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Is institutional herding efficient? Evidence from an investment efficiency and informational network perspective

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ABSTRACT

This paper proposes an informational network measure and an extended analysis method for network data envelopment, uncovering a negative relationship between institutional herding and investment efficiency. We also capture the investment efficiency loss of the herding institutions. The results show that the eccentric institutions outperform their herding peers by over 1.4% annually. Our evidence indicates that herding actions weaken the positive role of active management, leading to inefficiency. Further analyses show that a stressed market and herding strategy implemented by poorly performing institutions with inadequate past performance can aggravate the negative effect of institutional herding. Moreover, we support the positive effect of institutional herding on an increasing rise and mitigating effect concerning the intensification of persistent crashes.

1. Introduction

A large body of financial literature shows the critical effect of institutional herding on institutions' uncertainty avoidance and yield (Chen et al., 2018; Keswani et al., 2020; Lin et al., 2021; Lu et al., 2022). Many studies have shown that the impacts of the herding are of first-order significance when it comes to generating the strategies of asset allocation, industry selection, and balancing the risk-return performance (Economou et al., 2015; Hudson et al., 2020; Rubbaniy et al., 2022). Unlike retail investors, institutions are more skilled and have more complex social connections, indicating more intricate information exchange in their social network (Cohen et al., 2008). Accordingly, the effect of institutional herding seems more enigmatic and deserves in-depth investigation. Whether institutions are following or leading peers remains unclear, which could bias the estimation of the herding effect; the extant literature has thus far overlooked this issue. This paper innovatively attempts to measure the propensity of herding based on the relative importance of institutions by constructing an informational network of them to address this issue and investigate the effect of institutional herding on institutional performance, particularly on the return efficiency of investment.[1]

Previous studies on herding and its sources commonly classify herding into intentional and spurious herding. Intentional herding originates from an actual intent by market participants to imitate the actions of others (Bikhchandani and Sharma, 2000). The reason for intentional herding could be that investors believe other peers and decide to imitate the observed decisions rather than follow their information or judgment (Fei and Liu, 2021). Previous studies have shown there are several reasons for intentional herding, such as belief in better-informed peers (Spyrou, 2013), incentives provided by the compensation scheme and terms of employment (Boyson, 2010), and the innate preference for conformity (Bikhchandani and Sharma, 2000). Unlike intentional herding, spurious herding is unintentional investors may herd if they trade based on similar information sets (Guo et al., 2020). The reason for spurious herding may be that managers with standard features exhibit correlation in their trades, thus generating the impression of herding; another reason is that style investing would also lead to herding without being due to intent (Gavriilidis et al., 2013).

For empirical evidence, one stream of studies provides market-wide herding evidence on whether herding exists in various markets and industries (Spyrou, 2013; Celiker et al., 2015), causes of herding (Kremer and Nautz, 2013), and asymmetry of herding (Hwang and Salmon, 2004). In comparison, another stream of

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[1] For brevity, we use "investment efficiency" to indicate "return efficiency of investment".

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studies provides micro-herding evidence of retail investor herding and institutional herding. Retail investors are generally seen as primary contributors to noise trading. Wang et al. (2022) found that non-fundamental herding primarily characterizes the Chinese stock market in a market dominated by individual investors. Compared to retail investors, institutional investors are generally considered more professional; however, institutional investors would take intuitively irrational actions such as herding for many reasons, as mentioned above. Managers of institutions have more complex social network connections than retail investors. A growing body of literature indicates that social network connections between managers may lead to more similar stock holdings between institutions and are more likely to buy or sell the same stocks contemporaneously (Pool et al., 2015; Liang et al., 2022). Despite various reasons for their herding behavior, what interests us more is whether this behavior is efficient, that is, whether institutional herding is effective.

Intuitively, herding behavior may induce inefficient investments since it is considered passive and purely imitative. In contrast, herding can also improve the performance of institutions in some cases where the herding institutions follow other peers' reliable decisions based on private information. Therefore, the relationship between institutional herding and investment efficiency deserves in-depth investigation because it carries significant implications for investors interested in investing in the institutions and for institutions that need to strengthen supervision of the actions of managers as well as herding managers who wonder whether their portfolio management is efficient.

Two significant concerns have not been solved in the literature concerning the relationship between institutional herding and investment efficiency. The first concern is how to identify and gauge institutional herding. Previous studies measured herding by calculating the proportion of institutions that buy or sell the same stock in the same quarter or year (Lakonishok et al., 1992; Sias, 2004); however, this traditional herding measure cannot identify whether an institution is following or leading the crowd, which is crucial for investigating the link between institutional herding and investment efficiency. If an institution leads the crowd instead of herding, the estimation based on the traditional herding measure may deviate from the facts. The second concern is how to measure the investment efficiency of institutions. Prior herding studies mainly focus on the relationship between herding and returns, flow performance, and other financial performance (Dasgupta et al., 2011; Brown et al., 2014; Salganik-Shoshan, 2016; Jiang and Verardo, 2018). None of these studies investigate the link between institutional herding and investment efficiency; however, investment efficiency seems to be essential to evaluate the herding effect on the overall performance considering heterogeneous characteristics of different institutions because a single financial performance indicator is biased in evaluating the performance of institutions. To the best of our knowledge, this is the first comprehensive study on the link between institutional herding and investment efficiency. We make two contributions to address the unresolved concerns mentioned above.

First, we attempt to construct a mutual-holding network and detect herding by using two network measures based on the mutual-holding network. The two network measures – eccentricity and betweenness – allow us to address the most notable concern of detecting whether the institutions are leaders or followers. Both measures reflect the relative importance of institutions in the network, but they measure the propensity of herding differently. Briefly, eccentricity indicates the distance between an institution and its affiliated institutions. At the same time, betweenness indicates the mediating power of an institution between the other two institutions connected with it. Following this logic, the higher eccentricity of an institution implies its relatively lower importance in connections because other connected institutions are not close; therefore, higher eccentricity implies a higher propensity to herd. In comparison, the higher betweenness of an institution implies its relatively higher importance in connections because other institutions need it to be connected; hence, higher betweenness implies a lower propensity to herd. We use its alternative measure that equals one minus betweenness to indicate herding.

Second is our effort to construct the proxy of investment efficiency. Considering the heterogeneity of institutional herding, we construct a more integrated framework for performance measurement using an analysis method for network data envelopment, i.e., the robust return efficiency under management (RREM) model, to evaluate the investment efficiency as comprehensively as possible. The RREM model has a multiple-index system with risk-return indexes and other characteristics, and its conceptual framework is consistent with institutional herding. The model proposes a two-stage framework reflecting a coherent assessment process that the uncertainty avoidance performance is assessed first, then the yield is evaluated. By using the measure derived from the RREM model, we can directly evaluate institutions' investment efficiency, specifically, the efficiency variations influenced by their herding behavior in the informational network.

We contribute to the literature by providing innovative evidence of the institutional herding effect on investment efficiency. In our baseline test, we link the herding measured by the informational network to the investment efficiency of the institutions derived by the RREM model and replace the RREM as the uncertainty avoidance and yield to examine the robustness of our results. Furthermore, we attempt to explore the mechanism of the herding effect on investment efficiency by exploiting a mediating test that uses active management as the proxy variable. Considering the macro context, we examine whether the herding effect in a stressful market exhibits a diverse effect compared to a normal market. To test the reliance of institutional herding on information from past institutional performance, we also identify the asymmetric effect of the herding in the groups of "winners" and "losers" classified by their past performance. Furthermore, the long-term effect of herding is examined. Finally, the herding effects on the aggravation of the crash risk and the facilitation of continuous rise are recognized.

Our sample comprises all mutual funds established in China over seven years. Given the typical characteristics of mutual funds, we attempt to concentrate on mutual funds' associations of common-holding information to detect the effect of institutional herding. To satisfy the requirement of the RREM on the balance of the sample, we filter out the unbalanced funds to guarantee a more precise measure. An increasingly skewed herding distribution is captured over time, and by the end of the sample, the standard deviation drops from 2.160 in 2015 to 1.691 in 2020, indicating universal herding in the market.

Our study contributes to the extensive literature on institutional herding, which suggests that institutional herding has a significant impact on various perspectives, including price impact (Cai et al., 2019; Iqbal et al., 2021), risk-return relationship (Huang et al., 2016), stock returns (Hsieh, 2013), short-selling bans (Bohl et al., 2014), investor sentiment (Hudson et al., 2020; Kim et al., 2022), corporate governance compliance (Orihara and Eshraghi, 2022) and market volatility (Fei and Liu, 2021). Conversely, latent connections and associations among the institutions are informationally significant for institutional herding. Our results estimate the institutional herding effect on institutions' investment efficiency from an informational network perspective. At the same time, more work is needed to understand the causes of institutional herding, the asymmetric effect of the herding in different trading timings, and the bellwether effect of the herding.

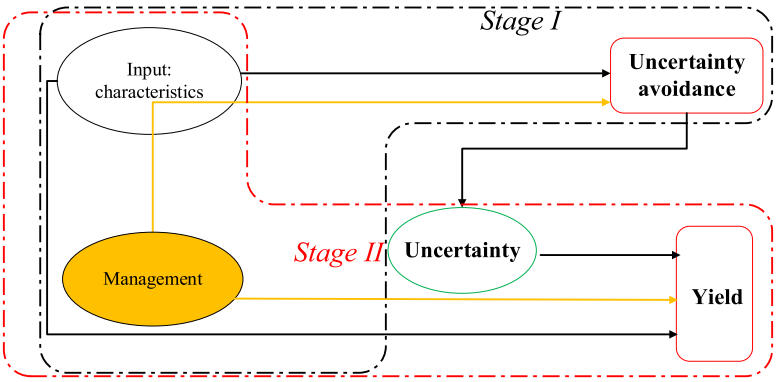

Fig. 1. The framework of the RREM model.

Our paper also contributes to the literature on the investment efficiency of institutional investors, which typically focuses on mutual funds (Buchner et al., 2020; Rohleder et al., 2022). Some studies have explored investment performance from various perspectives (Fang et al., 2017; Lin et al., 2021; Rösch et al., 2022; Wanidwaranan and Padungsaksawasdi, 2022); however, we propose an innovative method to measure the institutions' investment efficiency by combing a multiple-index system and a two-stage framework measuring the RREM and investigate the institutional herding effect on the efficiency. The relationship has statistical and economic significance, and the new measurement of investment efficiency for institutional investors contributes significantly to institutional herding.

The remainder of this paper is organized as follows. Section 2 briefly introduces the methodology, including measuring institutional herding and investment efficiency, Section 3 presents the data and statistical description, and Section 4 provides the results of baseline tests. Section 5 explores the possible mechanisms, Section 6 presents the robustness checks, and Section 7 concludes.

2. Methodology and data

2.1. Measurement of investment efficiency

A primary hurdle in evaluating institutions' performance has been to comprehensively and fairly compare various indexes of the institutions; therefore, a strong incentive arises to exploit a better assessment method with a multi-perspective and peer-evaluated system. Traditional indexes measure pointedly, while they have difficulties in comprehensive and comparative measures. Extending the traditional form of the network data envelopment analysis (DEA) approach (Seiford and Zhu, 1999), we seek to propose a modified form of the network DEA approach using a multiple-index and peer-evaluated framework, the RREM model, considering manager capacity both in the two stages. It is used to measure the fund investment efficiency variation. It transforms the traditional framework of the network DEA and constructs a trans-intermediate output changing the original sequential flow path to a curved one. Considering the manager capacity, which could lead to significant efficiency heterogeneity, we extend the traditional network DEA model to the RREM, as shown in Fig. 1.

Fig. 1 shows two stages that evaluate the institutions' performance of uncertainty avoidance and yield. In stage I, we first detect the performance of evading uncertainties of the institution. In this stage, the institutional characteristics and the manager's capacity and skill are considered the inputs, and uncertainty avoidance is regarded as the output. Between stages I and II, the uncertainty avoidance variable are transformed into the uncertainty variable to link the two stages[2] to guarantee a positive relationship between the inputs and outputs, which is required by the DEA framework. In stage II, we evaluate the performance of creating values of the institutions, namely yield. In this stage, the uncertainty variable and the manager's capacity and skill are considered the inputs, and the yield performance is the output. We can measure the overall efficiency of the institutions by constructing this network framework. Note that the efficiency measured by the RREM model is not a simple sum or multiplier of the efficiency of stages I and II; instead, it is a synthetic efficiency measure involving the two stages and their connections. The radical causation of the herding is that the herding institutions believe their herding actions could create values, evade uncertainties, or both. Following this stream, we can judge whether the herding behavior is efficient (creating values, evading uncertainties, or both) or not (neither creating values nor evading uncertainties). Accordingly, our RREM model resolves this problem by evaluating the overall efficiency combining the two stages' performance, thereby identifying the efficiency variations influenced by institutional herding.

To account for this, we suggest the following to describe the RREM model mathematically:

$$RREM = \max \frac{Yield^t * \mathbf{W}_1^{t\mathbf{T}} + UA^t * \mathbf{S}_1^{t\mathbf{T}}}{\mathbf{Ichara}^t * \mathbf{U}_1^{t\mathbf{T}} + Uncertainty^t * \mathbf{V}_1^{t\mathbf{T}} + \mathbf{Management}^t * \mathbf{X}_1^{t\mathbf{T}}}, \tag{1}$$

Subject to

$$UA^t * \mathbf{S}_1^{t\mathbf{T}} - (Fundchara^t * \mathbf{U}_1^{t\mathbf{T}} + Uncertainty^t * \mathbf{V}_1^{t\mathbf{T}}) \le 0,$$

$$Yield^t * \mathbf{W}_1^{t\mathbf{T}} - (Inschara^t * \mathbf{U}_1^{t\mathbf{T}} + UA^t * \mathbf{S}_1^{t\mathbf{T}}) \le 0,$$

$$UA^t = 1 - Uncertainty^t,$$

$$\mathbf{Ichara}^t * \mathbf{U}_1^{t\mathbf{T}} = Isize^t * \partial_1^t + Iage^t * \partial_2^t,$$

$$\mathbf{Management}^t * \mathbf{X}_1^{t\mathbf{T}} = Maturity * \Omega_1^t + Capability * \Omega_2^t,$$

$$+ Products * \Omega_3^t,$$

$$\mathbf{U}_1 = (u_{11}, u_{12}, \ldots, u_{1h})^{\mathrm{T}}, \mathbf{V}_1 = (v_{11}, v_{12}, \ldots, v_{1i})^{\mathrm{T}},$$

$$\mathbf{W}_1 = (w_{11}, w_{12}, \ldots, w_{1j})^{\mathrm{T}}, \mathbf{S}_1 = (s_{11}, s_{12}, \ldots, s_{1k})^{\mathrm{T}},$$

$$\mathrm{X}_1 = (\mathrm{x}_{11}, \mathrm{x}_{12}, \ldots, x_{1l})^{\mathrm{T}},$$

$$\mathbf{U}_1 \ge 0, \mathbf{V}_1 \ge 0, \mathbf{W}_1 \ge 0, \mathbf{S}_1 \ge 0, \mathbf{X} \ge 0,$$

$$t \in \{1, 2, \ldots, r\}, a \in \{1, 2, \ldots, h\}, b \in \{1, 2, \ldots, i\},$$

$$c \in \{1, 2, \ldots, j\}, d \in \{1, 2, \ldots, k\}, \mathrm{e} \in \{1, 2, \ldots, l\},$$

[2] The mathematical description of the linkage can be seen in model (1).

where *Yield* represents the yield variable, proxied by the annualized return on asset. *UA* represents the uncertainty avoidance variable, equal to one minus the institutions' annualized volatility, which are the expected outputs. *Uncertainty* represents the risk variable, which equals the difference of 1 minus *UA*. **Ichara** denotes the institutional-characteristic variables, including age and size of institutions, while **Management** includes the manager maturity, manager capability, and the average product number under management for managers. The inequalities restrict that the sum of the outputs must be less than the sum of the inputs in both stages. $UA^t = 1 - Uncertainty^t$ describe the transformation equation of the link. All the weights are nonnegative.

2.2. Measurement of institutional herding

Compared to individual investors, institutional investors have more incentives to herd since most poor investment decisions can be justified by the agents straying not too far from the crowd (Casavecchia, 2016). Moreover, institutional herding is more informational and contains numerous connections among institutional managers. General studies on institutional herding often use cross-sectional dispersion of the factor sensitivity, such as beta. In contrast, we attempt to use a complex network approach to depict the institutional herding in an institutional network and quantify the propensity of herding. The network comprises institutions and their associations. This paper considers the associations as identical holdings among institutions; if the institutions have the same holding, they are associated. The common amount of the holding is regarded as the extent of the association, namely the weight of the edge in a complex network. By constructing the associations and the edges in the network, we can detect the existence and the magnitude of institutional herding. In the field of complex networks, scholars mostly use degree connectedness indicators, such as degree centrality (Lin et al., 2021) and degree closeness (Hochberg et al., 2007). From the perspective of the affinity–disaffinity relationship, we utilize an eccentricity measure as the proxy variable of herding, calculated by the following equation:

$$Herding1 = Eccentricity_i = \max\{Steps_{i,j}, \forall j \ni \vee\}, \tag{2}$$

where $Steps_{i,j}$ denotes the required minimum steps for institution i to institution j, and $\max\{Steps_{i,j}, \forall j \ni \vee\}$ denotes the steps of the longest path of the required minimum steps for institution i to institution j.[3] More specifically, the paths are defined as the shortest path between institution i and other institutions; therefore, $\max\{Steps^k_{i,j}, \forall j \ni \vee\}$ denotes the number of institutions to cross in the longest path. The definition of eccentricity is consistent with the measure connotation of the affinity–disaffinity relationship among the institutions. Compared to the traditional herding measures, it conveys more information about the herding associations among the institutions, resulting in a deeper comprehension and a more precise measurement. Note that $Eccentricity_i$ indicates the tendency of "herding" instead of "leading" (viz. institution importance)[4] for institution i through the following logic. If the farthest institution j connects with institution i directly ($Eccentricity = 0$), indicating no other institutions are between their connection (i to j), then institution i has a higher tendency to lead than follow. In contrast, if many other institutions are between their connection (i to j), i.e., $Eccentricity_i$ is high, then institution i is more likely to follow rather than lead. Therefore, $Eccentricity_i$ measures the tendency of herding for institution i, and higher *Eccentricity* implies more herding.

As an auxiliary, we also use the betweenness index to test our results, which can be mathematically described as follows:

$$Betweennessi = \sum_{k=1}^{n-1} \sum_{j=2, j\neq k}^{n} \frac{Pathskj\,(i)}{Pathskj}, \tag{3}$$

where $Pathskj\,(i)$ denotes the number of the shortest paths between institution j and k that go through institution i. *Betweenness* represents the mediating power of the herding institutions, which measures how vital an institution is in connecting other institutions. Therefore, if an institution has a high *Betweenness*, it tends to lead rather than herd. Because *Betweenness* is a value between [0,1], to make the second herding measure positively gauge herding, we transform *Betweenness* into a positive herding measure as follows:

$$Herding2 = 1 - Betweennessi = \sum_{k=1}^{n-1} \sum_{j=2, j\neq k}^{n} \frac{Pathskj - Pathskj\,(i)}{Pathskj}, \tag{4}$$

Through Eq. (4), we obtain the second herding measure *Herding*2, which implies more herding with a higher *Herding*2. Therefore, the two network indexes, *Herding*1 and *Herding*2, are regarded as the herding measures that allow us to gauge the magnitude of institutional herding impact on investment efficiency from an informational network perspective.

2.3. Empirical design

We utilize three progressive model specifications. In the first and the second specifications, the two-way fixed effect (FE) model is employed to examine whether the herding impacts the institutions' yield and uncertainty avoidance, respectively, helping us to provide two separate inspections for investment performance under the herding effect. In the third specification, we use the two-way FE model to detect the impact of the herding on the *RREM* of institutions. It allows us to evaluate the investment efficiency under the herding effect directly. The three model specifications are shown as follows:

$$\begin{aligned} Yeild = {} & \alpha_0 + \alpha_1 * Herding1(Herding2) + \alpha_2 * Isize + \alpha_3 * Iage \\ & + \alpha_4 * Maturity + \alpha_5 * Capability + \alpha_6 * Products \\ & + \alpha_7 * Feeratio + \alpha_8 * Institution + \alpha_9 * Patience \\ & + \alpha_{10} * Concentration + \alpha_{11} * Lev + YearFE + IFE + \varepsilon \end{aligned} \tag{5}$$

$$\begin{aligned} Uncertainty = {} & \beta_0 + \beta_1 * Herding1(Herding2) + \beta_2 * Isize \\ & + \beta_3 * Iage + \beta_4 * Maturity + \beta_5 * Capability + \beta_6 * Products \\ & + \beta_7 * Feeratio + \beta_8 * Institution + \beta_9 * Patience \\ & + \beta_{10} * Concentration + \beta_{11} * Lev + YearFE + IFE + \varepsilon \end{aligned} \tag{6}$$

$$\begin{aligned} RREM = {} & \chi_0 + \chi_1 * Herding1(Herding2) + \chi_2 * Isize \\ & + \chi_3 * Iage + \chi_4 * Maturity + \chi_5 * Capability + \chi_6 * Products \\ & + \chi_7 * Feeratio \\ & + \chi_8 * Institution + \chi_9 * Patience + \chi_{10} * Concentration \\ & + \chi_{11} * Lev + \chi_{12} * Volatility + \chi_{13} * Return + YearFE + IFE + \varepsilon \end{aligned} \tag{7}$$

The control variables in the above models are selected from the perspectives of institutional characteristics, manager capacity, and investment characteristics. Regarding the institutional

[3] According to prior literature (Dotsika and Watkins, 2017), we also use an alternative measure of $EccentricityNew_i$ to test the validity of our analysis, which is calculated by the following equation: $EccentricityNew_i = \frac{\sum_{j=1, j\neq i}^{n} Steps_{i,j}}{n}$, where $Steps_{i,j}$ denotes the required minimum steps for institution i to institution j and we compute the average of the required minimum steps for all paths. $EccentricityNew_i$ allows us to avoid the bias of using the single longest path to detect the whole nature of herding. The regression results using the $EccentricityNew_i$ are reported in Section 6.

[4] See more detailed explanations in Bastidon and Parent (2022).

characteristic, we define the following variables. *Isize* denotes the total asset of the institutions and is generally regarded as a typical factor influencing institutions' performance in previous studies, i.e., Basso and Funari (2017), Alserda et al. (2018), and Cici et al. (2018). The unit of the *Isize* is measured in billions of Chinese yuan (CNY), and *Iage* denotes the established years of the institutions. Institutions that were founded earlier generally have accumulated more experience in portfolio management, potentially leading to the promotion of investment efficiency (He et al., 2019; Kenchington et al., 2019). Institutions charge different types of fees for their asset management services that aim to improve management outcomes, influencing investment efficiency significantly (Servaes and Sigurdsson, 2022). *Feeratio* denotes the ratio of the management fee divided by the institution size; other institutions hold institutions tend to obtain outperformance (Ratanabanchuen and Saengchote, 2020). Accordingly, *Institution* denotes the ratio institutional investors hold (He and Mi, 2022). Furthermore, strategies of investment and financing are regarded as essential factors affecting investment efficiency in prior studies, such as holding time (Lee et al., 2020), investment concentration (Andreu et al., 2019), and leverage (Wang et al., 2019). *Patience* denotes the average holding time of each security, *Concentration* denotes the ratio of investment concertation, and *Lev* denotes the leverage ratio of the institutions. In addition to our *RREM* indicator, we exploit two traditional indexes to measure the investment performance to provide a multi-perspective analysis.

Regarding the management of institutions, managers play a crucial role in asset allocation, industry research, and fundamental analysis. Several characteristics and indexes were evidenced to have an important effect on institutions' efficiency, such as maturity (Chen et al., 2022), capacity (Moraes et al., 2021), and institution amount under management (Bai et al., 2021). Furthermore, strategies of investment and financing are regarded as essential factors affecting investment efficiency in prior studies, such as holding time (Lee et al., 2020), investment concentration (Andreu et al., 2019), and leverage (Wang et al., 2019). Specifically, *Maturity* represents the managers' maturity, proxied by the average working years of each manager. *Capability* denotes the managers' capacity, proxied by the average asset size that the managers oversee. *Products* denotes the product amount that the managers oversee, indicating the manager's ability to conduct multi-assignment management.

2.4. Data

Mutual funds may be one type of the most typical institutional investors with frequent information exchanges and various social networks among them. Stimulated by the post-financial crisis rally in equity and bond markets, assets of mutual funds grew substantially in China, with total assets under management increasing to about 15 trillion CNY by the middle of 2020, an additional 1.86 trillion CNY relative to 2008. Since China's mutual fund market has significant retail participation in trading – implying ample noise trading – it is inundated with information asymmetry and irrational decisions, leading to a substantial loss of investment efficiency (Jun et al., 2014). In addition to retail investors, institutional investors may also make irrational investment decisions, such as herding behavior. Prior studies found that China has a more complex concept of relationships (called "guanxi" in Chinese), indicating that people attach importance to connections with others in society (Wong and Chan, 1999; Dunfee and Warren, 2001). In China's mutual fund industry, various connections in social networks play crucial roles in allocating assets and portfolio management. Generally, institutional investors such as mutual fund managers are considered more rational and mature than retail investors; however, due to various cognitive biases, mutual fund managers may mimic other peers' actions for a couple of reasons. For example, fund managers that face significant pressure of being replaced according to their underperformance may choose to follow the portfolio management strategy of the outperforming managers. Managers with a superior network position tend to perform better because of the advantage of information acquisition, which the literature has documented.[5] Therefore, investigating the network positions of funds (or managers) seems vital in understanding institutional herding in China, which inspires us with a behavioral finance concept to detect the institutional herding effect on investment efficiency from an informational network view. Drawn by the characteristic of fund institutions and China's local fund market, in this paper, we attempt to investigate the institutional herding effect on investment efficiency by using a sample of China's open-end funds. To obtain a balanced and latest sample as far as possible, we filter and construct our fund sample by the following criteria:

1. The funds are collected from the Wind database, China's most authoritative financial database
2. The mutual fund in China has a relatively short history, and it presented a surge after 2015 (Jiang et al., 2020). Our sample period ranges from 2015 to 2020 to guarantee balanced panel data, and the frequency of the data is the year.
3. All the funds announce comprehensive information, particularly containing the holding details
4. We delete the unbalanced funds to guarantee the panel balance strictly required by the *RREM* measurement.

We arrive at a final sample that includes 2,103 open-end mutual funds, including 452 equity funds, 999 mixed funds, 372 bond funds, 186 money market funds, 15 alternative investment funds, and 79 QDII funds.[6] We report the nature of the sample funds in Table A.1 of Appendix. Furthermore, the mutual-holding data, consisting of all the invested securities' names and investment amounts of the institutions, is gathered and handled using a Python program.

Table 1 reports the results of the summary statistics and the nature of sample funds. Panel A of Table 1 shows that the two herding measures of the funds are 3.115 (mean *Herding1*) and 0.213 (mean *Herding2*) in the full sample. Furthermore, we categorize the funds into those that herd in the network and have connections with other funds by investing the same securities versus eccentric funds in the network that are not connected with others. Panels B and C show the summary statistics for herding and eccentric funds, respectively.

Panels B and C of Table 1 show that funds herding in the network appears to be similar to those eccentric funds that are unconnected. First, they have similar fund ages. The average age for herding funds is 0.259 years, while the corresponding number for eccentric funds is 0.226 years. Moreover, the two groups have similar manager maturity average size and products under the management of fund managers; however, some characteristics differ. For example, the herding group has a higher transaction fee ratio, lower institutional investor ratio, shorter holding time,

[5] Lin et al. (2021) found that more central network positions of hedge fund managers are associated with better risk-adjusted fund performance.

[6] Alternative investment funds are funds that invest in types of investments other than traditional publicly traded equity assets, fixed income assets, and currency assets, including real estate, retail, mining, energy, securitized assets, hedge funds, commodities, private equity, infrastructure, gold, art, and other areas. QDII funds are qualified domestic institutional investors that are approved by the relevant authorities in China to engage in stocks, bonds, and other securities business in overseas securities markets.

Table 1
Summary statistics.

Panel A: The whole sample								
Variable	N	Mean	SD	Min	P25	P50	P75	Max
RREM	16765	0.476	0.363	0	0.051	0.528	0.801	1
Uncertainty	16765	0.296	0.228	0	0.066	0.274	0.482	1
Yield	16765	0.277	0.233	−0.462	0.143	0.302	0.438	1
AMP	16765	0.369	0.351	0	0.001	0.338	0.681	1
Herding1	16765	3.115	1.678	0	3	3	4	11
Herding2	16765	0.213	0.257	0	0.025	0.134	0.283	1
Isize	16765	0.004	0.024	0	0	0.001	0.002	1
Iage	16765	0.253	0.242	0	0.045	0.168	0.39	1
Maturity	16765	0.47	0.372	0	0	0.333	0.667	1
Capability	16765	0.01	0.006	0	0.005	0.01	0.014	0.033
Products	16765	3.556	0.728	1	3.135	3.64	4.132	5.167
Feeratio	16765	1.023	0.494	0	0.6	1	1.5	3
Institution	16765	0.316	0.351	0	0.013	0.147	0.605	1
Patience	16765	0.259	0.381	0	0.002	0.037	0.361	1
Concentration	16765	0.117	0.263	0	0	0.009	0.069	1
Lev	16765	0.428	0.183	0	0.384	0.478	0.546	1
Family	16765	140.426	85.733	2	67	116	211	299
Panel B: The sample of herding funds								
Variable	N	Mean	SD	Min	P25	P50	P75	Max
RREM	13722	0.396	0.326	0	0.033	0.435	0.667	1
Uncertainty	13722	0.344	0.215	0	0.168	0.347	0.513	1
Yield	13722	0.263	0.242	−0.462	0.092	0.298	0.440	1.216
AMP	13722	0.294	0.306	0	0	0.207	0.569	1
Herding1	13722	3.780	0.910	0	3	4	4	11
Herding2	13722	0.260	0.262	0	0.0820	0.179	0.327	1
Isize	13722	0.003	0.014	0	0	0.00100	0.002	0.765
Iage	13722	0.259	0.248	0	0.0400	0.175	0.413	1
Maturity	13722	0.474	0.372	0	0.333	0.333	1	1
Capability	13722	0.010	0.006	0	0.005	0.0100	0.014	0.033
Products	13722	3.549	0.726	1	3.135	3.588	3.970	5.167
Feeratio	13722	1.141	0.448	0	0.700	1.500	1.500	3
Institution	13722	0.296	0.340	0	0.0100	0.129	0.545	1
Patience	13722	0.223	0.344	0	0.006	0.037	0.270	1
Concentration	13722	0.143	0.285	0	0.003	0.019	0.104	1
Lev	13722	0.396	0.326	0	0.0330	0.435	0.667	1
Family	13722	0.344	0.215	0	0.168	0.347	0.513	1
Panel C: The sample of eccentric funds								
Variable	N	Mean	SD	Min	P25	P50	P75	Max
RREM	3043	0.841	0.293	0	0.891	0.967	0.998	1
Uncertainty	3043	0.079	0.144	0	0.00200	0.0290	0.0590	0.981
Yield	3043	0.356	0.171	0	0.186	0.380	0.432	0.942
AMP	3043	0.710	0.338	0	0.542	0.865	0.974	1
Herding1	3043	0	0	0	0	0	0	0
Herding2	3043	0	0	0	0	0	0	0
Isize	3043	0.011	0.048	0	0	0.001	0.006	1
Iage	3043	0.226	0.213	0.001	0.080	0.153	0.283	0.922
Maturity	3043	0.449	0.374	0	0	0.333	0.667	1
Capability	3043	0.011	0.006	0	0.005	0.011	0.014	0.033
Products	3043	3.586	0.733	1	3.160	3.750	4.132	5.167
Feeratio	3043	0.490	0.308	0	0.300	0.330	0.650	1.850
Institution	3043	0.406	0.382	0	0.036	0.267	0.826	1
Patience	3043	0.421	0.484	0	0	0.032	1	1
Concentration	3043	0.002	0.0210	0	0	0	0	0.532
Lev	3043	0.841	0.293	0	0.891	0.967	0.998	1
Family	3043	0.079	0.144	0	0.002	0.029	0.059	0.981

and larger investment concentration than the eccentric group. Notably, we find a distinct difference in *RREM* between the two groups. The eccentric group has a mean *RREM* of 0.841 versus 0.396 of the herding group. Regarding return and uncertainty, the herding group has a lower mean yield of 0.344 and higher mean uncertainty of 0.263, while the yield and uncertainty of the eccentric group are 0.356 and 0.079, respectively. This finding is consistent with the hypothesis that funds herding more in the network are more underperformed and inefficient.

3. Empirical results

3.1. Baseline results

We first detect the institutional herding effect on yield and uncertainty. Table 2 presents the results of estimating models (5) and (6). Columns (1) and (3) show the univariate regression results. Columns (2), (4), (6), and (8) present the multivariate regression results when controlling the fund characteristics, fund

Table 2
Impact of institutional herding on yield and uncertainty.

Variables	(1) *Yield*	(2) *Yield*	(3) *Yield*	(4) *Yield*	(5) *Uncertainty*	(6) *Uncertainty*	(7) *Uncertainty*	(8) *Uncertainty*
Herding1	−0.005***	−0.003***			0.003**	0.011***		
	(−3.64)	(−4.12)			(2.53)	(8.67)		
Herding2			−0.022*	−0.021***			0.021*	0.018**
			(−1.95)	(−3.17)			(1.83)	(2.11)
Isize		0.019		0.028		−0.482**		−0.541**
		(0.97)		(1.20)		(−2.30)		(−2.32)
Iage		0.023***		0.025***		−0.018		−0.020
		(5.09)		(5.49)		(−1.47)		(−1.61)
Maturity		−0.004		−0.005*		0.017*		0.019**
		(−1.55)		(−1.73)		(1.91)		(2.02)
Capability		1.211***		1.238***		1.968***		1.991***
		(6.10)		(6.18)		(2.82)		(2.74)
Products		0.000		0.000		0.006		0.007
		(0.28)		(0.04)		(1.11)		(1.24)
Feerate		0.076***		0.075***		0.233***		0.246***
		(22.88)		(22.61)		(26.31)		(27.42)
Institution		0.029***		0.029***		−0.067***		−0.064***
		(8.22)		(8.34)		(−11.15)		(−10.55)
Patience		0.011		0.006		0.078***		0.069***
		(0.80)		(0.40)		(5.52)		(4.94)
Concentration		−0.005		−0.015		0.285***		0.301***
		(−0.29)		(−0.78)		(14.01)		(14.27)
Lev		−0.019		−0.020		−0.012		−0.013
		(−1.23)		(−1.28)		(−0.83)		(−0.85)
Constant	0.280***	0.189***	0.268***	0.186***	0.385***	0.097***	0.375***	0.114***
	(53.69)	(16.05)	(74.00)	(15.72)	(78.88)	(4.21)	(55.78)	(4.83)
Observations	16765	16765	16765	16765	16765	16765	16765	16765
R-squared	0.649	0.316	0.649	0.309	0.557	0.464	0.556	0.439
Cluster Fund	YES	YES	YES	YES	YES	YES	YES	YES
Fund FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents the results of the effect of institutional herding on institutional yield and its uncertainty. Columns (1)–(4) present the impact of *Herding1* and *Herding2* on the yield, and Columns (5)–(8) present the impact of *Herding1* and *Herding2* on the uncertainty. *Herding1* and *Herding2* are proxy variables of institutional herding. Columns (1), (3), (5), and (7) show the regression results without control variables and fixed effect, while Columns (2), (4), (6), and (8) present the regression results, which controls the fund characteristics, time effect, and individual effect. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively. The robust standard errors clustered at the fund level are reported in parentheses.

manager attributes, and investment strategies. In Columns (1)–(4), the coefficients of *Herding1* and *Herding2* are negative and statistically significant at 1%, indicating a negative effect of institutional herding on the yield of funds. In Columns (5)–(8), the coefficients of *Herding1* and *Herding2* are positive and statistically significant at the level of 10% at least, indicating a positive impact of institutional herding on the return uncertainty of funds. Regarding the economic magnitude, the results in Columns (2) and (6) indicate that increasing *Herding1* by one hundred percent decreases yield by 0.3% and increases uncertainty by 1.1%. Simultaneously, the results in Columns (4) and (8) show that increasing *Herding2* by one hundred percent decreases yield by 2.1% and increases uncertainty by 1.8%. These results imply that institutional herding leads to lower yield and higher return uncertainty, which is consistent with previous studies (Kremer and Nautz, 2013; Yüksel, 2015).

Moreover, we investigate the institutional herding effect on investment efficiency. Table 3 presents the results of estimating model (7). Columns (1) and (3) show the univariate regression results. Columns (2) and (4) present the multivariate regression results when controlling the fund characteristics, fund manager attributes, and investment strategies. In Columns (1) and (3), the coefficients of the two herding variables (*Herding1* and *Herding2*) are both negative and statistically significant at the level of 1%. Columns (2) and (4) show that the coefficients of the network *Herding1* and *Herding2* have slight decreases. At the same time, they are still both negative and statistically significant at the level of 1%, suggesting that institutional herding has a significantly negative impact on the investment efficiency of mutual funds. The herding effect is also economically significant. Based on our estimates in Columns (2) and (4), increasing *Herding1* by one hundred percent decreases *RREM* by 1.4%; increasing *Herding2* by one hundred percent decreases *RREM* by 7.7%. According to our results, we seem to provide the answer that institutional herding is inefficient to the basic question.

3.2. Endogeneity

The variation in yield and uncertainty avoidance of the funds we document may be driven by omitted variables leading to biases in our estimated coefficient of interest, which is a potential issue with the interpretation of the results in Section 3.1. The latent endogeneity may reflect underlying differences in fund family characteristics predicting fund performance. Even though involving fund controls or individual fixed effects in baseline regressions mitigates the problem to some extent, it is unlikely to address it; therefore, we take advantage of two instrumental variables (IV) regarding fund family characteristics: the fund numbers of the fund family (excluding fund (*i*) and the total size of the fund family (excluding fund *i*'s size). These two variables satisfy the conditions for being good IV based on the following reasons. First, fund numbers of the fund family and the total size of the fund family are highly correlated to fund herding because funds in a bigger family can easily share private information internally and adopt similar investment strategies (Gaspar et al., 2006), i.e., IV are correlated to the endogenous independent variables. Second, the fund numbers of the fund family (excluding fund (*i*) and the total size of the fund family (excluding fund *i*'s size) are less likely to directly influence the yield, uncertainty, and *RREM* performance of funds, i.e., IVs are not correlated to the dependent

Table 3
Impact of institutional herding on investment efficiency.

Variables	(1) *RREM*	(2) *RREM*	(3) *RREM*	(4) *RREM*
Herding1	−0.049***	−0.014***		
	(−23.08)	(−7.36)		
Herding2			−0.132***	−0.077***
			(−3.34)	(−6.40)
Isize		0.279***		0.311***
		(3.89)		(3.56)
Iage		0.001		0.008
		(0.16)		(0.83)
Maturity		0.191***		0.190***
		(30.35)		(29.64)
Capability		−0.946**		−0.787*
		(−2.29)		(−1.85)
Products		0.006		0.004
		(1.47)		(1.12)
Feerate		−0.013*		−0.014*
		(−1.91)		(−1.91)
Institution		0.000		−0.000
		(0.05)		(−0.02)
Patience		−0.014***		−0.014***
		(−5.35)		(−5.02)
Concentration		0.067***		0.057***
		(5.23)		(4.53)
Lev		0.000		0.000
		(1.31)		(1.43)
Uncertainty		−0.654***		−0.685***
		(−41.37)		(−45.16)
Yield		0.352***		0.352***
		(23.28)		(23.21)
Constant	0.693***	0.624***	0.551***	0.607***
	(65.91)	(32.07)	(49.07)	(31.41)
R-squared	0.451	0.592	0.382	0.590
Observations	16765	16765	16765	16765
Cluster institution	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Note: Robust t-statistics in parentheses; *** = p<0.01, ** = p<0.05, and * = p<0.1.

variables. Our improved results strongly support the hypothesis that the herding of funds negatively affects yield, uncertainty avoidance, and investment efficiency.

By utilizing the fund numbers of the fund family and the total size of the fund family as IVs, we conduct a two-stage least squares-IV regression to test our baseline results further. Table 4 reports the results. The main independent variables are *Herding1* and *Herding2*, two types of herding measures. Our model also includes characteristics of funds, fund managers, and investment strategies, such as size, age, Maturity, capability, products, Feeratio, institution, patience, concentration, and Lev. We cluster standard errors at the fund level to account for possible cross-correlation in residuals. In Columns (1) and (2), it can be found that the coefficients of *Herding1* and *Herding2* are negative and statistically significant, indicating that the two herding measures negatively affect the yield performance of the funds. In Columns (3) and (4), the coefficients of *Herding1* and *Herding2* are both positive and statistically significant, indicating that two measures of fund herds have a positive impact on the uncertainty. While in Columns (5) and (6), the results seem more direct that the two herding measures present a negative effect on the *RREM* of the funds. It indicates that the herding dilutes the yields and aggravates the uncertainties, ultimately leading to the downward adjustment of the funds' *RREM*. We conduct the under-identification test, weak IV, and over-identification test for the IV variable, and the result strongly supports the validity of our IV variable selection; see the Kleibergen–Paap rk LM statistic, Cragg–Donald Wald F statistic and Hansen J statistic (*P*-value) in Table 4. The detailed results are available upon request. The results alleviating the endogeneity strongly support our baseline results, which are consistent with Chen et al. (2021) and Spilker (2022).

4. Possible mechanisms

Our herding measures can reflect the propensity of funds to herd in the crowd, i.e., whether the funds are more likely to herd or to lead; therefore, it allows us to further explore the potential mechanism of the herding effect by examining the direct consequence of herding behavior.[7] A large body of empirical literature documents that herding funds following more conventional actions appears to impair the managers' active-management ability (Economou et al., 2015; Casavecchia, 2016; Lewellen and Lewellen, 2022). Sarpong (2014) argued that fund managers adapting dependent strategies underperform contrarian ones. Based on this evidence, we seek to explore the possible mechanism that active management primarily mediates the herding effect on fund performance. To quantify the active-management performance of mutual funds, we followed the methodology of Petajisto (2013). We employ the active share of a fund to assess the actual performance of the active management, defined as follows:

$$AMP = \frac{[\![Activeshare]\!] + [\![Trackingerror]\!]}{2} = \frac{\left[\!\left[\frac{1}{2}\sum_{j=1}^{M}\left|w_{fund,j} - w_{index,j}\right|\right]\!\right] + [\![stdev(R_{fund} - R_{index})]\!]}{2} \quad (8)$$

[7] If we use traditional herding measures such as LSV herding measures (Lakonishok et al., 1992; Sias, 2004), we cannot detect the real effect of herding for each fund. Because the traditional herding measures fail to identify whether the funds herd or lead in the crowd, we cannot guarantee whether the estimation of herding is truly the herding effect or the leading effect for each fund.

Table 4
Impact of institutional herding estimated by an instrumental variable approach.

Variables	(1) *Yield*	(2) *Yield*	(3) *Uncertainty*	(4) *Uncertainty*	(5) *RREM*	(6) *RREM*
Herding1	−0.057***		0.103***		−0.144***	
	(−5.31)		(9.02)		(−7.14)	
Herding2		−0.661***		1.372***		−1.759***
		(−4.92)		(7.01)		(−6.19)
Isize	−0.251**	−0.090	−0.099**	−0.382***	0.118	0.525***
	(−2.40)	(−1.10)	(−2.03)	(−3.73)	(1.52)	(4.50)
Iage	0.017***	0.068***	−0.013*	−0.117***	0.048***	0.183***
	(2.63)	(5.89)	(−1.81)	(−6.74)	(4.12)	(7.48)
Maturity	0.002	−0.010**	0.005	0.028***	0.230***	0.198***
	(0.36)	(−2.16)	(0.91)	(3.80)	(27.80)	(19.45)
Capability	1.335***	2.171***	1.369***	−0.378	−1.537***	0.694
	(4.43)	(5.88)	(3.90)	(−0.68)	(−2.63)	(0.87)
Products	0.005*	−0.005	−0.000	0.018***	0.012**	−0.013*
	(1.74)	(−1.60)	(−0.09)	(3.79)	(2.34)	(−1.90)
Feeratio	0.150***	0.177***	0.078***	0.002	0.009	0.089**
	(10.06)	(8.35)	(4.81)	(0.06)	(0.31)	(1.99)
Institution	0.024***	0.042***	−0.129***	−0.166***	0.124***	0.171***
	(4.87)	(6.66)	(−21.35)	(−16.64)	(12.63)	(12.21)
Patience	0.125***	0.028	0.188***	0.360***	0.032	−0.213***
	(4.32)	(1.34)	(5.87)	(11.08)	(0.61)	(−5.06)
Concentration	0.028	−0.214***	0.252***	0.735***	0.429***	−0.206**
	(1.11)	(−5.28)	(9.97)	(12.83)	(10.65)	(−2.54)
Lev	−0.000	−0.000	−0.000	−0.000	−0.000	0.000
	(−1.04)	(−0.70)	(−1.05)	(−1.24)	(−0.42)	(1.44)
Constant	0.347***	0.281***	−0.020	0.097***	0.803***	0.636***
	(19.42)	(23.65)	(−1.04)	(5.25)	(23.48)	(24.51)
Kleibergen–Paap rk LM statistic	38.183***	31.478***	42.105***	27.565***	45.703***	26.256***
Cragg–Donald Wald F statistic	61.109***	28.348***	60.299***	31.103***	51.299***	32.709***
Hansen J statistic (*P*-value)	0.202	0.386	0.167	0.328	0.249	0.151
R-squared	0.218	0.146	0.327	0.145	0.218	0.145
Observations	16765	16765	16765	16765	16765	16765
Cluster institution	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Note: This table presents the results of the institutional herding effect on institutional yield and its uncertainty by using two instrumental variables- fund numbers of the fund family and the total size of the fund family. Columns (1) and (2) present the impact of *Herding1* and *Herding2* on the yield; Columns (3) and (4) present the impact of *Herding1* and *Herding2* on the uncertainty; Columns (5) and (6) present the impact of *Herding1* and *Herding2* on the *RREM*. All the columns present the results of controlling for other fund-level variables that influence the dependent variables and the fixed effects of individual funds and years. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively. The robust standard errors clustered at the fund level are reported in parentheses.

where $w_{fund,j}$ is the weight of security j in the fund's portfolio. $w_{index,j}$ is the weight of the same security in the fund's benchmark index, and the sum is computed over the universe of all assets; hence, *Active share* denotes the proportion of the fund's portfolio which deviated from the fund's benchmark index. *Active share* is a value between 0 and 1 if a mutual fund has no leveraged or short positions, while *Tracking error* is computed as the time-series standard deviation of the difference between the individual fund return R_{fund} and its benchmark index return R_{index}. It quantifies the proportion of the return volatility of the fund not explained by movements in the fund's benchmark index. Following Petajisto (2013), active shares and tracking errors describe two essential aspects of the active management of funds. The former provides a reasonable proxy variable for stock selection, while the latter proxies the systematic factor risk. We standardize the two measures into [0,1], which are described as ⟦*Active share*⟧ and ⟦*Tracking error*⟧,[8] to combine them and compute their weighted average to obtain the final value, *AMP*. Generally, a higher *AMP* presents a better active-management performance for fund managers since it outperforms other funds in the two aspects. Our sample contains tracker funds, whether funds tracking the market portfolio may introduce biases in the sample here in the estimations; thus, what might appear as herding among low active share funds would be a reflection of these funds' investment strategy. Therefore, we exclude tracker funds to avoid this bias.[9] Based on the *AMP*, we conduct a mediation effect test by regressing the following models:

$$Yield/Uncertainty/RREM = \lambda 0 + \theta * Herding1(Herding2) + Controls + IFE + YearFE + \varepsilon \quad (9)$$

$$AMP = \lambda_1 + \theta_1 * Herding1(Herding2) + Controls + IFE + YearFE + \varepsilon \quad (10)$$

$$Yield/Uncertainty/RREM = \lambda_2 + \theta\prime * Herding1(Herding2) + \theta_2 * AMP + Controls + IFE + YearFE + \varepsilon, \quad (11)$$

where the coefficient θ represents the magnitude of the total effect, the coefficient θ' denotes the magnitude of the direct effect, and the coefficient θ_2 represents the magnitude of the mediating effect. Following Yuan et al. (2020), the coefficients θ and θ_1 should be significant first to detect a mediating effect; an indirect effect can be recognized by estimating the coefficient of θ_2 if the coefficient of θ_1 is statistically significant. The estimated results of model (9) were reported in our baseline tests; therefore,

[8] For the convenience of combination, we change the *Tracking error* into its opposite number before the standardization to ensure that the *Tracking error* is an expected value.

[9] We also rerun the regressions by using the whole sample, and the main findings remain unchanged. The results can be available from the authors.

Table 5
Impact of institutional herding on active-management performance.

Variables	(1) *AMP*	(2) *AMP*
Herding1	−0.030***	
	(−12.26)	
Herding2		−0.032**
		(−2.27)
Isize	0.462***	0.573***
	(3.23)	(5.06)
Iage	0.053***	0.052***
	(5.66)	(5.43)
Maturity	0.170***	0.167***
	(22.68)	(25.29)
Capability	2.536***	2.853***
	(4.79)	(5.94)
Products	0.006	0.004
	(1.40)	(1.01)
Feeratio	−0.120***	−0.159***
	(−12.64)	(−23.12)
Institution	0.043***	0.044***
	(4.33)	(5.59)
Patience	−0.011***	−0.009
	(−3.62)	(−1.42)
Concentration	0.018**	0.010
	(2.49)	(0.85)
Lev	0.000*	0.000***
	(1.90)	(2.71)
Constant	0.551***	0.497***
	(24.55)	(28.89)
Observations	16765	16765
R-squared	0.407	0.393
Cluster institution	YES	YES
Individual FE	YES	YES
Year FE	YES	YES

Note: This table presents the results of the impact of institutional herding on active-management performance (AMP). Column (1) presents the regression result of the effect of *Herding1* on AMP. Column (2) presents the result of the effect of *Herding2* on AMP. Both columns present the results of controlling for other fund-level variables that influence the dependent variables and the fixed effects of individual funds and years. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively. The robust standard errors clustered at the fund level are reported in parentheses.

we only report the estimated results of models (10) and (11) in Tables 5 and 6.

Table 5 shows that the coefficients of the two herding measures are negative and statistically significant at the level of 5% or above. It suggests that the herding behaviors of managers significantly weaken active-management performance. Furthermore, we derive two interesting findings in Table 6. First, the coefficients of active-management performance (AMP) in Columns (3), (5), (6), and (8) are positive and statistically significant, while the coefficients of AMP in Columns (4) are negative and statistically significant. These results indicate that active management significantly positively affects investment efficiency. Second, the coefficients of the two herding measures are negative and statistically significant at 1% in Columns (1) and (2), indicating a negative herding effect on active management, which is consistent with our estimated results in Table 5. While in Columns (3)–(8), we find that the signs of the coefficients of the two herding measures are entirely consistent with the coefficients of AMP. It reveals a plausible conduction mechanism that institutional herding impairs active management, and the degeneration of active management leads to an investment efficiency loss. Our findings support the hypothesis of inefficient institutional herding (Philippas et al., 2020; Caglayan et al., 2021) and provide a unique understanding of the conduction mechanism of inefficient herding.

5. Further analysis

5.1. Market stress and institutional herding

Some studies investigated the relationship between market pressure and institutional herding. For example, Lin and Lin (2014) found that institutional investors tend to sell past losers upon significant market price declines and buy past winners in a stressful market. Lu et al. (2022) provided significant evidence of asymmetric herding of energy funds in a stressful market after formulating a negative carbon policy. To examine the possible asymmetry, we follow Jin et al. (2021) to define *CIVI* as an indicator variable that equals the average China Implied Volatility Index (CIVI)[10] in a given year. Since our sample contains open-ended funds, the panic of retail and institutional holders of open-ended fund shares may be enough to motivate herding on behalf of fund managers (through fire sales); therefore, we also construct a *sellshareratio* variable proxied by the shares of redemption divided by total shares at the beginning of the year for funds.

Then we combine the *CIVI*, *sellshareratio,* and the two herding measures in our baseline regression, as follows:

$$\begin{aligned} Yield = {} & \rho_0 + \rho_1 * Herding1(Herding2) + \rho_2 CIVI + \rho_3 sellshareratio \\ & + \rho_4 CIVI\_sellshareratio + \rho_5 Herding1(Herding2)\_CIVI + \\ & \rho_6 Herding1(Herding2)\_sellshareratio \\ & + \rho_7 Herding1(Herding2)\_CIVI\_sellshareratio \\ & + \sum Controls + YearFE + IFE + \varepsilon \end{aligned} \quad (12)$$

$$\begin{aligned} Uncertainty = {} & \kappa_0 + \kappa_1 * Herding1(Herding2) + \kappa_2 CIVI + \kappa_3 sellshareratio \\ & + \kappa_4 CIVI\_sellshareratio + \kappa_5 Herding1(Herding2)\_CIVI + \\ & \kappa_6 Herding1(Herding2)\_sellshareratio \\ & + \kappa_7 Herding1(Herding2)\_CIVI\_sellshareratio \\ & + \sum Controls + YearFE + IFE + \varepsilon \end{aligned} \quad (13)$$

$$\begin{aligned} RREM = {} & \tau_0 + \tau_1 * Herding1(Herding2) + \tau_2 CIVI + \tau_3 sellshareratio \\ & + \tau_4 CIVI\_sellshareratio + \tau_5 Herding1(Herding2)\_CIVI \\ & + \tau_6 Herding1(Herding2)\_sellshareratio \\ & + \tau_7 Herding1(Herding2)\_CIVI\_sellshareratio \\ & + \sum Controls + YearFE + IFE + \varepsilon \end{aligned}, \quad (14)$$

where *Herding1_CIVI*, *Herding1_sellshareratio*, *Herding2_sellshareratio*, and *Herding2_CIVI*, *Herding1_CIVI_sellshareratio,* and *Herding2_CIVI_sellshareratio* are interaction variables of institutional herding, *CIVI,* and *sellshareratio*. Table 7 presents the estimated results, indicating that the coefficients of *CIVI* are negative and statistically significant in Columns (1), (2), (5), and (6), while the coefficients of *CIVI* are positive and statistically significant in column (4). The results indicate an overall negative effect of the stress market on institutional efficiency, consistent with Philippas et al. (2021) and Fong et al. (2022). Moreover, the coefficients of *Herding1* and *Herding2* are negative and statistically significant in Columns (1), (2), (5), and (6), while the coefficients of *Herding1* and *Herding2* are positive in Columns (3) and (4) and statistically significant in column (3). Regarding interaction terms, we find that *Herding1_CIVI* and *Herding2_CIVI* are negative and statistically significant in Columns (5) and (6). This finding indicates that

[10] The China Implied Volatility Index is published by Tsinghua University Financial Technology Research Institute, which is available at http://xyfintech.pbcsf.tsinghua.edu.cn/yjcg/zsyj.htm.

Table 6
The mediating role of active-management performance in institutional herding effect.

Variables	(1) *AMP*	(2) *AMP*	(3) *Yield*	(4) *Uncertainty*	(5) *RREM*	(6) *Yield*	(7) *Uncertainty*	(8) *RREM*
AMP			0.232***	−0.085***	0.392***	0.222***	−0.006	0.457***
			(36.38)	(17.20)	(45.35)	(36.05)	(−0.98)	(54.07)
Herding1	−0.030***		−0.014***	0.017***	−0.033***			
	(−12.26)		(−9.28)	(15.28)	(−16.72)			
Herding2		−0.032**				−0.001	0.201***	−0.221***
		(−2.27)				(−0.07)	(20.97)	(−15.49)
Isize	0.462***	0.573***	−0.123	−0.095	0.179	−0.211**	−0.511***	0.414***
	(3.23)	(5.06)	(−1.39)	(−1.39)	(1.49)	(−2.36)	(−6.23)	(3.39)
Iage	0.053***	0.052***	0.015**	0.030***	−0.011	0.024***	0.057***	−0.019*
	(5.66)	(5.43)	(2.07)	(5.18)	(−1.09)	(3.19)	(8.11)	(−1.84)
Maturity	0.170***	0.167***	−0.042***	−0.008*	0.124***	−0.039***	0.018***	0.106***
	(22.68)	(25.29)	(−7.99)	(−1.87)	(17.42)	(−7.35)	(3.67)	(14.59)
Capability	2.536***	2.853***	1.210***	0.233	−0.537	0.887**	−1.788***	0.849
	(4.79)	(5.94)	(3.23)	(0.80)	(−1.06)	(2.35)	(−5.15)	(1.64)
Products	0.006	0.004	−0.002	0.001	0.003	−0.003	0.001	0.000
	(1.40)	(1.01)	(−0.54)	(0.23)	(0.66)	(−1.06)	(0.19)	(0.06)
Feeratio	−0.120***	−0.159***	0.100***	0.283***	−0.114***			
	(−12.64)	(−23.12)	(17.56)	(64.01)	(−14.78)			
Institution	0.043***	0.044***	0.019***	−0.094***	0.044***	−0.027***	−0.246***	0.114***
	(4.33)	(5.59)	(3.06)	(−19.79)	(5.32)	(−4.93)	(−48.27)	(14.96)
Patience	−0.011***	−0.009	−0.144***	−0.072***	−0.146***	−0.152***	−0.095***	−0.136***
	(−3.62)	(−1.42)	(−30.50)	(−19.69)	(−22.80)	(−31.83)	(−21.64)	(−20.83)
Concentration	0.018**	0.010	−0.088***	−0.022***	−0.060***	−0.066***	0.095***	−0.136***
	(2.49)	(0.85)	(−9.62)	(−3.15)	(−4.79)	(−7.25)	(11.30)	(−10.85)
Lev	0.000*	0.000***	0.000	−0.000***	0.000	−0.000	−0.000***	0.000***
	(1.90)	(2.71)	(0.29)	(−4.25)	(1.61)	(−1.03)	(−10.78)	(4.35)
Constant	0.551***	0.497***	0.170***	−0.072***	0.531***	0.267***	0.358***	0.292***
	(24.55)	(28.89)	(13.10)	(−7.13)	(30.08)	(25.04)	(36.57)	(20.05)
Observations	16765	16765	16765	16765	16765	16765	16765	16765
R-squared	0.407	0.393	0.227	0.271	0.157	0.271	0.213	0.369
Cluster institution	YES	YES	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents the results of the mediating role of AMP in the effect of *Herding1* and *Herding2* on fund performance. Columns (1) and (2) duplicate the results in Table 5 to recognize the regression results of model (11). Columns (3)–(5) present the mediating effect of AMP in the effect of *Herding1* on yield, uncertainty, and *RREM*, respectively. Columns (6)–(8) present the mediating effect of AMP in the effect of *Herding2* on yield, uncertainty, and *RREM*, respectively. All the columns present the results of controlling for other fund-level variables that influence the dependent variables and the fixed effects of individual funds and years. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively. The robust standard errors clustered at the fund level are reported in parentheses.

even though institutional herding alleviates its negative effect on return, it exaggerates the effect of high market-implied volatility on return uncertainty and investment efficiency loss to a certain extent; however, the coefficients of *sellshareratio* and its interactive variables are all statistically insignificant, indicating that the changes in investment flow have less impact on the herding effect. Compared to previous studies suggesting a negative effect on macro-market stability (Hwang and Salmon, 2004; Kremer and Nautz, 2013), we provide micro-herding evidence that the herding behavior of funds relieves the market stress effect on their return; however, it exaggerates the effect of high market-implied volatility on return uncertainty and investment efficiency because of blindly following more skilled peers to withstand market stress (Jiang and Verardo, 2018).

5.2. Reliance on information from past institutional performance

Prior studies provided evidence that investors would systematically punish the funds and fund managers who take bold actions leading to poor performance, and they seem to tolerate the underperforming managers who follow conventional actions and herd (Casavecchia, 2016; Cui et al., 2019). Unsurprisingly, investors' withdrawals exert significant pressure on fund advisors to replace their underperforming managers following poor performance. These investor responses drive fund managers to herd more, especially when they experience poor performance compared to the mean market returns. This section aims to detect the impact of the funds' herding after a poor performance on the investment efficiency at t period. We exploit a proxy *Loser* as 1 if the funds' ranking performance at the t - 1 period is lower than 25 quantile; otherwise, the *Loser* is 0. We evaluate the impact of post-poor-performance herding on investment efficiency by estimating the following regression model:

$$RREM = \mu_1 Herding1(Herding2) + \mu_2 Loser + \mu_3 Loser\_Herding1(Herding2) + \sum Controls + IFE + YearFE \quad (15)$$

$$Yield = \psi_1 Herding1(Herding2) + \psi_2 Loser + \psi_3 Loser\_Herding1(Herding2) + \sum Controls + IFE + YearFE \quad (16)$$

$$Uncertainty = \xi_1 Herding1(Herding2) + \xi_2 Loser + \xi_3 Loser\_Herding1(Herding2) + \sum Controls + IFE + YearFE, \quad (17)$$

where $Loser\_Herding1(Herding2)$ denotes the interacting variable of the two institutional herding measures. Other variables can refer to the previous descriptions. Table 8 presents the results, showing that the coefficients for *Loser* are negative and statistically significant in Columns (1), (2), (5), and (6), while it is positive and statistically significant in Columns (3) and (4). It indicates that the poor performance of funds exhibits persistence. Interestingly, the coefficient of $Loser\_Herding1$ and $Loser\_Herding2$

Table 7
Institutional herding effect in a stressful market.

Variables	(1) *Yield*	(2) *Yield*	(3) *Uncertainty*	(4) *Uncertainty*	(5) *RREM*	(6) *RREM*
Herding1	−0.077***		−0.032***		−0.104***	
	(−21.10)		(−11.55)		(−14.17)	
Herding2		−0.191***		−0.008		−0.297***
		(−6.12)		(−0.33)		(−5.52)
CIVI	−0.014***	−0.007***	−0.000	0.005***	−0.008***	−0.003***
	(−32.15)	(−23.52)	(−0.44)	(18.27)	(−6.84)	(−4.06)
sellshareratio	−0.002	0.000	−0.002	0.002	0.004	−0.000
	(−1.61)	(0.27)	(−1.09)	(1.12)	(0.90)	(−0.09)
CIVI_sellshareratio	0.000	−0.000	0.000	−0.000	−0.000	−0.000
	(1.05)	(−0.24)	(0.54)	(−0.98)	(−0.66)	(−0.09)
Herding1_sellshareratio	0.000		0.001		−0.003**	
	(0.54)		(1.57)		(−2.06)	
Herding2_sellshareratio		−0.004		0.007		−0.025
		(−0.35)		(0.65)		(−1.02)
Herding1_CIVI	0.002***		0.002***		−0.002***	
	(18.89)		(15.05)		(−7.63)	
Herding2_CIVI		0.007***		0.002**		−0.007***
		(6.17)		(2.05)		(−3.39)
Herding1_CIVI_sellshareratio	0.000		−0.000		0.000	
	(0.12)		(−0.92)		(1.50)	
Herding2_CIVI_sellshareratio		0.001		0.000		0.001
		(1.18)		(0.13)		(1.14)
Constant	0.618***	0.419***	0.131***	0.018	0.807***	0.584***
	(41.62)	(33.09)	(6.43)	(0.91)	(23.30)	(20.47)
Observations	13,632	13,632	13,632	13,632	13,632	13,632
Controls	YES	YES	YES	YES	YES	YES
R-squared	0.200	0.181	0.341	0.329	0.276	0.238
Cluster Fund	YES	YES	YES	YES	YES	YES
Fund FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Note: This table presents the results of the effect of *Herding1* and *Herding2* on fund performance in a stressful market. *CIVI* denotes the China Implied Volatility Index, and *sellshareratio* denotes the shares of redemption divided by total shares at the beginning of the year for funds. *Herding1_CIVI*, *Herding1_sellshareratio*, *Herding2_sellshareratio*, *Herding2_CIVI*, *Herding1_CIVI_sellshareratio*, and *Herding2_CIVI_sellshareratio* are interaction variables of institutional herding, *CIVI*, and *sellshareratio*. Columns (1), (3), and (5) present the effect of *Herding1* and market stress on yield, uncertainty, and *RREM*, respectively. Columns (2), (4), and (6) present the effect of *Herding2* and market stress on yield, uncertainty, and *RREM*, respectively. All the columns present the results of controlling for other fund-level variables that influence the dependent variables and the fixed effects of individual funds and years. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively. The robust standard errors clustered at the fund level are reported in parentheses.

are negative in Columns (1)–(6) and statistically significant in Columns (2)–(6), suggesting a homogenous effect of the two herding measures on fund performance. Moreover, it indicates that the two herding measures negatively affect the fund's yield and uncertainty, ultimately exhibiting a negative effect on the funds' *RREM*. Our findings are consistent with Cui et al. (2019) and provide evidence that the herding of the funds whose past performance is poor can impair their yield performance and investment efficiency, even though the herding mitigates uncertainty to some extent. The result also indicates the reliance of institutional herding on information from past institutional performance. Furthermore, the coefficients of the other variables change slightly, and our main conclusions remain unchanged.

5.3. Long-term effect of institutional herding

Unlike a large body of empirical literature that documented the herding of buying and selling, we concentrate on the herding in the informational network constructed by a common-holding relationship. Herding may maintain for a couple of months until some funds change the related portfolio in a common-holding relationship, which inspires us to detect the subsequent effect of herding on investment efficiency. We utilize the lagged term of the herding measures to evaluate this long-term effect.[11] Table 9 reports the results. In Columns (1)–(2), the coefficients of *L. Herding1* and are *L. Herding1* are positive and statistically significant, indicating that the herding effect on yield will reverse in the next year. Conversely, in Columns (3)–(6), the coefficients of *L. Herding1* and *L. Herding1* are all negative and statistically significant, indicating that even though the negative herding effect on yield reverses, the positive effect of herding on uncertainty and RREM remain unchanged. Our results reveal that institutional herding increases return uncertainties at time t and time t + 1, leading to investment efficiency loss, despite its reverse effect on yield.

5.4. The herding effect on continuous rises and crashes

Herding behavior is a type of co-movement that magnifies the consequences of actions, such as aggravating the crash risk or facilitating continuous rise (Li and Jiang, 2022). From this horizon, we develop two variables to quantify persistent crashes and rises. *Rise* denotes the extent of the funds' continuous rise, proxied by the greatest rise in the month experiencing the most extended continuous rise in a year. *Crash* denotes the extent of the return crash of the funds, proxied by the most significant drop in the month experiencing the most prolonged continuous decline in a year. By replacing the original variables of fund performance as the two variables, we repeat our baseline regressions; Table 10 presents the results.

In Columns (1)–(4) of Table 10, the coefficients of *Herding1* and *Herding2* are all positive and statistically significant, indicating the positive effect of the herding on the continuous rise of the funds. This result suggests that the funds' herding can further

[11] We also extend the one-year lagged term to two- and three-year lagged terms for the variables to repeat our regressions; the main results remain unchanged.

Table 8
Reliance of institutional herding effect on information from past performance.

Variables	(1) *Yield*	(2) *Yield*	(3) *Uncertainty*	(4) *Uncertainty*	(5) *RREM*	(6) *RREM*
Herding1	−0.005***		0.014***		−0.004*	
	(−6.74)		(10.68)		(−1.92)	
Herding2		−0.024***		0.032***		−0.041**
		(−3.72)		(3.53)		(−2.25)
Loser_Herding1	−0.000		−0.010***		−0.014***	
	(−0.34)		(−8.15)		(−4.81)	
Loser_Herding2		−0.012*		−0.060***		−0.074***
		(−1.82)		(−4.93)		(−2.67)
Loser	−0.202***	−0.200***	0.054***	0.036***	−0.053***	−0.073***
	(−67.99)	(−86.85)	(16.52)	(13.66)	(4.82)	(−10.22)
Constant	0.295***	0.288***	0.075***	0.096***	0.676***	0.845***
	(27.22)	(26.27)	(3.26)	(4.06)	(33.31)	(33.84)
Observations	12,516	12,516	12,516	12,516	12,516	12,516
Controls	YES	YES	YES	YES	YES	YES
R-squared	0.599	0.600	0.264	0.268	0.189	0.222
Cluster institution	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Note: This table presents the results of the effect of *Herding1* and *Herding2* on the performance of past-underperformed funds. Loser funds' ranking performance at the t−1 period is lower than 25 quantiles; otherwise, the *Loser* is 0. *Loser_Herding1* and *Loser_Herding2* are two interaction variables of institutional herding *Loser*. Columns (1), (3), and (5) present the effect of *Herding1* and *Loser_Herding1* on yield, uncertainty, and *RREM*, respectively. Columns (2), (4), and (6) present the effect of *Herding2* and *Loser_Herding2* on yield, uncertainty, and *RREM*, respectively. All the columns present the results of controlling for other fund-level variables that influence the dependent variables and the fixed effects of individual funds and years. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively. The robust standard errors clustered at the fund level are reported in parentheses.

Table 9
The long-term effect of institutional herding.

Variables	(1) *Yield*	(2) *Yield*	(3) *Uncertainty*	(4) *Uncertainty*	(5) *RREM*	(6) *RREM*
L. Herding1	0.001**		0.015***		−0.021***	
	(2.02)		(12.33)		(−10.44)	
L. Herding2		0.023***		0.078***		−0.035***
		(3.53)		(7.75)		(−2.73)
Constant	0.286***	0.287***	0.096***	0.082***	0.755***	0.722***
	(42.12)	(42.11)	(5.67)	(4.58)	(39.63)	(37.51)
Observations	12,515	12,515	12,516	12,516	12,516	12,516
Controls (one-year lagged)	YES	YES	YES	YES	YES	YES
R-squared	0.421	0.421	0.529	0.427	0.515	0.504
Cluster institution	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Note: This table presents the results of the effect of *Herding1* and *Herding2* at the t−1 period on fund performance at the t period. *L.Herding1* and *L.Herding2* denote the two institutional herding measures at the t−1 period. Columns (1), (3), and (5) present the effect of *L.Herding1* on yield, uncertainty, and *RREM*, respectively. Columns (2), (4), and (6) present the effect of *L.Herding2* on yield, uncertainty, and *RREM*, respectively. All the columns present the results of controlling for other fund-level variables that influence the dependent variables and the fixed effects of individual funds and years. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively. The robust standard errors clustered at the fund level are reported in parentheses.

facilitate the extent of a continuous rise by co-movement. In contrast, in Columns (5)–(8), the coefficients of *Herding1* and *Herding* are all negative and statistically significant, indicating the negative effect of the herding on the persistent crash of the funds. This finding implies that the funds' herding mitigates the magnitude of the return crashes in a persistent decline. These results provide unique evidence of the positive effect of the funds' herding in responding to a persistent and extreme situation. Note that our herding measures are consistent with the relative importance of funds in herding. A high *Herding1* or *Herding2* indicates a high tendency for funds to herd; however, it does not indicate a market-wide measure of herding. This finding means a high *Herding1* or *Herding2* only denotes a high tendency to herd for a specific individual fund, and it does not suggest a future high crash risk of stocks. Instead, our results seem to suggest a "smart herding" in portfolio selection, suggesting that even if the herding cannot improve general investment efficiency, it still presents some positive aspects in portfolio selection. From an information exchange perspective, institutions may follow other peers to invest in stocks with high profitability (high rise) or stocks with more robust performance (low crash risk). In other words, herding impairs the investment independence of institutions leading to investment efficiency loss; however, it benefits the continuous rises and avoids extreme drops. Indeed, it does not equal a general improvement; instead, it only suggests a peculiar advantage in extreme situations and accounts for the incentives of the institutional managers' following actions when facing extreme drops or rises.

6. Robustness checks

We also conducted additional robustness tests. First, we used an alternative herding measure to test our results. Thus far, we have documented the negative institutional herding effect on investment efficiency based on the two herding measures. Note that the herding measures are constructed by the actual amount

Table 10
Institutional herding effects in persistent rises and crashes.

Variables	(1) Rise	(2) Rise	(3) Rise	(4) Rise	(5) Crash	(6) Crash	(7) Crash	(8) Crash
Herding1	3.180***	1.151***			−1.216***	−0.886***		
	(30.60)	(8.48)			(−14.72)	(−9.63)		
Herding2			8.618***	6.264***			−1.396*	−1.582**
			(3.17)	(4.93)			(−1.68)	(−2.39)
Isize		−6.356*		4.812		251.366***		280.043***
		(−1.68)		(0.50)		(3.58)		(3.80)
Iage		4.049***		3.985***		−0.615		−0.418
		(5.28)		(4.42)		(−1.31)		(−0.85)
Maturity		0.352		0.609		−0.649*		−0.794**
		(0.70)		(1.04)		(−1.94)		(−2.28)
Capability		160.593***		148.934***		−30.958		−30.861
		(4.31)		(3.64)		(−1.30)		(−1.23)
Products		0.244		0.264		−0.315*		−0.396**
		(0.82)		(0.77)		(−1.65)		(−2.00)
Feeratio		14.205***		14.994***		−4.482***		−5.371***
		(24.11)		(24.77)		(−12.56)		(−14.94)
Institution		−1.999***		−1.423**		4.334***		4.332***
		(−3.57)		(−2.13)		(12.29)		(12.00)
Patience		13.001***		16.591***		−8.795***		−9.478***
		(5.62)		(6.02)		(−7.86)		(−8.33)
Concentration		18.865***		23.715***		−16.775***		−18.412***
		(5.93)		(9.47)		(−10.98)		(−11.45)
Lev		−1.718		−13.222***		−0.546		−0.653
		(−0.80)		(−11.23)		(−0.61)		(−0.73)
Constant	29.228***	21.834***	38.360***	3.938***	−19.227***	−14.679***	−23.516***	−16.302***
	(37.65)	(11.56)	(39.20)	(2.59)	(−38.74)	(−13.85)	(−52.23)	(−15.14)
Observations	19388	19388	19388	19388	19388	19388	19388	19388
R-squared	0.504	0.437	0.474	0.381	0.140	0.501	0.592	0.528
Cluster institution	YES	YES	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table presents the results of the effect of *Herding1* and *Herding2* on funds' rises and crashes. *Rise* and *Crash*describe funds' rise and crash under extreme conditions, respectively. *Rise* denotes the extent of the continuous rise of the funds, which is proxied by the greatest rise in the month experiencing the longest continuous rise in a year. *Crash* denotes the extent of the return crash of the funds, which is proxied by the greatest drop in the month experiencing the longest continuous decline in a year. Columns (1)–(4) present the effect of *Herding1* and *Herding2* on rises, respectively. Columns (5)–(8) present the effect of *Herding1* and *Herding2* on crashes, respectively. All the columns present the results of controlling for other fund-level variables that influence the dependent variables and the fixed effects of individual funds and years. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively. The robust standard errors clustered at the fund level are reported in parentheses.

Table 11
Institutional herding effect by an alternative measure.

Variables	(1) *Yield*	(2) *Uncertainty*	(3) *RREM*
Network	−0.007**	0.140***	−0.107***
	(−2.45)	(18.54)	(−11.45)
Constant	0.187***	0.078***	0.630***
	(30.11)	(4.53)	(32.86)
Observations	16765	16765	16765
Controls	YES	YES	YES
R-squared	0.662	0.585	0.596
Cluster institution	YES	YES	YES
Individual FE	YES	YES	YES
Year FE	YES	YES	YES

Note: This table presents the results of the effect of the alternative herding measure *Network* on fund performance. *Network* is set as 1 if a fund herd in the network which means it has connections with other funds; otherwise, it is 0. Columns (1)–(3) present the effect of *Network* on yield, uncertainty, and *RREM*, respectively. All the columns present the results of controlling for other fund-level variables that influence the dependent variables and the fixed effects of individual funds and years. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively. The robust standard errors clustered at the fund level are reported in parentheses.

of the common-holding data in a directed network instead of an undirected network. This section extends a new herding measure generated by the network connections in an undirected network with unweighted edges. *Network* is set as 1 if a fund herds in the network; otherwise, it is 0. We regress the baseline models using the alternative variable; Table 11 presents the results, indicating that the coefficients for *Network* are negative and statistically significant in Columns 1 and 3. In contrast, the coefficient for *Network* is positive and statistically significant in column 2, which is consistent with the conclusion that the herding negatively affects institutions' investment efficiency. Therefore, the main results remain unchanged.

Second, COVID-19 has swept the world and shocked the financial markets significantly; thus, the post-event sample may be biased. Hence, we have omitted the sample during 2020–2022 and repeated our tests. Table 12 presents the results, indicating that the herding measures both negatively affect investment efficiency.

Third, we have winsorized the sample at 1% and 99% levels to exclude the effect of the extremes; the regression results can be seen in Table 13, showing that the results are consistent with our baseline.

Fourth, our herding measures are mutual-holding-based; thus, whether the funds of similar styles amplify herding and network effects is unclear. A concern is that funds following the same style may trade similarly without having any other connection with each other, i.e., spurious herding. To detect this possible effect, we construct three dummy variables of fund styles (*val, ret,* and *bal*) based on their portfolio[12] and interact them with

[12] According to the valuation of stocks held by funds, we classify funds into three categories, which are valuation-oriented funds (mainly focus on stocks with low PE and PB), return-oriented funds (mainly invest in bonds and special shares), and balanced funds (mixed type investing in stocks, bonds, and special shares). The detailed classification was obtained from the CSMAR database.

Table 12
Institutional herding effect estimated by eliminating the impact of COVID-19.

Variables	(1) *Yield*	(2) *Yield*	(3) *Uncertainty*	(4) *Uncertainty*	(5) *RREM*	(6) *RREM*
Herding1	−0.006***		0.012***		−0.016***	
	(−8.51)		(9.96)		(−8.39)	
Herding2		−0.022***		0.011***		−0.045***
		(−3.35)		(2.24)		(−3.17)
Constant	0.206***	0.185***	0.123***	0.139***	0.654***	0.613***
	(19.07)	(17.52)	(5.15)	(5.67)	(18.45)	(17.06)
Observations	10,917	10,917	10,917	10,917	10,917	10,917
Number of id	2,184	2,184	2,184	2,184	2,184	2,184
R-squared	0.240	0.239	0.163	0.169	0.220	0.222
Cluster institution	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Note: This table presents the results of the effect of institutional herding on fund performance when eliminating the impact of COVID-19. Since the post-event sample may be biased because of the impact of COVID-19, we omitted the sample in 2020 and repeated the baseline regressions. All the columns present the results of controlling for other fund-level variables that influence the dependent variables and the fixed effects of individual funds and years. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively. The robust standard errors clustered at the fund level are reported in parentheses.

Table 13
Institutional herding effect estimated by eliminating the errors of extreme values.

Variables	(1) *Yield*	(2) *Yield*	(3) *Uncertainty*	(4) *Uncertainty*	(5) *RREM*	(6) *RREM*
Herding1	−0.003***		0.011***		−0.014***	
	(−3.78)		(9.16)		(−7.29)	
Herding2		−0.026***		0.022**		−0.076***
		(−3.65)		(2.30)		(−5.82)
Constant	0.186***	0.182***	0.096***	0.113***	0.634***	0.614***
	(15.94)	(15.66)	(4.18)	(4.81)	(32.40)	(31.68)
Observations	16596	16596	16596	16596	16596	16596
R-squared	0.118	0.442	0.453	0.258	0.392	0.593
Controls	YES	YES	YES	YES	YES	YES
Cluster institution	YES	YES	YES	YES	YES	YES
Individual FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Note: This table presents the results of the effect of the institutional herding on fund performance when deleting the extreme values. All the columns consistent with the baseline regressions present the results of controlling for other fund-level variables that influence the dependent variables and the fixed effects of individual funds and years. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively. The robust standard errors clustered at the fund level are reported in parentheses.

our herding measures to repeat our baseline regressions. Table 14 presents the results, showing that either the style variables or the interaction terms are all statistically insignificant in Columns 1–6, indicating no significant style-amplify effect in herding effect on investment efficiency.[13] The main reason may be that this paper uses more in-depth network measures to detect institutions' latent influence in the network by gauging the relative importance of connecting funds. Compared to directly calculating the network degree of nodes (the number of funds connected with fund *i*), we use the two herding measures to evaluate the propensity of funds to herd or lead. To some extent, our measures may alleviate the bias from style investment because they allow us to recognize whether the funds herd with (connected with) others and measure how likely the funds are to herd or lead. To summarize, our conclusions remain unchanged after conducting the robustness checks.

7. Conclusions

The growth of institutional investors raises essential questions regarding the subsequences of their herding, particularly in investment efficiency. Unlike most herding studies only focusing on the joint actions of institutions, we have detected the propensity of herding based on its relative importance in connections from an informational network perspective. We provided a direct answer to the question of whether institutional herding is efficient. Our results indicate a negative relation between institutional herding and institutional efficiency. Furthermore, we examined the mechanism of the herding effect by considering active management and found a significant mediating role of active management in the herding effect on investment efficiency.

Moreover, we have conducted several tests to deepen our study of the link between institutional herding and its efficiency. First, we examined whether a stressful market leads to efficiency differentials that are large and significant. The results indicate an exacerbation of the negative herding effect on investment efficiency in a stressful market. Second, we found evidence of the negative "loser effect" in the herding effect on investment efficiency, indicating that the underperforming institutions become more inefficient because of their herding behavior. Third, we recognized a long-term herding effect, indicating that institutional herding increases return uncertainties at time t and time t + 1, leading to investment efficiency loss, despite its reverse effect on yield. Fourth, we confirmed the positive effect of institutional herding on the facilitation of an increasing rise and the mitigating effect on the intensification of continuous crashes, which indicates that herding can affect both sides in these extreme contexts. Last, we conducted several other robustness tests, and our main conclusions remain unchanged.

[13] We do not report the other regressions using yield and uncertainty as dependents; the results are available upon request.

Table 14
Institutional herding effect estimated by considering the effect of investment style.

Variables	(1) *RREM*	(2) *RREM*	(3) *RREM*	(4) *RREM*	(5) *RREM*	(6) *RREM*
Herding1	−0.015***		−0.013***		−0.015***	
	(−5.69)		(−4.60)		(−6.95)	
Herding2		−0.071***		−0.105***		−0.089***
		(−3.09)		(−5.58)		(−5.57)
val			0.013	−0.006		
			(1.01)	(−0.77)		
val_ Herding1			−0.003			
			(−0.84)			
val_Herding2				0.041		
				(1.32)		
bal					−0.030	0.012
					(−0.55)	(0.62)
bal_Herding1					0.010	
					(0.68)	
bal_Herding2						−0.027
						(−0.49)
ret	−0.011	0.004				
	(−0.80)	(0.44)				
ret_Herding1	0.001					
	(0.40)					
ret_Herding2		−0.034				
		(−1.15)				
Constant	0.657***	0.633***	0.645***	0.637***	0.651***	0.635***
	(27.54)	(26.89)	(27.22)	(27.98)	(28.39)	(27.92)
R-squared	0.471	0.474	0.471	0.474	0.471	0.474
Observations	10,402	10,402	10,402	10,402	10,402	10,402
Controls	YES	YES	YES	YES	YES	YES
Cluster Fund	YES	YES	YES	YES	YES	YES
Fund FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Note: This table presents the results of the effect of institutional herding on fund performance considering style investment. Three dummy variables (*val, ret, bal*) are fund styles based on their portfolio. All the columns consistent with the baseline regressions present the results of controlling for other fund-level variables that influence the dependent variables and the fixed effects of individual funds and years. The superscripts ***, **, and * indicate two-tailed statistical significance at the 1%, 5%, and 10% levels, respectively. The robust standard errors clustered at the fund level are reported in parentheses.

Our results directly support the inefficiency of institutional herding from an informational network view. They carry several critical implications and provide actionable instructions for stakeholders, including the investment community and regulators. From a general perspective, our findings uncover the inefficient herding that influences institutional performance from multiple perspectives, including but not limited to yield and uncertainty resistance. For investors, ranking institutions with our herding measures can help them distinguish between more herding institutions and more leading institutions and get closer to more efficient institutions. For institutions, it is crucial to take measures to eliminate drawbacks in their compensation scheme and terms of employment that could be exploited by employers (managers) to alleviate principal–agent problems, e.g., prolonging the period of manager performance evaluation. Establishing a real-time monitoring mechanism capable of reflecting complex portfolio decisions of own managers and comparing these decisions to those of managers of other institutions holds considerable merit in identifying and characterizing potential herding tendencies among managers. It also helps institutions to distinguish between dependent managers and independent managers. For managers, broadening information channels and dampening the information asymmetry is the key to curtailing the investment efficiency loss from herding. For institutions, herding in a stressful market requires close attention since managers are likely to take more joint actions to confront price pressure, given that they may believe in benefiting from herding to eliminate uncertainties. Our findings emphasize the importance of concerning the latent linkages and actions among institutions for the market regulators who need to take charge of the co-movements in markets and detect the potential changes in the informational network and their subsequent impacts.

Table A.1
Nature of sample funds.

Number	Fund type	Fund number	Observations	Percent
1	Equity fund	452	3603	21.49%
2	Mixed fund	999	7979	47.59%
3	Bond fund	372	2954	17.62%
4	Money market fund	186	1480	8.83%
5	Alternative investment fund	15	119	0.71%
6	QDII fund	79	630	3.76%
1	Index tracker	319	2536	15.13%
2	Non-index tracker	1784	14,229	84.87%
Total		2103	16,765	

CRediT authorship contribution statement

Shuai Lu: Conceptualization, Methodology, Writing – original draft, Software. **Shouwei Li:** Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

See Table A.1.

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