The Quality of Your Network Matters: Professional Connections and Mutual Fund Performance

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We examine whether the professional networks of mutual fund managers serve as a conduit of information that benefits fund investors. We find investors enjoy higher returns when their funds are led by well-connected managers. A long-short portfolio strategy of funds ranked upon the quality of fund managers' networks yields positive and statistically significant mean and risk-adjusted returns to investors for both in-sample and out-of-sample testing. The results suggest that manager networks enable information flows that benefit fund investors. Additionally, we present evidence that fund managers do not act on material non-public information gathered from contemporaneous board appointments.

Keywords: mutual funds, network centrality, performance evaluations, performance predictions

INTRODUCTION

The purpose of this study is to analyze the link between the professional networks of mutual fund managers and fund investor welfare. We consider mutual fund manager professional networks in the context of work relationships formed from sitting on boards. Despite the extensive literature covering managerial network connections, the literature investigating the influence of U.S. mutual fund manager network connections on fund performance using verifiable direct relationships is limited. For example, while Cohen et al. (2008) show, using educational overlap as a proxy for connections, that fund managers place larger bets on connected firms leading to better performance relative to their non-connected holdings[1], our paper differently considers past and present professional connections, examines the quality of fund manager immediate connections, and uses third-party verified professional connections between U.S. mutual fund managers and U.S. corporate board members to empirically construct measures of manager network size and quality within the broad network of all corporate and non-profit executive and non-executive professionals. As such we are able to measure the degree to which a manager enjoys an advantageous informational and reputational position relative to other professionals, which in turn sheds light on the efficacy of networks to reduce information asymmetry amongst market participants.

Mutual fund research documents the importance of social ties. Hong et al. (2005) find information transfers occur among mutual fund managers living in the same city. Christoffersen and Sarkissian (2009) extend Hong et al. (2005) by examining the performance due to the social ties and argue mutual fund managers living in the same city have better learning and networking possibilities, which lead to better fund performance. Pool et al. (2015) use a neighborhood distance measure based on zip codes when proxying for implied social interactions among fund managers and find a long-short strategy based on neighborhood trades yields a positive and significant abnormal return of 6% to 7% per year. Cohen et al. (2008) examine connections between mutual fund managers and corporate board members using shared education networks and find fund managers place larger bets on connected firms, which result in better performance relative to their non-connected holdings. Butler and Gurun (2012) find mutual fund managers with educational ties to CEOs have a higher propensity for voting against shareholder-initiated proposals aimed at limiting executive compensation. Using advisory contracts to identify direct business connections between fund directors and fund advisors, Kuhnen (2009) argues the connections between fund directors and fund advisors in the U.S. give rise to preferential hiring among these two parties. Rossi et al. (2018) also measure network connections directly by exploiting a unique database containing verifiable connections between defined benefit pension fund managers in the UK, in which they find a greater number of connections for a manager translate into better portfolio performance.

There is also a growing literature involving the use of heterogeneous information sets to address information asymmetries in the market by enabling more sophisticated or informed traders to outperform those less sophisticated (Grossman and Stiglitz, 1980; Hellwig, 1980; Kyle, 1985). Recent literature explores the importance of investor networks on trading behavior and the implications on asset pricing (Colla and Mele, 2009; Ozsoylev and Walden, 2011; Han and Yang, 2013; Ozsoylev et al., 2014; Walden, 2019[2]). These studies suggest that trading behavior and investor profits are partially determined by the information dissemination that occurs through the networks of market participants. Ozsoylev et al. (2014) consider two traders to be connected if they exhibit similar trading patterns and find traders more central in the network trade earlier and enjoy greater profits than traders less central in the network, suggesting that more central actors enjoy an informational advantage compared to less central market participants, Walden (2019) introduces a dynamic network model and finds central agents to be more profitable in trading. More importantly, the author hypothesizes and empirically tests that information diffuses more rapidly through denser networks; volatility after an information shock is more persistent in less central networks. Akbas et al. (2016) argue sophisticated traders are better at collecting and aggregating “bits and pieces” of information dropped by more well-connected board members, which they act upon, leading to profitable trades.

The above-mentioned studies using bilateral ties have two limitations. First, interpersonal ties are not formed frequently. In other words, a deep, strong, or close association or acquaintance between two individuals is rare. Second, and more importantly, studies of bilateral ties by design cannot capture the concept of social hierarchy. Bilateral ties, in many instances, do not have an equal impact on connected parties. People in higher social hierarchical positions enjoy superior opportunities for transmitting, gathering, and controlling information, making such individuals more influential and powerful (e.g. Mizruchi and Potts, 1998). Consequently, recent studies have instead focused on the effect of the overall position of an individual in the large social network of all business executives.

This article combines the two literature streams discussed above and adopts the concept of network centrality to examine the social hierarchy effects of mutual fund managers’ network positions. In contrast to previous studies based on bilateral ties, we strive to capture the mutual fund managers’ ability to receive and process information even in the absence of direct links to various counterparties. Following extensive research in graph theory (e.g., Proctor and Loomis, 1951; Sabidussi, 1966; Freeman, 1977; Bonacich, 1972), we argue that network centrality – a set of measures that characterize the position of an individual within a network – captures the concept of network hierarchy and describes a network participant’s ability to efficiently gather and process information flows (e.g. Padgett and Ansell, 1993; Jackson, 2010). In a related manner, it should be less costly and more efficient for others to recognize and comprehend information-related signals sent by individuals more central in the network. If networks represent the infrastructure through which information flows, the network centrality of mutual fund managers should play a role in information dissemination and, consequently, affect the performance of funds led by more central managers. We utilize two network centrality variables frequently used in social network studies. Degree centrality is measured as the number of direct ties between the fund manager and all other network participants; it is the size of one's immediate network. Eigenvector centrality measures the "importance" or "quality" of one's network, as it weighs degree centrality by the degree centralities of one's connections. Eigenvector thus measures the extent to which one's connections are also well-connected. Studies of network effects document two primary advantages of higher centrality. First, higher centrality is associated with more efficient information flows around more central figures, making it less costly to gather and transmit material information (Burt, 2010; Jackson, 2010; Newman, 2010, Egginton and McCumber, 2019). Second, networks enable reputation effects. Truthful disclosures and the honoring of explicit and implicit obligations enhance reputation, while networks also curtail suboptimal behaviors in that poor performance leads to decreased network influence, e.g. fewer professional opportunities in the future for more central figures (Boot et al., 1993; Burt, 2005; Brass and Labianca, 2006; McCumber and Sun, 2021). Combined, these arguments suggest that more central managers should have an advantage in acquiring material and "soft" information and a greater career incentive to perform well relative to those with fewer connections and poorer network quality.

In this study we report that funds led by managers with board experience – those who are connected to executive and non-executive directors – enjoy superior performance. Funds led by connected managers display average annual returns of 9.14% while funds led by managers with no board connections report average annual returns of 6.79%. The 2.35% average annual difference in returns is both economically and statistically significant. In addition, controlling for known partial determinants of fund performance, we present evidence that performance is increasing in the quality of the manager's network; managers have greater advantage when they are connected to directors who are well-connected themselves. Finally, we present an important caveat that the advantage appears to come primarily via past professional relationships. Fund managers with current board appointments have material non-public information about the firms they serve. Fund managers who possess insider information must be careful not to use it, even on behalf of the investors they serve. The fact that fund performance is increasing in ties to well-connected directors, and the fact that advantage appears to come via past relationships, also provides empirical evidence to support Granovetter's "strength of weak ties" argument. Indirect connections, e.g. between a fund manager and a director's connections, provide novel information that managers may find actionable (Granovetter, 1973).[3]

The remainder of the paper is as follows. Section II discusses the data. Section III discusses the empirical results and robustness check. Section IV concludes.

DATA

Connected Mutual Fund Managers

The data for this study come from myriad sources. We obtain annual mutual fund characteristics, fund manager information, and monthly return data from CRSP Mutual Fund Database. We extract U.S. executive and non-executive identities, professional appointments, and identifying information from the BoardEx database. BoardEx contains biographical data for board members and firm executives of private and public companies around the world and tracks information on interpersonal bilateral links created through past work relationships, joint educational overlaps, and memberships in social organizations.

A unique process is used to identify mutual fund managers with board experience. Fund managers with board experience will have their profiles in BoardEx. However, the cross-referencing process is not straight forward due to certain impediments that make it harder to ensure reliable matches. First, the BoardEx dataset (manager-year observations) does not contain a fund identifier variable, only a company identifier variable that is also present in the mutual fund dataset. Second, if a fund is managed by a team, the mutual fund dataset (fund-year observations) contains only the fund managers' last name. To work around these issues, after restricting the BoardEx observations to only individuals with board appointments, we compare the two datasets and match based on individual last name, company name, and observation year. This initial match yields 3,418 manager-year observations with matching mutual fund data. For each of these manager-year observations, we use a variety of online resources to look up the full name of the mutual fund manager to verify it matches the director name variable found in BoardEx. This process provides assurance that the matches are reliable, which overcomes the problem associated with matching on individual last name. Once the verification process is complete, we are left with 3,085 manager-year observations for the period 2006 to 2017. Next, we exclude observations that have missing data for expense ratio, management fee, and/or total net asset. The expense ratio and/or management fee is set to missing if a negative value is present. After this procedure, 3,024 manager-year observations are left. Overall, we identify 207 unique fund managers with board experience and 912 unique funds in our final dataset. Panel A of Table 1 lists the number of unique funds represented each year in relation to the 3,024 manager-year observations.

TABLE 1
SUMMARY STATISTICS ON THE NUMBER OF UNIQUE FUNDS

Panel A		Panel B		Panel C	
Unique Funds		Unique Funds		Unique Funds	
Year	Count	Year	Count	Year	Count
2006	85	2006	85	2006	34
2007	117	2007	113	2007	59
2008	151	2008	150	2008	61
2009	157	2009	142	2009	112
2010	168	2010	153	2010	131
2011	207	2011	174	2011	147
2012	258	2012	213	2012	170
2013	290	2013	267	2013	215
2014	306	2014	269	2014	219
2015	339	2015	300	2015	212
2016	332	2016	314	2016	235
2017	300	2017	280	2017	217
Full Sample	912	Full Sample	873	Full Sample	609

To control for other mutual fund characteristics shown in other studies to partially determine mutual fund annual returns, we collect and calculate annual measures of said characteristics. These characteristics include the expense ratio, management fee, turnover ratio, fund past return, fund size, fund age, fund flow, return volatility, and number of fund managers. Data are collected from CRSP. All continuous variables are winsorized at the 1% and 99% levels to control for outliers. Fund size is represented as the natural log of the fund’s total net assets. Table 2 provides the summary statistics of the mutual fund characteristics for the full sample.

TABLE 2
SUMMARY STATISTICS OF MUTUAL FUND DESCRIPTORS

	N	Mean	Median	p10	p90	Std
Expense Ratio	2,744	1.27	1.20	0.63	2.00	0.54
Management Fee	2,403	0.68	0.64	0.32	1.09	0.35
Turnover Ratio	2,744	1.18	0.72	0.23	1.97	2.21
Annual Return	2,977	7.43	5.61	-8.31	28.53	16.72
Size (Log TNA)	3,024	3.35	3.58	-0.69	6.81	2.79
Fund Age (Log Fund Age)	3,014	7.42	7.60	5.85	8.91	1.36
Fund Flow	2,977	0.61	0.00	-0.04	0.15	10.27
Return Volatility	2,939	3.17	2.79	0.58	6.41	2.34
Number of Managers	3,024	2.02	2.00	1.00	3.00	0.75

Centrality

Centrality variables are generated from the raw data on professional appointments from the BoardEx database. For each year we construct a network of the links between all executives in the database, wherein a link is formed when two people serve on the same board. We generate two measures of network centrality for all executives in the network, degree and eigenvector, to capture the size and importance (quality) of executives' networks, respectively. We define connections (bilateral links) in two different manners to calculate two sets of measures for network centrality, a *current* and *cumulative* set. The current centrality measures include only contemporaneous professional relationships. For example, if two people serve on a board in 2014 they are linked. If one of the pair leaves the board in 2015 the link is severed, and they are no longer linked in the 2015 network. Conversely, in cumulative networks, the pair above continue to be linked and both executives' centrality measures will reflect the continuing relationship until one of the pair dies (El Khatib et al., 2015). By construction, the cumulative networks therefore are increasing over time.

Though degree centrality is intuitive, in that 77 connections is thought to be more advantageous than 7 connections, eigenvector centrality is less so. We therefore normalize centrality variables such that an equal number of executives are placed in percentiles from 1 to 100. As such, an executive in the 76th percentile in eigenvector centrality enjoys a network quality greater than 75% of all other executives in any given year. It is important to note that the rankings are inclusive of all network participants, not solely amongst mutual fund managers. Table 3 presents summary statistics for centrality measures.

TABLE 3
SUMMARY STATISTICS FOR CENTRALITY MEASURES

	Full Sample							
	N	Mean	Std	p25	p50	p75	min	max
Degree (Cumulative)	3,024	74.41	18.95	62	78	90	11	100
Eigenvector (Cumulative)	3,024	72.20	18.01	59	74	89	18	100
Degree (Current)	2,982	67.54	23.66	53	72	89	2	98
Eigenvector (Current)	2,982	68.75	21.57	59	75	85	1	100

	Live Funds							
	N	Mean	Std	p25	p50	p75	min	max
Degree (Cumulative)	2,210	75.26	18.55	63	80	90	11	100
Eigenvector (Cumulative)	2,210	72.69	17.75	59	75	88	18	100
Degree (Current)	2,183	67.71	22.34	54	72	87	2	98
Eigenvector (Current)	2,183	68.81	20.70	60	75	84	1	100

	Defunct Funds							
	N	Mean	Std	p25	p50	p75	min	max
Degree (Cumulative)	814	72.13	19.81	58	74	89	11	98
Eigenvector (Cumulative)	814	70.86	18.65	59	73	90	18	99
Degree (Current)	799	67.08	26.94	51	71	92	2	98
Eigenvector (Current)	799	68.59	23.77	54	76	87	3	100

In network terminology, a "node" represents an individual and a "link" is a relationship between nodes. The links are free of self-reporting bias since they can be reliably verified. A hypothetical small network of 11 nodes (circles) and 20 links (lines) can be seen in Figure 1.

Due to its ease of calculation and interpretation, degree centrality is the metric most found in social network studies. Degree measures the number of direct connections an individual has with other individuals in the network. It is an obvious indicator of influence, visibility, and reach. Thus:

$$\text{Degree}_i = \sum_{j \neq i} X_{ij} \tag{1}$$

where $X_{ij} = 1$ if individuals[4] i and j serve/served on the same board at the same time, and 0 otherwise.

However, degree may overstate an individual's effective network if his or her network is not well-connected. Eigenvector centrality is an extension of degree centrality and measures the importance of an individual in the network. It considers the extent to which an individual is connected – both directly and indirectly – to other individuals who themselves are highly connected and influential. For example, holding degree constant, an individual is advantageously positioned if his or her connections are also well positioned.

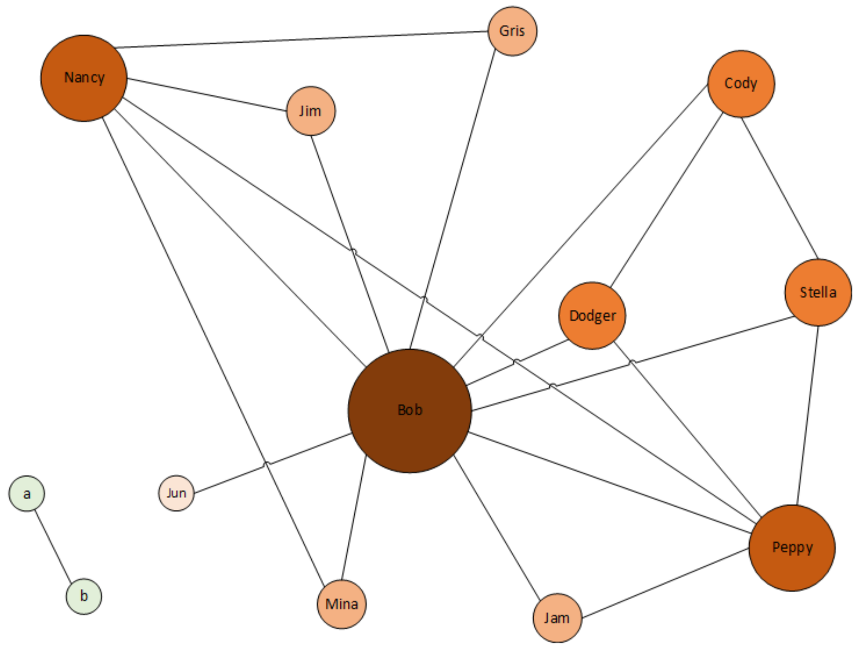
By iteratively calculating the centralities of one's connections, we find K eigenvalues of adjacency matrix A. Eigenvector centrality is proportional to the sum of the centralities of one's neighbors, such that:

$$\text{Eigenvector}_i = K_1^{-1} = \sum_j A_{ij} X_j \ , \tag{2}$$

where K_1 is the largest eigenvalue of the adjacency matrix. Thus, it is therefore possible for an individual to be poorly positioned regarding degree centrality but advantageously positioned if his or her fewer connections are with highly connected individuals. As such, we can think of eigenvector as a measurement of the "quality" of one's immediate network (how connected your connections are). In other words, individuals with high eigenvector centrality have more power and access to more information because they can access more individuals indirectly through their immediate connections.

In figure 1, the larger nodes are associated with a higher degree centrality, while the darker nodes are associated with a higher eigenvector centrality. For example, Bob is directly connected with 10 other nodes, which makes him the most central node in the network with regards to degree centrality. Bob also ranks the highest in eigenvector centrality since his direct connections are also highly connected to others. Nodes *a* and *b* represent a disconnected subnetwork. Nodes *a*, *b*, and Jun all have a degree centrality of one since each node is directly connected to only one other node. However, Jun, has a higher eigenvector centrality than nodes *a* and *b* since he is directly connected to Bob, who happens to be highly connected to other influential individuals. Hence, for the purpose of this study, we consider Jun's network to be higher quality than the network of nodes *a* and *b*.

FIGURE 1
SMALL NETWORK REPRESENTATION



Source: Author

EMPIRICAL RESULTS

Do Connections Matter?

Our first question is whether board appointments confer benefits to fund managers and, by extension, to fund investors. We investigate the performance of U.S. mutual funds led by "connected" managers – those with current or previous board appointments – relative to funds led by managers without board appointments. The baseline regression takes the following form:

$$R_{it} = \alpha + \beta_{i,t}\mathit{Connected\_Fund} + \gamma_{i,t-1}\mathit{Controls} + \gamma \mathit{yearFE} + \varepsilon_i \qquad (3)$$

where *Connected_Fund* is an indicator variable equal to 1 if a fund is associated with a fund manager who possesses board connections from sitting on boards, *Controls* is a vector of fund characteristics for fund *i* (i.e. fund size, turnover ratio, expense ratio, management fee, fund age, fund flow, return volatility, fund past return, number of fund managers, fund investment objective category) lagged by one year. *Connected_Fund* is measured contemporaneously with return to explain performance, not predict it. The specification includes year fixed effects and robust errors clustered by fund.

Model 1 of Table 4 reports the result of the regression without controls. We regress annual return on *Connected_Fund*, which gives a positive and statistically significant coefficient of 0.78 (t = 3.22). Model 2 introduces controls from extant studies that have been shown to partially determine mutual fund return. The inclusion of control variables bolsters the significance of *Connected_Fund*, increasing the coefficient of *Connected_Fund* increases to 2.35 (t = 8.17). "Connected" funds are associated with an increase of 2.35% in annual returns over their "non-connected" counterparts.[5]

TABLE 4
FUND-LEVEL CROSS-SECTIONAL RETURN REGRESSIONS W/ "CONNECTED" FUNDS

	(1)	(2)
Connected_Fund $_{t}$	0.78*** (3.22)	2.35*** (8.17)
Size (Log TNA) $_{t-1}$		-0.15*** (-10.87)
Turnover Ratio $_{t-1}$		-0.06*** (-8.99)
Expense Ratio $_{t-1}$		-1.29*** (-15.04)
Management Fee $_{t-1}$		0.11 (0.77)
Fund Age $_{t-1}$		0.60*** (14.82)
Fund Flow $_{t-1}$		0.01 (1.72)
Return Volatility $_{t-1}$		0.80*** (3.61)
Annual Return $_{t-1}$		-0.11*** (-18.45)
Number_Fund_Managers $_{t-1}$		-0.19*** (-5.00)
Constant	6.63*** (288.32)	2.79*** (5.84)
Adj R-squared	0.55	0.58
Year Fixed Effects	Yes	Yes
Invest Obj $_{t-1}$	No	Yes
Number of obs	314,475	136,709

Errors are clustered by fund.
, **, and * designate statistical significance at the better than 10%, 5%, and 1% levels, respectively.*
T-statistics are reported in parentheses.

Next, we perform marginal effects analysis after running Model 2 in Table 4. Panel A of Table 5 shows us, on average, "non-connected" funds are associated with annual returns of 6.79%. On the other hand, "connected" funds are associated with annual returns of 9.14%. Panel B of Table 5 shows the results of a pairwise comparison that contrasts the annual return difference between "connected" versus "non-connected" funds. We see a difference of 2.35% in annual returns, which is both economically and statistically significant (t = 8.17). The results here reflect the regression results found in Model 2 of Table 4.

TABLE 5
MARGINAL EFFECTS ANALYSIS ON CONNECTED VS. NON-CONNECTED FUNDS

Panel A: Marginal Effects Analysis

$Connected\_Fund_t$	Margin	[95% Conf. Interval]	
0	6.79	6.74	6.84
1	9.14	8.58	9.70

Panel B: Pairwise Comparison

$Connected\_Fund_t$	Contrast	t-stat	[95% Conf. Interval]	
1 vs 0	2.35***	8.17	1.79	2.92

, **, and * designate statistical significance at the better than 10%, 5%, and 1% levels, respectively.*

To eliminate a greater portion of a potential bias from unpaired data analysis thus far, we perform propensity score matching to observe the average treatment effect on the treated ("connected" funds). Both large and small sample theory show adjusting for the scalar propensity score suffices in reducing the bias in the estimation of the treatment effects due to all observed covariates (Rosenbaum and Rubin, 1983; Becker and Ichino, 2002). We match connected and non-connected funds via a procedure that identifies like funds across several dimensions (i.e., all previous partial determinants of annual return per equation (1) with the exception of management fee[6]). The result is that treated and control funds are statistically "identical" with regard to other covariates, only differing in whether or not the fund is led by a manager with board connections. When more than one control fund is a "match" with a treatment fund, we include all possible matching funds in the control group but do not use a control fund more than once. We confirm the sort order is random before conducting propensity score matching. To ensure the propensity score successfully balanced the data on the observed covariates, we confirmed the standardized bias for matched samples is under 10% as a rule of thumb (Rosenbaum and Rubin 1985b). Additionally, evidence of a high level of "Common Support" for all treated and untreated observations is confirmed (regarding propensity score alignment), which provides additional confidence on the quality of the matching procedure. Table 6 reports results, which support the baseline regression results (Model 2 of Table 4). For example, the average treatment effect on the treated ("connected" funds), regarding annual return, is 2.01% (t = 3.27).

TABLE 6
MATCHED FUNDS: ATT

Variable	Sample	Treated	Controls	Difference	T-stat
$Annual\ Return_t$	Matched	8.04	6.03	2.01***	3.27

Errors are clustered by fund.
, **, and * designate statistical significance at the better than 10%, 5%, and 1% levels, respectively.*

When we restrict our sample to equity funds only and rerun Model 2 of Table 4, the economic and statistical significance of *Connected_Fund* decreases (coefficient = 1.57, t = 5.59) but remains significant at the 1% level. This makes intuitive sense as debt funds have a larger universe of securities to work with. Additionally, when compared to equity securities, debt securities are less liquid and deal with greater information asymmetry. Prior research documents the use of heterogeneous information sets from investor networks to address information asymmetries in the market (Ozsoylev et al., 2014; Walden, 2019). As such, fund managers possessing director connections are more likely to have an information advantage. We investigate whether the relation between "connected" fund and fund return is affected by fixed income (debt) funds. We argue that fixed income funds managed by managers possessing director connections is significant for reducing information asymmetry. If connected fund managers have an information advantage and debt securities involve more information asymmetry, then the benefits from a "connected" fund will have a more pronounced effect on fund return when dealing with fixed income funds. We test this prediction in Table 7 by including the interaction term of "connected" fund and "debt" fund. We find that "connected" fund increases fund return, but this relation is stronger when it involves fixed income funds.

TABLE 7
FUND-LEVEL CROSS-SECTIONAL RETURN REGRESSION W/ INTERACTION TERM

	DV: Annual Return $_t$
Connected_Fund $_t$	1.91*** (6.50)
Debt_Fund $_t$	-4.79*** (3.84)
Connected_Fund $_t$ + Debt_Fund $_t$	1.81*** (2.16)
Size (Log TNA) $_{t-1}$	-0.15*** (-10.89)
Turnover Ratio $_{t-1}$	-0.06*** (-8.99)
Expense Ratio $_{t-1}$	-1.29*** (-15.06)
Management Fee $_{t-1}$	0.12 (0.84)
Fund Age $_{t-1}$	0.61*** (14.85)
Fund Flow $_{t-1}$	0.01 (1.72)
Return Volatility $_{t-1}$	0.80*** (3.61)
Annual Return $_{t-1}$	-0.11*** (18.45)
Number_Fund_Managers $_{t-1}$	-0.19*** (-4.97)
Constant	7.57*** (5.27)
Adj R-squared	0.58
Year Fixed Effects	Yes
Invest Obj $_{t-1}$	Yes
Number of obs	136,709

Errors are clustered by fund.
, **, and * designate statistical significance at the better than 10%, 5%, and 1% levels, respectively.*
T-statistics are reported in parentheses.

Results support the conclusion that funds managed by fund managers possessing director connections benefit the fund (especially for funds primarily made up of debt securities), which ultimately benefit fund investors through the fund managers' informational advantage. If being connected provides an advantage to fund managers, do all connected fund managers benefit equally? To address this question, we look beyond 0/1 connectedness of funds to network centrality rankings of managers to investigate whether advantageous network size and quality affects fund performance. As such, the remainder of this paper considers the performance of funds led by managers with board experience as it relates to managers' network size and quality.

Univariate Analysis

We compare the monthly fund return (net) for the above median and below median *cumulative* eigenvector centrality group. Recall, eigenvector is a centrality measure that captures the quality or importance of a fund managers' immediate network. On average, the monthly return for the above median group (0.74%) is higher than the below median group (0.50%) with a statistically significant difference of 0.24% ($t = 5.02$). This comparison provides initial evidence that indirect network connections are important to fund managers. In other words, fund managers benefit from indirect connections when their immediate connections are highly connected themselves, in support of extant literature documenting informational advantages for connected boards (Mizruchi, 1990; Mol, 2001; Larcker et al., 2013).

Multiple Cross-Sectional Regression Methodology

In this section we examine the cross-sectional relation between cumulative centrality measures and annual return[7] while controlling for various other common partial determinants of fund returns. All regressions include year fixed effects and robust standard errors clustered by fund. Models 1 and 2 of table 8 regress annual return on cumulative eigenvector and cumulative degree centrality, respectively. The coefficients for both cumulative eigenvector and degree centrality are positive and statistically significant ($t = 4.46$ and $t = 3.50$). The inclusion of control variables in subsequent models again increases both the size and significance of centrality coefficients ($t = 6.75$ and $t = 5.52$).[8] The results are similar in Table 9 when we run a predictive model lagging all independent variables by a year.[9]

The results in Tables 8 and 9 suggest high centrality mutual fund managers are associated with better fund performance. Specifically, fund managers who are well-connected and/or have access to higher quality professional networks exhibit better performance. Importantly, it is not only the presence of a connection that matters but the size and quality of one's network that affects performance.

TABLE 8
MANAGER-LEVEL CROSS-SECTIONAL RETURN REGRESSIONS W/ CENTRALITY

	DV: Annual Return $_t$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Eigenvector (cumulative) $_t$	0.07***				0.10***			
	(4.46)				(6.75)			
Degree (cumulative) $_t$		0.05***				0.07***		
		(3.50)				(5.52)		
Eigenvector (current) $_t$			-0.03***				-0.04***	
			(-2.84)				(-3.60)	
Degree (current) $_t$				0.00				-0.01
				(0.15)				(-1.65)
Size (Log TNA) $_t$					0.25**	0.26**	0.29**	0.28**
					(2.35)	(2.35)	(2.50)	(2.45)
Turnover Ratio $_t$					1.11***	1.13***	1.11***	1.11***
					(6.03)	(6.33)	(6.94)	(6.88)
Expense Ratio $_t$					-0.75	-0.56	-0.68	-0.66
					(-1.38)	(-0.98)	(-1.23)	(-1.16)
Management Fee $_t$					1.63	1.99**	1.92**	1.77
					(1.59)	(2.03)	(2.10)	(1.90)
Fund Age $_t$					-0.36	-0.35	-0.38	-0.39
					(-1.34)	(-1.28)	(-1.35)	(-1.39)
Fund Flow $_t$					-0.15***	-0.16***	-0.15***	-0.15***
					(-3.96)	(-3.91)	(-3.89)	(-3.78)
Return Volatility $_t$					-1.47***	-1.46***	-1.48***	-1.44***
					(-2.85)	(-2.79)	(-2.75)	(-2.72)
Number_Fund_Managers $_t$					-0.56	-0.61	-0.74**	-0.65**
					(-1.77)	(-1.95)	(-2.23)	(-1.98)
Constant	2.69**	3.73***	9.62***	7.36***	-4.29	-2.68	7.81**	5.69
	(2.42)	(3.36)	(11.63)	(10.20)	(-1.40)	(-0.95)	(2.25)	(1.76)
Adj R-squared	0.45	0.44	0.45	0.45	0.58	0.58	0.57	0.57
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Invest Obj $_t$	No	No	No	No	Yes	Yes	Yes	Yes
Number of obs	2,976	2,976	2,934	2,934	2,403	2,403	2,370	2,370

Errors are clustered by fund.
, **, and * designate statistical significance at the better than 10%, 5%, and 1% levels, respectively.*
T-statistics are reported in parentheses.

TABLE 9
MANAGER-LEVEL CROSS-SECTIONAL RETURN REGRESSIONS W/ CENTRALITY

	DV: Annual Return $_t$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Eigenvector (cumulative) $_{t-1}$	0.10***				0.09***			
	(5.58)				(4.70)			
Degree (cumulative) $_{t-1}$		0.08***				0.06***		
		(4.72)				(3.57)		
Eigenvector (current) $_{t-1}$			-0.01				0.02	
			(-0.48)				(1.15)	
Degree (current) $_{t-1}$				0.01				0.01
				(1.41)				(0.64)
Size (Log TNA) $_{t-1}$					-0.17	-0.18	-0.17	-0.17
					(-1.23)	(-1.25)	(-1.18)	(-1.17)
Turnover Ratio $_{t-1}$					0.57	0.43	0.18	0.19
					(1.80)	(1.46)	(0.65)	(0.67)
Expense Ratio $_{t-1}$					-1.82***	-1.61***	-1.44**	-1.45**
					(-2.97)	(-2.63)	(-2.33)	(-2.35)
Management Fee $_{t-1}$					1.17	1.57	1.12	1.22
					(1.01)	(1.36)	(1.00)	(1.08)
Fund Age $_{t-1}$					-0.37	-0.35	-0.39	-0.39
					(-1.14)	(-1.08)	(-1.14)	(-1.14)
Fund Flow $_{t-1}$					0.04	0.03	0.05	0.05
					(0.81)	(0.56)	(1.08)	(1.04)
Return Volatility $_{t-1}$					1.89***	1.98***	2.01***	2.00***
					(4.41)	(4.62)	(4.61)	(4.65)
Annual Return $_{t-1}$					-0.17***	-0.16***	-0.17***	-0.17***
					(-3.19)	(-3.13)	(-3.14)	(-3.15)
Number_Fund_Managers $_{t-1}$					0.74	-0.72	-0.58	-0.62
					(-1.80)	(-1.74)	(-1.32)	(-1.41)
Constant	-0.82	0.56	6.61***	5.26***	-8.17	-6.56	-1.57	-0.98
	(-0.63)	(0.45)	(7.66)	(6.83)	(-1.49)	(-1.22)	(-0.28)	(-0.18)
Adj R-squared	0.44	0.44	0.44	0.44	0.57	0.57	0.57	0.57
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Invest Obj $_{t-1}$	No	No	No	No	Yes	Yes	Yes	Yes
Number of obs	1,750	1,750	1,724	1,724	1,377	1,377	1,358	1,358

Errors are clustered by fund.
, **, and * designate statistical significance at the better than 10%, 5%, and 1% levels, respectively.*
T-statistics are reported in parentheses.

Current Centrality

Next, we examine the current set of centrality measures, which are a function of fund managers currently sitting on boards. Recall, for current centrality measures, we define a connection if two individuals simultaneously serve on the same board until one individual from the pair leaves. Hence, current centrality measures do not account for all relationships formed from sitting on boards, only current board relationships. Models 7 and 8 of Table 8 regresses annual return on the current centrality measures and control variables. The coefficients are negative for both with only statistical significance for current eigenvector ($t = -3.60$). This suggests fund managers currently sitting on boards with access to better quality professional networks do not positively affect fund performance. It is an obvious conjecture, given the above, that more central managers possess material non-public information but choose not to act on that information in the face of insider trading laws and/or reputational erosion in the appearance of impropriety. Prior research documents that institutional investors are reluctant to use private information in a traceable manner (Griffin et al., 2012).

Centrality-Sorted Mutual Fund Portfolios

In this section we follow the methodology found in Carhart (1997) and form portfolios of mutual funds based on the cumulative eigenvector centrality measure (network quality) and estimate the performance on the resulting portfolios. On January 1st of each year we form four equal-weighted portfolios of mutual funds using reported monthly returns, which include distributions but are net of total expenses[10]. We hold the portfolios for one year, then rebalance them. This gives a time series of monthly returns for each quartile portfolio from 2006 to 2017.

If a fund has two or more fund managers in a given year, for portfolio testing, we keep only the manager-year observation for the fund manager with the highest cumulative eigenvector centrality measure since we are arguing fund managers with higher quality professional networks have an advantage in obtaining relevant information from well-connected corporate board members. This leaves us with 2,460 manager-year observations for portfolio testing. However, it is possible that the structure of fund managers (single-managed vs. team-managed funds) may be explaining the higher returns of more central fund managers since multi-manager funds increase the probability a high-centrality fund manager is a part of the team. As such, table 8 and 9 controls for the number of fund managers. We see the explanatory power of cumulative eigenvector (network quality) as a partial determinant of fund return remains significant even with the addition of that control, which provides our justification in using the fund manager with the highest quality professional network for portfolio testing.

In portfolio testing, we examine the mean returns in addition to the Sharpe Ratios and the Information Ratios. We also employ four models of performance measurement for abnormal return: the standard market model, the Fama-French 3-factor model, the Carhart 4-factor model (Carhart, 1997), and a hybrid model utilizing the Carhart 4-factor model as the base plus three additional factors from the Fung-Hsieh 7-factor model to be used as bond risk factors since our sample includes all mutual fund types, not only equity funds. We estimate the performance relative to these four models as:

$$R_{it} - r_{ft} = \alpha_{it} + \beta_{it}(R_{mt} - r_{ft}) + \varepsilon_{it} \tag{4}$$

$$R_{it} - r_{ft} = \alpha_{it} + \beta_{it}(R_{mt} - r_{ft}) + s_{it}SMB_t + h_{it}HML_t + \varepsilon_{it} \tag{5}$$

$$R_{it} - r_{ft} = \alpha_{it} + \beta_{it}(R_{mt} - r_{ft}) + s_{it}SMB_t + h_{it}HML_t + p_{it}PR1YR_t + \varepsilon_{it} \tag{6}$$

$$R_{it} - r_{ft} = \alpha_{it} + \beta_{it}(R_{mt} - r_{ft}) + s_{it}SMB_t + h_{it}HML_t + p_{it}PR1YR_t + t_{it}PTFS_{B,t} + u_{it}BM_t + v_{it}BS_t + \varepsilon_{it} \tag{7}$$

where R_{it} is the return on portfolio i, R_{mt}[11] is the market return, and r_{ft} is the risk-free rate. SMB, HML, and PR1YR represent the factor-mimicking portfolios for size, book-to-market equity, and one-year momentum in stock returns. $PTFS_{B,t}$, BM_t, and BS_t are bond factors found in Fung and Hsieh (2001) which represent the bond trend-following factor[12], the bond market factor[13], and the credit spread factor[14]. The inclusion of these additional 3 bond factors is used to produce a cleaner risk-adjusted return, alpha, since fixed income funds are included.

For the in-sample testing, forming portfolios based on the cumulative eigenvector centrality measure demonstrates a strong variation in mean return and many of the associated risk-adjusted performance measures, as shown in Table 10. The Q4-Q1 (long-short) trading strategy longing the highest cumulative eigenvector centrality quartile and shorting the quartile of funds with the lowest cumulative eigenvector centrality produces a positive and statistically significant mean and risk-adjusted return (alpha). This trading strategy produces a mean return of 0.47% (t = 2.45) and an alpha of 0.54% (t = 2.80). Additionally, the mean returns, alphas, Sharpe Ratios, and Information Ratios are, for the most part, monotonically increasing in portfolio rank.

Next, we form portfolios of mutual funds based on lagged one-year cumulative eigenvector centrality and estimate out-of-sample performance on the resulting portfolios. The Q4-Q1 trading strategy looking one year ahead produces a positive and statistically significant mean return and alpha, as shown in Table 11. The out-of-sample testing produces a mean return of 0.44% (t = 1.81) and an alpha of 0.75% (t = 3.65). Like the in-sample testing, the mean returns, alphas, Sharpe Ratios, and Information Ratios are, for the most part, monotonically increasing in portfolio rank. The significance of the Q4-Q1 FungH alpha (4-Factor model + three additional bond risk factors) for both in-sample and out-of-sample testing is robust to the CAPM, the Fama-French 3-Factor model, and the Carhart 4-Factor model.

Past studies involving bonds generally rely on long-established stock and bond market factors for return prediction. However, the cross-sectional predictive power is limited for bond-level returns since these commonly used factors are generally constructed from stock-level data or aggregated macroeconomic variables (Bai et al., 2019). As such, we now restrict the portfolio analysis for both in-sample and out-of-sample testing to equity funds only and form terciles based on the cumulative eigenvector centrality measure. Additionally, we use data from 2009 to 2017 as the sample period for testing, which gives us a minimum of 100 unique funds represented each year (refer to Table 1, Panel C). Tables 12 and 13 show the long-short strategy still holds for both in-sample and out-of-sample testing when only equity funds are considered.

TABLE 10
IN-SAMPLE PERFORMANCE SINGLE-VARIABLE PORTFOLIOS

In-Sample (2006-2017 monthly return series)

Rank Using: cumulative eigenvector	Return (t-stat)	Std. Dev.	Min	Max	FungH α (t-stat)	FF3M α (t-stat)	FF4M α (t-stat)	CAPM α (t-stat)	Sharpe Ratio (z-stat)	Info Ratio
Quartile 1 (Low)	0.46 (1.49)	3.70	-18.00	10.16	-0.26** (-2.07)	-0.24** (-2.02)	-0.23** (-1.99)	-0.22* (-1.82)	0.10	0.10
Quartile 2	0.49 (1.52)	3.86	-14.65	14.41	-0.18 -(0.87)	-0.16 (-0.81)	-0.17 (-0.87)	-0.14 (-0.70)	0.10	0.11
Quartile 3	0.69*** (2.64)	3.15	-9.41	11.29	0.04 (0.30)	0.14 (1.04)	0.14 (1.08)	0.13 (0.96)	0.19	0.19
Quartile 4 (High)	0.93*** (3.38)	3.30	-8.66	14.22	0.28* (1.91)	0.39*** (2.71)	0.40*** (2.77)	0.36** (2.34)	0.26	0.26
Q4-Q1	0.47** (2.45)	2.30	-4.58	14.72	0.54*** (2.80)	0.63*** (3.44)	0.63*** (3.44)	0.59*** (3.13)	0.20*** (2.84)	0.20

, **, and * designate statistical significance at the better than 10%, 5%, and 1% levels, respectively.*
(Refer to Table 1 (Panel B) for number of unique funds represented each year.)

TABLE 11
OUT-OF-SAMPLE PERFORMANCE SINGLE-VARIABLE PORTFOLIOS

Out-Of-Sample (2007-2017 monthly return series)

Rank Using: cumulative eigenvector	Return (t-stat)	Std. Dev.	Min	Max	FungH α (t-stat)	FF3M α (t-stat)	FF4M α (t-stat)	CAPM α (t-stat)	Sharpe Ratio (z-stat)	Info Ratio
Quartile 1 (Low)	0.33 (0.96)	3.97	-18.08	11.07	-0.46*** (-3.77)	-0.34*** (-2.72)	-0.33*** (-2.70)	-0.35*** (-2.78)	0.07	0.07
Quartile 2	0.53 (1.48)	4.13	-18.85	11.27	-0.13 (-0.65)	-0.17 (-0.95)	-0.18 (-0.95)	-0.12 (-0.63)	0.11	0.12
Quartile 3	0.62** (2.45)	2.91	-9.52	11.12	0.03 (0.19)	0.11 (0.77)	0.11 (0.76)	0.17 (1.11)	0.19	0.19
Quartile 4 (High)	0.77*** (3.02)	2.93	-7.34	10.22	0.29** (2.08)	0.27* (1.89)	0.26* (1.88)	0.31** (2.12)	0.24	0.24
Q4-Q1	0.44* (1.81)	2.76	-9.86	13.56	0.75*** (3.65)	0.60*** (2.80)	0.59*** (2.82)	0.65*** (3.03)	0.16*** (2.63)	0.16

, **, and * designate statistical significance at the better than 10%, 5%, and 1% levels, respectively.*

TABLE 12
IN-SAMPLE PERFORMANCE SINGLE-VARIABLE PORTFOLIOS (EQ FUNDS)

In-Sample (2009-2017 monthly return series)

Rank Using: cumulative eigenvector	Return (t-stat)	Std. Dev.	Min	Max	FF3M α (t-stat)	FF4M α (t-stat)	CAPM α (t-stat)	Sharpe Ratio (z-stat)	Info Ratio
Tercile 1 (Low)	0.89** (2.41)	3.82	-11.01	12.01	-0.33*** (-2.95)	-0.34*** (-2.98)	-0.31*** (-2.61)	0.23	0.23
Tercile 2	0.96*** (2.68)	3.71	-9.95	12.19	-0.20* (-1.91)	-0.20** (-2.08)	-0.21** (-2.04)	0.25	0.26
Tercile 3 (High)	1.17*** (3.12)	3.89	-8.66	14.22	-0.04 (-0.41)	-0.04 (-0.49)	-0.06 (-0.57)	0.30	0.30
T3-T1	0.28*** (2.66)	1.09	-3.98	5.78	0.30*** (2.68)	0.29*** (2.73)	0.25** (2.22)	0.26** (2.41)	0.26

, **, and * designate statistical significance at the better than 10%, 5%, and 1% levels, respectively.*

TABLE 13
OUT-OF-SAMPLE PERFORMANCE SINGLE-VARIABLE PORTFOLIOS (EQ FUNDS)

Out-Of-Sample (2010-2017 monthly return series)

Rank Using: cumulative eigenvector	Return (t-stat)	Std. Dev.	Min	Max	FF3M α (t-stat)	FF4M α (t-stat)	CAPM α (t-stat)	Sharpe Ratio (z-stat)	Info Ratio
Tercile 1 (Low)	0.71** (1.98)	3.54	-10.39	11.59	-0.36*** (-3.09)	-0.34*** (-2.92)	-0.39*** (-3.19)	0.20	0.20
Tercile 2	0.72** (2.06)	3.42	-9.04	10.35	-0.36*** (-3.53)	-0.33*** (-3.31)	-0.36*** (-3.61)	0.21	0.21
Tercile 3 (High)	0.96*** (2.75)	3.42	-8.32	10.53	-0.10 (-1.34)	-0.11 (-1.38)	-0.13 (-1.48)	0.28	0.28
T3-T1	0.25*** (2.86)	0.84	-1.49	2.07	0.26*** (2.78)	0.23** (2.56)	0.26*** (2.83)	0.29*** (3.08)	0.29

, **, and * designate statistical significance at the better than 10%, 5%, and 1% levels, respectively.*

Sharpe Ratio Test

The results of the long-short trading strategy, where we formed portfolios of mutual funds based on cumulative eigenvector (network quality), yields positive and statistically significant mean and abnormal returns for both in-sample and out-of-sample testing. We also investigate whether there is statistical significance in the difference between the Sharpe ratios of the top and bottom portfolios of the long-short trading strategy. We employ a significance test proposed by Jobson & Korkie (1981). The test-statistic (z-score) for significance is provided in Tables 10-13. For both in-sample and out-of-sample portfolio testing, the Sharpe ratio difference is significantly positive, which holds true when we consider all fund types or restrict portfolio testing to equity funds only. This provides strong evidence of a difference in the risk-adjusted performance between the top and bottom portfolios.

Informational Advantage and Reputation/Fame Effects

Firms may want fund managers who are more experienced and/or well-known to sit on their boards, which may be especially true for fast-growing companies that want to benefit from fund managers' experience and/or fame which may affect the firm's ability to raise capital. Additionally, strong performing fund managers may also be asked to sit on more boards.[15] Since one's fame may lead to additional board appointments and therefore higher centrality, we wish to examine if our results are driven by director visibility – fame, reputation, and experience. We therefore empirically remove the effects of reputation and fame from our centrality measure to isolate the effects resultant of informational advantage. We first collect observable manager characteristics likely to be correlated with centrality. These include professional credentials, e.g. CFA or CPA, advanced degrees, whether the executive graduated from an elite institution of higher learning, the number of prestigious awards won by an executive, e.g. *Institutional Investor* magazine's "Best of the Best Money Managers," years of professional experience, and the number of funds managed. These variables proxy for reputation, fame, and experience. We regress the first principal component of our centrality measures against these proxies to create "informational centrality" from the residuals of this first stage. We argue that informational centrality controls for a manager's "visibility" that potentially leads to board appointments and higher centrality. Table 14 reports results of regressions testing models excluding and inclusive of control variables. Models 1 and 2 substitute the first principal component of centrality, which includes both information and reputation effects, while models 3 and 4 isolate the information channel. Models 1 and 2 find, unsurprisingly, that the combined measure of centrality positively and significantly contributes to annual returns.[16] Models 3 and 4 find that the coefficients on informational centrality are smaller, but remain economically and statistically significant in positively determining annual returns[17], strongly suggesting that managers with larger and more influential networks enjoy informational advantages compared to less connected managers. Thus, both experience (inclusive of fame/reputation) and informational advantages contribute to fund returns. The results are similar when we lag all independent variables by a year in Table 15.[18]

TABLE 14
MANAGER-LEVEL CROSS-SECTIONAL RETURN REGRESSIONS W/ INFO. CENTRAL.

	DV: Annual Return $_t$			
	(1)	(2)	(3)	(4)
Centrality $_t$	0.80***	1.18***		
	(4.08)	(6.23)		
Informational Centrality $_t$			0.43**	0.87***
			(2.23)	(4.69)
Size (Log TNA) $_t$		0.25**		0.26**
		(2.34)		(2.30)
Turnover Ratio $_t$		1.13***		1.14***
		(6.14)		(6.30)
Expense Ratio $_t$		-0.66		-0.52
		(-1.18)		(-0.91)
Management Fee $_t$		1.87		1.66
		(1.87)		(1.73)
Fund Age $_t$		-0.36		-0.34
		(-1.31)		(-1.21)
Fund Flow $_t$		-0.15***		-0.15***
		(-3.95)		(-3.86)
Return Volatility $_t$		-1.47***		-1.48***
		(-2.83)		(-2.82)
Number_Fund_Managers $_t$		-0.59		-0.58
		(-1.86)		(-1.86)
Constant	7.43***	2.63	7.43***	3.46
	(32.59)	(0.94)	(32.55)	(1.21)
Adj R-squared	0.44	0.58	0.44	0.57
Year Fixed Effects	Yes	Yes	Yes	Yes
Invest Obj $_t$	No	Yes	No	Yes
Number of obs	2,976	2,403	2,976	2,403

Errors are clustered by fund.
, **, and * designate statistical significance at the better than 10%, 5%, and 1% levels, respectively.*
T-statistics are reported in parentheses.

TABLE 15
MANAGER-LEVEL CROSS-SECTIONAL RETURN REGRESSIONS W/ INFO. CENTRAL.

	DV: Annual Return $_t$			
	(1)	(2)	(3)	(4)
Centrality $_{t-1}$	1.20***	1.02***		
	(5.20)	(4.21)		
Informational Centrality $_{t-1}$			0.70***	0.62**
			(3.43)	(2.50)
Size (Log TNA) $_{t-1}$		-0.18		-0.18
		(-1.26)		(-1.25)
Turnover Ratio $_{t-1}$		0.51		0.38
		(1.67)		(1.33)
Expense Ratio $_{t-1}$		-1.72***		-1.56**
		(-2.80)		(-2.52)
Management Fee $_{t-1}$		1.45		1.19
		(1.26)		(1.04)
Fund Age $_{t-1}$		-0.36		-0.34
		(-1.12)		(-1.04)
Fund Flow $_{t-1}$		0.03		0.04
		(0.63)		(0.80)
Return Volatility $_{t-1}$		1.93***		1.98***
		(4.51)		(4.58)
Annual Return $_{t-1}$		-0.17***		-0.16***
		(-3.16)		(-3.13)
Number_Fund_Managers $_{t-1}$		-0.73		-0.70
		(-1.77)		(-1.69)
Constant	6.23***	-2.23	6.16***	-1.22
	(23.15)	(-0.44)	(22.24)	(-0.23)
Adj R-squared	0.44	0.57	0.44	0.57
Year Fixed Effects	Yes	Yes	Yes	Yes
Invest Obj $_{t-1}$	No	Yes	No	Yes
Number of obs	1,750	1,377	1,750	1,377

Errors are clustered by fund.
, **, and * designate statistical significance at the better than 10%, 5%, and 1% levels, respectively.*
T-statistics are reported in parentheses.

Reverse Causality

The design of this study makes endogeneity due to reverse causality unlikely, since professional appointments, and therefore connections, are made years prior to the observation of a fund return (e.g., Cohen et al., 2008). This is especially true in given that our findings that centrality bestows benefits on managers, and by extension fund investors, is driven by past as opposed to current relationships.

Omitted Variables

Per Tables 14 and 15, many manager-specific omitted variables (i.e., reputation, fame, and experience) have been controlled for through our informational centrality tests. However, fund managers who are highly confident may also be more likely to form social ties, possibly even with other individuals who are also highly confident themselves, which would result in more connections with other well-connected individuals. There is a potential concern that network centrality is a proxy for fund manager overconfidence. Eshraghi and Taffler (2012) find evidence suggesting excessive overconfidence from U.S. mutual fund managers is associated with diminished future returns. This negative relationship differs from the relationship found in this study between cumulative network centrality and fund performance, which provides assurance network centrality is not proxying for overconfident fund managers.

To examine whether fund manager age may be driving our results, we rerun model 5 of Table 8 and 9, but this time control for fund manager age. Cumulative eigenvector retains the same sign and significance (results not shown) at the 1% level (Table 8 rerun: $t = 3.68$, p-value = 0.000; Table 9 rerun: $t = 2.81$, p-value = 0.005). As such, we find evidence that our results are not determined by fund manager age.

CONCLUSION

In this study we examine whether the professional networks of mutual fund managers, in the context of professional relationships formed from individuals sitting on corporate boards, affect fund investor welfare. The network centrality measures, degree and eigenvector, capture the size and importance (quality) of the fund managers' immediate network. We use network centrality as the theoretical lens to show fund managers who are advantageously positioned within a greater network are associated with better fund performance. We find both the size and the quality of a fund managers' professional network are important partial determinants of fund performance. In other words, fund managers that are higher up in the social network hierarchy due to their network positions are better able to utilize their professional networks to obtain relevant information, where the opportunity for obtaining relevant information increases as the quality of the fund managers' network increases. Next, we find the fund managers' information set from current board relationships is not as meaningful as the information set resultant of all current and past relationships a fund manager has formed, and potentially fostered, over time from sitting on boards. Finally, we find a long-short trading strategy based on cumulative eigenvector, a measure that assesses the quality of the fund managers' immediate connections, is successful in generating a positive and statistically significant mean and risk-adjusted return for both in-sample and out-of-sample testing.

ENDNOTES

1. Studies of educational ties or regional proximity are potentially problematic in that they typically rely upon inferred relationships - two people attended the same institution of higher learning during overlapping years or live in the same zip code - as opposed to verifiable relationships, e.g., two people are connected if they work in the same department of the same firm at the same time.
2. Walden (2019) finds that among traders, a centrality measure akin to eigenvector centrality is a strong determinant of profitability. Eigenvector centrality is a measure of not only one's direct connections (degree centrality), but also of the degree centralities of one's connections (connected to many people who are also connected to many people).
3. The argument follows the intuition that directly connected people already possess significantly overlapping information sets, while an indirect connection has a higher likelihood of providing new information.
4. Executives and non-executives.
5. Restricting fund type to equity funds only yields similar results. The coefficient of Connected_Fund is 1.57 ($t = 5.59$).
6. Standardized bias for management fee over 10% when included as a covariate.
7. Monthly returns are compounded to create annual returns.
8. Our results remain economically and statistically significant while following the same pattern when we restrict fund type to equity funds only.

9. Our results remain economically and statistically significant while following the same pattern when we restrict fund type to equity funds only.
10. Net of all operating expenses (expense ratios) and security-level transaction costs, but do not include sales charges.
11. Value weighted return of all CRSP firms incorporated in the U.S. and listed on the NYSE, AMEX, or NASDAQ.
12. Trend-following factor for bonds. (http://people.duke.edu/~dah7/DataLibrary/TF-Fac.xls)
13. The monthly change in the 10-year treasury constant maturity yield (month end-to-month end).
14. The monthly change in the Moody's Baa yield less 10-year treasury constant maturity yield (month end-to-month end).
15. The confounding concerns of strong performing managers on network centrality is mitigated when considering it is the past relationships or cumulative centrality measures that appear to matter, which the out-of-sample portfolio testing strongly supports.
16. Our results remain economically and statistically significant when we restrict fund type to equity funds only.
17. Our results remain economically and statistically significant when we restrict fund type to equity funds only.
18. Our results remain economically and statistically significant when we restrict fund type to equity funds only.

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APPENDIX

Variable Name	Variable Description
Connected_Fund	A dummy variable equal to 1 to indicate a "connected" fund; More specifically, Connected_Fund = 1 if a fund observation is associated with a fund manager that has board experience, 0 otherwise.
Size (Log TNA)	Natural log of tna_latest (Latest Month-end TNA).
Turnover Ratio	Fund Turnover Ratio is defined as the minimum of aggregated sales or aggregated purchases of securities divided by the average twelve-month TNA of the fund.
Expense Ratio	Ratio of total investment that shareholders pay for the fund's operating expenses, which include 12b-1 fees.
Management Fee	Management fee ($) / Average Net Assets ($). The fee is calculated using ratios based on the line items reported in the Statement of Operations.
Fund Age	Natural log of (caldt - first_offer_dt).
Fund Flow	The average value of monthly fund flow for each year. Fund Flow = $[TNA_t - (1+r_t) TNA_{t-1}] / TNA_{t-1}$, where TNA_t is total net asset at time t, and r_t is the return from month t-1 to month t (Sirri and Tufano, 1998).
Return Volatility	The standard deviation of the monthly returns for each fund in each year.
Annual Return	Annual return calculated from monthly returns.
Number_Fund_Managers	Number of fund managers.
Debt_Fund	A dummy variable equal to 1 to indicate a fixed income fund, 0 otherwise.
Invest Obj	lipper_obj_cd (Lipper Objective Code) used as a proxy for fund investment objective category. Lipper's objective codes are assigned based on the language that the fund uses in its prospectus to describe how it intends to invest.
Number_Funds_Managed	Number of funds managed by manager.
Top_50_School	A dummy variable equal to 1 to indicate whether a fund manager attended a top 50 school globally, 0 otherwise.
PhD	A dummy variable equal to 1 to indicate whether a fund manager earned a PhD, 0 otherwise.
Masters_Degree	A dummy variable equal to 1 to indicate whether a fund manager earned a Masters Degree, 0 otherwise.
Prof_Certifications	A dummy variable equal to 1 to indicate whether a fund manager has a professional certification, 0 otherwise.
Number_Awards	Number of prestigious awards won by manager.