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Can network centrality explain mutual fund alpha: Evidence from China☆

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ABSTRACT

This study examines how network centrality influences mutual fund performance among Chinese equity funds from 2007–2024. We construct networks using quarterly top-ten holdings where edges represent shared significant positions, and employ five complementary centrality measures: degree, closeness, betweenness, eigenvector, and structural holes to capture different dimensions of information access. Our findings reveal that funds occupying central network positions generate significantly higher risk-adjusted returns. We identify two key channels through which network effects operate. First, network advantages require active human management processes to transform soft information into returns, including dynamic portfolio rebalancing, discretionary strategy positioning, and strategic risk adjustment. Second, technological adoption disrupts this transformation pathway for funds with higher FinTech adoption and quantitative investment strategies, as automated systems substitute for the human judgment capabilities necessary to capitalize on network-derived information. Our results highlight the evolving trade-offs in modern asset management, where optimal investment strategies require balancing technological capabilities with the preservation of human management processes necessary to capitalize on discretionary information advantages.

1. Introduction

Information advantages fundamentally drive mutual fund performance, with managers seeking superior returns through access to diverse, timely, and high-quality information (Bai et al., 2021; Grossman & Stiglitz, 1980). Beyond public channels, fund managers access valuable information through networks formed by social connections (Cohen et al., 2005, 2008), geographic proximity (Hong et al., 2000; Pool et al., 2014), and shared investment strategies (Ozsoylev et al., 2013). These networks facilitate information transmission, with a fund's position determining its informational advantages and subsequent performance (Chen et al., 2021; Hochberg et al., 2007).

This paper examines mutual fund network positions and their impact on alpha in China's market for several compelling reasons. First, China's mutual fund industry has experienced explosive growth, with total net assets reaching RMB 32.83 trillion by December 2024, representing a 2.5-fold increase since the end of 2019. Over the same period, assets in equity funds more than doubled, rising from RMB 3.19 trillion to RMB 7.94 trillion, thereby providing rich cross-sectional and time-series variation for empirical analysis.

Second, unlike developed markets China's stock market is retail-dominated, with individual investors holding 99.71% of accounts and RMB 10.7 trillion in holding shares, relatively higher than that of institutional investors (RMB 9.5 trillion).[1] This retail dominance creates unique behaviors, including speculative trading, sentiment-driven decisions, and increased volatility (Leippold et al., 2022), requiring professional expertise to outperform.

Third, although the Chinese stock market has evolved to aggregate useful information about future profits and investment since 2004, frictions such as retail noise, post-2008 stimulus distortions for state-owned enterprises, and limited participation of foreign capital, market segmentation persists (Carpenter et al., 2021). Combined with less mature regulation and information asymmetries, price discovery remains relatively inefficient in the Chinese stock market than other mature markets (Gu et al., 2018). This inefficiency creates exploitable alpha for sophisticated domestic players and makes information channels, and thus central positions in the information network, considerably more valuable in China than in developed economies.

We construct fund networks using quarterly top-ten holdings, where nodes represent funds and edges capture shared significant positions.

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[1] According to the Shanghai Stock Exchange Statistics Annual 2024 (latest official document), as of year-end 2023, retail (natural person) investors held 4549.32 million fund accounts, representing 99.71% of all fund accounts (page 745).

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This approach reflects the premise that significant portfolio positions reveal managers' informational advantages (Bushee & Goodman, 2007; Crane et al., 2019), such that overlapping holdings indicate shared information access. We employ multiple centrality measures, including degree, closeness, betweenness, eigenvector, and structural holes, to capture different dimensions of information access.

Our main findings reveal that centrally positioned funds generate significantly higher risk-adjusted returns. We identify two key channels through which network effects operate on fund performance. First, network advantages are amplified when combined with active management behaviors, including dynamic portfolio rebalancing, discretionary strategy positioning, and strategic risk adjustment. Second, we document substitution effects where technological adoption diminishes the marginal benefits of network centrality.

We also document important heterogeneity in network effects across different market conditions and fund characteristics. The benefits of network centrality are most pronounced during bull markets, where information about investment opportunities creates significant value for well-connected funds, while these advantages largely disappear during bear markets. Additionally, we find that network effects exhibit a pronounced size gradient, with larger funds deriving substantially greater benefits from central network positions than smaller funds, suggesting important complementarities between network positioning and organizational resources.

These findings contribute to the literature in several ways. First, we extend network theory in finance by demonstrating that mutual fund networks based on common holdings can explain performance differentials in an emerging market context. Second, we identify an amplification channel through which network positioning enhances fund performance, showing that informational advantages require active managerial implementation to generate alpha. Third, we document a substitution channel whereby technological adoption undermines funds' ability to capitalize on network advantages, providing novel insights into how modern asset management is evolving.

The remainder of this paper proceeds as follows. Section 2 reviews relevant literature and develops our hypotheses. Section 3 describes our data and methodology. Section 4 presents the baseline empirical results. Section 5 examines the amplification and substitution channels. Section 6 discusses the heterogeneity across different market conditions and fund characteristics. Section 7 concludes.

2. Literature review and hypotheses

2.1. Fund networks, information transmission and fund performance

In the competitive landscape of asset management, the pursuit of superior returns is fundamentally a pursuit of information advantages (Grossman & Stiglitz, 1980). A growing body of literature recognizes that information is often idiosyncratic and diffuses through social and professional networks, creating significant performance heterogeneity among managers (Ozsoylev et al., 2013; Rossi et al., 2018). Understanding how these networks function has become increasingly critical as institutional investors manage larger and more complex portfolios.

Financial literature has identified two primary mechanisms through which fund managers acquire and share information, leading to superior investment performance. First, social networks provide direct channels for information transmission. Cohen et al. (2005) documented that fund managers are more likely to invest in companies with which they share alumni connections, and these connected holdings significantly outperform non-connected holdings, particularly around earnings announcements. This finding suggests that social networks provide fund managers with material informational advantages. Similarly, Cici et al. (2016) examined investment networks within fund families and found that while funds with similar styles exhibit high portfolio overlap, communication between funds with different styles expands their collective information sets, thereby enhancing overall family performance.

Second, physical proximity facilitates information sharing through enhanced social interactions (Christoffersen & Sarkissian, 2009; Coval & Moskowitz, 2001). Hong et al. (2000) showed that fund managers located in the same city exhibit significant mutual influence in their trading decisions, even after controlling for local preferences and investment styles, indicating the value of face-to-face interactions. Pool et al. (2014) provided more granular evidence, demonstrating that fund managers living within one mile of each other exhibit remarkably similar portfolio and trading behaviors that cannot be attributed solely to shared investment preferences.

The third type of study constructs networks based on overlap of the portfolios. The rationale is straightforward and well-grounded: regardless of whether valuable information originates from social ties, geographic proximity, or other channels, managers ultimately express their strongest informational edge in the stocks they weight most heavily in their portfolios (Crane et al., 2019; Kacperczyk et al., 2016). A large body of evidence shows that institutions taking sizable active positions in a stock are significantly more likely to be acting on private information and to earn superior returns on those positions (Bushee & Goodman, 2007; Ke & Petroni, 2004; Maffett, 2012; Yan & Zhang, 2009). Consequently, when two otherwise unrelated funds both allocate a large proportion of their portfolio to the same stock in the same quarter, this overlap is highly informative of shared private information rather than coincidence or public-signal-driven herding. This outcome-based inference is not speculative. Studies that first established a clean causal direction from observable social or geographic ties to portfolio and trading similarity (Cohen et al., 2008; Hong et al., 2005; Pool et al., 2014) imply that the reverse inference is valid when overlap is sufficiently large and deliberate. Pareek (2012) explicitly employs this reverse logic on U.S. mutual fund data, constructs quarterly networks from the same 5% high-conviction threshold, and demonstrates through extensive tests that the common-holding network captures genuine information diffusion. Ozsoylev et al. (2013) use a parallel outcome-based approach, inferring links from synchronized trading instead of holdings, confirm both in simulations and real data that the reconstructed network accurately recovers true information centrality.

Having established methods to identify information networks, the next critical question is how a fund's specific position within these networks affects its ability to access and benefit from shared information. Network centrality measures have emerged as the primary tools for quantifying positional advantages. Centrality analysis, widely used in social network theory, captures both an individual's strategic position and the strength of connections between network members (Ahern, 2017). Bonacich (2007) demonstrated that eigenvector centrality effectively measures information dissemination mechanisms by accounting for the quality of connections, not just their quantity. Bajo et al. (2016) provided empirical evidence that individuals with higher centrality measures exhibit greater information diffusion effects, translating network position into measurable outcomes.

The literature presents two competing theoretical perspectives on how network positions affect fund performance. *The information advantage hypothesis* suggests that networks enhance information transmission efficiency (He & Li, 2022). Under this view, centrally positioned fund managers receive signals earlier and access higher-quality information compared to peripheral managers, leading to superior investment decisions and positive performance effects (Cai & Sevilir, 2012; Hochberg et al., 2007; Rossi et al., 2018). Empirical support comes from studies showing that funds with higher closeness and eigenvector centrality achieve better risk-adjusted returns (Liu & Lee, 2010).

The free-rider hypothesis, however, suggests that network connections may actually harm performance through behavioral distortions (Han & Yang, 2013; Zhu, 2016). This perspective argues that social relationships reduce incentives for fund managers to acquire costly private information, as they can potentially free-ride on others' research efforts. Moreover, network connections may lead to herding behavior and groupthink, interfering with independent judgment and ultimately resulting in inferior performance for highly connected funds.

These competing perspectives reflect a fundamental tension in the network literature. Our study contributes to this debate by examining the Chinese mutual fund industry, where significant information asymmetries and prevalent informal information channels make network positioning particularly valuable for testing these competing theories. Based on the theoretical arguments favoring information advantages and the unique characteristics of the Chinese market, we propose our first hypothesis:

H1: Mutual funds with more central network positions generate higher risk-adjusted returns than their peripheral counterparts.

2.2. Active management behaviors and fund performance

While network centrality may provide informational advantages, the translation of these advantages into superior performance is not automatic but requires active managerial intervention. Understanding how fund managers actively utilize network-derived information is crucial for explaining the mechanism through which network centrality affects performance.

The literature on active management has established several key measures for identifying managerial behaviors that distinguish skilled managers from passive index followers. Grinold and Kahn (1999) introduced Tracking Error to measure active risk-taking relative to benchmarks, while Cremers and Petajisto (2009) developed Active Share to capture portfolio deviations from benchmark holdings, demonstrating that actively managed funds with higher Active Share generate superior risk-adjusted returns. Chen et al. (2000) established turnover ratios as indicators of trading intensity, and Kacperczyk et al. (2006) formalized the Return Gap measure to capture unobserved trading behaviors and their performance implications. More recently, Agarwal et al. (2024) developed Unobserved Performance measures that effectively capture active management through risk-adjusted return differences between reported and inferred returns.

However, this literature has largely focused on individual manager capabilities in isolation. A complementary stream of research demonstrates that fund managers operate within interconnected networks that fundamentally shape their information acquisition and decision-making processes (Cohen et al., 2008, 2010; Hong et al., 2004). Stein (2008) developed a theoretical framework showing that fund managers can generate superior insights through information exchange with competitors, provided they actively process and implement these insights. Hong et al. (2005) documented that fund managers' investment decisions are systematically influenced by interactions with peers, suggesting that network-derived information shapes active management strategies.

The mechanism through which network position enhances active management operates through several channels. First, central network positions provide access to diverse information sources, enabling fund managers to identify opportunities that peripheral managers might miss (Ozsoylev et al., 2013). Second, centrally positioned managers receive information earlier, allowing for more timely portfolio adjustments (Borgatti & Halgin, 2011). Third, network connections facilitate the validation and refinement of investment ideas through peer interactions, reducing uncertainty and enabling more confident active bets (Kaustia & Rantala, 2015).

Critically, these informational advantages only translate into superior performance when managers actively exploit them. Network-derived insights must be converted into concrete portfolio actions, whether through dynamic trading, strategic positioning, or calculated risk-taking, to generate measurable alpha. Passive recipients of network information who fail to act decisively may not capture the full benefits of their positional advantages. Based on this theoretical foundation, we propose our second hypothesis:

H2: The positive relationship between network centrality and fund performance is stronger for funds that exhibit higher levels of active management.

FinTech innovations, including artificial intelligence, machine learning algorithms, and big data analytics, fundamentally alter the investment management process by automating decision-making functions that previously required human judgment and discretion. Similarly, quantitative investment strategies rely on systematic, model-driven approaches that minimize subjective human interpretation and the contextual knowledge typically derived from professional networks. These technological approaches disrupt the transformation pathway through which network-derived information translates into investment performance.

This technological evolution creates a substitution effect whereby automated systems replace the active human management processes necessary to capitalize on network-based information advantages. As funds adopt more sophisticated technology or quantitative strategies, they lose the human discretionary capabilities required to interpret and act upon nuanced, peer-referenced insights. Funds with advanced FinTech capabilities or systematic investment approaches cannot effectively leverage network centrality because their automated decision-making systems lack the contextual judgment needed to convert social information into actionable investment strategies.

H3: The positive relationship between network centrality and fund performance is weaker for funds with higher FinTech adoption or those employing quantitative investment strategies.

3. Data, variables, and descriptive statistics

3.1. Data

For our empirical analysis, we examine equity mutual funds in China from 2007 to 2024, covering the rapid development period of China's mutual fund industry. Our primary data source is the China Stock Market & Accounting Research (CSMAR) database, supplemented by the Mingshi Database. CSMAR provides comprehensive information on Chinese mutual funds, including quarterly top ten holdings, total net assets, monthly returns, fund manager characteristics, and factor data necessary for risk-adjusted performance calculations. This sample period captures the full evolution of China's mutual fund network structure and provides sufficient variation for robust statistical analysis.

We apply several filters to construct our final sample. First, we focus exclusively on domestic actively managed equity mutual funds, excluding passive index funds, enhanced index funds, bond funds, money market funds, QDII (Qualified Domestic Institutional Investor) funds, and fund-of-funds (FOF) to ensure our analysis captures active management decisions. Second, we exclude funds with total net assets (TNA) below RMB 10 million to mitigate incubation bias, as these funds may exhibit atypical behavior during their early stages (Evans, 2010).

We implement additional filters to address potential confounding effects from extreme market events. Coval and Stafford (2007) demonstrate that massive capital flows can mechanically alter fund holdings independent of managerial decisions, potentially distorting network centrality measures. Our sample period encompasses significant market disruptions, including the 2015 Chinese stock market turbulence and the 2020 COVID-19 pandemic, both of which triggered substantial fund flows. Following Coval and Stafford (2007), we exclude fund-quarter observations with extreme flow-induced changes, specifically removing observations where quarterly TNA changes exceed 200% (indicating massive inflows) or fall below −50% (indicating massive outflows).[2] This filter ensures our network measures reflect genuine information-driven portfolio decisions rather than flow-induced mechanical adjustments.

[2] his exclusion removes 1078 observations, constituting only 2.72% of the total sample. The (unreported) results show that including these observations yields virtually identical estimates, suggesting that the exclusion does not introduce systematic selection bias.

3.2. Measuring network structure

The quarterly holdings disclosures form the foundation of our network construction. Chinese regulations require mutual funds to disclose their top ten equity holdings at the end of each quarter, representing the fund managers' most significant investment decisions and the valuable information they have processed throughout that period (Crane et al., 2019; Kacperczyk et al., 2016). These holdings reflect the cumulative impact of information acquisition, analysis, and portfolio implementation over the quarter. Since fund managers continuously incorporate new information into their investment decisions, the end-of-quarter positions represent the equilibrium outcome of their information processing and strategic positioning. This makes quarterly holdings an ideal basis for constructing information networks that capture the underlying patterns of information sharing and competitive positioning among fund managers.

We construct fund networks based on portfolio overlap, following the established approach of Pareek (2012). In our network representation, nodes represent individual mutual funds, and edges capture information linkages inferred from shared significant holdings. We establish a connection between two funds if they simultaneously hold the same stock, with each fund allocating more than 5% of its portfolio to that stock.[3] This 5% threshold ensures we capture meaningful strategic positions rather than incidental holdings, as funds typically concentrate their largest convictions in their top holdings.

The weight of each edge quantifies the connection strength as the number of such overlapping significant positions. Formally, for funds i and j in quarter q, the edge weight $w_{i,j,q}$ is:

$$w_{i,j,q} = \sum_{k=1}^{K} \mathbb{I}(w_{i,k,q} > 0.05 \text{ and } w_{j,k,q} > 0.05),$$

where $w_{i,k,q}$ represents fund i's portfolio weight in stock k during quarter q, and $\mathbb{I}(\cdot)$ is an indicator function. This approach generates a time-varying, weighted adjacency matrix that captures the evolving information network structure.

We employ five complementary centrality measures to capture different dimensions of informational advantage within the network. These measures collectively provide a comprehensive view of fund positioning: degree centrality captures the breadth of direct connections, closeness centrality measures information access efficiency, betweenness centrality identifies information brokers, eigenvector centrality weights connection quality, and structural holes measure access to diverse information sources. This multi-dimensional approach ensures our analysis is robust to alternative conceptualizations of network advantage.

Degree centrality measures the breadth of a fund's direct network connections, reflecting its potential access to diverse information sources (Freeman, 1978). For fund i in quarter q, degree centrality is defined as:

$$Degree_{i,q} = \frac{d_{i,q}}{N_q - 1},$$

where $d_{i,q}$ represents the number of funds directly connected to fund i, and N_q is the total number of active funds in quarter q. This normalized measure ranges from 0 to 1, where higher values indicate more extensive direct connections.

Closeness centrality measures how efficiently a fund can access information from all other network participants, capturing the speed of potential information acquisition (Sabidussi, 1966). For fund i in quarter q:

$$Closeness_{i,q} = \frac{N_q - 1}{\sum_{j \neq i} l_q(i,j)},$$

where $l_q(i,j)$ represents the shortest path distance between funds i and j. Higher values indicate that a fund can reach other network participants through fewer intermediaries, suggesting faster information transmission.

Betweenness centrality measures a fund's role as an information intermediary, capturing its ability to control information flows between other network participants (Freeman, 1977). For fund i in quarter q:

$$Betweenness_{i,q} = \sum_{j \neq i, k \neq i, j \neq k} \frac{\sigma_{jk}(i)}{\sigma_{jk}},$$

where σ_{jk} is the number of shortest paths between funds j and k, and $\sigma_{jk}(i)$ is the number of those paths passing through fund i. The measure is normalized by the maximum possible betweenness centrality. Funds with high betweenness centrality occupy strategic positions as information gatekeepers.

Eigenvector centrality extends beyond simple connectivity by weighting connections according to the centrality of connected nodes. A fund achieves high eigenvector centrality when connected to other highly central funds, reflecting access to high-quality information sources (Wang, 2024). For fund i in quarter q:

$$Eigenvector_{i,q} = \frac{1}{\lambda} \sum_{j=1}^{N_q} A_{i,j,q} \cdot Eigenvector_{j,q},$$

where $A_{i,j,q}$ is the adjacency matrix element indicating connection strength between funds i and j, and λ is the largest eigenvalue of the adjacency matrix. This measure captures information quality rather than quantity.

Structural holes measure a fund's ability to bridge disconnected network segments, providing access to diverse, non-redundant information (Burt, 1992). Funds spanning structural holes connect otherwise separate groups, potentially accessing unique information combinations. We calculate structural holes as:

$$StructureHole_{i,q} = 1 - \sum_{j} \left(p_{i,j,q} + \sum_{k \neq i,j} p_{i,k,q} p_{k,j,q} \right)^2,$$

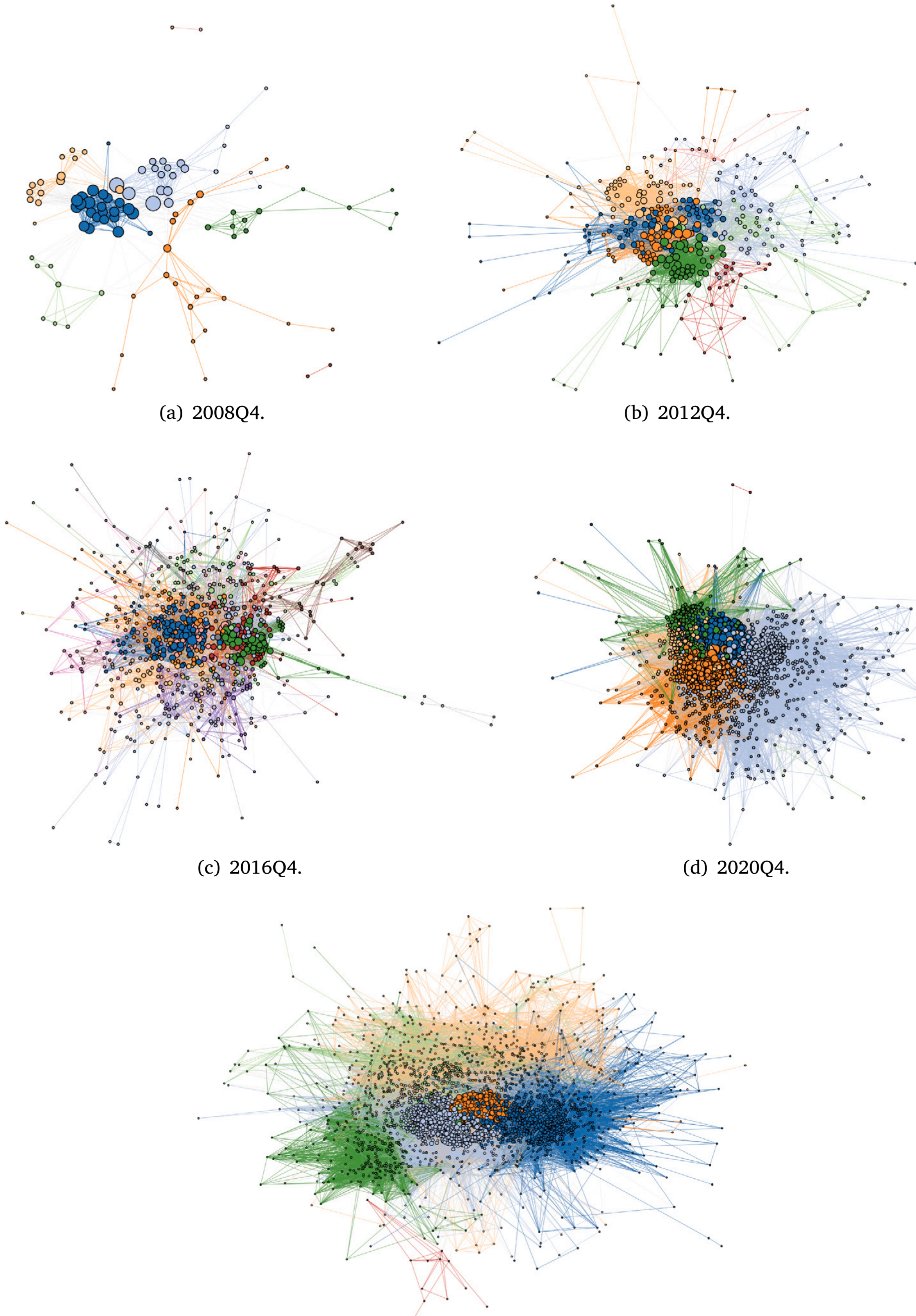
where $p_{i,j,q}$ represents the proportion of fund i's network connections allocated to fund j, calculated as the ratio of the connection strength between i and j to fund i's total connection strength. The term $\sum_k p_{i,k,q} p_{k,j,q}$ captures indirect connections between funds i and j through intermediary k. The constraint term (subtracted from 1) measures how much a fund's connections overlap, with higher constraint indicating redundant information sources.

Understanding the evolution of fund networks is crucial for establishing that network positioning represents a meaningful and time-varying source of informational advantage. Fig. 1 illustrates the structural transformation of China's mutual fund network from 2008 to 2024.

The network exhibits substantial growth and densification over time, creating increasingly integrated information structures. In early periods (2008Q4), the fragmented network with numerous isolated nodes and small clusters suggests limited information sharing across the industry. As the network evolves through 2012Q4 and 2016Q4, we observe the formation of a more cohesive central core surrounded by connected peripheral nodes.

By 2024Q4, the network transforms into a highly integrated and dense structure where most funds are interconnected within a single large component. This evolution demonstrates a shift from fragmented information silos to an integrated information environment where network positioning becomes crucial for accessing information flows.

[3] For example, suppose Fund A holds 6% of its portfolio in Stock X, and Fund B holds 4% of its portfolio in Stock X. Even though they share a common holding, no connection is formed because Fund B's allocation is below the 5% threshold. However, if Fund B increases its allocation in Stock X to 7%, a connection (edge) is established between Fund A and Fund B, as both funds now hold Stock X at a weight exceeding 5%. The weight of this edge would then be calculated based on the number of such qualifying overlapping stocks.



(a) 2008Q4. (b) 2012Q4.

(c) 2016Q4. (d) 2020Q4.

(e) 2024Q4.

Fig. 1. Evolution of mutual funds network.
Note: Each subfigure displays the mutual fund co-holding network for the specified quarter. Nodes represent mutual funds (sized by degree centrality), and colors denote detected communities based on the Leiden Community Detection Algorithm. Network visualization begins in 2008Q4 when sufficient funds existed to form meaningful network structures.

The increasing network density and the emergence of a cohesive network structure provide the empirical foundation for testing whether network positioning creates informational advantages. The evolved network offers sufficient variation in centrality measures to examine whether funds' positions within the interconnected structure are associated with performance differentials, which we investigate in our subsequent empirical analysis.

3.3. Mutual funds alpha

To evaluate fund performance, we use risk-adjusted returns (alpha) estimated from factor models. Given the unique characteristics of China's equity market, we employ the Chinese four-factor model proposed by Liu et al. (2019), which adapts the international factor framework to better capture Chinese market dynamics. This model includes:

(1) MKT: market excess return over risk-free rate; (2) SMB: size factor capturing small-minus-big market capitalization effects; (3) VGM: value-growth-momentum factor based on earnings-to-price ratios; and (4) PMO: sentiment factor capturing momentum effects specific to Chinese markets. We calculate fund alpha using a three-step procedure designed to avoid look-ahead bias while maintaining statistical reliability:

First, we estimate factor loadings using 24-month rolling window regressions:

$$R_{i,m} = \alpha_{i,m} + \beta_{MKT,i,m} MKT_m + \beta_{SMB,i,m} SMB_m + \beta_{VGM,i,m} VGM_m + \beta_{PMO,i,m} PMO_m + \epsilon_{i,m}, \tag{1}$$

where $R_{i,m}$ is fund i's monthly excess return over the risk-free rate.[4] Factor loadings are estimated monthly using the most recent 24 months of data to capture time-varying risk exposures.

Second, we compute expected returns using lagged factor loadings to avoid look-ahead bias:

$$R^{expected}_{i,m} = \hat{\beta}_{MKT,i,m-1} MKT_m + \hat{\beta}_{SMB,i,m-1} SMB_m + \hat{\beta}_{VGM,i,m-1} VGM_m + \hat{\beta}_{PMO,i,m-1} PMO_m. \tag{2}$$

Finally, quarterly alpha is calculated as the difference between realized and expected returns:

$$Alpha_{i,q} = R_{i,q} - \left[\prod_{m \in q} \left(1 + R^{expected}_{i,m} \right) \right] + 1, \tag{3}$$

where quarterly expected returns are geometrically compounded from monthly estimates.

3.4. Control variables

To isolate the effect of network positioning on fund performance, we include comprehensive controls for alternative explanations of performance variation. Our control variables operate at two levels: fund characteristics and manager characteristics.

Fund-level controls include fund size (total net assets), fund family size, fund flow (capturing investor demand), fund age (experience proxy), turnover ratio (trading intensity), and volatility (risk preference). These variables control for scale effects, institutional resources, and fund-specific risk characteristics that may correlate with both network positioning and performance.

Manager-level controls capture team composition and educational background that may influence investment decisions independently of network effects. We include team size (number of named managers), educational credentials (PhD dummy, CFA designation), and elite education (graduates from China's top four universities: Peking, Tsinghua, Fudan, or Shanghai Jiao Tong). In addition, manager forecasting skill controls are crucial for addressing potential omitted variable bias. If managerial abilities simultaneously influence both fund performance and network positions, failing to control for these skills could bias our estimates of network effects. Following Kacperczyk et al. (2014), we construct measures of market timing and stock picking skills using funds' top 10 holdings:

Market timing skill captures managers' ability to anticipate market movements:

$$Timing_{i,q} = \sum_{s=1}^{10} (w^i_{s,q} - w^m_{s,q})(\beta_{s,q} R^m_{q+1}).$$

Stock picking skill measures managers' ability to forecast individual stock performance:

$$Picking_{i,q} = \sum_{s=1}^{10} (w^i_{s,q} - w^m_{s,q})(R_{s,q+1} - \beta_{s,q} R^m_{q+1}),$$

where $w^i_{s,q}$ and $w^m_{s,q}$ are stock weights in fund and market portfolios, $\beta_{s,q}$ is the stock's market beta, and R^m_{q+1} is market return in quarter $q+1$. The intuition underlying both measures is that skilled managers can forecast future returns and position their portfolios accordingly. Positive values indicate that managers successfully overweighted assets that subsequently outperformed and underweighted those that underperformed.

Table 1 presents descriptive statistics for our sample of 38,496 fund-quarter observations. Our dependent variable, $Alpha_{q+1}$, shows positive average risk-adjusted performance (1.66%) with substantial cross-sectional variation (standard deviation of 7.54%), ranging from −84.71% to 102.93%, providing sufficient performance heterogeneity for our analysis.

The network centrality measures exhibit considerable variation across funds, indicating heterogeneous network positions. Degree centrality has a mean of 12.67% with a wide interquartile range (2.42% to 21.64%), spanning from near-isolation (0.03%) to 62.09% connectivity, reflecting that some funds maintain extensive direct connections while others remain relatively isolated. Betweenness centrality is highly skewed, with most funds having minimal bridging roles (median = 0.02%) while a few occupy critical intermediary positions (maximum = 8.58%). Eigenvector centrality shows similar patterns, where most funds have limited connections to other central funds (median = 0.51%) but some achieve highly influential network positions (maximum = 22.73%).

Table 2 reports the correlations among the five centrality measures. While Degree and Closeness are highly correlated ($\rho = 0.77$), other measures capture distinct network roles. Notably, Betweenness is weakly correlated with Degree ($\rho = 0.12$) and virtually uncorrelated with Closeness, highlighting that the bridging function is unique compared to mere connectivity. Eigenvector shows a moderate correlation with Degree ($\rho = 0.65$), suggesting that connection quality is distinct from quantity. Finally, StructureHole is associated with Closeness ($\rho = 0.76$) but shares only modest overlap with Degree ($\rho = 0.37$). Overall, these varying correlations indicate that these measures reflect different dimensions of information advantage.

Fund characteristics show typical patterns for the Chinese mutual fund industry. The average fund manages approximately 520 million RMB (log size = 6.23) and belongs to fund families managing around 31 billion RMB (log family size = 10.34). Funds experience negative average flows (−0.35%), reflecting the competitive nature of the Chinese mutual fund market. Manager skill measures reveal positive average timing ability (2.21%) but negative stock picking ability (−1.76%), consistent with the difficulty of security selection in emerging markets.

The sample demonstrates strong managerial credentials: for 30.77% of the 38,496 fund-quarter observations, the managing team includes a Top4 graduate; 13.01% of observations are managed by a team including a PhD holder; and 4.80% of observations possess a CFA certification. The substantial variation in all key variables provides adequate power for identifying network effects on fund performance.

4. Main results

4.1. Network centrality and fund performance

We examine the relationship between network centrality and risk-adjusted performance using the following specification:

$$Alpha_{i,q+1} = \alpha + \beta \cdot Centrality_{i,q} + \gamma \cdot Controls_{i,q} + \delta_t + \mu_i + \epsilon_{i,q} \tag{4}$$

where $Alpha_{i,q+1}$ is fund i's risk-adjusted return in quarter $q+1$, $Centrality_{i,q}$ represents various network centrality measures in quarter q, $Controls_{i,q}$ includes fund and manager characteristics, δ_t and μ_i are year and fund fixed effects, respectively. We use year fixed effects rather than quarter fixed effects following Crane et al. (2019), as macroeconomic factors that may affect fund performance typically vary

[4] Our monthly risk-free rate is the monthly one-year deposit rate published by the People's Bank of China, which are obtained from the Shanghai Mingshi Database.

Table 1
Descriptive statistics.

	Obs	Mean	Median	Std	P25	P75	Min	Max
$Alpha_{q+1}$	38 496	0.0166	0.0084	0.0754	−0.0248	0.0521	−0.8471	1.0293
Degree	38 496	0.1267	0.0752	0.1254	0.0242	0.2164	0.0003	0.6209
Closeness	38 496	0.4671	0.4793	0.0816	0.4235	0.5270	0.0002	0.6702
Betweenness	38 496	0.0009	0.0002	0.0023	0.0000	0.0008	0.0000	0.0858
Eigenvector	38 496	0.0145	0.0051	0.0206	0.0009	0.0224	0.0000	0.2273
StructureHole	38 496	0.9340	0.9838	0.1422	0.9452	0.9935	−0.3889	0.9973
$Alpha_{q-1}$	38 496	0.0186	0.0100	0.0762	−0.0239	0.0547	−0.8471	1.8354
$Alpha_{q-2}$	38 496	0.0202	0.0120	0.1867	−0.0222	0.0577	−33.3401	1.8354
Timing	38 496	0.0221	0.0122	0.0501	−0.0069	0.0477	−0.2962	0.4004
Picking	38 496	−0.0176	−0.0166	0.0483	−0.0420	0.0062	−0.3788	0.4471
logSize	38 496	6.2314	6.3227	1.5765	5.0771	7.4114	2.3074	11.4063
logFamilySize	38 496	10.3446	10.4471	1.4442	9.5359	11.4227	2.3934	13.1267
FundFlow	38 496	−0.0035	−0.0416	0.2512	−0.1118	0.0360	−0.4995	1.9945
FundAge	38 496	7.4697	6.4167	3.9986	4.2500	9.7500	2.0833	22.2500
Turnover	38 496	6.8534	5.0648	11.4623	3.2462	7.8043	0.0000	1003.5755
Volatility	38 496	0.0878	0.0823	0.0300	0.0679	0.1004	0.0260	0.4209
TeamSize	38 496	1.4622	1.0000	1.0330	1.0000	2.0000	1.0000	10.0000
PhD	38 496	0.1301	0.0000	0.3364	0.0000	0.0000	0.0000	1.0000
Top4	38 496	0.3077	0.0000	0.4616	0.0000	1.0000	0.0000	1.0000
CFA	38 496	0.0480	0.0000	0.2138	0.0000	0.0000	0.0000	1.0000

This table presents descriptive statistics for our sample of 38,496 fund-quarter observations. $Alpha_{q+1}$ is the fund's risk-adjusted return using the Chinese four-factor model (Liu et al., 2019). Network centrality measures include degree centrality (Degree), closeness centrality (Closeness), betweenness centrality (Betweenness), eigenvector centrality (Eigenvector), and structural hole measure (StructureHole). Past performance controls include $Alpha_{q-1}$ and $Alpha_{q-2}$ measured in quarters $q-1$ and $q-2$, respectively. Manager skill variables follow Kacperczyk et al. (2014): Timing captures market timing ability and Picking measures stock selection skill, both calculated using funds' top 10 holdings. Fund characteristics include logSize (logarithm of total net assets), logFamilySize (logarithm of fund family size), FundFlow (quarterly net fund flows calculated as the change in fund size minus return-adjusted growth, scaled by lagged size), FundAge (years since fund inception), Turnover (quarterly portfolio turnover based on top 10 holdings), and Volatility (24-month rolling standard deviation of returns). Manager characteristics include TeamSize (number of fund managers), and three education dummies: PhD (any team member holds a PhD), Top4 (any team member graduated from Tsinghua, Peking, Fudan, or Shanghai Jiao Tong University), and CFA (any team member holds CFA certification).

Table 2
Correlation matrix of centrality measures.

Variable	Degree	Closeness	Betweenness	Eigenvector	StructureHole
Degree	1.0000				
Closeness	0.7726	1.0000			
Betweenness	0.1173	−0.0031	1.0000		
Eigenvector	0.6484	0.3744	0.4306	1.0000	
StructureHole	0.3744	0.7566	0.0412	0.2119	1.0000

This table presents the correlation matrix for the network centrality measures used in the analysis. The measures include degree centrality, closeness centrality, betweenness centrality, eigenvector centrality, and structural hole measure.

at an annual frequency. Standard errors are clustered at the fund level to account for serial correlation.

Table 3 presents our main results. All centrality measures yield positive coefficients, and four out of five are statistically significant, generally supporting H1 that centrally positioned funds outperform peripheral peers. Degree centrality shows a positive and highly significant effect (β = 0.0240, t = 6.55), where a one-standard-deviation increase corresponds to a 0.30% quarterly alpha gain, representing 18.1% of mean performance. The intuition is that funds with extensive direct connections can aggregate diverse information from numerous network participants, enabling them to identify mispriced securities before this information becomes widely available. In China's high-turnover market where information asymmetries are pronounced, this breadth of information access provides a significant competitive advantage.

The remaining centrality measures yield positive effects with varying degrees of statistical significance. Closeness centrality (β = 0.0523, t = 8.75), eigenvector centrality (β = 0.0730, t = 3.17), and structural hole positioning (β = 0.0131, t = 4.91) are all significant at the 1% level. Betweenness centrality demonstrates a much smaller coefficient (β = 0.0241) and is not statistically significant (t = 0.11), contrary to the findings for other measures.

The positive and significant effects across most centrality dimensions demonstrate that network positioning creates multiple pathways to informational advantage. These results support our core hypothesis that information networks generate systematic performance differentials. However, the economic magnitudes vary substantially across centrality measures, ranging from 0.3% to 25.7% of mean quarterly alpha per standard-deviation change in centrality. Closeness centrality generates the largest economic effect (25.7% of mean alpha), while betweenness centrality shows a negligible economic impact, suggesting that certain network advantages are more economically relevant than others.

4.2. Identification and endogeneity concern

A potential concern in network analysis is endogeneity arising from reverse causality. Specifically, the "imitation hypothesis" suggests that successful funds attract copycats, mechanically increasing the centrality of past winners. We address this identification challenge through two complementary approaches: institutional constraints and information decay dynamics.

First, we exploit the unique disclosure timeline of the Chinese market to rule out mechanical imitation. As illustrated in Fig. A.1, detailed portfolio holdings in China are disclosed with a mandatory lag of up to 15 trading days after quarter-end. Consequently, a fund attempting to imitate a peer in quarter q can only observe that peer's holdings from quarter $q-1$. Since our network is constructed based on concurrent overlapping positions in quarter q, the connections we observe cannot be the result of real-time imitation, as the peer's current portfolio is not yet public.

Second, to distinguish between temporary information advantages and persistent managerial skill (or sticky imitation), we examine the predictive power of network centrality over longer horizons ($q+2$ through $q+8$). If centrality proxied for persistent skill or mechanical herding, its predictive power should remain stable over time. In con-

Table 3
Baseline results.

	(1) $Alpha_{q+1}$	(2) $Alpha_{q+1}$	(3) $Alpha_{q+1}$	(4) $Alpha_{q+1}$	(5) $Alpha_{q+1}$
Degree	0.0240***				
	(6.55)				
Closeness		0.0523***			
		(8.75)			
Betweenness			0.0241		
			(0.11)		
Eigenvector				0.0730***	
				(3.17)	
StructureHole					0.0131***
					(4.91)
$Alpha_{q-1}$	−0.0706***	−0.0716***	−0.0692***	−0.0697***	−0.0699***
	(−9.56)	(−9.70)	(−9.44)	(−9.50)	(−9.54)
$Alpha_{q-2}$	0.0255***	0.0256***	0.0273***	0.0269***	0.0269***
	(4.62)	(4.63)	(4.96)	(4.87)	(4.88)
Timing	0.1046***	0.1058***	0.1056***	0.1047***	0.1058***
	(11.67)	(11.84)	(11.78)	(11.69)	(11.81)
Picking	0.7662***	0.7658***	0.7631***	0.7636***	0.7637***
	(58.25)	(58.39)	(58.15)	(58.24)	(58.25)
logSize	−0.0064***	−0.0064***	−0.0063***	−0.0063***	−0.0063***
	(−9.25)	(−9.34)	(−9.10)	(−9.11)	(−9.21)
logFamilySize	−0.0003	−0.0002	−0.0000	0.0001	0.0000
	(−0.21)	(−0.16)	(−0.02)	(0.04)	(0.02)
FundFlow	0.0034**	0.0036**	0.0029*	0.0031*	0.0031*
	(2.12)	(2.26)	(1.83)	(1.95)	(1.96)
FundAge	−0.0084***	−0.0086***	−0.0084***	−0.0083***	−0.0085***
	(−8.03)	(−8.20)	(−7.99)	(−7.94)	(−8.11)
Turnover	−0.0002***	−0.0003***	−0.0002***	−0.0002***	−0.0002***
	(−3.97)	(−4.01)	(−3.78)	(−3.88)	(−3.88)
Volatility	0.1503***	0.1595***	0.1491***	0.1500***	0.1525***
	(6.75)	(7.15)	(6.72)	(6.75)	(6.88)
TeamSize	−0.0003	−0.0002	−0.0003	−0.0003	−0.0003
	(−0.58)	(−0.46)	(−0.58)	(−0.54)	(−0.51)
PhD	−0.0001	−0.0003	−0.0000	−0.0001	−0.0001
	(−0.05)	(−0.14)	(−0.00)	(−0.05)	(−0.07)
Top4	−0.0001	−0.0001	−0.0002	−0.0001	−0.0002
	(−0.04)	(−0.06)	(−0.12)	(−0.07)	(−0.11)
CFA	0.0014	0.0012	0.0010	0.0011	0.0009
	(0.46)	(0.41)	(0.35)	(0.37)	(0.31)
Cons	−0.0322	−0.0547**	−0.0283	−0.0333	−0.0400*
	(−1.39)	(−2.34)	(−1.16)	(−1.42)	(−1.70)
Fund FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	38 496	38 496	38 496	38 496	38 496
R^2	0.330	0.331	0.329	0.329	0.330

This table examines the impact of network centrality on mutual funds' risk-adjusted returns. Columns (1) through (5) present regression results for degree centrality, closeness centrality, betweenness centrality, eigenvector centrality, and structural hole measures, respectively. The dependent variable $Alpha_{q+1}$ is the fund's alpha in the subsequent quarter using the Chinese four-factor model proposed by Liu et al. (2019). $Alpha_{q-1}$ and $Alpha_{q-2}$ are past performance in quarters $q-1$ and $q-2$, respectively. Following Kacperczyk et al. (2014), Timing and Picking are fund managers' time-varying market timing and stock picking skills. logSize is the logarithm of fund size (total net assets). logFamilySize is the logarithm of fund family size. FundFlow is the net inflow into a fund in a quarter, defined as the change in fund size relative to the prior quarter minus the return on the prior quarter's fund size, divided by the prior quarter's size. Turnover is the fund's quarterly turnover ratio, calculated by summing the absolute changes in market value across the top 10 holdings from the previous quarter to the current quarter, then dividing this total by twice the average fund size over the period. FundAge is the time elapsed since the fund's inception. Volatility is the standard deviation of a fund's return using a 24-month rolling window. TeamSize is the number of managers in a fund. PhD is a dummy variable that equals 1 if any fund manager in the team has a PhD, and 0 otherwise. Top4 is a dummy variable that equals 1 if any fund manager in the team graduated from Tsinghua University, Peking University, Fudan University, or Shanghai Jiaotong University, and 0 otherwise. CFA is a dummy variable that equals 1 if any fund manager in the team has CFA certification, and 0 otherwise. T-statistics are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively. Standard errors are clustered at the fund level.

trast, Table A.1 reveals that while centrality strongly predicts alpha in the immediate subsequent quarter ($q+1$), this predictive power decays rapidly and even reverses in $q+2$ before becoming insignificant. This pattern aligns with Hong and Stein (1999)'s model of information diffusion, where early information access yields immediate returns followed by a reversal as the signal becomes crowded. The transitory nature of these effects supports our interpretation that network centrality captures short-lived informational edges rather than persistent skill or mechanical imitation.

4.3. Robustness test

We examine the robustness of our empirical results through several alternative specifications to ensure our findings are not driven by specific methodological choices.

First, we test whether our results are sensitive to the choice of asset pricing model used to calculate fund alpha. Our baseline analysis uses the Chinese four-factor mode, but different risk models may yield different risk-adjusted performance measures. We re-estimate our main regressions using four alternative models: the Chinese three-factor model (Liu et al., 2019), which controls for market, size, and value factors tailored to Chinese market characteristics; the Fama–French three-factor model (Fama & French, 1993), which controls for market, size, and book-to-market factors; the Carhart four-factor model (Carhart, 1997), which extends the Fama–French model by adding a momentum factor; and the Fama–French five-factor model (Fama & French, 2015), which additionally includes profitability and investment factors. Table 4 shows that our results remain robust across all specifications. Notably, only the betweenness centrality coefficient becomes insignificant in the Carhart four-factor model (Panel C), while all other centrality measures maintain their positive and significant effects across all risk models.

Second, we examine whether our findings are sensitive to the specific definition of network connections. Our baseline network uses a 5% threshold for common holdings among the top 10 positions, which may be somewhat restrictive. We reconstruct the network using a more lenient (3% and 4%) and more stringent threshold (6% and 7%), which respectively create denser and looser connections between funds. Table 5 presents the results. While betweenness and eigenvector centrality lose significance under this alternative specification, degree, closeness, and structure hole centrality remain positively significant, confirming that our main findings are robust to reasonable variations in network construction.

5. The role of managerial activeness

Having established the positive effect of network centrality on fund performance, we investigate how managerial activeness moderates this relationship. Our theoretical framework posits that managerial activeness plays a central role in converting network-derived information advantages into superior performance (H2). This hypothesis reflects the fundamental insight that information advantages do not automatically translate into alpha but require deliberate managerial intervention to materialize as outperformance. Conversely, when technological tools substitute for active human decision-making, the value of traditional network-based information channels diminishes (H3).

5.1. Active portfolio management strategies

We examine three dimensions of managerial activeness that enable the conversion of network-derived information into alpha: dynamic portfolio rebalancing, discretionary strategy positioning, and risk shifting behavior. Together, these measures capture how managers can actively exploit their informational edge to generate superior risk-adjusted returns.

5.1.1. Dynamic portfolio rebalancing

Network-positioned managers who receive timely information about individual stocks or market conditions must act on these insights through active trading to generate alpha. To capture this unobserved trading activity, we employ the absolute return gap measure, which reflects interim trades not captured in periodic portfolio disclosures.

Following Kacperczyk et al. (2006), we calculate the return gap as the difference between a fund's reported gross return and the buy-and-hold return of its disclosed positions:

$$RG_{i,q} = RF_{i,q} - (RH_{i,q} - EXP_{i,q}), \tag{5}$$

where $RF_{i,q}$ represents fund i's quarterly gross return:

$$RF_{i,q} = \frac{NAV_{i,q} + D_{i,q} + CG_{i,q} - NAV_{i,q-1}}{NAV_{i,q-1}}, \tag{6}$$

and $RH_{i,q}$ captures the hypothetical buy-and-hold return based on disclosed holdings:

$$RH_{i,q} = \sum_{s=1}^{n} \widetilde{w}_s^i R_{s,q}. \tag{7}$$

Here, $EXP_{i,q}$ is the fund's expense ratio, $D_{i,q}$ and $CG_{i,q}$ represent dividends and capital gains distributions, $\widetilde{w}_s^i$ is the disclosed weight of stock s in fund i's most recent portfolio filing, and $R_{s,q}$ is stock s's quarterly return.

The return gap captures unobserved managerial actions between disclosure periods. When managers make value-creating interim trades based on new information, fund returns $RF_{i,q}$ will reflect these gains while the buy-and-hold return $RH_{i,q}$ remains unaffected until the next disclosure. Following Gupta-Mukherjee (2013), we focus on the absolute return gap to isolate trading intensity from performance direction:

$$|RGap_{i,q}| = |RF_{i,q} - (RH_{i,q} - EXP_{i,q})|. \tag{8}$$

This measure serves as a pure proxy for trading intensity and dynamic rebalancing activity, allowing us to capture managerial activeness independent of whether interim trades were profitable.

To test whether network-positioned managers generate higher alpha through active rebalancing, we estimate:

$$\begin{aligned} Alpha_{i,q+1} =& \alpha + \beta_1 Centrality_{i,q} + \beta_2 ABSRG_{i,q} + \beta_3 Centrality_{i,q} \\ &\times ABSRG_{i,q} \\ &+ \gamma Controls_{i,q} + \delta_t + \mu_i + \epsilon_{i,q}, \end{aligned} \tag{9}$$

where $ABSRG_{i,q}$ is a dummy variable equal to one if fund i's absolute return gap $|RGap_{i,q}|$ exceeds the median. The coefficient β_3 captures the incremental alpha generated when network advantages combine with active portfolio management.

Table 6 presents the results. The positive and statistically significant coefficients on all interaction terms except confirm that dynamic portfolio rebalancing serves as a critical channel through which network-positioned funds convert information advantages into alpha.

The standalone network effects reveal an important insight: except for closeness centrality ($\beta = 0.0217$, $t = 3.33$), network positions generate limited or insignificant alpha without active portfolio management. For example, in column (5), structural hole positioning alone yields an insignificant coefficient of 0.0042 ($t = 1.37$), but when combined with high rebalancing activity ($StructureHole \times ABSRG$), it generates a 0.19% additional alpha gain ($\beta \times \sigma = 0.0160 \times 0.1422 \approx 0.00227$), significant at the 1% level ($t = 3.33$). This stark contrast demonstrates that network-derived information advantages require managerial action to materialize as superior performance.

The economic magnitudes are substantial. The coefficient on $Degree \times ABSRG$ (0.0412, $t = 8.13$) indicates that a one-standard-deviation increase in degree centrality, combined with high rebalancing activity, raises next-quarter alpha by 0.52%, equivalent to 31.1% of mean quarterly alpha. Similarly, the interactions for closeness ($Closeness \times ABSRG = 0.0533$) and eigenvector centrality ($Eigenvector \times ABSRG = 0.1651$) show large and significant effects, confirming that both the efficiency and quality of information require dynamic execution to generate alpha.

These findings support our central thesis that information advantages derived from network positioning translate into outperformance primarily through active managerial intervention. Managers must dynamically adjust their portfolios to exploit informational edges, transforming network connectivity into measurable risk-adjusted returns.

5.1.2. Discretionary strategy positioning

In addition to portfolio rebalancing, how funds position their strategic bets also matters. Discretionary strategy positioning refers to a manager's willingness to deviate from benchmark-driven or factor-neutral strategies to pursue idiosyncratic investment opportunities based on their unique insights and convictions. A manager with an information advantage may choose to deviate from conventional, factor-driven strategies to capitalize on unique insights.

To capture this dimension of activeness, we use Fund IVOL, which is fund's idiosyncratic volatility to represent fund manager's discretionary strategy positioning. This measure is computed as the standard

Table 4
Robustness checks: alternative factor models.

	(1) $Alpha_{q+1}$	(2) $Alpha_{q+1}$	(3) $Alpha_{q+1}$	(4) $Alpha_{q+1}$	(5) $Alpha_{q+1}$
Panel A: Chinese three-factor model					
Degree	0.0179***				
	(5.22)				
Closeness		0.0320***			
		(5.53)			
Betweenness			0.1287		
			(0.58)		
Eigenvector				0.0514**	
				(2.30)	
StructureHole					0.0069***
					(2.62)
N	38 496	38 496	38 496	38 496	38 496
R^2	0.333	0.333	0.333	0.333	0.333
Panel B: Fama–French five-factor model					
Degree	0.0357***				
	(9.94)				
Closeness		0.0684***			
		(11.02)			
Betweenness			0.1881		
			(0.75)		
Eigenvector				0.1217***	
				(4.83)	
StructureHole					0.0143***
					(4.88)
N	38 496	38 496	38 496	38 496	38 496
R^2	0.266	0.267	0.265	0.265	0.265
Panel C: Carhart four-factor model					
Degree	0.0293***				
	(8.79)				
Closeness		0.0639***			
		(10.72)			
Betweenness			0.0559		
			(0.26)		
Eigenvector				0.0897***	
				(3.95)	
StructureHole					0.0145***
					(5.17)
N	38 496	38 496	38 496	38 496	38 496
R^2	0.279	0.280	0.278	0.278	0.278
Panel D: Fama–French three-factor model					
Degree	0.0328***				
	(9.82)				
Closeness		0.0618***			
		(10.54)			
Betweenness			0.1621		
			(0.79)		
Eigenvector				0.0900***	
				(3.84)	
StructureHole					0.0147***
					(5.37)
N	38 496	38 496	38 496	38 496	38 496
R^2	0.349	0.349	0.347	0.347	0.347
Controls	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

This table presents robustness checks for the relationship between network centrality and fund performance using different factor models to calculate alpha. Panel A uses the Chinese three-factor model. Panel B uses the Fama–French five-factor model. Panel C uses the Carhart four-factor model. Panel D uses the Fama–French three-factor model. Columns (1) through (5) present regression results for degree centrality, closeness centrality, betweenness centrality, eigenvector centrality, and structural hole measures, respectively. The dependent variable is fund alpha in the subsequent quarter. All regressions include fund characteristics, manager characteristics, and fund and year fixed effects. T-statistics based on standard errors clustered at the fund level are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

deviation of the residuals from a regression on common equity risk factors, thus capturing the idiosyncratic component of a fund's return distribution not explained by systematic risks (G. Bali & Weigert, 2024). A high Fund IVOL indicates that the fund's returns are driven primarily by manager-specific actions and strategic positioning rather than broad market movements. Hence, funds with high Fund IVOL exhibit strong idiosyncratic patterns in their investment strategies that reflect a manager's subjective initiative and conviction.

We follow the core methodology of G. Bali and Weigert (2024) to construct our $Fund\ IVOL$ measure, using residuals ($\epsilon_{i,m}$) derived

Table 5
Robustness check: changing the threshold.

	(1) $Alpha_{q+1}$	(2) $Alpha_{q+1}$	(3) $Alpha_{q+1}$	(4) $Alpha_{q+1}$	(5) $Alpha_{q+1}$
Panel A: Threshold 3%					
Degree	0.0167***				
	(7.17)				
Closeness		0.0558***			
		(6.39)			
Betweenness			−0.1335		
			(−0.19)		
Eigenvector				0.0083	
				(0.33)	
StructureHole					0.0162**
					(2.45)
N	47 992	47 992	47 992	47 992	47 992
R^2	0.314	0.314	0.314	0.314	0.314
Panel B: Threshold 4%					
Degree	0.0230***				
	(8.41)				
Closeness		0.0707***			
		(9.92)			
Betweenness			−0.0816		
			(−0.21)		
Eigenvector				0.0517**	
				(2.33)	
StructureHole					0.0153***
					(3.52)
N	44 321	44 321	44 321	44 321	44 321
R^2	0.321	0.321	0.319	0.319	0.320
Panel C: Threshold 6%					
Degree	0.0297***				
	(6.29)				
Closeness		0.0343***			
		(5.97)			
Betweenness			−0.0974		
			(−0.80)		
Eigenvector				0.1386***	
				(5.50)	
StructureHole					0.0070***
					(3.08)
N	31 094	31 094	31 094	31 094	31 094
R^2	0.345	0.345	0.344	0.345	0.344
Panel D: Threshold 7%					
Degree	0.0327***				
	(5.34)				
Closeness		0.0353***			
		(6.02)			
Betweenness			−0.0228		
			(−0.20)		
Eigenvector				0.1157***	
				(4.74)	
StructureHole					0.0059***
					(2.79)
N	23 782	23 782	23 782	23 782	23 782
R^2	0.359	0.359	0.358	0.360	0.359
Controls	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

This table presents a robustness check for the relationship between network centrality and fund performance by changing the threshold for variable construction from 3% to 7% with a 1% gap. Columns (1) through (5) present regression results for degree centrality, closeness centrality, betweenness centrality, eigenvector centrality, and structural hole measures, respectively. The dependent variable is fund alpha in the subsequent quarter. All regressions include fund characteristics, manager characteristics, and fund and year fixed effects. T-statistics based on standard errors clustered at the fund level are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

from a 24-month rolling window estimation of the Chinese four-factor model. This measure captures the idiosyncratic component of the fund's return not explained by systematic risk factors.

$$R_{i,m} = \alpha_{i,m} + \beta_{MKT,i,m}MKT_m + \beta_{SMB,i,m}SMB_m + \beta_{VGM,i,m}VGM_m + \beta_{PMO,i,m}PMO_m + \epsilon_{i,m}, \tag{10}$$

Specifically, the monthly Fund IVOL[5] for fund i in month m is then computed as the standard deviation of the residuals ($\epsilon_{i,m}$) from the

[5] To ensure data quality, the calculation of Fund IVOL strictly requires at least 15 valid daily trading observations per month. We exclude any fund-quarter where the 24-month estimation window includes a month failing this

Table 6
Network centrality, dynamic portfolio rebalancing, and fund performance.

	(1) $Alpha_{q+1}$	(2) $Alpha_{q+1}$	(3) $Alpha_{q+1}$	(4) $Alpha_{q+1}$	(5) $Alpha_{q+1}$
Degree	0.0011				
	(0.27)				
Closeness		0.0217***			
		(3.33)			
Betweenness			−0.4518*		
			(−1.95)		
Eigenvector				−0.0129	
				(−0.51)	
StructureHole					0.0042
					(1.37)
Degree × ABSRG	0.0412***				
	(8.13)				
Closeness × ABSRG		0.0533***			
		(6.35)			
Betweenness × ABSRG			0.8666**		
			(2.33)		
Eigenvector × ABSRG				0.1651***	
				(4.88)	
StructureHole × ABSRG					0.0160***
					(3.33)
ABSRG	−0.0009	−0.0206***	0.0037***	0.0020**	−0.0106**
	(−0.89)	(−5.13)	(5.06)	(2.41)	(−2.33)
Controls	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	38 496	38 496	38 496	38 496	38 496
R^2	0.331	0.331	0.329	0.329	0.329

This table examines whether dynamic portfolio rebalancing, measured by high Absolute Return Gap (ABSRG), acts as a channel for information advantages. Columns (1) through (5) present regression results for degree centrality, closeness centrality, betweenness centrality, eigenvector centrality, and structural hole measures, respectively. ABSRG is a dummy variable that equals 1 if the fund's absolute return gap is above the median, and 0 otherwise. The dependent variable is fund alpha in the subsequent quarter using the Chinese four-factor model proposed by Liu et al. (2019). All regressions include fund characteristics (past performance, fund size, fund family size, fund flow, turnover, fund age, volatility), manager characteristics (team size, PhD, Top 4 university graduation, CFA certification, market timing and stock picking skills), and fund and year fixed effects as control variables. T-statistics based on standard errors clustered at the fund level are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

preceding 24 monthly observations in the rolling window:

$$\text{Fund IVOL}_{i,m} = \text{STDEV}(\epsilon_{i,j} \quad \text{for } j = m-23 \text{ to } m) \tag{11}$$

The quarterly Fund IVOL for fund i in quarter q is then calculated as the average of the monthly Fund IVOL within that quarter:

$$Fund\ IVOL_{i,q} = AVG(Fund\ IVOL_{i,m})_{t\in quarter\ q}. \tag{12}$$

To examine whether informative funds employing discretionary strategy positioning generate higher alpha, we estimate the following regression model:

$$\begin{aligned} Alpha_{i,q+1} =& \alpha + \beta_1 Centrality_{i,q} + \beta_2 IVOL_{i,q} + \beta_3 Centrality_{i,q} \times IVOL_{i,q} \\ &+ \gamma Controls_{i,q} + \delta_t + \mu_i + \epsilon_{i,q}. \end{aligned} \tag{13}$$

We define $IVOL$ as a dummy variable that equals one if a fund's quarterly Fund IVOL is above the median and zero otherwise. Our focus is on the coefficient of the interaction term, β_3, which captures the synergistic effect of network advantage and discretionary positioning. The regression includes the same set of control variables as the baseline model.

In Table 7, the interaction terms between centrality measures and IVOL reveal the alpha-generating potential of combining network-derived information with a willingness to execute distinctive strategies. The coefficient on $Degree \times IVOL$ (0.0205, t = 3.43) is highly significant. A one-standard-deviation increase in degree centrality (0.1214) for a fund with high discretionary positioning (IVOL = 1) elevates next-quarter alpha by approximately 0.26 percentage points (0.0205 × 0.1254), representing roughly 15.5% of the mean quarterly alpha.

Similarly, the coefficients on $Closeness \times IVOL$ and $Eigenvector \times IVOL$ are statistically and economically significant. It is noteworthy that for eigenvector centrality, the main effect is not significant while the interaction effect is substantial, which sharpens our interpretation that the value of occupying a well-connected position in the network is only unlocked when the manager has the initiative to pursue bold, idiosyncratic investment strategies. The patterns for betweenness centrality and structural hole measures show similar directional effects, though with varying levels of statistical significance.

These findings confirm that discretionary strategy positioning serves as a critical transmission mechanism. Network-positioned managers who are willing to pursue unconventional, idiosyncratic strategies can more effectively convert their information advantages into superior risk-adjusted returns. It is not enough to be well-connected, a fund must also possess the managerial initiative to translate that access into deliberate and distinctive portfolio strategies.

5.1.3. Risk taking behavior

Managers possessing superior information access may be willing to take risks that appear unjustified to less-informed outsiders. While portfolio holdings themselves do not directly disclose this behavioral adjustment, we can infer a manager's risk-taking behavior by comparing the fund's current positions with its historical return volatility.

Following Huang et al. (2011), we quantify risk shifting using the difference between the implied volatility of the most recent holdings and the realized volatility of past returns:

$$RiskShift_{i,q} = \sigma^H_{i,q} - \sigma^R_{i,q}.$$

threshold, thereby eliminating noise from newly established, suspended, or liquidating funds.

Table 7
Network centrality, fund IVOL, and fund performance.

	(1) $Alpha_{q+1}$	(2) $Alpha_{q+1}$	(3) $Alpha_{q+1}$	(4) $Alpha_{q+1}$	(5) $Alpha_{q+1}$
Degree	0.0149***				
	(3.85)				
Closeness		0.0420***			
		(6.78)			
Betweenness			−0.1094		
			(−0.44)		
Eigenvector				0.0244	
				(1.00)	
StructureHole					0.0120***
					(4.21)
Degree × IVOL	0.0205***				
	(3.43)				
Closeness × IVOL		0.0262***			
		(2.71)			
Betweenness × IVOL			0.2642		
			(0.59)		
Eigenvector × IVOL				0.1266***	
				(3.03)	
Structurehole × IVOL					0.0027
					(0.51)
IVOL	−0.0024*	−0.0120**	−0.0000	−0.0017	−0.0023
	(−1.71)	(−2.55)	(−0.01)	(−1.34)	(−0.46)
Controls	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	38 496	38 496	38 496	38 496	38 496
R^2	0.330	0.331	0.329	0.330	0.330

This table examines whether discretionary strategy positioning, measured by fund IVOL, acts as a channel for network advantages. Columns (1) through (5) present regression results for degree centrality, closeness centrality, betweenness centrality, eigenvector centrality, and structural hole measures, respectively. IVOL is a dummy variable that equals 1 if the fund's idiosyncratic volatility is above the median, and 0 otherwise. The dependent variable is fund alpha in the subsequent quarter using the Chinese four-factor model proposed by Liu et al. (2019). All regressions include fund characteristics (past performance, fund size, fund family size, fund flow, turnover, fund age, volatility), manager characteristics (team size, PhD, Top 4 university graduation, CFA certification, market timing and stock picking skills), and fund and year fixed effects as control variables. T-statistics based on standard errors clustered at the fund level are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Here, $\sigma^H_{i,q}$ is the volatility of the current holdings, calculated using the most recently disclosed positions and the estimated variance–covariance matrix of the underlying assets. $\sigma^R_{i,q}$ represents the realized return volatility of fund i over the preceding 24 months, computed as the standard deviation of actual monthly returns. This realized volatility captures the total risk profile associated with the fund's historical investment behavior.

The intuition behind this forward-looking measure is that if a fund maintains stable portfolio weights, the volatility of current holdings should closely resemble past realized volatility. A positive value of $RiskShift_{i,q}$ suggests an increase in portfolio risk, indicating that the fund has recently shifted toward riskier positions or reduced diversification. Conversely, a negative value indicates de-risking, as the current holdings reflect a more conservative allocation relative to historical behavior. This metric reflects a manager's ex-ante choice to either amplify or reduce portfolio risk in anticipation of future return opportunities or changing market conditions.

To explore whether fund managers with information advantages shift risk appetite to create value for investors, we estimate the following regression:

$$\begin{aligned} Alpha_{i,q+1} = &\alpha + \beta_1 Centrality_{i,q} + \beta_2 RS_{i,q} + \beta_3 Centrality_{i,q} \times RS_{i,q} \\ &+ \gamma Controls_{i,q} + \delta_t + \mu_i + \epsilon_{i,q}. \end{aligned} \tag{14}$$

We define $RS_{i,q}$ as a dummy variable that equals one if a fund's risk shifting $RiskShift_{i,q}$ is above zero and zero otherwise. Our focus is on the coefficient of the interaction term, β_3, which captures whether network-advantaged funds generate additional alpha through risk-increasing behavior. The regression includes the same control variables as the baseline model.

The results in Table 8 provide evidence that risk-increasing behavior serves as a mechanism through which well-connected funds generate alpha. The positive and significant coefficients on the interaction terms for degree, closeness, and eigenvector centrality indicate that the alpha-generating power of network positions is significantly enhanced when managers concurrently increase portfolio risk.

The patterns suggest that information-advantaged managers strategically increase portfolio risk when they possess private signals about future return opportunities. This behavior differentiates informed managers from their less-connected peers, who may lack the confidence or information necessary to justify such risk-taking.

Our findings confirm that for funds with advantages in the breadth (degree), efficiency (closeness), and quality (eigenvector) of network connections, active risk-taking serves as a validated channel for translating informational advantages into superior performance. The risk shifting mechanism complements the discretionary positioning and dynamic rebalancing channels, collectively demonstrating how network-derived information manifests in observable portfolio behaviors.

These patterns align closely with the broader literature on active fund skill and trading behavior, particularly (Pástor et al., 2017). They document that skilled active mutual funds optimally increase trading activity when profitable opportunities are abundant, resulting in higher gross benchmark-adjusted returns. In our context, centrally positioned funds enjoy privileged access to private information through the network, effectively facing a richer opportunity set marked by transient mispricings. The active-management behaviors we examine, including dynamic portfolio rebalancing, discretionary strategy positioning, and strategic risk adjustment, represent the amplification mechanism through which managers exploit these opportunities, consistent with the finding of Pástor et al. (2017)'s that gross performance improves when funds "trade more" in response to better informational advantages.

Table 8
Network centrality, risk taking, and fund performance.

	(1) $Alpha_{q+1}$	(2) $Alpha_{q+1}$	(3) $Alpha_{q+1}$	(4) $Alpha_{q+1}$	(5) $Alpha_{q+1}$
Degree	0.0101** (2.27)				
Closeness		0.0421*** (5.89)			
Betweenness			−0.2330 (−0.79)		
Eigenvector				0.0337 (1.15)	
StructureHole					0.0136*** (3.92)
Degree × RS	0.0267*** (4.98)				
Closeness × RS		0.0231*** (2.71)			
Betweenness × RS			0.6918 (1.62)		
Eigenvector × RS				0.0940** (2.51)	
StructureHole × RS					−0.0006 (−0.14)
RS	0.0001 (0.14)	−0.0070* (−1.72)	0.0031*** (3.97)	0.0023*** (2.66)	0.0043 (0.98)
Controls	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	38 496	38 496	38 496	38 496	38 496
R^2	0.331	0.331	0.330	0.330	0.330

This table examines whether active risk taking acts as a channel for network advantages. Columns (1) through (5) present regression results for degree centrality, closeness centrality, betweenness centrality, eigenvector centrality, and structural hole measures, respectively. RS is a dummy variable that equals 1 if the fund's active risk taking measure is greater than 0, and 0 otherwise. The dependent variable is fund alpha in the subsequent quarter using the Chinese four-factor model proposed by Liu et al. (2019). All regressions include fund characteristics (past performance, fund size, fund family size, fund flow, turnover, fund age, volatility), manager characteristics (team size, PhD, Top 4 university graduation, CFA certification, market timing and stock picking skills), and fund and year fixed effects as control variables. T-statistics based on standard errors clustered at the fund level are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

5.2. Technology-driven substitution effects

5.2.1. FinTech adoption

The rapid advancement of FinTech has fundamentally altered how market participants generate, process, and act upon information (Goldstein et al., 2023). In the asset management industry, firms increasingly leverage proprietary technology for data analysis and investment decision-making as a source of competitive advantage (Begenau et al., 2018). This technological transformation may alter how asset managers generate alpha, potentially changing their reliance on traditional information channels such as human networks. We investigate this potential substitution effect by examining the adoption of FinTech within mutual fund families and its interaction with network-based information advantages.

To capture financial technology adoption, we construct a time-varying measure, $FT_{i,q}$, based on software copyright registrations by mutual fund companies. Our data source is the Wind Database, which provides comprehensive records of intellectual property registrations in China. We employ a multi-layered verification and filtering process to ensure our measure captures technology that is actually deployed in the investment process, rather than serving as a proxy for general firm sophistication or unimplemented R&D.

First, we identify software copyrights specifically relevant to the investment function. We rigorously filter the universe of registrations using keywords indicating applications in investment analysis, portfolio management, or risk controls (e.g., "smart investment research", "smart risk control", "quantitative strategy execution"). Crucially, to distinguish investment-specific Fintech capability from general organizational sophistication, we systematically exclude software related to sales, compliance, client relations, human resources, or back-office operations. This ensures that $FT_{i,q}$ exclusively reflects technology aimed at enhancing information processing and alpha generation.[6]

To further address concerns that registrations might not reflect operational systems, we cross-validated a random sample of registrations against open-source data. We examined official company websites, annual reports, and media coverage to confirm that the registered systems correspond to active tools. For instance, systems such as Zheshang Fund's "iValue" appear in our dataset upon registration and are simultaneously corroborated by public disclosures as fully implemented components of the investment process.

We construct the Fintech adoption variable at the fund family level, as funds within the same family typically share technological infrastructure. For each fund family, we create a cumulative count variable based on the registration approval date, rather than the earlier first publication date. The approval date represents the moment the software receives formal legal protection, a step firms are economically incentivized to take only for systems that are valuable and operational. We further impose a one-quarter lag, incrementing the count in the quarter immediately following the approval. This lag accommodates the typical implementation period required for registered systems to integrate into the workflow. Consequently, $FT_{i,q}$ measures the cumulative number of verified, investment-relevant Fintech systems operational within fund i's family by the beginning of quarter q.

To test whether Fintech adoption affects the value of network-based information advantages, we estimate:

$$\begin{aligned} Alpha_{i,q+1} = &\alpha + \beta_1 Net_{i,q} + \beta_2 FT_{i,q} + \beta_3 Net_{i,q} \times FT_{i,q} \\ &+ \gamma Controls_{i,q} + \delta_t + \mu_i + \epsilon_{i,q}. \end{aligned} \tag{15}$$

[6] See Table A.2 for illustrative examples of the specific FinTech systems.

Table 9
Network centrality, FinTech, and fund performance.

	(1) $Alpha_{q+1}$	(2) $Alpha_{q+1}$	(3) $Alpha_{q+1}$	(4) $Alpha_{q+1}$	(5) $Alpha_{q+1}$
Degree	0.0257***				
	(6.79)				
Closeness		0.0554***			
		(9.01)			
Betweenness			0.0374		
			(0.17)		
Eigenvector				0.0787***	
				(3.36)	
StructureHole					0.0136***
					(4.99)
Degree × FT	−0.0080***				
	(−2.81)				
Closeness × FT		−0.0163***			
		(−3.92)			
Betweenness × FT			−0.9253		
			(−1.05)		
Eigenvector × FT				−0.0580**	
				(−2.50)	
StructureHole × FT					−0.0042*
					(−1.93)
FT	0.0026***	0.0095***	0.0017***	0.0023***	0.0055***
	(3.66)	(4.67)	(2.81)	(3.39)	(2.67)
Controls	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	38 496	38 496	38 496	38 496	38 496
R^2	0.330	0.331	0.329	0.330	0.330

This table examines how FinTech affects the relationship between network centrality and fund performance. Columns (1) through (5) present regression results for degree centrality, closeness centrality, betweenness centrality, eigenvector centrality, and structural hole measures, respectively. FinTech is a cumulative variable that measures a fund's usage of financial technology. The dependent variable is fund alpha in the subsequent quarter using the Chinese four-factor model proposed by Liu et al. (2019). All regressions include fund characteristics (past performance, fund size, fund family size, fund flow, turnover, fund age, volatility), manager characteristics (team size, PhD, Top 4 university graduation, CFA certification, market timing and stock picking skills), and fund and year fixed effects as control variables. T-statistics based on standard errors clustered at the fund level are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Our primary interest lies in the coefficient β_3, which captures how FinTech adoption moderates the relationship between network centrality and fund performance.

In Table 9, the coefficients on the interaction terms between network measures and FinTech adoption ($Degree \times FT$, $Closeness \times FT$, $Eigenvector \times FT$, $StructureHole \times FT$) are consistently negative and statistically significant. This indicates that the marginal benefit of information advantages from network positions diminishes for funds belonging to families that have adopted more FinTech systems.

We interpret this negative interaction through three complementary theoretical channels: the substitution of human processing, the reprioritization of information types, and organizational transition costs.

First, it primarily suggests a substitution in information processing, where automated systems displace the human judgment required to capitalize on network-derived information. Network information is inherently "soft", context-dependent, and ambiguous, requiring human discretion to filter and interpret. However, the adoption of automated analytics reduces the reliance on such labor-intensive judgment. This mechanism resonates with Dugast and Foucault (2018), who model how the abundance of low-cost, automated signals crowds out the production of high-precision information that requires costly human attention. Similarly, Farboodi and Veldkamp (2020) demonstrate that data-processing technology induces a strategic shift, leading investors to pivot away from deep, fundamental research toward scalable, quantitative strategies.

In our context, this theoretical shift manifests as the operational displacement of the discretionary channels essential for network advantages. By automating the information and investment-decision process, FinTech tools constrain the application of the human judgment that is often required to leverage "soft" signals. This mechanism is empirically supported by Grennan and Michaely (2021), who find that FinTechs streamline financial information processing, crowding out human-intensive private information production. Moreover, Cao et al. (2024) find that while AI excels at processing transparent, voluminous data, it underperforms in analyzing "soft" institutional knowledge, precisely the domain where human networks generate value.

Second, the negative interaction suggests a shift in the relative value of information. As funds adopt technology capable of processing vast amounts of quantitative "hard" data, the relative marginal value of "soft" network information declines. This mechanism parallels (Bonelli & Foucault, 2025), who find that the rise of alternative data devalues the traditional, relationship-intensive expertise (e.g. from education, geographical proximity, social network) of active managers. However, given that our specific FT measure tracks decision-support software rather than pure data ingestion, we interpret the result primarily as *automation displacing human discretion* rather than solely a devaluation of soft information.

Finally, the negative interaction may reflect the "transition costs" of technological reorganization. Adopting investment-relevant FinTech is not a frictionless process, it requires significant restructuring of workflows and retraining of analysts. This friction aligns with the "productivity J-curve" where the adoption of general-purpose technologies initially depresses performance due to unmeasured investments in intangible organizational capital (Brynjolfsson et al., 2021). A historical parallel is found by Juhász and Lane (2024), who find that productivity gains from mechanized manufacturing were delayed by the time-intensive "trial-and-error" required to reorganize production away from human-centric systems. In our context, funds undergoing this shift away from decentralized human judgment toward systematic, tech-assisted decision-making may experience a temporary degradation in their ability to effectively utilize network signals during the adjustment phase.

Table 10
Network centrality, quant, and fund performance.

	(1) $Alpha_{q+1}$	(2) $Alpha_{q+1}$	(3) $Alpha_{q+1}$	(4) $Alpha_{q+1}$	(5) $Alpha_{q+1}$
Degree	0.0246***				
	(6.31)				
Closeness		0.0506***			
		(8.02)			
Betweenness			0.0015		
			(0.01)		
Eigenvector				0.0690***	
				(2.80)	
StructureHole					0.0127***
					(4.52)
Degree × Quant	−0.0392*				
	(−1.93)				
Closeness × Quant		−0.0804***			
		(−3.20)			
Betweenness × Quant			0.5808		
			(1.23)		
Eigenvector × Quant				0.0908	
				(1.02)	
StructureHole × Quant					−0.0246**
					(−2.07)
Quant	−0.1329***	−0.1022***	−0.1359***	−0.1381***	−0.1137***
	(−6.39)	(−4.24)	(−6.66)	(−6.73)	(−4.88)
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	38 496	38 496	38 496	38 496	38 496
R^2	0.399	0.399	0.398	0.398	0.398

This table examines how quantitative investment strategies (Quant) affect the relationship between network centrality and fund performance. Columns (1) through (5) present regression results for degree centrality, closeness centrality, betweenness centrality, eigenvector centrality, and structural hole measures, respectively. Quant is a dummy variable that equals 1 if the fund name contains the word "quantitative" or if its contract explicitly states a primary investment strategy reliant on quantitative models or algorithms. The dependent variable is fund alpha in the subsequent quarter using the Chinese four-factor model proposed by Liu et al. (2019). All regressions include fund characteristics (past performance, fund size, fund family size, fund flow, turnover, fund age, volatility), manager characteristics (team size, PhD, Top 4 university graduation, CFA certification, market timing and stock picking skills), and year fixed effects as control variables. T-statistics based on standard errors clustered at the fund level are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Taken together, these results demonstrate that FinTech and network centrality are not additive sources of performance. Instead, technological adoption creates a strategic trade-off. As organizational infrastructure shifts toward automated decision-making and hard data, the capacity to exploit context-dependent advantages is diminished.

5.2.2. Quantitative investment strategies

To further examine the technology substitution hypothesis, we investigate funds that represent an extreme case of systematic, technology-driven investment approaches. Specifically, we examine funds that employ quantitative, model-driven strategies. We construct a dummy variable, $Quant_i$, which equals one if the fund's name contains "quantitative" or if its prospectus explicitly states a primary investment strategy reliant on quantitative models, algorithms, or systematic factors.

Table 10 reports the results. The coefficients on the interaction terms $Degree \times Quant$, $Closeness \times Quant$, and $StructureHole \times Quant$ are negative and statistically significant, indicating that the positive relationship between network centrality and future alpha is significantly weaker for quantitative funds. This finding provides additional evidence for our substitution hypothesis: quantitative funds derive significantly less value from network connections as their advantage relies primarily on algorithmic analysis rather than information flows.

The negative main effect of the $Quant$ variable in columns (3) and (4) suggests that complete commitment to quantitative strategies may not represent the optimal technological approach. Unlike incremental FinTech adoption that enhances specific operational capabilities, wholesale quantitative strategies may involve premature abandonment of network advantages without achieving sufficient technological sophistication to compensate for this loss. This pattern indicates that the timing and extent of technological substitution matters for performance outcomes.

These findings demonstrate that while technological and network-derived information processing involve substitution effects rather than pure complementarity, the optimal strategy requires careful balance rather than exclusive commitment to either approach. The negative interaction effects confirm that funds face trade-offs when attempting to leverage both discretionary information advantages and technology-driven capabilities simultaneously, as each approach requires different organizational infrastructure and decision-making processes. However, the performance implications suggest that moderate technological adoption, when combined with human information channels, may outperform complete specialization in either direction, emphasizing the importance of strategic balance in the digital transformation of asset management.

6. Heterogeneity in network effects

6.1. Market condition heterogeneity

Network centrality benefits vary substantially across different market conditions. Table 11 Panel A shows that during bull markets (quarterly market return > 5%), all centrality measures but betweness centrality provide significant positive benefits. For example, degree centrality contributes 0.0724 to future alpha, while eigenvector centrality shows a stronger effect of 0.1835. The consistency across different network measures, from direct connections to strategic bridging positions, indicates that diverse forms of network advantage become valuable during market upswings.

Table 11
Network centrality and fund performance across different market conditions.

	(1) $Alpha_{q+1}$	(2) $Alpha_{q+1}$	(3) $Alpha_{q+1}$	(4) $Alpha_{q+1}$	(5) $Alpha_{q+1}$
Panel A: Bull market					
Degree	0.0724***				
	(8.29)				
Closeness		0.1155***			
		(8.16)			
Betweenness			0.2343		
			(0.60)		
Eigenvector				0.1835***	
				(4.06)	
StructureHole					0.0323***
					(5.12)
N	8479	8479	8479	8479	8479
R^2	0.329	0.330	0.322	0.324	0.325
Panel B: Neutral market					
Degree	−0.0065				
	(−1.42)				
Closeness		−0.0141**			
		(−1.99)			
Betweenness			0.4822**		
			(2.26)		
Eigenvector				−0.0095	
				(−0.40)	
StructureHole					0.0018
					(0.59)
N	23 490	23 490	23 490	23 490	23 490
R^2	0.356	0.356	0.356	0.356	0.356
Panel C: Bear market					
Degree	0.0117				
	(1.32)				
Closeness		0.0021			
		(0.16)			
Betweenness			−0.5059		
			(−1.31)		
Eigenvector				0.0339	
				(0.75)	
StructureHole					−0.0042
					(−0.80)
N	6527	6527	6527	6527	6527
R^2	0.621	0.621	0.621	0.621	0.621
Controls	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

This table examines how the relationship between network centrality and fund performance varies across different market conditions. The sample is divided into three market states based on quarterly market returns: Panel A reports results for bull markets (quarterly market return ≥ 5%), Panel B for neutral markets (absolute quarterly market return ≤ 5%), and Panel C for bear markets (quarterly market return < −5%). Columns (1) through (5) present regression results for degree centrality, closeness centrality, betweenness centrality, eigenvector centrality, and structural hole measures, respectively. The dependent variable is fund alpha in the subsequent quarter. All regressions include fund characteristics, manager characteristics, and fund and year fixed effects as control variables. T-statistics based on standard errors clustered at the fund level are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Network advantages largely disappear during neutral and bear markets (Panels B and C). In neutral markets (absolute quarterly market return ≤ 5%), most centrality measures lose statistical significance, with only closeness centrality (−0.0141, t = −1.99) and betweenness centrality (0.4822, t = 2.26) showing significant coefficients. During bear markets (quarterly market return < −5%), none of the network measures yield statistically significant benefits.

The pattern is consistent with a large behavioral literature showing that information transmission is state-dependent and skewed toward positive outcomes, a phenomenon known as self-enhancing transmission bias (SET), which states that investors like to inform others about their investment victories more than their failures (Han et al., 2022). When managers' high-conviction positions perform well, as is more common in rising markets, they have strong psychological and reputational incentives to share these "wins" with professional contacts, either directly or indirectly through visible portfolio overlaps in mandated disclosures or advertising (Lou, 2014). The resulting network therefore aggregates genuine, return-relevant private signals.

Conversely, in bear markets, high-conviction positions often generate losses. Consistent with SET bias, managers become selectively silent to protect their reputations, withholding or downplaying negative signals. As a result, the observable overlap network becomes noisy and sparse, rendering centrality ineffective as a predictor of future alpha. This interpretation is reinforced by Kaustia and Knüpfer (2012), who find that peer interactions influence investment behavior primarily after positive personal experiences, suggesting that failures are rarely communicated.

Collectively, these findings indicate that our network primarily captures "offensive" information regarding undervalued opportunities

Table 12
Network centrality and fund performance across different fund sizes.

	(1) $Alpha_{q+1}$	(2) $Alpha_{q+1}$	(3) $Alpha_{q+1}$	(4) $Alpha_{q+1}$	(5) $Alpha_{q+1}$
Panel A: Small funds (<¥1B)					
Degree	0.0202***				
	(4.18)				
Closeness		0.0448***			
		(5.55)			
Betweenness			−0.0738		
			(−0.19)		
Eigenvector				0.1045***	
				(2.85)	
StructureHole					0.0108***
					(2.96)
N	24 309	24 309	24 309	24 309	24 309
R^2	0.325	0.326	0.325	0.325	0.325
Panel B: Medium funds (¥1B–¥5B)					
Degree	0.0297***				
	(4.73)				
Closeness		0.0598***			
		(5.91)			
Betweenness			0.3659		
			(1.10)		
Eigenvector				0.0708**	
				(2.06)	
StructureHole					0.0162***
					(3.82)
N	11 791	11 791	11 791	11 791	11 791
R^2	0.335	0.336	0.334	0.334	0.335
Panel C: Large funds (>¥5B)					
Degree	0.0704***				
	(4.65)				
Closeness		0.1635***			
		(5.80)			
Betweenness			0.3041		
			(0.63)		
Eigenvector				0.1463**	
				(2.49)	
StructureHole					0.0475***
					(3.02)
N	2396	2396	2396	2396	2396
R^2	0.320	0.324	0.313	0.315	0.317
Controls	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

This table examines how the relationship between network centrality and fund performance varies across different fund sizes. The sample is divided into three size categories based on total net assets: Panel A reports results for small funds (total net assets < RMB 1 billion), Panel B for medium funds (total net assets between RMB 1–5 billion), and Panel C for large funds (total net assets > RMB 5 billion). Columns (1) through (5) present regression results for degree centrality, closeness centrality, betweenness centrality, eigenvector centrality, and structural hole measures, respectively. The dependent variable is fund alpha in the subsequent quarter. All regressions include fund characteristics, manager characteristics, and fund and year fixed effects as control variables. T-statistics based on standard errors clustered at the fund level are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

rather than "defensive" hedging signals. While network-building strategies are highly valuable during favorable conditions, they offer limited downside protection, necessitating independent risk management strategies during market downturns.

6.2. Fund size heterogeneity

Network centrality benefits exhibit a pronounced size gradient across funds. Table 12 shows that small funds (total net assets < RMB 1 billion) experience modest network effects, with degree centrality contributing 0.0202 to future alpha and closeness centrality adding 0.0448. Betweenness centrality remains statistically insignificant for this group, suggesting that small funds may lack sufficient scale to exploit intermediary network positions effectively.

Medium-sized funds (RMB 1–5 billion) demonstrate similar effects but enhanced network benefits. Eigenvector centrality drops to 0.0708, while degree centrality, closeness centrality, and the structure hole increase.

Large funds (>RMB 5 billion) derive the most substantial network advantages. Degree centrality reaches 0.0704 and closeness centrality peaks at 0.1635. The structural hole measure also shows its strongest effect for large funds (0.0475, t = 3.02), suggesting that these funds are particularly effective at bridging information gaps between disconnected network clusters.

This size gradient suggests significant complementarities between network position and organizational resources. Larger funds likely possess greater analytical capacity to process network-derived information, more sophisticated trading infrastructure to implement network-informed strategies, and established corporate relationships that validate and enrich network intelligence.

These results indicate that while network connections provide value across all fund sizes, the ability to translate network positions into

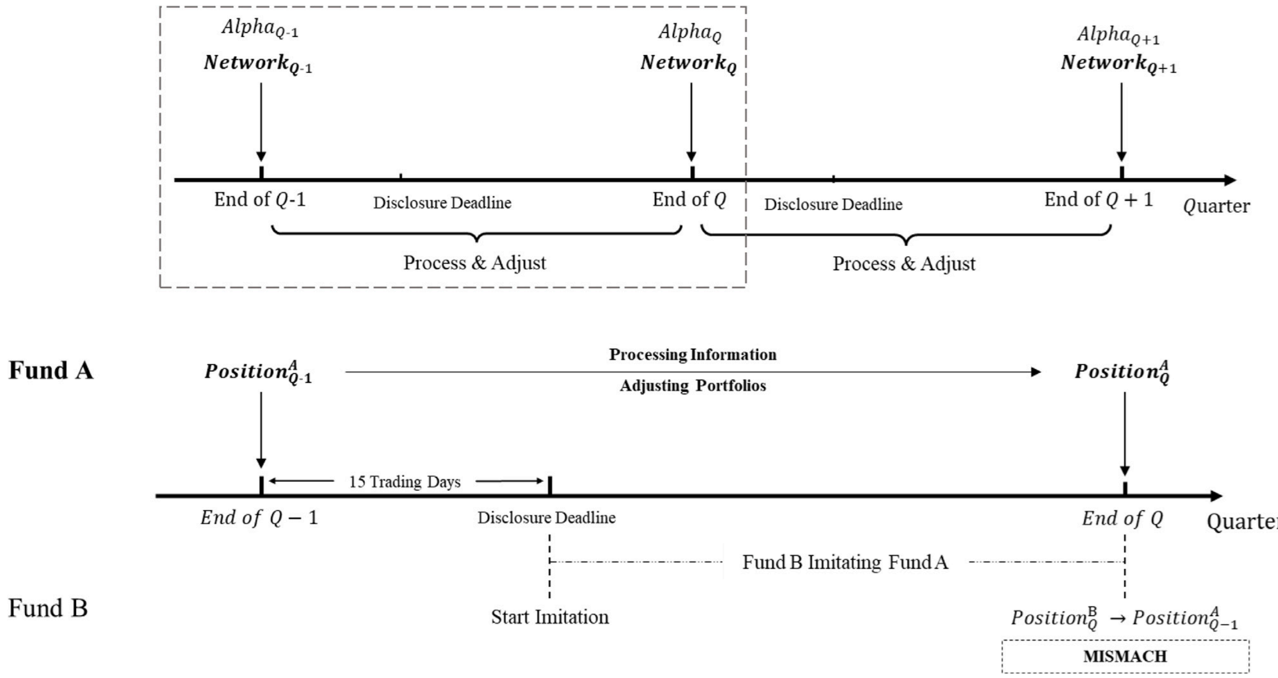


Fig. A.1. Timeline of mutual fund portfolio disclosure and structural mismatch precluding concurrent imitation. The figure illustrates the institutional constraint against reverse causality in the Chinese market. It shows that due to the mandatory disclosure lag of up to 15 trading days, Fund B, acting as a pure imitator based on publicly available data, can only mirror Fund A's stale holdings from Quarter $Q-1$. Since Fund A's concurrent position at the end of Quarter Q ($Position^A_Q$) reflects new information and active management, the resulting network overlap cannot be a mechanical consequence of imitating public information, thus isolating the genuine information advantage channel.

measurable alpha increases substantially with organizational scale and complementary resources typically found in larger asset management firms.

7. Conclusion

This study investigates how network structure influences mutual fund performance in China's asset management industry using a comprehensive dataset spanning 2007–2024. Our primary finding confirms that mutual funds occupying central positions in information networks generate superior risk-adjusted returns, with the effect holding consistently across multiple centrality measures. These results provide strong support for the information advantage hypothesis, demonstrating that network positioning creates systematic informational advantages that translate into measurable outperformance.

We identify three critical mechanisms through which network advantages manifest in superior performance: dynamic portfolio rebalancing, discretionary strategy positioning, and strategic risk adjustment. Importantly, network-derived information advantages require deliberate managerial intervention to materialize as alpha, with passive recipients capturing minimal benefits. Our analysis also reveals that FinTech adoption significantly weakens network-based information advantages. Funds with higher FinTech adoption and quantitative investment strategies derive significantly less benefit from network positions, as technological systems substitute for human management capabilities required to capitalize on context-specific information.

Our findings make important contributions to both academic literature and practical fund management. Theoretically, we extend network theory in finance by demonstrating that fund networks explain systematic performance differences and identifying specific transmission mechanisms. We also find that FinTech adoption weakens the value of network-based information advantages, as algorithmic systems replace the human management processes necessary to transform interpersonal relationship information into investment returns.

From a practical perspective, our results offer guidance for multiple stakeholders. For fund managers, performance optimization requires balancing network positioning with active management capabilities, as network advantages materialize only through dynamic trading, discretionary positioning, and strategic risk-taking. The trade-off between network-based and technology-driven approaches suggests that wholesale adoption of quantitative systems may sacrifice valuable informational advantages without sufficient compensating benefits. For fund investors, preference for centrally positioned funds should be conditional on market conditions and fund characteristics. For regulators, while information networks do not necessarily indicate insider trading, evidenced by rapid effect decay and reliance on active human processing, they may amplify systemic risks through pro-cyclical information transmission, warranting enhanced monitoring of interconnected fund families during market stress.

Despite these contributions, our study has limitations that suggest directions for future research. Our network construction relies on quarterly top 10 holdings data, which may not capture the full extent of information networks among fund managers. Future research could explore alternative methodologies for measuring information networks, examine broader implications of network positioning, and investigate how the relationship between traditional and technological information sources evolves across different market contexts. Understanding how technological advancement affects the ability to capitalize on network-derived insights will remain crucial as financial markets continue to evolve.

Table A.1
Impact of network centrality on future alpha: summary by lead quarter ($q+2$ to $q+8$).

Dependent variable: $Alpha_{q+lead}$	Degree	Closeness	Betweenness	Eigenvector	StructureHole
	(1)	(2)	(3)	(4)	(5)
Panel A: Alpha($q+2$)					
Coefficient	−0.0429***	−0.0325***	0.0459	−0.0746***	−0.0031
t-statistic	(−11.02)	(−4.88)	(0.21)	(−3.25)	(−1.03)
N	38 143	38 143	38 143	38 143	38 143
R^2	0.132	0.130	0.129	0.130	0.129
Panel B: Alpha($q+3$)					
Coefficient	−0.0139***	−0.0213***	0.2050	−0.0549**	−0.0034
t-statistic	(−3.58)	(−3.34)	(1.01)	(−2.50)	(−1.12)
N	37 833	37 833	37 833	37 833	37 833
R^2	0.123	0.123	0.122	0.122	0.122
Panel C: Alpha($q+4$)					
Coefficient	0.0015	0.0012	0.3226*	−0.0519**	0.0041
t-statistic	(0.38)	(0.20)	(1.80)	(−2.56)	(1.48)
N	37 568	37 568	37 568	37 568	37 568
R^2	0.141	0.141	0.141	0.141	0.141
Panel D: Alpha($q+5$)					
Coefficient	−0.0217***	−0.0534***	0.3244*	−0.0911***	−0.0081***
t-statistic	(−5.67)	(−8.69)	(1.95)	(−4.65)	(−3.01)
N	37 326	37 326	37 326	37 326	37 326
R^2	0.100	0.101	0.099	0.100	0.099
Panel E: Alpha($q+6$)					
Coefficient	−0.0318***	−0.0602***	−0.0142	−0.1537***	−0.0085***
t-statistic	(−8.20)	(−9.26)	(−0.08)	(−7.75)	(−2.96)
N	35 265	35 265	35 265	35 265	35 265
R^2	0.122	0.122	0.120	0.121	0.120
Panel F: Alpha($q+7$)					
Coefficient	−0.0098***	0.0050	0.0496	−0.0759***	0.0017
t-statistic	(−2.60)	(0.78)	(0.31)	(−4.06)	(0.60)
N	33 297	33 297	33 297	33 297	33 297
R^2	0.102	0.102	0.102	0.102	0.102
Panel G: Alpha($q+8$)					
Coefficient	−0.0014	0.0077	−0.1153	−0.0387**	−0.0055**
t-statistic	(−0.34)	(1.19)	(−0.88)	(−2.04)	(−1.99)
N	31 491	31 491	31 491	31 491	31 491
R^2	0.129	0.129	0.129	0.129	0.129
Controls	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Table A.2
Examples of investment-relevant FinTech software copyrights (FT Variable).

Fund family	System name	Description
Zheshang fund	iValue Intelligent Investment System	An AI-driven platform using Knowledge Graphs and NLP to process unstructured data (news, financial reports). It autonomously constructs relationships between macro factors and companies to generate predictive quantitative signals, substituting for traditional human fundamental analysis.
E fund	Ark.ESG	A comprehensive ESG evaluation platform. Utilizing artificial intelligence and big data technologies, the platform conducts in-depth analysis of ESG data to support E Fund's responsible investment initiatives. The analytical framework of Ark.ESG is based on E Fund's proprietary ESG evaluation model, which is regularly updated to adapt to evolving internal and external conditions and requirements. The system provides a data dashboard that displays the ESG performance of listed companies.
E fund	Ark.James	An ESG data collection and processing system. This system operates around the clock, automatically identifying and gathering ESG-related data from over 70,000 public data sources. It extracts the latest relevant ESG information and converts it into a structured format. In addition, the system incorporates ESG data purchased from third-party providers, both domestic and international. Currently, the E Fund ESG database covers more than 5000 A-share listed companies in China and over 4000 credit bond issuers, with historical data tracing back more than five years.
CICC fund	Dian Jing Large Model System	A platform integrating Large Language Models (LLMs) with internal analyst insights. It features automated "viewpoint extraction" and "intelligent summarization", allowing researchers to quickly distill core perspectives from extensive market reports, thereby streamlining the information processing workflow.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Claude in order to improve language clarity, refine sentence structure, and enhance the overall readability of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Declaration of competing interest

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

Appendix. Supplementary materials

This appendix provides supplementary materials for the main analysis. Fig. A.1 illustrates the institutional timeline of portfolio disclosure in China, which supports our identification strategy by ruling out mechanical imitation as an alternative explanation. Table A.1 examines the persistence of network centrality effects across different forecast horizons (quarters Q+2 through Q+8), demonstrating that network advantages reflect transient informational edges rather than persistent managerial skill. Table A.2 provides illustrative examples of the investment-relevant FinTech systems used to construct our FinTech adoption measure, ensuring transparency in variable construction.

Data availability

The authors do not have permission to share data.

References

Agarwal, V., Ruenzi, S., & Weigert, F. (2024). Unobserved performance of Hedge funds. *The Journal of Finance*, *79*, 3203–3259.

Ahern, K. R. (2017). Information networks: Evidence from illegal insider trading tips. *Journal of Financial Economics*, *125*, 26–47.

Bai, J. J., Tang, Y., Wan, C., & Yüksel, H. Z. (2021). Fund manager skill in an era of globalization: Offshore concentration and fund performance. *Journal of Financial Economics*, *145*, 18–40.

Bajo, E., Chemmanur, T. J., Simonyan, K., & Tehranian, H. (2016). Underwriter networks, investor attention, and initial public offerings. *Journal of Financial Economics*, *122*, 376–408.

Begenau, J., Farboodi, M., & Veldkamp, L. (2018). Big data in finance and the growth of large firms. *Journal of Monetary Economics*, *97*, 71–87.

Bonacich, P. (2007). Some unique properties of eigenvector centrality. *Social Networks*, *29*(4), 555–564.

Bonelli, M., & Foucault, T. (2025). Does big data devalue traditional expertise? Evidence from active funds. *SSRN Electronic Journal*.

Borgatti, S. P., & Halgin, D. S. (2011). On network theory. *Organization Science*, *22*, 1168–1181.

Brynjolfsson, E., Rock, D., & Syverson, C. (2021). The productivity J-curve: How intangibles complement general purpose technologies. *American Economic Journal: Macroeconomics*, *13*, 333–372.

Burt, R. S. (1992). *Structural holes: The social structure of competition*. Harvard University Press.

Bushee, B. J., & Goodman, T. H. (2007). Which institutional investors trade based on private information about earnings and returns? *Journal of Accounting Research*, *45*(2), 289–321.

Cai, Y., & Sevilir, M. (2012). Board connections and M&A transactions. *Journal of Financial Economics*, *103*, 327–349.

Cao, S., Jiang, W., Wang, J., & Yang, B. (2024). From man vs. machine to man + machine: The art and AI of stock analyses. *Journal of Financial Economics*, *160*, Article 103910.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, *52*, 57–82.

Carpenter, J. N., Lu, F., & Whitelaw, R. F. (2021). The real value of China's stock market. *Journal of Financial Economics*, *139*, 679–696.

Chen, Y., Huang, J., Li, T., & Pittman, J. (2021). It's a small world: The importance of social connections with auditors to mutual fund managers' portfolio decisions. *Journal of Accounting Research*, *60*, 601–903.

Chen, H.-L., Jegadeesh, N., & Wermers, R. (2000). The value of active mutual fund management: An examination of the stockholdings and trades of fund managers. *Journal of Financial and Quantitative Analysis*, *35*, 343–368.

Christoffersen, S. E., & Sarkissian, S. (2009). City size and fund performance. *Journal of Financial Economics*, *92*, 252–275.

Cici, G., Jaspersen, S., & Kempf, A. (2016). Speed of information diffusion within fund families. *The Review of Asset Pricing Studies*, *7*, 144–170.

Cohen, R. B., Coval, J. D., & Pástor, L. (2005). Judging fund managers by the company they keep. *The Journal of Finance*, *60*, 1057–1096.

Cohen, L., Frazzini, A., & Malloy, C. (2008). The small world of investing: board connections and mutual fund returns. *Journal of Political Economy*, *116*, 951–979.

Cohen, L., Frazzini, A., & Malloy, C. (2010). Sell-Side school ties. *The Journal of Finance*, *65*, 1409–1437.

Coval, J. D., & Moskowitz, T. J. (2001). The geography of investment: informed trading and asset prices. *Journal of Political Economy*, *109*, 811–841.

Coval, J., & Stafford, E. (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics*, *86*, 479–512.

Crane, A. D., Koch, A., & Michenaud, S. (2019). Institutional investor cliques and governance. *Journal of Financial Economics*, *133*(1), 175–197.

Cremers, K. J. M., & Petajisto, A. (2009). How active is your fund manager? A new measure that predicts performance. *Review of Financial Studies*, *22*, 3329–3365.

Dugast, J., & Foucault, T. (2018). Data abundance and asset price informativeness. *Journal of Financial Economics*, *130*, 367–391.

Evans, R. B. (2010). Mutual fund incubation. *The Journal of Finance*, *65*, 1581–1611.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*, 3–56.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*, 1–22.

Farboodi, M., & Veldkamp, L. (2020). Long-run growth of financial data technology. *The American Economic Review*, *110*, 2485–2523.

Freeman, L. C. (1977). A set of measures of centrality based on betweenness. *Sociometry*, *40*, 35–41.

Freeman, L. C. (1978). Centrality in social networks conceptual clarification. *Social Networks*, *1*, 215–239.

G. Bali, T., & Weigert, F. (2024). Hedge funds and the positive idiosyncratic volatility effect. *Review of Finance*, *28*, 1611–1661.

Goldstein, I., Yang, S., & Zuo, L. (2023). The real effects of modern information technologies: Evidence from the EDGAR implementation. *Journal of Accounting Research*, *61*, 1699–1733.

Grennan, J., & Michaely, R. (2021). FinTechs and the market for financial analysis. *Journal of Financial and Quantitative Analysis*, *56*, 1877–1907.

Grinold, R., & Kahn, R. (1999). *Active portfolio management: a quantitative approach for producing superior returns and selecting superior returns and controlling risk*. McGraw Hill Professional.

Grossman, S. J., & Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. *The American Economic Review*, *70*, 393–408.

Gu, M., Kang, W., & Xu, B. (2018). Limits of arbitrage and idiosyncratic volatility: Evidence from China stock market. *Journal of Banking & Finance*, *86*, 240–258.

Gupta-Mukherjee, S. (2013). When active fund managers deviate from their peers: Implications for fund performance. *Journal of Banking & Finance*, *37*, 1286–1305.

Han, B., Hirshleifer, D., & Walden, J. (2022). Social transmission bias and investor behavior. *Journal of Financial and Quantitative Analysis*, *57*, 390–412.

Han, B., & Yang, L. (2013). Social networks, information acquisition, and asset prices. *Management Science*, *59*, 1444–1457.

He, Y. E., & Li, T. (2022). Social networks and Hedge fund activism*. *Review of Finance*, *26*, 1267–1308.

Hochberg, Y. V., Ljungqvist, A., & Lu, Y. (2007). Whom you know matters: Venture capital networks and investment performance. *The Journal of Finance*, *62*, 251–301.

Hong, H., Kubik, J. D., & Stein, J. C. (2004). Social interaction and stock-market participation. *The Journal of Finance*, *59*, 137–163.

Hong, H., Kubik, J. D., & Stein, J. C. (2005). Thy neighbor's portfolio: Word-of-mouth effects in the holdings and trades of money managers. *The Journal of Finance*, *60*, 2801–2824.

Hong, H., Lim, T., & Stein, J. C. (2000). Bad news travels slowly: size, analyst coverage, and the profitability of momentum strategies. *The Journal of Finance*, *55*, 265–295.

Hong, H., & Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance*, *54*, 2143–2184.

Huang, J., Sialm, C., & Zhang, H. (2011). Risk shifting and mutual fund performance. *The Review of Financial Studies*, *24*, 2575–2616.

Juhász, R., & Lane, N. (2024). The political economy of industrial policy. *Journal of Economic Perspectives*, *38*, 27–54.

Kacperczyk, M., Nieuwerburgh, S. V., & Veldkamp, L. (2014). Time-varying fund manager skill. *The Journal of Finance*, *69*, 1455–1484.

Kacperczyk, M., Sialm, C., & Zheng, L. (2006). Unobserved actions of mutual funds. *The Review of Financial Studies*, *21*, 2379–2416.

Kacperczyk, M., Van Nieuwerburgh, S., & Veldkamp, L. (2016). A rational theory of mutual funds' attention allocation. *Econometrica*, *84*, 571–626.

Kaustia, M., & Knüpfer, S. (2012). Peer performance and stock market entry. *Journal of Financial Economics*, *104*, 321–338.

Kaustia, M., & Rantala, V. (2015). Social learning and corporate peer effects. *Journal of Financial Economics*, *117*, 653–669.

Ke, B., & Petroni, K. (2004). How informed are actively trading institutional investors? Evidence from their trading behavior before a break in a string of consecutive earnings increases. *Journal of Accounting Research*, *42*, 895–927.

Leippold, M., Wang, Q., & Zhou, W. (2022). Machine learning in the Chinese stock market. *Journal of Financial Economics*, *145*, 64–82.

Liu, X., & Lee, L.-f. (2010). GMM estimation of social interaction models with centrality. *Journal of Econometrics*, *159*(1), 99–115.

Liu, J., Stambaugh, R. F., & Yuan, Y. (2019). Size and value in China. *Journal of Financial Economics*, *134*, 48–69.

Lou, D. (2014). Attracting investor attention through advertising. *The Review of Financial Studies*, *27*, 1797–1829.

Maffett, M. (2012). Financial reporting opacity and informed trading by international institutional investors. *Journal of Accounting and Economics*, *54*, 201–220.

Ozsoylev, H. N., Walden, J., Yavuz, M. D., & Bildik, R. (2013). Investor networks in the stock market. *The Review of Financial Studies*, *27*, 1323–1366.

Pareek, A. (2012). Information Networks: Implications for mutual fund trading behavior and stock returns. *SSRN Electronic Journal*.

Pástor, Ľ., Stambaugh, R. F., & Taylor, L. A. (2017). Do funds make more when they trade more? *The Journal of Finance*, *72*, 1483–1528.

Pool, V. K., Stoffman, N., & Yonker, S. E. (2014). The people in your neighborhood: social interactions and mutual fund portfolios. *The Journal of Finance*, *70*, 2679–2732.

Rossi, A. G., Blake, D., Timmermann, A., Tonks, I., & Wermers, R. (2018). Network centrality and delegated investment performance. *Journal of Financial Economics*, *128*, 183–206.

Sabidussi, G. (1966). The centrality index of a graph. *Psychometrika*, *31*, 581–603.

Stein, J. C. (2008). Conversations among competitors. *American Economic Review*, *98*, 2150–2162.

Wang, D. (2024). Beyond active share: Boosting fund performance through common holdings with same-benchmark mutual funds. *International Review of Financial Analysis*, *92*, Article 103095.

Yan, X. S., & Zhang, Z. (2009). Institutional investors and equity returns: Are short-term institutions better informed? *The Review of Financial Studies*, *22*, 893–924.

Zhu, A. (2016). Social connections and information production: Evidence from mutual fund portfolios and performance. *SSRN Electronic Journal*.