Proceedings of the 5th International Conference on Financial Technology and Business Analysis
DOI: 10.54254/2754-1169/2026.39192

Do Fund Flows Respond to Past Market Returns

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Abstract. This paper investigates whether the return on the China Securities Index (CSI) stock market index in the preceding quarter affects the flows into Chinese equity and mixed funds. This section describes the data and empirical procedure used to answer the question raised above. The sample includes 52,380 fund-quarter observations from 2,619 funds retrieved from Wind from the beginning of 2020 through the end of 2024. The pooled ordinary least squares regressions regress Flow on the proportional quarterly change in fund shares with both conventional and quarter-clustered standard errors calculated separately for each of the two groups of funds. The estimates indicate that the coefficients are positive yet statistically insignificant for the full sample and mixed funds regardless of error clustering, whereas the positive coefficient is significant for equity funds based on conventional standard errors and becomes insignificant otherwise. A close scrutiny of the results suggests a low R^2 value in all equations, implying that most variations in Flow remain unexplored.

Keywords: Fund flows, Market returns, Chinese mutual funds, CSI 300

1. Introduction

The amount of money that fund managers hold depends on subscriptions and redemptions made by investors. Understanding fund flows helps understand the conditions under which the managers invest in the stock market. Most studies have focused on past fund performance and its influence on subscriptions and redemptions. The return of the market provides another signal to interpret investor behaviour, as investors holding multiple funds receive it collectively. This study will analyse whether past CSI 300 return is a determinant of subscriptions and redemptions made by Chinese investors in equities and mixed funds.

A market rally can lead to subscriptions because investors will feel optimistic about future returns, while profit taking can drive redemptions of appreciated securities. Rebalancing presents another possible motive for selling shares. For instance, Parker et al. report counterflows of shares in underlying equity mutual funds caused by rebalancing in target-date funds in the United States [1]. The above motives can overlap within a single transaction; hence, an investor buys shares to offset another's redemptions. Without observing actual motives behind the observed flows, it is impossible to tell the relationship between subscriptions and redemptions with market returns from a coefficient alone. In practice, The research utilises quarterly Wind observations between 2020 and 2024 for 2,619 Chinese funds. Simple OLS regressions are estimated on the pool with usual and quarter-clustered standard errors. All estimated coefficients are positive, yet none is significant with

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DOI: 10.54254/2754-1169/2026.39192

clustering. Moreover, the R^2 value is extremely low, suggesting a weak explanatory power of the market measure. This finding leaves considerable space for fund performance and other determinants of individual investments examined below.

2. Literature review

Fund managers have more money available when investors subscribe and less when they redeem. Cash and portfolio decisions by these parties will affect the timing of trade execution. An expansion of the market will motivate some investors to purchase in anticipation of higher returns and others to sell to realise profits. This study examines whether the return of the previous quarter's CSI 300 helps explain the flow of funds to Chinese equities and mixed funds.

Most of the research focuses on the performance of individual funds. Huang et al. found that flows are less responsive to past performance when the performance is more volatile [2]. They interpret this through investor learning, and when the returns are unstable, it is less informative about management ability. Investors' access to performance information also matters. Hong et al. have found in China that investors are more likely to chase performance after funds enter fintech platforms due to the centralised information provided by these platforms [3]. In short, the above research has shown that investors are interested in both the level of a fund's returns and how to interpret or compare that information. A market index provides all investors with a general index, but does not offer information on which fund to choose relatively. Therefore, evidence of responses to a fund's own performance cannot establish the strength of the relationship with market returns examined here.

Investor sentiment is one possible explanation. Market gains may boost people's optimism and subscriptions; losses may lead to withdrawals. Wu and Zhang found that Chinese fund flows are positively correlated with the previous quarter's fund performance but negatively correlated with the current quarter's performance. Positive sentiment reduces the negative effect by decreasing redemptions [4]. Therefore, the actual impact of a rise in returns on investor behaviour may be influenced by the timing of the rise. A positive correlation with lagged market returns is a reasonable expectation of the present study. However, the CSI 300 return does not directly measure sentiment, and therefore it cannot identify this mechanism.

Profit-taking would respond differently to the rise in prices. A disposition effect is a kind of investor behaviour in which winners are sold too early and losers are held onto for too long. Da Silva et al. found evidence of this behaviour among mutual fund investors at a Portuguese bank [5]. Chinese evidence is not very supportive. Researchers did not find strong support in their sample for investors to systematically redeem funds with outstanding past performance [6]. The above results leave room for profit-taking but do not provide a general explanation for Chinese fund flows. Even if it occurs, a profitable investor may sell and another investor may buy the same fund for further profit. Net flows combine both decisions and can conceal their motives.

Parker et al. offer a different reason for selling after a market gain. In their study of US target-date funds, rebalancing leads to a counter-flow in the underlying equity mutual funds [1].

The allocation decision may be shown differently in the fund flow data. One person has equity funds and a separate bond fund, so they can rebalance by redeeming one and subscribing to the other. A mixed fund allows the manager to alter the asset allocation in the portfolio without changing the number of units held by investors. The internal trades are not considered external funds flows. Equity funds invest in stocks, and mixed funds have a relatively higher proportion of other assets. Separate regressions can be carried out to solve this problem, but the labels alone do not indicate

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which group should respond more strongly. The holdings and selected investors of the funds in the same category differ.

Evidence from Portuguese bank clients and US retirement funds does not address the problem in China. Hu et al. have shown that capital controls restrict the overseas investment of Chinese capital [7]. The distribution platforms in China also affect the investors' responses to fund performance, local institutions will thus affect the appearance of the earlier mechanisms in fund data. The above studies support studying Chinese funds directly; however, they have not determined whether the coefficient of past market returns should be positive or negative.

Changes in the flow during 2020-2024 may also be due to the pandemic and its aftermath. Falato et al. studied US corporate bond funds in the COVID-19 crisis and found that there were large-scale withdrawals from funds with illiquid assets and fire-sale risk [8]. Liquidity problems may be the reason for withdrawal that a regression of only past returns would fail to capture. As the evidence is based on US bonds, it cannot provide the same explanation for Chinese equities and mixed funds. The average coefficient over the past few years may also fail to show differences between stress periods and normal market conditions.

Empirically, this research examines whether the return of the CSI 300 in the previous quarter can explain the flow in this Chinese sample. The whole sample and the two fund groups are analysed separately, and no positive or negative signs are assumed in advance. Both signs have a possible reason in the literature. Since sentiment, purchase price and target portfolio weight have not been observed, the reason for the estimated relationship among investors is unknown. The regression shows how much variation in Flow the market signal explains. As funds in a quarter are subject to the same shocks, the analysis also compares the precision of the return coefficient using conventional and quarter-clustered standard errors.

3. Research methods

The Wind extracts provided cover 2,619 Chinese fund codes set up before January 1, 2019, including 736 equity funds and 1,883 mixed funds. For each code, the records run from 2019Q4 to 2024Q4. The provider describes these as surviving funds. There is no special status field for this information in the files, and it has not been confirmed whether all the relevant funds have been included. The analysis uses the provided selection.

Sorting the records by fund code and quarter shows no duplicate code-quarter pairs, and all reported shares are present and positive. Flow and lagged return calculations need a starting quarter. That period is covered by 2019Q4; although included in the calculation, it was excluded from the estimation. Therefore, the balanced panel used for the regression ranges from 2020Q1 to 2024Q4 and has a total of 52,380 observations, including 14,720 equity and 37,660 mixed fund observations.

Flow records the proportional quarterly change in outstanding fund shares:

$$Flow_{i,t} = (Shares_{i,t} - Shares_{i,t-1}) / Shares_{i,t-1} \quad (1)$$

The subscripts i and t identify a fund code and a quarter. Shares are recorded in units of 10,000; this unit cancels when the change is divided by the previous holding. Thus Flow = 0.05 means a 5% increase in shares. It measures net unit changes, not cash flows or investment returns. The provider says these totals combine share classes. The above totals are used as provided and not further aggregated because the files lack a parent-fund mapping.

The market variable is the quarterly return of the CSI 300 divided by 100, in decimal form. Each flow observation is linked with the return from the previous quarter:

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$$Return_lag_i = Return_{i-1} \quad (2)$$

Under this matching rule, 2020Q1 flows use the 2019Q4 return, approximately 0.073942. Table 1 lists the variable definitions. No winsorization or trimming is applied to extreme Flow observations.

Table 1. Variable definitions and sources

Variable	Definition and unit	Source
Shares	Quarter-end outstanding fund shares, measured in 10,000 units.	Supplied Wind fund extract
Flow	Change in shares divided by the previous quarter's shares; decimal.	Calculated from Shares
Return	CSI 300 quarterly percentage return divided by 100; decimal.	Supplied Wind market extract
Return_lag	Previous quarter's Return, matched by quarter; decimal.	Calculated from Return
Fund type	Equity or mixed fund classification; used for separate regressions.	Supplied Wind fund extract

Note. Fund codes identify the records used in estimation. Share-class aggregation follows the data provider's description and has not been independently verified.

Pooled ordinary least squares is used to estimate the following equation for the full sample, and then for equity and mixed funds separately:

$$Flow_{i,t} = \alpha + \beta\, Return_lag_i + \varepsilon_{i,t} \quad (3)$$

In the equation, α is the intercept and ε the error term. The coefficient β relates Flow to the previous quarter's market return. No controls or fixed effects are included. The timing establishes that returns precede flows; it does not identify a causal effect.

Conventional OLS treats errors as independent across the fund observations. The assumption may be unreasonable if the funds have a quarterly market return and other common shocks. The comparison therefore allows errors within a quarter to be correlated. Cluster-robust inference allows within-cluster dependence, although few clusters can limit its reliability [9]. The quarter clustered estimates use 20 clusters, a finite-sample correction, and a t distribution with 19 degrees of freedom. The regression coefficients are unchanged, but their standard errors and significance tests differ. Inference is still limited by the small number of quarters and by dependence within funds across quarters, which this calculation does not address.

4. Results

4.1. Descriptive statistics

The median and mean of Flow give quite different accounts of the sample in Table 2. The median indicates a 2.03% decline, while the mean is positive (0.2636), and the median is negative (Flow = -0.0203). It has a long upper tail; the maximum is 4100.5337, the minimum is -0.9953, and the standard deviation is 18.6033. There are 148 cases of more than 1,000% growth in share per quarter. The statistics include all 52,380 fund-quarter observations from 2020Q1 to 2024Q4.

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There are many declines in the data: 33,854 fund quarters have a negative flow, which is about 64.6% of the sample. The worst was a decline of 99.53% in fund shares over three months. Therefore, one should be cautious about a positive mean. An increase from a small starting base can have a large effect on the mean. It cannot be interpreted as the growth rate of the total funds in the industry.

The range of Return_lag is -0.1516 to 0.1607, which is approximately -15.16% to 16.07%. Both the large-scale market decline and rise occur in the sample. Mean = 0.0065, Median = 0.0164, and Standard Deviation = 0.0878. The amounts are the same for all the funds in that quarter. Although the table counts 52,380 records, there are only 20 quarterly market observations, each shared by all funds observed at that time.

Table 2. Descriptive statistics

Variable	N	Mean	Std. dev.	Min.	Median	Max.
Flow	52,380	0.2636	18.6033	−0.9953	−0.0203	4100.5337
Return_lag	52,380	0.0065	0.0878	−0.1516	0.0164	0.1607

Note. Variables are decimals. N counts fund-quarter observations; Return_lag repeats across funds within each quarter. Data from Wind databases

4.2. Correlation

Flow and Return_lag are almost uncorrelated in Table 3: their Pearson correlation is 0.0063. Pooling the observations therefore gives little evidence of higher flows after stronger market returns, though responses may vary between funds and market conditions. With an intercept and just one explanatory variable, R^2 is the square of the correlation, so the near-zero value carries through to the regression's fit.

Table 3. Pearson correlation matrix

Variable	Flow	Return_lag
Flow	1.0000	0.0063
Return_lag	0.0063	1.0000

Note. N = 52,380 fund-quarter observations. Data from Wind databases

4.3. Full sample regression

A one percentage point rise in the previous quarter's market return is associated with a fitted increase of 1.3335 percentage points in Flow. The coefficient on Return_lag is 1.3335, with both variables entered as decimals. Its conventional standard error, 0.9257, is large relative to the coefficient; the test gives t = 1.4406 and p = 0.1497. At the 5% level, the estimate is too imprecise to conclude that the positive association holds beyond the fitted sample relationship.

With N = 52,380, R^2 is 0.00003962, approximately 0.00396%. Despite having many records, the market-return term accounts for a very small proportion of the fluctuation in Flow. The fitted Flow at a zero-lagged market return is 0.2550. This is the intercept, its standard error is 0.0815, and t = 3.1281 and p = 0.0018. Its significance concerns the fitted starting level, not whether market returns explain Flow.

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4.4. Equity fund regression

Traditional inference shows a more positive result for equity funds. The p value for Return_lag is 1.11e-05, below 1%, with t = 4.3952. A coefficient of 0.3547 and standard error of 0.0807 underlie that test. For every one percentage point increase in the market return, the fitted rise in next-quarter Flow is approximately 0.3547 percentage points. The constant is also positive: 0.0802, with a standard error of 0.0071, t = 11.2876, and p = 2.00e-29.

The fit is still weak in the 14,720 equity observations. Its R^2 is 0.00131078, or about 0.13108%. This exceeds the other two models, yet leaves more than 99.8% of Flow variation unexplained. A significant slope has not made the market return a good description of individual flows. The significance also depends on the standard-error calculation; the quarter clustered comparison below allows funds in the same quarter to share shocks when assessing that result.

4.5. Mixed fund regression

The 37,660 mixed fund observations give a larger slope, 1.7161, together with a larger standard error of 1.2871. The resulting t statistic is 1.3333 and p is 0.1824, above the 5% threshold. The constant is 0.3233 (standard error 0.1133, t = 2.8525, p = 0.0043). For this group, R^2= 0.00004721, or about 0.00472%. More observations have therefore produced neither a precise return coefficient nor much explanatory power.

Table 4 places these estimates side by side. The mixed sample has more observations than the equity sample, but its slope is less precisely estimated. Comparing their p values is also insufficient for deciding whether the slopes differ: each p value tests its own coefficient against zero. A test comparing the two coefficients directly would be needed to establish a group difference. The separate regressions reported here do not perform that test.

Table 4. Main regression results with conventional standard errors

Statistic	Full sample	Equity	Mixed
Constant	0.2550	0.0802	0.3233
Standard error	0.0815	0.0071	0.1133
t statistic	3.1281	11.2876	2.8525
p value	0.0018	2.00e-29	0.0043
Return_lag	1.3335	0.3547	1.7161
Standard error	0.9257	0.0807	1.2871
t statistic	1.4406	4.3952	1.3333
p value	0.1497	1.11e-05	0.1824
N	52,380	14,720	37,660
R^2	0.00003962	0.00131078	0.00004721

Note. The dependent variable is Flow. Each pooled OLS regression includes an intercept and Return_lag only. R^2 is a proportion, not a percentage. Small p values use scientific notation. Data from Wind databases

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4.6. Quarter clustered standard errors

The equity result changes most in Table 5. Clustering by quarter raises its standard error from 0.0807 to 0.2430, while the coefficient stays at 0.3547. With t = 1.4595 and p = 0.1608, the positive estimate loses its conventional significance. For the full sample, the slope likewise remains 1.3335. Its clustered standard error rises to 1.0940, giving t = 1.2190 and p = 0.2378, so the earlier insignificant result is unchanged.

The mixed fund slope of 1.7161 has a quarter clustered standard error of 1.4828. Its t statistic is 1.1574 and p is 0.2615. All three clustered tests thus fall short of significance at 5%. They use 20 quarter clusters and 19 degrees of freedom, while retaining the original coefficients and R^2. For equity funds in particular, the standard error is about three times its conventional value. The fitted line is identical, but the evidence for a positive slope is much weaker.

Table 5. Comparison of conventional and quarter clustered inference

Statistic	Full sample	Equity	Mixed
Return_lag coefficient	1.3335	0.3547	1.7161
Conventional SE	0.9257	0.0807	1.2871
Conventional t	1.4406	4.3952	1.3333
Conventional p	0.1497	1.11e-05	0.1824
Clustered SE	1.0940	0.2430	1.4828
Clustered t	1.2190	1.4595	1.1574
Clustered p	0.2378	0.1608	0.2615
N	52,380	14,720	37,660
Quarter clusters	20	20	20

Note. The comparison concerns the Return_lag slope. Clustered tests use 20 quarters, a finite-sample correction, and 19 degrees of freedom. Clustering leaves coefficients and R^2 unchanged. Source: Supplied Wind databases

5. Discussion

5.1. Low explanatory power

With a full-sample R^2 of approximately 0.00396%, the broad market measure misses almost all variation in Flow. It also misses differences between the returns of individual funds. An investor choosing between funds can compare their returns, whereas the CSI 300 has the same value for every fund in a quarter. It does not explain why the investors added shares to one fund and withdrew from another in the same quarter. Researchers have found that flows are less sensitive to past fund performance when it is volatile, consistent with investors' learning of management ability. Differences in performance histories and assessments of managers are absent from the current model.

Investors hope to obtain a relatively high return on their investment. Researchers find stronger performance-chasing behaviour after Chinese funds enter fintech platforms [3]. Therefore, one should pay attention to the information provided by the sales channel. Danish investors shifted into funds affiliated with their new banks following bank failures [10]. A well-known manager with low

DOI: 10.54254/2754-1169/2026.39192

fees, or promotion through a bank or online platform, could also attract subscribers. Size is in the denominator of the flow ratio; that is, for an increase of the same number of shares, a larger initial holding will lead to a lower ratio. Age may be related to existing client relationships in older funds. The regressions do not test these factors; their role in the different fund outcomes remains unknown.

The standard deviation of Flow is 18.6033 and the mean is 0.2636; therefore, there may be outliers. Small initial holdings can produce large ratios and residuals with considerable weight in OLS. The untrimmed estimates may be sensitive to these observations. Interest rates, inflation and sentiment are omitted as well. Falato et al. link pandemic withdrawals from US bond funds to liquidity fragility [8]. Liquidity needs may therefore matter during stress, although this does not establish that channel in Chinese equity and mixed funds. The analysis examines the extremes and adds variables to help determine the cause of the poor fit.

5.2. Practical implications

A fund company could learn little about subscriptions and redemptions from the previous quarter's market return alone in these estimates. Fund performance, the client base and sales channels are possible sources of additional information. The regressions offer investors no reliable timing rule, and no out-of-sample test has been carried out. For regulators, the maximum Flow of 4100.5337 would need to be considered alongside changes in shares and asset values. A small initial holding can generate a ratio of that size; the ratio alone cannot show a large monetary inflow or a threat to stability.

5.3. Limitations and future research

Five years of equity and mixed fund data give limited coverage of longer market cycles or other categories, such as bond and overseas-investing funds. Surviving-fund selection and unverified share-class aggregation may affect which funds are represented. Despite the many fund records, the market series has only 20 quarters. Clustering within those quarters leaves dependence across quarters within a fund unaddressed. No Controls are applied; extreme flows continue; endogeneity exist.

Fund returns, size, age, fees and manager characteristics can be added in the following work, and the raw-flow results could be compared with winsorised or robust estimates. Fund fixed effects could absorb persistent differences across funds. Quarterly fixed effects are also a problem because they absorb Return_lag, as all funds receive the same return in that quarter. An independent specification can be used to examine the combined effect of the market, for instance, through an interaction term with fund exposure. A longer series could also be employed in the market comparison. An instrument would require a credible reason why it isolates market returns.

6. Conclusion

There seems to be insufficient evidence for a relationship between the flow of funds in China and last quarter's return of the CSI 300 market index. Although the regression estimates suggest a positive slope, neither the pooled sample nor the mixed funds display any significant associations regardless of standard error clustering. Only the equity funds exhibit significance prior to addressing intra-quarter correlations. Low R^2 statistics indicate that the positive estimates have little power to explain the variability of the Flow variable.

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A possible response to rising markets might be increased subscriptions due to optimism, consistent with the positive slope. Alternatively, the rise could motivate investors to withdraw funds in pursuit of profits or rebalancing. The net change in the share number combines purchases and withdrawals; hence, the regression estimate lacks information on investors' motivations. These possibilities exist despite inconclusive results, and the discussion on characteristics and distribution in previous sections remains applicable. Nevertheless, such a regression test does not reveal whether any of these explanations dominates over others.

The period spanned by sample of five years may lack representation of an entire market cycle. This research observes surviving funds selected by Wind, and there is survivorship bias concerning funds. The inference rests upon an insufficient number of twenty quarterly clusters. Omission of controls for fund factors and retention of extreme values in Flow present limitations for the study. Possible avenues to explore for future research involve extending the sample window, incorporating bond funds, and comparing the effects with extreme values omitted. Controls for fund performance and other attributes can test whether weak finding holds.

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