Common Fund Flows in China: Flow Hedging and Factor Pricing

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Abstract. This paper investigates a novel mechanism of common mutual fund risk within the Chinese stock market, demonstrating that fund managers strategically adjust their portfolios to hedge against shared fund flow risks. These adjustments significantly influence stock prices, highlighting the critical role of common fund risk in market behavior. Utilizing Principal Component Analysis (PCA), the study extracts a characteristic of common fluctuations among active mutual funds, referred to as "common mutual fund flow." It calculates each stock's exposure to risk within the portfolio, denoted as flow beta, and finds that the high-low price spreads of flow beta are significant after grouping. The analysis reveals that mutual fund managers in the Chinese market exhibit a strong sensitivity to common mutual fund flow risk and actively adjust their portfolios to mitigate this risk, showing a marked tendency to acquire more low-beta stocks. This paper offers methods and evidence to enhance the understanding of the principles governing the Chinese stock market and fund manager behaviors, thereby enriching the empirical evidence of intermediary asset pricing models in China.

Keywords: Chinese Market, Mutual Funds, Fund Flow, Intermediary-Based Asset Pricing.

1. Introduction

The rapid expansion of China's mutual fund market has introduced complex dynamics in market behavior, risk management, and asset pricing, encouraging further research into the role of common fund flow risks. As China's financial markets continue to grow and deepen their integration with the global economy, mutual funds have become pivotal in shaping resource allocation, market liquidity, and financial stability[1]. This rise underscores the importance of understanding mutual fund managers' responses to synchronized flow risks, which is essential for promoting market resilience and sustainable growth.

Amid these developments, an important question arises: how do mutual fund managers respond to systemic risks such as economic downturns, liquidity constraints, and shifts in market sentiment? Furthermore, how do these responses, through portfolio adjustments, impact stock returns, asset pricing, and overall market stability? Portfolio rebalancing decisions made by fund managers not only reflect their risk management strategies but also exert substantial influence on market dynamics by shaping liquidity patterns and affecting investor confidence. While extensive research has explored these aspects within developed markets, there is a significant gap in understanding the unique characteristics of fund flow risks in emerging markets like China[2].

To address this gap, this paper investigates the influence of common fund flow risks in the Chinese stock market, focusing on how mutual fund managers adjust portfolios to hedge against synchronized liquidity risks. Using Principal Component Analysis (PCA), the study identifies systematic behavior among active mutual funds, with a dominant component explaining 69.00% of fund flow variance. This substantial percentage reveals a significant underlying factor driving common flow shocks across funds, underscoring the systemic nature of flow risk in China's market.

Additionally, the study employs Fama-MacBeth regressions to assess the pricing effects of these flow risks. By calculating each stock's flow beta, the measure of its exposure to common fund flows, the analysis shows that stocks with higher flow beta earn a distinct risk premium. This finding confirms flow beta as a significant pricing factor, revealing that exposure to synchronized liquidity shocks is compensated with higher returns, highlighting the role of flow risk in asset pricing within China's equity market.

This study provides new insights into the strategies of Chinese mutual funds, which actively mitigate liquidity risks by underweighting high-flow-beta stocks. By examining flow beta as a priced risk factor, this research deepens the understanding of asset pricing in emerging markets and offers valuable implications for investors and policymakers regarding liquidity risk management and market stability. Through this analysis, the paper addresses an empirical gap in the research on the Chinese mutual fund sector and contributes to the broader discourse on intermediary-based asset pricing models in rapidly growing markets.

2. Common mutual fund flow

Building on Winston Wei Dou's 2022 framework[3], this research empirically analyzes active equity fund flows in China's stock market, focusing on the factor structure of these flows. It examines how stock returns' sensitivity to common fund flow shocks—flow beta—affects market pricing, using a regression of individual stock returns on a principal component that captures systematic liquidity risk from fund flows.

2.1. New Facts on Intermediary Asset Pricing

2.1.1 Construction of Fund Flow Shocks.

This research defines fund-level flows as follows:

$$F_{i,t} = \frac{Q_{i,t} - Q_{i,t-1} \times (1 + Ret_{i,t})}{Q_{i,t-1}} \tag{1}$$

where $Q_{i,t}$ and $Ret_{i,t}$ are, respectively, the total net assets (TNA) and the net return for fund i in month t.

To address the persistence and unpredictability of fund flows, this paper controls for lagged fund flows and one-period lagged performance, accounting for inflow and outflow sensitivity to performance. The empirical measure $F_{i,t}$ serves as an imperfect proxy for fund flow shocks due to overlapping monthly flows and returns[4]. To mitigate this, this research applys a merged panel regression controlling for concurrent performance.

$$F_{i,t} = b_0 \sum_{k=1}^{2} b_k \times ExRet_{i,t-k+1} + b_3 \times F_{i,t-1} + \theta_t + \varepsilon_{i,t} \tag{2}$$

Where $ExRet_{i,t}$ is the fund excess return relative to the market return, R_t^{mkt}, over month t, $F_{i,t-1}$ represents the lagged fund flows, and θ_t represents the month fixed effects. Referring to Winston Wei Dou's theory[3], this paper then defines the fund-flow shock after controlling for the flow-performance sensitivity at the fund level as follows:

$$flow_{i,t} = \theta_t + \varepsilon_{i,t} \tag{3}$$

2.1.2 Construction of Common Fund Flow Shocks.

The analysis shows that most of the common variation in mutual fund liquidity shocks is driven by a single dominant factor with a high eigenvalue, indicating a strong underlying factor structure governing these shocks.

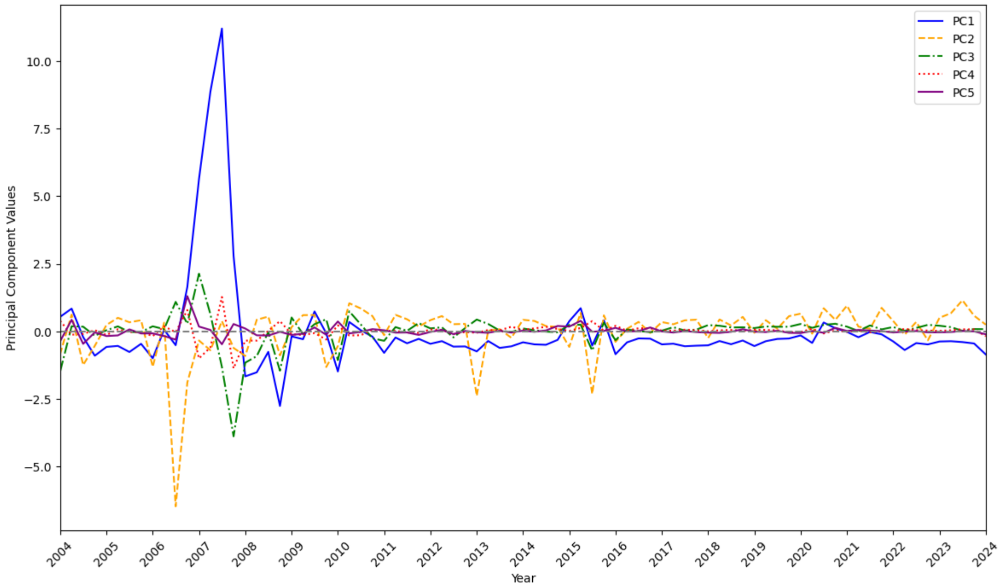

Figure 1. Mutual fund flows after removing relative performance and lagged flows

To empirically identify the common component, this essay categorizes active mutual funds into quintiles based on asset size, a key variable due to its strong link with fund flows and performance[5]. Our findings confirm a pronounced factor structure in fund flow shocks, suggesting significant spillover effects across funds. Figure 1 illustrates the monthly common fund flows constructed based on fund asset size using the CSMAR mutual fund data, showing the value-weighted average fund flow shocks for each asset size quintile, adjusted for relative performance and lagged flows[6, 7].

Principal component analysis reveals strong co-movement in fund flow shocks across different size groups, with the first principal component explaining 69.00% of the variance, and the second 19.98%. This indicates that liquidity shocks are highly interrelated across fund sizes, with only a few key factors driving these shocks. Notably, the magnitude and frequency of these co-movements exceed those associated with typical economic cycles, underscoring the role of fund size in systemic liquidity risk and market stability.

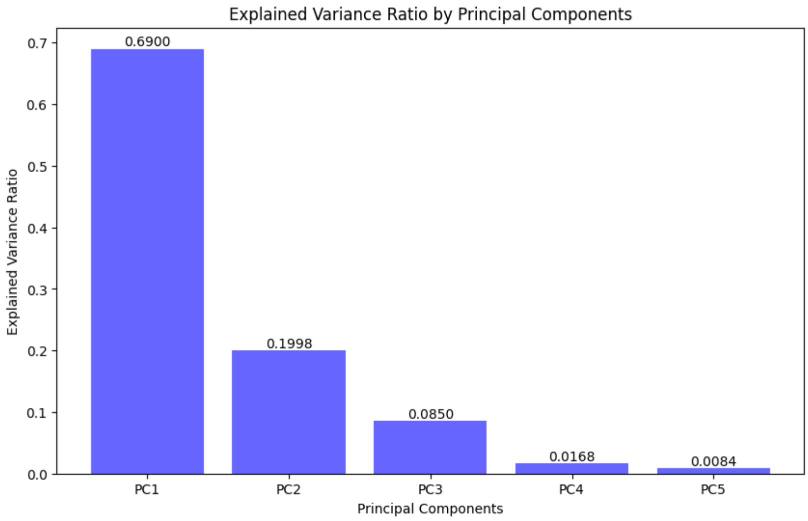

Figure 2: PCA analysis of flows sorted on asset size

The paper use PCA to identify common shocks in fund flows by capturing the primary source of cross-sectional variation. Figure 2 illustrates the fraction of variance explained by different principal components (PCs) according to the PCA of flows sorted by asset size. PC1 accounts for 69.00% of the total variance, demonstrating its dominance as the key driver of common fund flow shocks. To standardize PC1, the paper subtract its unconditional mean and scale it to an unconditional standard deviation of 1, designating it as the "common fund flow shock." This approach follows Herskovic[8], who similarly applied PCA to isolate common components in financial data.

The remaining principal components (PC2 to PC5) explain progressively less variance—19.98%, 8.50%, 1.68%, and 0.84%, respectively—highlighting the steep decline in explanatory power beyond PC1. This further supports the conclusion that a single common factor, represented by PC1, primarily drives fund flow variation, justifying its use as the key variable in subsequent analyses.

3. Mutual fund flow risk

3.1. Beta calculating

For each stock, the paper estimates its monthly flow beta by regressing its monthly excess return on mutual fund flows using a 3-year rolling window (if there are at least 12 quarterly observations in the rolling window, and if not, the stock is eliminated):

$$ret_{i,t-\tau} = a_{i,t} + \beta_{i,t}^{flow} \times flow_{t-\tau} + \varepsilon_{i,t},\ with\ \tau = 0,1, \dots ,11, \tag{4}$$

Where $flow_{t-\tau}$ denotes the common fund flow in month t−τ and $\beta_{i,t}^{flow}$ denotes stock i's flow beta in month t.

3.2. Sorting

Investors reallocating from active equity funds often direct assets to low-risk institutions such as bond funds and money market funds[9], which act as "counterparties" by absorbing these flows. Research shows a negative correlation between flows in low-risk bond funds and active equity funds.

The paper groups companies into quintiles based on flow betas each quarter. Table 1 shows that stocks with higher flow betas have higher excess returns and CAPM alphas, with significant return spreads. Using CSMAR data, the average excess return difference between the highest (Q5) and lowest (Q1) flow beta quintiles is 1.79%, comparable to size and value premiums in equity markets.

Table 1. Excess returns sorted on flow beta.

Parameters	CSMAR mutual funds					
β_i^{flow} quintiles	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Excess returns	0.69***	0.95***	1.16***	1.29***	1.39***	0.69*
T-value	[2.99]	[6.01]	[8.26]	[8.09]	[5.26]	[1.79]

Note: The table presents excess returns sorted by flow beta (β_i^{flow}) for CSMAR mutual funds across five quintiles (Q1 to Q5). The excess returns represent the average abnormal returns within each quintile. The difference between the highest quintile (Q5) and the lowest quintile (Q1) is also provided (Q5-Q1). T-values are shown in square brackets below the excess returns. Statistical significance is indicated by asterisks: ***p < 0.01, **p < 0.05, *p < 0.1.

Table 1 demonstrates a strong relationship between CSMAR mutual funds' excess returns and their sensitivity to common fund flow shocks, measured by flow beta (β_i^{flow}). The results show a clear, monotonic increase in excess returns across quintiles, from 0.69% in the lowest flow beta quintile (Q1) to 1.39% in the highest (Q5). This suggests that funds with higher flow betas tend to outperform those with lower betas.

All quintile returns are significant at the 1% level, with t-values ranging from 2.99 in Q1 to 5.26 in Q5, confirming the robustness of the relationship. The difference in excess returns between Q5 and Q1 is 0.69%, statistically significant at the 10% level (t = 1.79), indicating that higher sensitivity to flow shocks is associated with economically meaningful return spreads.

This evidence supports the hypothesis that mutual funds exposed to common flow shocks earn a risk premium[10]. Flow beta, as a priced risk factor, captures a unique dimension of risk that persists even after controlling for traditional factors, highlighting its significance in asset pricing and portfolio management[11].

3.3. Flow Betas, Returns, and Portfolio Holdings

The paper defines the formula of Fama-MacBeth regression as follows:

$$Ret_{i,t} = \alpha + \beta_{i,t-1}^{flow} + CVs + \varepsilon_{i,t} \tag{5}$$

Where $Ret_{i,t}$ denotes the return of stock i at time t, $\beta_{i,t-1}^{flow}$ represents the coefficient for the lagged sensitivity of stock i to common fund flow shocks, and CVs are the control variables.

Table 2. Fama-MacBeth regressions $Ret_{i,t}$ (%)

Parameters	(1)	(2)	(3)	(4)
$\beta_{i,t-1}^{flow}$	0.393* [1.896]	0.414* [1.941]	0.411** [1.962]	0.449** [2.018]
$\text{Ttl\_Ratio}_{i,t-1}$		0.2229*** [2.790]	0.1707** [2.521]	0.2176*** [2.726]
$\text{ROA TTM}_{i,t-1}$		0.0099 [0.455]	0.0105 [0.490]	0.0102 [0.492]
$\text{Return\_Rate}_{i,t-1}$			0.2012 [1.084]	-0.0668 [-0.822]
$\text{Cashflow\_to\_Price}_{i,t-1}$			0.4613*** [3.240]	0.6473*** [3.976]
$\text{ST\_Reversal}_{i,t-1}$				-2.1962*** [-5.433]
$\text{Momentum}_{,t-1}$				-0.1000* [-1.898]
Constant	-0.0243 [-0.021]	-0.0279 [-0.025]	-0.0279 [-0.025]	-0.0279 [-0.025]
Average obs. / month	3389	3389	3389	3389

Note: $\beta_{i,t-1}^{flow}$ represents the flow beta, which measures a stock's sensitivity to common fund flow shocks, indicating that stocks with higher flow betas are more exposed to liquidity risks. $\text{Ttl\_Ratio}_{i,t-1}$, the turnover ratio, reflects the trading activity of a stock and its liquidity in the market. $\text{ROA TTM}_{i,t-1}$ captures a firm's return on assets over the trailing twelve months, indicating its efficiency in generating profits from its assets. $\text{Return\_Rate}_{i,t-1}$ represents the stock's lagged return, used to capture potential momentum or mean-reversion effects in returns. $\text{Cashflow\_to\_Price}_{i,t-1}$ is the cash flow-to-price ratio, suggesting undervaluation or strong cash generation relative to the stock's price. $\text{ST\_Reversal}_{i,t-1}$ measures short-term reversal tendencies, where stocks with recent poor performance might experience price rebounds. $\text{Momentum}_{,t-1}$represents past performance trends, reflecting whether stocks that performed well continue to do so. Statistical significance is indicated by asterisks: ***p < 0.01, **p < 0.05, *p < 0.1.

Based on the regression results in Table 2, the paper conducted Fama-MacBeth regressions using monthly stock return data from the CSMAR database, starting in January 2008. This period coincides with the global financial crisis, allowing us to capture the effects of liquidity shocks and subsequent recovery on stock returns.

The results show that the flow beta is positive and significant across all models, with coefficients ranging from 0.393 to 0.449. This indicates that stocks exposed to common mutual fund flow shocks earn a risk premium, supporting the notion that flow beta is a priced risk factor[12]. The turnover ratio is also positive and highly significant, suggesting a liquidity premium for stocks with higher trading activity.

The cash flow-to-price ratio is another key factor, showing strong significance in models 3 and 4, with coefficients of 0.4613 and 0.6473, respectively, indicating that undervalued stocks with higher cash flows deliver superior returns. In contrast, the short-term reversal factor is negative and significant, consistent with the short-term reversal anomaly, where recent underperformance leads to positive corrections.

Despite controlling for several established risk factors, flow beta remains significant, underscoring its distinct role in predicting stock returns. This suggests that investors demand compensation for exposure to mutual fund flow risks, which may be particularly relevant in markets like China, where fund flows heavily influence liquidity and volatility[13].

4. Evidence for portfolio tilting

Building on earlier analysis, this paper confirms, through Dou's framework[3], that flow beta reflects a fund's sensitivity to common market flow shocks, explaining its role in asset pricing.

This paper shows that active equity funds tilt their portfolio holdings (relative to their benchmarks) away from stocks with higher flow betas. The research runs the following regression:

$$w_{i,t}^{MF} - w_{i,t}^{mkt} = a + b_1 \times \beta_{i,t-1}^{flow} + \varepsilon_{i,t}, \tag{6}$$

Where $\beta_{i,t-1}^{flow}$, $w_{i,t}^{MF}$, and $w_{i,t}^{mkt}$ are the flow beta, the market beta, the weight of the aggregate active equity fund portfolio, and the weight of the market portfolio for stock i in quarter t, respectively. Specifically, the weight of the market portfolio, $w_{i,t}^{mkt}$, is defined as the market cap of stock i in month t divided by the aggregate market cap across all stocks in the CSMAR stock universe in month t. The term, $w_{i,t}^{MF} - w_{i,t}^{mkt}$, is the deviation of the weight of the aggregate active equity fund portfolio, $w_{i,t}^{MF}$, from that of the market portfolio, $w_{i,t}^{mkt}$, for stock i in quarter t.

The columns Coefficient and t-Value show the regression results. The paper performs panel regressions with quarter-fixed effects in Panel A, and Fama-MacBeth regressions in Panel B. Both settings describe the cross-sectional relation between the portfolio tilts of active equity funds and the lagged flow betas of stocks. This paper finds that the estimated coefficient b_1 is significantly negative, suggesting that active equity funds tilt their portfolio holdings away from high-flow-beta stocks relative to the market portfolio. The findings are robust to the use of the CSMAR sample.

Since active equity funds have different benchmarks, using the market portfolio as a universal benchmark can be problematic. To address this, the paper uses each fund's self-declared benchmarks, focusing on commonly used ones like the Shanghai Composite and CSI 800. The paper aggregate portfolio holdings by benchmark and run separate regressions for each:

$$w_{i,t}^{MF} - w_{i,t}^{Benchmark} = a + b_1 \times \beta_{i,t-1}^{flow} + CVs + \varepsilon_{i,t}, \tag{7}$$

Where $w_{i,t}^{MF}$ is the weight of stock *i* held by the aggregate portfolio of active equity funds with the corresponding self-declared benchmark in quarter *t*, and $w_{i,t}^{Benchmark}$ is the weight in the self-declared benchmark portfolio in quarter *t*.

The significantly negative coefficients for $\beta_{i,t-1}^{flow}$ in both the panel regressions and Fama-MacBeth regressions of Table 3 and Table 4 demonstrate that active equity funds consistently underweight stocks with higher flow betas. This indicates a strategic response by fund managers to reduce exposure to liquidity risks associated with flow-sensitive stocks. The robustness of these results across the

Shanghai Composite and CSI 800 Index benchmarks further confirms the systematic nature of this behavior.

Table 3: Panel regressions with time FE

Benchmark	Shanghai Composite Index	CSI 800 Index
$\beta_{i,t-1}^{flow}$	-0.087***	-0.052***
	[-2.820]	[-6.683]
$Ttl_{Ratio_{i,t-1}}$	-0.002	-0.047***
	[-0.085]	[-6.516]
$Momentum_{i,t-1}$	0.084	0.010
	[1.590]	[1.441]
ln_$Cashflow_to_Price_{i,t-1}$	-0.015	0.128***
	[-0.455]	[18.301]
Quarter FE	Yes	Yes
Observations	1479	23809

Table 4: Fama-MacBeth regressions

Benchmark	Shanghai Composite Index	CSI 800 Index
$\beta_{i,t-1}^{flow}$	-0.667***	-0.228**
	[-2.781]	[-2.130]
$Ttl_{Ratio_{i,t-1}}$	-1.877	-1.132**
	[-1.633]	[-2.327]
$Momentum_{i,t-1}$	0.048	0.076
	[0.631]	[-1.555]
ln_$Cashflow_to_Price_{i,t-1}$	-0.010	0.051*
	[-0.228]	[1.727]
Observations	1479	23809

Note: $\beta_{i,t-1}^{flow}$ is the flow beta of stock i in the previous period, measuring the sensitivity of a stock's returns to common fund flow shocks. $Ttl_{Ratio_{i,t-1}}$, the turnover ratio of stock i in the previous period, representing the trading volume relative to the stock's float. $Momentum_{i,t-1}$, reflects the tendency of stocks that have performed well in the past to continue performing well in the future. ln_$Cashflow_to_Price_{i,t-1}$, measures the firm's cash flow relative to its market price. A higher value suggests that the stock is generating strong cash flows relative to its valuation, potentially indicating financial stability or undervaluation. Statistical significance is indicated by asterisks: ***p < 0.01, **p < 0.05, *p < 0.1.

To address potential concerns about small-cap stocks, the analysis is focused on large-cap stocks within benchmark portfolios, ensuring that the tilting away from high-flow beta stocks is a deliberate strategy rather than an aversion to small-cap stocks. Additionally, the significant positive coefficient for the cash flow-to-price ratio shows a preference for stocks with strong cash flows, reinforcing fund managers' focus on stability.

5. Conclusion

By employing PCA method to analyze mutual fund flows, this study investigates the impact of common fund flow risks in the Chinese stock market. The findings reveal that the first principal component (PC1) accounts for 69% of the variance, indicating a significant systematic factor. Additionally, the analysis demonstrates that stocks with high flow beta, which reflect greater sensitivity to flow shocks, yield notably higher returns, with a 0.69% spread between the highest and lowest quintiles. This establishes flow beta as a key priced risk factor.

Further validation through Fama-MacBeth regressions confirms that higher flow beta stocks earn a risk premium. Additionally, the results indicate that active equity funds systematically underweight high-flow-beta stocks to mitigate liquidity risks, reflecting the defensive strategies employed by fund managers in response to synchronized liquidity shocks. This highlights the essential role of flow beta in stock return dynamics and portfolio management.

Overall, this study underscores the importance of understanding flow beta for managing liquidity risk in financial markets, which is crucial for market stability and efficient resource allocation. Future research could extend this analysis to other emerging markets to determine whether flow beta acts as a universal risk factor or varies by market characteristics. Moreover, examining flow beta under different economic conditions, particularly during periods of volatility, could provide valuable insights into its interaction with broader market cycles.

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