Financial Economics Research; Vol.3, No.5; 2026
E-ISSN: 3006-3663 P-ISSN: 3006-3655
DOI: https://doi.org/10.70267/fer.v3n5.7591
Published by: Zeus Press

Herding Effect in Public Mutual Funds under Extreme Market Conditions: A Literature Review

Jiayu Zhou*

School of Economics and Management, South China Normal University, Guangzhou 510006, China

**Corresponding author: Jiayu Zhou.*

Abstract

The concentrated trading of public mutual funds may affect stock prices, liquidity and market stability. Identifying changes in herding behavior in extreme markets and their asymmetry helps to explain the relationship between institutional transactions and market volatility. The existing conclusions are influenced by the definition of behavior, measurement methods and market-state classification, which motivates this analytical literature review. This study compares what the LSV, Wermers and Sias methods identify and what data they require, examines formation mechanisms in relation to information learning, career concerns, relative performance and fund flows, and compares international evidence and research on Chinese public mutual funds along three dimensions: market conditions, trading direction and market pressure. The analysis shows that contemporaneous concentration, directional differences and intertemporal following belong to different measurement dimensions, and the results cannot be directly compared. Changes in herding behavior under extreme market conditions depend on the information environment, transaction constraints and fund characteristics, and common transactions cannot directly prove intentional imitation. Future research should match the market conditions and data frequency, compare different indicators under a unified sample, and identify the source of behavior and market consequences in combination with fund flows, institutional changes and price performance over multiple horizons.

Keywords

public mutual funds, herding effect, extreme market conditions, measurement methods

1. Introduction

Adjustments to the holdings of public mutual funds may affect stock demand, price discovery and market volatility. Extreme market conditions will change the quality of information, fund flows and risk constraints at the same time, so that concentrated trading and intertemporal following have a different meaning from normal periods. This study focuses on how extreme market conditions affect the herding effect of public mutual funds, and whether this impact varies depending on the market direction, trading direction and fund characteristics.

The LSV method measures the concentration of transactions in the same period, the Wermers method distinguishes between buy-side and sell-side herding, and the Sias method examines the cross-period correlation of institutional demand and its source [1,2,3]. Subsequent studies have provided evidence of return comovement, volatility and fund performance in the Chinese market, but the measurement objects, disclosure

© 2026 The Author(s). Authors retain copyright in their articles.

frequency and market-state classification of each study are different, and their conclusions lack direct comparability [4,5,6]. In particular, the distinctions between contemporaneous concentration and intertemporal following, extreme rises and falls, and active holdings adjustments and redemption-driven transactions still need to be clarified when explaining the differences in research.

This study takes the three types of institutional herding measurement and their related research as the main line, compares their identification boundaries, analyzes the role of information, incentives and fund-flow mechanisms in extreme markets, and then sorts out asymmetry and Chinese market evidence. The contribution of this study is to clarify the sample and market-state conditions under which different conclusions hold, discuss trading concentration, behavioral motives and price consequences separately, and put forward testable research directions accordingly.

2. Measurement Methods for the Herding Effect in Public Mutual Funds under Extreme Market Conditions

2.1 The LSV Measure and the Basic Logic for Measuring Herding under Extreme Market Conditions

The LSV method uses securities and time periods as units of observation to examine whether the number of institutions trading in the same direction exceeds the random level expected under independent decision-making. Its holdings data allow for the identification of specific groups of funds, making it suitable for comparing the concentration of trading activity across normal periods, periods of extreme gains, and periods of extreme losses. This statistic describes observable co-trading but does not directly prove that fund managers intentionally follow others [1,7].

Calculating the indicator requires holdings data from at least two consecutive periods. After adjusting for corporate actions such as stock splits, funds showing an increase in shareholdings are classified as buyers, those showing a decrease as sellers, and those with no change are typically excluded. Let $B_{i,t}$ and $S_{i,t}$ denote the number of funds with net purchases and net sales of stock i, respectively; let $N_{i,t}$ be the sum of the two; and let $p_{i,t}$ be the proportion of buyers. End-of-period holdings reflect only net changes and fail to capture within-period round-trip trades—where assets are bought and then sold, leaving the final holdings unchanged [1,2].

The benchmark p_t for the period can be constructed by dividing the number of fund buy transactions across all stocks by the total number of buy and sell transactions, allowing for an overall fund bias toward increasing or decreasing holdings. The greater the deviation of the stock buyer ratio from the benchmark, the more concentrated the directional trading. However, the finite number of traders can itself create an imbalance between buyers and sellers; therefore, the expected absolute deviation under independent binomial choices, $AF_{i,t}$, must be deducted.

Under the null hypothesis, $B_{i,t}$ follows a binomial distribution with parameters $N_{i,t}$ and p_t. The adjustment term depends on the number of active funds and the aggregate buying propensity; consequently, identical proportional deviations observed with different numbers of traders cannot be regarded as equally anomalous [1, 8].

The basic form of the LSV indicator is:

$$\mathrm{HM}_{i,t} = \left|p_{i,t} - p_t\right| - \mathrm{AF}_{i,t} \tag{1}$$

Averaging the $HM_{i,t}$ values across stock-period observations allows for a measure of the sample's abnormal concentration. A positive average HM indicates that same-direction trading exceeds the random benchmark. Since the indicator for a specific stock during a given period can be negative, a negative value alone does not warrant a direct conclusion of contrarian herding [2].

Comparisons across market states require consistency in institutional definitions, stock coverage, and data frequency. Mutual funds and pension funds have different liability structures, and account data from foreign institutions during a crisis cannot serve as a direct proxy for domestic public mutual funds. These applications indicate that sample differences must be considered before comparing indicator magnitudes [9, 10, 11, 12, 13].

© 2026 The Author(s). Authors retain copyright in their articles.

Common news, benchmark adjustments, and redemption shocks during periods of extreme stress may cause funds to trade in the same direction independently. Changes in benchmark constituents can explain some instances of surface-level herding, whereas trade-based metrics often struggle to distinguish between intentional imitation and reactions to common information [14, 15]. Therefore, the rise in HM still needs to be interpreted in conjunction with market returns, fund flows, and shared holdings.

LSV counts each fund once, without distinguishing between small-scale increases in holdings and large-scale purchases. Quarterly holdings data aggregate reverse trades occurring within the period, thereby obscuring the identification of short-lived market stress. Initial holdings and short-selling constraints influence the set of sellable shares, while measurement bias may also shift in response to the number of traders and their actual trading inclinations [8, 16]. Comparisons during extreme periods should report the thresholds for active funds, adjustments for corporate actions, and the handling of missing values, as well as test results under alternative thresholds.

2.2 The Wermers Measure and the Distinction Between Buy and Sell Herding under Extreme Market Conditions

The Wermers directional indicator adopts the LSV contemporaneous count framework to further identify whether concentration occurs predominantly on the buy side or the sell side. Capital inflows during extreme surges and redemptions during extreme slumps may impose different constraints; distinguishing between these directions helps prevent the unconditional HM measure from masking such differences.

When $p_{i,t}$ exceeds p_t, the stock is classified into the “buy-side herding” sample for the period; when the value is below the benchmark, it is classified into the "sell-side herding" sample, and $BHM_{i,t}$ and $SHM_{i,t}$ are calculated separately. The stochastic adjustment terms are also calculated based on the corresponding directional conditions, allowing each of the two types of indicators to be compared against the conditional stochastic benchmark [2].

The form of the Wermers directional indicator is:

$$\mathrm{BHM}_{i,t} = \left|p_{i,t} - p_t\right| - \mathrm{E}\left(\left|p_{i,t} - p_t\right| \middle| p_{i,t} > p_t\right), \text{The condition is } p_{i,t} > p_t \tag{2}$$

$$\mathrm{SHM}_{i,t} = \left|p_{i,t} - p_t\right| - \mathrm{E}\left(\left|p_{i,t} - p_t\right| \middle| p_{i,t} < p_t\right), \text{The condition is } p_{i,t} < p_t \tag{3}$$

BHM and SHM should be calculated separately for normal periods, extreme upturns, and extreme downturns, and then grouped according to stock liquidity, historical returns, and fund objectives. Studies from different countries have yielded divergent results, indicating that trading indicators are also influenced by holdings disclosure requirements, fund structures, and trading systems [8, 10, 11, 17].

Directional indicators can be combined with price paths. By constructing stock portfolios based on BHM and SHM and comparing returns across pre-stress, stress, and recovery periods, one can examine whether concentrated trading is accompanied by temporary price impact. Subsequent reversals are consistent with explanations regarding price pressure, while the persistence of returns may reflect the gradual incorporation of information into prices; however, risk and liquidity must be controlled for in both cases. Studies on analyst recommendations and corporate bonds have employed similar designs [18, 19], and their conclusions cannot be determined solely by the direction of contemporaneous returns.

In addition to data on adjacent holdings, price impact analysis requires data on returns and stock characteristics; fund objectives, fund families, and fund flows can be used to control for heterogeneity. Some funds disclose their holdings only semi-annually, so uniform quarterly snapshots may miss certain trades; altering the minimum number of funds or the threshold for changes in holdings would also change the implications of the sample [2].

Directional differentiation still cannot determine who traded first, nor can it identify the trading volume within the period. During market downturns, selling activity by sellers is constrained by initial holdings, while redemptions and risk limits may simultaneously trigger holdings reductions [8]. Therefore, the fact that SHM exceeds BHM may stem from a combination of behavioral differences and changes in the tradable set; an assessment requires integrating fund flows with securities liquidity.

© 2026 The Author(s). Authors retain copyright in their articles.

Market direction and trading direction should be cross-classified: BHM and SHM should be reported for both rising and falling periods. If one is further interested in whether the trading of other funds extends over time, cross-period measurement is required.

2.3 The Sias Measure and the Dynamic Measurement of Herding under Extreme Market Conditions

The Sias method focuses on the intertemporal persistence of institutional demand and distinguishes between the continuation of an institution's own trades and following trades by other institutions [3]. When applied to extreme market conditions, it can test whether the concentrated buying and selling observed before market stress persists into the stress or recovery periods, thereby complementing the contemporaneous assessments made by LSV and Wermers.

The raw demand $\mathrm{Raw}\Delta_{k,t}$ represents the proportion of institutions that purchase security k during period t out of all institutions actively trading that security. For each period, the cross-sectional mean is subtracted from the ratio, which is then divided by the cross-sectional standard deviation to obtain the standardized demand $\Delta_{k,t}$. This procedure eliminates scale differences in the aggregate buying propensity and the degree of dispersion across periods [3].

The basic regression for the Sias method is:

$$\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}, \text{and } \beta_t = \beta_{self,t} + \beta_{other,t} \tag{4}$$

Researchers conduct cross-sectional regressions on securities observable in two consecutive periods and then calculate the time-series average of β_t. A positive coefficient indicates that securities with a relatively high proportion of buyers in the previous period tend to maintain a high proportion of buyers in the current period. The correspondence between coefficients and correlation coefficients depends on consistency regarding standardization and the scope of the regression sample; the entry and exit of sample observations cannot be overlooked. The original study found that demand persistence cannot be primarily explained by past returns [3].

Let $D_{n,k,t}$ denote the trading direction of institution n, where 1 represents a buy and 0 represents a sell. β_t can be decomposed into the covariance contribution of inter-period transactions by the same institution and inter-period transactions by different institutions, and weighted according to the number of active institutions and the standard deviation of demand. The former reflects the continuation of the institution's own trades, whereas the latter more closely resembles inter-institutional herding behavior. Consequently, the practice of building or reducing holdings in stages is no longer entirely categorized as inter-institutional herding behavior [3].

Dynamic methods can be extended to following within industries and across institutional types, and can also separate a fund's own contribution from those of other funds using holdings data with fund identifiers [20,21]. Industry-allocation research using both LSV and Sias shows that contemporaneous imbalance and intertemporal persistence provide complementary information [22]. These designs provide a methodological basis for testing leader-follower relationships among funds during the stress period.

The dynamic estimate must match the observation frequency with the duration of the extreme state. Studies of monthly pension fund allocations, institutional trading at different frequencies and cross-country holdings have made corresponding adjustments [23,24,25]. Applications to asset classes and corporate bonds further indicate that the scope of assets and the continuity of transactions will affect the interpretation of indicators [19,26].

Suspensions, fund withdrawals and missing reports in extreme periods may occur simultaneously, changing the cross-period matching and cross-sectional distribution. Stable institution identifiers, security codes and clear rules for missing values are therefore necessary conditions for dynamic measurement. When the number of assets is limited or the allocation weight is subject to adding-up constraints, it is also necessary to adjust the estimate and test the impact of sample changes [23,26].

A positive cross-institution pairing component is still insufficient to establish causal imitation. Funds may receive correlated signals over successive periods or trade in batches under joint redemption and risk constraints. Industry-level and cross-country research both suggest the importance of the information

© 2026 The Author(s). Authors retain copyright in their articles.

environment [20,25]. To judge whether there is intentional imitation in extreme periods, it is still necessary to combine public news, fund flow and common benchmarks.

Adjacent period correlation may omit rapid response and non-adjacent period follow-up. Low-frequency data aggregate trades before and after shocks, and high-frequency data may be affected by order splitting. Persistence indicators based on consecutive periods of net trading provide additional information on duration, but differ from the institution-pair decomposition in the Sias method [27].

2.4 A Comparison of DIFFERENT Herding Measures under Extreme Market Conditions

Table 1 compares the aspects of herding identified by the three types of methods. LSV assesses whether trading is abnormally concentrated during an extreme period. Wermers retains trade direction, and Sias examines demand persistence before and after market stress. The three share holdings or transaction data with institutional identifiers, but correspond to different time relationships.

The same episode of extreme market conditions may produce different index results. If concentrated selling only occurs in one stress period, HM and SHM can be higher, while the Sias correlation in the recovery period is lower; if modest holdings reductions persist across periods, the result may be lower HM and higher dynamic correlation. Contemporaneous concentration is related to intertemporal persistence, but they cannot replace each other [22,25].

Data frequency, state threshold and direction definition will further change the result. After daily trades are aggregated, the herding level and stock-size effect may change [24,28]. The return threshold, high volatility and liquidity contraction correspond to different windows. When identifying trading by the number of shares, amount or allocation weight, the decision represented by each measure should be specified; the higher active fund threshold may also make the sample biased towards large-cap stocks.

Pooling all institutions may offset the opposite transactions during the stress period, and excessive grouping may reduce the number of usable observations. Studies that group observations by fund objectives, institutional types and pension fund characteristics provide a basis for dealing with heterogeneity [2,20,26]. The research of public mutual funds should also specify whether the decision-making unit is the individual fund or the fund family.

LSV and Wermers rely on random selection benchmarks, and changes in the initial holdings and the number of traders affect their interpretation; Sias relies more on matching samples across periods and standardization [3,8,16]. Short-lived extreme states can exacerbate small-sample problems, so it is necessary to compare the estimates under the alternative window, state threshold and fund threshold.

When the research problem involves concentration, trading direction and continuity at the same time, three types of indicators can be used jointly under the same sample and market-state classification. Extreme states should be defined independently of herding indicators, and studies should report how common benchmarks, fund flows and liquidity are treated. The function of multi-indicator comparison is to identify the dimension in which a change occurs, rather than requiring each indicator to get the same value or significance [19,22,23].

Table 1: Identification Boundaries of the LSV, Wermers, and Sias Measures under Extreme Market Conditions

Comparison Dimension	LSV Measure	Wermers Directional Measure	Sias Measure
Core unit of observation	Stock and period	Stock and period, while retaining trade direction	Security and adjacent periods
Primary statistical relationship	Deviation of the contemporaneous proportion of buyers from the overall buying tendency	Conditional imbalance between the numbers of buyers and sellers	Correlation between standardized institutional demand in the current and previous periods
Primary data requirements	Mutual fund holdings in adjacent periods or transaction data with identifiable institutional ownership	Holding data, supplemented by stock returns and stock characteristics to analyze price effects	Multi-period holding data with stable institutional and security identifiers
Can identify	Abnormal contemporaneous trading concentration	Buy-side and sell-side herding and their associated price performance	Demand persistence, own-trade continuation, and

© 2026 The Author(s). Authors retain copyright in their articles.

Comparison Dimension	LSV Measure	Wermers Directional Measure	Sias Measure
			inter-institutional herding behavior
Cannot directly identify	Common shocks during extreme periods, trade sequencing, trading volume, and subjective trading motives	Who follows whom, within-period trading order, and redemption-driven trading	Causal imitation and rapid responses within extreme market periods
Applicable research questions	The existence of herding during extreme market periods, cross-sectional differences, and comparisons across market conditions	Directional asymmetry between bull and bear markets under extreme conditions and subsequent returns	Dynamic herding behavior, leader–follower relationships, and persistence before and after market stress

Note. Compiled based on the relevant literature [1, 2, 3, 19, 22, 23].

3. Theoretical Foundations of the Herding Effect in Public Mutual Funds under Extreme Market Conditions

3.1 Conceptual Definition of the Herding Effect in Public Mutual Funds under Extreme Market Conditions

This study focuses on public mutual fund managers and distinguishes intentional following from independent responses to common shocks when examining same-direction trading in extreme markets. The former refers to funds adjusting their decisions in response to other institutions' actions or the information those actions convey, and the latter may come from the same news, benchmarks and redemption constraints. The similarity of the transaction results is not enough to determine the motivation of the behavior [7,15,29].

The analysis covers allocation changes involving the same stocks, industries and investment styles. Observable patterns include contemporaneous concentration, buy-sell differences and intertemporal correlation. Market-wide herding research uses return dispersion, and it is difficult to identify the participants [30,31]. Therefore, the convergence of returns in the extreme period cannot be directly used as evidence of the herding behavior of public mutual funds.

Public mutual funds are also subject to delegated management, relative-performance evaluation, and subscription and redemption constraints. Their liability structure differs from that of individual accounts and other institutions. The correlation between changes in institutional shareholdings and returns may have both feedback trading and price influences, so the behavior of different investor groups should not be interpreted as a single category [32]. The types of funds and tradable sets in the extreme period should be clarified in empirical research.

3.2 Theoretical Mechanisms of the Herding Effect in Public Mutual Funds under Extreme Market Conditions

3.2.1 Information Learning Mechanism and Information Cascade Theory

In extreme markets, prices include both fundamental information and liquidity pressure, and funds may reduce trust in private signals and turn to observing peer trading. The information cascade model shows that the information contained in previous actions can make subsequent decision-makers give up contrary private signals [33,34]. Price adjustment can limit some following behavior, but when multi-dimensional uncertainty and information quality are difficult to identify, herding and mispricing may still occur [35].

Peer buying in the rising period may be regarded as a confirmation of prospects, and the reduction of holdings in the falling period may convey risk information. Short-term evaluation will also increase the fund’s attention to the information that other traders pay attention to [36]. Institutional demand persistence and returns following concentrated fund trading are consistent with information dissemination, but this evidence from normal periods cannot directly prove that information learning is stronger in extreme periods [2,3]. Comparisons across market states still need to examine the quality of the private signal and the subsequent price path.

© 2026 The Author(s). Authors retain copyright in their articles.

3.2.2 Reputation Maintenance Mechanism and Career Concern Theory

Career concerns may lead fund managers to choose to stay close to their peers even when they retain their own private judgments. When managers' ability is difficult to observe directly, common failure is more likely to be attributed to the external environment, thus reducing the reputation cost of independent decision-making failure [37]. Relative underperformance during extreme rises and losses from independent decisions during extreme declines may increase the career costs of deviating from peers.

The dismissal risk of young managers is more sensitive to performance and portfolio deviation, which provides fund-level evidence for this mechanism [38]. The career-concerns model also links institutional imitation with transaction continuity, short-term price continuation and long-term reversal [39]. These results suggest that the degree of follow-up of managers at different career stages before and after pressure should be compared, and the overall changes in the market should not be attributed to reputation maintenance.

3.2.3 Relative Performance, Fund Rankings, and Fund Flow Mechanisms

The response of fund flows to historical performance is non-linear, and the ranking changes the risk choice [40,41]. Funds that underperform by mid-year may subsequently increase portfolio risk, and benchmark constraints will form different risk-shifting regions [42,43]. The extreme market quickly changes the rankings and subscription and redemption conditions, so that these incentives may be concentrated in the short term.

The impact of relative performance incentives on the herding effect may operate in opposite directions. Some managers align their holdings with peers to reduce relative underperformance, while other underperforming funds may take more differentiated risks to improve the ranking. Redemptions during downturns may force funds at different ranks to reduce their holdings together. Therefore, the average indicator needs to be interpreted in combination with fund ranking, fund flows and market direction.

3.2.4 Common Decision Bases and Style Investing Theory

Common benchmarks, valuation methods and risk constraints can enable funds to make similar decisions independently. Funds' shared preferences regarding stock visibility and transaction costs, the movement of funds between styles, and the differences in relative benchmark deviations are supported by relevant research [44,45,46]. Industry concentration may also reflect the information advantages of active funds [47]. The similarity or differentiation of the portfolio in the extreme period must be related to the investment strategy, and imitation cannot be inferred from overlapping holdings alone.

Information learning, reputation maintenance and common constraints may work at the same time. Quarterly holdings cannot observe the sequential relationship between news, redemption and trading intentions, and high-frequency data cannot automatically exclude common information. The mechanism test should be combined with the manager's characteristics, fund ranking, fund flows, common benchmark and transaction timing.

3.3 The Role of Theoretical Mechanisms under Extreme Market Conditions

The extreme market condition also involves the direction of returns, volatility and liquidity, and higher pressure should not be assumed to produce stronger herding. The study of market return dispersion provides a reference for state division, but it cannot directly replace the evidence of fund transactions [48]. Theoretical analysis needs to further explain how information and constraints change in a specific state.

The enhancement of public signals may reduce the value of the fund's peer observation, and heterogeneous constraints may also differentiate transactions. Market-level research has found that the herding index decreased during the crisis period, and South Korean foreign investor research also found that the herding in crisis was weaker than before the crisis [12,49]. Neither of the two types of samples can directly represent China's public mutual funds, but these findings show that there is no fixed positive relationship between market pressure and herding.

Redemption pressure will turn the market decline into the fund's cash demand. Fund flows generate liquidity-driven transactions and costs. Funds experiencing large outflows tend to sell existing holdings, so joint holdings may form synchronous selling pressure [50,51]. Poor asset liquidity will enhance the redemption

© 2026 The Author(s). Authors retain copyright in their articles.

response after poor performance, and the relevant liquidity shock will also increase the sensitivity of stocks to non-fundamental demand [52,53].

The above concentrated selling may be a passive holdings adjustment, or it may include a reaction to the expected orders of other funds. Evidence on flow-driven trading shows temporary price impacts and longer-term reversals [54]. Therefore, explanations of sell-side herding in extreme periods should distinguish active informed trading, cash constraints and anticipatory following, and test the price consequences of different periods.

The increase in trading demand does not necessarily increase the observed herding. Insufficient market depth may hinder simultaneous selling by funds, and differences in information positions will make institutions choose different directions. The evidence of institutional turnover on days of large market movements and the differences between resident and non-resident institutions before and after the crisis all suggest the importance of investor categories [13,55]. Therefore, market-state comparison needs to observe the transaction motivation and the execution constraints at the same time.

4. Asymmetry of the Herding Effect in Public Mutual Funds under Extreme Market Conditions

4.1 State Asymmetry Between Rising and Falling Markets

The market conditions and transaction direction should be identified separately. There may be buy-side or sell-side herding in both rising and falling periods. Market returns describe the price state, and the Wermers direction indicator describes the concentration of trading on a single stock. Equating rising markets with buying and falling markets with selling confuses price changes with fund behavior, and it will be difficult to distinguish the reaction of the fund to the market, peer trading and common information.

There is no fixed positive relationship between market pressure and institutional herding. Emerging market fund herding is related to volatility, but synchronous selling during crisis cannot be entirely attributed to panic [10]. South Korea's transaction records show that herding among foreign investors weakened during the crisis, and the changes in resident and non-resident institutions were also different [12,13]. Falling prices may increase the motivation to follow, but may also widen differences in information and constraints, lowering the average herding indicator.

The joint subscription and relative ranking pressure of the rising period may lead funds to increase their holdings together, and the redemption and cash demand of the falling period may form a joint selling pressure. Funds may also adjust their holdings in advance due to the expectation that other institutions will continue to sell. The same selling concentration may come from passive constraints or strategic reactions, and the price consequences of the two need to be tested separately [51,53,54].

The market-state comparison should report the results of four groups of buying during the rising period, selling during the rising period, buying during the falling period and selling during the falling period at the same time. Average HM does not retain directional information, and comparing BHM and SHM alone will ignore the market background. Stock size, liquidity, historical returns and the overall buying tendency of the fund should also be comparable to avoid interpreting the difference in trading opportunities as a state effect.

The state comparison also depends on the frequency of observation. Quarterly or semi-annual holdings will offset the reverse transactions during the period, and daily data may count order splitting as trading persistence. The level and price impact of institutional herding will change with the aggregation frequency [24,28]. Therefore, it should be estimated at a uniform frequency, and an alternative window should be used to test whether the conclusion depends on the period division.

4.2 Directional Asymmetry Between Buy-Side and Sell-Side Herding

BHM and SHM enable the concentration of trading in the same market condition to be compared separately [2]. But the opportunity sets on the two sides are not the same. The fund can buy new stocks. Selling usually requires holdings at the beginning of the period. Short selling restrictions and disclosure definitions will affect

© 2026 The Author(s). Authors retain copyright in their articles.

the set of sellers [8]. Unadjusted indicator differences may include both herding behavior and transaction constraints.

Fund flows further affect comparisons between trading directions. Net subscription allows the establishment of holdings in batches, net redemption requires cash raising, and the assets sold may be concentrated on common holdings with high liquidity. SHM during extreme market downturns may therefore mainly reflect cash demand. Controlling holdings, redemption pressure and stock liquidity at the beginning of the period is a necessary condition to explain the degree of concentration of selling.

Buy-side herding may also have downside risks. Mutual fund herding is related to the poor information environment and disclosure quality, and the association with subsequent crash risk is mainly concentrated on the buying side [56]. This is consistent with the explanation that the negative information did not enter the price in time, but this does not imply that all buy-side herding is destabilizing. The direction and consequences still need to be judged in combination with subsequent returns, volatility and information environment.

The direction difference may also depend on the investment horizon. The term effect of U.S. Treasury mutual funds mainly exists on the buying side and is more obvious in funds with shorter investment horizons [57]. This cross-asset evidence suggests that stock research should also consider the investment horizon and holdings period of the fund, and not just compare the average BHM and SHM.

The transaction system can change the constraints and information at the same time. China's short-selling pilot study found that the short-selling eligibility has increased herding among public mutual funds on related stocks, and the role is stronger in companies with weak information environments [58]. The author links it with the decline of information asymmetry and increased correlation among fund signals. Therefore, the relaxation of selling restrictions does not necessarily reduce the herding, but may also increase common transactions through information production.

Neither BHM nor SHM can identify the trading motivation or market stability alone. The price of the current period has changed and there is no subsequent reversal, which is consistent with the interpretation of the information entering the price; if the risk of subsequent reversal, continuous volatility or collapse increases, it is necessary to consider price pressure and information accumulation. The indicators on both sides should be compared with the same result variables and observation period.

4.3 Differences in the Herding Effect under DIFFERENT Levels of Market Stress

Measures of market stress should distinguish returns, volatility, liquidity and sources of fund flows. Defining extreme states solely by return quantiles may mix information, liquidity and institutional shocks. Estimating these states and their interactions separately helps to judge what kind of constraints correspond to the changes in herding.

There is also a problem of direction identification in the relationship between pressure and the herding. Emerging market fund herding is associated with volatility, but the behavior during the crisis is not mainly manifested in panic [10]. Chinese research found that fund herding predicts subsequent idiosyncratic volatility, and the effect during periods of high investor sentiment is stronger [5]. The former examines the relationship between state and behavior, and the latter examines the market consequences of behavior. The two types of evidence cannot be combined into the conclusion that pressure inevitably strengthens the herding.

The joint sale caused by redemption may cause temporary price pressure and subsequent reversal [51,54]. If the fund responds to the potential sale of other funds in advance, the transaction includes a strategic response. Distinguishing between the two requires the joint use of fund flow, cash holding and stock liquidity, which is difficult to identify by end-of-period holdings alone.

The conclusion of transaction restrictions also depends on the observation level. Research on crisis-period short-selling bans used return dispersion and found that the herding in some markets did not increase or the dispersion increased [59]. The holdings study of China's short-selling pilot found that the fund herding increased [58]. The two observe market returns and institutional common transactions respectively, which cannot be regarded as the opposite test of the same indicator.

The suspension, delisting and fund withdrawal during the pressure period will also change the sample. LSV requires enough active trading funds, and Sias requires cross-period matching of securities and institutions.

© 2026 The Author(s). Authors retain copyright in their articles.

The market-state comparison should report the coverage rate and check the common sample, suspension processing and minimum trading fund threshold, so as to avoid interpreting changes in sample composition as changes in herding.

5. Evidence on the Herding Effect in China's Public Mutual Funds

5.1 The Existence and Characteristics of the Herding Effect in China's Public Mutual Funds

A multi-index study of China's public mutual funds found that the trading direction in the same period was concentrated beyond the random benchmark. LSV, the adjusted LSV and the structural herding measure obtained similar evidence of herding, which reduces the possibility that the conclusion is completely generated by a single adjustment term [4,5]. However, this consistency is still evidence of the transaction result, and it cannot be directly confirmed that the fund manager intended to imitate.

The consequences of the herding are not evenly distributed. Its effect on reducing future return comovement is stronger in low-volatility and high-fund holding stocks [4]. Stocks with high fund ownership also show a stronger idiosyncratic volatility response after herding [5]. Therefore, the concentration of stock holdings may affect both information incorporation into prices and volatility. Market effects cannot be judged solely from holdings concentration.

China's holdings evidence is limited by the frequency and coverage of disclosure. Quarterly or half-year net stock holding changes cannot identify round-trip transactions and execution order, and some holdings disclosures may also mix real exits and holdings ranking changes. HM is closer to the concentration of net portfolio rebalancing during the reporting period. When comparing the average indicators between studies, the sample period, holdings coverage and fund screening criteria should be unified first.

The dynamic indicators at the fund level reveal another type of difference. China's long-term sample shows that the tendency of fund managers to follow previous institutional transactions is related to lower performance [6]. This indicator observes the cross-period behavior of a single fund, which is suitable for analyzing manager characteristics and performance; BHM and SHM at the stock level are suitable for analyzing the transaction direction and price impact, and the two cannot replace each other.

5.2 Asymmetry of the Herding Effect in China's Public Mutual Funds under Extreme Market Conditions

China's direct holdings-based evidence on extreme markets is still limited, and few studies jointly compare rising and falling markets with buying and selling within the same model. High investor sentiment will strengthen the impact of the herding on subsequent idiosyncratic volatility [5], but this is a difference in the state of market consequences, and it cannot be determined that the level of the herding during the period of high sentiment is higher.

The research after the full circulation reform also shows different consequences. The effect of fund herding on reducing return comovement becomes stronger [4], and the effect of increasing idiosyncratic volatility is also more obvious [5]. Both of them involve information entering prices and volatility respectively, suggesting that the institutional environment can change the information role and risk consequences of common transactions at the same time.

The market-state comparison also needs to control the flow of funds. Joint subscription may promote the concentration of buying in the rising period, and joint redemption may promote the concentration of selling in the falling period. If these capital needs are not distinguished from active transactions, the market conditions coefficient will mix multiple sources. The existing evidence is not enough to judge whether sell-side herding during downturns is stronger than buy-side herding during upturns under consistent holdings definitions.

Research on fund returns provides supplementary evidence. The convergence of returns of China's open-ended funds is more obvious in rising markets and periods of high volatility or high policy uncertainty [60]. However, the study uses CSAD to examine portfolio returns rather than the buying and selling directions of individual stocks. Common market exposure and similar benchmarks can also produce returns convergence, so it cannot replace LSV or Sias holdings testing.

© 2026 The Author(s). Authors retain copyright in their articles.

5.3 The Effects of Institutional and Information Environments on the Herding Effect in Public Mutual Funds

Institutional research helps to distinguish information sources. The Shanghai-Hong Kong and Shenzhen-Hong Kong Stock Connect programs have reduced domestic institutional herding in eligible stocks, with stronger effects in companies with small scale, less analyst coverage or low liquidity. Improving corporate transparency is an important channel [61]. This is consistent with the explanation of the reduction of dependence on peer transactions after the improvement of private information.

The short-selling pilot has increased herding among public mutual funds and reduced information asymmetry through informed trading and liquidity channels [58]. This difference does not mean that the information mechanism is contradictory. Information improvement can not only improve the reliability of the judgment of individual funds, but also enable different funds to receive more highly correlated signals, which may increase common transactions under independent decision-making.

Corporate site visits are associated with lower subsequent fund herding, and this association is stronger in companies with less analyst coverage or low liquidity [62]. The result supports the explanation that independent information acquisition reduces the need to follow. Whether information acquisition reduces the herding depends on whether it mainly improves private judgment or provides similar signals to multiple funds.

The manager network may increase information sharing. Chinese fund managers with alumni connections have a higher degree of overlap in holdings, buying and selling, and are more likely to conduct joint corporate site visits; the associated stocks more frequently exhibit positive earnings surprises [63]. However, the common educational background, style and research resources may also overlap, and it is necessary to explain the role of the network after controlling for fund family, school characteristics and stock selection.

These results show that institutional analysis should examine the quality of information, signal correlation and transaction feasibility respectively. A single measure of information asymmetry cannot adequately explain why herding may rise or fall after the information environment improves.

5.4 Market Impacts of Herding Behavior in Public Mutual Funds

Some Chinese evidence is consistent with information-driven common trading. The fund herding reduced the future return comovement [4], and other studies found contemporaneous price impacts without significant subsequent reversals [58,62]. These results support the interpretation of information entering the price, but the non-reversal itself is not enough to confirm that all common transactions are based on information.

Other evidence shows the possible market cost. Herding increased idiosyncratic volatility over several subsequent reporting periods, and the reaction of high sentiment and high fund holding stocks was stronger [5]. The LSV study also found that fund herding is related to the lower stock price information content, and affects the company's value through the information content and agency costs [64]. Therefore, volatility and information environments need to be tested separately.

Fund performance does not necessarily improve. Chinese dynamic research found that the tendency to follow is related to lower performance, and the age, gender and experience of managers will change this relationship [6]. Similar results of American funds are more obvious among managers with stronger career concerns [65]. The information response of the stock price and the investment returns of the following fund are different results and cannot be inferred from each other.

The direction and duration of the evaluation of market impact should be unified. Lower return comovement and the absence of subsequent reversals are consistent with information incorporation into prices. Idiosyncratic volatility, information content and crash risk reflect different costs. The relationship between buy-side herding and the subsequent crash risk is stronger than that of sell-side herding [56], which further indicates that selling should not be presumed to be more destabilizing. The role of short-term information can coexist with the risk of long-term joint holdings.

© 2026 The Author(s). Authors retain copyright in their articles.

Table 2: Major Micro-Level Evidence on the Herding Effect in China's Public Mutual Funds

Study	Sample and Measure	Main Findings	Identification Implications
Caglayan et al. [4]	Chinese public mutual funds; LSV, ADJHM, and FHW measures	Herding reduces future return comovement, with stronger effects among low-volatility stocks, stocks with high mutual fund ownership, and after the full circulation reform.	Information incorporation into prices and institutional conditions
Zhao et al. [61]	Domestic institutional investors; LSV-type measure and the Stock Connect shock	Stock Connect reduces herding in eligible stocks, with stronger effects for firms with greater information asymmetry.	Market liberalization and transparency
Wang and Xiong [64]	Chinese securities investment funds; LSV measure	Herding is associated with lower stock price informativeness and affects firm value through stock price informativeness and agency costs.	Information environment and corporate consequences
Feng and Xiang [58]	Chinese public mutual funds; LSV measure and the short-selling pilot program	Short-selling eligibility increases herding and strengthens its price impact, without subsequent price reversal.	Short-selling signals and trading institutions
Quan et al. [62]	Chinese public mutual funds; LSV measure and corporate site visits	Corporate site visits are associated with lower subsequent herding, and the price impact of post-visit herding does not exhibit significant reversal.	Private information acquisition
Xue et al. [5]	Chinese public mutual funds; LSV, ADJHM, and FHW measures	Herding increases subsequent idiosyncratic volatility, with stronger effects among high-sentiment stocks and stocks with high mutual fund ownership.	State dependence and market stability
Fan et al. [6]	Chinese public mutual funds; dynamic fund-level following measure	A stronger tendency to follow other funds is associated with poorer fund performance, and this relationship is moderated by fund manager characteristics.	Intertemporal herding behavior and fund managerial ability

Note. ADJHM denotes the adjusted LSV measure proposed by Brown et al. [18], and FHW denotes the structural herding measure developed by Frey et al. [16]. The studies summarized in this table employ fund or institutional holdings, trade-direction data, or intertemporal following measures. Because the underlying statistics differ across measures, their numerical values are not directly comparable.

6. Review and Future Research Directions

6.1 Major Consensus and Divergences in the Existing Literature

Existing studies consistently support the concentration of institutional transactions in the same period that exceeds the independent benchmark, and buying and selling need to be examined separately [1,2,25]. China's multi-index research obtained similar results [4,5]. This consensus is aimed at statistical patterns, and intentional imitation still needs additional identification.

The strength of the herding varies with stock liquidity, information environment, institutional holdings and fund characteristics. Concentration in the same period is not the same as persistence across periods. Funds may only trade together in one period, or maintain weak co-directional demand in multiple periods [3]. Therefore, findings on herding obtained with different indicators can complement each other, but cannot be directly sorted by numerical values.

There is no unified direction for whether the extreme market will strengthen the herding. Herding among foreign investors in South Korea may weaken during the crisis period [12,13], and the high sentiment period in China shows an increased impact of the herding on subsequent volatility [5]. These studies deal with behavioral levels and market consequences respectively. The difference in conclusion should first be explained from the subject, state and result variables.

The direction and consequences also depend on the constraints and time limits. Crash risk and the term effect of bonds are mainly seen in buy-side herding [56,57], while redemption pressure can form joint sales

© 2026 The Author(s). Authors retain copyright in their articles.

and temporary price shocks [51,54]. Buying and selling comparison requires controlling the tradable set, fund flows and observation period at the same time.

Some studies found no subsequent reversal or found lower return comovement, which was consistent with the information entering the price [2,4,58]. Other studies have found price reversals, idiosyncratic volatility, crash risk or lower performance [5,18,56,65]. Differences in the source, result variables and duration will affect the judgment.

6.2 Major Limitations of the Existing Literature

First of all, result-based indicators cannot directly confirm the motivation. Contemporaneous trading concentration and intertemporal demand persistence can come from common information, benchmarks, fund flows or transaction restrictions. Even if the cross-institution pairing component is positive, correlated signals and batch transactions cannot be ruled out. The identification of intentional imitation still depends on tests of the underlying mechanisms.

Secondly, the definition of extreme state is not yet unified. Return thresholds, volatility, liquidity and crisis events describe different constraints. If they are combined into a single dummy variable, they may lose interpretive information, and if they are used alone, they may omit interaction. Using the whole sample to determine the boundary after the fact may also introduce look-ahead bias.

Third, low-frequency holdings net out the transactions during the period, and it is difficult to identify trading order or distinguish active from passive adjustments. Although high-frequency data improves the timing, it increases the identification problems of order splitting and intraday liquidity supply. Cross-frequency conclusions need to be compared under the same data source.

Fourth, accounting for heterogeneity involves sample-size trade-offs. The combination of funds with different targets, benchmarks, fund flows and manager characteristics may offset the opposite behavior; excessive grouping will reduce the number of active funds. The joint treatment of fund characteristics and market conditions in existing research is still limited.

Fifth, there are problems of reverse causality and omitted variables in market consequences. Funds may trade together due to expected volatility or company information. Institutional reform and corporate site visits provide identification conditions, but they may be accompanied by other market changes, and the absence of subsequent reversals alone cannot establish informed trading.

Finally, the changes in China's fund industry and trading system have increased the difficulty of cross-period comparison. The information environment, investor structure and tradable set may be adjusted at the same time, and it is necessary to report the sample entry and exit, survivorship bias and overlapping institutional changes, and clarify the scope of application of the reform effect.

6.3 Future Research Directions

Future research can incorporate return direction, volatility, liquidity and fund flow into the model respectively, and set up interaction terms with economic implications. Use the out-of-sample rule or rolling window to determine the threshold, and then report the alternative threshold result to test the impact of the state definition.

The joint use of LSV, Wermers and Sias methods in the same sample can connect the concentration of the same period, the direction of buying and selling and the continuation of the cross-period. The simultaneous rise of different indicators can strengthen the evidence of continuous trading, but common shocks still need to be tested; when only single-period indicators rise, we should focus on short-term shocks and execution factors.

Dynamic indicators at the fund level can further connect herding behavior, manager characteristics and performance [6,65]. Combining them with institutional pairing decomposition helps to identify funds that trade first, following funds and their role changes in extreme markets.

Transaction data should also be matched with subscription and redemption, cash and derivative exposure to distinguish between information transactions and liquidity adjustment. When only low-frequency holdings

© 2026 The Author(s). Authors retain copyright in their articles.

can be used, the impact of end-of-period netting can be evaluated, and corporate actions, trading suspensions and newly initiated positions can be handled uniformly.

The heterogeneity of funds should be included in the core model. The benchmark and redemption structure of different fund types, as well as the manager's career stage, fund family and network, will change information and incentives. Grouping results should be combined with interaction or hierarchical models to reduce the limitations of small sample mean comparison.

Changes in China's system can be used to distinguish information quality, signal correlation and transaction constraints. The study of Stock Connect, expansions in short-selling eligibility and information disclosure reform should test policy expectations, parallel trends and reforms in the same period, and estimate the buying, selling and intertemporal following effects respectively.

Market consequences should be assessed using returns over multiple horizons, volatility, liquidity, crash risk and fund performance. The role of short-term information can coexist with the risk of long-term joint holdings. Linking the source of behavior, transaction direction and subsequent results helps to clarify the formation conditions and market impact of fund herding under extreme market conditions.

References

[1] Lakonishok, J., Shleifer, A., & Vishny, R. W. (1992). The impact of institutional trading on stock prices. *Journal of Financial Economics, 32*(1), 23–43. https://doi.org/10.1016/0304-405X(92)90023-Q

[2] Wermers, R. (1999). Mutual fund herding and the impact on stock prices. *The Journal of Finance, 54*(2), 581–622. https://doi.org/10.1111/0022-1082.00118

[3] Sias, R. W. (2004). Institutional herding. *The Review of Financial Studies, 17*(1), 165–206. https://doi.org/10.1093/rfs/hhg035

[4] Caglayan, M. O., Hu, Y., & Xue, W. (2021). Mutual fund herding and return comovement in Chinese equities. *Pacific-Basin Finance Journal, 68*, 101599. https://doi.org/10.1016/j.pacfin.2021.101599

[5] Xue, W., He, Z., & Hu, Y. (2023). The destabilizing effect of mutual fund herding: Evidence from China. *International Review of Financial Analysis, 88*, 102611. https://doi.org/10.1016/j.irfa.2023.102611

[6] Fan, Y., Song, Q., Guan, R., Ly, K. C., & Jiang, Y. (2024). Mutual fund herding and performance: Evidence from China. *International Review of Financial Analysis, 95*, 103503. https://doi.org/10.1016/j.irfa.2024.103503

[7] Devenow, A., & Welch, I. (1996). Rational herding in financial economics. *European Economic Review, 40*(3–5), 603–615. https://doi.org/10.1016/0014-2921(95)00073-9

[8] Wylie, S. (2005). Fund manager herding: A test of the accuracy of empirical results using U.K. data. *The Journal of Business, 78*(1), 381–403. https://doi.org/10.1086/426529

[9] Grinblatt, M., Titman, S., & Wermers, R. (1995). Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. *American Economic Review, 85*(5), 1088–1105.

[10] Borensztein, E., & Gelos, R. G. (2003). A panic-prone pack? The behavior of emerging market mutual funds. *IMF Staff Papers, 50*(1), 43–63. https://doi.org/10.2307/4149947

[11] Voronkova, S., & Bohl, M. T. (2005). Institutional traders' behavior in an emerging stock market: Empirical evidence on Polish pension fund investors. *Journal of Business Finance & Accounting, 32*(7–8), 1537–1560. https://doi.org/10.1111/j.0306-686X.2005.00639.x

[12] Choe, H., Kho, B. C., & Stulz, R. M. (1999). Do foreign investors destabilize stock markets? The Korean experience in 1997. *Journal of Financial Economics, 54*(2), 227–264. https://doi.org/10.1016/S0304-405X(99)00037-9

[13] Kim, W., & Wei, S. J. (2002). Foreign portfolio investors before and during a crisis. *Journal of International Economics, 56*(1), 77–96. https://doi.org/10.1016/S0022-1996(01)00109-X

© 2026 The Author(s). Authors retain copyright in their articles.

[14] Walter, A., & Weber, F. M. (2006). Herding in the German mutual fund industry. *European Financial Management, 12*(3), 375–406. https://doi.org/10.1111/j.1354-7798.2006.00325.x

[15] Bikhchandani, S., & Sharma, S. (2000). Herd behavior in financial markets. *IMF Staff Papers, 47*(3), 279–310. https://doi.org/10.2307/3867650

[16] Frey, S., Herbst, P., & Walter, A. (2014). Measuring mutual fund herding: A structural approach. *Journal of International Financial Markets, Institutions and Money, 32*, 219–239. https://doi.org/10.1016/j.intfin.2014.05.006

[17] Lobão, J., & Serra, A. P. (2007). Herding behavior: Evidence from Portuguese mutual funds. In G. N. Gregoriou (Ed.), *Diversification and portfolio management of mutual funds* (pp. 167–197). Palgrave Macmillan. https://doi.org/10.1057/9780230626508_8

[18] Brown, N. C., Wei, K. D., & Wermers, R. (2014). Analyst recommendations, mutual fund herding, and overreaction in stock prices. *Management Science, 60*(1), 1–20. https://doi.org/10.1287/mnsc.2013.1751

[19] Cai, F., Han, S., Li, D., & Li, Y. (2019). Institutional herding and its price impact: Evidence from the corporate bond market. *Journal of Financial Economics, 131*(1), 139–167. https://doi.org/10.1016/j.jfineco.2018.07.012

[20] Choi, N., & Sias, R. W. (2009). Institutional industry herding. *Journal of Financial Economics, 94*(3), 469–491. https://doi.org/10.1016/j.jfineco.2008.12.009

[21] Hung, W., Lu, C.-C., & Lee, C. F. (2010). Mutual fund herding and its impact on stock returns: Evidence from the Taiwan stock market. *Pacific-Basin Finance Journal, 18*(5), 477–493. https://doi.org/10.1016/j.pacfin.2010.06.001

[22] Celiker, U., Chowdhury, J., & Sonaer, G. (2015). Do mutual funds herd in industries? *Journal of Banking & Finance, 52*, 1–16. https://doi.org/10.1016/j.jbankfin.2014.11.006

[23] Raddatz, C., & Schmukler, S. L. (2013). Deconstructing herding: Evidence from pension fund investment behavior. *Journal of Financial Services Research, 43*(1), 99–126. https://doi.org/10.1007/s10693-012-0155-x

[24] Kremer, S., & Nautz, D. (2013). Short-term herding of institutional traders: New evidence from the German stock market. *European Financial Management, 19*(4), 730–746. https://doi.org/10.1111/j.1468-036X.2011.00607.x

[25]Choi, N., & Skiba, H. (2015). Institutional herding in international markets. *Journal of Banking & Finance, 55*, 246–259. https://doi.org/10.1016/j.jbankfin.2015.02.002

[26] Blake, D., Sarno, L., & Zinna, G. (2017). The market for lemmings: The herding behavior of pension funds. *Journal of Financial Markets, 36*, 17–39. https://doi.org/10.1016/j.finmar.2017.03.001

[27] Dasgupta, A., Prat, A., & Verardo, M. (2011). Institutional trade persistence and long-term equity returns. *The Journal of Finance, 66*(2), 635–653. https://doi.org/10.1111/j.1540-6261.2010.01644.x

[28] Kremer, S., & Nautz, D. (2013). Causes and consequences of short-term institutional herding. *Journal of Banking & Finance, 37*(5), 1676–1686. https://doi.org/10.1016/j.jbankfin.2012.12.006

[29] Hirshleifer, D., & Teoh, S. H. (2003). Herd behaviour and cascading in capital markets: A review and synthesis. *European Financial Management, 9*(1), 25–66. https://doi.org/10.1111/1468-036X.00207

[30] Christie, W. G., & Huang, R. D. (1995). Following the Pied Piper: Do individual returns herd around the market? *Financial Analysts Journal, 51*(4), 31–37. https://doi.org/10.2469/faj.v51.n4.1918

[31] Chang, E. C., Cheng, J. W., & Khorana, A. (2000). An examination of herd behavior in equity markets: An international perspective. *Journal of Banking & Finance, 24*(10), 1651–1679. https://doi.org/10.1016/S0378-4266(99)00096-5

[32] Nofsinger, J. R., & Sias, R. W. (1999). Herding and feedback trading by institutional and individual investors. *The Journal of Finance, 54*(6), 2263–2295. https://doi.org/10.1111/0022-1082.00188

© 2026 The Author(s). Authors retain copyright in their articles.

[33] Banerjee, A. V. (1992). A simple model of herd behavior. *The Quarterly Journal of Economics, 107*(3), 797–817. https://doi.org/10.2307/2118364

[34] Bikhchandani, S., Hirshleifer, D., & Welch, I. (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy, 100*(5), 992–1026. https://doi.org/10.1086/261849

[35] Avery, C., & Zemsky, P. (1998). Multidimensional uncertainty and herd behavior in financial markets. *American Economic Review, 88*(4), 724–748.

[36] Froot, K. A., Scharfstein, D. S., & Stein, J. C. (1992). Herd on the street: Informational inefficiencies in a market with short-term speculation. *The Journal of Finance, 47*(4), 1461–1484. https://doi.org/10.1111/j.1540-6261.1992.tb04665.x

[37] Scharfstein, D. S., & Stein, J. C. (1990). Herd behavior and investment. *American Economic Review, 80*(3), 465–479.

[38] Chevalier, J., & Ellison, G. (1999). Career concerns of mutual fund managers. *The Quarterly Journal of Economics, 114*(2), 389–432. https://doi.org/10.1162/003355399556034

[39] Dasgupta, A., Prat, A., & Verardo, M. (2011). The price impact of institutional herding. *The Review of Financial Studies, 24*(3), 892–925. https://doi.org/10.1093/rfs/hhq137

[40] Sirri, E. R., & Tufano, P. (1998). Costly search and mutual fund flows. *The Journal of Finance, 53*(5), 1589–1622. https://doi.org/10.1111/0022-1082.00066

[41] Chevalier, J., & Ellison, G. (1997). Risk taking by mutual funds as a response to incentives. *Journal of Political Economy, 105*(6), 1167–1200. https://doi.org/10.1086/516389

[42] Brown, K. C., Harlow, W. V., & Starks, L. T. (1996). Of tournaments and temptations: An analysis of managerial incentives in the mutual fund industry. *The Journal of Finance, 51*(1), 85–110. https://doi.org/10.1111/j.1540-6261.1996.tb05203.x

[43] Basak, S., Pavlova, A., & Shapiro, A. (2007). Optimal asset allocation and risk shifting in money management. *The Review of Financial Studies, 20*(5), 1583–1621. https://doi.org/10.1093/rfs/hhm026

[44] Falkenstein, E. G. (1996). Preferences for stock characteristics as revealed by mutual fund portfolio holdings. *The Journal of Finance, 51*(1), 111–135. https://doi.org/10.1111/j.1540-6261.1996.tb05204.x

[45] Barberis, N., & Shleifer, A. (2003). Style investing. *Journal of Financial Economics, 68*(2), 161–199. https://doi.org/10.1016/S0304-405X(03)00064-3

[46] Cremers, K. J. M., & Petajisto, A. (2009). How active is your fund manager? A new measure that predicts performance. *The Review of Financial Studies, 22*(9), 3329–3365. https://doi.org/10.1093/rfs/hhp057

[47] Kacperczyk, M., Sialm, C., & Zheng, L. (2005). On the industry concentration of actively managed equity mutual funds. *The Journal of Finance, 60*(4), 1983–2011. https://doi.org/10.1111/j.1540-6261.2005.00785.x

[48] Tan, L., Chiang, T. C., Mason, J. R., & Nelling, E. (2008). Herding behavior in Chinese stock markets: An examination of A and B shares. *Pacific-Basin Finance Journal, 16*(1–2), 61–77. https://doi.org/10.1016/j.pacfin.2007.04.004

[49] Hwang, S., & Salmon, M. (2004). Market stress and herding. *Journal of Empirical Finance, 11*(4), 585–616. https://doi.org/10.1016/j.jempfin.2004.04.003

[50] Edelen, R. M. (1999). Investor flows and the assessed performance of open-end mutual funds. *Journal of Financial Economics, 53*(3), 439–466. https://doi.org/10.1016/S0304-405X(99)00028-8

[51] Coval, J., & Stafford, E. (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics, 86*(2), 479–512. https://doi.org/10.1016/j.jfineco.2006.09.007

[52] Chen, Q., Goldstein, I., & Jiang, W. (2010). Payoff complementarities and financial fragility: Evidence from mutual fund outflows. *Journal of Financial Economics, 97*(2), 239–262. https://doi.org/10.1016/j.jfineco.2010.03.016

© 2026 The Author(s). Authors retain copyright in their articles.

[53] Greenwood, R., & Thesmar, D. (2011). Stock price fragility. *Journal of Financial Economics, 102*(3), 471–490. https://doi.org/10.1016/j.jfineco.2011.06.003

[54] Lou, D. (2012). A flow-based explanation for return predictability. *The Review of Financial Studies, 25*(12), 3457–3489. https://doi.org/10.1093/rfs/hhs103

[55] Dennis, P. J., & Strickland, D. (2002). Who blinks in volatile markets, individuals or institutions? *The Journal of Finance, 57*(5), 1923–1949. https://doi.org/10.1111/0022-1082.00484

[56] Deng, X., Hung, S. M., & Qiao, Z. (2018). Mutual fund herding and stock price crashes. *Journal of Banking & Finance, 94*, 166–184. https://doi.org/10.1016/j.jbankfin.2018.07.014

[57] Huo, X., Liu, X., & Zheng, W. (2023). The term structure of mutual fund herding. *European Financial Management, 29*(3), 901–929. https://doi.org/10.1111/eufm.12379

[58] Feng, L., & Xiang, C. (2023). Short-selling and mutual fund herding: The Chinese evidence. *Finance Research Letters, 52*, 103517. https://doi.org/10.1016/j.frl.2022.103517

[59] Bohl, M. T., Klein, A. C., & Siklos, P. L. (2014). Short-selling bans and institutional investors' herding behaviour: Evidence from the global financial crisis. *International Review of Financial Analysis, 33*, 262–269. https://doi.org/10.1016/j.irfa.2014.03.004

[60] Wang, H., Li, S., & Ma, Y. (2021). Herding in open-end funds: Evidence from China. *The North American Journal of Economics and Finance, 57*, 101417. https://doi.org/10.1016/j.najef.2021.101417

[61] Zhao, Y., Xiang, C., & Cai, W. (2021). Stock market liberalization and institutional herding: Evidence from the Shanghai-Hong Kong and Shenzhen-Hong Kong Stock Connects. *Pacific-Basin Finance Journal, 69*, 101643. https://doi.org/10.1016/j.pacfin.2021.101643

[62] Quan, X., Xiang, C., Li, D., & Tan, K. J. K. (2023). To see is to believe: Corporate site visits and mutual fund herding. *Financial Management, 52*(4), 711–740. https://doi.org/10.1111/fima.12421

[63] Shen, Y., Mao, X., & Liu, Y. (2024). Alumni network, mutual fund herding and information spillover: Evidence from China. *Pacific-Basin Finance Journal, 83*, 102265. https://doi.org/10.1016/j.pacfin.2024.102265

[64] Wang, L., & Xiong, X. (2022). The impact of herding behaviour of Chinese securities investment funds on firm value: The mediating effects of stock price informativeness and agency cost. *Applied Economics Letters, 29*(14), 1248–1255. https://doi.org/10.1080/13504851.2021.1923633

[65] Jiang, H., & Verardo, M. (2018). Does herding behavior reveal skill? An analysis of mutual fund performance. *The Journal of Finance, 73*(5), 2229–2269. https://doi.org/10.1111/jofi.12699

Funding

This research received no external funding.

Conflicts of Interest

The authors declare no conflict of interest.

Acknowledgment

This paper is an output of the science project.

Copyrights

Copyright for this article is retained by the author (s), with first publication rights granted to the journal. This is an open-access article distributed under the terms and conditions of the Creative Commons Attribution license (http://creativecommons.org/licenses/by/4.0/).

© 2026 The Author(s). Authors retain copyright in their articles.