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Fund Network Centrality and Stock Price Informativeness: A Mechanism Study Based on Information Transmission and Governance Effects

Yuxi Li*

Institute of Economics and Management, Southwestern University of Finance and Economics, Chengdu 610000, China

**Corresponding author: Yuxi Li.*

Abstract

Using Chinese A-share listed companies from 2014 to 2024 as the sample, this paper constructs a mutual shareholding network of public mutual funds based on complex network theory. It employs social network analysis to measure fund network centrality and empirically examines its impact on stock price informativeness as well as the underlying mechanisms. The results show that fund network centrality significantly reduces stock price informativeness: higher network centrality is associated with stronger stock price synchronicity and lower efficiency in incorporating firm-specific information into prices. This conclusion remains robust after a series of robustness checks, including lagging the explanatory variable by one period and excluding special years. Heterogeneity analysis reveals that the negative effect is more pronounced in small-scale firms. Mechanism analysis discusses two potential channels of influence: first, the “information crowding-out” channel, whereby fund network centrality may weaken analysts’ incentives for information discovery and firm monitoring; second, the “agency cost” channel, whereby network centrality may increase the likelihood of collusion between management and institutional investors, thereby raising agency costs and suppressing the release of firm-specific information. The heterogeneity evidence supports the first channel but is inconsistent with the second, suggesting the effect operates mainly as a systemic information-homogenization phenomenon rather than firm-level collusion. This study extends the research framework on capital market pricing efficiency from a micro-network perspective and provides policy implications for regulators to identify and mitigate market risks arising from coordinated institutional behavior.

Keywords

fund network centrality, stock price informativeness, stock price synchronicity, social network analysis, information transmission

1. Introduction

Stock price synchronicity serves as a key indicator of capital market information efficiency. Morck et al. [1] found that stock price synchronicity is relatively high in emerging markets, implying insufficient incorporation of firm-specific information. This information transmission process is not isolated; Pareek [2] demonstrated that information networks significantly influence the trading behavior and returns of mutual funds. Ozsoylev et al. [3] further constructed an investor network model in the stock market, highlighting the importance of interconnected structures. Building on Roll's [4] classic decomposition of R^2 in return volatility, subsequent studies have been able to quantify information efficiency. Cohen et al. [5] discovered that "small-world" connections in the investment community can generate excess returns, suggesting the value of network resources. However, deterioration of the information environment may exacerbate risks; Hutton et al. [6] confirmed that opaque financial reporting increases synchronicity and heightens crash risk. Jin and Myers [7] conducted a cross-country comparison emphasizing the decisive role of investor protection institutions in determining R^2.

Focusing on the Chinese market, Chen Kang and Liu Qi [8] found that institutional network connections are a major driver of stock price crash risk. Xu Nianxing et al. [9] added that institutional herding behavior further amplifies this risk. Wang Yaping et al. [10] analyzed the heterogeneous effects of institutional investors on stock price synchronicity from the perspective of information transparency. Although existing literature has addressed the impact of institutional investors on information efficiency, most studies treat them as a homogeneous group and lack a fine-grained examination of the dual pathways—"information congestion" and "collusive governance"—through which network centrality operates in normal market conditions. Against this backdrop, this paper uses data from 2014 to 2024 to construct a mutual shareholding network of public funds and systematically investigates the impact of network centrality on stock price informativeness, aiming to provide new insights into identifying the micro-origins of systemic risk and enhancing regulatory penetration.

This paper is organized as follows: Section 1 is the introduction; Section 2 reviews the literature on institutional investor networks and stock price informativeness, identifying existing gaps; Section 3 describes the research design, including sample selection, variable construction, and model specification; Section 4 presents the empirical analysis, reporting descriptive statistics, baseline regressions, robustness checks, heterogeneity analysis, and mechanism tests; Section 5 concludes with a summary of findings, discussion of limitations, and policy implications.

2. Literature Review

To precisely characterize network position, this paper adopts the social network centrality indicators defined by Freeman [11]. For mechanism testing, the paper follows Baron and Kenny's [12] principles for distinguishing mediating variables. Piotroski and Roulstone [13] analyze how analysts, institutions, and insiders jointly influence the incorporation of information into stock prices. Finally, the paper draws on the mediation-effect framework of Wen Zhonglin and Ye Baojuan [14] to motivate its analysis of the deep mechanisms through which network centrality affects stock price informativeness. Existing studies have largely focused on extreme risk perspectives and lack a detailed depiction of information transmission mechanisms in normal market environments. This paper attempts to re-examine the classic question—"Can institutional investors stabilize the market?"—from the perspective of network topology.

Despite the abundant achievements in the existing literature, clear logical gaps remain. Based on the "information congestion hypothesis" and the "collusion hypothesis," this paper proposes the following research hypotheses.

2.1 Main Effect: Fund Network and Stock Price Informativeness

When a stock is heavily held by funds (or fund clusters) located at the center of the network, its pricing process is profoundly influenced by the network structure. First, high centrality implies significant overlap in holdings with a large number of other funds. According to the "information cascade" theory in social psychology, funds at the network center often serve as key information nodes; their trading behavior is quickly observed and imitated by other members in the network. When substantial capital flows in the same direction based on the same type of signals (typically macroeconomic or industry-level signals), firm-specific fluctuations are overwhelmed by massive capital movements. Second, fund managers positioned in such network structures tend to adopt conservative, herd-following strategies to avoid performance deviation from the average (tracking error) caused by holding idiosyncratic stocks. This collective tendency toward mediocrity directly causes stock prices to reflect market index fluctuations more than firm-level fundamental changes.

Accordingly, the following hypothesis is proposed:

H1: Fund network centrality is negatively correlated with stock price informativeness; that is, higher fund network centrality is associated with higher stock price synchronicity (higher R^2).

2.2 Information Transmission Mechanism: Crowding Out of Analyst Attention

Securities analysts are an important external source of information in capital markets. However, strengthened fund networks may exert a "substitution effect" or "crowding-out effect" on analyst behavior. On one hand, when major shareholders (public funds) form tight information-sharing networks, they may perceive internal information exchange as sufficient, thereby reducing demand for external analyst reports and leading to lower sell-side analyst coverage. On the other hand—and more critically—tightly knit institutional networks often imply strong buy-side influence. To maintain price stability within the network, clustered funds may exert pressure on analysts issuing negative ratings, or management and institutions may collude to reduce information transparency, increasing the cost for analysts to obtain truthful information. The decline in analyst attention directly severs external channels for firm-specific information to enter stock prices.

Accordingly, the following hypothesis is proposed:

H2a: Fund network centrality reduces stock price informativeness by lowering analyst attention (substitution effect/crowding-out effect).

To further distinguish the information-crowding-out explanation from a firm-level collusion explanation, this paper also tests a competing hypothesis (H2b): if the network effect operated primarily through collusion between funds and management (raising agency costs), it would be more pronounced in firms with weaker governance structures. Evidence inconsistent with this pattern would support a systemic market-structure interpretation of the observed network effect.

2.3 Moderating Role of Firm Size

In China's distinctive dual economic structure, large-scale and small-scale enterprises differ fundamentally in information environment and governance logic. Large enterprises typically have more comprehensive disclosure systems and greater analyst coverage, resulting in relatively transparent information environments. In contrast, small-scale enterprises operate fully in competitive market settings, with more severe information asymmetry and greater reliance on institutional investors for governance and information discovery functions. Therefore, when the "herding effect" and "governance failure" induced by fund networks occur in small-scale enterprises, the crowding-out effect on firm-specific information is more pronounced.

Accordingly, the following hypothesis is proposed:

H3: The negative impact of fund network centrality on stock price informativeness (i.e., increasing stock price synchronicity) is more significant in small-scale enterprises.

3. Research Design

3.1 Sample Selection and Data Sources

This paper selects Chinese A-share listed companies from 2014 to 2024 as the initial research sample. This time window is particularly critical: 2014 marks the starting point of the "New Nine National Policies" for the capital market and the acceleration of institutionalization in China. It encompasses the sharp market volatility in 2015, the return to value investing in 2017, the clustering around core assets in 2019–2020, and the unwinding of clusters along with style rotation in 2021–2024. This period enables a comprehensive and dynamic reflection of the evolution patterns of fund networks across different market environments.

To ensure the representativeness of the sample data and the robustness of the research conclusions, this paper follows common practices in the relevant literature (Hutton et al., 2009; Chen Kang & Liu Qi, 2018) and applies systematic data cleaning to the initial sample. The specific screening criteria are as follows: First, financial and insurance companies are excluded due to significant differences in their financial statement structures and business models compared to ordinary non-financial firms. Second, companies subject to special treatment (ST or *ST) or suspended from listing (PT) during the sample period are removed, as these firms are typically in abnormal operating conditions and their stock prices may be severely distorted by non-fundamental factors. Third, to control for speculative noise in the early post-IPO price fluctuations, observations with less than one full year of listing are excluded. Fourth, to ensure the reliability of stock price synchronicity estimates, only observations with at least 30 valid trading weeks in the year are retained. Finally, observations with missing values in key financial variables, fund shareholding data, or other core variables are dropped. After these steps, the final sample suitable for empirical analysis is obtained.

Following the above screening, the final dataset consists of an unbalanced panel comprising more than 3,000 listed companies and approximately 24,516 firm-year observations. Fund shareholding details are sourced from the CSMAR Fund Research Database and include all actively managed public funds (ordinary equity funds, partial equity hybrid funds, balanced hybrid funds, etc., excluding index funds, bond funds, and guaranteed funds). Firm financial data, market trading data, and analyst data are obtained from the Wind Financial Terminal and the CSMAR database. To mitigate the impact of extreme outliers on regression results, all continuous micro-level variables are winsorized at the 1% and 99% percentiles.

3.2 Variable Definitions

3.2.1 Dependent Variable: Stock Price Informativeness (INF)

Following the standard approach established by Roll (1988) and Morck et al. (2000), this paper uses stock price synchronicity as an inverse proxy for stock price informativeness.

First, for each firm ii in year tt, the weekly return data are regressed using the following expanded market model:

$$r_{i,w,t}=\alpha_i+\beta_{1,i}r_{m,w,t}+\beta_{2,i}r_{ind,w,t}+\varepsilon_{i,w,t} \quad (1)$$

where $r_{i,w,t}$ is the weekly individual stock return of firm i in week w of year t, adjusted for cash dividend reinvestment; $r_{m,w,t}$ is the market weekly return weighted by circulating market capitalization (reflecting overall A-share market movements); and $r_{ind,w,t}$ is the industry weekly return weighted by circulating market capitalization (based on the China Securities Regulatory Commission's 2012 industry classification guidelines). The inclusion of industry returns helps isolate industry-level common shocks.

The goodness-of-fit measure $R^2_{i,t}$ obtained from this regression measures the proportion of stock return variance explained by market and industry fluctuations. A higher R^2 indicates greater synchronicity with the market and less incorporation of firm-specific information. Since R^2 is bounded in [0,1] and does not satisfy the normality assumption required for OLS regression on the dependent variable, this paper applies a logistic transformation to R^2 to construct the final dependent variable INF: $\mathrm{INF_{i,t}}=\ln\left(\frac{1-\mathrm{R^2_{i,t}}}{\mathrm{R^2_{i,t}}}\right)$. A larger INF value indicates lower stock price synchronicity and higher stock price informativeness; conversely, a smaller INF indicates higher synchronicity and lower informativeness.

3.2.2 Core Explanatory Variable: Fund Network Centrality (fund_network)

This paper constructs the indicator in three steps:

Step 1: Construction of the Mutual Shareholding Network of Funds. The fund mutual shareholding network is constructed based on the top 10 holdings data disclosed at the end of each quarter. Network nodes are defined as all actively managed public mutual funds. The edge (connection) rule is defined as follows: if two funds AA and BB simultaneously hold the same stock as a top holding at the end of quarter tt (with the holding proportion accounting for ≥5% of each fund's net asset value), then the two funds are considered to have an information linkage. In this case, the corresponding element in the adjacency matrix is set to $A_{ab,t}$=1; otherwise, $A_{ab,t}$=0. This procedure constructs an undirected, unweighted binary network (also referred to as a simple binary graph).

Step 2: Measurement of Fund-Level Centrality. Unlike prior studies that often rely solely on degree centrality (number of connections), this paper adopts the more refined eigenvector centrality (EC). The core idea of eigenvector centrality is that a node's importance depends not only on the number of its neighbors but also on the importance of those neighbors (Bonacich, 1972). If a fund shares top holdings with many other funds that occupy central positions in the network—such as "star funds" or "large-scale funds" with substantial influence—then this fund clearly exerts greater informational influence within the network.

The eigenvector centrality is computed as: $EC_j = \frac{1}{\lambda} \sum_{k \in N(j)} EC_k$, where λ is the largest eigenvalue of the adjacency matrix.

Step 3: Mapping to the Firm Level. Since the research focuses on listed companies, fund-level centrality is aggregated to the firm level using a weighted average. For firm ii in year tt, the fund network centrality is defined as the weighted average of the eigenvector centralities of all funds that hold the firm as a top holding:

$$\mathrm{Centrality}_{i,t} = \sum_{j=1}^{M} \left(\frac{\mathrm{Shares}_{j,i,t}}{\mathrm{TotalShares}_{i,t}} \times \mathrm{EC}_{j,t} \right) \tag{2}$$

where $Shares_{j,i,t}$ denotes the number of shares of firm ii held by fund jj, and $TotalShares_{i,t}$ represents the total number of shares of firm ii held by all sample funds. The final annual measure is obtained by taking the arithmetic average across the four quarters.

A higher value of this indicator indicates that the funds holding the company occupy more central positions in the overall capital market network, reflecting deeper clustering and greater pressure for information homogenization.

3.2.3 Control Variables

To mitigate confounding effects from other factors on stock price informativeness, the following firm fundamental characteristics are included as control variables, following prior literature (Piotroski & Roulstone, 2004; Gul et al., 2010). Their definitions are presented in Table 1.

Table 1: Variable definitions

Variable Type	**Variable Name**	**Symbol**	**Definition and Explanation**
Dependent Variable	Stock Price Informativeness	INF	$ln((1-R2)/R2)$, inverse indicator of synchronicity
Core Explanatory Variable	Fund Network Centrality	fund_network	Weighted average of eigenvector centrality of funds holding the company
Control Variables	Firm Size	size	Natural logarithm of total assets
	Financial Leverage	lev	Total liabilities / Total assets
	Profitability	ROA	Net profit / Total assets
	Book-to-Market Ratio	BM	Book value / Market value
	Growth	growth	Operating revenue growth rate
	Board Size	board	Natural logarithm of number of board members
	Independent Director Ratio	indep	Number of independent directors / Total board members
	CEO Duality	dual	1 if chairman and CEO are the same person, 0 otherwise
	Tobin's Q	tobinq	Market value of firm / Replacement cost of assets

3.2.4 Model Specification

To test Hypothesis H1, the following two-way fixed effects regression model is constructed:

$$INF_{i,t} = \alpha_0 + \beta_1 Centrality_{i,t} + \sum_{k=1}^{K} \gamma_k Controls_{k,i,t} + \lambda_t + \mu_j + \varepsilon_{i,t} \tag{3}$$

Where ii denotes the firm, tt denotes the year; $INF_{i,t}$ is stock price informativeness; $Centrality_{i,t}$ is fund network centrality; Controls represent all the aforementioned control variables; λt is year fixed effects to absorb time-varying macroeconomic and market cycle factors common to all firms; μj is industry fixed effects to control for time-invariant industry-specific unobserved characteristics; and $\varepsilon_{i,t}$ is the random error term.

To address cross-sectional correlation and heteroskedasticity, standard errors are clustered at the firm level. If the coefficient β1 is significantly negative, it supports H1: higher fund network centrality is associated with higher stock price synchronicity and lower informativeness.

4. Empirical Analysis

4.1 Descriptive Statistics and Distribution Analysis

This study selects Chinese A-share listed companies from 2014 to 2024 as the research sample. After excluding financial industry firms, ST/*ST samples, and observations with missing values, the final dataset comprises approximately 24,516 firm-year observations.

Table 2: Descriptive Statistics of Main Variables

Variable	Observations	Mean	Std. Dev.	Min	Median	Max
INF	24,516	-0.824	0.980	-2.850	-0.795	1.430
fund_network	24,516	0.045	0.032	0.001	0.038	0.187
size	24,516	22.15	1.240	19.88	21.97	26.08
lev	24,516	0.421	0.210	0.051	0.413	0.892
RoA	24,516	0.038	0.064	-0.185	0.035	0.188
BM	24,516	0.612	0.271	0.105	0.598	1.442
growth	24,516	0.152	0.381	-0.495	0.101	2.847
board	24,516	2.178	0.198	1.609	2.197	2.708
indep	24,516	0.374	0.053	0.333	0.357	0.571
dual	24,516	0.248	0.432	0.000	0.000	1.000
tobinq	24,516	2.014	1.245	0.865	1.628	8.941

For the dependent variable, stock price informativeness (INF), the sample mean is -0.824 with a standard deviation of 0.980, indicating substantial variation in the incorporation of firm-specific information across listed companies. Regarding the core explanatory variable, fund network centrality (fund_network), the sample mean is 0.045 with a standard deviation of 0.032. The indicator spans a wide range from a minimum of 0.001 to a maximum of 0.187. This substantial dispersion carries important economic implications: it reveals a highly uneven distribution of institutional investors within the network topology. For certain "clustered stocks," the funds holding them occupy central positions in the network, forming tightly interconnected communities with high information linkage. In contrast, peripheral stocks are held by institutions that remain in information silos. Such rich heterogeneity in the network structure provides abundant variation, offering a strong empirical foundation for identifying and quantifying network effects in this study.

Among the control variables, the sample firms' characteristics are generally consistent with expectations: the average leverage ratio (Lev) is 42.1%, within a reasonable range; the mean return on assets (ROA) is 3.8%, reflecting the basic level of profitability among the listed companies during the sample period.

4.2 Correlation Analysis and Multicollinearity Test

Prior to multivariate regression, this paper first examines linear relationships among variables using a Pearson correlation coefficient matrix, as reported in Table 3.

Table 3: Correlation Matrix of Main Variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) INF	1.000										
(2) fund_network	-0.006	1.000									
(3) size	0.023*	0.254*	1.000								
(4) lev	0.007	0.060*	0.612*	1.000							
(5) ROA	-0.016	0.124*	-0.089*	-0.271*	1.000						
(6) BM	0.005	-0.109*	0.609*	0.494*	-0.281*	1.000					
(7) growth	-0.009	-0.002	-0.009	0.002	-0.020*	0.000	1.000				
(8) board	0.005	0.046*	0.398*	0.234*	-0.046*	0.237*	-0.004	1.000			
(9) indep	0.012	0.039*	0.051*	0.016	0.001	0.019*	0.000	-0.432*	1.000		
(10) dual	-0.004	-0.001	0.205*	0.137*	-0.012	0.152*	-0.011	0.215*	-0.102*	1.000	
(11) tobinq	0.002	0.064*	-0.162*	-0.132*	0.111*	-0.297*	-0.002	-0.062*	-0.001	-0.030*	1.000

**** p<0.01, ** p<0.05, * p<0.1*

*Note: This table reports Pearson correlation coefficients; ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.*

First, regarding the relationship between the core explanatory variable and the dependent variable, Table 3 shows that the correlation coefficient between fund_network and INF is -0.006 and statistically insignificant. This indicates that, at the univariate level, no clear linear relationship exists between the two, and Hypothesis

H1 does not receive direct support in the correlation analysis stage. This may be due to the interference of uncontrolled confounding factors, and further verification is required through multivariate regression analysis.

Among the control variables, firm size (size) exhibits a significant positive correlation with INF (coefficient 0.023), suggesting that larger firms tend to have lower stock price synchronicity (i.e., higher INF). Correlations between lev, ROA, and other variables with INF are generally small and mostly insignificant.

To ensure estimation accuracy, multicollinearity diagnostics were conducted. The correlation matrix shows that most pairwise absolute correlations among control variables are below 0.5, with only a few exceptions (e.g., size and lev at 0.612), which remain acceptable. Variance Inflation Factor (VIF) tests indicate all VIF values are far below the critical threshold of 10, with an average VIF below 2. Thus, severe multicollinearity is not present, allowing subsequent regression analysis to proceed.

4.3 Baseline Regression: Impact of Fund Network Centrality on Stock Price Informativeness

To systematically test the effect of fund network centrality on stock price informativeness, this paper employs a stepwise regression approach while strictly controlling for year and industry fixed effects, with standard errors clustered at the firm level. Detailed results are reported in Table 4.

Table 4: Baseline Regression Results of Fund Network Centrality on Stock Price Informativeness

	(1)	(2)	(3)
VARIABLES	**Model_1**	**Model_2**	**Model_3**
fund_network	-0.001*	-0.001**	-0.001**
	(0.000)	(0.000)	(0.000)
size		0.016	0.006
		(0.014)	(0.015)
lev		0.018	0.054
		(0.095)	(0.096)
ROA		-0.525*	-0.547*
		(0.318)	(0.320)
BM		-0.051	-0.052
		(0.079)	(0.096)
growth		-0.001	-0.001
		(0.001)	(0.001)
board			0.007
			(0.010)
indep			0.245
			(0.298)
dual			-0.003
			(0.031)
tobinq			-0.004
			(0.009)
Constant	1.974***	1.949***	1.850***
	(0.015)	(0.051)	(0.174)
Observations	24,516	24,095	23,571
R-squared	0.225	0.225	0.224

*Note: Standard errors clustered at the firm level in parentheses; ***, **, * indicate significance at 1%, 5%, and 10% levels, respectively.*

4.3.1 Interpretation of Regression Results

Column (1) includes only the core explanatory variable fund_network along with year and industry fixed effects. The regression results show that the coefficient on fund_network is -0.001 and is significantly negative at the 10% level. This suggests that, without controlling for other firm characteristics, fund network centrality has a significant negative effect on stock price nonsynchronicity (INF).

Column (2) progressively adds control variables reflecting firm fundamentals (size, lev, RoA, etc.). The coefficient on fund_network remains -0.001 and becomes significant at the 5% level (**). This indicates that the adverse network effect remains robust after controlling for financial characteristics. It is worth noting that the R-squared remains essentially flat (around 0.225) across columns (1)-(3), indicating that the current control set explains little additional variation in INF beyond fixed effects; this is a limitation of the present control-variable selection and is left for future refinement.

Column (3) further incorporates governance structure variables (e.g., board, indep, dual) and market characteristic variables (tobinq), forming the full baseline model. The regression results show that the coefficient on fund_network remains stable at -0.001 and is statistically significant and negative at the 5% level.

Since INF measures stock price nonsynchronicity (i.e., firm-specific information content), the negative coefficient on the core explanatory variable implies that higher fund network centrality is associated with lower nonsynchronicity. This provides empirical support for Hypothesis H1: funds at network centers exhibit convergent trading behavior; such "clustering" causes individual stock prices to reflect more network-common information, thereby suppressing the incorporation of firm-specific information and elevating synchronicity.

4.3.2 Economic Significance

Beyond statistical significance, assessing economic magnitude is crucial for understanding the substantive impact of network effects. Based on the estimated coefficient of -0.001 in column (3), we can derive the following economic implications: Given that the sample standard deviation of fund_network is 0.032 and the sample standard deviation of INF (stock price nonsynchronicity) is 0.980, if a firm's fund network centrality increases by one standard deviation, its stock price nonsynchronicity (INF) would decrease by approximately 0.00003 (calculated as 0.001×0.032).

This change magnitude accounts for approximately 0.003% of the standard deviation of INF. Although, in absolute terms, the marginal impact of the network effect on firm-specific information appears relatively modest, the sample contains more than 20,000 observations and the coefficient remains statistically significant at the 5% level. This indicates that the influence of fund networks on stock price synchronicity represents a pervasive and robust micro-level market mechanism. In practical terms, when a listed company becomes heavily locked in by "clustered funds" positioned at the core of the network, its stock price fluctuation pattern undergoes a significant shift—stock price nonsynchronicity (INF) declines markedly, while synchronicity rises substantially. The "noise" of firm-specific information is drowned out by the "chorus" of the network structure, resulting in a notable suppression of the price discovery function. For investors, this implies that fundamental analysis-based stock selection strategies will be significantly less effective when applied to such stocks.

4.4 Robustness Checks

Although baseline results are significant, to rule out endogeneity, sample selection bias, and noise from extreme market conditions, this paper conducts rigorous robustness tests from three dimensions.

First, to address the potential reverse causality issue in the baseline regression—namely, that stocks with high price synchronicity may be more likely to attract clustered holdings from central-network funds due to their "core asset" status, rather than the network structure itself causing the increase in synchronicity—this paper employs a one-period lag of the explanatory variable. By lagging the core explanatory variable fund_network by one period (L.fund_network) and using the previous period's network centrality to explain the current period's stock price nonsynchronicity (INF), we can partially mitigate the endogeneity bias arising from bidirectional causality. As shown in Column (1) of Table 5, the coefficient on the lagged fund_network is -0.001 and significantly negative at the 10% level. This result indicates that, even after ruling out contemporaneous reverse causality, the erosive effect of fund network structure on stock price informativeness persists, with causal inference supported by temporal precedence.

Second, to alleviate sample selection bias (self-selection bias) arising from observable variables, this paper applies the propensity score matching (PSM) method. Specifically, a dummy variable High_Cent is constructed, taking the value of 1 if a firm's fund_network in the current year exceeds the annual median and 0 otherwise. All control variables (such as size, lev, ROA, etc.) are used as covariates in a Logit model to estimate propensity scores, followed by 1:1 nearest-neighbor matching. The balance test results in Figure 1 show that, after matching, the standardized percentage bias (Standardized %bias) for all covariates between the treatment and control groups is substantially reduced to within 10% (with x-markers closely hugging the zero line), and t-tests are no longer significant. This confirms that covariate distributions are well balanced post-matching, effectively addressing the "apples-to-oranges" comparison problem. Regression results based on the matched sample, as reported in Column (2) of Table 5, show that the coefficient on fund_network remains -0.001 and is highly significant at the 1% level (***). This demonstrates that the baseline conclusion remains robust even after controlling for selection bias.

Finally, considering that the sample period (2014–2024) includes the 2015 stock market crash and the early 2020 COVID-19 shock—extreme market events that could induce systematic panic or liquidity dry-ups and thereby generate spuriously high synchronicity—this paper excludes all observations from 2015 and 2020 and re-estimates the model using the remaining years. As shown in Column (3) of Table 5, the coefficient on fund_network remains around -0.001 and is statistically significant at the 5% level (**). This provides strong evidence that the erosive effect of fund networks on information efficiency is a regular, normal-market mechanism rather than a byproduct of crisis periods.

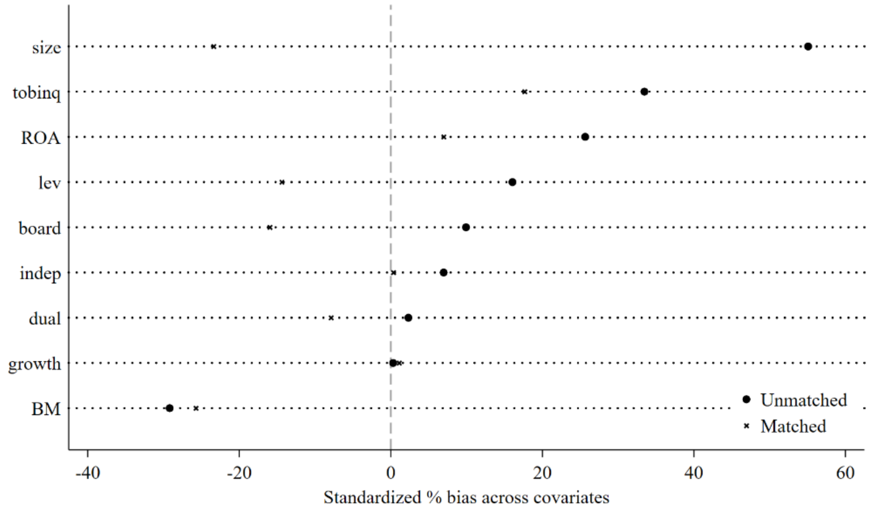
In summary, across these three robustness checks—lagging the explanatory variable to address reverse causality, PSM to mitigate observable selection bias, and exclusion of extreme-year observations—the sign, magnitude, and statistical significance of fund_network remain highly consistent, reinforcing the reliability of the main findings.

Table 5: Robustness Check Results

Variables	**(1)**	**(2)**	**(3)**
	Lagged_IV	**PSM_Matched**	**Exclude_2015_2020**
L.fund_network / fund_network	-0.001*	-0.001***	-0.001**
	(0.000)	(0.000)	(0.000)
size	0.008	0.009	0.013
	(0.017)	(0.019)	(0.016)
lev	0.055	0.013	0.048
	(0.103)	(0.118)	(0.101)
ROA	-0.535	-0.184	-0.638*
	(0.341)	(0.379)	(0.346)
BM	-0.077	-0.038	-0.144
	(0.104)	(0.125)	(0.104)
growth	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
board	0.008	0.019	0.006
	(0.011)	(0.012)	(0.011)
indep	0.144	0.414	0.306
	(0.310)	(0.347)	(0.311)
dual	0.013	-0.006	-0.003
	(0.032)	(0.038)	(0.033)
tobinq	-0.006	0.002	-0.015
	(0.010)	(0.010)	(0.011)
Constant	1.848***	1.659***	1.924***
	(0.183)	(0.200)	(0.183)
Observations	20,892	15,223	20,700
R-squared	0.232	0.228	0.225
Control variables	Controlled	Controlled	Controlled
Year/Industry fixed effects	Controlled	Controlled	Controlled

*Note: Standard errors clustered at the firm level are reported in parentheses; ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Column (1) presents the regression with the explanatory variable lagged by one period; Column (2) shows results based on the PSM-matched sample; Column (3) reports results after excluding observations from 2015 and 2020.*

Figure 1: PSM Balance Test Results



Note: Dots (Unmatched) represent pre-matching standardized biases; crosses (Matched) represent post-matching biases. Post-matching biases converge toward 0, indicating good matching quality.

4.5 Heterogeneity Analysis

To clarify the boundary conditions and contextual dependence of the fund network effect, this paper conducts an in-depth subgroup analysis based on the dimension of firm size. Firms of different scales exhibit significant differences in information transparency, market attention, and risk resilience, which may result in asymmetric impacts of fund networks on stock price informativeness.

Heterogeneity by Firm Size (Small vs. Large Firms)

The sample is divided into "small-size" and "large-size" groups based on the median of size, with results reported in Table 6.

Table 6: Heterogeneity Analysis by Firm Size

	(1)	(2)
VARIABLES	**Small_Size**	**Large_Size**
fund_network	-0.004**	-0.001**
	(0.002)	(0.000)
size	-0.003	0.015
	(0.037)	(0.023)
lev	-0.022	0.199
	(0.122)	(0.149)
ROA	-0.928**	0.467
	(0.397)	(0.555)
BM	-0.003	-0.057
	(0.149)	(0.139)
growth	-0.001*	-0.000
	(0.001)	(0.002)
board	0.012	0.003
	(0.016)	(0.013)
indep	0.338	0.086
	(0.441)	(0.403)
dual	0.023	-0.042
	(0.038)	(0.050)
tobinq	0.001	-0.004
	(0.012)	(0.022)
Constant	1.762***	1.869***
	(0.300)	(0.230)

	(1)	(2)
VARIABLES	**Small_Size**	**Large_Size**
Observations	11,824	11,747
R-squared	0.224	0.232

*Note: Firm-level clustered standard errors in parentheses; ***, **, * denote significance at 1%, 5%, and 10%, respectively.*

Results show that fund_network is significantly negative in both groups, but the magnitude differs markedly. Specifically, in the small-size group, the coefficient is -0.004 (significant at 5%); in the large-size group, it is -0.001 (also significant but smaller in absolute value).

This finding supports the information asymmetry hypothesis. Small firms typically have poorer disclosure quality, lower analyst coverage, and higher information asymmetry. In such "information vacuums," trading signals from central-network funds are more likely to be interpreted as "smart money" by retail investors, triggering stronger herding. The "information cascade" propagated by the fund network crowds out scarce firm-specific information more severely in small firms, leading to substantially higher synchronicity (lower INF). In contrast, large firms benefit from better disclosure and more analyst coverage, diluting network-induced noise and weakening the dominance of network structure in pricing.

In summary, the erosive effect of fund networks on stock price informativeness is more severe in small-cap, low-transparency firms. This suggests regulators should pay particular attention to institutional clustering in small-cap stocks to prevent systemic risks from information homogenization.

4.6 Mechanism Analysis

Building on the robust association documented above, this section explores two potential transmission channels—"information transmission blockage" and "corporate governance"—in conjunction with heterogeneity results, to shed light on the underlying process.

4.6.1 Mechanism 1: Information Transmission Channel — Moderating Role of Information Environment

Securities analysts and external investors are key suppliers of firm-specific information in capital markets. According to the "information congestion hypothesis," overly dense fund networks may lead to excessive internal signal sharing, crowding out independent external information and causing prices to reflect more network-common noise.

Empirical evidence: The firm-size heterogeneity in Table 6 provides strong support. The negative effect of fund_network on informativeness is significantly stronger in small firms (coefficient -0.004**) than in large firms (-0.001**). Logic: Small-scale firms typically face more severe information asymmetry, with lower external analyst coverage and greater investor reliance on publicly available information. Consequently, when the "homogenized trading signals" generated by the fund network flood in, the "crowding-out effect" on the already scarce firm-specific information environment becomes far more pronounced. In contrast, large-scale firms benefit from diversified information channels and stronger resilience to noise. This result indirectly confirms that "information transmission blockage" constitutes an important channel through which fund networks affect stock price informativeness.

4.6.2 Mechanism 2: Corporate Governance Channel — Universality of Network Effects

Institutional investors are expected to exert governance oversight. However, under complex interpersonal networks and interest entanglements, their behavior may deviate. To further test the role of governance environment, this paper conducts subgroup regressions based on the median of independent director ratio (indep), with results in Table 7.

Table 7: Subgroup Regression by Independent Director Ratio

	(1)	(2)
VARIABLES	**Low_Independence**	**High_Independence**
fund_network	-0.000	-0.001***
	(0.000)	(0.000)
size	-0.026	0.021

	(0.023)	(0.020)
lev	0.100	0.017
	(0.136)	(0.128)
ROA	-0.128	-0.878**
	(0.481)	(0.433)
BM	-0.017	-0.053
	(0.143)	(0.128)
growth	0.000*	-0.001***
	(0.000)	(0.000)
board	0.023	0.001
	(0.017)	(0.013)
indep	-2.823	0.126
	(2.273)	(0.457)
dual	0.001	0.008
	(0.047)	(0.040)
tobinq	-0.003	-0.003
	(0.012)	(0.012)
Constant	2.787***	1.890***
	(0.726)	(0.249)
Observations	10,879	12,692
R-squared	0.229	0.225

*Note: Firm-level clustered standard errors in parentheses; ***, **, * denote significance at 1%, 5%, and 10%, respectively.*

Empirical evidence and interpretation: Table 7 shows that the negative effect of fund_network is concentrated in the high independent director ratio group (coefficient -0.001***), while insignificant in the low-independence group. This reveals the complexity of network effects: they are not limited to weak-governance "collusion" scenarios but are more pronounced in firms with relatively strong governance structures and higher institutional attention. This may imply that the impact of fund networks on stock price informativeness is more a market-level phenomenon of "information homogenization" rather than merely isolated instances of firm-level governance failure. Funds positioned at the network core tend to preferentially allocate to well-governed, highly liquid "core assets." This collective allocation behavior itself drives up stock price synchronicity—even in companies with relatively high independent director ratios. These findings suggest that the loss of information efficiency induced by fund networks constitutes a systemic market structure issue, rather than a defect attributable to the governance shortcomings of individual firms.

5. Conclusion and Discussion

5.1 Summary of Findings

With the accelerating institutionalization of China's capital market, the complex social networks formed among fund managers through mutual shareholdings have become an overlooked "dark matter" influencing asset pricing efficiency. Utilizing data on Chinese A-share listed companies from 2014 to 2024, this paper constructs a dynamic fund network topology, measures eigenvector centrality using social network analysis (SNA), and systematically evaluates its impact on stock price informativeness (proxied inversely by stock price synchronicity via INF) as well as the underlying mechanisms.

The empirical analysis yields three progressively layered core conclusions:

First, fund network centrality significantly reduces stock price informativeness. Baseline regression results show that the coefficient on fund_network is significantly negative (approximately -0.001), indicating that shareholding structures dominated by funds at central network positions markedly increase stock price synchronicity and suppress the incorporation of firm-specific information. A series of robustness checks—including lagging the explanatory variable by one period and excluding special years—confirm that this negative effect is robust. Economic significance analysis indicates that a one-standard-deviation increase in fund network centrality reduces stock price nonsynchronicity (INF) by only a very small magnitude, so the network effect, though statistically robust, is economically modest.

Second, the information environment moderates the network effect. Heterogeneity analysis reveals that this loss of information efficiency is more pronounced in small-scale firms. Subgroup regressions show that the absolute value of the fund_network coefficient is significantly larger in the small-firm subsample than in the large-firm subsample. This suggests that the “herding effect” induced by fund networks more readily dominates pricing in “information-weak” zones characterized by higher information asymmetry and weaker external monitoring, causing firm-specific information to be overwhelmed by network noise.

Third, the mechanisms primarily manifest through “information crowding-out” and systemic structural effects. Although direct mediation effect tests were limited by data availability, theoretical reasoning combined with heterogeneity results indicates that high-centrality network structures may, on one hand, crowd out external independent analyst attention, severing supply chains for firm-specific information (supported by the stronger effect in small firms); on the other hand, subgroup results based on independent director ratios show that the network effect remains significant even in firms with relatively sound governance structures. This implies that the impact of fund networks on stock price informativeness is more a systemic market-structure phenomenon than isolated instances of firm-level governance failure or collusion.

5.2 Theoretical Contributions and Reflections on Limitations

5.2.1 Theoretical Contributions

This study theoretically extends the intersection of asset pricing and social network analysis. While prior literature has primarily focused on the level of institutional ownership, this paper demonstrates the critical importance of ownership topology, showing that “who holds the stock” and “the network position of the holders” matter more than “how much is held.” Furthermore, the evidence presented here—information crowding-out supported by the size-heterogeneity results, and a systemic information-homogenization effect rather than firm-level agency-cost escalation supported by the independent-director results—challenges simplistic versions of the “institutional monitoring hypothesis” and provides new micro-level evidence for understanding the complex behavior of institutional investors in transition economies.

5.2.2 Reflections on Limitations Arising from Code Implementation and Data Characteristics

Despite striving for rigor in research design and empirics, this study is constrained by data availability and methodological limitations, which are candidly discussed here and point to directions for future deepening.

Static nature of network construction: The fund mutual-shareholding network relies primarily on top-10 holdings disclosed in quarterly reports, resulting in essentially static “snapshots” at quarter-ends. In reality, fund managers’ decisions and trades are continuous and dynamic; intra-quarter adjustments and short-term information interactions cannot be effectively captured with existing data. This approach may underestimate the actual strength and speed of network effects. Future research integrating higher-frequency holding or transaction flow data to construct truly time-varying dynamic network models would enable more precise depiction of information transmission paths.

Data constraints in mechanism testing: Due to database access restrictions, detailed analyst tracking records and management expense breakdowns were unavailable, preventing direct application of standard mediation models (e.g., via analyst attention or corporate governance proxies as mediators). The current mechanism analysis relies mainly on theoretical deduction and indirect evidence from heterogeneity results. While logically consistent, it lacks direct empirical support. Future studies could collect finer-grained data on corporate governance and analyst behavior to rigorously verify the specific pathways of “information crowding-out” and “governance collusion.”

Challenges in causal identification: Although lagging and PSM were employed to mitigate endogeneity, social network analysis inherently faces the “reflection problem”—it is difficult to fully disentangle whether network structure influences individual behavior or whether individuals with similar characteristics self-select into the network. The associations identified here are best interpreted as robust causal suggestive evidence. To achieve cleaner causal identification, future research could exploit more exogenous sources of network structure variation, such as regulatory policy changes or unexpected departures of key fund managers, in quasi-natural experiment settings.

5.3 Policy Implications

The empirical conclusions of this study offer clear policy guidance and practical reference for various participants in the capital market.

For regulators, the findings reveal that the micro-origins of systemic risk may lie not in the size or concentration of individual institutions, but deep within the intricate network interconnections among institutions. Traditional "point-based" institutional supervision must therefore evolve toward "network-based" systemic risk monitoring. Regulators should consider introducing complex network analysis and other big-data tools to build a routine "Institutional Investor Interconnection Monitoring System." Such a system should prioritize identifying "super nodes" with abnormally elevated centrality that may serve as risk hubs, as well as tightly connected "clustering subgroups" prone to collective behavior. When assessing market risk, in addition to conventional valuation and liquidity metrics for individual stocks, regulators should penetrate to the "network topology of holders" behind them, issuing targeted early warnings for assets with high network vulnerability, thereby preemptively preventing liquidity dry-ups and price collapses triggered by network resonance.

For listed companies—especially small-scale firms in relatively weak information environments—management should be wary of the long-term risks inherent in over-reliance on institutional investor networks. While being heavily held by core funds may bring short-term valuation premiums and liquidity benefits, this study confirms that such benefits may come at the cost of reduced stock price informativeness and pricing efficiency. Companies should therefore strive to build more diversified and balanced investor bases, avoiding excessive concentration of influence in any single network cluster. At the same time, firms should shift from passive to proactive strategies by enhancing voluntary and forward-looking information disclosure, strengthening effective communication with independent analysts and retail investors, and cultivating diversified external information channels. This would reduce dependence on singular information dissemination networks and bolster the endogenous resilience of stock price stability.

For investors and market evaluation systems, this study calls for reflection on the prevailing fund performance evaluation culture. Evaluation mechanisms centered on short-term relative rankings have been shown to incentivize fund managers to abandon independent research and embed themselves in mainstream networks for the "safety of mediocrity." Fund evaluation agencies and large asset owners should therefore promote diversified evaluation standards, incorporating indicators such as investment strategy independence, deviation from market consensus (i.e., contribution to idiosyncratic risk), and other metrics into assessments. This would guide investment institutions back to the core functions of fundamental research and value discovery. For individual and institutional investors, when selecting fund products, they should look beyond short-term performance to assess the independence of investment behavior and degree of network embeddedness, thereby discerning asset managers who possess genuine Alpha-generating capabilities.

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Conflicts of Interest

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