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Network of public equity funds and investment performance in South Korea

Yongwon Kim
Department of Business Administration, Darla Moore School of Business, University of South Carolina, Columbia, South Carolina, USA and Department of Finance, Business School, Sungkyunkwan University, Seoul, South Korea, and
Inwook Song and Young Kyu Park
Department of Finance, Business School, Sungkyunkwan University, Seoul, South Korea

Abstract
Using overlapped portfolio data on public equity funds in Korea, the authors construct several types of fund-stock weighted bipartite networks and measure fund network centrality. The authors also examine the relationship between network centrality and fund investment performance. The authors' results are three-fold. First, the authors find that the fund centrality of the network in which funds and stocks are connected based on the most active investing behavior positively affects the fund performance. Second, the funds with a high centrality level based on the same network generate higher returns by holding stocks with high value uncertainty. Third, the authors find that fund centrality is not associated with herd behavior. Based on these results, the authors argue that fund centrality is a proxy of information advantage and skill of fund managers. The authors' paper shows that network analysis could be a new way to identify funds with better performance and measure the skill and information advantage to construct an optimal portfolio.

Keywords Network analysis, Centrality, Excess return, Value uncertainty, Herd behavior
Paper type Research paper

1. Introduction

Public equity funds provide investors with an opportunity to access diversified portfolios with lower costs. A fund manager with the ability to create an efficient portfolio could protect retail investors who are exposed to high risk. However, decreasing demand for public equity funds after the financial crisis in 2008 implies that the fund's performance does not fulfill the fund investors' expectations. The various research efforts on the performance of public equity funds could provide important information on how funds can enhance management efficiency and attract more investors. In this paper, we use network analysis to identify a fund's position within the network which could enhance their investment performance.

Previous literature indicates that institutional investors could learn information related to their investment through their individual networks (Baik *et al.*, 2010; Coval and Moskowitz, 1999, 2001; Hong *et al.*, 2005; Pool *et al.*, 2015). The information transmitted

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among institutional investors predicts future stock returns, because of its high quality that is less accessible to retail investors. We could identify investors who have better investment performance based on their individual networks. Rossi *et al.* (2018) build a network based on the connection between fund managers and consultants and show that fund managers who are in the central position of the network have higher risk-adjusted returns. Using a network between brokers and managers based on their past six-month transaction records, Maggio *et al.* (2019) provide evidence that the trade placed by central brokers generates high abnormal returns. Walden (2019) explores the relationship between investor position in the network linked by neighboring postal codes and trading profit. Evgeniou *et al.* (2021) form a network based on interindustry trade-flow data and find the U-shape relationship between the firm centrality and the return after their share repurchases.

Network position based on social connection is also useful to evaluate the value of those unlisted companies that have less information on stock value. Hochberg *et al.* (2007) create a network based on a venture capital's syndicate member information and find that funds with more central parents perform better and are more likely to get investment in another funding round. Bajo *et al.* (2016) find that the market value of a firm increases after its IPO when this firm is underwritten by a central investment bank in the network, which banks are connected if they have been in the same IPO syndicates in the past. Other papers discuss that central directors of the boardroom network positively affect firm performance and trading profitability (Goergen *et al.*, 2019; Larcker *et al.*, 2013).

A network based on investor trading behavior could consider more channels of relationships compared to networks based on social relations. Investor trading behaviors could be affected by their optimal decisions based on the information and knowledge they possess [1]. Hu *et al.* (2020) construct the network based on overlapped portfolios of mutual funds. Central funds in the network have higher investment profits and use the stock that has higher value uncertainty to generate profit. Bajo *et al.* (2020) use a similar network, which is based on an overlapped portfolio of institutional investors and find that central institutional investors can increase the firm value by certifying those firms they invest in.

Using public equity fund monthly portfolio composition from January 2014 to March 2021, we construct a network based on fund portfolio holdings and identify the position of funds that have better performance. In our network, funds and stocks are connected when the fund holds the stock. However, networks based on investor trading behavior could include several other factors that increase the fund return. Therefore, we need to construct several types of networks and analyze the network effect in detail.

Hu *et al.* (2020) define an information network between a fund and a stock when a stock accounts for more than 5% of the fund's total net asset. Our analysis constructs several types of networks by changing the weight of each connection based on the fund's stock-holding characteristics. We consider four types of weight: (1) portfolio weight (*Weighted network*), (2) excess portfolio weight compared to its market portfolio weight (*Over-index Network*), (3) excess portfolio weight compared to its previous portfolio weight (*Over-past Network*) and (4) *Over-past Network* with both portfolio weight and previous portfolio weight exceeds market portfolio weight (*Over-index Rise to Over-index Network*).

Compared to a network without weight, the weighted network contains more information about the fund's investment decision, such as the manager's skill to determine portfolio weight. This aspect is important in creating the networks because stock selection and portfolio weights affect fund performance directly (Baker *et al.*, 2010; Chen *et al.*, 2000; Kacperczyk *et al.*, 2005). In addition, weights used in the other network methodologies listed above could also capture the fund's active investing behaviors, which deviate from both the market indices benchmark strategy and fund past strategies. Therefore, we expect that each network identifies different central funds. Based on the different performances of these central funds in each network, we pinpoint the most useful network that captures the stock selection skill and information advantage of fund managers.

Previous literature considers centrality as a measure of nodes' influence based on node position within the network. For example, Hu *et al.* (2020) employ three types of centrality, including (1) closeness centrality, (2) betweenness centrality and (3) eigenvector centrality. Closeness centrality is calculated based on the efficiency of the focal fund to reach other nodes. Funds with high closeness centrality levels have higher accessibility to information in the network. Betweenness centrality is measured by the percentage of focal funds included in the shortest path of other nodes. Therefore, this methodology emphasizes the intermediation role of funds in the network. Eigenvector centrality increases when the focal fund is connected to important funds that have a high eigenvector centrality level. Funds with a high level of eigenvector centrality have better access to value-relevant information provided by other central funds.

We expect closeness and betweenness centrality might misinterpret the connection of funds as an information transmission route even though some connections are constructed due to their similar investment strategies in our networks. We focus on eigenvector centrality as our main measure. Theoretically, the eigenvector centrality of the fund is determined based on its similarity of portfolio composition to the network's representative portfolio. A fund with a high centrality level has a better performance if the network's representative portfolio is similar to the most efficient portfolio of the network. In this perspective, information advantage is not the only channel that explains the efficiency of a representative portfolio. Therefore, we interpret fund centrality as representing both manager skill and information advantage that increase return.

Our results show that the eigenvector centrality level, measured by the *Weighted Network* (*W*) and *Over-index Rise to Over-index Network* (*Oiroi*), positively affects the fund performance. However, the coefficient of *W* becomes insignificant on the fund return (*Return*) and excess return (*Excessreturn*), while the effect of *Oiroi* continues to hold for all alternative measures of the fund performance. Therefore, we conclude that the central funds in the network that are built by the most active investment have the characteristics that lead to better investment performance.

Next, we further investigate whether funds with high *Oiroi* can better manage stocks with high uncertainty levels. Fund managers have less incentive to hold these stocks if they are less capable of managing these stocks because holding these stocks negatively affects their investment performance. However, we find that funds with high levels of *Oiroi* perform better when they hold additional stocks with high-value uncertainty. The result suggests that *Oiroi* measures a manager's skill and information advantage to manage hard-to-value stocks.

Finally, we examine how herd behavior influences our network and centrality. By imitating the central fund's portfolio, non-central funds could increase their centrality levels. We first check whether market conditions affect fund herd behavior. When the market is in extreme condition, herd behaviors are prevalent (Chang *et al.*, 2000; Christie and Huang, 1995). We find that the dispersion of fund return does not decrease in extreme market conditions. We also check the heterogenous effects of market conditions on fund herd behavior by centrality level. Our results show that network centrality can't explained by fund herd behavior in the period of extreme market conditions.

Our research contributes to existing literature that constructs the network based on overlapped portfolios (Bajo *et al.*, 2020; Hu *et al.*, 2020). We constrain our sample to funds that use the most consistent strategy, which alleviates the concern that our results are driven by different styles of risk management. In addition, our study provides a variety of methodologies that can be used when building a network based on investment behavior. These methods could show which characteristics of fund investing behavior are essential to make networks better explain the fund performance.

2. Data and methodology

2.1 Network structure

We build various networks based on fund portfolio data and examine the relationship between the fund position in the network and the investment performance. A network structure is characterized by nodes (Actors) and edges (Connections). We include all types of actors, which are funds and stocks, and construct the fund-stock bipartite network. In this network, funds are connected only through the stocks they hold and the connection between funds becomes stronger when fund portfolios are similar. To reflect the different magnitudes of each connection, we assign different weights to edges. We measure the influence of nodes to identify the central funds within a network.

Public equity funds in Korea can be classified into four categories based on different investment styles: General equity fund, small equity fund, dividend equity fund and sector equity fund. However, including all categories of public equity funds in the same network creates noise that is not related to fund manager skills or information advantage. If several fund categories exist in the same network, the fund network position could be affected by the different levels of risk of each investment style. Therefore, the relationship between fund network position and performance is affected by different levels of risk. To alleviate this concern, we only include funds categorized as “general equity funds”, which use benchmark portfolios based on the KOSPI 200 index [2].

To help understand the fund-stock bipartite network, we construct the network based on the fund portfolio in March 2021. In Figure 1, we only include 20 main funds (Right nodes) and stocks (Left nodes) in which the fund invests more than 3% of total net assets. Funds are mostly interested in holding large stocks such as Samsung Electronics (005930), SK Hynix (000660), Hyundai Motor Company (005380), NAVER (035420) and LG Chem (051910) [3]. Therefore, the connections between funds become stronger as the portfolio weights for large stocks increase.

We construct several fund-stock bipartite networks using different weights, such as portfolio weight (*Weighted Network*), excess portfolio weight above the market portfolio weight (*Over-index Network*) and excess portfolio weight above the previous portfolio weight (*Over-past Network*). In addition, we construct a network in which funds and stocks are connected when both current and previous portfolio weights are over market portfolio weight and weighted by excess portfolio weight above previous portfolio weight (*Over-index Rise to Over-index Network*).

In Figure 2, the *Weighted Network* consists of 274 funds (Right nodes) and 471 stocks (Left nodes). The funds and the stocks are connected when the stocks are included in the fund portfolio. Funds are intensely connected to large stocks as Figure 1, because funds follow the market index-based benchmark. The *Over-index Network* also shows a similar pattern as the *Weighted Network*. But weights of the *Over-index Network* are different from the *Weighted Network*. Strong connections between funds and stocks now indicate that both funds have similar strategies in addition to their market-based benchmark strategy or have access to similar information sources.

The *Over-past Network* reflects the changes in the fund portfolio, which is driven by the time-varying fund strategy or the information flow. Fund managers will buy stocks when they receive value-relevant information about the stock or if the stock is more aligned with their strategy. While the number of funds in the network is equal to the *Weighted* or the *Over-*

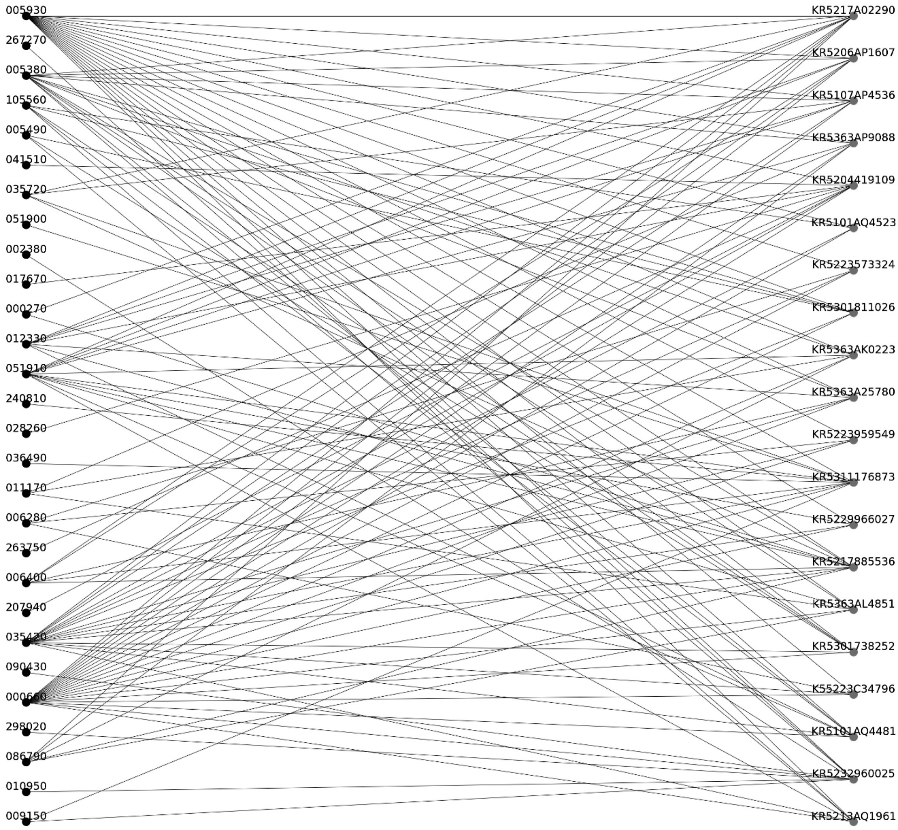


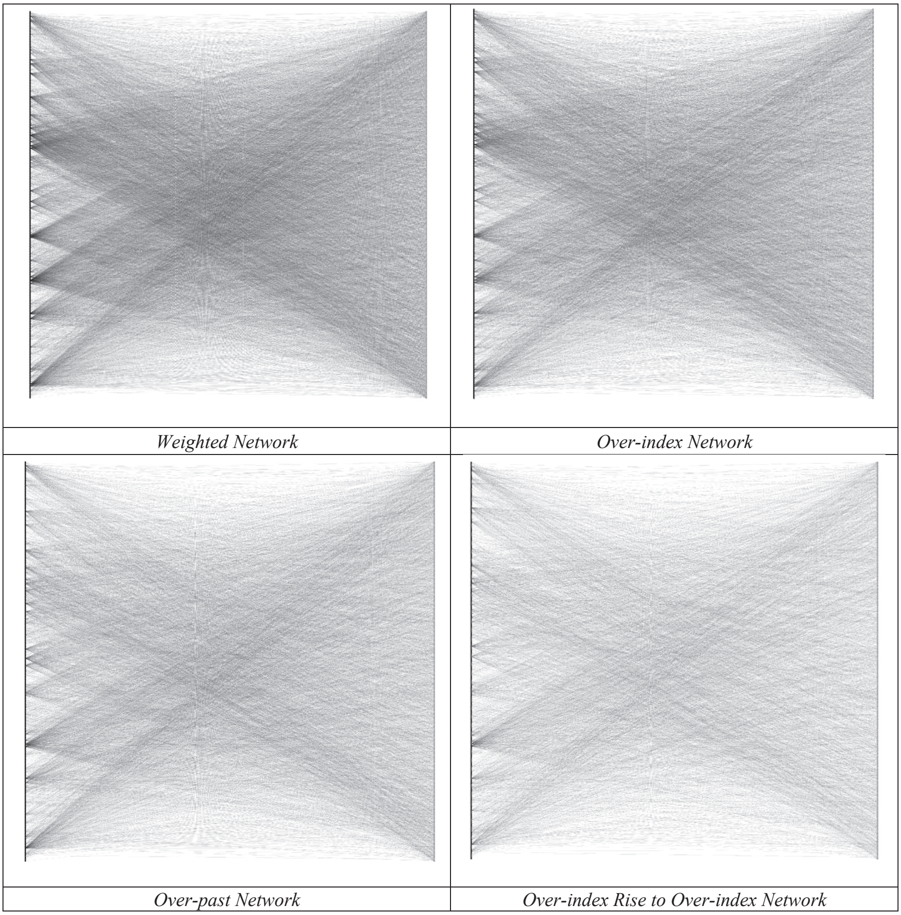
Figure 1.
Subsample of fund-stock bipartite network in March 2021

Note(s): Figure 1 shows the bipartite network between the top 20 central funds (right nodes) and stocks (left nodes) based on the stock holding information in March 2021. The edges of the network indicate that a fund holds a stock of more than 3% of its total net asset
Source(s): Author's work

*index Network*s, the number of stocks decreases to 385. The number of edges between funds and stocks decreased substantially compared to the other networks. Therefore, we expect that the central funds of the *Over-past Network* are different from the central funds of previous networks.

Lastly, the *Over-index Rise to Over-index Network* includes 343 stocks, and the number of edges between funds and stocks decreased compared to the *Over-past Network*. Normally, fund managers in general equity funds rebalance the portfolio to be more diversified as a market portfolio. The manager of a general equity fund still increases the holding weight of the concentrated stock, if they have strong confidence in the stock.

We mainly use monthly portfolio data of public equity funds from January 2014 to March 2021, which is provided by Korea Fund Ratings (KFR). Funds are included in the data if the total net asset of the fund is over 1 billion won. Each fund portfolio in the data covers up to 30 main holding stocks which comprises 78% of the total net asset on average. KFR also provides fund characteristics, including fund return (*Return*), size (*Netasset*), family size (*Familysize*), expense ratio (*Expense*), turnover ratio (*Turnover*) and



Note(s): Figure 2 shows the bipartite network between funds (right nodes) and stocks (left nodes) in March 2021 based on 30 main holding stocks of the fund. The edges of the Weighted Network indicate that the fund holds the stock. The edges of the Over-index Network indicate that the fund holds the stock more than the market portfolio weight. The edges of the Over-past Network indicate that the fund holds stock more than the past month's portfolio weight. The edges of the Over-index Rise to Over-index network indicate the fund holds the stock more than the past month's portfolio weight, where all the past and current portfolio weights are greater than market portfolio weights

Source(s): Author's work

Figure 2.
Fund-stock bipartite network in March 2021

operating period (*Fundage*) by each month. In addition, we obtain monthly factor returns and stock characteristics, including the return, size, age and trading volume from DataGuidePro [4]. Based on the size information of each stock in KOSPI 200, we calculate the market portfolio weight. Stock market returns and risk-free interest rates are obtained from the Market data system of the Korea Exchange (KRX). The final sample contains 18,730 fund-month observations, which suggest that around 217 funds are included each month on average [5].

2.2 Centrality

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1s} \\ \vdots & \ddots & \vdots \\ a_{f1} & \cdots & a_{fs} \end{bmatrix} \tag{1}$$

$$A^{FS} = \begin{bmatrix} 0 & A \\ A' & 0 \end{bmatrix} \tag{2}$$

Centrality measures the importance of the node within the network. To measure the centrality of a bipartite network, we need to create an adjacency matrix, which provides the connection information of the network in matrix form. Eq. (1) shows the basic form of an adjacency matrix. There are f numbers of fund nodes and s numbers of stock nodes within a network and each $a_{fs} = 1$ if they are connected. In Eq. (2), we generate sociomatrix (A^{FS}), which is composed of $f + s$ numbers of rows and columns. a_{fs}^{FS} stands for the element of the sociomatrix. In our study, all elements in both matrices are changed to the holding weight to calculate the centrality of the weighted bipartite network [6].

$$Degree_{i,t} = \sum_{j=1}^{f+s} a_{ij}^{FS} \tag{3}$$

Degree centrality is the importance of a node based on the number of connections. Eq. (3) presents the method of calculating the degree centrality of fund i (Faust, 1997). The centrality of fund i equals the sum of all elements of row i in Eq. (2). In a bipartite network, fund nodes cannot be connected with other fund nodes and $\sum_f a_{ij}^{FS} = 0$. Therefore, the degree centrality of the fund is calculated by $\sum_s a_{ij}^{FS}$. For a weighted network, a_{ij}^{FS} becomes weights instead of indicators of ties between funds and stocks.

$$Closeness_{i,t} = \frac{f + s - 1}{\sum_{j=1}^{f+s-1} min\, d(i,j)} \tag{4}$$

The concept of closeness centrality is based on how the position of the node is easily accessible to all other nodes in a network. The method of calculating closeness centrality is mentioned in Eq. (4) (Freeman, 1979). We calculate the closest distance between fund i and an other fund or stock j ($min\, d(i,j)$). The inverse of the average of minimum distance to all other nodes is the closeness centrality of fund i. Therefore, the centrality increases as the minimum distance to other nodes decreases.

$$Betweenness_{i,t} = \sum_{s_l, s_k \in S} \frac{\sigma(s_l, s_k | f_i)}{\sigma(s_l, s_k)} \tag{5}$$

Betweenness centrality is calculated based on the number of cases a node is included in the shortest path of two other nodes as compared to all combinations of their shortest path. The method of measuring betweenness centrality is provided in Eq. (5) (Brandes, 2001). In our setting, we consider the shortest path from all combinations of nodes (s_l, s_k) within the stock group (S). The number of combinations between each node is denoted as $\sigma(s_l, s_k)$, and the number of paths including the focal node is denoted as $\sigma(s_l, s_k|f_i)$. For example, if two stock nodes have 2 shortest paths and fund i is included in one of the paths, $\frac{\sigma(s_l,s_k|f_i)}{\sigma(s_l,s_k)}$ becomes 1/2. As the number of fund i included in the shortest path increases, fund i's betweenness centrality increases.

$$\lambda \begin{bmatrix} c^F \\ c^S \end{bmatrix} = A^{FS} \begin{bmatrix} c^F \\ c^S \end{bmatrix} \tag{6}$$

Eigenvector centrality is the importance of focal nodes based on the importance of other neighbor (or connected) nodes. If connected nodes have a high eigenvector centrality level, then the focal node's centrality increases. Eq. (6) shows the result of eigen decomposition of A^{FS}, which is defined in Eq. (2) (Bonacich, 1991). Vectors (c^F, c^S) within the eigenvector of A^{FS} are the eigenvector centrality of each fund (F) and stock nodes (S) [7].

In our analysis, we mainly use eigenvector centrality as our measure of fund centrality. Eigenvector centrality is widely used in finance and effectively shows its significant impact on investment performance (Hochberg *et al.*, 2007; Hu *et al.*, 2020; Maggio *et al.*, 2019). The fund's eigenvector centrality increases when the fund has a strong connection with other funds with a high eigenvector centrality level. We interpret that eigenvector centrality is measured based on the fund portfolio's similarity to the one representative portfolio that best accounts for the fund-stock network. If this portfolio represents the most efficient investment in our sample, the fund performance level will be higher as its eigenvector centrality increases.

In contrast to the eigenvector centrality, other measures are less suitable for our analysis. Closeness or betweenness centrality focuses on the intermediation role of the node. These centralities are more applicable when the network is constructed based on social interaction, where the real intermediation of the information plays an important role in the network. In our Appendix, estimation results based on closeness and betweenness centrality are reported.

2.3 Regression model

$$4factoralpha_{it} = \beta_0 + \beta_1 centrality_{it-1} + X\beta + \alpha_i + \gamma_t + e_{it} \tag{7}$$

If fund centrality could measure the fund manager's skill and information advantage, a fund located in the central position within the network have better investment performance. We test this hypothesis based on Eq. (7). To measure a fund investment performance, we calculate the fund's performance of month t (*4factoralpha*) based on the four-factor model (Fama and French, 1993; Carhart, 1997). The main independent variables in the model are a set of eigenvector centralities, which are calculated from the *Weighted Network* (*W*), the *Over-index Network* (*Oi*), the *Over-past Network* (*Op*) and the *Over-index Rise to Over-index Network* (*Oiroi*) of month $t-1$. We normalize each centrality measure to be in the range of 0–1 [8]. We control for various fund characteristics such as investment performance (*Return*), net asset value (*Netasset*), the net asset value of fund family (*Familysize*), expense ratio (*Expense*), turnover ratio (*Turnover*) and operating period (*Fundage*) in month $t-1$. We also control for the sum of portfolio holding weight to ensure that our results are not influenced by different data coverage of each fund. To control the time-invariant characteristics of funds and time trends, fund and year-month fixed effects are considered. In our Appendix, we show the effect of centrality on alternative performance measures (*Return, Excessreturn, Capmalpha*) and prove that our results are not influenced by measurement error.

$$4factoralpha_{it} = \beta_0 + \beta_1 centrality_{it-1} + \beta_2 VU_{it} + \beta_3 centrality_{it-1} * VU_{it} + X\beta + \alpha_i + \gamma_t + e_{it} \tag{8}$$

We further investigate whether funds located in a central position in the network could generate more profit from stocks with high-value uncertainty. Kumar (2009) finds that disposition effects from investors are more prevalent when the value of a stock has high uncertainty (i.e. idiosyncratic volatility and turnover ratio of a stock is high or the period after the stock first listed in the market is short). We hypothesize that funds could manage stocks with high-value uncertainty and earn profit using the behavioral bias from other investors. To measure the value uncertainty score of the fund's portfolio (*VU*), we first sort all stocks in an ascending order based on three characteristics of stocks with high value uncertainty and divided into 10 groups. For the stock with the lowest (highest) idiosyncratic volatility, turnover ratio, or stock that traded in the market for the longest (shortest) period, we assign a score of 1 (10). For each fund, the value-weighted average of scores based on portfolio weights is *Idiovol*, *Turnover_stock* and *Stockage* used as a proxy of the *VU* score. Based on Eq. (8), we could estimate the heterogenous effect of centrality on fund performance conditioning on its *VU* score. For robustness checks, we also apply alternative measures of fund performance and reported in Appendix.

Next, we examine whether network centrality could be driven by the herd behavior of the fund. Fund nodes are linked based on the overlapped portfolio in our network settings, which indicates that herd behavior could make fund managers select the same stocks and affect their centrality.

Previous research has highlighted that the investment decisions of market participants could herd around extreme market conditions (Chang *et al.*, 2000; Christie and Huang, 1995). Herd behavior due to bubbles and crashes in the market could impact the measure of centrality, which is not driven by the fund manager's skill and information advantage.

$$CSSD_t = \sqrt{\frac{\sum_{i=1}^{N} \left(Return_{i,t} - R_{m,t}\right)^2}{N-1}} \tag{9}$$

$$CSSD_t = \beta_0 + \beta_1 D_t^L + \beta_2 D_t^H + e_t \tag{10}$$

Based on Christie and Huang (1995), we measure cross-sectional standard deviations of fund returns using Eq. (9) (*CSSD*). *CSSD* shows the standard deviation of fund excess returns, fund's return (*Return*) minus market return (R_m). Its value decreases if herd behavior exists in the fund market. In Eq. (10), we regress *CSSD* on market indicators of market boom (D^H) and crash (D^L). If coefficients of market indicators are negative, this suggests that the fund market shows herd behavior in extreme market conditions.

$$CSAD_t = \frac{\sum_{i=1}^{N} \left|R_{i,t} - R_{m,t}\right|}{N-1} \tag{11}$$

$$CSAD_t = \beta_0 + \beta_1 R_{m,t} + \beta_2 R_{m,t}^2 + e_t \tag{12}$$

Chang *et al.* (2000) investigate the non-linear relation between the cross-sectional absolute deviation of stock returns, which is Eq. (11) and market returns to identify herd behavior. We calculate the cross-sectional absolute deviation of fund returns (*CSAD*). Using the regression model of Eq. (12), we examine whether *CSAD* and R_m has a non-linear relationship. If the sign of β_2 in Eq. (12) is negative, *CSAD* decreases when the market return is placed in the extreme tail of its distribution, which suggests herd behavior. We also test the asymmetric fund market behavior by splitting the sample into two, when the market return is positive ($R_{m(Up)}$) and negative ($R_{m(Down)}$) [9].

Overall, we construct four different networks based on the monthly fund's investment portfolio and examine which network position could increase the fund's performance. We further investigate whether the fund manager of central funds in the network can manage stocks with high-value uncertainty. To alleviate the concern that our methods are highly affected by fund herd behavior, we also examine whether the financial market's extreme condition could affect the fund return dispersion. Table 1 presents detailed descriptions of all the variables [10].

3. Results

3.1 Fund network centrality and performance

Table 2 presents summary statistics for all variables included in our analysis. We find a significant variation in each network centrality measure. On average, *W*, *Oi*, *Op* and *Oiroi* are 0.68, 0.34, 0.11 and 0.12, respectively. 25 percentile of *W* exceeds 0.5, which suggests that the

Variables	Description
W	Standardized fund eigenvector centrality from the *Weighted Network*, where funds and stocks connections are weighted by portfolio weights
Oi	Standardized fund eigenvector centrality from the *Over-index Network*, where funds and stocks connections are weighted by the fund's holding weight minus market portfolio weights
Op	Standardized fund eigenvector centrality from the *Over-past Network*, where funds and stocks connections are weighted by the fund's holding weight minus past portfolio weights
Oiroi	Standardized fund eigenvector centrality from the *Over-index Rise to Over-index Network*, where funds and stocks connections are weighted by the fund's holding weight minus past portfolio weights only when both weights are greater than market portfolio weights
Return (%)	Monthly fund return
4factoralpha (%)	Monthly fund return after risk adjustment for the four-factor model
Netasset (Billion Won)	Monthly fund total net asset (in billions of wons)
Expense (%)	Monthly fund expense ratio
Familysize (Billion Won)	Monthly total net asset of the fund family (in billions of wons)
Turnover	Monthly minimum of the total value of purchases or sales adjusted by *Netasset*
Fundflow (%)	Monthly net volume of capital flow adjusted by past month *Netasset*
Fundage (Month)	The number of dates from the fund's founding date divided by 30
Top30 (%)	The monthly total percentage that Top30 holding stocks represent by each fund
Idiovol	The average decile of idiosyncratic volatility of holding stocks
Turnover_stock	The average decile of turnover of holding stocks
Stockage	The average decile of the age of holding stocks multiplied by −1
CSSD	Cross-sectional standard deviation (standard deviation of excess fund return)
CSAD	Cross-sectional absolute deviation (sample mean of the absolute value of the excess return)
$D_L D_U$	The indicator of market return lies in its distribution at 2.5% or 5% lower (upper) tail
R_M	Equally weighted monthly return of all available securities
$R_{M(UP)}$, $R_{M(DOWN)}$	Equally weighted monthly return of all available securities when the market is up or down

Source(s): Authors' work

Table 1.
Variables description

Table 2.
Summary statistics

	Variables	N	Mean	SD	Min	p25	p50	p75	Max
Centrality	*W*	18,730	0.6849	0.2416	0.0065	0.5893	0.7716	0.8524	0.9836
	Oi	18,730	0.3373	0.1945	0.0170	0.1956	0.3028	0.4412	0.9805
	Op	18,730	0.1071	0.1394	0.0001	0.0231	0.0610	0.1351	0.7359
	Oiroi	18,730	0.1183	0.1605	0.0000	0.0160	0.0580	0.1561	0.8455
Fund characteristics	*4factoralpha* (%)	18,730	−0.1533	1.6916	−4.6517	−1.0658	−0.1554	0.7262	4.4753
	Netasset (Billion Won)	18,730	65.5820	163.5540	1.0913	4.6691	14.8666	53.2595	867.3460
	Familysize (Billion Won)	18,551	961.2044	980.6763	7.8632	164.0470	646.0371	1,451.2998	4,400.6733
	Fundage (Month)	18,730	132.4201	55.2681	40.4333	97.2667	131.2667	163.4667	247.8333
	Expense (%)	18,730	0.6313	0.1558	0.1760	0.5490	0.6700	0.7450	0.9300
	Turnover	18,730	9.7146	8.1191	0.0000	4.1483	7.7787	12.9500	38.9621
	Return (%)	18,730	0.6624	4.5429	−13.0778	−1.7582	0.5728	3.0696	13.5281
	Fundflow (%)	18,692	−1.4962	10.2029	−20.3387	−3.0399	−1.0851	−0.0716	20.4401
	Top30 (%)	18,730	78.1369	11.3818	45.6384	71.9003	78.3313	85.3953	100.0000
Value uncertainty measures	*Idiovol*	18,730	0.2941	0.1724	0.0332	0.1672	0.2658	0.3863	0.8782
	Turnover_stock	18,730	0.2309	0.1656	0.0203	0.1181	0.1902	0.2938	0.8887
	Stockage	18,730	−0.6304	0.1653	−0.9664	−0.7377	−0.6419	−0.5451	−0.1218

Note(s): Table 2 shows the summary statistics of the centrality measures, fund characteristics and value uncertainty measures. Detailed variable definitions are in Table 1
Source(s): Authors' work

distribution of eigenvector centrality in the *Weighted Network* skews to the left. *Oi* is less tilted toward its maximum value and shows that the 75 percentile is still less than 0.5. For *Op* and *Oiroi*, they show a large difference between the 75 percentile and its maximum, which suggests that an intense connection is made by a small group of fund nodes within the network.

The average *Return* is 0.66% per month, which is relatively higher than its average *4factoralpha*, which is −0.15%. Therefore, we could expect that a positive fund's return comes from risk-premium. *Netasset* and *Familysize* of funds are 65.58 and 961.20 on average (in units of 1 billion won). The size of funds is affected by declining investor's preference for funds, as *Fundflow* drops 1.5% per month on average. In our sample, we only include the funds operated for more than 2 years, so the average *Fundage* is 132 months. The mean *Expense* and *Turnover* is 0.63% and 9.71%. The average *VU* score of the fund portfolio is 0.29, 0.23 and −0.63 for each *Idiovol, Turnover_stock and Stockage*, which suggests that the fund prefers to hold stocks with less uncertainty [11].

Table 3 reports the correlation matrix. We find correlation between each variable is less severe to affect our results. In addition, the variance inflation factor provides more evidence that our results are affected by multicollinearity.

Table 4 reports the relation between the centrality of each network and investment performance. The coefficient estimates in the regression indicate that one standard deviation of *W* (which is 0.24) significantly increases the *4factoralpha* by about 0.07%p per month (0.85%p per year). One standard deviation increment of *Oiroi* is associated with a 0.06%p increment of *4factoralpha* (0.78%p per year). The coefficients of both *Oi* and *Op* centrality are insignificant.

We also examine whether our results are robust to other measures for the fund performance in Table A.3. *Oiroi* consistently shows a significant relation to all types of return measures. However, we find no statistical significance between *W* and *Return* or *W* and *Excessreturn*. We conclude that the important characteristics of funds to increase their performance are only captured by *Oiroi*.

Given that the eigenvector centrality of a fund shows its portfolio similarity to the representative portfolio of the whole network, we interpret that the representative portfolio from the *Weighted*, the *Over-index* and the *Over-past Network*s does not contain important features to enhance their performance. The linkage between funds and stocks in the *Over-index Rise to Over-index Network* is based on the most active investment behavior of funds. Therefore, we could expect that the network might include important strategic investments or informed trading which significantly improve the fund performance.

An alternative method to construct a network is using their decreasing portfolio weights. Decreasing portfolio weights could also capture the fund's investment strategy to avoid loss. Therefore, the fund manager of the central funds will successfully cut their losses and could show better performance compared to other peripheral funds. We re-analyze Eq. (7) based on centralities of the *Under-index*, *Under-past* and *Under-index Reduced to Under-index Network* and present the results in Table A7. The relation between *Ui, Up, Uirui and 4factoralpha* doesn't show any statistical significance. The possible reason may be that stock selections made by fund managers are constrained by their investment mandates. They can only invest in a limited number of stocks, so decreasing weights might comprise other reasons including the manager's decision to avoid loss. In Table A7, we also report the results focusing on how closeness and betweenness centrality could affect fund performance. Our results provide some evidence of a significant relation between other types of centrality and *4factoralpha*.

3.2 Fund network centrality, value uncertainty and performance

To help understand the characteristics of central funds in the network, we further investigate whether stocks with high-value uncertainty could increase fund performance. If β_3 of Eq. (8) is

Table 3.
Correlation matrix

	W	*Oi*	*Op*	*Oiroi*	*Netasset*	*Familysize*	*Fundage*	*Expense*	*Turnover*	*Return*	*Fundflow*	*Top30*	*Idiovol*	*Turnover_ stock*	*Stockage*
W	1.00														
Oi	−0.07***	1.00													
Op	0.17***	0.11***	1.00												
Oiroi	0.12***	0.28***	0.20***	1.00											
Netasset	−0.05***	0.09***	−0.08***	−0.05***	1.00										
Familysize	−0.02*	0.19***	−0.12***	−0.05***	0.34***	1.00									
Fundage	0.25***	−0.12***	0.03***	0.05***	0.03***	−0.06***	1.00								
Expense	0.11***	0.09***	0.07***	0.10***	0.05***	−0.12***	0.14***	1.00							
Turnover	−0.04***	0.01	0.40***	0.23***	−0.19***	−0.30***	0.01	0.10***	1.00						
Return	0.04***	−0.05***	0.05***	0.01*	−0.02**	−0.03***	0.06***	−0.02***	−0.00	1.00					
Fundflow	−0.06***	−0.03***	−0.06***	−0.06***	0.02**	−0.01	0.01	−0.11***	−0.01	−0.14***	1.00				
Top30	0.19***	0.56***	0.17***	0.22***	−0.01	0.03***	0.02**	0.14***	0.07***	0.03***	−0.06***	1.00			
Idiovol	−0.25***	0.43***	0.11***	0.12***	−0.02*	−0.03***	−0.18***	0.14***	0.22***	−0.06***	−0.03***	0.44***	1.00		
Turnover_ stock	−0.19***	0.33***	0.13***	0.14***	−0.09***	−0.11***	−0.08***	0.13***	0.26***	0.02**	−0.01	0.39***	0.84***	1.00	
Stockage	−0.61***	−0.30***	−0.13***	−0.17***	−0.01	−0.05***	−0.10***	−0.15***	0.03***	−0.03***	0.06***	−0.62***	−0.03***	−0.03***	1.00

Note(s): Table 3 shows the correlation matrix for the full sample. All variables are winsorized at a 1% level for both tails to mitigate the effect of outliers. Detailed variables definitions are in Table 1. ***, ** and * denote significance at the 0.1, 1 and 5% level, respectively
Source(s): Authors' work

	W	*Oi*	*Op*	*Oiroi*
Centrality	0.292**	−0.0805	−0.0840	0.402***
	(0.116)	(0.124)	(0.134)	(0.0923)
Netasset(log)	−0.220***	−0.226***	−0.227***	−0.228***
	(0.0432)	(0.0427)	(0.0428)	(0.0428)
Familysize(log)	−0.140***	−0.139***	−0.141***	−0.138***
	(0.0517)	(0.0513)	(0.0513)	(0.0522)
Fundage(log)	0.0611	0.0973	0.0857	0.0806
	(0.198)	(0.195)	(0.196)	(0.197)
Expense	−0.779	−0.776	−0.775*	−0.793*
	(0.486)	(0.473)	(0.468)	(0.473)
Turnover	−0.00212	−0.00266	−0.00205	−0.00423**
	(0.00199)	(0.00202)	(0.00209)	(0.00200)
Return	−0.00315	−0.00291	−0.00344	−0.00595
	(0.00830)	(0.00824)	(0.00839)	(0.00829)
Fundflow	0.00181	0.00148	0.00149	0.00160
	(0.00280)	(0.00277)	(0.00277)	(0.00278)
Top30	−0.00193	−0.000676	−0.00137	−0.00268
	(0.00212)	(0.00224)	(0.00206)	(0.00208)
Constant	9.608***	9.712***	9.880***	9.912***
	(1.976)	(1.938)	(1.949)	(1.965)
No. of Obs	18,476	18,476	18,476	18,476
R squared	0.186	0.185	0.185	0.186
Fund FE	yes	yes	yes	yes
Time FE	yes	yes	yes	yes

Note(s): Table 4 shows the coefficients of the panel regression result of the equation below. All models include fund characteristics(X), fund(α_i) and year-month(γ_t) fixed effect. All variables except *Top30* and value uncertainty measures are lagged variables. We use the logarithm of *Netasset*, *Familysize* and *Fundage* variables as used in the regression model. All variables are winsorized at a 1% level for both tails to mitigate the effect of outliers. Detailed variable definitions are in Table 1. Standard errors clustered at the firm level are in parentheses. ***, ** and * denote significance at the 1, 5 and 10% level, respectively

$4factoralpha_{it} = \beta_0 + \beta_1 centrality_{it-1} + X\beta + \alpha_i + \gamma_t + e_{it}$

Source(s): Authors' work

Table 4. Fund network centrality and performance

significantly positive, funds with high centrality levels will have higher abnormal returns when they hold more hard-to-value stocks. This suggests that centrality captures the fund manager's skill to earn profit through the high disposition effect of the stocks (Kumar, 2009). Table 5 reports the coefficient of the interaction term between the fund value uncertainty indexes. The coefficients of *Op* and *Oiroi* interacting with the *VU* score of the fund are significant.

In Table 6, we calculate the marginal effect of each centrality on fund performance and compare funds where their value uncertainty score is in the 25th percentile and the 75th percentile. When *Idiovol* (*Turnover_stock*) is 25th percentile, the marginal effect of *W* is 0.852%p (0.642%p) and it decreases to 0.835%p (0.600%p) when it is 75th percentile. *W* increased when the fund portfolio is the most similar to the representative portfolio of the network. We expect the representative portfolio might be similar to the market portfolio because most of the funds use market portfolio benchmarks. Therefore, networks that reflect the funds' market index-based benchmark are less likely to identify the fund using stocks with high-value uncertainty to generate higher returns.

On the contrary, the marginal effect of *Oiroi* on fund performance significantly increases as *VU* scores are increased from the 25th percentile to the 75th percentile. In the 25th percentile of *Idiovol*, *Turnover_stock* and *Stockage*, the marginal effect of *Oiroi* on

	W	*Oi*	*Op*	*Oiroi*
VU = Idiovol				
Centrality	0.864***	−0.125	−0.922***	−0.226
	(0.181)	(0.232)	(0.293)	(0.200)
Idiovol	2.567***	2.318***	1.838***	1.922***
	(0.295)	(0.259)	(0.180)	(0.173)
*Centrality*Idiovol*	−0.0759	−0.359	2.184***	1.666***
	(0.377)	(0.575)	(0.814)	(0.505)
VU = Turnover_stock				
Centrality	0.671***	−0.314	−0.960***	−0.0358
	(0.152)	(0.201)	(0.233)	(0.160)
Turnover_stock	1.907***	1.383***	1.148***	1.365***
	(0.327)	(0.271)	(0.181)	(0.181)
*Centrality*Turnover_stock*	−0.241	0.490	2.891***	1.307***
	(0.440)	(0.594)	(0.758)	(0.432)
VU = Stockage				
Centrality	1.614***	0.879**	2.553***	1.026***
	(0.321)	(0.432)	(0.591)	(0.358)
Stockage	−0.369	−0.318	−0.188	0.154
	(0.416)	(0.308)	(0.232)	(0.213)
*Centrality*Stockage*	1.863***	1.482***	4.090***	0.929*
	(0.478)	(0.562)	(0.844)	(0.494)
No. of Obs	18,476	18,476	18,476	18,476
Control variables	yes	yes	yes	yes
Fund FE	yes	yes	yes	yes
Time FE	yes	yes	yes	yes

Note(s): Table 5 shows the coefficients of the panel regression result of the equation below. All models include fund characteristics(X), value uncertainty measures (VU), fund(α_i) and year-month(γ_t) fixed effect. All variables except *Top30* and value uncertainty measures are lagged variables. We use the logarithm of *Netasset*, *Familysize* and *Fundage* variables as used in the regression model. All variables are winsorized at a 1% level for both tails to mitigate the effect of outliers. Detailed variable definitions are in Table 1. Standard errors clustered at the firm level are in parentheses. ***, ** and * denote significance at the 1, 5 and 10% level, respectively
$4factoralpha_{it} = \beta_0 + \beta_1 centrality_{it-1} + \beta_2 VU_{it} + \beta_3 centrality_{it-1} * VU_{it} + X\beta + \alpha_i + \gamma_t + e_{it}$
Source(s): Authors' work

Table 5.
Fund network centrality and performance of hard-to-value portfolio

4factoralpha is 0.052%p, 0.119%p and 0.341%p. When those three dimensions of the *VU* score are 75th percentile, all the marginal effects increased to 0.417%p, 0.348%p and 0.520%p (in order of *Idiovol*, *Turnover_stock* and *Stockage*). These results suggest that the eigenvector centrality of the network based on the fund's most active investment could capture the skill and information advantage of fund managers about high-value uncertainty stocks.

Most of the marginal effect of *Oi* on *4factoralpha* shows that returns of central funds decrease as they hold more stocks with higher *Idiovol*. In other types of the *VU* score, the increasing *VU* score and *Oi* make no significant increase in *4factoralpha*. The marginal effect of *Op* on *4factoralpha* is significantly increased when the fund holds the stocks with higher value uncertainty stems from *Stockage*. However, the impact becomes insignificant when funds have high scores on *Idiovol* and *Turnover_stock*.

In our Appendix, we continue to find statistical significance for the coefficient of interaction between *Oiroi* and two types of value uncertainty measures (*Idiovol* and *Turnover_stock*) when the dependent variables are alternative measures for the fund performance (Table A4 – Table A6). In addition, we also check that funds with high closeness, betweenness centrality of the *Weighted*, the *Over-index*, the *Over-past* and the *Over-index Rise*

	W	*Oi*	*Op*	*Oiroi*
VU = Idiovol				
p25	0.852***	−0.186	−0.557***	0.052
	(0.141)	(0.156)	(0.177)	(0.132)
P75	0.835***	−0.264**	−0.078	0.417***
	(0.122)	(0.118)	(0.125)	(0.096)
VU = Turnover_stock				
p25	0.642***	−0.256*	−0.618***	0.119
	(0.124)	(0.149)	(0.163)	(0.123)
P75	0.600***	−0.170	−0.111	0.348***
	(0.118)	(0.115)	(0.121)	(0.094)
VU = Stockage				
p25	0.240*	−0.214*	−0.463***	0.341***
	(0.138)	(0.112)	(0.133)	(0.092)
P75	0.599***	0.071	0.324*	0.520***
	(0.130)	(0.158)	(0.171)	(0.119)
No. of Obs	18,476	18,476	18,476	18,476
Control Variables	yes	yes	yes	yes
Fund FE	yes	yes	yes	yes
Time FE	yes	yes	yes	yes

Note(s): Table 6 shows the average marginal effect of centrality at the 1st and 3rd quantiles of value uncertainty. The panel regression model is as below. All models include fund characteristics(X), value uncertainty measures (VU), fund(α_i) and year-month(γ_t) fixed effect. All variables except *Top30* and value uncertainty measures are lagged variables. We use the logarithm of *Netasset*, *Familysize* and *Fundage* variables as used in the regression model. All variables are winsorized at a 1% level for both tails to mitigate the effect of outliers. Detailed variable definitions are in Table 1. Standard errors clustered at the firm level are in parentheses. ***, ** and * denote significance at the 1, 5 and 10% level, respectively

$4factoralpha_{it} = \beta_0 + \beta_1 centrality_{it-1} + \beta_2 VU_{it} + \beta_3 centrality_{it-1} * VU_{it} + X\beta + \alpha_i + \gamma_t + e_{it}$

Source(s): Authors' work

Table 6. Marginal effects of the centrality

to Over-index Network, or funds with high eigenvector centrality level based on alternative networks (*Under-index*, *Under-past* and *Under-index Reduce to Under-index*) can't increase *4factoralpha* as the fund holds more stocks with high value uncertainty (Table A8 – Table A10).

3.3 Fund network centrality and herd behavior

We construct an additional sample to examine whether herd behavior could affect our network. In Table 7, we report the summary statistics for this sample, composed of 87 months of fund return variance measures (*CSSD* and *CSAD*) and market return. *CSSD* and *CSAD* are 0.027 and 0.024 on average and always less than 0.08. This suggests that fund returns are less dispersed due to their similar benchmark portfolio. For Eq. (10), D^H (D^L) is one (zero) when the market lies within 2.5% or 5% upper (lower) tail of its return distribution. In Eq. (12), we use the nominal market return (R_m) and its square term (R_m^2) as our main independent variables. We also split our samples into two, where 57 months of up periods and 30 months of down periods of market return. During an up (down) period, market return is written as $R_{m(UP)}$ ($R_{m(Down)}$) [12]. Because we use time-series regression in this section, we check whether our measures of fund return variance and market return are stationary. In Table 7, we find that our variables in the analysis are all stationary based on the Dicky–Fuller test statistics.

The results for Eq. (10) are reported in Table 8. *CSSD* and *CSAD* increased significantly during the market boom period (when D^H is 1). In addition, we observe that the coefficient for R_m^2 is significantly positive. When we split the sample and re-estimate Eq. (12), the relation

Variables	N	Mean	SD	min	p25	p50	p75	max
CSSD	87	0.0267	0.0138	0.0094	0.0165	0.0227	0.0341	0.0774
CSAD	87	0.0236	0.0140	0.0072	0.0128	0.0198	0.0326	0.0756
D_L (2.5%)	87	0.0345	0.1835	0.0000	0.0000	0.0000	0.0000	1.0000
D_L (5%)	87	0.0575	0.2341	0.0000	0.0000	0.0000	0.0000	1.0000
D_U (2.5%)	87	0.0345	0.1835	0.0000	0.0000	0.0000	0.0000	1.0000
D_U (5%)	87	0.0575	0.2341	0.0000	0.0000	0.0000	0.0000	1.0000
R_M	87	0.0123	0.0466	−0.1671	−0.0056	0.0137	0.0331	0.1636
R_M^2	87	0.0023	0.0046	0.0000	0.0001	0.0008	0.0028	0.0279
$R_{M(UP)}$	57	0.0361	0.0313	0.0004	0.0139	0.0304	0.0530	0.1636
$R_{M(UP)}^2$	57	0.0023	0.0042	0.0000	0.0002	0.0009	0.0028	0.0268
$R_{M(DOWN)}$	30	0.0330	0.0363	0.0008	0.0054	0.0237	0.0527	0.1671
$R_{M(DOWN)}^2$	30	0.0024	0.0055	0.0000	0.0000	0.0006	0.0028	0.0279

Variables	Lag1	Lag2	Lag3	Lag4	Lag5	DF-test
CSSD	0.0227	0.0165	−0.0263	0.0617	−0.0480	−6.169***
CSAD	0.0289	0.0191	−0.0379	0.0501	−0.0610	−6.137***
R_M	−0.0572	−0.0008	0.0140	−0.0067	−0.0064	−6.586***

Note(s): Table 7 shows the summary statistics of variables derived from time-series data composed of 87 months of fund's return standard deviation, absolute deviation, market return, and dummy variables that capture the extreme market movements. We also report the serial correlation of *CSSD*, *CSAD* and R_M along with the test statistics of the Dickey–Fuller Test. Detailed variables definitions are in Table 1. ***, ** and * denote significance at the 1, 5 and 10% level, respectively
Source(s): Authors' work

Table 7.
Summary statistics of *CSSD*, *CSAD*, and market return

between R_m^2 and *CSAD* is insignificant in both the up and down periods of market return. Overall, there is less evidence of herd behavior within the fund market due to extreme financial market conditions.

A potential concern with the results is that the herd behavior of funds could be correlated with *Oiroi*. In this case, the relation between centrality to investment performance could be largely influenced by herding. Therefore we construct five portfolios based on the value of *Oiroi* and re-estimate Eq. (12) to examine whether the magnitude of herd behavior is different in each portfolio.

Our baseline result uses the sample of Portfolio 1, which is composed of the most peripheral funds in the *Over-index Rise to Over-index Network*. In Portfolio 1, we can't observe any herd behavior. In other portfolios, our results are consistent with our baseline result and coefficients of R_m^2 are not significantly different. Therefore, the results in Table 9 suggest that *Oiroi* is less likely to be affected by fund herd behavior.

4. Conclusion

We construct four types of fund-stock weighted bipartite networks of general equity funds in Korea and examine the effect of fund network position on investment performance. We use eigenvector centrality as our main measure to calculate the importance of funds in the network based on their position. We further investigate the heterogenous effects of centrality when a fund holds more stocks with high-value uncertainty. We also check whether our centrality measure is highly affected by herd behavior.

Our findings are three-fold. First, the fund centrality in the *Over-index Rise to Over-index Network* (*Oiroi*), in which funds and stocks are linked when the stocks' portfolio weight exceeds its previous weight and both weights are over the market portfolio weights,

Table 8. Examination of herding behavior in the public equity fund market

	CSSD	*CSSD*	*CSAD*	*CSAD*	*CSAD*	*CSAD*	*CSAD*
D_L (2.5%)	−0.000109		0.00950				
	(0.00767)		(0.0137)				
D_U (2.5%)	0.0268***		0.0357**				
	(0.00767)		(0.0137)				
D_L (5%)		−0.000299		−0.000296			
		(0.00621)		(0.00634)			
D_U (5%)		0.0158**		0.0149**			
		(0.00621)		(0.00634)			
R_M					0.111***		
					(0.0280)		
R_M^2					1.069***		
					(0.283)		
$R_{M(UP)}$						0.267*	
						(0.137)	
$R^2_{M(UP)}$						−0.124	
						(1.032)	
$R_{M(DOWN)}$							0.147
							(0.129)
$R^2_{M(DOWN)}$							−0.383
							(0.859)
Constant	0.0261***	0.0257***	0.0231***	0.0227***	0.0198***	0.0173***	0.0139***
	(0.00145)	(0.00145)	(0.00148)	(0.00147)	(0.00148)	(0.00341)	(0.00305)
Observations	87	87	87	87	87	57	30
R-squared	0.080	0.127	0.079	0.132	0.278	0.277	0.125

Note(s): Table 8 shows the coefficients of the panel regression result of the equation below. Detailed variable definitions are in Table 1. Standard errors are in parentheses. ***, ** and * denote significance at the 1, 5 and 10% level, respectively

$CSSD_t \; or \; CSAD_t = \beta_0 + \beta_1 D_t^L + \beta_2 D_t^H + e_t$

$CSAD_t = \beta_0 + \beta_1 R_{m,t} + \beta_2 R^2_{m,t} + e_t$

Source(s): Authors' work

Centrality		Oiroi All	Up	Down
Portfolio1 (Smallest)	R_M	0.105***	0.326***	0.0805
		(0.0247)	(0.122)	(0.0985)
	R_M^2	0.968***	−0.818	0.123
		(0.250)	(0.920)	(0.656)
Portfolio2	R_M	0.119***	0.279*	0.104
		(0.0281)	(0.141)	(0.116)
	R_M^2	0.926***	−0.355	−0.247
		(0.284)	(1.066)	(0.772)
Portfolio3	R_M	0.113***	0.266*	0.107
		(0.0300)	(0.146)	(0.146)
	R_M^2	1.206***	−0.00659	0.0287
		(0.304)	(1.101)	(0.972)
Portfolio4	R_M	0.114***	0.276*	0.170
		(0.0309)	(0.149)	(0.152)
	R_M^2	1.151***	−0.0497	−0.509
		(0.312)	(1.121)	(1.012)
Portfolio5 (Biggest)	R_M	0.116***	0.216	0.285*
		(0.0329)	(0.156)	(0.166)
	R_M^2	1.132***	0.501	−1.409
		(0.332)	(1.175)	(1.102)
Observations		87	57	30

Note(s): Table 9 shows the coefficients of panel regression result of the equation below by each portfolio of funds sorted based on *Oiroi*. We only report the coefficient of R_M and R_M^2. Detailed variable definitions are in Table 1. Standard errors are in parentheses. ***, ** and * denote significance at the 1, 5 and 10% level, respectively

$CSAD_t = \beta_0 + \beta_1 R_{m,t} + \beta_2 R_{m,t}^2 + e_t$

Source(s): Authors' work

Table 9.
Examination of herding behavior in public equity fund market by centrality

positively affects the fund performance. Based on the robustness tests, we continue to find the significant effect of *Oiroi* on alternative measures of performance. We interpret that *Oiroi* can best identify the funds with better managerial skill and information advantage compared to the other centrality measures (*W*, *Oi* and *Op*). Second, we find that funds with high *Orioi* have better performance when they hold more hard-to-value stocks, which suggests that *Oiroi* explains the fund manager's skill or information advantage to utilize behavioral bias exhibited from these stocks. Third, we can't find any evidence that *Oiroi* is influenced by fund herd behavior. Therefore, our centrality measure could represent the fund manager's skill and information advantage which deviates from imitation skill.

The possible concern is that our networks might still be influenced by noises that are not related to fund manager skills or information advantage. Eliminating all noises is still challenging because there could be other several reasons for their active investment that we can't rule out. To overcome this problem, we can utilize external events that make exogenous changes in their portfolio composition. However, this analysis is limited based on the underlying reason that general equity funds are less likely to respond actively to those events due to their investment mandates. We suggest that it's worth for future research to consider our limitations.

Notes

1. Previous literature shows that informed trading is closely associated with large trades (Easley and O'Hara, 1987; Lin *et al.*, 1995). Bushee and Goodman (2007) highlight that significant changes in institutional ownership in firms are related to informed trading behaviors. Choi *et al.* (2017) also

show a positive relation between institutional investor portfolio concentration and their investment performance.

2. KOSPI 200 index consists of 200 largest securities in Korea Stock Exchange.
3. Sizes of these stocks are over 34 trillion won, and are listed among the 10 largest stocks in the Korean market.
4. For the four-factor model, DataGuidePro provides market, size, value and momentum factor returns in the Korean stock market calculated based on the methods mentioned in Fama and French (1993) and Carhart (1997).
5. Fund managers could also choose to decrease the portfolio weight to avoid further loss. Therefore, we also build networks based on decreasing holding weights and report results in Appendix. In the *Under-index Network*, funds and stocks are only connected when the fund portfolio weight is less than the market portfolio weight. The weight used in the network is excess market portfolio weights above portfolio weights. The weight of the *Under-past Network* is the amount of holding weight decreased from the previous month's portfolio weight. The *Under-index Reduces to Under-index Network* is weighted by the amount of holding weight decreased from the previous month's portfolio weight and funds and stocks are linked when both current and previous portfolio weights are less than the market portfolio weight.
6. See Faust (1997).
7. In Eq. (6), $\begin{bmatrix} c^F \\ c^S \end{bmatrix}$ is the corresponding eigenvector of the largest eigenvalue (λ). Because the trace of a matrix A^{FS} is 0 which is equal to the sum of all non-zero eigenvalues, λ is always positive. Given that all elements in A^{FS} is non-negative, eigenvector (eigenvector centrality) is always positive.
8. We standardize our measure based on equation, $\frac{centrality - centrality_{min}}{centrality_{max} - centrality_{min}}$, where $centrality_{min}$ is the minimum value of centrality and $centrality_{max}$ is the maximum value of centrality within a same network and *centrality* is the centrality of the fund.
9. D'Arcangelis and Rotundo (2021) measure network centrality based on correlation coefficient of daily return in fund market, and build another methodology to examine the herd behavior in fund market. However, in our analysis, we use fund's monthly return and portfolio, which has limits to apply this method.
10. In Table A.3 – A.10, we re-estimate Eq. (7) and Eq. (8) using alternative measures of fund centrality and performance. The descriptions of all these alternative measures are provided in Table A.1. Table A.2. gives summary statistics of all these alternative measures.
11. *Stockage* is the value-weighted stock's age multiplied by -1. Therefore, a higher *Stockage* level indicates that funds invested in stocks listed in the stock market more recently, have higher value uncertainty.
12. We apply absolute value to $R_{m(Down)}$, because the data only contains negative market return (when market is down).

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Appendix

The supplementary material for this article can be found online.

Corresponding author
Young Kyu Park can be contacted at: ykpark@skku.edu

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