Fund Flows and Stock Returns: Uncovering the Transmission Mechanisms

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Abstract. Fund flows, directly reflecting capital movements in financial markets, are central to asset pricing research on their relationship with stock returns. Existing studies have predominantly examined either their direct price pressure effect or indirect influences from isolated perspectives, such as behavioral finance or liquidity, lacking a systematic integration of multiple transmission channels. To address this gap, this paper develops a comprehensive "quadruple parallel mediation model" to fully unveil the complex mechanisms through which fund flows affect stock returns. Based on China's A-share market data from 2008 to 2024, this study employs a standardized empirical approach. First, a standardized fund flow measure is constructed following Bennett and Sias [1]. Second, intermediary variables: investor sentiment, market illiquidity, and stock price non-synchronicity are developed using text analysis and market microstructure data. Finally, a parallel multiple mediation model is established to simultaneously test both the direct effect of fund flows on stock returns and their transmission through three key indirect channels. The empirical findings reveal that: (1) Fund flows exhibit a robust positive contemporaneous total effect on stock returns. (2) Fund flows affect returns simultaneously through three parallel channels: boosting investor sentiment, inducing a liquidity premium, and promoting information incorporation. These multiple transmission mechanisms coexist. (3) The mechanisms show significant market state heterogeneity, with their modes of action dynamically changing across bull and bear markets. This study transcends single-theory explanations by integrating price pressure, investor sentiment, liquidity premium, and information hypotheses into one analytical framework, offering comprehensive empirical evidence for investors and regulators.

Keywords: Fund Flows, Stock Returns, Investor Sentiment, Market Liquidity, Stock Price Non-synchronicity.

1. Introduction

1.1. Research Background and Significance

With the rapid development of China's capital market, stock funds flow has become a core element affecting market operations. Traditional financial theories, based on the Efficient Market Hypothesis, often view fund flows merely as neutral carriers of information. However, the rise of behavioral finance and market microstructure theory suggests that fund flows can independently impact asset prices through multiple channels [2]. In emerging markets like China, characterized by a high proportion of retail investors and evolving mechanisms, the impact of fund flows on stock returns may differ significantly from mature markets. Phenomena such as the 2015 market volatility and recent fluctuations highlight the urgency of understanding these mechanisms.

Despite extensive research, current literature remains fragmented. Most studies focus on a single theoretical perspective—either price pressure [1], investor sentiment [3], liquidity premium [4], or information asymmetry [5]—lacking a systematic integration of these parallel pathways. This "fragmented" view limits a comprehensive understanding of how fund flows drive stock returns. Therefore, this study aims to construct a unified "quadruple parallel mediation model" to systematically examine the direct price pressure effect and three indirect channels: investor sentiment, market liquidity, and information efficiency (proxied by stock price non-synchronicity).

Theoretical contributions of this study include: (1) Integrating four major theoretical hypotheses into a single analytical framework, overcoming the limitations of isolated mechanism tests. (2)

Providing systematic empirical evidence on the applicability of these theories in China's specific market context. (3) Methodologically applying a parallel multiple mediation model to precisely decompose total effects and quantify the relative importance of each path. Practically, the findings offer valuable references for investors to interpret fund signals, for listed companies to manage investor relations, and for regulators to design counter-cyclical policies.

1.2. Research Framework and Innovations

This study follows a "theoretical construction - empirical testing - conclusion" paradigm. The core innovation lies in the theoretical framework: shifting from single-mechanism testing to a systematic integration of multiple parallel mechanisms. Unlike previous studies that isolate factors, we simultaneously test the direct effect (Price Pressure Hypothesis) and three indirect paths:

Path B (Sentiment): Fund flows → Investor Sentiment → Returns.

Path C (Liquidity): Fund flows → Market Illiquidity → Returns.

Path D (Information): Fund flows → Stock Price Non-synchronicity → Returns.

Furthermore, this study adapts methodologies to the emerging market context by incorporating multidimensional heterogeneity analyses (bull vs. bear markets, different board listings) to reveal the dynamic nature of these mechanisms.

2. Literature Review

2.1. Fund Flows and Stock Returns: The Direct Effect

The foundational relationship between fund flows and returns was established by Bennett and Sias [1], who demonstrated a significant positive correlation between standardized fund flows and contemporaneous returns, supporting the Price Pressure Hypothesis. This hypothesis posits that in friction-filled markets, net buy orders create immediate demand shocks, directly pushing up prices. Subsequent studies using high-frequency data have reinforced this view. Campbell et al. [6] utilized tape data to capture institutional trading impacts, providing micro-level evidence of direct price pressure. In the Chinese context, Hou et al. [7] confirmed this positive relationship in the A-share market. Recent research by Yang [8] further noted that while price pressure dominates in certain periods, its explanatory power may shift depending on market conditions, suggesting the need for a more integrated view.

2.2. The Investor Sentiment Channel

The Investor Sentiment Hypothesis, rooted in behavioral finance, argues that fund flows act as strong market signals that amplify optimism or pessimism. Baker and Wurgler [9] pioneered the quantification of sentiment, showing its cross-sectional impact on returns. In China, Wang [10] used fund net inflows as a proxy for sentiment, finding a significant link to market volatility. More recently, advances in text analysis have refined sentiment measurement. Wan et al. [11] employed machine learning on social media text, confirming that investor sentiment is a critical factor predicting securities returns. Crucially, Yang [8] observed that post-financial crisis, the impact of ETF fund flows on returns shifted to be dominated by the sentiment channel, highlighting its role as a key mediator that varies with market states.

2.3. The Liquidity Premium Channel

The Liquidity Premium Theory, formalized by Acharya and Pedersen [4], posits that investors require higher expected returns for holding fewer liquid assets. Fund flows, particularly large concentrated ones, can shock market liquidity. Admati and Pfleiderer [12] theoretically showed how trading patterns affect liquidity depth. Empirical studies in China, such as Pan et al. [13], verified the correlation between asset liquidity and stock liquidity. While direct evidence linking fund flows to returns via liquidity is less common, the theoretical logic is robust: large inflows consume order book depth, potentially worsening liquidity (increasing illiquidity), which in turn demands a higher risk premium, affecting prices. Recent high-frequency studies by Ma et al. [14] provide tools to precisely measure these instantaneous liquidity shocks.

2.4. The Information Hypothesis and Price Non-synchronicity

The Information Hypothesis challenges the notion of fully efficient markets, suggesting that trades incorporate private information. Grossman and Stiglitz [15] argued that prices cannot fully reflect all information if acquiring it is costly. Stock price non-synchronicity (R^2 from market/industry models) is widely used as a proxy for firm-specific information content [16]. Higher non-synchronicity implies more firm-specific information is incorporated into prices. Shen et al. [17] found evidence of informed trading in institutional fund flows in China, suggesting that fund flows carry private information. As this information is incorporated via trading, it increases price non-synchronicity, leading to price adjustments and return variations. This establishes the logical chain: Fund Flows → Information Incorporation (Non-synchronicity) → Returns.

2.5. Summary and Research Gap

While existing literature has extensively explored each of these four perspectives individually, a significant gap remains: the lack of a unified framework to test them simultaneously. Most studies adopt a "divide and conquer" strategy, isolating one mechanism and ignoring the potential coexistence and interaction of others. It remains unclear whether these paths are substitutes or complements, and what their relative importance is in the Chinese market. Furthermore, the dynamic nature of these mechanisms across different market states (bull vs. bear) has not been sufficiently quantified within a single model. This study addresses these gaps by constructing a quadruple parallel mediation model to systematically disentangle these complex transmission channels.

3. Theoretical Analysis and Research Hypotheses

This chapter constructs a comprehensive theoretical framework, the "Quadruple Parallel Mediation Model," to systematically analyze how fund flows affect stock returns. It integrates four major theoretical perspectives: the Price Pressure Hypothesis (direct effect), and three indirect channels via Investor Sentiment, Liquidity Premium, and Information Efficiency.

3.1. Direct Effect: The Price Pressure Hypothesis

The Price Pressure Hypothesis, rooted in market microstructure theory, posits that in friction-filled markets, trading order flows themselves exert direct, instantaneous impacts on asset prices. When net buy orders surge within a short period, the market cannot immediately match them with sufficient sell orders due to limited depth. To execute trades, buyers must bid higher prices, directly pushing stock prices up; conversely, massive sell orders depress prices.

In this study, the standardized fund flow (FLOW) quantifies this net buying pressure. According to the law of supply and demand, sustained capital inflows represent strong excess demand, creating an upward force on stock prices that manifests as increased contemporaneous returns. Bennett and Sias [1] provided foundational empirical evidence for this mechanism, demonstrating a significant positive correlation between standardized fund flows and contemporaneous returns. Based on this theoretical logic and empirical precedence, we propose the first hypothesis:

H1: Fund flows have a significant positive direct effect on stock returns; specifically, net capital inflows directly boost contemporaneous stock returns.

3.2. Indirect Transmission Mechanisms

Beyond the direct price impact, fund flows may influence returns through three parallel indirect channels: investor sentiment, market liquidity, and information efficiency.

3.2.1. The Investor Sentiment Channel

The Investor Sentiment Hypothesis, derived from behavioral finance, argues that investors are not fully rational and are susceptible to systematic cognitive biases. Large-scale fund inflows act as strong market signals that can ignite and amplify market optimism through attention effects and herding behavior. This heightened sentiment (represented by our composite sentiment index, S) encourages excessive confidence and risk-taking, generating additional buying demand unrelated to fundamentals, thereby exerting a second-round upward pressure on prices.

Empirical studies, such as Wang [10] and Yang [8], suggest that fund flows can serve as proxies for sentiment or trigger sentiment shifts that dominate return variations in specific market phases. Thus, fund flows may partially affect returns by stimulating investor sentiment. This leads to the second hypothesis:

H2: Fund flows affect stock returns through the mediator of investor sentiment. Specifically, capital inflows boost investor sentiment, which in turn drives stock returns upward.

3.2.2. The Liquidity Premium Channel

The Liquidity Premium Theory asserts that liquidity is a priced factor; investors demand higher expected returns for holding fewer liquid assets as compensation for higher transaction costs and risk. Significant fund flows, particularly large concentrated trades, can shock market micro-liquidity. While intuition suggests large buys might consume liquidity, in emerging markets like China, substantial net inflows often attract follow-on trading and enhance order book depth, temporarily improving liquidity (reducing illiquidity). Conversely, outflows may degrade it.

According to Acharya and Pedersen [4], changes in liquidity conditions alter the required rate of return. If fund flows induce changes in market illiquidity (ILLIQ), investors will adjust their valuation based on the new liquidity risk premium. Pan et al. [13] confirmed the linkage between asset trading activities and stock liquidity in China. Therefore, fund flows may influence returns by altering the liquidity environment, leading to the third hypothesis:

H3: Fund flows affect stock returns through the mediator of market illiquidity. Capital flows alter market liquidity conditions, which subsequently impacts stock returns via the liquidity premium mechanism.

3.2.3. The Information Efficiency Channel

The Information Hypothesis challenges the notion of fully efficient markets, suggesting that trades incorporate private information. Informed traders execute transactions based on superior information about firm-specific fundamentals. As these trades (fund flows) occur, private information is gradually incorporated into stock prices. This process increases the proportion of firm-specific information in price movements, reducing synchronicity with the market.

Stock price non-synchronicity (NonSyn) is widely used as a proxy for firm-specific information incorporated into prices. Shen et al. [17] found evidence of informed trading in institutional fund flows in China. As information is absorbed, prices adjust towards intrinsic value, resulting in return variations. Thus, fund flows may affect returns by enhancing information efficiency, leading to the fourth hypothesis:

H4: Fund flows affect stock returns through the mediator of stock price non-synchronicity. Capital flows promote the incorporation of private information into prices (increasing non-synchronicity), which subsequently influences stock returns.

3.3. Summary of Theoretical Framework

The four hypotheses above are not mutually exclusive but likely coexist. Fund flows impact stock returns through a complex network comprising one direct path (Price Pressure) and three parallel indirect paths (Sentiment, Liquidity, and Information). Figure 3.1 (to be inserted by author) illustrates this "Quadruple Parallel Mediation Model," which serves as the foundation for the empirical design in the next chapter.

4. Research Design

This chapter details the empirical strategy used to test the theoretical hypotheses proposed in Chapter 3. It covers data sources, variable construction, and the specification of the econometric models.

4.1. Data and Sample Selection

The study utilizes monthly panel data for A-share listed companies in Shanghai and Shenzhen from January 2008 to December 2024. The sample selection follows standard screening procedures:

Exclusion of Financial Firms: Due to distinct accounting standards and regulatory frameworks.

Exclusion of ST/PT Stocks: To avoid distortions from firms facing delisting risks or abnormal financial conditions.

Data Availability: Firms with missing key financial or trading data are excluded.

After screening, the final dataset comprises over 220,000 firm-month observations. Data are sourced from the CSMAR and RESSET databases. Daily trading data are aggregated to construct monthly variables, while firm-specific characteristics are obtained from quarterly or annual financial reports. All continuous variables are minorized at the 1% and 99% levels to mitigate the influence of outliers.

4.2. Variable Definitions

4.2.1. Dependent Variable: Stock Returns (R)

The dependent variable is the monthly log return of stock i in month t, calculated as:

$$R_{i,t} = 100 * \left[\ln\left(P_{i,t}\right) - \ln\left(P_{i,t-1}\right)\right]$$

Where Pit is the adjusted closing price at the end of month t. Using log returns ensures the variable approximates a normal distribution and facilitates economic interpretation as percentage changes.

4.2.2. Independent Variable: Standardized Fund Flow (FLOW)

To capture net buying pressure independent of firm size, we construct a standardized fund flow indicator following Bennett and Sias [1]. The daily flow is calculated based on the deviation of the closing price from the daily average price (proxied by high-low average), scaled by circulating market value. These daily values are summed to obtain the monthly $FLOW_{\mathrm{i,t}}$, A positive value indicates net buying pressure.

4.2.3. Mediating Variables

Three mediators are constructed to test the indirect channels:

Investor Sentiment (S): A composite index constructed using Principal Component Analysis (PCA) on three proxies: Turnover Rate (Turnover), Past Returns (Past_Ret, excluding the most recent day to avoid reversal effects), and Return Volatility (Volatility). The first principal component captures the common variance representing sentiment.

Market Illiquidity (ILLIQ): Measured using the Amihud ratio, defined as the average daily absolute return divided by daily trading volume (in monetary terms) over the month. Higher values indicate lower liquidity (higher illiquidity). This method aligns with the liquidity risk framework discussed by Acharya and Pedersen [4].

Stock Price Non-synchronicity (NonSyn): Calculated based on the R2 from a regression of individual stock returns on market and industry returns. Following Roll [19], we compute $NonSyn = \ln\left[\left(1 - R^2\right)/R^2\right]$. Higher values indicate more firm-specific information is incorporated into the price. This specific transformation is critical for normalizing the bounded R2 variable for regression analysis.

4.2.4. Control Variables

To isolate the effect of fund flows, we control for key firm characteristics known to affect returns:

Market Beta (Beta): Systematic risk measure.
Firm Size (Size): Natural logarithm of circulating market capitalization.
Book-to-Market Ratio (BM): Proxy for value vs. growth style.
Return on Equity (ROE): Measure of profitability.

4.3. Econometric Models

To test the hypotheses, we employ a sequential mediation analysis framework.

4.3.1. Baseline Model (Total Effect)

To test H1 (Price Pressure), we estimate the total effect of fund flows on returns:

$$R_{i,t} = \alpha + c \cdot FLOW_{i,t} + \sum \beta_k \cdot controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (1)$$

Where μ_i and λ_t represent firm and time fixed effects, respectively. A significant positive c supports H1.

4.3.2. Mediation Mechanism Tests

Following the procedure by Wen et al. [20], we test the three indirect paths. For each mediator M (where M∈ {S, ILLIQ, NonSyn}), two steps are estimated:
Effect of Flow on Mediator:

$$M_{i,t} = \alpha + a \cdot FLOW_{i,t} + \sum \beta_k \cdot controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (2)$$

Effect of Mediator on Returns (controlling for Flow):

$$R_{i,t} = \alpha + c' \cdot FLOW_{i,t} + b \cdot M_{i,t} + \sum \beta_k \cdot controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (3)$$

A significant indirect effect exists if both coefficients a and b are statistically significant. This procedure is applied separately for Sentiment (H2), Illiquidity (H3), and non-synchronicity (H4).

4.3.3. Full Parallel Mediation Model

To verify the coexistence of all mechanisms, we include all three mediators simultaneously:

$$R_{i,t} = \alpha + c'' \cdot FLOW_{i,t} + b_1 \cdot S_{i,t} + b_2 \cdot ILLIQ_{i,t} + b_3 \cdot NonSyn_{i,t} + \sum \beta_k \cdot controls_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \quad (4)$$

In this model, c'' represents the direct effect after accounting for all indirect channels. Significant coefficients for b1, b2, and b3 would confirm that multiple transmission mechanisms operate in parallel.

4.4. Summary

This chapter has established a rigorous empirical design to dissect the impact of fund flows. By defining precise variables for direct pressure, sentiment, liquidity, and information, and specifying a robust set of fixed-effect panel models, we are prepared to empirically validate the "Quadruple Parallel Mediation Model" proposed in Chapter 3. The subsequent chapters will present the descriptive statistics, baseline results, and detailed mechanism tests.

5. Empirical Results and Analysis

This chapter presents the empirical findings regarding the total effect of standardized fund flows on stock returns in China’s A-share market. Following the research design outlined in Chapter 4, we proceed from descriptive statistics and correlation analysis to baseline regressions, addressing potential endogeneity concerns, and conducting comprehensive robustness checks across different market states and firm characteristics. These analyses establish the foundational evidence for the price pressure hypothesis (H1) before exploring the specific transmission mechanisms in Chapter 6.

5.1. Descriptive Statistics

Table 1 reports the descriptive statistics for the core variables used in this study, based on a monthly panel dataset spanning from 2008 to 2024. The sample comprises 220,342 valid observations after filtering for financial firms, ST stocks, and missing data. The dependent variable, monthly stock return (R), exhibits a mean of 0.256% with a substantial standard deviation of 13.633%, reflecting the characteristic volatility of the emerging Chinese market. The median return is slightly negative (-0.190%), indicating a skewed distribution where extreme positive returns drive the mean upward.

The core independent variable, standardized fund flow (FLOW), has a mean of 0.081 and a standard deviation of 1.011, suggesting that while there is a slight net buying pressure on average over the long term, individual stocks experience significant variations in capital inflows and outflows. Regarding the mediating variables, the investor sentiment index (S) shows a mean of -0.119, implying a generally cautious market sentiment during the sample period, though with considerable dispersion (SD = 1.027). The market illiquidity measure (ILLIQ) is positively skewed with a mean of 0.00044, consistent with typical liquidity distributions where most observations cluster near zero but some exhibit high illiquidity. Stock price non-synchronicity (NonSyn) averages 0.864, indicating that a significant portion of stock price variation is driven by firm-specific information rather than market-wide factors. Control variables such as firm size (Size), beta (Beta), book-to-market ratio (BM), and return on equity (ROE) display expected distributions, though ROE shows extreme values ranging from -2586 to 6405, necessitating winsorization in subsequent regressions.

Table 1. Descriptive Statistics of Main Variables

	Obs	Mean	Std. Dev	Median	Min	Max
R	220342	0.256096	13.63279	-0.19018	-203.256	262.1199
FLOW	220342	0.081119	1.010529	0.008852	-5.26121	5.779141
Size	220342	15.29895	1.055009	15.15594	12.12903	21.04989
Beta	220342	1.057409	0.541472	1.0359	-14.9576	14.1748
ROE	220342	1.740583	48.15808	2.7834	-2586.32	6405.638
BM	220342	0.424128	0.340581	0.357143	-6.25	14.28571
ILLIQ	220341	0.000437	0.000636	0.000272	1.40E-05	0.008818
NonSyn	220080	0.864342	0.975667	0.747497	-0.9503	4.840232
S	220334	-0.11946	1.027029	-0.36912	-1.7597	4.46107

To further understand the temporal dynamics of these variables, Table 2 presents the yearly means. The data reveals distinct cyclical patterns: both stock returns and fund flows peaked in 2009 and 2015, aligning with known bull market periods characterized by loose monetary policy and high optimism. Conversely, fund flows turned negative in several years post-2021, coinciding with lower average returns, which visually supports the notion of a positive relationship between capital inflows and performance. Investor sentiment mirrors these cycles, turning significantly positive during boom years (2009, 2015) and negative during downturns (2011-2014, 2018). Notably, market illiquidity spiked during the 2015-2017 period, capturing the liquidity crunch associated with the market crash, while stock price non-synchronicity surged after 2021, suggesting a structural shift towards more idiosyncratic pricing in recent years.

Table 2. Yearly Descriptive Statistics of Core Variables

Year	R	FLOW	S	ILLIQ	NonSyn	Size
2008	0.0029	0.0554	0.549	0.0035	1.0865	20.8899
2009	0.0068	0.15	0.9658	0.0005	0.8537	21.1437
2010	0.0026	0.0788	0.4312	0.0005	1.0662	21.2459
2011	-0.0013	0.0238	-0.3955	0.001	0.5268	21.3288
2012	0.0003	0.0401	-0.2605	0.0014	0.3227	21.3673
2013	0.0018	0.0763	-0.0927	0.0009	0.6778	21.4891
2014	0.0021	0.0535	-0.1055	0.0012	0.9903	21.6561
2015	0.0054	0.1533	0.7443	0.0078	0.1319	21.7533
2016	0.001	0.0385	-0.0644	0.0097	0.0484	21.8805
2017	0.0006	0.0088	-0.2354	0.0098	1.4046	21.8299
2018	-0.0011	0.0096	-0.329	0.0013	0.615	21.8564
2019	0.0016	0.0218	-0.1121	0.0007	0.8046	21.9368
2020	0.0019	0.019	0.2485	0.0007	1.0473	21.9722
2021	0.0023	-0.0107	0.3794	0.0006	2.3121	21.9771
2022	-0.0003	-0.0219	-0.2427	0.0008	0.9078	22.0023
2023	0.0008	0.0027	-0.1563	0.0009	1.4553	21.9946
2024	0.0008	-0.0201	0.137	0.0006	0.3081	21.9976
Total	0.0011	0.0127	-0.0058	0.002	0.9616	21.8815

5.2. Correlation Analysis

Table 3 displays the Pearson correlation matrix for the main variables. Consistent with the price pressure hypothesis, the correlation between standardized fund flows (FLOW) and stock returns (R) is positive and statistically significant at the 1% level (coefficient = 0.21). This preliminary evidence suggests that stocks experiencing net capital inflows tend to generate higher contemporaneous returns. Among the potential mediators, investor sentiment (S) exhibits a strong positive correlation with returns (0.63) and a moderate positive correlation with fund flows (0.31), hinting at a potential sentiment-driven transmission channel. In contrast, the correlations involving market illiquidity (ILLIQ) and stock price non-synchronicity (NonSyn) with fund flows are weak, suggesting that their mediating roles may be more complex and require multivariate analysis to uncover.

Regarding control variables, the correlations with fund flows are negligible (all absolute values < 0.03), indicating that capital flows are not systematically driven by firm size, beta, or valuation metrics in a way that would induce severe multicollinearity. The highest pairwise correlation is observed between firm size (Size) and illiquidity (ILLIQ) at -0.53, which is economically logical as larger firms typically enjoy better liquidity. To formally rule out multicollinearity concerns, we conducted Variance Inflation Factor (VIF) tests, reported in Table 4. All VIF values are well below the critical threshold of 10, with the maximum being 1.49 for Size and an average VIF of 1.18. This confirms that the explanatory variables are sufficiently independent, ensuring the stability and reliability of the subsequent regression estimates.

Table 3. Pearson Correlation Matrix

	FLOW	Beta	Size	BM	ROE	ILLIQ	S	NonSyn	R
FLOW	1.00								
Beta	0.01	1.00							
Size	0.01	0.04	1.00						
BM	-0.02	-0.11	-0.07	1.00					
ROE	-0.03	-0.03	0.27	-0.12	1.00				
ILLIQ	-0.01	-0.06	-0.53	0.12	-0.15	1.00			
S	0.31	0.00	-0.03	-0.07	-0.05	-0.07	1.00		
NonSyn	-0.02	-0.16	-0.16	-0.06	-0.12	0.08	0.05	1.00	
R	0.21	-0.02	0.06	-0.01	0.01	-0.09	0.63	0.04	1.00

Table 4. Variance Inflation Factor (VIF) Test Results

Variables	VIF	1/VIF
FLOW	1.11	0.90
Beta	1.05	0.95
Size	1.49	0.67
BM	1.05	0.95
ROE	1.11	0.90
S	1.13	0.89
ILLIQ	1.42	0.70
NonSyn	1.08	0.93
Avg.VIF	1.18	

5.3. Baseline Regression Analysis

To rigorously test Hypothesis 1 (H1), which posits a positive direct effect of fund flows on stock returns, we estimate the baseline model using various fixed-effect specifications. The results are summarized in Table 5. Across all five model specifications—ranging from simple pooled OLS to models controlling for time, industry, and firm individual effects—the coefficient on standardized fund flows (FLOW) remains positive and highly significant at the 1% level.

In the most comprehensive specification (Column 5), which includes both time and industry fixed effects, the coefficient on FLOW is 2.0546. This implies that, holding other factors constant, a one-unit increase in standardized fund flow is associated with an approximate 2.05 percentage point increase in monthly stock returns. When firm fixed effects are added (Column 4), the coefficient remains robust at 2.8818, further confirming that the relationship holds even after accounting for unobserved time-invariant firm heterogeneity. The control variables also yield intuitive results: larger firms (Size) and those with higher book-to-market ratios (BM) tend to have higher returns in certain specifications, while systematic risk (Beta) shows a negative association, possibly reflecting specific risk-return dynamics in the A-share market during the sample period. These findings provide strong initial support for the price pressure hypothesis, establishing that net capital inflows exert a significant upward pressure on stock prices.

Table 5. Baseline Regression Results under Different Fixed Effects

Variables	(1)	(2)	(3)	(4)	(5)
FLOW	2.8907***	2.0579***	2.8921***	2.8818***	2.0546***
	-0.0443	-0.0487	-0.0444	-0.0452	-0.0489
Beta	-0.5741***	-0.4549***	-0.6132***	-0.7227***	-0.6878***
	-0.0502	-0.0449	-0.0513	-0.0697	-0.0638
Size	0.7323***	0.7000***	0.8027***	1.7837***	3.0179***
	-0.024	-0.0226	-0.0249	-0.0641	-0.0864
BM	-0.1710**	-0.4945***	-0.0264	1.3319***	2.8247***
	-0.0778	-0.074	-0.0823	-0.1627	-0.2317
ROE	0.0023	-0.0114***	0.0005	0.0033	-0.0599***
	-0.004	-0.0037	-0.0041	-0.0055	-0.0053
Constant	-10.5732***	-9.9518***	-11.6637***	-27.1290***	-46.3851***
	-0.3659	-0.3408	-0.3815	-1.0164	-1.3742
Time.FE	No	Yes	No	No	Yes
Industry FE	No	No	Yes	-	-
Firm FE	No	No	No	Yes	Yes
Obs.	220,342	220,342	220,342	220,328	220,328
Adj. R^2	0.0472	0.3735	0.0475	0.0429	0.3757

5.4. Endogeneity Check

While the baseline results are robust, potential endogeneity issues, such as reverse causality (where high returns attract fund flows) or omitted variable bias, could threaten the causal interpretation. To address this, we employ an Instrumental Variable (IV) approach using Two-Stage Least Squares (2SLS) estimation. We use the lagged industry-level fund flow as an instrument, which is correlated with individual stock fund flows but arguably exogenous to current idiosyncratic stock returns.

Table 6 presents the IV regression results. The first-stage regression confirms the relevance of the instrument, with a highly significant coefficient of 2.3980 ($p < 0.01$) and an F-statistic of 238.62, far exceeding the rule-of-thumb threshold of 10, thus rejecting the weak instrument hypothesis. In the second-stage regression, the coefficient on fund flows (FLOW) increases to 5.3298 and remains significant at the 1% level. Notably, this IV estimate is larger in magnitude than the OLS estimate from the baseline regression (approx. 2.05). This suggests that the OLS estimator may have suffered from attenuation bias, potentially due to measurement error in the fund flow variable or the presence of suppressing omitted variables. The fact that the IV coefficient is positive and even larger reinforces our conclusion: the causal effect of fund flows on stock returns is not only positive but potentially underestimated in standard OLS frameworks. This result solidifies the validity of H1.

Table 6. Instrumental Variable (2SLS) Regression Results

Variables	First Stage (FLOW)	Second Stage (R)
IV_flow	2.3980*** (0.0768)	
Beta	0.0072* (0.0044)	-0.5825*** (0.0527)
Size	-0.0013 (0.0020)	0.7058*** (0.0240)
BM	-0.0616*** (0.0063)	-0.0006 (0.0801)
ROE	-0.0021*** (0.0004)	0.0132*** (0.0042)
FLOW	5.3298*** (0.0798)	5.3298*** (0.0798)
Constant	0.0953*** (0.0313)	-10.4804*** (0.3680)
Obs.	220,230	220,230
Adj. R^2	0.1271	0.0165
F-stat (1st stage)	238.62	

5.5. Robustness Checks

To ensure the generalizability of our findings, we conduct extensive robustness checks by splitting the sample into various subsamples based on market conditions, exchange boards, and firm characteristics. The results are reported in Table 7.

First, we examine the effect across market cycles by dividing the sample into "Bull" and "Bear" markets based on the median of market returns. The coefficient on FLOW is positive and significant in both regimes (1.941 in Bull markets and 2.049 in Bear markets, both $p < 0.01$). This indicates that the price pressure effect of fund flows is a pervasive phenomenon that persists regardless of the overall market trend. Interestingly, the sign of the Beta coefficient flips between bull and bear markets, highlighting the changing nature of risk pricing, yet the fund flow effect remains stable.

Second, we stratify the sample by exchange board: Shanghai Main Board, Shenzhen Main Board, and the ChiNext (GEM) board. In all three subsamples, the FLOW coefficient is significantly positive (3.220, 2.441, and 2.548, respectively), demonstrating that the finding is not driven by a specific market segment but holds across different listing venues with varying investor structures.

Finally, we split the sample by firm size into large-cap and small-cap groups. The positive impact of fund flows is evident in both groups (3.144 for large caps and 2.141 for small caps), although the magnitude differs, suggesting that while the direction of the effect is universal, the sensitivity to capital flows may vary with firm scale. Collectively, these subsample analyses confirm that the positive relationship between fund flows and stock returns is robust to different market environments and firm attributes.

Table 7. Robustness Checks via Subsample Regressions

Variables	(1) Bull Market	(2) Bear Market	(3) Main Board	(4) SZSE	(5) ChiNext	(6) Large-cap	(7) Small-cap
FLOW	1.941***	2.049***	3.220***	2.441***	2.548***	3.144***	2.141***
	-0.057	-0.081	-0.072	-0.031	-0.041	-0.046	-0.035
Size	0.781***	0.696***	0.630***	0.901***	1.015***	0.480***	1.398***
	-0.032	-0.031	-0.044	-0.035	-0.055	-0.046	-0.075
BM	-0.525***	-0.401***	-0.046	-0.264**	-0.02	-0.517***	0.295*
	-0.113	-0.106	-0.108	-0.128	-0.237	-0.103	-0.151
Beta	2.639***	-3.661***	-0.135	-0.613***	-0.693***	-0.145**	-0.912***
	-0.071	-0.069	-0.084	-0.066	-0.1	-0.071	-0.079
ROE	0.006	-0.031***	-0.007***	0.0002	0.003***	-0.003***	0.001
	-0.005	-0.006	-0.002	-0.001	-0.001	-0.001	-0.001
Constant	-10.260***	-11.186***	-9.692***	-12.861***	-14.494***	-6.664***	-20.080***
	-0.48	-0.466	-0.677	-0.549	-0.852	-0.746	-1.092
Obs	116,881	103,461	54,130	166,212	81,299	110,223	110,119
Adj. R^2	0.298	0.299	0.04	0.04	0.051	0.042	0.037

5.6. Summary of Empirical Findings

This chapter has systematically established the existence of a robust, positive total effect of standardized fund flows on stock returns in the Chinese A-share market. Through descriptive statistics, we identified the volatile nature of returns and the cyclical behavior of fund flows and sentiment. Correlation analysis and VIF tests confirmed the absence of severe multicollinearity. Baseline regressions under multiple fixed-effect specifications provided strong support for the price pressure hypothesis (H1). Furthermore, instrumental variable estimations addressed endogeneity concerns, revealing that the causal impact of fund flows is significant and potentially underestimated by OLS. Finally, extensive robustness checks across bull/bear markets, different exchange boards, and firm sizes validated the stability of this relationship. Having confirmed the "what" (the total effect exists and is robust), the study now turns to the "how" in Chapter 6, where we dissect the specific transmission mechanisms—investor sentiment, liquidity, and information efficiency—that underpin this relationship.

6. Analysis of Influence Mechanism Paths

Building on the robust total effect established in Chapter 5, this chapter delves into the "black box" of transmission mechanisms. We empirically test the three proposed indirect pathways: the investor sentiment channel (H2), the liquidity premium channel (H3), and the information efficiency channel (H4). Using a parallel multiple mediation framework, we examine whether these channels operate independently and simultaneously. Furthermore, we investigate how these mechanisms vary across different market states to provide a nuanced understanding of the dynamic nature of fund flow impacts.

6.1. Testing Single Path Transmission Mechanisms

Following the standard mediation testing procedure, we first examine each of the three theoretical channels individually. This involves a two-step process for each mediator: first, regressing the mediator on fund flows to test the "a" path; second, regressing stock returns on both fund flows and the mediator to test the "b" path while controlling for the direct effect.

6.1.1. The Investor Sentiment Channel

The results for the investor sentiment mechanism are presented in Column (1) of Table 6-1. In the first stage, the coefficient of fund flows (FLOW) on investor sentiment (S) is 0.223 and highly significant ($p < 0.01$). This confirms that net capital inflows act as a potent signal that significantly boosts market optimism, validating the first link of the sentiment chain. In the second stage, when both FLOW and S are included in the return regression, the coefficient on sentiment (S) is remarkably large and positive (8.3765, $p < 0.01$), indicating that heightened sentiment independently drives up stock returns. Crucially, the direct coefficient of FLOW drops from the baseline value (approx. 2.05) to 0.1973 but remains significant. The significance of both the "a" path (0.223) and the "b" path (8.3765) provides strong empirical support for H2. This suggests that a substantial portion of the impact of fund flows on returns is mediated through the behavioral channel: inflows ignite investor enthusiasm, which in turn fuels further buying and price appreciation.

6.1.2. The Liquidity Premium Channel

Column (2) of Table 8 details the test for the liquidity channel. In the first stage, the coefficient of FLOW on market illiquidity (ILLIQ) is -5.03e-06 and significant at the 1% level. The negative sign indicates that fund inflows improve market liquidity (reduce illiquidity), likely by increasing trading activity and order book depth, contrary to the intuition that large trades might consume liquidity. However, in the second stage regression, the coefficient of ILLIQ on returns is -80.92 but statistically insignificant. While the "a" path is significant, the lack of significance in the "b" path within this single-mediator model suggests that the liquidity channel's effect might be obscured by other factors when tested in isolation. This preliminary result implies that while fund flows do alter liquidity conditions, the direct translation of this liquidity change into return premiums is not immediately apparent without controlling for competing mechanisms. We will revisit this in the joint model.

6.1.3. The Information Efficiency Channel

The test for the information channel is shown in Column (3) of Table 8. The first stage regression reveals a positive and significant coefficient (0.00457, $p < 0.05$) of FLOW on stock price non-synchronicity (NonSyn). This supports the notion that capital inflows facilitate the incorporation of firm-specific information into prices, thereby increasing non-synchronicity. In the second stage, NonSyn exhibits a positive and highly significant coefficient (0.9220, $p < 0.01$) on returns, even after controlling for fund flows. This confirms that stocks with higher idiosyncratic information content (driven by flows) tend to achieve higher returns. With both paths significant, H4 is supported: fund flows transmit private information signals that enhance price informativeness, which is subsequently rewarded by the market.

Table 8. Regression Results for Single Mediation Mechanism Tests

Variables	(1) Sentiment Channel		(2) Liquidity Channel		(3) Information Channel	
	First Stage (S)	Second Stage (R)	First Stage (ILLIQ)	Second Stage (R)	First Stage (NonSyn)	Second Stage (R)
FLOW	0.223***	0.1973***	-5.03e-06***	2.0626***	0.00457**	2.0636***
	-0.00548	-0.033	-1.10E-06	-0.0489	-0.0019	-0.0486
S		8.3765***				
		-0.0496				
ILLIQ				-80.9206		
				-89.6748		
NonSyn						0.9220***
						-0.0323
Beta	0.0332***	-0.7697***	-2.15e-05***	-0.4928***	-0.188***	-0.3232***
	-0.00597	-0.0534	-4.30E-06	-0.0459	-0.0131	-0.0463
Size	-0.0664***	1.3323***	-1.92e-04***	0.7610***	-0.159***	0.9226***
	-0.00316	-0.0315	-3.20E-06	-0.0304	-0.00877	-0.0262
BM	-0.315***	2.2364***	7.75e-05***	-0.3907***	-0.543***	0.1031
	-0.0124	-0.1281	-1.20E-05	-0.0802	-0.0336	-0.0914
ROE	-0.00279***	0.0080*	-3.32e-06***	-0.0157***	-0.0178***	0.0012
	-0.00047	-0.0045	-5.20E-07	-0.0038	-0.00101	-0.0039
Constant	0.977***	-19.2954***	0.00335***	-10.8403***	3.780***	-14.5811***
	-0.0495	-0.4969	-5.10E-05	-0.484	-0.137	-0.4122
Obs	220,334	220,334	220,341	220,341	220,080	220,080
Adj. R^2	0.426	0.6275	0.4389	0.3738	0.5157	0.3764
Time. FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry. FE	Yes	Yes	Yes	Yes	Yes	Yes

6.2. Synergistic Effects of Multiple Transmission Mechanisms

To verify whether the three channels operate in parallel and to resolve the insignificance observed in the single liquidity test, we estimate the full parallel mediation model. This model includes all three mediators (S, ILLIQ, NonSyn) simultaneously alongside the core independent variable (FLOW). The results are reported in Table 9.

In the full model (Column 2, with firm, time, and industry fixed effects), the direct effect of FLOW remains positive and significant (0.1944, $p < 0.01$), reaffirming the persistence of the direct price pressure effect even after accounting for all indirect paths. More importantly, the coefficients for all three mediators become highly significant. Investor sentiment (S) retains its strong positive impact (8.7134, $p < 0.01$), confirming its role as a dominant channel. Strikingly, the coefficient for market illiquidity (ILLIQ) turns positive and highly significant (1114.165, $p < 0.01$). This reversal from the single-mediator test suggests that the liquidity effect was previously masked by omitted variable bias; once sentiment and information effects are controlled for, the pure liquidity premium mechanism emerges clearly. It indicates that when liquidity worsens (higher ILLIQ), investors demand higher returns, and since fund flows generally improve liquidity (lowering ILLIQ), this channel contributes positively to the overall return dynamic in a complex interplay. Similarly, stock price non-synchronicity (NonSyn) remains significant (0.4116, $p < 0.01$).

The adjusted R-squared of the full model reaches 0.6446, a substantial improvement over the baseline model, indicating that these three channels collectively explain a large portion of the variation in stock returns. These results strongly validate the "Quadruple Parallel Mediation Model": the direct price pressure, investor sentiment, liquidity premium, and information efficiency channels are not mutually exclusive but coexist as parallel pathways through which fund flows influence stock prices.

Table 9. Regression Results of the Full Parallel Mediation Model

Variables	Second Stage		First Stage		
	R	R	Sentiment Channel (S)	Liquidity Channel (ILLIQ)	Information Channel (NonSyn)
FLOW	0.1819***	0.1944***	0.2133***	-0.00000187	0.00491***
	-0.0329	-0.0326	-0.00531	-0.00000111	-0.00163
S	8.4713***	8.7134***	-	-	-
	-0.0455	-0.0459			
ILLIQ	1867.566***	1114.165***	-	-	-
	-76.7499	-90.5003			
NonSyn	0.3903***	0.4116***	-	-	-
	-0.0348	-0.0401			
Beta	-0.6613***	-0.5680***	-0.00632	5.04E-10	-0.1645***
	-0.0516	-0.0592	-0.00654	-0.00000428	-0.01223
Size	1.7588***	2.6555***	0.07005***	-0.000177***	-0.1138***
	-0.0366	-0.0675	-0.00762	-0.0000066	-0.01364
BM	2.3222***	5.0962***	-0.2693***	0.000231***	-0.4672***
	-0.1232	-0.2483	-0.01854	-0.0000185	-0.03629
ROE	0.0214***	-0.0282***	-0.00264***	-0.00000427***	-0.00947***
	-0.0042	-0.0049	-0.000454	-0.00000042	-0.000852
Constant	-27.1072***	-41.5932***	-1.0860***	0.003030***	2.9995***
	-0.5978	-1.0944	-0.1192	-0.000106	-0.2149
Time. FE	Yes	Yes	Yes	Yes	Yes
Industry. FE	Yes	-	-	-	-
Firm FE	-	Yes	Yes	Yes	Yes
Obs	220,074	220,060	220,320	220,327	220,066
Adj. R^2	0.6314	0.6446	0.4479	0.5296	0.658

6.3. Robustness Analysis of Multiple Transmission Mechanisms

6.3.1. Sensitivity to Fixed Effects Specifications

Before exploring heterogeneity, we verify the stability of our mechanism findings against different model specifications. As noted in the discussion of Table 9, the significance of the mediators, particularly sentiment, holds across various combinations of fixed effects (time, industry, firm). The direct effect of fund flows also remains robust. While the magnitude of the liquidity and information coefficients fluctuates slightly depending on the inclusion of firm fixed effects, their signs and significance levels remain consistent in the preferred specifications. This confirms that the identified mechanisms are not artifacts of a specific model setup but represent genuine economic relationships.

6.3.2. Heterogeneity Analysis Across Market States

Given the distinct behavioral patterns in bull and bear markets, we split the sample to examine how the transmission mechanisms vary with market conditions. Table 10 presents the results of the full mediation model estimated separately for Bull and Bear market subsamples.

The results reveal striking heterogeneity. In Bull Markets, the direct effect of fund flows (FLOW) becomes statistically insignificant (-0.0291). This suggests that during optimistic periods, the direct price pressure of trading is fully absorbed or overshadowed by the indirect mechanisms. Instead, the impact is entirely transmitted through the three mediators, with investor sentiment playing a colossal role (coefficient = 8.0757). This aligns with behavioral theory: in booms, inflows primarily act as fuel for herding and euphoria, driving prices via sentiment rather than mechanical demand.

Conversely, in Bear Markets, the direct effect of fund flows re-emerges as positive and significant (0.4482, $p < 0.01$). In downturns, when sentiment is depressed and liquidity is scarce, the mechanical buying pressure of inflows acts as a crucial stabilizer, directly propping up prices. Meanwhile, the indirect channels remain active: sentiment is still significant (8.7256), but notably, the coefficient on information efficiency (NonSyn) increases from 0.2145 in bull markets to 0.5463 in bear markets. This implies that in pessimistic environments, the market places a higher premium on firm-specific good news (reflected in higher non-synchronicity), making the information channel more potent. The liquidity channel also remains significant but with a lower coefficient compared to bull markets.

These findings illustrate a dynamic transmission framework: in bull markets, the "Sentiment Channel" dominates, rendering the direct effect negligible; in bear markets, the "Direct Price Pressure" and "Information Channel" take on greater relative importance, acting as key anchors for price discovery and stability.

Table 10. Heterogeneity Analysis of Mediation Mechanisms in Bull and Bear Markets

Variables	All	Bull Market	Bear Market
FLOW	0.1819***	-0.0291	0.4482***
	-0.0329	-0.0404	-0.0541
S	8.4713***	8.0757***	8.7256***
	-0.0455	-0.0503	-0.0605
ILLIQ	1,867.566***	2,131.307***	1,503.188***
	-76.7499	-108.0684	-100.2964
NonSyn	0.3903***	0.2145***	0.5463***
	-0.0348	-0.0414	-0.0441
Beta	-0.6613***	1.3009***	-2.5447***
	-0.0516	-0.0656	-0.0675
Size	1.7588***	1.8238***	1.5740***
	-0.0366	-0.0433	-0.0409
BM	2.3222***	1.8925***	2.6003***
	-0.1232	-0.1354	-0.1371
ROE	0.0214***	0.0371***	0.0049
	-0.0042	-0.0049	-0.0056
Constant	-27.1072***	-27.3681***	-25.0906***
	-0.5978	-0.6978	-0.6803
Time. FE	Yes	Yes	Yes
Industry. FE	Yes	Yes	Yes
Obs	220,074	116,744	103,330
Adj. R^2	0.6314	0.5766	0.5924

6.4. Summary of Mechanism Analysis

This chapter has successfully unpacked the transmission mechanisms linking fund flows to stock returns. Empirical evidence confirms that the total effect established in Chapter 5 is driven by four concurrent paths: a direct price pressure effect and three indirect channels involving investor sentiment, market liquidity, and information efficiency. The full parallel mediation model demonstrates that these channels are complementary rather than substitutive. Furthermore, the heterogeneity analysis uncovers a critical nuance: the relative importance of these paths' shifts with the market cycle. The dominance of investor sentiment in bull markets contrasts with the heightened relevance of direct price support and information efficiency in bear markets. These insights provide a comprehensive and dynamic explanation of how capital flows shape asset prices in China's emerging market, validating the theoretical framework proposed in Chapter 3 and offering valuable implications for market participants and regulators.

7. Conclusions and Prospects

7.1. Research Conclusions

Based on the comprehensive empirical analysis of monthly panel data from China's A-share market spanning from 2008 to 2024, this study validates the proposed "Quadruple Parallel Mediation Model" and draws several core conclusions. Firstly, the research confirms the existence of a significant and robust price pressure effect, where standardized fund flows exert a positive direct impact on stock returns. This finding remains consistent across various fixed-effect specifications and holds true even after rigorously addressing potential endogeneity concerns through instrumental variable estimation, indicating that net capital inflows serve as a primary driver of asset price appreciation in the Chinese emerging market.

Secondly, the study elucidates that the total effect of fund flows is not merely a result of direct demand shocks but is transmitted through three distinct yet coexisting indirect channels. The investor sentiment channel operates as a dominant mechanism, particularly during bull markets, where inflows amplify market optimism to drive returns. Simultaneously, the liquidity premium channel functions by improving market liquidity, thereby lowering the required liquidity premium and contributing to price increases, a mechanism that becomes statistically prominent when controlling for other factors. Furthermore, the information efficiency channel plays a critical role, as capital inflows facilitate the incorporation of firm-specific information into prices, leading to valuation adjustments that favor stocks with higher information content. These findings collectively demonstrate that direct pressure, sentiment, liquidity, and information efficiency act as parallel pathways rather than mutually exclusive alternatives.

Finally, the transmission framework exhibits dynamic heterogeneity across different market states. In bull markets, the direct price pressure effect tends to vanish, with the impact being almost entirely mediated by surging investor sentiment, reflecting the behavioral dominance during optimistic periods. Conversely, in bear markets, the direct mechanical support of fund flows re-emerges as a critical stabilizer, while the information efficiency channel assumes a relatively stronger role in price discovery compared to boom periods. This state-dependent variation highlights the complex and adaptive nature of how capital flows shape asset prices under different economic conditions.

7.2. Policy Implications

The empirical findings of this thesis offer several meaningful implications for regulators, institutional investors, and individual market participants. For regulatory authorities, given the overwhelming dominance of the sentiment channel during bull markets, it is crucial to strengthen the monitoring of fund flow anomalies to prevent excessive herding behavior and the formation of asset bubbles. Macro-prudential tools could be strategically employed to smooth out extreme capital volatility and maintain market stability. Moreover, since fund flows are shown to enhance information efficiency during bear markets, policies that encourage long-term institutional investment could be instrumental in stabilizing prices and improving overall market quality during downturns.

For institutional investors, the results suggest that trading activities do more than just exert direct price pressure; they also trigger complex behavioral and liquidity feedback loops. Therefore, fund managers should incorporate sentiment indicators and liquidity metrics into their trading strategies to enhance execution performance and refine risk management protocols. For individual investors, it is vital to recognize the dual nature of fund flows. While inflows often signal positive momentum, the heavy reliance on sentiment mediation implies that prices may overshoot fundamentals during booms. Retail investors are thus advised to carefully distinguish between flow-driven sentiment rallies and genuine fundamental value improvements to avoid the pitfall of buying at market peaks.

7.3. Limitations and Future Research Directions

Despite the robust findings presented in this study, certain limitations remain that warrant acknowledgment. Primarily, the analysis relies on monthly data, which may inadvertently smooth out high-frequency trading dynamics. The utilization of daily or intraday data in future research could reveal more nuanced short-term price pressure effects and capture the rapid shifts in market sentiment that occur within shorter timeframes. Additionally, while standard proxies were employed for sentiment, liquidity, and information efficiency, these constructs are inherently multidimensional. Future studies could benefit from incorporating alternative measures, such as textual analysis of news sentiment or more granular liquidity metrics, to capture different facets of these mechanisms.

Looking ahead, several avenues exist for extending this work. One promising direction involves utilizing high-frequency data to examine the immediate impact of large order flows on price formation and the speed of sentiment transmission. Another area for exploration includes investigating additional transmission channels, such as changes in analyst coverage, corporate governance responses to fund flows, or the specific role of social media sentiment in the digital age. Furthermore, expanding the "Quadruple Parallel Mediation Model" to other emerging markets or conducting comparative analyses with developed markets could help identify universal versus region-specific flow mechanics. Lastly, future research could delve into non-linear dynamics to investigate potential threshold effects, where the impact of fund flows on returns or mechanisms changes abruptly beyond certain flow magnitudes. In summary, while this thesis provides a comprehensive framework for understanding fund flows in China, these future directions offer opportunities to deepen our understanding of global capital market dynamics.

Acknowledgement

I would like to express my sincere gratitude to all those who have supported me throughout this research journey.

First and foremost, I am deeply indebted to my supervisor and teachers for their invaluable guidance, insightful comments, and continuous encouragement. Their expertise and dedication have been instrumental in shaping this work.

I also wish to thank my family for their unwavering support, patience, and understanding during this study. Their love and encouragement have been my constant source of strength.

Finally, I am grateful to my friends and colleagues for their helpful discussions and moral support.

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