulative returns, we rank them using the following composite variable.

$$V = (1 - w)\frac{CR_i - \overline{CR_i}}{Std(CR_i)} + w \cdot \text{sgn}(CR_i)\frac{IP_i - \overline{IP_i}}{Std(IP_i)}, \tag{5}$$

where CR_i represents past cumulative returns, and IP_i denotes institutional ownership. The parameter w controls the relative weight of institutional ownership in the ranking process, taking values between 0 and 1. When $w = 0$, the ranking follows a standard momentum strategy based purely on past returns. When $w = 1$, stocks are ranked solely by institutional ownership.

A key adjustment in this sorting method is the inclusion of $\text{sgn}(CR_i)$, which assigns a negative sign to the institutional ownership term for stocks with past returns below the average. This adjustment ensures that stocks with high institutional ownership but below-average past returns are placed in the lowest-ranked deciles, ensuring that such stocks are positioned in the selling portfolio. The rationale behind this approach is that if stocks with higher institutional ownership are more likely to maintain their past return trends, then the momentum effect should be stronger among stocks with high institutional ownership. Consequently, buying high-institutional-ownership stocks with strong past returns and selling high-institutional-ownership stocks with weak past returns should generate higher or more robust momentum profits.

Figure 10 examines how the inclusion of institutional ownership in the sorting process influences momentum portfolio returns and their statistical significance. The figure plots the mean return (blue line, left axis) and the t statistic (red line, right axis) of the long-short momentum strategy as a function of w, which determines the relative weight assigned to institutional ownership in the ranking process. When $w = 0$, the resulting momentum return is 0.41, but its t statistic remains low at 1.5, indicating that momentum effects are statistically insignificant under the traditional approach. However, as institutional ownership is incorporated into the classification process ($w > 0$), the t statistic gradually increases, reaching values above 3.0 when institutional ownership is given greater weight. This suggests that incorporating institutional ownership significantly improves the statistical reliability of the momentum effect.

Despite this improvement in significance, the magnitude of momentum returns exhibits a declining trend, decreasing from 0.41 to 0.33 as w increases. This decline can be attributed to the fact that as institutional ownership plays a greater role in the ranking process, the relative weight of past returns in the sorting decreases. As a result, the selected stocks no longer represent the most extreme winners and losers purely based on past performance, leading to a weaker return spread. Even if momentum effects exist, their magnitude naturally diminishes because the formation step no longer isolates stocks with the strongest return continuation potential. However, the increasing t statistic suggests that the incorporation of institutional ownership improves the reliability of momentum effects by reducing noise and improving statistical significance, although it slightly moderates the return spread.

7 Summary and Conclusion

This study explores the disappearance of momentum effects in the Chinese stock market and identifies two main reasons: first, the presence of noise trading in the Chinese market may obscure the momentum effect, and second, large-scale sell-offs by major shareholders also play a significant role in this process. By analyzing changes in market structure following the split-share reform, we found that market volatility and turnover increased, suggesting the presence of more noise trading. At the same time, the rise in insider trading led to price corrections that weakened the continuation of price trends.

A limitation of this study is that, while our analysis reveals the role of shareholder sell-offs and information flow, further verification is needed to assess the generalizability of these factors in other markets. Additionally, more direct identifications on noise trading and insider trading would contribute to a more comprehensive understanding of the impact on momentum effects.

Future research could further explore how different types of investors in the Chinese market, such as retail vs. institutional investors, play distinct roles in the structural change by Split-Share Structure Reform, or investigate the impact of other market reforms or policy change.

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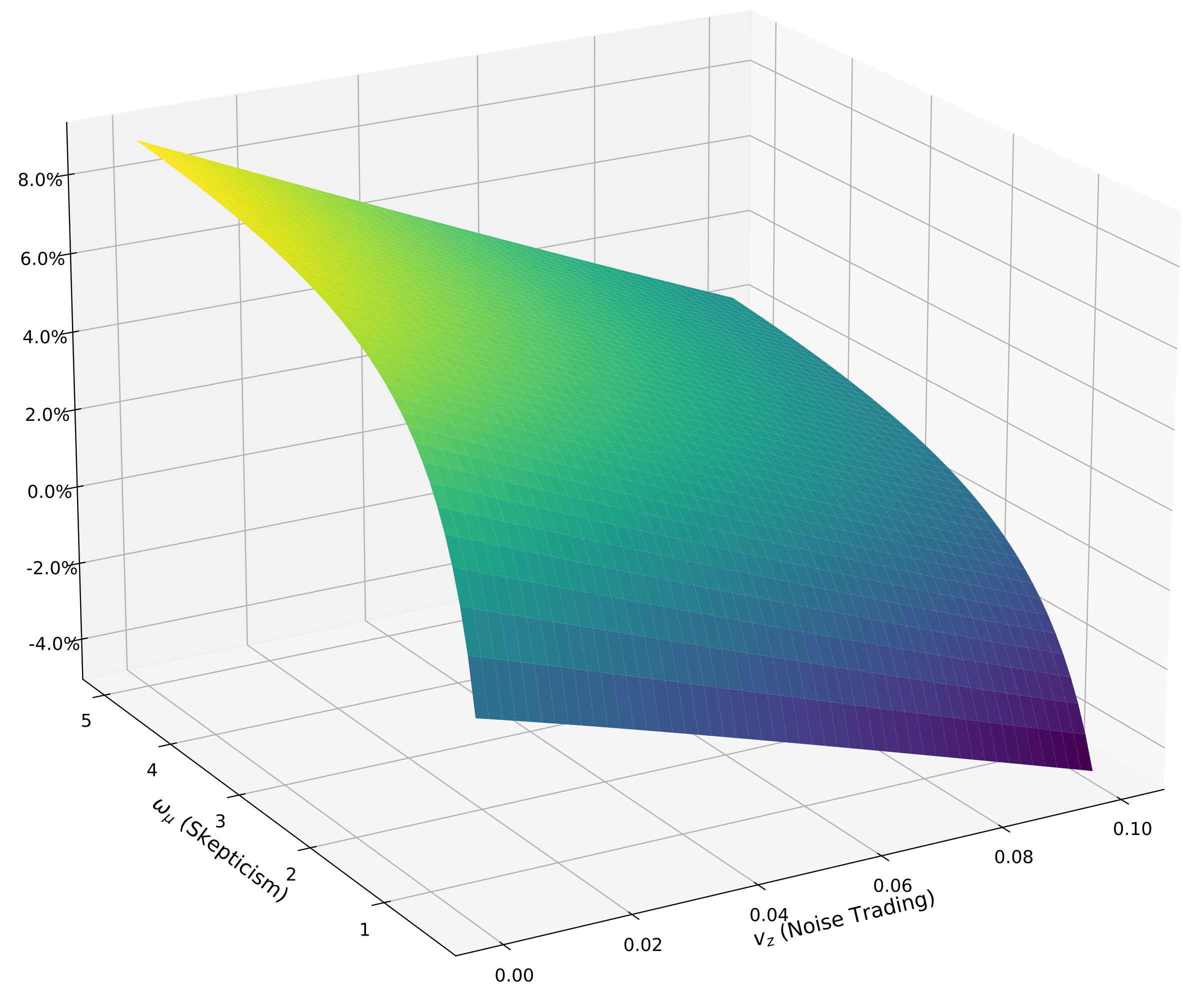
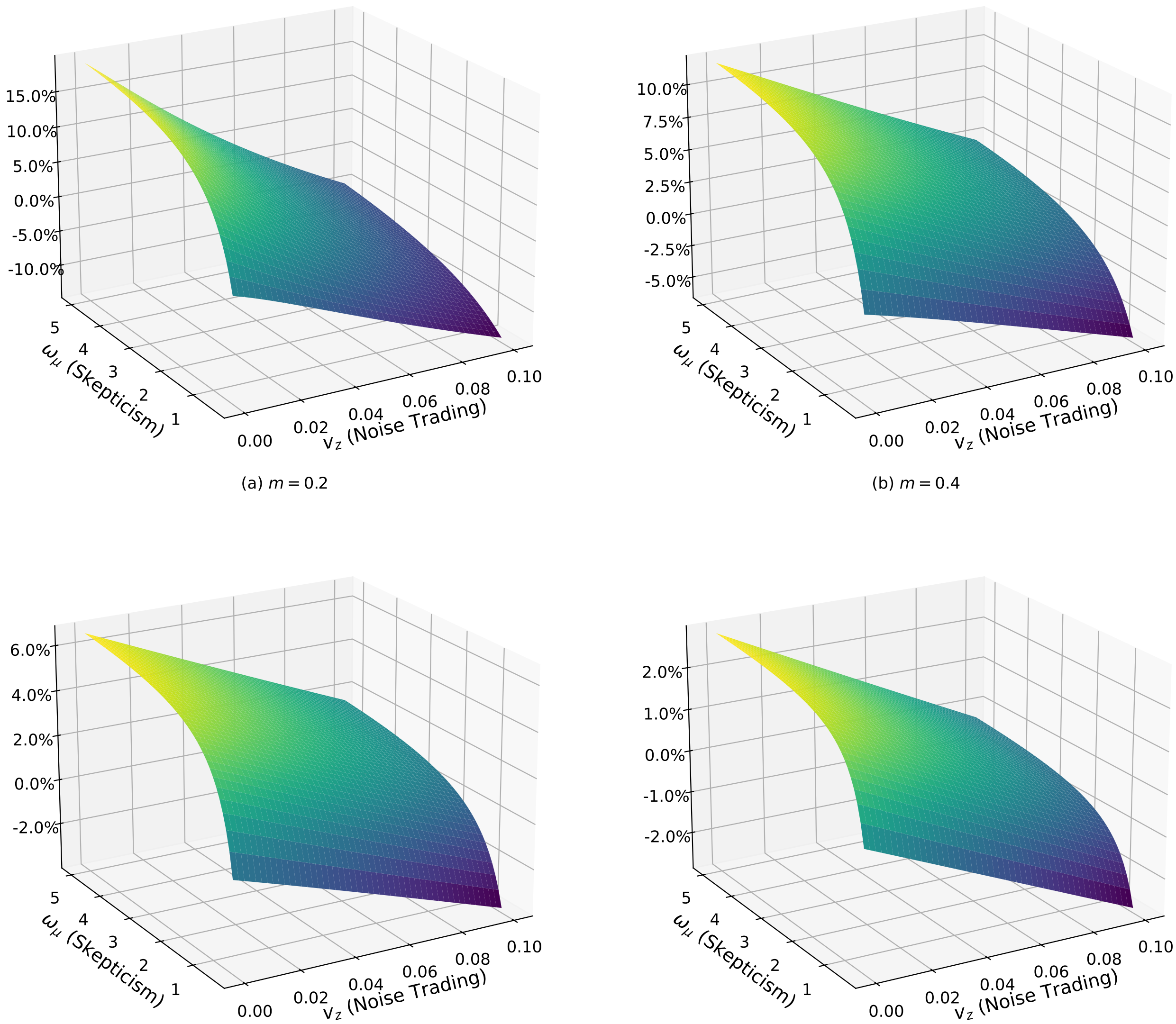


Figure 2: Momentum annual return as a function of skepticism and noise trading. This graph plots the momentum parameter $\overline{MOM}$ as a function of the parameters representing late-informed investors' skepticism about the precision of the early Date 1 information (κ_ϵ) and level of noise trading (ν_z). We assume the parameter values $m = 0.5$, $\lambda = 0.1$, $A = A_N = 2$, $\nu_\theta = 1$, $\nu_\mu = 0.4$, and $\nu_\epsilon = 0.3$.



(a) $m = 0.2$

(b) $m = 0.4$

(c) $m = 0.6$

(d) $m = 0.8$

Figure 3: Momentum annual return under different proportions of informed investor. This graph illustrate how the momentum parameter $\overline{MOM}$ varies with the level of informed investor participation. In each subplot, momentum parameter $\overline{MOM}$ is plotted as a function of the parameters representing late-informed investors' skepticism about the precision of the early Date 1 information (κ_ϵ) and level of noise trading (ν_z). We assume the parameter values $\lambda = 0.1$, $A = A_N = 2$, $\nu_\theta = 1$, $\nu_\mu = 0.4$, and $\nu_\epsilon = 0.3$.

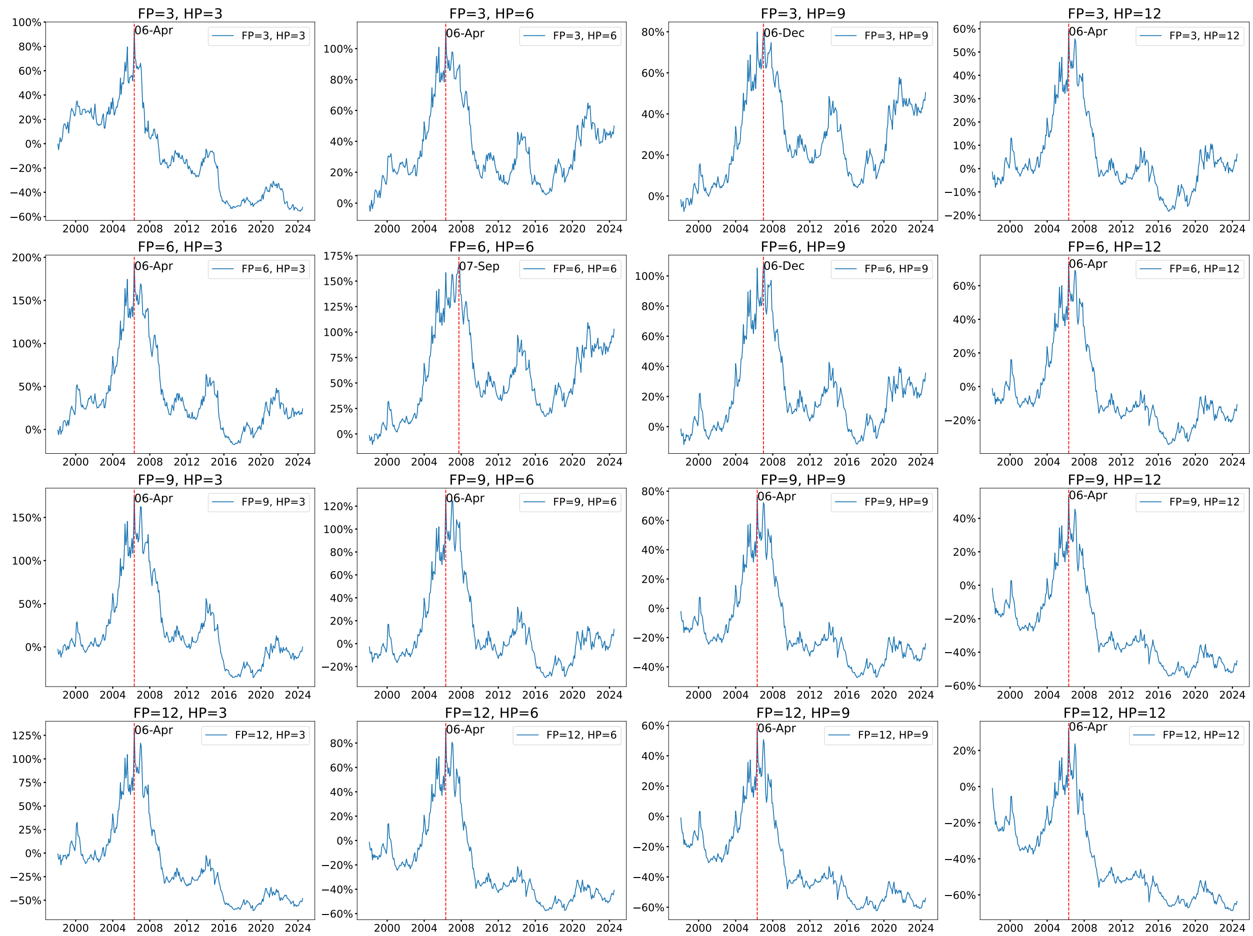


Figure 4: Cumulative return of momentum portfolios with different formation and holding periods. This figure displays the cumulative returns of momentum strategies in the China A-share stock market using various formation periods (FP) and holding periods (HP). Each subplot represents a different combination of formation and holding periods, with FP ranging from 3 to 12 months and HP ranging from 3 to 12 months. The cumulative returns are expressed as percentages, covering the sample period from January 1998 to June 2024. The red dashed line marks the month at which the cumulative return reaches its maximum over the entire period.

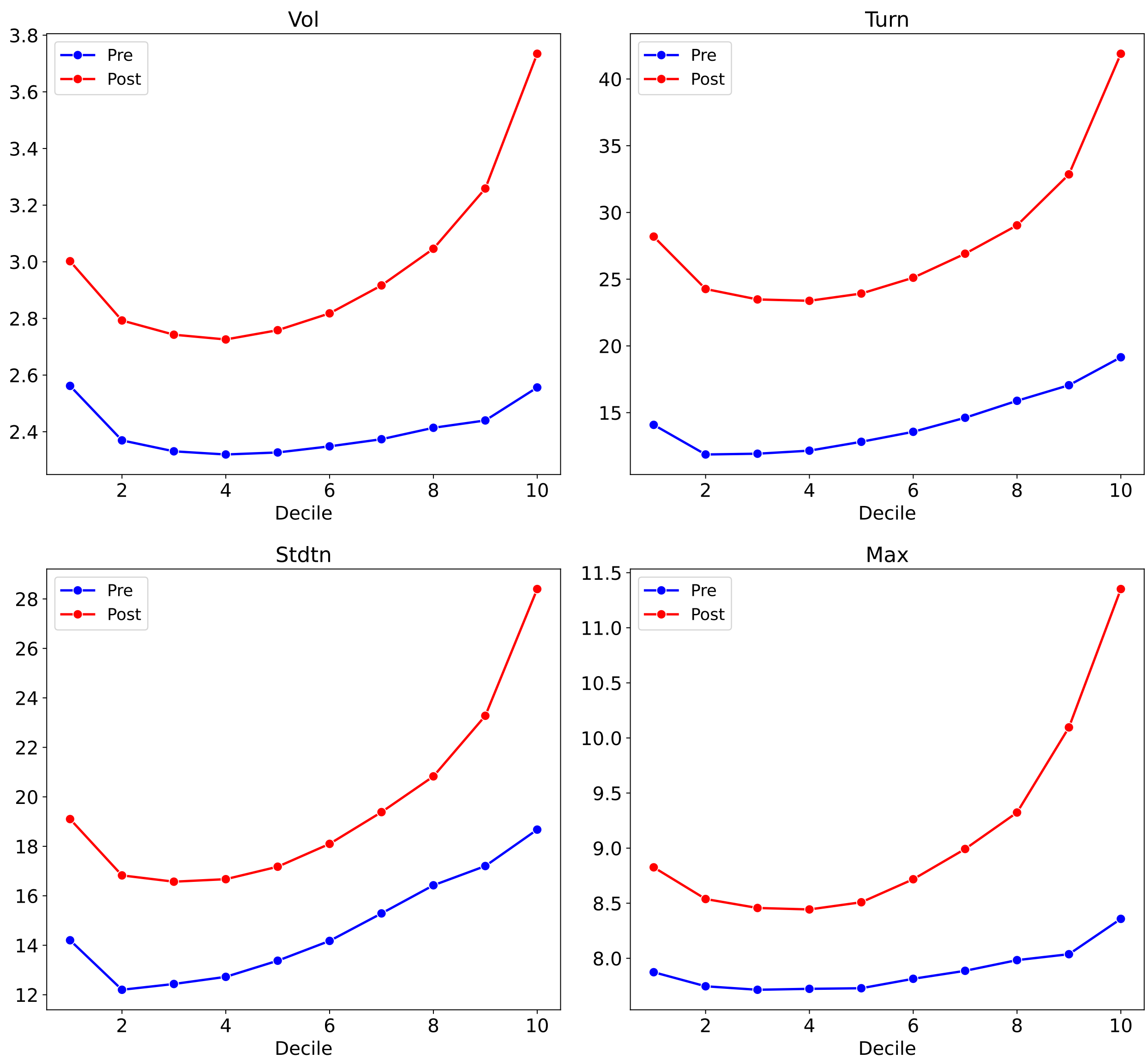


Figure 5: Stock trading characteristics before and after the split share structure reform. The figure presents four subplots comparing stock trading characteristics across momentum deciles, measured by cumulative monthly returns from $t-2$ to $t-7$, before (blue) and after (red) the split-share structure reform (SSSR). Each subplot reports a distinct measure based on daily data from $t-1$ month to $t-6$ months, requiring at least 60 trading days. The subplot labeled Vol shows overall volatility, measured as the standard deviation of daily returns. The subplot labeled $Turn$ presents the average daily turnover rate, while $StdTn$ captures its standard deviation. The subplot labeled Max reports the maximum daily return. All y-axis values are expressed in percentage terms.

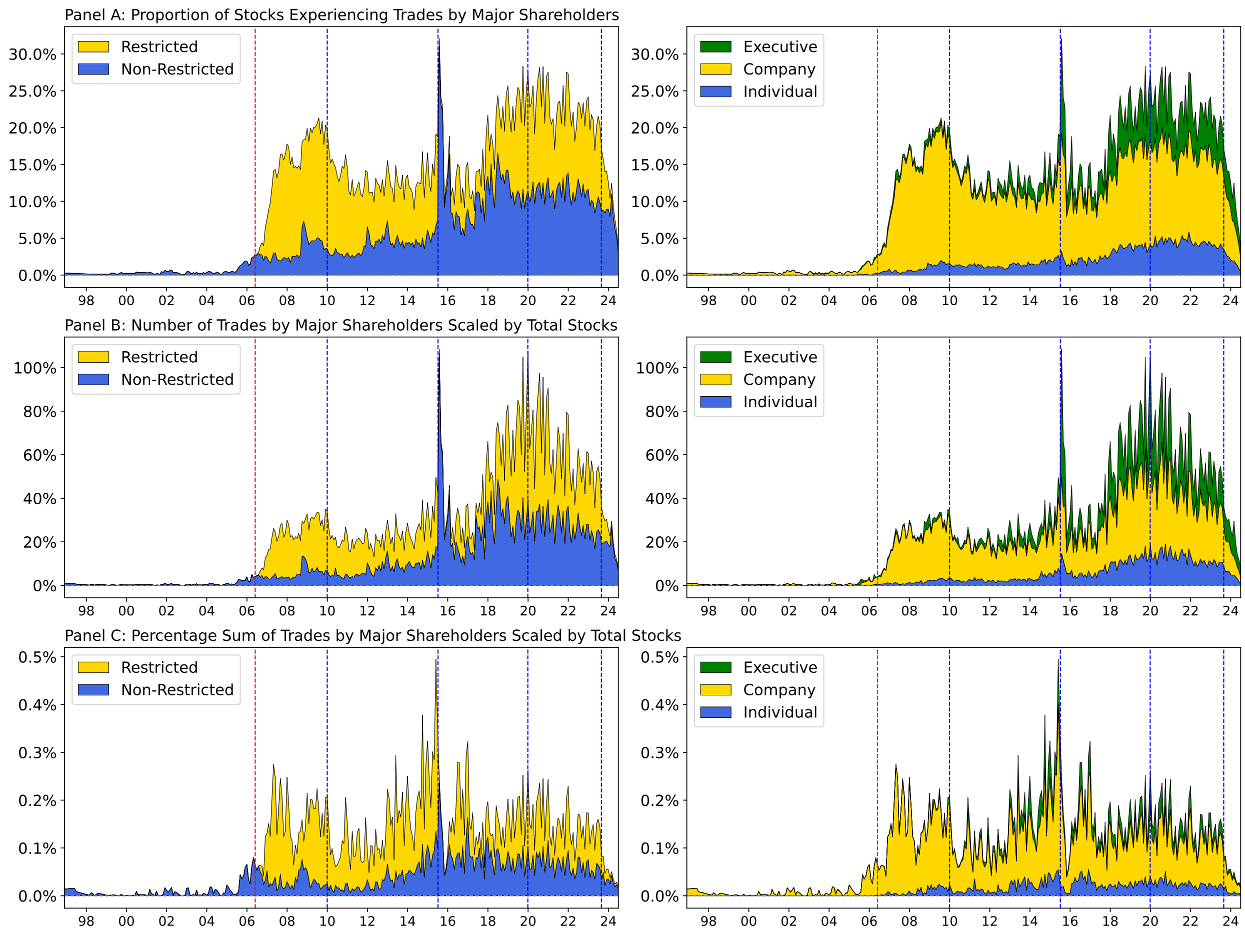


Figure 6: Trades by Major Shareholders Over Time. This figure shows the time series of major shareholder trades in the China A-share market from May 1997 to June 2024. The red vertical dashed line marks June 2006, when the full circulation of previously restricted shares officially began in both the Shanghai and Shenzhen stock markets. The blue vertical dashed lines indicate key event dates, after which trading activities experienced a notable decline for some time. Panel A presents the number of trades by major shareholders, scaled by the total number of stocks in the market. Panel B shows the proportion of stocks with trades, calculated as the number of stocks with trades divided by the total number of listed stocks. Panel C illustrates the percentage of shares traded by major shareholders, scaled by the total number of stocks.

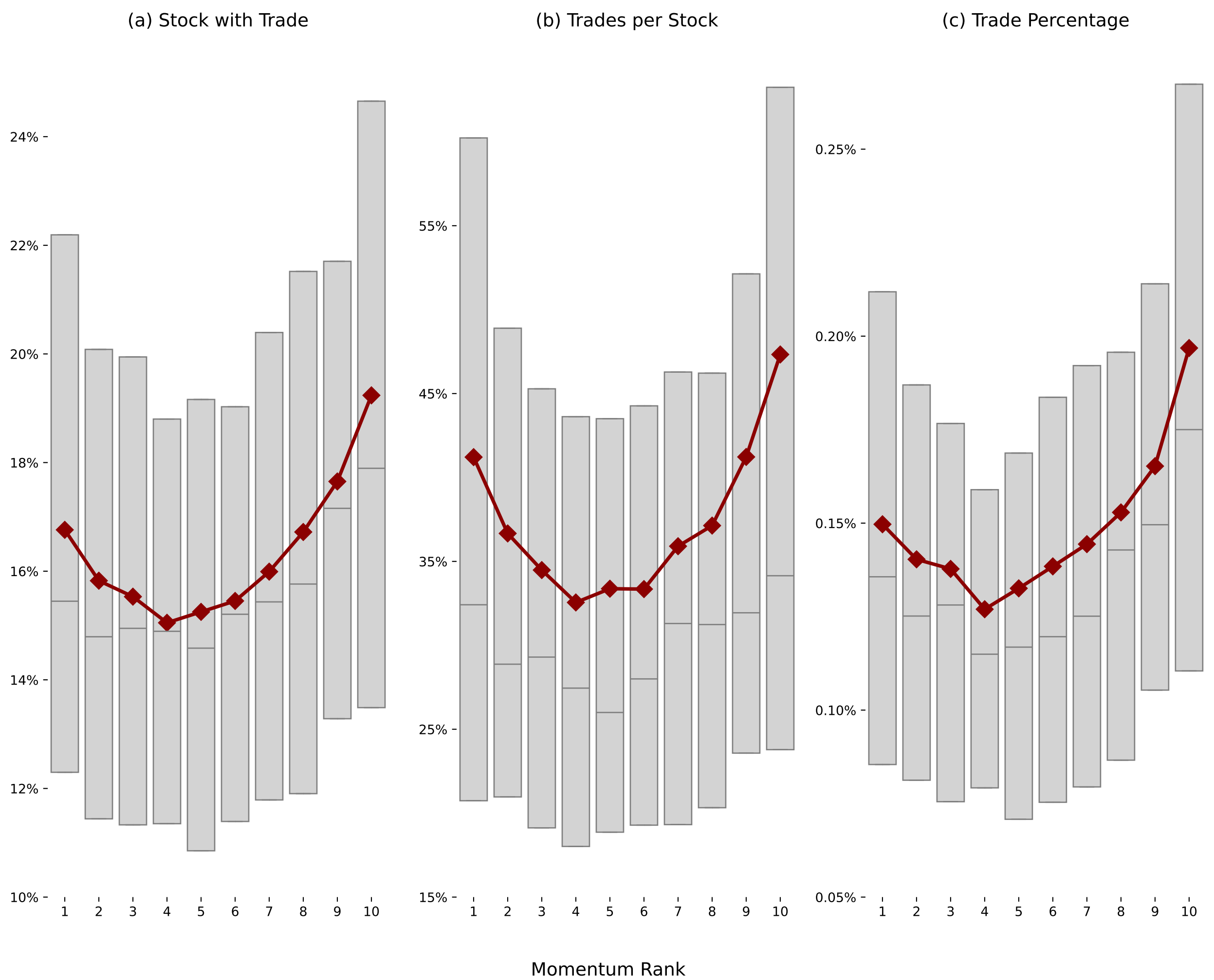


Figure 7: Major shareholder trades across past return-sorted portfolios. This figure presents box plots displaying major shareholder trading activity in portfolios sorted by past performance. The momentum rank is determined by sorting stocks into deciles based on their lagged six-month cumulative returns in ascending order. Panel (a) shows the proportion of stocks with trades, Panel (b) illustrates the average number of trades per stock, and Panel (c) depicts the percentage of shares traded. The red line in each panel represents the trend across different momentum ranks. The data covers major shareholder trades in the China A-share market from June 2006 to June 2024.

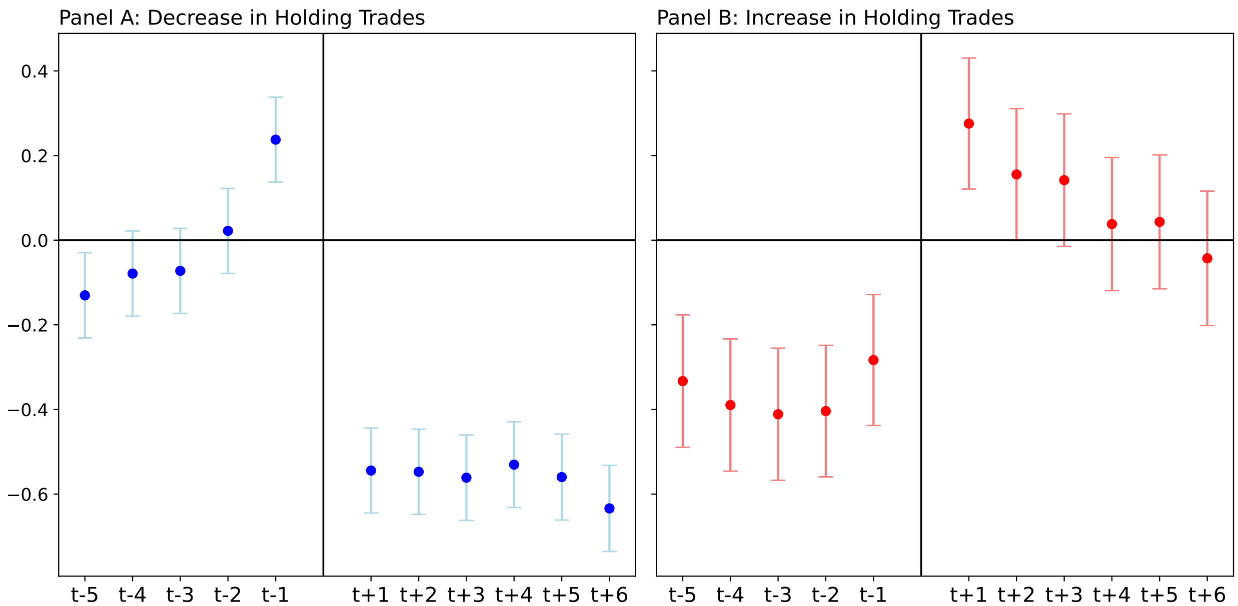


Figure 8: Event Study Results for Stock Returns Around Major Shareholder Trades. This figure presents the estimated coefficients from event studies examining the impact of major shareholder trades on stock returns in the China A-share market. The stock returns are analyzed using the following regression model:

$$Ret_{i,t} = \alpha + \sum_{k=-5}^{6} \beta_k \mathbf{1}(EventMonth_{i,t} = k) + \tau_t + \nu_i + \epsilon_{i,t},$$

where $\mathbf{1}(EventMonth_{i,t} = k)$ is an indicator variable for months relative to the trading event. $Ret_{i,t}$ represents the stock return of stock i in month t, measured in percentage terms. The left panel shows the results for trades involving a decrease in holdings, while the right panel presents the results for trades involving an increase in holdings. The horizontal axis represents event months, ranging from $t-5$ (five months before the event) to $t+6$ (six months after the event). Dots represent the point estimates of the coefficients, with vertical lines indicating the 95% confidence intervals. The regression uses monthly data from June 2006 to June 2024.

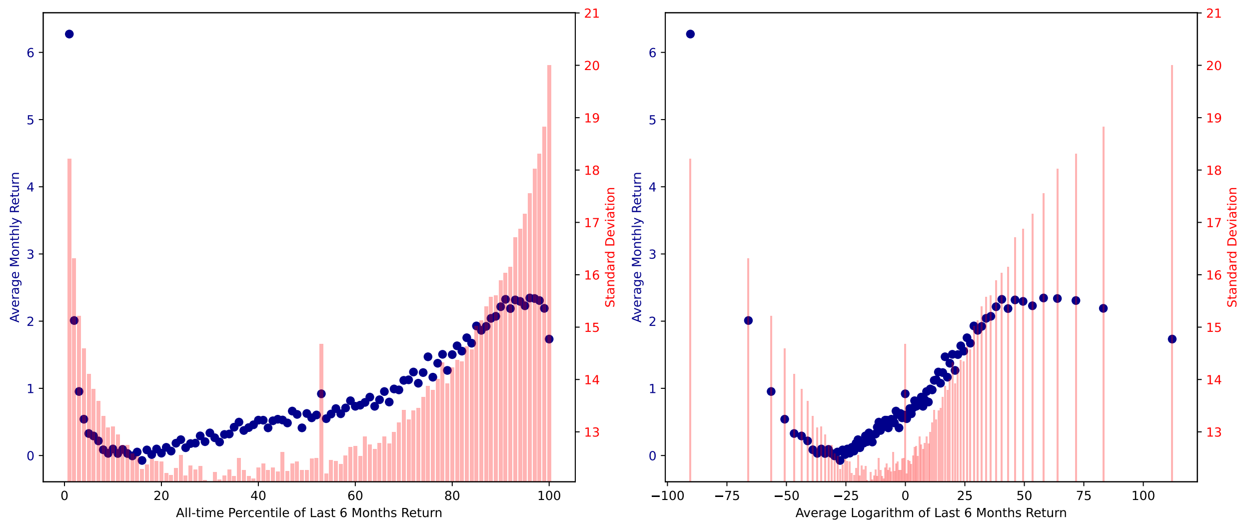


Figure 9: Absolute return strength and future Performance. The figure contains two panels that visualize the relationship between the average monthly returns over the next six months (y-axis) and the percentage rank of the cumulative returns over the past six months (x-axis), with a one-month gap between them. Both panels use dual y-axes to simultaneously display future average monthly returns and standard deviation. The left panel plots future average monthly returns against the all-time percentile of past six-month cumulative returns, with standard deviation represented by red bars. The right panel presents future average monthly returns as a function of the average logarithm of past six-month cumulative returns, alongside standard deviation values. All y-axis values are expressed in percentage terms.

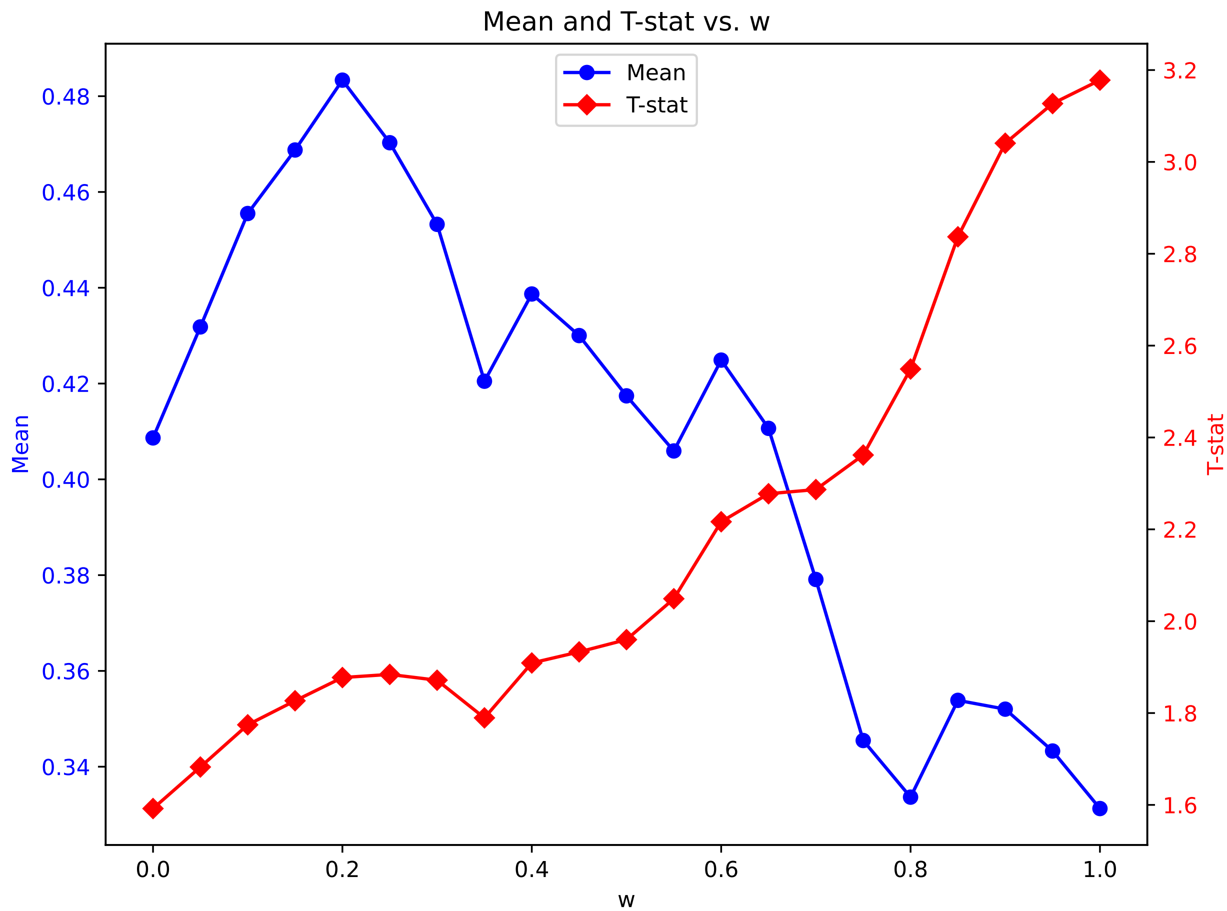


Figure 10: Portfolio Return with Different Influences of Institutional Ownership. The table reports the momentum portfolio return and t-value under varying degrees of institutional ownership influence, with stocks ranked according to the variable V defined by

$$V = (1-w)\frac{CR_i - \overline{CR_i}}{Std(CR_i)} + w \cdot \operatorname{sgn}(CR_i)\frac{IP_i - \overline{IP_i}}{Std(IP_i)}.$$

The coefficient w determines the relative importance of institutional ownership and past cumulative returns in the sorting process, ranging from 0 to 1. When $w = 0$, stocks are ranked purely by past cumulative returns, following a standard momentum strategy. When $w = 1$, stocks are first grouped by institutional ownership, and within each group, those with past cumulative returns below the average have their ranking variable multiplied by -1, leading them to the low decile selling groups. For values of w between 0 and 1, both past cumulative returns and institutional ownership jointly determine the ranking order. The function $\operatorname{sgn}(CR_i)$ adjusts the influence of institutional ownership based on the sign of past returns.

Table 1: Return of momentum portfolios. This table presents the mean returns and t-statistics of the winner and loser portfolios from January 1998 to June 2024. The portfolios are formed based on J-month lagged returns and held for K months, with the values of J and K specified in the first column and row, respectively. Stocks are ranked in ascending order based on J-month lagged returns, with an equally weighted portfolio of stocks in the lowest past return decile forming the loser portfolio, and an equally weighted portfolio of stocks in the highest return decile forming the winner portfolio. Panel A shows the portfolios formed immediately after the lagged returns are measured, while Panel B presents the portfolios formed with a one-month gap after the lagged returns are measured. The final row (W-L) presents the difference in returns between the winner and loser portfolios. The t-statistics, reported in parentheses, are adjusted using the Newey-West method with a lag of four.

		Panel A: 1-Month Gap					Panel B: Immediate Formation				
J	Port	K =	3	6	9	12	K =	3	6	9	12
3	Losers		1.07	0.91	0.94	1.01		1.43	1.09	1.04	1.05
			(1.71)	(1.51)	(1.57)	(1.68)		(2.24)	(1.79)	(1.73)	(1.74)
3	Winners		0.92	1.09	1.11	1.06		0.61	0.91	1.01	1.02
			(1.66)	(1.90)	(1.92)	(1.83)		(1.10)	(1.62)	(1.75)	(1.77)
3	W-L		-0.14	0.18	0.17	0.06		-0.82	-0.18	-0.03	-0.03
			(-0.62)	(1.04)	(1.11)	(0.40)		(-2.96)	(-0.88)	(-0.21)	(-0.20)
6	Losers		0.84	0.84	0.93	1.02		1.16	0.97	0.97	1.04
			(1.37)	(1.38)	(1.54)	(1.69)		(1.81)	(1.58)	(1.60)	(1.71)
6	Winners		1.03	1.15	1.11	1.05		0.79	1.01	1.06	1.02
			(1.81)	(1.99)	(1.91)	(1.82)		(1.40)	(1.77)	(1.84)	(1.77)
6	W-L		0.19	0.32	0.18	0.03		-0.38	0.04	0.09	-0.02
			(0.70)	(1.32)	(0.82)	(0.16)		(-1.16)	(0.16)	(0.37)	(-0.12)
9	Losers		0.94	0.94	1.03	1.09		1.14	1.00	1.05	1.10
			(1.51)	(1.55)	(1.69)	(1.81)		(1.80)	(1.62)	(1.72)	(1.80)
9	Winners		1.08	1.11	1.05	1.00		0.82	1.02	1.01	0.97
			(1.91)	(1.92)	(1.82)	(1.73)		(1.44)	(1.78)	(1.75)	(1.69)
9	W-L		0.14	0.16	0.02	-0.10		-0.32	0.02	-0.04	-0.12
			(0.49)	(0.60)	(0.08)	(-0.42)		(-0.97)	(0.07)	(-0.17)	(-0.52)
12	Losers		1.05	1.04	1.10	1.15		1.19	1.10	1.12	1.16
			(1.70)	(1.72)	(1.82)	(1.90)		(1.87)	(1.78)	(1.83)	(1.90)
12	Winners		1.00	1.02	0.98	0.94		0.90	0.97	0.97	0.94
			(1.75)	(1.76)	(1.69)	(1.63)		(1.57)	(1.69)	(1.67)	(1.63)
12	W-L		-0.04	-0.03	-0.12	-0.21		-0.29	-0.13	-0.15	-0.22
			(-0.14)	(-0.09)	(-0.45)	(-0.81)		(-0.85)	(-0.43)	(-0.54)	(-0.84)

Table 2: Returns of winner and loser portfolios in pre- and post-reform periods. This table presents the mean returns and t-statistics of the winner and loser portfolios during two periods: Pre-Reform, from January, 1998 to April, 2005, and Post-Reform, from January, 2008, when over 95% of listed companies completed the Split-Share Structure Reform, to June, 2024. The portfolios are formed based on 3, 6, 9, and 12-month formation (J) and holding (K) periods. The winner portfolios consist of stocks with the highest past returns, while the loser portfolios consist of stocks with the lowest past returns. The final row (W-L) presents the difference in returns between the winner and loser portfolios. The values in parentheses are t-statistics adjusted using Newey-West method with a lag of three.

		Panel A: Pre-Reform					Panel B: Post-Reform				
J	Port	K =	3	6	9	12	K =	3	6	9	12
3	Losers		-0.31	-0.42	-0.31	-0.25		0.72	0.57	0.58	0.63
			(-0.36)	(-0.50)	(-0.36)	(-0.29)		(0.98)	(0.80)	(0.82)	(0.90)
3	Winners		0.35	0.40	0.31	0.21		0.39	0.54	0.57	0.55
			(0.43)	(0.48)	(0.38)	(0.26)		(0.57)	(0.80)	(0.83)	(0.80)
3	W-L		0.66	0.82	0.62	0.46		-0.33	-0.02	-0.01	-0.08
			(1.93)	(2.39)	(2.05)	(1.67)		(-1.17)	(-0.11)	(-0.03)	(-0.50)
6	Losers		-0.58	-0.52	-0.41	-0.30		0.54	0.54	0.61	0.67
			(-0.68)	(-0.59)	(-0.45)	(-0.34)		(0.75)	(0.75)	(0.87)	(0.97)
6	Winners		0.66	0.58	0.40	0.29		0.39	0.54	0.54	0.51
			(0.78)	(0.70)	(0.50)	(0.36)		(0.57)	(0.78)	(0.77)	(0.73)
6	W-L		1.24	1.10	0.81	0.60		-0.16	0.00	-0.07	-0.16
			(2.34)	(2.20)	(1.81)	(1.46)		(-0.50)	(0.00)	(-0.28)	(-0.74)
9	Losers		-0.50	-0.44	-0.32	-0.24		0.65	0.64	0.70	0.76
			(-0.54)	(-0.48)	(-0.34)	(-0.26)		(0.90)	(0.91)	(1.01)	(1.10)
9	Winners		0.64	0.47	0.29	0.18		0.42	0.51	0.50	0.47
			(0.81)	(0.59)	(0.37)	(0.23)		(0.61)	(0.72)	(0.71)	(0.67)
9	W-L		1.15	0.91	0.61	0.42		-0.23	-0.14	-0.20	-0.28
			(2.04)	(1.70)	(1.23)	(0.90)		(-0.68)	(-0.44)	(-0.72)	(-1.09)
12	Losers		-0.39	-0.35	-0.24	-0.17		0.75	0.74	0.78	0.81
			(-0.42)	(-0.38)	(-0.26)	(-0.19)		(1.06)	(1.07)	(1.14)	(1.19)
12	Winners		0.55	0.36	0.21	0.07		0.37	0.45	0.44	0.46
			(0.68)	(0.45)	(0.27)	(0.09)		(0.54)	(0.64)	(0.63)	(0.65)
12	W-L		0.94	0.71	0.46	0.24		-0.37	-0.29	-0.34	-0.35
			(1.63)	(1.28)	(0.87)	(0.48)		(-1.06)	(-0.88)	(-1.09)	(-1.21)

Table 3: Alphas of the 6-6 momentum portfolios. This table reports the risk-adjusted returns (alphas) of the 6-6 momentum portfolios. Alphas are calculated as the intercepts from the market model (CAPM) and the Fama-French three-factor and five-factor regressions (FF3 and FF5). For ease of comparison, the "Raw" model presents the average raw portfolio returns. P1 represents the equal-weighted portfolio of the bottom 10% of stocks with the lowest past six-month returns, P2 includes the next 10%, and so on. The post-reform sample period is from January 2008 to June 2024, and the pre-reform period is from January 1998 to April 2005. The t-statistics in parentheses are adjusted using the Newey-West method with a lag of three.

	Momentum portfolios (P1 = losers, P10 = winners)											
Model	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	W-L	*t*-stat
Panel A: Post-Reform												
					Momentum portfolio returns							
Raw	-0.52	-0.07	0.06	0.16	0.25	0.27	0.31	0.29	0.35	0.58	1.10	(2.20)
					Momentum portfolio alphas							
CAPM	-0.38	0.07	0.20	0.29	0.39	0.40	0.44	0.43	0.49	0.71	1.09	(2.15)
FF3	-0.75	-0.31	-0.17	-0.02	0.08	0.08	0.18	0.27	0.43	0.86	1.61	(3.04)
FF5	-0.55	-0.17	-0.07	0.07	0.16	0.14	0.22	0.29	0.41	0.82	1.37	(2.80)
Panel B: Pre-Reform												
					Momentum portfolio returns							
Raw	0.54	0.78	0.92	0.99	0.97	1.00	0.96	0.87	0.75	0.54	0.00	(0.00)
					Momentum portfolio alphas							
CAPM	0.42	0.67	0.81	0.87	0.86	0.89	0.85	0.76	0.64	0.42	0.00	(0.02)
FF3	-0.29	-0.06	0.06	0.11	0.10	0.13	0.09	0.04	-0.04	-0.15	0.13	(0.53)
FF5	-0.18	0.05	0.16	0.21	0.18	0.21	0.16	0.08	-0.02	-0.15	0.03	(0.19)

Table 4: Enhanced momentum strategy post reform. The table summarizes the returns of momentum portfolios constructed by excluding stocks in the winners group corresponding to the top 10% to 50% of each trading characteristics each month. In the "None" row, no filtering is applied based on trading characteristics, but stocks are required to have trading characteristic data from the previous $t-1$ month. The highlighted cells indicate the momentum portfolio returns and values in parentheses represent standard errors. The columns denote the variables used for exclusion: Vol (overall volatility), $Turn$ (turnover), $Stdtn$ (standard deviation of turnover), Max (maximum daily return), and All (simultaneous exclusion based on all variables). All trading characteristic variables are calculated based on the daily returns of the previous $t-1$ month with at least 10 trading days of data for the calculation. T-values in parentheses are adjusted using the Newey-West method with a lag of three.

Filter	Port	Var =	Vol	Turn	Stdtn	Max	All
None	Losers		0.39	0.39	0.39	0.39	0.39
			(0.56)	(0.56)	(0.56)	(0.56)	(0.56)
None	Winners		0.61	0.61	0.61	0.61	0.61
			(0.92)	(0.92)	(0.92)	(0.92)	(0.92)
None	W-L		0.22	0.22	0.22	0.22	0.22
			(0.80)	(0.80)	(0.80)	(0.80)	(0.80)
10%	Losers		0.39	0.39	0.39	0.39	0.39
			(0.56)	(0.56)	(0.56)	(0.56)	(0.56)
10%	Winners		0.81	0.84	0.80	0.75	0.92
			(1.24)	(1.28)	(1.21)	(1.13)	(1.43)
10%	W-L		0.42	0.44	0.40	0.36	0.52
			(1.49)	(1.53)	(1.38)	(1.27)	(1.81)
20%	Losers		0.39	0.39	0.39	0.39	0.39
			(0.56)	(0.56)	(0.56)	(0.56)	(0.56)
20%	Winners		0.87	0.90	0.87	0.82	0.98
			(1.36)	(1.40)	(1.33)	(1.25)	(1.56)
20%	W-L		0.48	0.51	0.47	0.43	0.58
			(1.68)	(1.70)	(1.57)	(1.57)	(1.93)
30%	Losers		0.39	0.39	0.39	0.39	0.39
			(0.56)	(0.56)	(0.56)	(0.56)	(0.56)
30%	Winners		0.90	0.95	0.92	0.83	0.99
			(1.41)	(1.50)	(1.43)	(1.28)	(1.60)
30%	W-L		0.50	0.56	0.52	0.44	0.59
			(1.75)	(1.81)	(1.69)	(1.63)	(1.95)
40%	Losers		0.39	0.39	0.39	0.39	0.39
			(0.56)	(0.56)	(0.56)	(0.56)	(0.56)
40%	Winners		0.93	0.99	0.96	0.87	1.03
			(1.50)	(1.57)	(1.52)	(1.35)	(1.72)
40%	W-L		0.54	0.59	0.57	0.48	0.64
			(1.90)	(1.86)	(1.78)	(1.80)	(2.11)
50%	Losers		0.39	0.39	0.39	0.39	0.39
			(0.56)	(0.56)	(0.56)	(0.56)	(0.56)
50%	Winners		0.92	0.98	0.97	0.89	1.08
			(1.48)	(1.58)	(1.55)	(1.38)	(1.80)
50%	W-L		0.52	0.58	0.57	0.50	0.68
			(1.85)	(1.78)	(1.73)	(1.89)	(2.24)

Table 5: Diversified Actual Controllers and Their Metrics. This table lists the diversified actual controllers and their respective metrics. Controllers are considered diversified if, prior to the Split-Share Structure Reform, they controlled more than five listed companies.The metrics include the name of each controller, the number of listed firms under their control, the average size in billion yuan of these firms, and their average 36-month roling beta. All metrics are based on data from the end of April 2005, just before the Split-Share Structure Reform began.

Diversified Actual Controller Name	Number of Listed Firms Controlled	Average Size of Firms	Average Beta of Firms
SASAC of the State Council	148	1.30	1.14
SASAC of Shanghai City	52	0.85	1.06
SASAC of Beijing City	16	0.83	1.01
SASAC of Shenzhen City	15	0.98	1.17
SASAC of Shandong Province	12	0.95	0.95
SASAC of Hunan Province	11	0.54	1.07
SASAC of Anhui Province	10	0.84	1.18
SASAC of Yunnan Province	9	0.89	1.01
SASAC of Shanxi Province	9	1.55	1.00
SASAC of Jiangxi Province	9	0.42	1.31
SASAC of Liaoning Province	8	0.52	1.04
SASAC of Fujian Province	8	0.43	1.16
SASAC of Hebei Province	7	1.39	0.97
SASAC of Shenyang City	7	0.48	1.21
SASAC of Qingdao City	7	0.72	1.12
Tsinghua University	6	0.73	1.34
SASAC of Dalian City	6	0.45	1.14
SASAC of Shaanxi Province	6	0.30	1.23
SASAC of Tianjin City	6	1.00	1.05
SASAC of Ningxia Hui Autonomous Region	6	0.28	1.29
SASAC of Pudong New Area, Shanghai City	5	0.82	1.23
SASAC of Jilin City	5	0.45	1.17
SASAC of Jiangsu Province	5	0.40	1.15
Ministry of Education	5	0.52	1.38
SASAC of Mianyang City	5	0.97	1.02
China North Industries Group Corporation Limited	5	0.20	1.29
SASAC of Gansu Province	5	0.40	1.02
SASAC of Wuhan City	5	0.43	1.20
Total	398	19.63	1.14
Corrlation with Number of Listed Firms Controlled	/	0.53	-0.38
p-value	/	(0.004)	(0.047)

Table 6: Regression results of past and future returns across periods and controller structures. This table presents the results of the following pooled cross-sectional regression:

$$\overline{R}_{i,t+1:t+6} = \alpha_0 + \alpha_1 CR_{i,t-7:t-2} + \alpha_2 \log(Size) + \alpha_3 \beta_{i,t} + u_{i,t},$$

$\overline{R}_{i,t+1:t+6}$ represents the average return of stock i over the future six-month holding period from $t+1$ to $t+6$. $CR_{i,t-7:t-2}$ denotes the cumulative return of stock i over the formation period from $t-7$ to $t-2$. $\log(Size)$ is the natural logarithm of the market capitalization of stock i at time t. $\beta_{i,t}$ is the market beta estimated from daily returns over the past 12 months. $u_{i,t}$ is the regression error term. The coefficients and the standard error are estimated using the Fama–MacBeth method.

	Panel A: Pre-Reform		Panel B: Post-Reform	
Category	Diversified	Non-Diversified	Diversified	Non-Diversified
α_1 (CR)	0.0173	0.0094	-0.0058	0.0014
(t-stat.)	(6.73)	(4.22)	(-2.72)	(0.77)
α_2 ($\log(Size)$)	-0.0046	-0.0044	-0.0029	-0.0032
(t-stat.)	(-3.60)	(-3.60)	(-5.13)	(-5.14)
α_3 (β)	-0.0020	-0.0027	-0.0069	-0.0052
(t-stat.)	(-1.31)	(-2.80)	(-4.96)	(-4.93)
α_0 (const)	0.0972	0.0918	0.0771	0.0821
(t-stat.)	(3.60)	(3.51)	(5.59)	(5.44)
Observations	26,556	52,376	73,008	157,805
Adj R-Squared	0.1063	0.0788	0.0668	0.0570

Table 7: Momentum Portfolio returns across different subsamples and time periods. This table examines how momentum returns differ across time periods and subsamples. The portfolios are formed using a 6-6 long-short momentum strategy, where stocks are ranked by their lagged six-month cumulative returns, and the strategy involves buying winners and selling losers within each subsample. Subsamples are "All" (the full sample), "Div" (listed firms with diversified controllers before the Split Share Structure Reform, controlling more than five listed companies), and "Non-Div" (listed firms with non-diversified controllers before the Split Share Structure Reform). The panels report returns for three distinct time periods: before the Split-Share Structure Reform (January 1998 to April 2005), after the reform (January 2008 to June 2024), and over the entire sample period (January 1998 to June 2024). In Panel A and B, the t-values in parentheses are adjusted using the Newey-West method with a lag of three. In Panel C, the t-values are adjusted using the Newey-West method with a lag of four.

	Panel A: Pre-Reform			Panel B: Post-Reform			Panel C: Full Period		
Port	Div	All	Ndiv	Div	All	Ndiv	Div	All	Ndiv
Losers	-0.56	-0.52	-0.28	0.51	0.54	0.43	0.86	0.84	0.86
	(-0.64)	(-0.59)	(-0.33)	(0.73)	(0.75)	(0.63)	(1.43)	(1.38)	(1.46)
Winners	0.60	0.58	0.47	-0.02	0.54	0.45	0.86	1.15	1.05
	(0.75)	(0.70)	(0.57)	(-0.04)	(0.78)	(0.68)	(1.50)	(1.99)	(1.87)
W-L	1.16	1.10	0.75	-0.53	0.00	0.01	-0.01	0.32	0.19
	(2.27)	(2.20)	(1.59)	(-1.80)	(0.00)	(0.04)	(-0.02)	(1.32)	(0.79)

Table 8: Firm features of the momentum portfolio. This table presents characteristics of portfolios sorted by deciles based on cumulative returns over the lagged past six months. The first row categorizes the variables, including the sort variables and anomalies identified by Liu et al. (2019). The second row provides variable abbreviations: $Cmret$ is the cumulative return of the lagged six months, Pst represents the persistence of stocks, measured by the proportion of stocks that remain in the same momentum decile in the following month. EP is the earnings-to-price ratio, BM is the book-to-market ratio, CFP is the cash flow-to-price ratio, Vol is the one-month volatility, Max is the one-month maximum daily return, $Turn$ is the average daily turnover rate over 12 months with at least 120 days, $StdTn$ is the standard deviation of turnover over one month with at least 10 days, $Beta$ is the regression coefficient of daily excess returns on the market portfolio's excess returns over the past 12 months witn on less than 120 days, $Size$ is the market capitalization (in billion yuan), ROE is the return on equity, and $Lgret$ is the one-month return. The metrics are in percentages except for $Size$ (in billion yuan). Data are based on monthly observations from January 1998 to June 2024. The 'W-L' row reports the difference between the winner and loser portfolios, with t-statistics in parentheses adjusted using the Newey-West method of lag 4.

	Sort Statistics		Value			Volatility		Turnover		Beta	Size	Profit	Reversal
Port	Cmret	Pst	EP	BM	CFP	Vol	Max	Turn	StdTn	Beta	Size	ROE	Lgret
Losers	-25.95	55.20	-1.24	34.02	-0.51	2.84	5.84	29.21	13.25	1.12	6.13	3.46	1.91
P2	-14.49	28.51	1.01	41.55	-0.10	2.64	5.40	25.45	11.60	1.12	6.41	4.37	1.60
P3	-8.59	22.24	1.41	44.17	0.02	2.59	5.28	24.09	11.28	1.10	6.57	1.71	1.65
P4	-3.75	19.93	1.66	45.93	-0.04	2.56	5.20	23.34	11.26	1.10	6.64	2.14	1.53
P5	0.90	19.16	1.74	45.50	0.19	2.58	5.25	23.27	11.59	1.09	6.75	2.57	1.54
P6	5.87	19.43	1.87	45.15	0.05	2.62	5.30	23.62	11.89	1.08	7.02	1.91	1.44
P7	11.67	20.64	1.92	44.03	0.39	2.69	5.44	24.33	12.56	1.07	7.44	1.75	1.36
P8	19.25	23.66	1.96	41.99	0.23	2.76	5.56	25.37	13.08	1.07	8.39	2.85	1.15
P9	30.99	31.60	2.03	39.25	0.31	2.91	5.85	27.04	14.06	1.06	9.29	5.25	0.87
Winners	65.21	62.46	1.92	33.87	0.63	3.17	6.31	31.15	16.15	1.05	10.41	3.85	0.52
W-L	91.16	7.26	3.16	-0.16	1.04	0.33	0.47	1.95	2.89	-0.07	4.28	0.39	-1.39
	(19.90)	(11.51)	(5.66)	(-0.09)	(4.28)	(4.41)	(3.31)	(1.95)	(4.99)	(-4.24)	(3.31)	(0.18)	(-2.98)

Table 9: Semi-annual changes in institutional investor holdings across momentum-sorted stock groups. This table presents the semi-annual changes in institutional investor holdings in percentage, based on the holdings reported in semi-annual and annual reports. The rows represent stock groups sorted by one-month lagged six-month cumulative return, while the columns capture changes in holdings by different types of institutional investors. The columns include Insts (institutional investors), Fund (funds), SecFund (social security funds), QFII (qualified foreign institutional investors), Insurance (insurance companies), Entrust (trust companies), Broker (brokerage firms), Finance (financial companies), NonFin (non-financial listed companies), Other (other institutions), and Bank (banks). The row "W-L" represents the difference in holdings between the winner and loser momentum portfolios. The data covers the period from StartDate to 2024Q2. T-statistics shown in parentheses are adjusted using the Newey-West method with a lag of two.

	Insts	Fund	SecFund	QFII	Insurance	Entrust	Finance	Broker	NonFin	Other	Bank
Losers	-0.95	-1.82	-0.11	-0.17	-0.03	-0.28	-0.09	-0.13	-0.20	-0.58	0.11
P2	-0.21	-1.04	-0.12	-0.05	-0.01	-0.27	-0.07	-0.06	-0.33	-0.47	-0.15
P3	0.22	-0.60	-0.09	-0.15	-0.01	-0.18	-0.10	-0.11	-0.02	-0.58	-0.16
P4	0.42	-0.32	-0.04	-0.01	-0.09	-0.12	-0.05	-0.14	-0.13	-0.52	0.06
P5	0.62	-0.13	-0.05	-0.01	0.02	0.03	-0.09	-0.10	-0.24	-0.46	-0.18
P6	0.89	0.06	-0.00	0.20	-0.00	-0.03	-0.08	0.01	-0.16	-0.39	-0.34
P7	1.04	0.36	-0.04	-0.03	0.01	-0.13	-0.09	-0.01	-0.08	-0.56	0.12
P8	1.48	0.76	0.02	-0.04	0.07	-0.06	-0.12	-0.04	-0.16	-0.59	-0.35
P9	1.90	1.38	0.08	0.06	-0.12	-0.13	-0.05	-0.16	-0.30	-0.74	-0.53
Winners	2.85	2.66	0.13	0.05	0.05	-0.24	-0.09	-0.14	-0.54	-0.94	-0.73
W-L	3.80	4.48	0.23	0.22	0.09	0.04	0.00	-0.02	-0.33	-0.36	-0.84
	(9.61)	(8.32)	(2.20)	(1.59)	(1.22)	(0.33)	(0.09)	(-0.28)	(-2.27)	(-1.72)	(-1.98)
StartDate	1998Q4	1998Q4	2003Q4	2003Q4	2003Q4	2003Q4	2003Q4	2003Q4	2003Q4	2003Q4	2003Q4

Table 10: Momentum sorting conditional on institutional ownership. The table reports the returns and t-statistics from a conditional sorting procedure based on institutional ownership and cumulative returns. Stocks are first ranked in ascending order of institutional ownership and then grouped into quintile portfolios. Within each institutional ownership quintile, stocks are further ranked in ascending order of cumulative returns from the past 2 to 7 months and assigned to quintile portfolios, forming a total of 25 portfolios. The time series of equal-weighted monthly returns for a six-month holding period strategy is then computed. The row labeled "5-1" represents the return spread between the highest and lowest past return quintiles. Figures in brackets indicate t-statistics computed using Newey-West standard errors with four lags.

	Inst 1	Inst 2	Inst 3	Inst 4	Inst 5
Mom 1	1.16	0.90	1.05	0.91	0.66
Mom 2	1.35	1.17	1.27	1.31	0.94
Mom 3	1.47	1.21	1.36	1.38	1.10
Mom 4	1.39	1.18	1.44	1.40	1.30
Mom 5	1.18	1.09	1.23	1.40	1.29
Mom 5-1	0.02	0.20	0.18	0.49	0.63
	(0.09)	(1.02)	(0.91)	(2.21)	(2.17)

Appendix

A Proofs

Proof of Proposition 1: We solve for the equilibrium using backward induction.

Date 1: The ith informed investor observes γ. The investor believes that $\theta|\gamma \sim \mathcal{N}\left(\nu_\theta \nu_\gamma^{-1}\gamma, H(\nu_\theta,\nu_\gamma)^{-1}\right)$, where the function $H(\cdot)$ is defined in (2). Write the investor's wealth at Date 2 as $W_{i2} = W_{i1} + X_{i1}(\theta - P_1)$. The demand X_{i1} maximizes

$$E\left[U_N(W_{i2})|\gamma\right] = E\left[-\exp\left(-AW_{i1} - AX_{i1}(\theta - P_1)\right)|\gamma\right].$$

$$= -\exp\left[-AW_{i1} - AX_{i1}(\nu_\theta\nu_\gamma^{-1}\gamma - P_1) + 0.5A^2X_{i1}^2 H(\nu_\theta,\nu_\gamma)^{-1}\right], \tag{A1}$$

where the second equality is based on the normality assumption. The first-order condition (f.o.c.) with respect to (w.r.t.) X_{i1} implies that the demand can be expressed as:

$$X_{\eta 1} = A^{-1}H(\nu_\theta,\nu_\gamma)(\nu_\theta\nu_\gamma^{-1}\gamma - P_1). \tag{A2}$$

The second-order condition holds obviously in the previous case, and all other cases following, so we omit referencing it in the rest of the proofs.

We can use a similar analysis to show that the ith skeptical uninformed investor, who learns τ from price $P_1 = B\tau$ has the belief indicated by $\omega_\tau = \omega_\gamma + \delta^2\nu_z$, has the demand

$$X_{\ell 1} = A^{-1}H(\nu_\theta,\omega_\tau)(\nu_\theta\omega_\tau^{-1}\tau - P_1).$$

The ith rational uninformed investor, who also learns τ from price P_1 with rational belief $\nu_\tau = \nu_\gamma + \delta^2\nu_z$, and has the risk-aversion coefficient A_N, has the demand

$$X_{N1} = A_N^{-1}H(\nu_\theta,\nu_\tau)(\nu_\tau\nu_\tau^{-1}\tau - P_1).$$

The market-clearing condition, $z = mX_{\eta 1} + (1-m)X_{\ell 1} + \lambda_N X_{N1}$, implies that the parameters in price $P_1 = B(\gamma - \delta z)$ in (1), B and δ, is as specified in this proposition.

Date 0: Consider the ith early-informed investor's expected utility in Equation (A1). Substitute for the demand from Equation (A2) and the previously derived $P_1 = B\tau$, and write the wealth at Date 1 as $W_{i1} = \tilde{W}_{i0} + X_{i0}(P_1 - P_0)$. Then, we have

$$E\left[U_\eta(W_{i2})|\gamma\right] \propto -\exp\left(-AW_{i1}\right) = -\exp\left[-A\tilde{W}_{i0} - AX_{i0}(B\tau - P_0)\right],$$

where Σ is a positive definite matrix, which depends on exogenous parameters. The investor's belief is $\tau \sim \mathcal{N}(0, \tau)$. The demand X_{i0} maximizes

$$E\left[U_\eta(W_{i2})\right] = E\left[E\left[U_\eta(W_{i2})|\tau\right]\right] \propto -\exp\left[-A\tilde{W}_{i0} - AX_{i0}(-P_0) + 0.5(AX_{i0}B)^2\nu_\tau\right].$$

The f.o.c. w.r.t. X_{i0} implies that the demand is proportional to $-P_0$, that is, $X_{\eta 0} \propto -P_0$. We can use a similar derivation to show that the ith skeptical uninformed or rational uninformed investor's demand is also proportional to $-P_0$, that is, $X_{\ell 0}, X_{N0} \propto -P_0$. The market-clearing requirement, $0 = mX_{\eta 0} + (1-m)X_{\ell 0} + \lambda X_{N0}$, implies $P_0 = 0$.