

Article

Institutional Investor Diversity, Herding Behavior, and Systemic Financial Risk: Evidence from China

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Abstract

Institutional investors exert significant influence on the operations and development of financial institutions, with different categories of investors playing distinct roles. We contend that institutional investor diversity may affect systemic financial risk. This study proposes novel measures of institutional investor diversity across 84 China's financial institutions and employs Extreme Value Theory (EVT) to estimate systemic financial risk. Based on this, we empirically examine the relationship and underlying mechanisms. Baseline regression indicates that greater institutional investor diversity plays an effective role in controlling systemic financial risk. We further find that institutional investor diversity significantly suppresses herding behavior, thereby indirectly reducing systemic risk. Moreover, this effect is more pronounced in financial institutions operating in more developed market environments, under stronger external supervision, and with higher levels of technological advancement, as well as in securities firms. These findings not only contribute to the literature on the economic impact of institutional investors but also provide valuable insights for strengthening systemic financial risk control.

Keywords: institutional investor diversity; herding behavior; systemic financial risk



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1. Introduction

The effective prevention and control of systemic financial risk is crucial for maintaining financial stability and achieving high-quality economic development. Currently, as financial markets continue to evolve, the external constraints on the sound operation of financial institutions and the mitigation of their risks stem not only from regulatory tools but are also significantly shaped by the behavior of market investors. In October 2023, Silicon Valley Bank collapsed within just 48 h due to a severe asset-liability mismatch and a depositor run, marking the largest bank failure in the United States since 2008. Despite swift government intervention and a series of market stabilization measures, panic spread uncontrollably, causing spillover effects through the U.S. financial system and even affecting European markets. This highlights the crucial importance of risk prevention from the perspective of market investors in strengthening the foundation of financial markets and preventing the materialization of systemic risks. Therefore, leveraging market discipline serves as an essential complement to governmental efforts to enhance modern financial regulation.

Since the global financial crisis, the prevention and control of systemic financial risk have remained a prominent topic in academic research. Existing literature primarily focuses on the dimension of financial regulation, which can be categorized into four aspects.

First, extracting reserve capital and countercyclical capital, and maintaining additional capital buffers. This approach aims to control the expansion of banks' risk-bearing assets by optimizing capital structure and allocation, thereby mitigating risk correlation and loss contagion (Miao et al. 2025). Second, strengthening the lender-of-last-resort function to resolve liquidity difficulties for financial institutions, thereby reducing their failure risk and contagion risk (Hasman and Samartín 2025). Third, refining risk-based deposit insurance systems and risk resolution mechanisms to enhance the effectiveness of deposit insurance, controlling run risks and liquidity crises (Ni et al. 2024). Fourth, intensifying financial regulatory penalties to leverage their deterrence effect (Koster and Pelster 2017) and peer warning effect (D'Acunto et al. 2019), thereby curbing the accumulation and contagion of financial risks.

Although these research outcomes provide crucial foundations for constructing frameworks to guard against systemic financial risks, the frequent occurrence of financial risk events has revealed their inherent limitations. Garriga (2017) identified certain deficiencies in the implementation of regulatory tools, including time lags in execution and the potential to incentivize risk-taking behaviors and trigger abrupt shifts in market sentiment (Andries et al. 2020). Consequently, relying solely on financial regulatory measures proves inadequate for comprehensively addressing risk fluctuations within complex financial networks.

Against this backdrop, some scholars have shifted their research focus towards the potential role of market investment entities, particularly institutional investors, in risk prevention. Institutional investors typically possess advantages such as more specialized expertise, more abundant capital, and more sophisticated models (Zhang et al. 2025). They exert critical influence on corporate governance and operational performance through direct "voice" (voting with their hands) and indirect "exit" (voting with their feet) mechanisms (Cui et al. 2025; Li and Xiao 2025). It is noteworthy that existing literature predominantly treats institutional investors as a homogeneous group, concentrating on their aggregate impact on corporate information disclosure, financial performance, or stock price efficiency while overlooking the potential differentiated effects of their intrinsic heterogeneity on the risk behaviors of financial institutions (Ren et al. 2025; Zhang et al. 2025).

When a limited number of scholars analyze the heterogeneity of institutional investors, they merely categorize them into distinct types. Bushee (1998) classified institutional investors into quasi- and nonexponential traders. Chen et al. (2007) classified investors as long- or short-term based on their investment horizon. Liu et al. (2024) divided institutional investors into pressure-resistant and pressure-sensitive types. However, Knyazeva et al. (2018) argued that a simplistic binary classification of institutional investors may obscure the differences in their motivations and capabilities for gathering and analyzing information. This simplified treatment could limit our understanding of how heterogeneous groups composed of different types of institutional investors influence the development of financial institutions. Therefore, this study seeks to identify the degree of institutional investor diversity within financial institutions, examine its impact on financial institutions' risk management and the underlying mechanisms, thereby offering new perspectives for strengthening financial market functions and preventing and controlling systemic financial risks.

This study examines the relationship between institutional investor diversity and systemic financial risk using a sample of China's listed financial institutions from 2016 to 2024. The rationale for selecting China's financial institutions as our research sample is threefold: (1) Global significance of economic scale. As the world's second-largest economy and the largest emerging market, China has garnered extensive attention from academia and policymakers (Shi et al. 2024). According to official data from the International Monetary Fund (IMF), China's GDP reached \$18.94 trillion in 2024, and its contribution to global economic

growth has long ranked among the highest worldwide. Consequently, the intrinsic financial structure and market dynamics of China hold global research significance.

(2) Global spillover effects of financial stability. The risk profile of China's financial system has non-negligible implications for global stability. [Yang et al. \(2019\)](#), through quantitative risk spillover network analysis, confirmed that China's financial sector serves as a critical node in the global risk contagion network, exhibiting significant risk spillover effects on major economies. Therefore, studying the internal stability mechanisms of China's financial system contributes, to some extent, to safeguarding global financial stability.

(3) Uniqueness and representativeness of market transition. China's financial market remains in a process of deepening reform, transitioning from a state-controlled dominance toward a more diversified and market-oriented shareholder structure ([Lin and Fu 2017](#)). This unique institutional context provides an opportunity to investigate how the introduction of diversified institutional investors influences systemic risk during the active cultivation of market forces. Thus, the China's sample offers irreplaceable representativeness for understanding the patterns of risk prevention and control in emerging markets during financial transitions. The findings can provide crucial theoretical references and practical insights for other economies undergoing similar developmental stages.

Based on the above three considerations and with reference to relevant literature on institutional investors ([Cui et al. 2025](#); [Fu et al. 2025](#); [Li and Xiao 2025](#); [Qiu et al. 2025](#); [Zhang et al. 2025](#)), we ultimately select China's financial institutions as the sample for this study.

The findings demonstrate that greater institutional investor diversity may reduce systemic financial risk, and that this effect is achieved by mitigating herding behavior. Moreover, this risk-mitigating effect is particularly pronounced in financial institutions with more developed market environments, stronger external supervision, and greater technological advancement, as well as in securities firms specifically.

This study makes contributions in three aspects: (1) We enrich the literature on systemic financial risk prevention and control by extending the perspective from traditional financial regulation to the level of market participants. While existing literature predominantly focuses on the role of regulatory measures in financial risk prevention ([Miao et al. 2025](#)), it has relatively neglected the potential functions that institutional investors, as market forces, may fulfill. This paper systematically analyzes the impact of institutional investor diversity on systemic risk, providing new empirical evidence for understanding the role of market participants in financial stability.

(2) We exploratorily construct a measure for institutional investor diversity in financial institutions. Existing studies predominantly focus on specific behaviors of institutional investors, such as cross-ownership ([Cui et al. 2025](#)), network attention ([Fu et al. 2025](#)), and site visits ([Li and Xiao 2025](#)), or discuss institutional investors by grouping them based on a single dimension ([Qiu et al. 2025](#); [Shi et al. 2024](#)). However, few studies explore the degree of heterogeneity within institutional investor groups. By integrating the coefficient of variation and the entropy weighting method, this paper develops a comprehensive index reflecting institutional investor diversity across multiple dimensions, including investment scale, experience, and concentration, thereby deepening the understanding of the economic consequences of institutional investor structure.

(3) We identify the suppressive effect of institutional investor diversity on systemic financial risk and reveal its underlying mechanisms and heterogeneous characteristics. Existing literature indicates that institutional investors with richer investment experience, more concentrated portfolios, and long-term equity holdings are more adept at gathering and analyzing information and are more motivated to perform monitoring functions ([Fich et al. 2015](#); [Knyazeva et al. 2018](#)). Building upon this research, we reveal that when a financial institution's shareholder structure accommodates multiple heterogeneous insti-

tutional types simultaneously, the internal checks-and-balances and collaborative mechanisms that form may attenuate herding effects, thereby controlling the financial institution's risk volatility. Our findings not only enrich the discourse on the governance effects of institutional investors but also provide empirical evidence for financial institutions to optimize their ownership structures and attract diversified investors.

The remainder of this paper is organized as follows: In Section 2, we develop the research hypotheses through theoretical analysis. In Section 3, we detail the methodology, variable definitions, and sample selection. In Section 4, We present the empirical results and discusses the relationships among institutional investor diversity, herding behavior, and systemic financial risk. In Section 5, we examine how the risk-mitigating effect varies under different conditions. Finally, we conclude the study by summarizing the main findings, discussing policy implications, and acknowledging limitations.

2. Theoretical Analysis and Hypothesis Development

2.1. Institutional Investor Diversity and Systemic Financial Risk

According to investment decision theory, professional investors follow a three-stage process of information collection, analysis, and decision-making (Sirbiladze et al. 2014). As major market players, institutional investors exhibit superior information acquisition and analytical skills (Shleifer and Vishny 1986). These capabilities endow them with sharp investment acumen and a forward-looking perspective (Zhang et al. 2024), enabling them to significantly impact financial institutions' performance and compliance, as well as to mitigate systemic risk. In particular, institutional investors with government background are more motivated to enhance corporate governance, curb managerial opportunism, and reduce default risk (Brunnermeier et al. 2022).

However, existing evidence indicates that although institutional investors play a crucial role in monitoring and guiding corporate operations and governance (Jiang and Yuan 2018), in markets characterized by information asymmetry, they may disregard their own information and follow the decisions of other investors, thereby triggering herding effects (Avery and Zemsky 1998). Under the influence of herding behavior, some investment information fails to be incorporated into stock prices, leading to reduced market transparency and pricing efficiency (Fu et al. 2024). This can subsequently cause market overreactions and amplify systemic risk (Loang 2025). Against this backdrop, we focus on institutional investor diversity and examine it through a three-stage framework: (1) the systematic gathering of relevant information on target institutions by institutional investors; (2) the quantitative analysis and in-depth evaluation of the collected information; and (3) the formulation of final investment decisions based on the information and analysis from the previous two stages. We posit that institutional investor diversity mitigates systemic financial risk by amplifying heterogeneity in the investment decision-making process, thereby reducing herding behavior among investors.

2.1.1. Diverse Information Sources

Information asymmetry theory posits that severe information asymmetry in financial transactions can trigger irrational behavior (Hu et al. 2024)—a key mechanism contributing to systemic risk. This problem is particularly pervasive between institutional investors and corporate management (Linder and Sperber 2020). Xie et al. (2003) found that weak corporate governance structures incentivize managers to pursue self-interest and even disseminate misleading information to influence investors. Such conduct not only exacerbates risk accumulation within individual institutions but also facilitates cross-institutional risk contagion, thereby amplifying the vulnerability of the system (Battaglia and Gallo 2017).

As key actors in financial markets, institutional investors possess extensive management experience and superior information acquisition capabilities (Knyazeva et al. 2018). A high degree of investor diversity ensures that financial institutions face multifaceted oversight. This fosters higher-quality information disclosure, which in turn mitigates systemic financial risk.

Substantial shareholders often have direct access to management and possess both the incentive and capacity to monitor financial institutions. In particular, stable long-term investors are more willing to engage in corporate governance (Auvray and Brossard 2012), which reduces the likelihood of bad news being concealed (Chen et al. 2007) and lowers stock price crash risk (Callen and Fang 2013). In contrast, investors with smaller stakes have limited influence and often struggle to obtain high-quality private information. As a result, they rely more heavily on public disclosures and regulatory signals, and through the mechanism of “voting with their feet” (Dressler and Mugerman 2023), they pressure financial institutions to proactively reduce risk levels.

Thus, a diverse body of institutional investors draws on varied information sources, which helps prevent “information silos.” This diversity facilitates effective information complementarity and cross-verification, enhancing the overall information quality and credibility assessment capabilities of the investor group. This helps to reduce herding behavior and allows potential risks to be identified and contained earlier.

2.1.2. Different Analytical Methods

From the perspective of behavioral finance, whether institutional investors can fully utilize and accurately analyze acquired information constitutes a critical factor influencing their investment behavior (Baker and Wurgler 2013). That is, even when investment entities obtain valuable information, a lack of professional analytical capacity makes it difficult for them to accurately assess investment targets. This forces them to rely on group behavior for sightless decision-making, thereby generating herding effects and amplifying systemic financial risk.

When the investor structure is relatively homogeneous, market sentiment can become concentrated and amplified, exposing financial institutions to risks such as sudden capital outflows and sharp stock price fluctuations. In contrast, when institutional investors possess diverse investment experience and information analysis methods (Amiram et al. 2016), their risk assessments of the same project or firm yield different estimates. This creates complementarity and dispersion in market investment behaviors, thereby reducing risk resonance.

First, institutional investors with richer investment experience are typically supported by mature information analysis models and specialized teams, enabling them to more effectively filter out market noise and identify genuine risk fluctuations (Chiang et al. 2011). Second, less experienced institutional investors, constrained by limited information analysis methods, tend to rely more heavily on market signals or external rating agencies. They are susceptible to mainstream opinions or market sentiment, engaging in simple imitation behaviors (Neupane et al. 2023).

Institutional investor diversity fosters greater heterogeneity in information interpretation and market judgment. This helps mitigate herding effects, manifesting as more dispersed and asynchronous investment behaviors that contribute to a reduction in systemic financial risk.

2.1.3. Independent Investment Decisions

When market participants face information gaps or lack the capacity to effectively analyze available information, they become more susceptible to group influence, resulting

in herding behavior (Ottaviani and Sørensen 2000). It can disrupt the balance between market supply and demand, causing prices to deviate from fundamental values (Rahayu et al. 2021). Under the influence of collective decision-making, when a majority of investors heavily invest in a particular portfolio, demand surges abruptly, triggering sharp price increases. Conversely, when a majority engages in large-scale selling of a portfolio, it leads to steep price declines. Thus, uniform directional decisions by the crowd induce severe fluctuations in financial markets, potentially culminating in the materialization of systemic financial risk.

Although institutional investors typically maintain professional teams capable of precise information analysis and risk assessment, the investors themselves remain subject to cognitive biases (Hribar and McNnis 2012; Koutmos 2024). Diverse institutional investors differ significantly in their information sources and analytical approaches, enabling relatively independent decision-making. This diversity helps counterbalance cognitive biases within collective decision-making processes, curbs irrational uniform behavior, and mitigates systemic financial risk triggered by herding.

Therefore, institutional investor diversity—manifested in varied information sources, differentiated processing methods, and relatively independent decision-making capacities—helps reduce herding behavior. It lowers financial loss and risk contagion, thereby contributing to the control of systemic financial risk. Based on this reasoning, we propose the following hypotheses:

H1. *Institutional investor diversity may mitigate systemic financial risk.*

H2. *Institutional investor diversity may mitigate systemic financial risk by suppressing herding behavior.*

2.2. Heterogeneity Analysis

Given that the environment shapes the information capacity of institutional investors (McCahery et al. 2016) and the operational characteristics of financial institutions influence the effectiveness of market forces, this paper examines the heterogeneous effects of institutional investor diversity on systemic risk from four dimensions: market environment, external supervision, technological development, and institution type.

The degree of market development is a critical factor that determines whether institutional investor diversity can effectively fulfill its risk-controlling function. First, well-developed market environments enhance the timeliness and adequacy of information disclosure (Beyer et al. 2010), enabling institutional investors with varying risk preferences and investment experience to make informed judgments based on the information obtained. This strengthens the heterogeneity of investment behavior among market participants, thereby reducing the likelihood of systemic risk accumulation and contagion. Second, clear regulatory frameworks and oversight mechanisms provide robust market conditions for diverse institutional investors to engage in corporate governance through multiple channels, thereby intensifying external disciplinary pressure on financial institutions for sound operation (Zhang et al. 2021). Moreover, developed market environments foster investor trust in market rules, encouraging more active interpretation and transmission of various market signals (Kanagaretnam et al. 2022), which in turn enhances the relevance and effectiveness of regulatory oversight. Based on the above analysis, this paper proposes the following research hypothesis:

H3. *The mitigating effect of institutional investor diversity on systemic risk may be more pronounced in financial institutions operating in developed market environments than in those with less developed market conditions.*

Effective external supervision helps uncover and disseminate financial institutions' private information, thereby reducing informational disadvantages among market participants and enabling a more accurate assessment of their true operational conditions and latent risks (Chang et al. 2025). First, mechanisms of such supervision—such as analyst coverage and investment research reports—improve overall market transparency by disclosing information on profitability, risk management practices, and capital adequacy (Fosu et al. 2018). This not only broadens the information channels for diverse institutional investors but also, when combined with their heterogeneous interpretation approaches, leads to non-synchronous investment behaviors that help diversify systemic risk at the decision-making level. Second, scrutiny from analysts and research institutions subjects financial institutions to effective oversight (Boubakri et al. 2015), with continuous information updates prompting revised forecasts (Fosu et al. 2018). Furthermore, to avoid stock price volatility and capital outflows, financial institutions are motivated to respond positively to institutional investors, thereby accelerating their transition toward more robust and prudent business models and further reducing exposure to systemic financial risk (Lee et al. 2023). Based on the above analysis, this paper proposes the following research hypothesis:

H4. *The mitigating effect of institutional investor diversity on systemic risk may be more pronounced in financial institutions subject to strong external supervision than in those with weaker external oversight.*

The impact of institutional investor diversity on systemic financial risk is closely linked to the level of digital and financial technology (FinTech) development. First, the widespread application of digital technologies has enhanced the information acquisition and risk assessment capabilities of market participants, thereby reducing information asymmetry in financial markets (Shi et al. 2024). These technologies not only provide institutional investors with dynamic data on financial institutions but also improve the efficiency of their participation in corporate governance, thereby strengthening the monitoring role of a diverse investor base over financial institutions' operations. Second, institutional investors differ in their ability to collect and process information (Amiram et al. 2016). With the advancement of digital technology, different institutional investors develop divergent expectations regarding financial institutions, which amplifies disagreement among investors (Hong and Stein 2015). This heterogeneity helps institutional investor diversity exert its risk-controlling effect. Based on the above analysis, this paper proposes the following research hypothesis:

H5. *The mitigating effect of institutional investor diversity on systemic risk may be more pronounced in financial institutions with higher levels of technological development than in those with lower levels of technological advancement.*

The substantial variations in business models across financial institutions are likely to lead to heterogeneous impacts of institutional investor diversity on their systemic risk. On one hand, for financial institutions typified by banks, their profitability relies heavily on net interest margins and medium-to-long-term credit operations. This structure renders them relatively resilient to isolated funding fluctuations, consequently limiting the capacity of institutional investor diversity to significantly alter their risk exposure. Furthermore, implicit regulatory guarantees may further diminish the effectiveness of market monitoring. On the other hand, for institutions representative of securities firms, their operations are highly dependent on capital markets and exhibit strong sensitivity to market volatility. When facing liquidity shocks, homogeneous funding sources can easily trigger collective sell-offs. Diversified institutional investors can provide heterogeneous funding sources and improve

client structures, thereby effectively dispersing risks and curbing herding behavior, which may consequently exert a significant negative impact on systemic risk. Additionally, for insurance institutions, their long-term, stable liability structure and asset allocation strategies lead to risk decisions being more reliant on internal actuarial models than on short-term market pressures. Therefore, we predict that the marginal impact of institutional investor diversity on the systemic risk of insurance institutions may be relatively limited. Based on the above analysis, this paper proposes the following research hypothesis.

H6. *The impact of institutional investor diversity on systemic risk may exhibit heterogeneity across different types of financial institutions.*

3. Study Design

3.1. Empirical Methodology

This study employs an unbalanced panel dataset of China's financial institutions and constructs a two-way fixed effects regression model to examine the impact of institutional investor diversity on systemic financial risk.

$$Sfr_{i,t+1} = \alpha_0 + \alpha_1 iid_{i,t} + \sum \theta_k Controls_{i,t} + u_i + v_t + \varepsilon_{i,t} \quad (1)$$

where $iid_{i,t}$ is a comprehensive indicator reflecting institutional investor diversity. To address potential estimation bias arising from reverse causality, we define the dependent variable $sfr_{i,t+1}$ as the systemic risk of financial institution i in period $t + 1$. $Control_{i,t}$ is a series of control variables. u_i is an individual-fixed effect; v_t is the time-fixed effect; $\varepsilon_{i,t}$ is a random disturbance term.

This study constructs a mediating effect test model to explore whether the herding behavior plays an intermediary role in the impact of institutional investor diversity on systemic financial risk (Wu et al. 2023). Specifically, the process involves three steps:

The first step is to determine whether the influence of $iid_{i,t}$ on $sfr_{i,t+1}$ is significant based on the regression results of Model (1). If the coefficient is significant, proceed with the subsequent steps.

The second step is to construct the regression model of $iid_{i,t}$ against the herding behavior variable $herd_{i,t}$.

$$herd_{i,t} = \beta_0 + \beta_1 iid_{i,t} + \sum \rho_k Control_{i,t} + u_i + v_t + \varepsilon_{i,t} \quad (2)$$

The third step is to construct the mediating effect models of $iid_{i,t}$, $herd_{i,t}$ and $sfr_{i,t+1}$.

$$sfr_{i,t+1} = \gamma_0 + \gamma_1 iid_{i,t} + \gamma_2 herd_{i,t} + \sum \eta_k Control_{i,t} + u_i + v_t + \varepsilon_{i,t} \quad (3)$$

Based on the above three steps, determine whether institutional investor diversity influence systemic financial risk by influencing herding behavior. When α_1 in Model (1), β_1 in Model (2) and γ_2 in Model (3) are all significant, it can be proved that the mediating effect of herding behavior exists. On this basis, if γ_1 in Model (3) is not significant, it indicates that herding behavior plays a complete mediating role; conversely, it indicates that herding behavior only plays a partial mediating role.

3.2. Systemic Financial Risk

This study focuses on financial institutions as the main subjects, including banks, insurance companies, and securities firms. Although prior literature commonly employs indicators such as Marginal Expected Shortfall (MES) and Systemic Risk Index (SRISK) to capture the systemic risk of financial institutions (Acharya et al. 2016; Brownlees and

Engle 2017), these measures still exhibit notable limitations (Huang and Jiang 2025). As these indicators incorporate the prudential capital ratio, they are better suited to a single type of financial institution—particularly banks—rather than being applicable across different types of institutions (Löffler and Raupach 2018). Applying these approaches in our context could overlook cross-sector regulatory differences, thereby compromising the comparability of risk measures across the sample. Therefore, following Van Oordt and Zhou (2019) and Huang and Jiang (2025), we adopt Extreme Value Theory (EVT) and measure systemic financial risk by estimating the coefficient (β_i) in a linear tail model, as shown in the following formula:

$$R_{it} = \beta_i R_{mt} + \varepsilon_{i,t}, R_{mt} < -VaR_m(\alpha) \quad (4)$$

$$\beta_i = \lim_{\alpha \rightarrow 0} \tau_i(\alpha)^{1/\xi_m} \frac{VaR_i(\alpha)}{VaR_m(\alpha)} \quad (5)$$

where R_{it} represents the daily stock return rate of the financial institution and R_{mt} represents the market return rate. β_i serves as the measurement metric for systemic risk (*sfr*), capturing the degree of risk linkage between an individual financial institution and the financial market under extreme market shocks.

$VaR_m(\alpha)$ refers to the Value at Risk. $\tau_i(\alpha) = \Pr(R_i < -VaR_i(\alpha) | R_m < -VaR_m(\alpha))$, represents the tail dependence between R_{it} and R_{mt} . ξ_m is the tail index of the heavy-tailed distribution for R_{mt} .

In the baseline regression analysis, we use the Shanghai Stock Exchange Composite Index (SSEC) as the market portfolio. When a tail risk event occurs, the market portfolio's return rate is less than the value at risk under the α -quantile. $\alpha = n/T$. n represents the number of observations that have suffered extreme losses, and T represents the total number of observations. Therefore, α represents the probability of extreme losses occurring. Referring to the methodology of Huang and Jiang (2025), we set the tail threshold n/T at 10% and calculate the systemic risk of financial institutions using two years of daily stock return data and a quarterly rolling window. The specific formula is as follows:

$$\hat{\beta}_i = \hat{\tau}_i(n/T)^{1/\hat{\xi}_m} \frac{\widehat{VaR}_i(n/T)}{\widehat{VaR}_m(n/T)} \quad (6)$$

Ultimately, we obtain the systemic risk variable ($sfr_{i,t+1}$) of financial institutions. This metric captures an institution's susceptibility to severe financial system shocks. This property also makes it well-suited for gauging financial institutions' contributions to systemic risk (Fang et al. 2023).

3.3. Institutional Investor Diversity

A core tenet of behavioral finance is that investor decision-making is not fully rational but constitutes a multi-stage process constrained by cognitive capacity and psychological biases (Kahneman 2003). Grounded in the theoretical framework of investor decision analysis, this study divides institutional investors' decision-making into three stages: information acquisition, processing and analysis, and final decision-making (Hirshleifer 2001). The systematic differences exhibited by heterogeneous institutional investors across these three stages form the basis for their behavioral divergence and subsequent market interactions.

Drawing on the methodology of Knyazeva et al. (2018), we construct a comprehensive metric to capture institutional investor diversity across these three dimensions. This process can be divided into two parts: (1) calculating the coefficients of variation for financial institution i across the three dimensions, and (2) using the entropy method to synthesize the three sets of coefficients of variation into our core explanatory variable $iid_{i,t}$.

3.3.1. Diverse Information Sources: The Coefficient of Variation in Investment Scale

The disparity in shareholding scale among institutional investors is a critical factor determining the heterogeneity of their information structures (Shin 2020). The theory of economies of scale posits that expanding business operations helps reduce unit costs and improve efficiency. From the perspective of institutional investors, information acquisition involves significant fixed costs¹ (Ramalingegowda et al. 2021), including expenses related to due diligence, hiring specialized analytical teams, and establishing connections with company management. Institutional investors with larger shareholding scales can allocate these costs across a broader asset portfolio, thereby significantly lowering the unit cost of information acquisition. This scale effect further motivates and enables them to develop more extensive and in-depth information channels. Consequently, institutional investors with varying shareholding scales exhibit heterogeneity in the breadth and depth of their information sources.

We use an institutional investor's shareholding ratio in a financial institution as a proxy for its investment scale. For financial institution i in period t , the shareholding scale data of its m institutional investors are denoted as $scale_{i|j,t}$ ($j = 1, 2, \dots, m$). We further compute the coefficient of variation $diff_{i,t}^1$ for this metric to measure the diversity in information acquisition capacity among institutional investors.

3.3.2. Different Analytical Methods: The Coefficient of Variation in Investment Experience

Differences in investment experience among institutional investors are a key factor determining the heterogeneity in their information analysis capabilities. The learning-by-doing theory posits that the enhancement of knowledge and abilities stems from the accumulation of and reflection on experience through continuous practice. Experienced investors can continuously learn from historical cases (Kempf et al. 2017), more effectively filter out market noise, extract core information, and thus develop more mature information processing capabilities. Consequently, differences in investment experience reflect heterogeneity in information processing frameworks and analytical abilities.

We calculate the duration from an institutional investor's establishment date to the observation year (with the number of days logarithmically transformed) as a proxy for its investment experience. For financial institution i in period t , the investment experience data of its m institutional investors are denoted as $experience_{i|j,t}$ ($j = 1, 2, \dots, m$). We further compute the coefficient of variation $diff_{i,t}^2$ for this metric to measure the diversity in information processing capabilities among institutional investors.

3.3.3. Independent Investment Decisions: The Coefficient of Variation in Investment Concentration

Differences in investment concentration among institutional investors reflect varying risk preferences and investment strategies. Principal-agent theory suggests that principals, to safeguard their own interests, will enhance effective oversight to mitigate moral hazard issues arising from information asymmetry. Investors with more concentrated portfolios, acting as active principals, possess stronger incentives to understand and scrutinize financial institutions, thereby promoting stable operations through the "voice mechanism" (Fich et al. 2015). In contrast, diversified investors rely more on portfolio management models, mitigating losses through diversification and thus exerting discipline on financial institutions via the "exit mechanism." Therefore, differences in investment concentration directly reflect heterogeneity in investors' decision-making approaches. Drawing on the methodology of Yin and Zhu (2022), we employ the Herfindahl Index ($HHI_{i|j,t}$) to calcu-

late the concentration of an institutional investor's shareholdings within its portfolio, as detailed below:

$$HHI_{i|j,t} = \sum_{i=1}^N \left(\frac{\text{institutional}_{i|j,t}}{\text{institutional}_{j,t}} \right)^2 \quad (7)$$

where $\text{institutional}_{i|j,t}$ represents the market value of stock i held by the j -th institutional investor at the end of period t , and $\text{institutional}_{j,t}$ denotes the total market value of the investment portfolio held by the j -th institutional investor at the end of period t . For financial institution i in period t , the shareholding concentration data of its m institutional investors are denoted as $HHI_{i|j,t}$ ($j = 1, 2, \dots, m$). We further compute the coefficient of variation $\text{diff}_{i,t}^3$ for this metric to measure the diversity in investment decision-making styles among institutional investors.

Finally, following the methodology of [Knyazeva et al. \(2018\)](#) and [Yin and Zhu \(2022\)](#), we employ the entropy method to determine the weights of $\text{diff}_{i,t}^1$, $\text{diff}_{i,t}^2$, and $\text{diff}_{i,t}^3$ in the composite index. The entropy method is an objective weighting technique that relies on the degree of dispersion in the indicator data itself. When the dispersion of the data is greater, the indicator's contribution to distinguishing institutional investor diversity is more significant, and thus its weight is higher. This method enables a more precise calculation of the institutional investor diversity examined in this study. Furthermore, it avoids subjective arbitrariness and ensures the objectivity of the index construction. The specific computational procedure is as follows:

(1) For financial institution i , we employ three dimensions ($\text{diff}_{i,t}^1$, $\text{diff}_{i,t}^2$ and $\text{diff}_{i,t}^3$) to measure the diversity of its institutional investors. Each indicator contains n observations over the sample period. We construct a $n \times 3$ judgment matrix based on these indicators and normalize it to obtain the normalized judgment matrix $\mathbf{D} = (\text{diff}_{pq})_{n \times 3}$.

(2) Calculate the proportion of the p -th observation under the q -th indicator:

$$\text{prop}_{pq} = \text{diff}_{pq} / \sum_{p=1}^n \text{diff}_{pq}, q = 1, 2, 3 \quad (8)$$

(3) Following the definition of entropy, we calculate the entropy for the q -th indicator as

$$E_q = -(\ln n)^{-1} \sum_{p=1}^n \text{prop}_{pq} \ln \text{prop}_{pq}, p = 1, \dots, n; q = 1, 2, 3 \quad (9)$$

To make $\ln \text{prop}_{pq}$ meaningful, we assume that when $\text{prop}_{pq} = 0$, $\lim_{\text{prop}_{pq} \rightarrow 0} (\ln \text{prop}_{pq}) = 0$.

The weight for the q -th indicator is

$$W_q = (1 - E_q) / \left(3 - \sum_{q=1}^3 E_q \right), q = 1, 2, 3 \quad (10)$$

(4) We integrate the institutional investor diversity indicator by combining the judgment matrix with the weight vector:

$$\text{idd}_p = \sum_{q=1}^3 W_q \times \text{diff}_{pq}, p = 1, \dots, n \quad (11)$$

Through this computational process, we ultimately obtain the core explanatory variable $\text{idd}_{i,t}$ for financial institution i in period t .

3.4. Herding Behaviour

We refer to the classic LSV model and its derivative models proposed by [Lakonishok et al. \(1992\)](#) to measure herding behavior of institutional investors. The formula is as follows:

$$herd_{i,t} = |p_{i,t} - E(p_{i,t})| - E|p_{i,t} - E(p_{i,t})| \quad (12)$$

where $p_{i,t}$ is the proportion of institutional investors who increase their holdings of stocks i among all institutional investors holding the same stock. $E(p_{i,t})$ represents the expected value, which is generally replaced by the average proportion of institutional investors of all financial institutions in the industry where stock i is located during the same period. $|p_{i,t} - E(p_{i,t})|$ reflects the imbalance of institutional investors' buying and selling of stock i in period t . $E|p_{i,t} - E(p_{i,t})|$ is the adjustment part. When the trading behaviors of institutional investors are independent of each other, $herd_{i,t}$ should be 0. When $herd_{i,t}$ is not 0, we consider that there is herd behavior against financial institution i . The $herd_{i,t}$ measure is positively associated with the degree of herding behavior.

3.5. Control Variables

We control for two categories of factors that may confound systemic risk, including both the individual characteristics of financial institutions and the broader macroeconomic conditions. At the level of individual financial institutions, following [Cao \(2023\)](#) and [Fang et al. \(2023\)](#), we select the following as control variables: asset size (*size*), leverage ratio (*lev*), return on assets (*roa*), profit growth rate (*pro*), and book-to-market ratio (*bm*). Regarding macroeconomic conditions, following [Gu and Yu \(2020\)](#) and [Huang and Jiang \(2025\)](#), we choose the GDP growth rate (*gdp*), the growth rate of the money supply M2 (*m2*), and the level of financial market development (*stock*) as control variables.

3.6. Sample and Data

The research sample of this paper consists of 84 A-share listed financial institutions from the first quarter of 2016 to the fourth quarter of 2024. The sample includes 38 banks, 41 securities firms, and 5 insurance companies, covering all systemically important financial institutions in China and thus demonstrating strong representativeness. Drawing on the sample scope established in the literature on heterogeneous institutional investors ([Knyazeva et al. 2018](#); [Lin and Fu 2017](#); [Shi et al. 2024](#)), we select six types of financial institutions—funds, social security funds, insurance companies, securities brokers, trust companies, and Qualified Foreign Institutional Investors (QFII)—as our institutional investor sample. This selection is based on the following considerations:

(1) Strong connections to systemic risk networks: The core of systemic financial risk lies in the contagion chains formed through the interconnected balance sheets of financial institutions ([Yang et al. 2024](#)). As crucial components of the financial system, these six types of institutions engage in interbank activities with other financial entities, which makes them central nodes in risk transmission networks. In contrast, although non-financial enterprises may hold shares in financial institutions, they do not participate in financial intermediation and therefore remain outside the financial risk contagion networks.

(2) Professional and comparable investment motivations: Investment decisions by non-financial institutions are typically driven by non-financial factors such as business cycle fluctuations and industrial layout considerations. This may obscure the genuine relationship between their shareholding behavior and the risk profile of invested financial institutions. Conversely, although the financial institutional investors selected for this study differ in their business models, their investment behaviors are all guided by professional asset allocation strategies and well-defined risk preferences. Their shareholding

decisions better reflect professional assessments of risk, return, and liquidity, unaffected by confounding non-financial factors.

(3) Inherent fulfillment of “Diversity” requirements: This study focuses on examining the impact of institutional investor diversity, which necessitates that the sample itself demonstrates significant heterogeneity. The six selected institution types exhibit substantial differentiation in investment horizons (long-term orientation of social security funds vs. short-term focus of funds), risk preferences (conservative approach of insurance companies vs. aggressive stance of securities brokers), and pressure sensitivity (high liquidity of QFII vs. stability of domestic institutions). These characteristics provide ideal conditions for investigating complementarity and counterbalance effects among institutional investors.

We manually collected and compiled data on institutional investors from the Wind database. The data of financial institutions and macroeconomic data are from the China Stock Market & Accounting Research (CSMAR) database and the China Center for Economic Research (CCER) economic and financial database. To mitigate the influence of outliers, all continuous variables were winsorized at the 1st and 99th percentiles. The final dataset comprises 2419 observations.

4. Empirical Results and Analysis

4.1. Descriptive Statistics

Based on the descriptive statistics provided in Table 1, we achieve a detailed understanding of the main variables. The systemic financial risk (*sfr*) ranges from 0.309 to 2.139 with a standard deviation of 0.390, indicating significant differences in systemic risk levels across financial institutions. Consistent with the findings of [Van Oordt and Zhou \(2019\)](#) and [Huang and Jiang \(2025\)](#), the mean value of *sfr* is close to 1, suggesting that, on average, the risk exposure of individual financial institutions aligns with overall market fluctuations. Meanwhile, the diversity of institutional investors (*iid*) varies between 0.012 and 0.891, reflecting a relatively dispersed pattern of institutional investor diversity across financial institutions.

Table 1. Descriptive statistics.

Variables	Obs	Mean	Sds	Min	Median	Max
<i>sfr</i>	2419	1.049	0.390	0.309	1.024	2.139
<i>iid</i>	2419	0.296	0.233	0.012	0.295	0.891
<i>herd</i>	2419	0.222	0.055	0.072	0.210	0.466
<i>size</i>	2419	27.059	1.902	23.934	26.820	31.237
<i>lev</i>	2419	0.834	0.096	0.543	0.868	0.941
<i>roa</i>	2419	0.007	0.005	0.001	0.006	0.026
<i>pro</i>	2419	0.205	1.372	−2.416	−0.001	9.589
<i>bm</i>	2419	0.962	0.089	0.612	0.998	1.063
<i>gdp</i>	2419	5.515	4.070	−6.900	5.500	18.300
<i>m2</i>	2419	9.643	1.663	6.200	9.400	13.400
<i>stock</i>	2419	2.513	0.3102	1.689	2.524	3.118

4.2. Baseline Regression Results

Based on panel data from China’s listed financial institutions between 2016 and 2024, this study examines the impact of institutional investor diversity on systemic financial risk. To preliminarily assess the relationships among variables, we conducted Pearson correlation analysis. Table 2 reports the detailed correlation coefficients. A significantly negative correlation is observed between *iid* and *sfr*, indicating that diversity contributes to controlling systemic risk. This provides initial support for Hypothesis 1. Meanwhile, we performed variance inflation factor (VIF) tests on the main variables to evaluate potential mul-

ticollinearity. The results show that the mean VIF is 1.65, well below the critical threshold. This suggests that the variable selection is appropriate and that no severe multicollinearity is present.

Table 2. Pearson correlation analysis of basic variables.

Variables	<i>sfr</i>	<i>iid</i>	<i>size</i>	<i>lev</i>	<i>roa</i>	<i>pro</i>	<i>bm</i>	<i>gdp</i>	<i>m2</i>	<i>stock</i>
<i>sfr</i>	1.000									
<i>iid</i>	−0.054 ***	1.000								
<i>size</i>	−0.519 ***	0.169 ***	1.000							
<i>lev</i>	−0.454 ***	0.124 ***	0.743 ***	1.0000						
<i>roa</i>	0.282 ***	0.135 ***	−0.178 ***	−0.335 ***	1.000					
<i>pro</i>	0.0312	−0.157 ***	−0.022	−0.026	−0.089 ***	1.000				
<i>bm</i>	−0.561 ***	0.055 ***	0.590 ***	0.667 ***	−0.316 ***	−0.022	1.000			
<i>gdp</i>	−0.102 *	0.049 ***	0.007	−0.002	0.013	0.017	−0.040 ***	1.000		
<i>m2</i>	−0.041 ***	0.095 ***	0.014	0.016	−0.033	0.030	−0.033	−0.299 ***	1.000	
<i>stock</i>	−0.111 ***	−0.241 ***	0.011	0.022	−0.249 ***	0.151 ***	−0.028	0.188 ***	0.300 ***	1.000

*** and * indicate significant levels at 1% and 10%, respectively.

This study employs a regression analysis approach involving the stepwise addition of control variables and the adjustment of standard errors. Table 3 presents the regression results of various explanatory variables on systemic financial risk. Specifically, column (1) reports the results controlling only for time and individual fixed effects. Building upon this, column (2) introduces a set of control variables to mitigate endogeneity bias arising from omitted variables. To address potential heteroskedasticity and serial correlation in the model, column (3) further clusters the standard errors at the level of individual financial institutions. Finally, to simultaneously account for common issues in panel data such as heteroskedasticity, serial correlation, and cross-sectional dependence, column (4) employs a fixed-effects model estimated with Driscoll-Kraay standard errors. Given that the sample consists of quarterly data, the maximum lag order for the standard errors is set to 4.

The results show that the estimated coefficients of diversified institutional investors (*iid*) on systemic financial risk (*sfr*) are −0.152, −0.133, −0.038, and −0.133, respectively, all of which are statistically significant. This suggests that an increase in the diversity of institutional investors significantly reduces the level of systemic financial risk, thereby confirming Hypothesis 1. Furthermore, the leverage ratio and the book-to-market ratio exhibit significant exacerbating and mitigating effects on systemic financial risk, respectively. These findings are consistent with those reported by Cincinelli et al. (2022) and Huang and Jiang (2025).

The inhibitory effect of institutional investor diversity on systemic financial risk reflects the inherent logic of market-based governance within China's financial market reforms. After 2002, China progressively introduced diversified institutional investors such as QFII, social security funds, and insurance companies, thereby breaking the pattern of sole dominance by state-owned capital. Subsequently, the shareholding proportion of institutional investors rose significantly, shareholder types exhibited diversified characteristics, and a multi-type, multi-layered ownership structure gradually formed. As Lin and Fu (2017) noted, this fundamental transformation ended the scenario of single-shareholder control over financial institutions. Diversified institutional investors likely contribute to curbing systemic financial risk through two channels—reducing risk accumulation and controlling risk contagion—by enhancing supervision to optimize governance, improving information transparency to mitigate irrational panic, and balancing risk preferences to avoid homogeneous behavior.

Table 3. Baseline regression results.

	(1)	(2)	(3)	(4)
Variables	<i>sfr</i>	<i>sfr</i>	<i>sfr</i>	<i>sfr</i>
<i>iid</i>	−0.152 *** (0.038)	−0.133 *** (0.036)	−0.038 ** (0.019)	−0.133 * (0.069)
<i>size</i>		−0.036 (0.050)	−0.273 *** (0.060)	−0.036 (0.188)
<i>lev</i>		1.102 *** (0.244)	1.890 *** (0.502)	1.102 * (0.587)
<i>roa</i>		3.259 ** (1.603)	0.019 (1.439)	3.259 (3.765)
<i>pro</i>		0.003 (0.003)	0.007 * (0.004)	0.003 (0.003)
<i>bm</i>		−1.743 *** (0.115)	−2.217 *** (0.247)	−1.743 *** (0.350)
<i>gdp</i>		0.216 * (0.122)	−0.014 *** (0.001)	−0.016 (0.011)
<i>m2</i>		−0.042 (0.027)	−0.021 *** (0.004)	0.102 (0.121)
<i>stock</i>		−0.376 (0.242)	−0.066 ** (0.025)	0.639 (1.142)
Constant	1.320 *** (0.039)	2.938 ** (1.325)	9.461 *** (1.421)	
R-squared	0.385	0.450	0.631	0.478
Observations	2419	2419	2419	2419

***, **, * indicate significant levels at 1%, 5%, and 10%, respectively. It is important to note that due to the non-parametric nature of Driscoll-Kraay standard errors, the results do not provide the conventional adjusted R-squared. Therefore, this study reports the Within R-squared as a reference for the model's goodness-of-fit.

4.3. Robustness Test

4.3.1. Replacement of the Explained Variable

In our baseline regression, we employ the SSEC as the market portfolio for measuring systemic financial risk. To test the robustness of our findings, we recalculate the risk measure and re-run the regression using the China securities index (CSI) 300 as an alternative market portfolio (Huang and Jiang 2025). Column (1) of Table 4 reports the results. The impact of institutional investor diversity on systemic financial risk remains significantly negative at the 1% level. This result is fully consistent with our baseline findings.

Table 4. Results of replacing the explained variable and the core explanatory variable.

	(1)	(2)	(3)	(4)
Variables	<i>sfr</i>	<i>CoVaR</i>	$\Delta CoVaR$	<i>sfr</i>
<i>iid</i>	−0.001 ** (0.001)	−0.135 * (0.069)	−0.347 ** (0.171)	
<i>iid_m</i>				−0.019 * (0.011)
Controls	YES	YES	YES	YES
R-squared	0.505	0.319	0.580	0.447
Observations	2419	2419	2419	2419

** and * indicate significant levels at 5% and 10%, respectively; values in parentheses are Driscoll-Kraay standard errors. The regression models include individual-fixed effects and time-fixed effects.

To mitigate potential measurement errors and enhance the robustness of our findings, we re-estimate systemic financial risk using quantile regression, deriving alternative measures of Conditional Value at Risk (*CoVaR*) and Delta *CoVaR* ($\Delta CoVaR$) for financial institutions (Adrian and Brunnermeier 2016). Higher values of these metrics indicate that

an institution poses a greater systemic risk during stress periods. As shown in columns (2) and (3) of Table 4, the estimated coefficients for *iid* are -0.135 and -0.347 , respectively, both statistically significant. Institutional investor diversity maintains a significant negative relationship with systemic risk, confirming the robustness of our baseline conclusion.

4.3.2. Replacement of the Core Explanatory Variable

To ensure the robustness of the methodology for constructing the institutional investor diversity metric, this study draws on the network analysis framework proposed by Acemoglu et al. (2012) to reconstruct and calculate this index. Specifically, we define institutional investors' investment scale, investment experience, and investment concentration as core nodes within a complex network, using the correlation coefficient matrix between dimensions to characterize the strength of connections between nodes, thereby constructing a complete network topology. On this basis, we determine the optimal weight for each dimension based on the principle of eigenvector centrality. This method not only effectively incorporates the dispersion of each dimension itself but also captures the interactive relationships and information redundancy among sub-indicators, assigning higher weights to indicators that provide independent information and exhibit lower correlation with other dimensions, ultimately synthesizing a comprehensive institutional investor diversity index (*iid_m*). Higher values of *iid_m* indicate a greater degree of diversity among institutional investors. We substitute *iid_m* into the baseline model and reperform the regression analysis. The results are presented in column (4) of Table 4. The estimated coefficient for *iid_m* is significantly negative at -0.019 . This indicates that even after altering the variable construction methodology, institutional investor diversity continues to exert a significant risk-mitigating effect on systemic financial risk, thereby confirming the reliability of the baseline regression results.

4.3.3. Exclusion of the COVID-19 Pandemic Period

During the COVID-19 pandemic, market sentiment was extremely pessimistic, and financial market functioning was severely disrupted, which could have led to biased regression estimates. Therefore, we exclude this period and redefine the sample to focus on the pre-pandemic era. As shown in Column (1) of Table 5, the estimated coefficient for institutional investor diversity remains significantly negative at the 5% level. This confirms that the results in the previous text are stable.

Table 5. Results of excluding special periods, winsorizing the variables and eliminating extreme samples.

	(1)	(2)	(3)
Variables	<i>sfr</i>	<i>sfr</i>	<i>sfr</i>
<i>iid</i>	-0.250^{**} (0.111)	-0.119^{**} (0.057)	-0.133^{**} (0.063)
Controls	YES	YES	YES
R-squared	0.463	0.458	0.469
Observations	877	2419	2182

****** indicates significant level at 5%; values in parentheses are Driscoll-Kraay standard errors. The regression models include individual-fixed effects and time-fixed effects.

4.3.4. Winsorization of Variables at the 5% Level

In order to alleviate the influence of outliers on the regression results, we perform a two-sided 5% winsorization on the main variables. Column (2) of Table 5 shows the results, confirming that after excluding the influence of outliers, the estimated coefficient of diverse institutional investors remains significantly negative at the 5% level. This is consistent with the conclusion in the previous text.

4.3.5. Exclusion of Samples with Extreme Risk

We excluded financial institutions with either extremely high or extremely low levels of systemic risk during the observation period to mitigate the potential bias caused by outliers in the regression results. Column (3) of Table 5 presents the regression results. The results show that after removing the top and bottom 5% of samples based on risk extremes, the impact of institutional investor diversity on systemic financial risk remains significantly negative at the 5% level. This finding further confirms the robustness of our earlier conclusions.

4.3.6. Two-Stage Least Squares Regression

To address potential reverse causality, we employ an instrumental variable (IV) approach and implement a Two-Stage Least Squares (2SLS) regression. Following common practice for IV construction (John et al. 2008), we calculate the average institutional investor diversity ($iid_{i,t}$) of other financial institutions within the same period, categorized by sector (banking, securities, insurance).

The rationale for selecting this variable is twofold: (1) $iid_{i,t}$ is likely correlated with the explanatory variable $iid_{i,t}$. Within the same industry, financial institutions operate under highly similar models, and market participants exhibit information spillovers and imitation behaviors. Consequently, the structure of institutional investors across different financial institutions is highly interconnected. (2) There is no direct connection between $iid_{i,t}$ and $sfr_{i,t+1}$. A financial institution's systemic risk is primarily determined by its own accumulated risks and the contagion risk stemming from its business interconnections. After controlling for a series of individual characteristics and macroeconomic factors, there exists no direct channel through which the shareholder composition of peer institutions would affect the systemic risk exposure of a given financial institution. Therefore, this IV satisfies the conditions of relevance and exogeneity.

Column (1) of Table 6 shows the results. The Kleibergen-Paap rk LM statistic is statistically significant at the 1% significance level, indicating that the instrumental variables have a strong explanatory power for iid . The Kleibergen-Paap rk Wald F statistic far exceeds the 10% critical value of Stock-Yogo (16.38). The regression results indicate that the estimated coefficient for institutional investor diversity remains significantly negative at the 1% level, which further confirms the robustness of our baseline findings.

Table 6. Results of Two-Stage Least Squares regression, System Generalized Method of Moments estimation and Propensity Score Matching method.

	(1)	(2)	(3)
Variables	<i>sfr</i>	<i>sfr</i>	<i>sfr</i>
<i>iid</i>	−0.208 *** (0.051)	−0.041 *** (0.014)	−0.129 ** (0.059)
<i>L.sfr</i>		0.807 *** (0.021)	
Kleibergen-Paap rk LM statistic	48.498 ***		
Kleibergen-Paap rk Wald F statistic	2050.337 ***		
AR (1)-P		0.000	
AR (2)-P		0.322	
Hansen-P		0.756	
Controls	YES	YES	YES
R-squared	0.449		0.478
Observations	2419	2335	2401

*** and ** indicate significant levels at 1% and 5%, respectively; values in parentheses are Driscoll-Kraay standard errors. The regression models include individual-fixed effects and time-fixed effects.

4.3.7. System Generalized Method of Moments Estimation

To mitigate potential endogeneity concerns in the baseline model, this study employs the System Generalized Method of Moments (GMM) for robustness testing, following the approach of Ben Belgacem et al. (2024). The estimation results are presented in column (2) of Table 6. The coefficient of *iid* remains negative and statistically significant at the 1% level. Furthermore, the Arellano-Bond test indicates no second-order serial correlation in the disturbance terms. The *p*-value of the Hansen overidentification test exceeds 0.1, failing to reject the null hypothesis that all instruments are exogenous. These results indicate that the baseline findings remain robust after accounting for dynamic effects and potential endogeneity.

4.3.8. Propensity Score Matching Method

To mitigate selection bias arising from observable characteristics, this study employs the Propensity Score Matching (PSM) method to validate the baseline findings. We divide the sample into a treatment group (higher diversity) and a control group (lower diversity) based on the sample median of institutional investor diversity. Subsequently, using all control variables as covariates, we estimate propensity scores through a Logit model and implement nearest-neighbor one-to-one matching with a caliper of 0.05 for sample matching.

Post-matching balance tests indicate that the standardized differences for all covariates between the treatment and control groups were substantially reduced, showing no systematic disparities. The Average Treatment Effect on the Treated (ATT) calculated from the matched sample reveals that the treatment group exhibits significantly lower systemic risk than the control group, with an ATT of -0.106 , statistically significant at the 10% level ($t = -1.86$).

Furthermore, we reconduct the baseline regression using the matched sample. The results are presented in column (3) of Table 6. The estimated coefficient for *iid* is -0.129 , significant at the 5% level. This demonstrates that after controlling for systematic differences in observable characteristics, a robust negative association persists between institutional investor diversity and systemic financial risk, further confirming the reliability of the baseline conclusion.

4.4. Mediating Effect of Herding Behavior

Although institutional investors possess certain advantages in information acquisition and analysis compared to individual investors, they are not perfectly rational. Widespread herding behavior can still occur among them, potentially elevating systemic financial risk. We employ a mediating effect model to test if institutional investor diversity reduces systemic risk by mitigating herding behavior—thereby verifying Hypothesis 2. The regression results for Model (2) and Model (3) are presented in Table 7.

Column (1) presents the impact of institutional investor diversity on their herding behavior. The regression results show that the coefficient for *iid* is significantly negative at the 1% level, indicating that a higher degree of institutional investor diversity enhances non-synchronous investment behavior, thereby suppressing herding. Column (2) reports the regression results for Model (3), in which the coefficient for *herd* is significantly positive, suggesting that a reduction in herding behavior may help control systemic financial risk. Compared with the baseline regression results, the coefficient between *iid* and *sfr* remains significantly negative but decreases in magnitude, indicating that herding behavior may play a partial mediating role in the relationship between institutional investor diversity and systemic financial risk.

Given the incompatibility issues between Driscoll-Kraay standard errors and the Bootstrap test, this study employs the Sobel test to verify the mediating mechanism. The results show a Z-statistic of -2.885 , significant at the 1% level, indicating a statistically significant

indirect effect through herding behavior. Additionally, we further examine the mediating effect using a fixed-effects model with clustered standard errors and the Bootstrap method. The results show a Z-statistic of -2.030 , significant at the 1% level. This provides empirical support for the mediating role of herding behavior in the risk control process associated with institutional investor diversity.

Table 7. Results of the mediation effect test for herding behavior.

	(1)	(2)
Variables	<i>herd</i>	<i>sfr</i>
<i>iid</i>	-0.011^{***} (0.003)	-0.129^* (0.068)
<i>herd</i>		0.349^{**} (0.157)
Sobel test		-2.885^{***}
Bootstrap test		-2.030^{**}
Controls	YES	YES
R-squared	0.431	0.480
Observations	2419	2419

***, **, * indicate significant levels at 1%, 5%, and 10%, respectively; values in parentheses are Driscoll-Kraay standard errors. The regression models include individual-fixed effects and time-fixed effects.

The economic rationale may be explained as follows: (1) The core characteristic of herding behavior is that market participants, aiming to reduce or minimize losses, disregard their own information and follow the market consensus (Hasan et al. 2023). The synchronicity of such behavior creates a tightly interconnected risk network among numerous financial institutions, leading to the continuous accumulation of latent risks during stable economic periods and their concentrated release through chain reactions during crises. This amplifies systemic financial risk across both temporal and structural dimensions (Adrian and Brunnermeier 2016). Diversity among institutional investors implies not only a broader information set and interpretive capacity but, crucially, non-uniform investment behaviors. Different institutional investors make differentiated decisions based on their own judgments, reducing the blindness of following the crowd, thereby mitigating the herding effect and curbing systemic financial risk.

(2) It is noteworthy that herding behavior plays a partial mediating role in the relationship between institutional investor diversity and systemic financial risk. This suggests the potential existence of other channels of influence. For instance, institutional investor may strengthen differentiated monitoring of financial institutions, constraining managers' risk-taking incentives, and thus suppressing systemic risk through an improved governance channel. In contrast, this study focuses on the micro-transmission mechanism of market participant behavior, revealing its role in safeguarding financial stability.

5. Heterogeneity Test

5.1. Market Environment

With the continuous improvement and development of market, market participants are playing an increasingly important role in the risk management of financial institutions. Higher levels of regional marketization, better-developed intermediary organizations, and stronger legal frameworks contribute to more robust market rules and legal systems. The degree of economic and legal institutional development not only influences how institutional investors collect, analyze, and act on information but also shapes the internal governance of financial institutions, thereby potentially affecting the level of systemic financial risk. Drawing on Fan et al. (2003), we employ the marketization index (MI) and the market intermediary organization development and legal institution environment (MDI) of

the regions where financial institutions are located as grouping variables to examine cross-regional heterogeneity in external environments.

Table 8 presents the results of the grouped regression analyses. The results indicate heterogeneous effects of market environment factors. Specifically, the estimated coefficients for institutional investor diversity (*iid*) in financial institutions located in regions with low marketization index and low market development index are 0.028 and 0.005, respectively, and are statistically insignificant. In contrast, the coefficients for *iid* in regions with high marketization index and high market development index are -0.145 and -0.144 , respectively, both being significantly negative. These results indicate that a more developed and sound market environment enhances the ability of institutional investor diversity to control systemic financial risk, thus confirming Hypothesis 3.

Table 8. Heterogeneity test results of market environment.

	Low-MI	High-MI	Low-MDI	High-MDI
	(1)	(2)	(3)	(4)
Variables	<i>sfr</i>	<i>sfr</i>	<i>sfr</i>	<i>sfr</i>
<i>iid</i>	0.028 (0.044)	-0.145^{**} (0.070)	0.005 (0.041)	-0.144^{*} (0.072)
Controls	YES	YES	YES	YES
R-squared	0.790	0.437	0.800	0.426
Observations	419	2000	465	1954

The abbreviations are defined as follows: MI denotes the marketization index, and MDI stands for the development of market intermediary organizations and the legal institutional environment. ** and * indicate significant levels at 5% and 10%, respectively; values in parentheses are Driscoll-Kraay standard errors. The regression models include individual-fixed effects and time-fixed effects.

The economic rationale may lie in the fact that sound market mechanisms, developed intermediary organizations, and a robust legal system provide an institutional foundation that safeguards information access and protects shareholder rights for institutional investors. This, in turn, further incentivizes diverse institutional investors to actively engage in corporate governance through various channels and curb excessive risk-taking behaviors within financial institutions, thereby effectively reducing systemic risk.

5.2. External Supervision

Rigorous external supervision helps institutional investors standardize their investments and promote effective corporate governance. Stringent external monitoring helps institutional investors standardize their investments and promote effective corporate governance. As key external monitors of firms (Dyck et al. 2010), analysts' reports attract greater investor attention, thereby mitigating information asymmetry between investors and firms (Bowen et al. 2008) and increasing pressure on corporate managers, which helps constrain managerial misconduct to some extent. Meanwhile, site visits, as an important form of engagement for institutional investors with financial institutions, create significant reputational pressure on operations, exerting substantial market incentives and disciplinary effects (Li and Xiao 2025). We use the number of analyst reports covering a financial institution and the frequency of site visits by institutional investors as grouping variables to examine heterogeneity in external monitoring intensity, splitting the sample at the median for subgroup analysis.

Table 9 presents the subgroup regression results, indicating heterogeneous effects of external monitoring factors. Specifically, the estimated coefficients for institutional investor diversity (*iid*) are -0.039 and -0.112 in financial institutions with low analyst coverage and low research report coverage, respectively. In contrast, the coefficients for *iid* in institutions with high analyst coverage and high research report coverage are -0.179 and

−0.128, respectively, both being significantly negative. These results indicate that stronger external supervision enhances the role of institutional investor diversity in controlling systemic financial risk, thus confirming Hypothesis 4.

Table 9. Heterogeneity test results of external supervision.

	Low-Analysts Attention	High-Analysts Attention	Low-Site Visit	High-Site Visit
	(1)	(2)	(3)	(4)
Variables	<i>sfr</i>	<i>sfr</i>	<i>sfr</i>	<i>sfr</i>
<i>iid</i>	−0.039 (0.043)	−0.179 * (0.096)	−0.112 (0.080)	−0.128 ** (0.057)
Controls	YES	YES	YES	YES
R-squared	0.694	0.389	0.457	0.543
Observations	1096	1323	1258	1161

** and * indicate significant levels at 5% and 10%, respectively; values in parentheses are Driscoll-Kraay standard errors. The regression models include individual-fixed effects and time-fixed effects.

The economic rationale may lie in the fact that analysts’ professional interpretations and institutional investors’ site visits provide market participants with non-public information beyond what financial institutions voluntarily disclose. This enhances market participants’ ability to assess the risk profiles of financial institutions and intensifies pressure for sound operations, thereby amplifying the risk-mitigating effect of diverse institutional investors on systemic risk.

5.3. Technological Development

The advancement of science, technology, and artificial intelligence has enabled institutional investors to rapidly process vast amounts of information and more accurately identify potential risk exposures in financial institutions. Technological tools have reduced the cost for investors to access information about financial institutions and have also encouraged institutional investors to more actively engage in corporate governance—such as through board participation, shareholder meetings, or voting mechanisms—to curb high-risk operational strategies. Meanwhile, the digital transformation of financial institutions helps bolster their capacity to mine and analyze market sentiment, thereby enhancing the forward-looking nature of risk management and their resilience to risks. We employ the level of FinTech development in the institution’s region and the degree of digital transformation of the financial institution itself as grouping variables to examine heterogeneity in technological development. The FinTech indicator is constructed following the methodology in [Sheng and Fan \(2020\)](#), while the digital transformation data are sourced from the CSMAR database.

Table 10 presents the subgroup regression results, indicating heterogeneous effects of technological development factors. Specifically, the estimated coefficients for institutional investor diversity (*iid*) in financial institutions with low FinTech development and low technology market development are 0.072 and −0.104, respectively, and are statistically insignificant. In contrast, the coefficients for *iid* in institutions with high FinTech development and high technology market development are −0.160 and −0.158, respectively, both significantly negative. These results indicate that a higher level of technological development enhances the ability of institutional investor diversity to control systemic financial risk, thus confirming Hypothesis 5.

The economic rationale may lie in the fact that the development of FinTech and the establishment of digital governance platforms provide market participants with richer data resources and more powerful analytical tools. This likely assists institutional investors in

forming rational value judgments and mitigating blind herding behavior, thereby enhancing the risk-mitigating effect of investor diversity on systemic risk.

Table 10. Heterogeneity test results of technological development.

	Low-Financial Technology	High-Financial Technology	Low-Digital Technology	High-Digital Technology
	(1)	(2)	(3)	(4)
Variables	<i>sfr</i>	<i>sfr</i>	<i>sfr</i>	<i>sfr</i>
<i>iid</i>	0.072 (0.047)	−0.160 ** (0.075)	−0.104 (0.092)	−0.158 *** (0.057)
Controls	YES	YES	YES	YES
R-squared	0.778	0.440	0.422	0.544
Observations	432	1987	1170	1249

*** and ** indicate significant levels at 1% and 5%, respectively; values in parentheses are Driscoll-Kraay standard errors. The regression models include individual-fixed effects and time-fixed effects.

5.4. Institution Type

To further investigate the heterogeneous effects of institutional investor diversity on systemic risk, this study conducts subgroup analyses based on the type of financial institution. Since the sample contains only five insurance institutions, a separate regression yields merely 161 observations. Such a small sample size may lead to biased estimates. Therefore, we exclude insurance institutions from individual analysis.

Table 11 reports the regression results for the banking and securities subgroups. The results indicate significant differences in the impact of institutional investor diversity on systemic risk across different types of institutions. Institutional investor diversity shows no significant risk-controlling effect in the banking subgroup. In contrast, it demonstrates a significant risk-reducing effect in securities firms. These results verify Hypothesis 6.

Table 11. Heterogeneity test results of financial institution types.

	Banking Group	Securities Group
	(1)	(2)
Variables	<i>sfr</i>	<i>sfr</i>
<i>iid</i>	−0.044 (0.037)	−0.065 * (0.038)
Controls	YES	YES
R-squared	0.515	0.616
Observations	1070	1188

* indicates significant level at 10%; values in parentheses are Driscoll-Kraay standard errors. The regression models include individual-fixed effects and time-fixed effects.

The economic rationale may be explained as follows: (1) The banking industry is typically subject to stringent and standardized information disclosure requirements, with relatively transparent balance sheet structures and lending business. This diminishes the informational advantages derived from diversity among institutional investors, thereby limiting their risk-mitigating role. (2) Banking institutions are protected by financial safety nets, including prudential regulation, lender-of-last-resort facilities, and deposit insurance systems. Such robust risk containment frameworks partially weaken the disciplining function of market forces on bank risk. (3) Compared to other financial institutions, banks' core businesses are more established, and business model innovations are often tightly constrained by regulation. Consequently, risk fluctuations in banks are generally more stable, making the risk-mitigating effect of institutional investor diversity less pronounced.

In contrast, securities firms exhibit faster-paced business innovation and more complex structures, making it challenging for market participants to accurately assess their true risk profiles. In this context, professional institutional investors, as key market forces,

can—when sufficiently diverse—effectively perform information interpretation and monitoring functions, thereby mitigating systemic risk. This aligns with the findings of (Zhang et al. 2023). Due to their lower market capitalization, higher turnover rates, and greater susceptibility to herd behavior, securities institutions possess strong risk linkage capabilities within the systemic network. When institutional investors in securities firms are diverse, market herding behavior is reduced, thereby effectively curbing the risk contribution of securities institutions to the financial system.

6. Conclusions

Prior research has not extensively explored the role of market participants in preventing and controlling systemic financial risk. Most studies have focused on the operational behavior of financial institutions themselves (Billio et al. 2012; Li et al. 2025) or on financial regulation (Huang and Jiang 2025; Miao et al. 2025). This study enriches the literature on financial risk control by examining the issue from the perspective of institutional investors. Although scholars such as Shi et al. (2024) and Zhang et al. (2025) have showed that investor heterogeneity on corporate governance and firm behavior, this study develops a novel metric to measure institutional investor diversity, thereby extending the discourse on institutional investors. Through theoretical analysis and empirical testing, this paper draws conclusions regarding the influence of institutional investor diversity on systemic financial risk, offering unique insights into how market participants—specifically institutional investors—can contribute to financial stability. The findings demonstrate that institutional investor diversity helps control systemic financial risk by mitigating herding behavior. This risk-mitigating effect is more pronounced in financial institutions with more developed market environments, stronger external supervision, and higher technological advancement, as well as in securities firms.

Our research demonstrates that safeguarding against systemic financial risks requires full recognition of the role played by market participants in maintaining financial stability. We propose the following policy recommendations: (1) Financial institutions should provide data platforms enabling market investors to query operational metrics and access strategic interpretations. While meeting mandatory disclosure requirements, they should proactively showcase their intrinsic value and risk management capabilities. This can effectively attract institutional investors with diverse investment philosophies and horizon structures, thereby optimizing ownership composition and reducing collective behavioral biases stemming from information asymmetry. (2) Institutional investors should actively leverage cutting-edge technologies such as text mining, machine learning, and multimodal large-language models to build efficient information analysis systems. By conducting in-depth processing and cross-verification of analyst reports, site visits, and public data, they can form independent judgments, thereby reducing blind adherence to herding behavior. (3) Regulatory authorities should foster an incentive-compatible information environment. Relevant agencies could explicitly make information disclosure quality a core prerequisite for financial institutions to obtain policy benefits, incentivizing them to voluntarily enhance transparency. Simultaneously, regulators could periodically publish lists of financial institutions demonstrating excellent disclosure practices, thereby tightly linking information disclosure with market reputation and long-term development prospects.

Although the empirical context of this study is China, the findings offer valuable insights for other emerging market economies. Many emerging markets commonly face issues such as homogeneity in institutional investor types and high volatility in capital flows, which exacerbate financial fragility induced by convergent investor behavior. Combining with the conclusions of this research, we argue that regulators in emerging economies should encourage the development of institutional investors with varying investment hori-

zons, risk preferences, and decision-making models to mitigate the synchronicity of collective behavior and enhance financial system resilience. Furthermore, industry-wide stress tests could incorporate scenario analyses specifically addressing concentrated outbreaks of herding behavior, quantitatively assessing their potential systemic impact, and accordingly establishing forward-looking risk warning and buffer mechanisms.

It should be noted that this study has several limitations: (1) To measure institutional investor diversity, we select six types of financial intermediaries—funds, social security funds, insurance companies, securities brokers, trust companies, and QFII—as our research sample. As representative market forces within the financial system, the shareholding behaviors of these institutions can directly and effectively reflect the market-based governance mechanisms operating inside the financial system. Future research could expand the analytical framework to include non-financial corporate shareholders, allowing for comparison of the relative importance of different shareholder types in risk management. (2) While examining the potential mechanism between institutional investor diversity and systemic financial risk, we focus on the role of institutional investors' herding behavior. However, constrained by significant data availability issues and a lack of relevant metrics, we do not conduct a more in-depth investigation into the interactive relationships among institutional investors. Future research could explore additional modeling approaches to characterize the time-varying trading network structure of institutional investors. Furthermore, subsequent studies could more thoroughly investigate potential moderating factors. (3) The sample of this study is concentrated on China's financial institutions. As a large emerging market economy with a unique institutional context and developmental path, China's financial regulatory framework and market structure differ significantly from those of other countries. Consequently, our findings possess certain limitations when directly generalized to other markets. Future research could expand the sample to include more developed and emerging market countries, incorporating factors such as institutional background, regulatory environment, and market structure into the analysis to further deepen our understanding of the role market participants play in safeguarding financial stability.

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Abbreviations

The following abbreviations are used in this manuscript:

EVT	Extreme Value Theory
FinTech	Financial Technology
Obs	Observations
Sds	Standard deviations
VIF	Variance inflation factor
LSV	Lakonishok, Shleifer, and Vishny

GMM	Generalized Method of Moments
PSM	Propensity Score Matching
ATT	Average Treatment Effect on the Treated
MI	Marketization Index
MDI	Market Intermediary Organization Development and Legal Institution Environment

Note

- ¹ Institutional investors within the same industry often share similar business strategies and financial reporting characteristics. These commonalities lead to fixed components in the costs incurred when monitoring peer financial institutions (Ramalinge-gowda et al. 2021).

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