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Research Article

The Asymmetric Effect of Mutual Fund Herding on Price Deviation: Evidence from the Chinese Stock Market

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Abstract

Mutual funds, as significant participants in financial markets, play a crucial role in the formation of asset pricing. The relationship between herding behavior of mutual funds and mispricing has been a subject of intense debate among scholars. In this paper, we investigate the asymmetric impact of mutual fund herding on price deviation and explore the underlying mechanism. In terms of research design, this study selects relevant data on mutual fund holdings and stock trading in the Chinese A-share market from 2010 to 2023, we examine whether herding behavior leads to mispricing, specifically focusing on the asymmetric effects of herding buying and herding selling on stock price deviation from intrinsic value. This study distinguishes the trading direction of mutual fund herding behavior and separately examines the relationship between herding buying behavior and herding selling behavior with stock price deviation. Our empirical findings reveal that buying herding behavior is linked to positive price deviations from intrinsic value. However, selling herding behavior shows no significant relationship with price deviation. Furthermore, our results provide evidence that the herding buying of mutual funds stimulates similar trading sentiments among other market participants and contributes to the formation of market bubbles, while herding selling prompts counterbalancing trades, mitigating the impact of price deviation.

Keywords

Mutual Fund, Herding, Price Deviation, Asymmetric Effect

1. Introduction

Mutual funds, as significant participants in financial markets, play a crucial role in the formation of asset pricing. The relationship between herding behavior of mutual funds and mispricing has been a subject of intense debate among scholars [1-5]. Previous studies have primarily examined the overall mispricing behavior resulting from institutional herding behavior. Building upon this, this study extends the discussion by examining the herding behavior of mutual funds and the issue of mispricing in the Chinese stock market. Furthermore, this study focuses on a previously overlooked aspect by separately analyzing the mispricing caused by mutual fund herding behavior in terms of buying and selling trading behavior. The objective is to explore the potential asymmetry in the impact of buying and selling herding behavior on mispricing.

The choice for Chinese market is based on the following considerations. First, Chinese stock market is the largest emerging market and the second largest stock market in the

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world. Investigating the herding behavior of mutual funds and market efficiency in the Chinese context is of great significance. Secondly, the Chinese market provides transparency regarding the extent of margin trading and securities lending for individual stocks. While mutual funds in China are not completely prohibited from these activities, they seldom engage in them. It should be noted that more aggressive or sophisticated investors often employ margin trading and leverage strategies to enhance their investment performance. The availability of data on these transactions sheds light on the behavior of other sophisticated market participants beyond mutual funds. This allows us to examine whether these sophisticated investors follow the trading behavior of mutual funds or act as counterparties to balance the market.

This study reveals an asymmetry in the effects of herding buying and herding selling on stock mispricing. Specifically, it demonstrates that herding buying behavior is positively correlated with mispricing, indicating a potential overvaluation of stocks. However, no significant relationship is observed between mutual fund herding selling and the deviation of stock prices from their fundamental values. To understand the underlying reasons for this asymmetry in the impact of herding behavior, the study further investigates the behavior of margin traders and leveraged investors. The findings suggest that herding buying behavior triggers an increase in leveraged trading while reducing securities lending. This implies that mutual fund herding buying behavior stimulates the participation of other investors, leading to a positive mispricing effect. Conversely, herding selling behavior prompts other investors to engage in counterbalancing trades, which mitigates the impact of herding selling and results in insignificant mispricing. This suggests that the participation of other investors in response to herding selling helps restore market equilibrium and prevents significant deviations from fundamental values.

Regarding the methodology, previous empirical studies have typically validated mispricing caused by herding behavior by constructing portfolios that generate excess returns [2, 5]. However, this research approach assumes that stock market prices will swiftly revert to their efficient values. Nevertheless, numerous studies have demonstrated the existence of irrational behavior in financial markets, including both overreactions and underreactions, which cast doubt on this assumption. It becomes challenging to determine whether the market will indeed return to an efficient price, and if so, how long it might take. In light of these considerations, this paper adopts a different approach to measure mispricing by examining the deviation of market prices from fundamental values. By focusing on the deviation from intrinsic value, we aim to capture the extent of mispricing directly. This alternative approach acknowledges the potential limitations of assuming rapid market price reversions and offers a more nuanced perspective on the mispricing phenomenon. Based on the aforementioned considerations, this study employs the theory of surplus value, which incorporates the future growth potential of companies, to calculate their intrinsic value. The degree of mispricing is then measured by the deviation between stock prices and intrinsic value.

The contributions of this paper are as follows: (1) This study introduces a fundamental perspective of company analysis into the research on the mispricing issue caused by mutual fund herding behavior. (2) The paper provides direct evidence confirming the relationship between mutual fund herding behavior and the deviation of stock prices from their intrinsic values. (3) This study uncovers an asymmetry in the impact of herding buying and herding selling on stock mispricing. (4) This study suggests that the participation of sophisticated investors involved in margin trading and leverage transactions may contribute to this asymmetry.

The organization of the paper is as follows: Part 2 provides a literature review, Part 3 presents the research design, Part 4 presents the empirical analysis and discussion, and the final part presents the conclusion.

2. Literature Review

2.1. Research on Herding Behavior of Mutual Funds

Institutional investors, represented by mutual funds, have a clear advantage in terms of professional skills compared to individual investors. However, ample research has shown that the trading behavior of mutual funds is not entirely rational, and herding behavior is one important manifestation of this [6-9]. Existing literature has delved into the reasons behind herding behavior among mutual funds. Bikhchandani and Sharma (2000) argue that due to the relatively opaque information in emerging market, managers of mutual funds engage in direct imitation of their peers' investment strategies to reduce costs in information acquisition, leading to herding behavior [10]. Maug and Naik (2011) point out that fund managers, to avoid being penalized for underperforming, tend to follow the major investment strategies of their peers in order to achieve the average performance level [11]. Research by Cai et al. (2011) find evidence of herding behavior of securities analysts, with fund managers engaging in information reprocessing based on the information produced by analysts' research reports, thereby triggering herding behavior among mutual funds [12].

The examination of herding behavior among mutual funds is initially conducted by Lakonishok et al. (1992), who find no significant herding behavior among US mutual funds [1]. However, subsequent studies by Hudson et al. (2020) reveal varying degrees of herding behavior among the majority of US mutual funds [8]. In the study of Chinese market, Cheng et al. (2014) employ various measures and empirically examined the relationship between herding behavior of Qualified Foreign Institutional Investors (QFII) and domestic institutional investors [6]. Additionally, Yao and Wu (2018) show that

institutional investors exhibited stronger herding behavior than individual investors, and among institutional investors, mutual funds exhibited an increasing trend of herding over the years [7]. Wang et al. (2021) indicate that, except for income funds, all other types of funds have confirmed the existence of herding, which is mainly driven by non fundamental factors [9].

The research on the price effects of herding has not yet reached a consensus. Some studies suggest that herding behavior among mutual funds exacerbates mispricing, while others indicate that herding behavior may accelerate price adjustments to reasonable levels. Wermers (1999) argues that herding behavior among mutual funds is selective, with investors more willing to herding buy when stock price is undervalued and herding sell when it is overvalued [2]. Through trading, they facilitate the adjustment of price towards to the fundamental value, and reduce mispricing. Caglayan et al. (2021) provide evidence for rational herding behavior in mutual funds through empirical analysis, and the results show that herding behavior in mutual funds significantly reduces the return synergy between Chinese stocks [13]. On the other hand, studies by Brown et al. (2014) and Zhu et al. (2019) suggest that during the process of imitating and following the herd, investors neglect their private information, causing the information held by those being imitated to be further reinforced in trading, leading to overreaction and mispricing [4, 5]. Therefore, the impact of herding behavior among mutual funds on mispricing remains debatable.

2.2. Research on Measurement of Mispricing

Mispricing is a significant manifestation of market inefficiency in capital markets. Existing literature has discussed the reasons for mispricing from three aspects: information providing, information intermediaries, and information reception. Traditional financial research suggests that managers with information advantages have incentives to engage in earnings management to influence investors' judgments about the company's future development and value, leading to deviations in stock price and intrinsic value [14]. Media studies argue that news media and securities analysts, as important intermediaries connecting information providers and receivers, play a crucial role in improving investors' information interpretation abilities. Several studies have found that as news media coverage deepens and securities analysts become involved, firm-specific information is more thoroughly explored, thus alleviating the problem of stock mispricing [15]. Behavioral finance research focuses more on the decision-making process of information receivers, suggesting that investor irrational behavior and limited arbitrage are important factors leading to mispricing and the persistence of mispricing [16, 17].

From a methodological perspective, measurement methods for mispricing can be classified into three categories. The first category compares the deviation between stock price and a certain benchmark to reflect mispricing. The key challenge in this method lies in determining the benchmark value. Commonly used approaches include Relative Valuation [18], Absolute Valuation [19, 20], and Regression Valuation [21]. The second category employs Discretionary Accruals (DACCR) as a proxy variable for mispricing. Xie (2001) empirically confirms that companies with higher discretionary accruals tend to be overvalued by the market [22]. While discretionary accruals can to some extent reflect the degree of mispricing, their limitations, such as time delay, restrict their accuracy and reliability as a measurement of mispricing. The third category employs cumulative abnormal returns as a proxy variable for mispricing. This empirical research method implicitly assumes that pricing of stocks is efficient and the stock price reflect intrinsic value [23].

As significant participants in the stock market, mutual funds play a dual role as both information intermediaries and information recipients, exerting a significant influence on pricing. Traditional literature suggests that mutual funds typically have access to more information channels and professional information processing teams, enabling them to accurately assess value information and make correct trading decisions, thereby driving stock prices towards to their fundamental values [2]. Additionally, holding by mutual funds attracts more securities analysts to track and analyze stocks, leading to increased corporate information disclosure, and reduces mispricing [24]. Numerous empirical studies have confirmed the positive role of mutual funds in asset pricing [25]. However, some literature argues that managers of mutual funds, as information recipients, may not exhibit entirely rational information processing and trading decisions [7, 8]. Therefore, the impact of mutual funds on asset pricing remains debatable.

3. Research Design

3.1. Data and Sample

The data on holdings by mutual funds is sourced from the CSMAR database, while data on market trading of listed companies are obtained from the WIND database. The period of study spans from 2010 to 2023. Since mutual funds only disclose the top ten holdings in their quarterly reports, but provide detailed information on all stock holdings in their semi-annual and annual reports, this article only selects data from the semi-annual and annual reports. During the study period, data on holdings by 7,453 mutual funds was collected for analysis.

The following filters were applied to data on listed companies which are held by mutual funds: firstly, companies that have been listed for less than one year were excluded; secondly, financial companies were excluded; thirdly, companies with abnormal operations (identified as ST and *ST), suspended trading, or delisted were excluded. After applying these filters, the collected data in this article includes 1,369

listed companies. To ensure consistency in frequency of data, the article selects semi-annual and annual financial data, resulting in a sample of 25,671 observations.

Moreover, to eliminate the influence of outliers, all continuous variables were subject to trimming at the 1% upper and lower tails. In the subsequent empirical analysis, the sample sizes used in different sections may slightly vary due to the specific research focus.

3.2. Measurement

3.2.1. Stock Price Deviation

We focus on the impact of herding behavior on mispricing. We mainly use deviation between stock price and intrinsic value as the measure of mispricing:

$$sd_{i,t} = \frac{p_{i,t} - V_{i,t}}{V_{i,t}} \quad (1)$$

where $p_{i,t}$ represents the market price of the stock i at time t, and $V_{i,t}$ represents the intrinsic value calculated through fundamental analysis. If $sd_{i,t}$ is bigger than 0, the stock is considered overvalued. Conversely, if $sd_{i,t}$ is less than 0, it suggests that the stock is considered undervalued.

For this study, the approach proposed by Zhao (2003) is employed to estimate the intrinsic value of stocks [26]. According to the prevailing theory of value determination, the intrinsic value of a stock is determined by the present value of its future cash flows:

$$V_{i,t} = \sum_{\tau=1}^{\infty} E_t \left[\frac{x_{i,t+\tau}}{(1+r_{i,t})^{\tau}} \right] \quad (2)$$

where $x_{i,t}$ represents accounting earnings. $r_{i,t}$ represents the discount rate or cost of capital. $E_t(\cdot)$ represents taking the expectation.

The accounting earning $x_{i,t}$ can be expressed as the sum of normal earnings ${x_{i,t}}^n = r_{i,t} \times bv_{i,t-1}$ and abnormal earnings ${x_{i,t}}^a = x_{i,t} - r_{i,t} \times bv_{i,t-1}$, that is, $x_{i,t} = {x_{i,t}}^n + {x_{i,t}}^a$.

Assuming that investors' expectations regarding the return on net assets remain unchanged. And the company has an infinite lifespan, it is recognized that as external competition intensifies, the excess returns generated by innovation and monopoly tend to diminish over time. Eventually, after a certain period denoted as n, the company can only generate normal earnings. In light of this, the intrinsic value of a stock can be expressed as the summation of the present value of expected normal earnings and excess earnings.

$$V_{i,t} = \sum_{\tau=1}^{\infty} E_t \left[\frac{{x_{i,t+\tau}}^n}{(1+r_{i,t})^{\tau}} \right] + \sum_{\tau=1}^{n} E_t \left[\frac{{x_{i,t+\tau}}^a}{(1+r_{i,t})^{\tau}} \right] = bv_{i,t} + \sum_{\tau=1}^{n} E_t \left[\frac{x_{i,t+\tau} - r_{i,t+\tau} \times bv_{i,t+\tau-1}}{(1+r_{i,t})^{\tau}} \right] \quad (3)$$

Let $g_{i,t} = \frac{bv_{i,t} - bv_{i,t-1}}{bv_{i,t-1}}$ represent the growth rate of net asset, and $ROE_{i,t} = \frac{x_{i,t}}{bv_{i,t-1}}$ represent the return on net assets. Under the given condition of dividend payout ratio, Equation (4) can be rewritten as:

$$V_{i,t} = bv_{i,t} + \sum_{\tau=1}^{n} E_t \left[\frac{ROE_{i,t+\tau} - r_{i,t+\tau}}{(1+r_{i,t})^{\tau}} bv_{i,t+\tau-1} \right] \quad (4)$$

Assuming that $E_t[bv_{t+\tau-1}] = (1+g_{i,t})^{\tau-1} bv_{i,t}$, $E_t[ROE_{i,t+\tau}] = ROE_{i,t}$, $E_t[r_{i,t+\tau}] = r_{i,t}$. The intrinsic value can be expressed as:

$$V_{i,t} = \begin{cases} bv_{i,t} + bv_{i,t} \cdot \frac{ROE_{i,t} - r_{i,t}}{r_{i,t} - g_{i,t}} \cdot \left[1 - \left(\frac{1+g_{i,t}}{1+r_{i,t}} \right)^{n} \right], if\ g_{i,t} \neq r_{i,t} \\ bv_{i,t} + bv_{i,t} \cdot \frac{n(ROE_{i,t} - r_{i,t})}{1+r_{i,t}}, if\ g_{i,t} = r_{i,t} \end{cases} \quad (5)$$

It should be noted that, when calculating the intrinsic value of a company using Equation (5), $r_{i,t}$ represents the dividend discount rate, which consists of two components: risk-free rate and risk premium. In this study, we use the one-year benchmark interest rate for fixed deposits converted to a semi-annual rate is used as the risk-free rate, and the risk premium is calculated using the Carhart four-factor model. Additionally, n represents the limited period during which the company obtains excess returns. The simulation results by Zhao (2003) show that when the dividend payout ratio is 0.3 (the average dividend payout ratio in the sample studied in this paper) [26], the duration of excess returns obtained by the company is almost linearly related to the intrinsic value. In other words, the choice of n hardly affects the relationship between herd behavior and deviation of stock price. In fact, this study tests different values of n in the empirical section, and the regression results are consistent. In the subsequent report, we only present the empirical results for $n = 10$.

3.2.2. Herding Behavior

Lakonishok et al. (1992) introduced the classical Lakonishok-Shleifer-Vishny (LSV) model, which aims to assess the herding behavior exhibited by investors during the trading of individual stocks [1]. This approach quantifies the level of of herding by examining the percentage of investors engaged in one-sided trading in the stock market. Specifically, the herding behavior of investors when trading stock i at time t can be represented as follows:

$$HM_{i,t} = \left| P_{i,t} - E[P_{i,t}] \right| - \mathrm{AF}_{i,t} \quad (6)$$

where $P_{i,t} = \frac{B_{i,t}}{B_{i,t} + S_{i,t}}$ represents ratio of net buying, $B_{i,t}$ represents the number of investors who are net buyers, and $S_{i,t}$ represents the number of investors who are net sellers. The expected value of $P_{i,t}$ can be approximated by the arithmetic

average of this ratio across all stocks at time t, denoted by $\bar{P}_t$:

$$E[P_{i,t}] = \bar{P}_t = \frac{\sum_{i=1}^{n} B_{i,t}}{\sum_{i=1}^{n} B_{i,t} + \sum_{i=1}^{n} S_{i,t}} \quad (7)$$

$AF_{i,t}$ in Equation (7) represents the adjustment factor, which indicates the expected value of the absolute difference $|P_{i,t} - E[P_{i,t}]|$ when there is no herding effect present in the market. In the absence of herding behavior, investors' decisions are considered independent of one another. However, certain factors, such as a general market rise (fall), can cause investors to make similar buying or selling decisions, resulting in a nonzero value for $|P_{i,t} - E[P_{i,t}]|$. Under the assumption of independent investor decisions, the variable $B_{i,t}$ follows a binomial distribution $Binomial(N_{i,t}, \bar{P}_t)$, where $N_{i,t}$ is defined as the sum of net buyers and net sellers, given by $N_{i,t} = B_{i,t} + S_{i,t}$. We have:

$$P(B_{i,t} = k) = C_{N_{i,t}}^{k} \bar{P}_t^{\,k} (1 - \bar{P}_t)^{N_{i,t}-k} \quad (8)$$

$$AF_{i,t} = \sum_{k=0}^{N_{i,t}} \left| \frac{k}{N_{i,t}} - \bar{P}_t \right| C_{N_{i,t}}^{k} \bar{P}_t^{\,k} (1 - \bar{P}_t)^{N_{i,t}-k} \quad (9)$$

Wylie (2005) raises concerns about the assumption that $B_{i,t}$ follows a binomial distribution $Binomial(N_{i,t}, \bar{P}_t)$ [27]. The author argues that the investment probability of a mutual fund manager for a specific stock may not solely rely on $\bar{P}_t$ but also on factors like the initial size and net cash flow of the mutual fund. However, Wylie (2005) discovers that the herding effect, as measured by the LSV method, remains effective when a sufficient number of participating funds are involved [27]. To address the issue of stocks with a small number of participating funds, the study follows the approach outlined by Qi et al. (2006). Specifically, if the number of participating buying or selling funds is less than 5, these stocks are excluded from the sample [28].

The value of $HM_{i,t}$ calculated from Equation (6) represents the percentage of investors for stock i in period t, that exhibit unidirectional (can be either buying or selling) herding behavior in the market surpassing the expected number. The higher absolute value of $HM_{i,t}$ indicates a stronger presence of herding behavior among investors. Wermers (1999) distinguishes investor trading into buying and selling. If the net buying ratio of investors exceeds the expected level, it is categorized as herding buying [2]. Conversely, if the net buying ratio of investors falls below the expected value, it is classified as herding selling. Based on this framework, two indicators are proposed to measure the extent of buying and selling herding behavior:

$$BHM_{i,t} = HM_{i,t} \; if \; P_{i,t} > \bar{P}_t \quad (10)$$

$$SHM_{i,t} = HM_{i,t} \; if \; P_{i,t} < \bar{P}_t \quad (11)$$

According to the definition, it is important to note that, for stock i and period t, we can observe either BHM (Buying Herding Measure) or SHM (Selling Herding Measure). A large value of BHM indicates a strong buying herd, while a large value of SHM indicates a strong selling herd.

Several alternative measurements of investor herding based on the LSV method have been proposed by Shi (2001) and Xu et al. (2013) [3, 29]. If the difference $|P_{i,t} - E[P_{i,t}]|$ is close to its expected value $AF_{i,t}$, the herding behavior is not considered statistically significant. According to Xu et al. (2013), herding behavior is deemed to exist when the imbalance of net buying ratio $|P_{i,t} - E[P_{i,t}]|$, exceeds a specific threshold. This threshold is defined as the mean plus the standard deviation. In this study, we employ a similar approach by including only the sample data where $|P_{i,t} - E[P_{i,t}]|$ exceeds is greater than the threshold.

Shi (2001) proposed an alternative simplified method [29]

$$HM_{i,t} = \frac{MAX(B_{i,t}, S_{i,t})}{B_{i,t} + S_{i,t}} \quad (12)$$

According to the definition in Equation (12), the herding behavior measure obtained falls within the ranges of 0.5 to 1, indicating the proportion of funds that participate in the same buying or selling behavior for stock i in period t, relative to all stocks. A higher value signifies a more significant herding behavior.

In the subsequent empirical analysis, this paper utilizes the herding behavior measure proposed by Xu et al. (2013). Additionally, for robustness testing, we employ the methodology proposed by Shi (2001).

3.2.3. Control Variables

This study also incorporates several control variables that capture various aspects of the firm's characteristics. These variables, as referenced from Xu et al. (2013), are commonly used in empirical research and provide additional insights into the factors that influence stock mispricing [3]. The control variables included in this study are as follows: (1) Stock turnover rate (turn): This variable reflects investors' sentiment and is calculated as the ratio of the trading volume of a stock within a six-month period to its outstanding shares; (2) Stock volatility (sigma): This variable measures the level of individual stock risk and is represented by the standard deviation of weekly returns of the stock over a six-month period; (3) Size of the listed company (size),: This variable indicates the scale of the listed company and is measured by the natural logarithm of the total assets of the firm; (4) Book-to-market ratio (mb): This variable captures company growth using the ratio of equity to market value; (5) Return on total assets (roa): This variable evaluates the company's operational performance using the ratio of after-tax net profit to total assets. Descriptive statistics of the variables are presented in Table 1.

Table 1. *Descriptive statistics of variables.*

Variables	*N*	Mean	Sd	Min	Max
sd	30139	0.106	0.993	-1.560	12.106
HM	25671	0.110	0.109	-0.057	0.730
BHM	11819	0.105	0.113	-0.057	0.730
SHM	13852	0.115	0.106	-0.057	0.503
$turn$	38324	231.2	199.678	0.000	2353.1
$sigma$	38023	0.059	0.049	0.000	5.066
$size$	36398	2.629e+10	1.113e+11	0.000	2.753e+12
mb	36403	0.659	0.279	0.000	1.729
roa	37379	0.024	0.678	-31.296	108.366

The average deviation of stock prices in the selected sample is 0.106, indicating an overall positive deviation of stock prices from intrinsic value. This finding is consistent with the results reported by Zhao (2003) [26]. The average herding calculated using the classic LSV method in this study is 0.110, slightly higher than the findings of Qi et al. (2006) potentially due to the variation in the time window used [28]. Two HM indices used in this study indicate a higher measure for buying behavior compared to selling behavior, which is consistent with the findings of Yao and Wu (2018) [7].

3.3. Regression Models

This study employs the following model to examine the influence of the overall herding behavior of mutual funds, without distinguishing the trading direction, on the extent of stock price deviation from underlying fundamentals.

$$absd_{i,t} = \alpha + \beta_1 HM_{i,t} + \gamma control_{i,t} + \varepsilon_{i,t} \quad (13)$$

whereas, $absd_{i,t}$ represents the absolute degree of stock price deviation. $HM_{i,t}$ denotes the overall herding behavior. $control_{i,t}$ represents the control variables.

In order to account for the trading direction of herding behavior, his study aims to differentiate between buying and selling and examine their respective impacts on stock price overvaluation or undervaluation. Consequently, the dependent variable is defined as the stock price deviation, which can take on positive or negative values. A positive indicates that the stock price is overvalued, while a negative value suggests that the stock price is undervalued. The following regression model is constructed to test this relationship.

$$sd_{i,t} = \alpha + \beta_1 BHM_{i,t} + \gamma control_{i,t} + \varepsilon_{i,t} \quad (14)$$

$$sd_{i,t} = \alpha + \beta_1 SHM_{i,t} + \gamma control_{i,t} + \varepsilon_{i,t} \quad (15)$$

whereas, $sd_{i,t}$ represents the stock price deviation. The variable $BHM_{i,t}$ denotes herding buying, while $SHM_{i,t}$ represents herding selling. Additionally, $control_{i,t}$ represents the control variables included in the analysis.

4. Empirical Results

4.1. Herding Behavior and Stock Price Deviation

Table 2 presents the regression results examining the relationship between mutual fund herding behavior and stock price deviation. Columns (1), (3), and (5) utilize the classical LSV model proposed by Lakonishok et al. (1992) [1]. Columns (2), (4), and (6) use the simplified herding behavior index introduced by Shi (2001) [29].

It is important to note that when calculating the intrinsic value of a company using formula (5), the parameter 'n' represents the limited period during which the company obtains excess returns. According to Zhao 's (2003) simulation, which considers a dividend payout ratio is 0.3 (the average dividend payout ratio in this study's ample), the duration of excess returns obtained by the company exhibits a minimal impact on the relationship between herding behavior and stock price deviations [26]. In fact, we conducted empirical analysis testing different values of 'n', and the regression results remained consistent. In the subsequent report, we present the regression results solely for 'n=10'.

Table 2. *Herding behavior and stock price deviation (full sample).*

Variables	(1)	(2)
HM	0.008 (1.500)	0.008 (1.120)
$turn$	0.007 (0.940)	0.001 (0.120)
$sigma$	0.089*** (6.370)	0.101*** (7.110)
$size$	0.027*** (6.770)	0.032*** (7.190)
mb	-0.655*** (-50.520)	-0.691*** (-51.820)
roa	-0.256*** (-45.190)	-0.272*** (-45.420)
$cons$	1.757*** (53.750)	1.792*** (53.210)
$time$	$contraled$	$contraled$
$industry$	$contraled$	$contraled$
N	19616	19535
R^2	0.306	0.301
F	176.030***	170.950***

Note: The values in parentheses represent the t-values, while *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3. *Herding behavior and stock price deviation (subsample).*

	subsample of buying		subsample of selling	
Variables	(3)	(4)	(5)	(6)
BHM	0.018*** (2.920)	0.023*** (2.620)		
SHM			0.001 (0.170)	0.010 (1.100)
$turn$	0.35*** (3.650)	0.030*** (3.050)	0.010 (1.060)	0.011 (1.090)
$sigma$	0.068*** (3.900)	0.082*** (4.650)	0.068*** (4.140)	0.071*** (4.200)
$size$	0.022*** (4.210)	0.026*** (4.530)	0.015*** (3.280)	0.018*** (3.530)
mb	-1.255*** (-76.280)	-1.281*** (-76.180)	-1.247*** (-83.070)	-1.267*** (-80.790)
roa	-0.431*** (-61.040)	-0.447*** (-60.380)	-0.461*** (-69.170)	-0.479*** (-66.640)
$cons$	0.334*** (8.520)	0.357*** (8.860)	0.603*** (14.880)	0.621*** (14.690)
$time$	$contraled$	$contraled$	$contraled$	$contraled$
$industry$	$contraled$	$contraled$	$contraled$	$contraled$
N	9057	9060	10559	10475
R^2	0.775	0.769	0.771	0.758
F	631.470***	612.410***	722.540***	667.630***

Note: The values in parentheses represent the t-values, while *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Columns (1) and (2) of Table 2 present the empirical results based on the full sample. These results demonstrate that both the classical LSV method proposed by Lakonishok et al. (1992) and the simplified herding behavior index introduced

by Shi (2001) show a positive correlation between the herding behavior and the degree of stock price deviation from fundamentals. The result indicates that herding behavior of mutual funds may result in mispricing in stock market.

In addition, we differentiate between herding behavior in the buying and selling directions. Columns (3) and (4) of Table 2 present the test results based on the subsample of herding buying. The coefficient is significantly positive, suggesting that herding buying of mutual funds leads to the overvaluation of stock prices. On the other hand, Columns (5) and (6) of Table 2 present the test results based on the subsample of herding selling. These results indicate no significant relationship between mutual fund herding selling and the deviation of stock prices from fundamental. This finding suggests, to a certain extent, that there is an asymmetrical impact of herding buying and selling by mutual funds on mispricing.

Based on the above results, it can be concluded that while herding selling has little impact on mispricing, the observed effect on mispricing in the full sample analysis is primarily driven by the impact of herding behavior in the buying direction.

4.2. Portfolio Analysis

The above analysis reveals that stocks subjected to herding buying by mutual funds tend to be relatively higher valued compared to other stocks based on current information. However, it is crucial to explore whether this finding could be attributed to mutual funds having access to undisclosed information. It is plausible that herding behavior by mutual funds actually contributes to price discovery in the stock market. To investigate this, it is necessary to observe the subsequent price performance of the stocks following the herding buying. If the herding buying creates a price bubble rather than facilitating price discovery, one would expect the prices to decline and revert back to their intrinsic values in the subsequent period.

To gain insights into whether herding buying leads to mispricing or serves as a mechanism for price discovery, the study utilizes the methodologies proposed by Wermers (1999) and Zhu et al. (2019) to construct different portfolios based on the herding measure [2, 5]. The cumulative excess returns of these portfolios are examined to determine if herding behavior is associated with price reversals. The study employs a formation period of 6 months and holding periods of 1 and 6 months, respectively. The construction method for the portfolios is as follows: Stocks are sorted based on their herding effect during the formation period. The top 20% of stocks with the highest herding buying form the Strong Buying portfolio (BS), while the bottom 20% of stocks with the lowest herding buying form the Weak Buying portfolio (BW). Similarly, the top 20% of stocks with the highest herding selling form the Strong Selling portfolio (SS), and the bottom 20% of stocks with the lowest herding selling form the Weak Selling portfolio (SW). Additionally, the study includes a zero-cost hedge portfolio: Long the portfolio with the strongest herding buying and short the portfolio with the strongest herding selling (BS-SS). By analyzing the performance of these portfolios, the study aims to shed light on the relationship between herding behavior, mispricing, and price discovery in the stock market.

The excess return of a specific stock i during a given period t is calculated as the difference between its ordinary return and the weighted average return of all stocks in that period, $AR_{i,t} = R_{i,t} - R_{m,t}$. The excess return of each investment portfolio is then determined by taking the arithmetic average of the individual excess returns of all stocks within the portfolio, given by $AR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t}$, where N represents the number of stocks in the portfolio. Furthermore, the cumulative excess return of stock i over a specific time period (from T_1 to T_2) can be defined as the sum of its excess returns during that period, expressed as $CAR_{i,T_1,T_2} = \prod_{t=T_1}^{T_2}(1 + R_{i,t}) - \prod_{t=T_1}^{T_2}(1 + R_{m,t})$. Similarly, the cumulative excess return of a portfolio is calculated as the arithmetic average of the cumulative excess returns of all stocks within the portfolio, $CAR_{T_1,T_2} = \frac{1}{N}\sum_{i=1}^{N} CAR_{i,T_1,T_2}$.

In this study, the portfolios constructed using the LSV method and the simplified herding measures exhibit similar results. The subsequent presentation will focus solely on presenting the outcomes derived from the empirical analysis conducted using the LSV method.

Table 4. *Portfolio analysis.*

portfolio	(1)	(2)	(3)	(4)
BS	0.286*** (176.580)	0.225*** (24.089)	-0.008* (-1.749)	-0.017** (-2.121)
BW	-0.009*** -22.099)	0.013** (2.562)	-0.013*** (-3.243)	-0.021*** (-3.354)
SS	0.267*** (188.207)	-0.119*** (-24.459)	-0.024*** (-6.975)	-0.040*** (-7.398)
SW	-0.009*** (-22.264)	-0.041*** (-9.909)	-0.014** (-3.815)	-0.020*** (-3.678)
$BS - SS$	-	0.344*** (4.362)	0.015** (1.983)	0.023** (2.043)

Note: Column (1) presents the herding measure. Column (2) shows the accumulated excess returns in the formation period. Column (3) shows the accumulated excess returns after a three-month holding period. Column (4) shows the excess returns after a six-month holding period. The values in parentheses represent the t-values, while *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4 presents the cumulative excess returns of different investment portfolios. The empirical results reveal the follow-

ing observations: (1) Portfolios in which mutual funds exhibit herding behavior through buying (BS, BW) demonstrate positive excess returns in the current period. However, these returns become significantly negative after holding the portfolios for three month and six months. This suggests the presence of price reversal, indicating an overreaction. Notably, portfolio with strong buying activity by mutual funds (BS) exhibit a more pronounced degree of price reversal, aligning with the findings of Zhu et al. (2019). (2) Portfolios in which mutual funds exhibit herding behavior through selling (SS, SW) exhibit negative excess returns in the current period. These negative returns do not experience a subsequent reversal; instead, they persist and remain statistically significantly negative even after being held for three month and six months.

4.3. Mutual Fund Herding and the Role of Other Market Participants

The empirical findings demonstrate an intriguing asymmetry in the impact of mutual fund herding on price deviation, where buying herding behavior leads to positive price deviations, while selling herding behavior does not result in significant negative price deviation. This imbalance cannot be explained by the difference in the magnitude of buying and selling herding by mutual funds, as the descriptive statistics in Table 1 indicate similar mean and maximum values. Other market participants likely play a role in this disparity. When mutual funds engage in buying herding, their actions influence and encourage similar trading behavior among others, resulting in an overvaluation of stocks and positive price deviations. Conversely, in the case of selling herding, the absence of substantial negative price deviations suggests that other market participants absorb the selling pressure without initiating significant selling themselves. This leads to a more balanced market response, preventing significant undervaluation and negative price deviations.

In order to gain a deeper understanding of this issue, we will explore the involvement of other market participants alongside mutual funds in this analysis. It is important to note that, apart from exchange-traded open-end index funds, most mutual funds seldom engage in margin trading and securities lending. In this context, margin trading refers to the practice where investors borrow money to invest in stock market. On the other hand, securities lending refers to the process where investors borrow stocks from others to engage in short selling activities. As a result, the levels of margin trading and security lending can serve as a suitable proxy for capturing the sentiment of investors who are not mutual funds. To investigate how the buying and selling herding behavior of mutual funds influences the sentiments and trading directions of these other market participants, and subsequently creates asymmetric impacts on mispricing, this study constructs the following empirical mode:

$$Margin_{i,t} = \alpha_0 + \alpha_1 BHM_{i,t} + \varepsilon_{i,t} \quad (16)$$

$$Margin_{i,t} = \alpha_0 + \alpha_1 SHM_{i,t} + \varepsilon_{i,t} \quad (17)$$

$$Lending_{i,t} = \alpha_0 + \alpha_1 BHM_{i,t} + \varepsilon_{i,t} \quad (18)$$

$$Lending_{i,t} = \alpha_0 + \alpha_1 SHM_{i,t} + \varepsilon_{i,t} \quad (19)$$

Among them, $Margin_{i,t}$ is the balance of margin trading, while $Lending_{i,t}$ is the balance of securities lending. $BHM_{i,t}$ denotes the variable for herding buying, while $SHM_{i,t}$ represents the variable for herding selling.

Table 5. *Mutual fund herding, margin trading and security lending.*

	margin trading		**security lending**	
variables	**(1)**	**(2)**	**(3)**	**(4)**
BHM	0.056*** (5.230)		-0.031* (-1.880)	
SHM		0.115*** (9.990)		-0.049*** (-2.930)
$cons$	0.583*** (4.640)	0.184** (2.090)	-0.091 (-0.490)	-0.055 (-0.420)
$time$	$contraled$	$contraled$	$contraled$	$contraled$
$industry$	$contraled$	$contraled$	$contraled$	$contraled$
N	5696	7505	5735	7564
R^2	0.186	0.180	0.066	0.065
F	29.340***	37.110***	9.130***	11.920***

Note: The values in parentheses represent the t-values, while *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5 presents the regression results. In columns (1) and (3), we observe the results for models (16) and (18), respectively, with the regressor being BHM. The results reveals that the coefficient associated with the herding effect of mutual fund buying is significantly positive for margin trading. This indicates that other investors tend to follow the buying behavior of mutual funds and make similar purchase decisions.

However, the effect of mutual fund buying on securities lending is not statistically significant, suggesting that mutual fund buying does not have a significant impact on short selling activities. As a result, the upward stock price deviations are primarily driven by the co-directional leveraged trading, where investors amplify market trends by using margin trading to take advantage of the buying pressure. Short selling, on the other hand, does not play a significant role in balancing the buying pressure created by mutual fund buying.

In Columns (2) and (4) of the regression results (models 17 and 19), we observe the findings related to the herding effect of mutual fund selling. The results indicate that the coefficient associated with the herding effect of mutual fund selling is significantly positive for margin trading. However, for securities lending balance, the coefficient is non-significantly negative, which means that mutual fund selling does not have a significant impact on short selling activities. This suggests that when mutual funds engage in substantial selling activities, other investors do not follow suit by making corresponding selling decisions. Instead, they adopt buying decisions. This counter-directional leveraged trading works to prevent negative stock price deviations.

4.4. Robustness Test

As mentioned earlier, this study utilizes the well-established LSV method introduced by Lakonishok et al. (1992) and the simplified herd behavior measure indicator developed by Shi (2001) to conduct the regression analysis. The obtained regression results, which are presented in Table 2 and Table 3, consistently hold across the entire sample as well as the subsamples of herding buying and herding selling. This consistency across different samples indicates the robustness of the conclusions derived from the analysis.

In order to test the robustness of the results, this study considers using a different method to estimate the intrinsic value and measure the price deviation. It is acknowledged that the bankruptcy of a company carries significant economic and social costs, and authorities often strive to prevent such occurrences for listed companies. Therefore, as an alternative approach, this study employs the scenario where the company's survival period is limited, in contrast to assuming an infinite survival period as in the previous research. To recalculate the intrinsic value of the company and the degree of price deviation, we adopt the method proposed by Gu et al. (2011) to recalculate the intrinsic value and conduct regression analysis and report the results in Table 6 and Table 7 [30]. The empirical results are generally consistent with Table 2 and Table 3.

Table 6. *Robustness test (full sample).*

Variables	(1)	(2)
HM	0.008* (1.940)	0.014** (2.460)
$turn$	0.005 (0.072)	0.008 (1.270)
$sigma$	0.083*** (7.280)	0.079*** (7.070)
$size$	0.109*** (31.570)	0.115*** (30.800)
mb	-0.061*** (-5.870)	-0.051*** (-4.950)
roa	-0.076*** (-19.760)	-0.078*** (-20.300)
$cons$	0.774*** (28.860)	0.768*** (28.880)
$time$	$contraled$	$contraled$
$industry$	$contraled$	$contraled$
N	21200	21299
R^2	0.165	0.170
F	85.100***	88.530***

Note: The values in parentheses represent the t-values, while *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7. *Robustness test (subsample).*

Variables	subsample of buying		subsample of selling	
	(3)	(4)	(5)	(6)
BHM	0.013** (2.050)	0.015* (1.800)		
SHM			-0.001 (-0.160)	0.005 (0.550)
$turn$	0.008 (0.830)	0.011 (1.230)	0.001 (0.060)	0.006 (0.580)

Variables	subsample of buying		subsample of selling	
	(3)	(4)	(5)	(6)
sigma	0.098*** (5.870)	0.097*** (5.960)	0.086*** (4.990)	0.073*** (4.350)
size	0.105*** (20.040)	0.121*** (21.230)	0.107*** (21.390)	0.103*** (19.310)
mb	-0.086*** (-5.560)	-0.082*** (-5.420)	-0.073*** (-4.750)	-0.058*** (-3.800)
roa	-0.070*** (-12.100)	-0.072*** (-12.380)	-0.081*** (-14.530)	-0.083*** (-14.920)
cons	0.694*** (18.470)	0.689*** (18.470)	0.763*** (17.830)	0.749*** (17.680)
time	*contraled*	*contraled*	*contraled*	*contraled*
industry	*contraled*	*contraled*	*contraled*	*contraled*
N	9666	9751	11534	11548
R^2	0.175	0.187	0.159	0.159
F	41.58***	45.440***	44.200***	44.330***

Note: The values in parentheses represent the t-values, while *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

5. Conclusions

Mutual funds, as significant participants in the financial market, play a crucial role in shaping asset prices. Previous studies have extensively discussed the price effects of mutual fund herding behavior. However, this paper takes a novel empirical approach by examining stock mispricing from the perspective of company fundamentals. It confirms the relationship between mutual fund herding behavior and deviation from intrinsic value, providing direct evidence of the impact of mutual fund herding behavior on mispricing. Furthermore, this study specifically investigates the asymmetric nature of the price deviation induced by buying and selling herding behavior and explores the potential mechanisms behind this effect.

In terms of research design, this study selects relevant data on mutual fund holdings and stock trading in the Chinese A-share market from 2010 to 2023. The residual income model, which considers the future development potential of companies, is used to calculate the intrinsic value of the companies. The degree of deviation between stock prices and intrinsic value is used to measure mispricing, and the classical LSV method is employed to measure mutual fund herding behavior. This study distinguishes the trading direction of mutual fund herding behavior and separately examines the relationship between herding buying behavior and herding selling behavior with stock price deviation. The empirical results indicate that mutual fund herding buying behavior is related to the positive deviation of stock prices from intrinsic value. Portfolio analysis reveals that herding buying behavior leads to a positive deviation of stock prices from fundamentals, resulting in excess returns in the current period, followed by return reversals within three to six months. Moreover, our results provide evidence that the herding buying of mutual funds stimulates similar trading sentiments among other market participants and contributes to the formation of market bubbles, while herding selling does not exhibit a similar effect.

Abbreviations

QFII	Qualified Foreign Institutional Investors
DACCR	Discretionary Accruals
LSV	Lakonishok-Shleifer-Vishny

Author Contributions

Yujia Liu: Data curation, Software, Validation, Writing – original draft

Liang Wu: Conceptualization, Formal Analysis, Methodology, Project administration, Resources, Supervision, Writing – review & editing

Data Availability Statement

The data that support the findings of this study can be found at: https://data.csmar.com

Conflicts of Interest

The authors declare no conflicts of interest.

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Research Field

Yujia Liu: Statistics, Financial Markets, Financial behavior, Herding

Liang Wu: Spatial statistical methods, spatial double stochastic processes, Financial time series statistical methods, High frequency order flow statistics, Financial Risk and Liquidity Risk