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How Mutual Fund Manager Professional Networks Affect Investor Welfare

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HOW MUTUAL FUND MANAGER PROFESSIONAL NETWORKS AFFECT INVESTOR WELFARE

by

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ABSTRACT

This dissertation analyzes the link between the professional networks of mutual fund managers and its effect on fund investor welfare. A unique dataset is constructed for analysis based on third-party verified U.S. corporate board ties. Chapter 1 first examines whether U.S. mutual funds associated with fund managers possessing board connections ("connected" fund managers) have an advantage over mutual funds that are not associated with "connected" fund managers. The evidence I find suggests mutual funds associated with "connected" fund managers outperform their "non-connected" counterparts by an average of 1.57% in annual returns. Additionally, mutual funds with "connected" fund managers collect higher fees. Overall, the findings suggest "connected" mutual funds send higher returns to fund investors while keeping some for themselves in the form of fees.

Having established board connections matter on a fund level, in Chapter 2 the focus shifts from the fund level to the fund manager level by studying the "connected" fund managers' positioning within a social network hierarchy using the theory of network centrality. In other words, this chapter examines whether the professional networks of mutual fund managers, in the context of board director relationships, offer a mechanism of information flows to fund managers that ultimately affect fund investor welfare. The evidence points to fund managers enjoying higher returns when they are well-connected (via direct connections), and when their immediate connections are well-connected (via indirect connections). A long-short portfolio strategy based on eigenvector, a network centrality variable measuring how connected the fund managers' immediate connections are (network quality), yields positive and statistically significant mean and risk-adjusted returns for both in-sample and out-of-sample testing. The results suggest fund managers use their director networks as conduits for obtaining relevant information, where the opportunity for obtaining relevant information increases as the quality of the fund managers' professional network increases. Additional evidence also suggests fund managers may be holding back on utilizing the information from their current board appointment relationships.

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DEDICATION

I dedicate this dissertation to my mother, Nancy Chien. Thank you for your endless love, kindness, and support. Thank you for always believing in me.

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CHAPTER 1

MUTUAL FUND MANAGERS AND BOARD CONNECTIONS

Introduction

Do social connections matter? Research shows word-of-mouth communication can influence a professional investor's trade decisions (Hong et al., 2005; Christoffersen et al., 2009; Pool et al., 2015). The key idea being investors close in proximity are more likely to share information. Cohen et al. (2008) use shared educational networks as proxies for social ties between mutual fund managers and corporate board members to show fund managers place larger bets on firms that are within their network, which leads to better performance when compared to their non-connected holdings. The forementioned literature has taken important steps towards answering the question of whether social connections matter in financial settings.

In the context of the board of directors, prior research documents certain advantages afforded to well-connected boards. For example, well-connected boards have better access to information, which allows for better strategic decision-making (Mizruchi, 1990; Mol, 2001). Additionally, managers of firms with well-connected board directors forecast more accurately (Schabus, 2019), which the author claims may suggest well-connected directors assist managers in completing a mosaic of information by complementing the managers' information sets and helping to reinterpret public information more appropriately. If well-connected directors benefit firm managers by providing certain advantages, do well-connected directors also benefit other individuals that are within their network? More specifically, do board directors play an additional role in the dissemination of information within the financial market that extends into the mutual fund industry?

In the U.S., the total net assets for registered mutual funds doubled from 2006 to 2019 from $10.4 trillion to $21.29 trillion. This begs the question. Why do so many people entrust their savings to mutual fund managers? Are there certain advantages that exist for some mutual fund managers and not others? In this study, I examine whether U.S. mutual funds that are associated with fund managers possessing board connections (“connected” fund managers) have an advantage over funds that are not associated with “connected” fund managers. This research complements Cohen et al. (2008) and extends existing research by using third-party verified business connections, instead of implied connections from educational overlap, between U.S. mutual fund managers and U.S. corporate board members.

Funds that are associated with “connected” fund managers outperform their “non-connected” counterparts by an average of 1.57% in annual returns. In other words, board connections appear to matter for fund performance. Additionally, mutual funds with “connected” fund managers collect higher fees.

This study contributes to the literature on social connections by confirming, through verifiable connections, the role played by board directors in the dissemination of information within the mutual fund industry. The implication from the results of this paper suggests hiring mutual fund managers with board connections improve investor welfare.

Data

"Connected" Fund

The data used in this study are collected from several sources. I obtain annual mutual fund characteristics, fund manager information, and monthly return data from CRSP Mutual Fund Database. I 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. In this study, I focus on U.S. mutual fund managers with board experience.

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 straightforward 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, I compare the two datasets and match them 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, I use a variety of online resources to look up the full name of the mutual fund manager to verify it matches the director's name variable found in BoardEx. This process assures that the matches are reliable, which overcomes the problem associated with matching on individual last names. Once the verification process is complete, I am left with 3,195 manager-year observations for the period 1998 to 2017. The final sample period for testing is data from 2006 to 2017, which gives 3,085 manager-year observations. After cleaning procedures, 3,024 manager-year observations are left. Finally, I convert from manager-year observations to fund-year observations by removing duplicate observations based on the fund identifier and year since many funds have more than one fund manager, which leaves me with 2,710 fund-year observations. Overall, I identify 912 unique funds. Table 1.1 lists the number of unique funds represented each year concerning the 2,710 fund-year observations.

Table 1.1

Number of Unique Funds

Number of Unique Funds	
Year	Count
2006	85
2007	117
2009	151
2009	157
2010	168
2011	207
2012	258
2013	290
2014	306
2015	339
2016	332
2017	300
Full Sample	912

Summary Statistics

To control for other mutual fund characteristics shown in other studies to partially determine mutual fund annual return, I collect and calculate annual measures of said characteristics. These characteristics include the expense ratio, management fee, turnover ratio, fund size, fund age, fund flow, and return volatility. Data is 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.

The univariate analysis provides preliminary evidence that funds associated with fund managers possessing board connections from sitting on boards ("connected" funds) are associated with better fund performance, higher fee collections, and are on average larger funds. For example, the mean expense ratio is 1.27% for connected funds, while the mean expense ratio is 1.16% for non-connected funds. Using Welch's t-test, which assumes unequal variance for the unpaired data, it rejects the null hypothesis that connected funds, on average, have the same expense ratio as non-connected funds at the 1% level. The null regarding the difference in management fee is also rejected at the 1% level. The mean annual returns are 7.72% for connected funds, while the mean annual returns are 6.63% for non-connected funds. Welch's t-test rejects the null at the 1% level. The null regarding the difference in fund size (Log TNA) is rejected at the 5% level. Additionally, connected funds are younger, associated with lower fund flow, and experience lower return volatility.

Table 1.2 provides the summary statistics of the mutual fund characteristics for all fund-years by total sample (Panel A), connected funds only (Panel B), and non-connected funds only (Panel C).

Table 1.2

Summary Statistics of Mutual Fund Descriptors

Panel A: Summary Statistics for Total Sample

	N	Mean	Median	p10	p90	Std
Expense Ratio	260,045	1.16	1.10	0.41	2.00	0.69
Management Fee	230,648	0.60	0.59	0.17	0.99	0.36
Turnover Ratio	260,045	1.37	0.51	0.12	1.78	215.98
Annual Return	314,475	6.64	6.10	-9.41	26.60	17.42
Size (Log TNA)	311,530	3.23	3.57	-0.92	6.66	2.79
Fund Age (Log Fund Age)	314,525	7.64	7.88	6.08	8.84	1.17
Fund Flow	313,929	1.56	0.00	-0.04	0.11	155.79
Return Volatility	312,420	3.34	2.87	0.67	6.61	2.77

Panel B: Summary Statistics for Connected Funds

	N	Mean	Median	p10	p90	Std
Expense Ratio	2,462	1.27	1.20	0.63	2.01	0.55
Management Fee	2,161	0.69	0.65	0.32	1.10	0.36
Turnover Ratio	2,462	1.15	0.70	0.22	1.96	2.21
Annual Return	2,670	7.72	5.87	-7.90	29.01	16.89
Size (Log TNA)	2,710	3.37	3.57	-0.51	6.87	2.79
Fund Age (Log Fund Age)	2,702	7.45	7.63	5.90	8.91	1.34
Fund Flow	2,670	0.45	0.00	-0.04	0.14	9.00
Return Volatility	2,640	3.20	2.80	0.60	6.47	2.34

Panel C: Summary Statistics for Non-Connected Funds

	N	Mean	Median	p10	p90	Std
Expense Ratio	257,583	1.16	1.10	0.41	2.00	0.69
Management Fee	228,487	0.60	0.59	0.17	0.99	0.36
Turnover Ratio	257,583	1.37	0.51	0.12	1.78	217.01
Annual Return	311,805	6.63	6.10	-9.43	26.59	17.43
Size (Log TNA)	308,820	3.23	3.47	-0.92	6.65	2.79
Fund Age (Log Fund Age)	311,823	7.64	7.88	6.09	8.84	1.17
Fund Flow	311,259	1.57	0.00	-0.04	0.11	156.45
Return Volatility	309,780	3.34	2.87	0.67	6.62	2.78

To provide insight into the differences in fund characteristics for funds with and without connected fund managers, I present descriptive statistics for the connected versus non-connected funds and differences in means in Table 1.3.

Table 1.3

Summary Statistics for Connected vs Non-Connected Funds

Connected Funds vs Non-Connected Funds

	N	Connected	N	Non-Connected	Diff in Means	t-stat
Expense Ratio	2,462	1.27	257,583	1.16	0.11***	9.78
Management Fee	2,161	0.69	228,487	0.60	0.09***	12.02
Turnover Ratio	2,462	1.15	257,583	1.37	-0.22	-0.50
Annual Return	2,670	7.72	311,805	6.63	1.09***	3.31
Size (Log TNA)	2,710	3.37	308,820	3.23	0.14**	2.54

t statistics in parentheses
*p<0.10, **p<0.05, ***p<0.01

Analysis

Determinants of Fund Return

First, I investigate whether the performance of funds associated with fund managers possessing direct connections to corporate board members is associated with higher returns. If fund managers with professional ties to corporate board members are utilizing their networks for information, connected funds may benefit in the form of superior performance. Therefore, my null hypothesis is that there is no association between funds with connected fund managers and annual return. The baseline regression is the following form:

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

where *Connected_Fund* is a dummy 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, number of fund managers) lagged by one year. *Connected_Fund* is measured contemporaneous with return to explain performance, not predict it. The specification includes year fixed effects and robust errors clustered by fund.

Model 1 of Table 1.4 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 controls does little to diminish the significance of *Connected_Fund*. Instead, the coefficient of *Connected_Fund* increases to 1.64 (t = 5.93). In other words, “connected” funds are associated with an increase of 1.64% in annual returns over their “non-connected” counterparts.

Table 1.4

Fund-level Cross-Sectional Return Regressions with “Connected” Fund

	(1)	(2)
$Connected\_Fund_t$	0.78***	1.64***
	(3.22)	(5.93)
Size (Log TNA) $_{t-1}$		-0.13***
		(-8.80)
Turnover Ratio $_{t-1}$		-0.08***
		(-5.80)
Expense Ratio $_{t-1}$		-0.99***
		(-9.42)
Management Fee $_{t-1}$		0.55**
		(2.05)
Fund Age $_{t-1}$		0.80***
		(18.38)
Fund Flow $_{t-1}$		0.00
		(1.35)
Return Volatility $_{t-1}$		1.05***
		(8.03)
Number_Fund_Managers $_{t-1}$		-0.16***
		(-3.88)
Constant	6.63***	-1.54***
	(288.32)	(-3.21)
Adj R-squared	0.55	0.54
Year Fixed Effects	Yes	Yes
Number of obs	314,475	148,105

t statistics in parentheses
*p<0.10, **p<.05, ***p<0.01

Marginal Effects Analysis and Pairwise Comparison

Next, I perform marginal effects analysis after running Model 2 in Table 1.4. Panel A of Table 1.5 shows, on average, "non-connected" funds are associated with annual returns of 6.46%. On the other hand, "connected" funds are associated with annual returns of 8.10%. Panel B of Table 1.5 shows the results of a pairwise comparison contrasting the annual return difference between "connected" versus "non-connected" funds. A difference of 1.64% is seen for the annual returns, which is both economically and statistically significant (t = 5.93). The results here reflect the regression results found in Model 2 of Table 1.4.

Table 1.5

Marginal Effects Analysis / Pairwise Comparison

Panel A: Marginal Effects Analysis

$Connected\_Fund_t$	Margin	[95% Conf. Interval]	
0	6.46	6.40	6.52
1	8.10	7.57	8.64

Panel B: Pairwise Comparison

$Connected\_Fund_t$	Contrast	t-stat	[95% Conf. Interval]	
1 vs 0	1.64***	5.93	1.10	2.19

t statistics in parentheses
*p<0.10, **p<.05, ***p<0.01

The core question of interest is whether there is a difference in performance between connected versus non-connected funds. These initial results provide some evidence that connected funds perform better than non-connected funds. I argue the reason for seeing higher returns in funds associated with connected fund managers may be due to some informational advantage connected fund managers possess, which allows for more informed decision-making that results in better fund performance.

Propensity Score Matching

To eliminate a greater portion of bias from my unpaired data analysis thus far, I 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). I choose a sample from the control group (“non-connected” funds) that "matches" the treatment group (“connected” funds). In other words, I am using treated and controlled fund observations that are as similar as possible regarding all observed covariates. Any differences between the treatment and matched control groups are then assumed to be a result of the treatment. A fund is considered “connected” if the associated fund manager possesses board connections from sitting on boards. When more than one control fund is a “match” with a treatment fund, I include all possible matching funds in the control group. I confirm the sort order is random before conducting propensity score matching. To ensure the propensity score successfully balanced the data on the observed covariates, I 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.” Table 1.6 reports the results. The control variables (covariates) used for propensity score matching related to each respective outcome variable are shown below the results.

Table 1.6

Matched Funds using Propensity Score Matching

Variable	Sample	Treated	Controls	Difference	T-stat
Annual Return	Matched	7.66	6.09	1.57***	2.87
Management Fee	Matched	0.71	0.60	0.11***	10.35
Size (log TNA)	Matched	3.60	3.14	0.46***	5.44
Expense Ratio	Matched	1.28	1.17	0.11***	5.90

t statistics in parentheses

* p<0.10, **p<.05, ***p<0.01

Covariates	Annual Return	Management Fee	Size (Log TNA)	Expense Ratio
Size (Log TNA) $_{t-1}$	X	X		X
Turnover Ratio $_{t-1}$	X	X	X	X
Expense Ratio $_{t-1}$	X		X	
Fund Age (Log) $_{t-1}$	X	X	X	X
Fund Flow $_{t-1}$	X	X	X	X
Return Volatility $_{t-1}$	X	X	X	X
Number_Fund_Managers $_{t-1}$	X	X	X	X
Annual Return $_{t-1}$		X	X	X

The results support the baseline regression results (Model 2 of Table 1.4). For example, the average treatment effect on the treated (“connected” funds), regarding annual return, is 1.57% (t = 2.87).Next, I perform propensity score matching with a focus on other dependent variables (i.e., management fee, fund size, and expense ratio) while using many of the same variables from equation (1) as predictors. The results show the average treatment effect on the treated regarding expense ratio, management fee, and fund size is positive and statistically significant at the 1% level. In other words, fund performance, fees collected, and assets managed are larger for the treatment group (connected funds). Overall, these results support the idea that connected funds have an advantage over non-connected funds.

Interaction Effects

The percentage of funds managed by multiple-manager arrangements has been increasing since the 1990s. Single-managed funds are typically run by managers that are established and are thus well-entrenched figures in the industry. Qiu (2003) provides evidence that suggests single-managed funds alter their portfolios' risk more readily and to a much greater extent than mutual funds run by multiple managers. Overall, Qiu's results support the notion that multiple managers reduce the risk-taking incentives of funds in response to their relative performance. Sharpe's (1980) theoretical justification argues that employing multiple fund managers mitigates the danger of fund performance being damaged by the serious decision errors of a single manager. Barry and Starks (1984) argue that investors may benefit from the higher risk taken by multiple managers due to the risk-sharing arrangements between multiple managers. As such, the structure of fund managers (single-managed vs. team-managed funds) may be a reason for the higher returns of connected funds since multi-manager funds increase the probability a connected fund manager may be a part of the team.

Although an indicator variable is included in Table 1.4 (Model 2) to control for the number of fund managers (*Number_Fund_Managers*), I did not test whether an interaction exists between team-managed funds and connected funds. In Table 1.7, I control for multiple-manager arrangements (*Team_Managed*) and assess whether an interaction exists between funds run by multiple managers and funds associated with a connected fund manager. The results show both main effects (*Connected_Fund* and *Team_Managed*) remaining significant even when the interaction is included. However, the interactive coefficient is not significant.

Table 1.7

Interaction Between Connected Funds and Team-Managed Funds

	(1)	[95% Conf. Interval]	
$Connected\_Fund_{t}$	1.82***	0.81	2.82
	(3.54)		
$Team\_Managed_{t-1}$	-0.16***	-0.27	-0.05
	(-2.82)		
$Connected\_Fund_{t}$ * $Team\_Managed_{t-1}$	-0.96	-2.12	0.21
	(-1.61)		
Size (Log TNA) $_{t-1}$	-0.10***	-0.12	-0.08
	(-8.38)		
Turnover Ratio $_{t-1}$	-0.09***	-0.11	-0.06
	(-5.87)		
Expense Ratio $_{t-1}$	-0.98***	-1.14	-0.82
	(-11.97)		
Management Fee $_{t-1}$	0.23	-0.10	0.57
	(1.38)		
Fund Age $_{t-1}$	0.81***	0.74	0.87
	(23.02)		
Fund Flow $_{t-1}$	0.00**	0.00	0.00
	(2.21)		
Return Volatility $_{t-1}$	1.15***	0.94	1.37
	(10.42)		
Constant	-1.88***	-2.68	-1.09
	(-4.63)		
Adj R-squared	0.57		
Year Fixed Effects	Yes		
Number of obs	222,042		

t statistics in parentheses
* p<0.10, **p<.05, ***p<0.01

In Table 1.8, I examine whether the interaction becomes significant when we rerun the analysis using the "matched sampling" from Table 1.6. The results show the interaction is still not significant. Only the main effect for *Connected_Fund* is positive and significant now.

Table 1.8

Matched Funds: Interaction B/T Connected Funds and Team-Managed Funds

	(1)	[95% Conf.	Interval]
$\text{Connected\_Fund}_{t}$	3.22***	1.73	4.70
	(4.25)		
$\text{Team\_Managed}_{t-1}$	0.46	-0.80	1.72
	(0.72)		
$\text{Connected\_Fund}_{t}$ * $\text{Team\_Managed}_{t-1}$	-1.46	-3.21	0.29
	(-1.64)		
Size (Log TNA) $_{t-1}$	-0.35***	-0.54	-0.17
	(-3.76)		
Turnover Ratio $_{t-1}$	-0.05	-0.26	0.15
	(-0.51)		
Expense Ratio $_{t-1}$	-0.88	-1.90	0.13
	(-1.71)		
Management Fee $_{t-1}$	0.40	-1.40	2.20
	(0.43)		
Fund Age $_{t-1}$	0.61**	0.11	1.11
	(2.39)		
Fund Flow $_{t-1}$	0.02	-0.02	0.07
	(1.13)		
Return Volatility $_{t-1}$	1.14***	0.69	1.58
	(5.04)		
Constant	-0.69	-4.61	3.23
	(-0.34)		
Adj R-squared	0.53		
Year Fixed Effects	Yes		
Number of obs	3,856		

t statistics in parentheses
* p<0.10, **p<.05, ***p<0.01

Conclusion

In this study, I examine whether performance is stronger for funds managed by individuals possessing board connections. The initial unpaired data analysis shows funds with “connected” fund managers (“connected” funds) outperform their “non-connected” counterparts. The results are robust to a matched sampling analysis based on estimated propensity scores. Additionally, controlling for the number of fund managers does not take away the explanatory power of “connected” funds. The contribution of this study is using verifiable connections to show how board directors play an additional role in the dissemination of information within the mutual fund industry. The implication from the findings is that hiring mutual fund managers with board connections benefit investor welfare.

CHAPTER 2

THE QUALITY OF YOUR NETWORK MATTERS

Introduction

The purpose of this study is to analyze the link between the professional networks of mutual fund managers and the effect on fund investor welfare. I 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 exact linkages (relationships) is limited. For example, Cohen et al. (2008) find mutual fund managers with educational ties to corporate board members place larger bets on connected firms, which results in better performance relative to their non-connected holdings. This research complements their study and extends existing research by using third-party verified business connections between U.S. mutual fund managers and U.S. corporate board members, and goes beyond examining only bilateral ties by investigating the overall position of a network participant (fund manager) within a greater network to capture the concept of social hierarchy. This relationship is important because it offers insight into the interplay between the networks of market participants, adverse selection, and information asymmetries.

Research documents the importance of social ties – such as shared educational overlaps, shared past employment, or joint memberships in social organizations – in finance. Financial research documents both the benefits and costs of such connections. Social ties help enable the transmission of information among corporate decision-makers, which lead to stronger analyst performance (Cohen, Malloy, and Frazzini, 2010), more efficient loan contracting (Engelberg, Gao, and Parsons, 2012), better M&A synergies (Cai and Sevilir, 2012), enhanced portfolio manager performance (Cohen, Frazzini, and Malloy, 2008), and overall greater corporate performance (Fracassi, 2014). Conversely, interpersonal connections interfere with optimal corporate governance and the monitoring of managers (Fracassi and Tate, 2012), make possible collusion among contracting managers at the investors' expense (Ishii and Xuan, 2014), and increase transaction costs (Cai, Walkling, and Yang, 2016).

In the context of the social ties of mutual fund managers, finance studies so far have documented large benefits due to social ties. Hong et al. (2005) finds 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). These studies suggest 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 due to the ability to receive information more quickly. Walden (2019) introduces a dynamic network model and finds central agents to be more profitable in trading. More importantly, the author empirically tests how 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.

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 in addition to network centrality to examine the social hierarchy effects of mutual fund managers' network positions. In contrast to previous studies based on bilateral ties, I strive to capture the mutual fund managers' ability to receive and process information even in the absence of direct links to various counterparties. Following the works in graph theory (e.g., Proctor and Loomis, 1951; Sabidussi, 1966; Freeman, 1977; Bonacich, 1972), I argue network centrality – a set of measures that portray the position of an individual within a network – captures the concept of network hierarchy and describes a network participant's ability for efficiently gathering and processing 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, as such, impact the performance of fund managers. I utilize two network centrality variables frequently used in social science network studies: degree centrality (the number of direct ties between the fund manager and any other network participants; an obvious indicator for influence, visibility, and reach) and eigenvector centrality (a variable that evaluates the importance of a professional network by giving greater weight to highly-connected people directly tied to the fund manager). For this study, eigenvector is used as a proxy for network quality. Ultimately, greater network centrality allows a network participant to more easily receive and communicate material information (Burt, 2010; Jackson, 2010; Newman, 2010), and allows for reputational effects by punishing the negative behavior of highly visible network members, effectively bringing about highly-connected individuals voluntarily disclosing truthful information, and honoring both explicit and implicit contractual obligations (Boot et al., 1993; Burt, 2005; Brass and Labianca, 2006). Overall, the above arguments imply high-centrality mutual fund managers should have an advantage in gathering, transmitting, and processing information – both “soft” and material – over their less-connected counterparts.

In Chapter 1, I first establish fund managers with connections to corporate board members matter for mutual fund performance, which motivates my investigation of network structure beyond bilateral ties in this Chapter. As such, in Chapter 2, I consider regressions based on the centrality variables, degree and eigenvector, while controlling for common partial determinants of annual fund return. The regression models include two sets of centrality measures used to disentangle the effects of information that may be coming from only current board appointments. As such, one set (current centrality measures) considers only current board relationships, and the other set (cumulative centrality measures) considers all current and past board relationships. Finally, I form portfolios based on the centrality measures to assess whether a profitable long-short strategy exists.

I expect well-connected (degree) and/or more central (eigenvector) fund managers to have an advantage in accessing more useful information from their professional networks made up of corporate board members, especially if their immediate connections are highly connected themselves. For example, research has shown sophisticated traders (e.g., fund managers) who gather, analyze, and interpret data from multiple sources are better at collecting and aggregating "bits and pieces" of information dropped by more well-connected board members, which lead to profitable trades (Akbas et al., 2016). These well-connected boards have better access to information that they use for better strategic decision-making (Mizruchi, 1990; Mol, 2001). Additionally, traders more central in the network, as measured by eigenvector centrality, receive information more quickly than traders less central, which leads to earlier trades and greater profits (Ozsoylev et al.,2014). Lastly, I expect the information set associated with the set of centrality measures that consider all relationships formed over time from sitting on boards to be more beneficial than the information set associated with the set of centrality measures that only considers relationships of current board appointments. A reasonable conjecture is that current relationships are more easily traced, and it makes intuitive sense that institutional investors are reluctant to act upon material information that may raise suspicion of impropriety. Extant literature finds institutional investors are reluctant to use private information in a traceable manner (Griffin et al., 2012).

In summary, given mutual fund managers with educational ties to corporate board members benefit from information flows that help address information asymmetries (Cohen et al., 2008), I investigate whether these same advantages still apply when I consider the overall position of a mutual fund manager (with prior board experience) in the large professional network of all corporate board members. In this fashion, I consider the following questions. Do connections with corporate board members matter? If connections matter, do all "connected" fund managers benefit equally? If not, what is the differentiating factor? Finally, do current professional relationships impart meaningful information to fund managers? To answer these questions, I assemble a unique dataset that maps the direct and indirect network connections between mutual fund managers and corporate board members, resulting in annual director networks.

In Chapter 1, through OLS regression estimates, I find U.S. mutual funds that are associated with fund managers possessing board connections perform better than their "non-connected" counterparts. For example, "connected" funds are associated with annual returns of 8.10% while "non-connected" funds are associated with annual returns of 6.46%, which is a statistically significant difference of 1.64%. Having established board connections matter, in this Chapter, I present evidence that the overall position of a mutual fund manager within a hierarchy of network participants is an important determinant of fund return. More specifically, the OLS regression estimates of fund manager centrality on annual return, controlling for fund characteristics, show both the number of connections and the importance (quality) of the fund managers' immediate connections are important determinants of fund performance. Additionally, I find no evidence of suggested information advantage on performance when considering only the relationships of current board appointments (current centrality measures). That is, the relationships that are a function of fund managers currently sitting on the same board with other corporate board members are not helpful, whereas the cumulative relationships a fund manager has formed over time from sitting on boards are. Lastly, I form portfolios of mutual funds based on cumulative eigenvector (network quality) and find positive and significant mean and risk-adjusted returns for both in-sample and out-of-sample testing when applying a long-short strategy. This implies indirect connections within a fund managers' professional network may be more beneficial than direct connections, a finding in line with Granovetter's "strength of weak ties" argument that information sets formed from indirect ties present more novel information than those of network participants that are directly connected (Granovetter, 1973).

The findings make the following notable contributions: First, I add to the fast-growing literature on the role of social networks in finance. This paper is the first to use third-party verified network connections to uncover the ability of "connected" mutual fund managers with advantageous network positions to receive and process valuable information. Mutual fund managers occupying more significant positions in this network are more advantageously positioned within the social network hierarchy and are considered more influential and powerful (Mizruchi and Potts 1998). The findings suggest corporate board members are facilitating information flows to more influential and powerful fund managers. The implication of the results is that fund manager network centrality may be an important consideration when deciding who to hire. Second, I extend the literature on determinants of mutual fund performance. I show that in addition to known fund-specific determinants, the personal characteristics of the mutual fund manager, such as their influence and power, and network quality (both proxied by network centrality), matter for mutual fund performance.

Data

"Connected" Mutual Fund Manager

Chapter 2 identifies "connected" mutual fund managers based on the unique dataset constructed in Chapter 1. The data used in this study are collected from several sources. I obtain annual mutual fund characteristics, fund manager information, and monthly return data from CRSP Mutual Fund Database. I 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. In this study, I focus on U.S. mutual fund managers with board experience.

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 straightforward 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, I compare the two datasets and match them 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, I use a variety of online resources to look up the full name of the mutual fund manager to verify it matches the director's name variable found in BoardEx. This process assures that the matches are reliable, which overcomes the problem associated with matching on individual last names. Once the verification process is complete, we are left with 3,195 manager-year observations for the period 1998 to 2017. The final sample period for testing is data from 2006 to 2017, which gives 3,085 manager-year observations. After cleaning procedures, 3,024 manager-year observations are left. Overall, I identify 207 unique fund managers with board experience and 912 unique funds in the final dataset. Panel A of Table 2.1 lists the number of unique funds represented each year concerning the 3,024 manager-year observations.

Table 2.1

Number of Unique Funds

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 return, I collect and calculate annual measures of said characteristics. These characteristics include the expense ratio, management fee, turnover ratio, fund size, fund age, fund flow, and return volatility. Data is 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 2.2 provides the summary statistics of the mutual fund characteristics for the full sample.

Table 2.2

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

Centrality

The centrality variables are generated utilizing the BoardEx database. I utilize past employment relationships to construct annual networks made up of corporate board members. For each year I generate two measures of network centrality, degree and eigenvector, to capture the size and importance (quality) of a fund managers' immediate network, respectively. I define connections (bilateral links) in two different manners to calculate two sets of measures for network centrality, a *current* and *cumulative* set. For the *current* set, a connection is formed if two individuals simultaneously serve on the same board until one individual from the pair leaves. For the *cumulative* set, a connection that forms from two individuals simultaneously sitting on the same board continues to persist until someone in the pair dies (El Khatib et al., 2015). As a result, the annual network under the *cumulative* set continues to grow monotonically over time.

I normalize each centrality measure and generate percentile values for each to preserve their rank order and make them comparable across time, with 1 indicating the lowest centrality and 100 indicating the highest centrality. Table 2.3 presents the summary statistics for centrality measures.

Table 2.3

Summary Statistics of Centrality Measures

Panel A

	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

Panel B

	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

Panel C

	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 12 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:

$$\textbf{Degree}_{\mathbf{i}} = \sum_{j \neq i} X_{ij} ,$$

where $X_{ij} = 1$ if individuals[1] 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:

$\mathbf{Eigenvector_i} = K_1^{-1} = \sum_j A_{ij} X_j$,

where K_1 is the largest eigenvalue of the adjacency matrix. Thus, an individual can be poorly positioned regarding degree centrality but advantageously positioned if their 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 2.1, the larger nodes are associated with a higher degree centrality, while the darker nodes are associated with a higher eigenvector centrality.

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[1] executives and non-executives

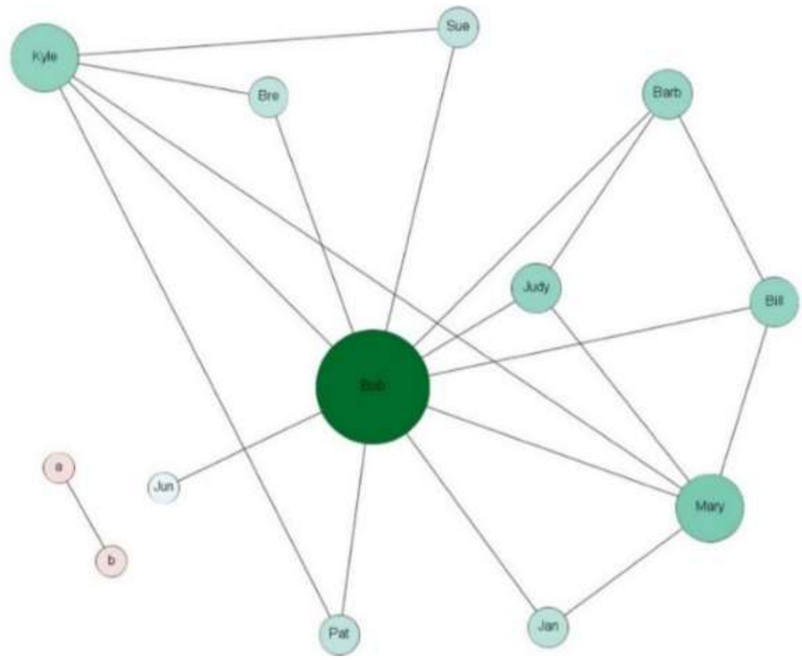

Figure 2.1: Small Network Representation. This is a sample representation of a small network with 11 nodes (circles) representing individuals and 20 edges (lines) illustrating relationships between nodes. Larger nodes have a higher degree of centrality. With the exception of nodes, *a* and *b* darker nodes represent those with higher eigenvector centrality. Nodes *a* and *b* are in a disconnected subnetwork. Source: Jared F. Egginton and William R. McCumber. Permission has been granted by the authors for the use of this figure.

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 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 this study, Jun's network is considered to be of higher quality than the network of nodes *a* and *b*.

Methodology

In this study, I 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 the sample includes all mutual fund types, not only equity funds. I estimate the performance relative to these four models as:

$$R_{it} - r_{ft} = \alpha_{it} + \beta_{it}(R_{mt} - r_{ft}) + \varepsilon_{it} \tag{1}$$

$$R_{it} - r_{ft} = \alpha_{it} + \beta_{it}(R_{mt} - r_{ft}) + s_{it}SMB_t + h_{it}HML_t + \varepsilon_{it} \tag{2}$$

$$R_{it} - r_{ft} = \alpha_{it} + \beta_{it}(R_{mt} - r_{ft}) + s_{it}SMB_t + h_{it}HML_t + p_{it}PR1YR_t + \varepsilon_{it} \tag{3}$$

$$R_{it} - r_{ft} = \alpha_{it} + \beta_{it}(R_{mt} - r_{ft}) + s_{it}SMB_t + h_{it}HML_t + p_{it}PR1YR_t + t_{it}PTFS_{B,t} + u_{it}BM_t + v_{it}BS_t + \varepsilon_{it} \tag{4}$$

where R_{it} is the return on portfolio i, R_{mt}[2] 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[3], the bond market factor[4], and the bond size spread factor[5]. The inclusion of these additional three bond factors is used to produce a cleaner risk-adjusted return, alpha, since fixed income funds are included.

I also consider two additional risk-adjusted performance measures, the Sharpe Ratio (Sharpe, 1966) and the Information Ratio. The Sharpe Ratio sheds light on how

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[2] Value weighted return of all CRSP firms incorporated in the U.S. and listed on the NYSE, AMEX, or NASDAQ.

[3] Trend following factors for bonds, currencies, and commodities.

[4] The monthly change in the 10-year treasury constant maturity yield (month end-to-month end).

[5] The monthly change in the Moody's Baa yield less 10-year treasury constant maturity yield (month end-to-month end).

much excess return is received for the additional volatility endured for holding a riskier asset. It is calculated as follows:

$$S(x) = \frac{(r_x - r_{ft})}{StdDev(r_x)} \tag{5}$$

where x is the investment, r_x is the average rate of return, and r_{ft} is the risk-free rate.

The Information Ratio (Treynor and Black, 1973) is a similar measure to the Sharpe Ratio with the key distinction being how excess return is defined. The Information Ratio standardizes returns by dividing the difference in their performances by their tracking error and is calculated as follows:

$$IR = \frac{Portfolio\ Return - Benchmark\ Return}{Tracking\ Error} \tag{6}$$

where the portfolio return minus benchmark return is the excess return and the tracking error is the standard deviation of the excess return. Thus, we can describe the information ratio as alpha divided by residual risk.

Testing the Equality of Sharpe Ratios

I employ a test proposed by Jobson & Korkie (1981) to test for the equality of the Sharpe ratios between the top and bottom portfolios of a long-short trading strategy. The test statistic can be formulated as:

$$Z = \frac{\sigma_a(\mu_b - R_f) - \sigma_b(\mu_b - R_f)}{\sqrt{\Theta}} \tag{7}$$

where μ_a are the mean returns of the bottom portfolio, μ_b are the mean returns of the top portfolio, R_f is the risk-free rate of return, which is assumed to be zero, and Θ is calculated as follows:

$$\Theta = \frac{1}{T}\left[2\sigma_a^2\ \sigma_b^2 - 2\sigma_a\sigma_b\sigma_{ab} + \frac{1}{2}\mu_a^2\sigma_b^2 + \frac{1}{2}\mu_b^2\sigma_a^2 - \frac{\mu_a\mu_b}{2\sigma_a\sigma_b}\ (\sigma_{ab}^2 + \sigma_a^2\sigma_b^2)\right] \tag{8}$$

where T equals the number of observations, σ_a and σ_b are respectively the estimates of the standard deviation of the excess returns of the bottom and top portfolios over the evaluation period, and σ_{ab} is an estimate of the covariance of the two portfolios.

Jobson & Korkie (1981) shows the test statistic Z is approximately normally distributed with a zero mean and a unit standard deviation for large samples. A significant Z statistic would reject the null hypothesis of equal risk-adjusted performance between the two portfolios.

Analysis

Univariate Analysis

Table 2.4 compares 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 is higher than the below-median group 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 (well-connected corporate board members) are highly connected themselves, which aligns with prior research documenting well-connected board of directors having better access to information when compared to less-connected board of directors (Mizruchi, 1990; Mol, 2001; Larcker et al., 2013).

Table 2.4

Univariate Analysis of Cumulative Eigenvector

eigenvector (cumulative)	N	Return (t-stat)	Std. Dev.	Min	Max
Above Median	15,007	0.74	3.92	-27.02	30.21
Below Median	14,513	0.50	4.19	-29.87	32.93
Difference		0.24*** (5.02)			

t statistics in parentheses
* p<0.10, **p<.05, ***p<0.01

Network Centrality as a Determinant of Fund Return

In this section, I examine the cross-sectional relation between the *cumulative* centrality measures and annual return[6] while controlling for various other common partial determinants of fund return. All regressions include time fixed effect for year and robust standard errors that account for fund clustering. Models 1 and 2 of Table 2.5 regresses 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 = 4.45 and t = 3.49). When control variables from Table 1.4 are included in Models 5 and 6, both coefficients for *cumulative* eigenvector and *cumulative* degree remain positive and statistically significant (t = 6.55 and t = 5.44). The results in Table 2.5 suggest high centrality mutual fund managers are associated with better fund

[6] Monthly returns are compounded to create annual returns.

performance. More specifically, fund managers who are well-connected and/or have access to higher quality professional networks enjoy better fund performance. As such, "connected" fund managers do not all benefit equally from having connections with corporate board members.

Table 2.5

Manager-Level Cross-Sectional Return Regressions with Centrality

	annual return							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
eigenvector (cumulative)	0.07***				0.08***			
	(4.45)				(6.55)			
degree (cumulative)		0.05***				0.07***		
		(3.49)				(5.44)		
eigenvector (current)			-0.03***				-0.05***	
			(-2.86)				(-4.59)	
degree (current)				0.00				-0.00
				(0.15)				(-0.24)
Size (Log TNA)					0.04	0.05	0.07	0.06
					(0.36)	(0.40)	(0.58)	(0.53)
Turnover Ratio					0.78***	0.79***	0.75***	0.76***
					(6.12)	(6.14)	(5.80)	(5.88)
Expense Ratio					-1.21**	-1.04	-1.08*	-1.01
					(-1.96)	(-1.63)	(-1.76)	(-1.61)
Management Fee					4.64***	4.88***	4.96***	5.02***
					(4.13)	(4.33)	(4.65)	(4.58)
Fund Age					-0.05	-0.01	-0.11	-0.16
					(-0.19)	(-0.04)	(-0.41)	(-0.56)
Fund Flow					-0.18***	-0.19***	-0.19***	-0.18***
					(-3.43)	(-3.38)	(-3.55)	(-3.33)
Return Volatility					0.14	0.09	0.07	0.08
					(0.74)	(0.45)	(0.33)	(0.41)
Number_Fund_Managers					-0.77**	-0.80**	-0.85**	-0.73**
					(-2.36)	(-2.47)	(-2.43)	(-2.14)
Constant	2.68**	3.73***	9.62***	7.36***	0.32	0.56	10.44***	6.85***
	(2.42)	(3.36)	(11.63)	(10.20)	(0.15)	(0.26)	(4.52)	(3.08)
Adj R-squared	0.45	0.44	0.45	0.45	0.51	0.51	0.51	0.51
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs	2,977	2,977	2,935	2,935	2,403	2,403	2,370	2,370

t statistics in parentheses
* p<0.10, **p<.05, ***p<0.01

Next, I examine the *current* set of centrality measures, which are a function of fund managers currently sitting on boards. Recall, for *current* centrality measures, I 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 developed from sitting on boards, only current board relationships. Models 7 and 8 of Table 2.5 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 = -4.59). This suggests fund managers currently sitting on boards with access to better quality professional networks are handicapped. Although corporate board members have access to material non-public information, there are laws requiring confidentiality. Investors face regulatory scrutiny and reputational costs if caught using private information. Additionally, current board relationships are easier to trace, and prior research documents institutional investors are reluctant to use private information in a traceable manner (Griffin et al., 2012).

An alternative explanation may be that there are relationship effects not being captured when considering only the information set of current board relationships. If well-connected directors have better access to relevant information (Mizruchi, 1990; Mol, 2001; Larcker et al., 2013), what determines if directors will share information with fund managers? It may be the case that relationships need time to foster before a certain level of information and reputational trust (i.e., social capital) can be accumulated. *Current* centrality measures fail to capture those relationship effects since it does not consider all relationships formed from sitting on boards, which the *cumulative* centrality measures do. The overall implication is that the fund managers' information set from current board relationships is not as meaningful as the information set coming from the cumulative relationships a fund manager has fostered over time from sitting on boards.

First Principal Component

Eigenvector and degree centrality are highly correlated with one another (refer to Table 2.6). As such, Table 2.7 reports regression results using the first principal component of eigenvector and degree to transform those variables into a linear combination of the two variables, which is designed to measure the main impact between the two centrality factors. Models 1 and 3 of Table 2.7 show the coefficients for the first principal component based on the *cumulative* centrality measures are positive and statistically significant for both models with and without control variables. Models 2 and 4 show the coefficients for the first principal component based on the *current* centrality measures are negative for both models with and without control variables. The coefficient is negative and statistically significant in model 4. Overall, the results reflect similarly to the findings in Table 2.5.

Table 2.6

Correlation Matrix for Centrality Variables

	Cumulative degree	Cumulative eigenvector	Current degree	Current eigenvector
Cumulative degree	1			
Cumulative eigenvector	0.89	1		
Current degree	0.39	0.28	1	
Current eigenvector	0.25	0.21	0.79	1

Table 2.7

Manager-Level Cross-Sectional Return Regressions with First Principal Component

	annual return			
	(1)	(2)	(3)	(4)
PC1_Cumulative_Centralit	0.80***		1.06***	
	(4.08)		(6.22)	
PC1_Current_Centrality		-0.27		-0.50***
		(-1.55)		(-2.72)
Size (Log TNA)			0.04	0.06
			(0.37)	(0.51)
Turnover Ratio			0.79***	0.75***
			(6.14)	(5.77)
Expense Ratio			-1.13*	-1.05*
			(-1.80)	(-1.69)
Management Fee			4.78***	5.00***
			(4.24)	(4.63)
Fund Age			-0.02	-0.14
			(-0.08)	(-0.50)
Fund Flow			-0.18***	-0.18***
			(-3.40)	(-3.45)
Return Volatility			0.11	0.07
			(0.59)	(0.38)
Number_Fund_Managers			-0.78**	-0.77**
			(-2.42)	(-2.24)
Constant	7.42***	7.46***	6.01***	6.75***
	(32.57)	(32.62)	(3.01)	(3.23)
Adj R-squared	0.45	0.45	0.51	0.51
Year Fixed Effects	Yes	Yes	Yes	Yes
Number of obs	2,977	2,935	2,403	2,370

t statistics in parentheses
* p<0.10, **p<.05, ***p<0.01

Centrality-Sorted Portfolio Performance

In this section, I 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, I form four equal-weighted portfolios of mutual funds using reported monthly returns, which include distributions but are net of total expenses.[7] I 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. Funds that no longer exist during the year are included in the equal-weighted average until they disappear, at which time the portfolio weights are readjusted.

If a fund has two or more fund managers in a given year, for portfolio testing, I keep only the manager-year observation for the fund manager with the highest *cumulative* eigenvector centrality measure since I am arguing fund managers with higher quality professional networks have an advantage in obtaining relevant information from well-connected corporate board members. This leaves me with 2,460 manager-year observations for portfolio testing. However, the structure of fund managers (single-managed vs. team-managed funds) may be the reason for 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, Tables 2.5 and 2.7 control for the number of fund managers. We see the explanatory power of *cumulative* eigenvector (network quality) as a partial determinant of fund return is still significant even with that control, which justifies using the fund manager with the highest quality professional network for portfolio testing.

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

[7] Net of all operating expenses (expense ratios) and security-level transaction costs, but do not include sales charges.

associated risk-adjusted performance measures, as shown in Table 2.8. 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.

Table 2.8

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

t statistics in parentheses
* p<0.10, **p<.05, ***p<0.01

Next, I form portfolios of mutual funds based on lagged one-year *cumulative* eigenvector centrality measure and estimate the 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 2.9. 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 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.

Table 2.9

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

t statistics in parentheses
* p<0.10, **p<.05, ***p<0.01

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, I 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, I 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 2.1, Panel C). Tables 2.10 and 2.11 show the long-short strategy still holds for both in-sample and out-of-sample testing when only equity funds are considered.

Table 2.10

In-Sample Performance Single-Variable Portfolios for Equity Funds

In-Sample (2009-2017 monthly return series)

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

t statistics in parentheses
* p<0.10, **p<.05, ***p<0.01

Table 2.11

Out-of-Sample Performance Single-Variable Portfolios for Equity 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

t statistics in parentheses
* p<0.10, **p<.05, ***p<0.01

Sharpe Ratio Test

The results of the long-short trading strategy, where I formed portfolios of mutual funds based on cumulative eigenvector (network quality), yield positive and statistically significant mean and abnormal returns for both in-sample and out-of-sample testing. I 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. I employ a significance test proposed by Jobson & Korkie (1981). The test-statistic (z-score) for significance is provided in Tables 2.8-2.11. For both in-sample and out-of-sample portfolio testing, the Sharpe ratio difference is significantly positive, which holds when I 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.

Robustness

Centrality Determinants and Excess Centrality

Fund manager centrality is related to various individual-specific factors. For example, companies may ask fund managers who are more experienced and/or well-known to sit on their boards, which may be especially true for young fast-growing companies that want to benefit from the fund managers' experience and/or high visibility status when it concerns the ability to raise capital. Additionally, strong-performing fund managers may also be asked to sit on more boards.[8] Over time, the demand to appoint these types of individuals may naturally cause an increase in the fund managers' cumulative network centrality measure. As such, I identify these types of individuals by considering whether fund managers hold an advanced degree, whether they come from an elite educational background, the number of professional certifications they hold, the number of professional awards they have won, and the total number of funds they have managed over their career, which are used as proxies for status, performance, and experience to create "excess centrality." More specifically, "excess centrality" is the winsorized linear combination residual from a regression of cumulative degree and eigenvector (using 1st principal component) on the following determinants: elite university degree dummy, Ph.D. dummy, master's degree dummy, number of professional certifications, number of funds managed over entire career (a proxy for

[8] 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.

experience),[9] and number of awards won (a proxy for performance). Using the residual provides a version of network centrality without the confounding effects of experience, performance, and status. In other words, this measure is equal to the difference between the actual and predicted (based on the above determinants) centrality value, thereby reducing endogeneity concerns that my results are due to omitted fund manager personal characteristics, proxied by network centrality. In Table 2.12, I rerun Models 1 and 3 from Table 2.7 with cumulative "excess centrality." The results share similar signs and significances, which further support the idea that the cumulative centrality measures reflect the impact of the mutual fund manager network as opposed to the effects of omitted variables.

[9] A variable counting the total number of funds managed over the fund managers' career. Fund managers who have had more opportunities managing funds have accumulated more experience.

Table 2.12

Manager-Level Cross-Sectional Return Regressions with Excess Centrality

	annual return	
	(1)	(2)
Excess Centrality	0.43**	0.80***
	(2.24)	(4.30)
Size (Log TNA)		0.05
		(0.40)
Turnover Ratio		0.80***
		(6.20)
Expense Ratio		-1.01
		(-1.60)
Management Fee		4.70***
		(4.25)
Fund Age		-0.08
		(-0.27)
Fund Flow		-0.18***
		(-3.34)
Return Volatility		0.10
		(0.53)
Number_Fund_Managers		-0.81**
		(-2.46)
Constant	7.43***	6.39***
	(32.51)	(3.11)
Adj R-squared	0.44	0.51
Year Fixed Effects	Yes	Yes
Number of obs	2,977	2,403

t statistics in parentheses
* p<0.10, **p<.05, ***p<0.01

The Impact of Fund Manager Age

In Table 2.13, I rerun Model 5 of Table 2.5 but this time include and interact fund manager age with cumulative eigenvector. Cumulative eigenvector as a main effect retains the same sign and significance at the 1% level, while age as the other main effect is negative and not statistically significant.

Table 2.13

Manager-Level Cross-Sectional Return Regressions with Age Interaction

	annual return
Age	-0.00 (-0.07)
High Eigenvector	14.05*** (3.12)
Age * High Eigenvector	-0.21** (-2.32)
Size (Log TNA)	0.19 (1.40)
Turnover Ratio	0.61*** (2.69)
Expense Ratio	-0.25 (-0.32)
Management Fee	3.86*** (2.77)
Fund Age	-0.35 (-1.05)
Fund Flow	-0.19*** (-3.01)
Return Volatility	-0.38** (-2.10)
Number_Fund_Managers	-0.74* (-1.67)
Constant	9.54*** (3.03)
Adj R-squared	0.53
Year Fixed Effects	Yes
Number of obs	1,550

t statistics in parentheses
* p<0.10, **p<.05, ***p<0.01

The interactive coefficient is negative and significant at the 5% level. This suggests fund manager age differences in overall fund performance depend on the level of fund manager eigenvector centrality, which is a measure of the importance of the fund managers' immediate professional network. More importantly, I find evidence that my results are not determined by fund manager age.

Reverse Causality

The relation between network centrality and fund return may be endogenous. I argue that reverse causality is inapplicable in this study by design. The formation of board connections is based on past work-related relationships, which predates the measurement of fund return and the fund performance sensitivities for years. As such, it is unlikely fund performance is determining fund manager past relationships.

Overconfident Fund Managers

Highly confident fund managers may 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. Naturally, there is a concern network centrality may 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.

Conclusion

In this study, I 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. I 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. I 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 use 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, I find the fund managers' information set from current board relationships is not as meaningful as the information set coming from all current and past relationships a fund manager has fostered over time from sitting on boards. Finally, a long-short 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.

CHAPTER 3

DISCUSSION AND CONCLUSION

In this chapter, I first summarize the findings of the two essays. Next, I discuss the limitations of the essays. Finally, I conclude with directions for future research.

Essay 1: Mutual Fund Managers and Board Connections

In Essay 1, I focus on mutual funds that have hired fund managers with corporate board connections ("connected" funds). The goal is to investigate the effects of "connected" funds on various fund characteristics by comparing them to their "non-connected" counterparts. This study complements Cohen et al. (2008) by using third-party verified business connections, instead of implied connections from educational overlap, between U.S. mutual fund managers and U.S. corporate board members. The findings show "connected" funds are associated with stronger performance and higher fees.

Essay 2: The Quality of Your Network Matters

In Essay 2, after establishing board connections matter in Essay 1, I go beyond examining only bilateral ties by investigating the overall position of a network participant (fund manager) within a greater network by incorporating network centrality to capture the concept of social hierarchy. I consider the following questions. Since board connections matter, do all "connected" fund managers benefit equally? If not, what is the differentiating factor? Finally, do current professional relationships impart meaningful information to fund managers? I find fund managers are associated with higher returns when they are well-connected, and when their immediate connections are well-connected. A long-short portfolio strategy based on cumulative eigenvector, a measure that captures how connected the fund managers' immediate connections are (a proxy for network quality), yields positive and statistically significant mean and risk-adjusted returns for both in-sample and out-of-sample testing. The results suggest fund managers use their director networks as conduits for obtaining relevant information, where the opportunity for obtaining relevant information appears to increase as the quality of the fund managers' professional network increases. Additionally, I find evidence suggesting fund managers hold back on utilizing the information coming from the relationships of boards they are currently sitting on. A reasonable explanation is that current relationships are more easily traced, and it makes intuitive sense that institutional investors are reluctant to act upon material information that may raise suspicion of impropriety.

Dissertation Limitations

Certain limitations do exist for this study. It may be the case that unobservable fund characteristics and managerial abilities are driving bilateral connections, centrality, and fund performance. Although I do attempt to address the omitted variable issue of bilateral connections in Essay 1 by using propensity score matching on observables as well as using "excess centrality" to address the endogenous issue in my centrality analysis for Essay 2, unobservables driving both connections and fund performance is still a concern (e.g., omitted variables related to human capital instead of social capital). As such, using instrumental variables may help to strengthen my argument.

Directions for Future Research

My research posits “connected” fund managers have an information advantage over “non-connected” fund managers, which leads to better decision-making and fund performance. Future research includes looking for the information being transferred through the professional network by examining fund holdings to compare if “connected” mutual fund managers are holding assets within their network. If they are, I plan to examine the performance of those positions against positions that are not a part of their network.

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APPENDIX A

VARIABLE DESCRIPTION

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.
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 (cal dt - first_offer_dt).
Fund Flow	The monthly fund flows of each fund annualized. 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	Standard deviation of monthly returns annualized.
Team_Managed	A dummy variable equal to 1 if an observation related to a fund has more than one fund manager listed.
Number_Fund_Managers	An indicator variable counting the number of fund managers.

APPENDIX B

DESCRIPTIVE SUMMARY STATISTICS

Summary Statistics: Asset Allocation

Additional summary statistics of the mutual fund characteristics for the full sample (Essay 2).

* per = percent

	Full Sample					
	N	Mean	Median	p10	p90	Std
per Common Stock	2,950	54.69	67.36	0.00	96.90	39.83
per Preferred Stock	2,950	0.62	0.00	0.00	0.60	3.86
per Convertible Bonds	2,950	0.08	0.00	0.00	0.00	0.55
per Corporate Bonds	2,950	8.44	0.00	0.00	29.77	20.55
per Municipal Bonds	2,950	2.20	0.00	0.00	0.06	14.23
per Government Bonds	2,950	5.42	0.00	0.00	15.05	17.13
per Other Securities	2,950	7.81	1.10	0.00	30.58	16.97
per Cash	2,950	5.01	2.21	-0.04	13.99	9.95
per All Bonds	2,950	8.86	0.00	0.00	35.30	26.56
per Asset-Backed Securities	2,950	1.53	0.00	0.00	1.55	6.71
per Mortgage-Backed Securities	2,950	2.35	0.00	0.00	2.71	10.10
per Other Equities	2,950	1.99	0.00	0.00	6.50	4.38
per Other Fixed-Income Securitie	2,950	1.00	0.00	0.00	2.11	4.16

	Live Funds					
	N	Mean	Median	p10	p90	Std
per Common Stock	2,177	56.66	68.28	0.00	96.76	38.50
per Preferred Stock	2,177	0.59	0.00	0.00	0.65	3.61
per Convertible Bonds	2,177	0.08	0.00	0.00	0.00	0.51
per Corporate Bonds	2,177	8.74	0.00	0.00	29.76	21.07
per Municipal Bonds	2,177	2.73	0.00	0.00	0.08	15.95
per Government Bonds	2,177	6.29	0.00	0.00	16.90	18.66
per Other Securities	2,177	7.87	1.27	0.00	32.48	16.43
per Cash	2,177	4.01	1.85	-0.12	11.49	8.32
per All Bonds	2,177	6.45	0.00	0.00	0.00	23.23
per Asset-Backed Securities	2,177	1.62	0.00	0.00	1.72	6.85
per Mortgage-Backed Securities	2,177	1.85	0.00	0.00	2.09	8.09
per Other Equities	2,177	2.13	0.00	0.00	6.65	4.67
per Other Fixed-Income Securitie	2,177	1.00	0.00	0.00	2.33	4.16

	Defunct Funds					
	N	Mean	Median	p10	p90	Std
per Common Stock	773	49.13	62.22	0.00	97.42	42.91
per Preferred Stock	773	0.72	0.00	0.00	0.42	4.49
per Convertible Bonds	773	0.07	0.00	0.00	0.00	0.65
per Corporate Bonds	773	7.60	0.00	0.00	36.95	18.99
per Municipal Bonds	773	0.72	0.00	0.00	0.00	7.29
per Government Bonds	773	3.00	0.00	0.00	5.38	11.42
per Other Securities	773	7.65	0.47	0.00	27.89	18.42
per Cash	773	7.85	3.32	0.00	22.30	13.14
per All Bonds	773	15.67	0.00	0.00	88.30	33.34
per Asset-Backed Securities	773	1.25	0.00	0.00	1.28	6.26
per Mortgage-Backed Securities	773	3.77	0.00	0.00	4.77	14.24
per Other Equities	773	1.59	0.00	0.00	5.86	3.42
per Other Fixed-Income Securitie	773	0.99	0.00	0.00	1.82	4.17

Summary Statistics: Team-Managed and Number_Fund_Managers

Pertaining to the connected + non-connected full sample of funds. *Team_Managed* is a dummy variable equal to 1 if an observation related to a fund has more than one fund manager listed, 0 otherwise. *Number_Fund_Managers* is an indicator variable counting the number of fund managers. The number of funds managers cannot be identified for observations where it is stated that the fund is "team managed," hence the smaller total for *Number_Fund_Managers*.

Team_Managed	Freq.	Percent
0	68,316	24.75%
1	207,732	75.25%
Total	276,048	100.00%

Number_Fund_Managers	Freq.	Percent
1	68,316	37.41%
2	72,838	39.88%
3	41,468	22.71%
4	10	0.01%
Total	182,632	100.00%

Summary Statistics: Team-Managed and Number_Fund_Managers (Connected)

Pertaining to the connected fund sample only. *Team_Managed* is a dummy variable equal to 1 if an observation related to a fund has more than one fund manager listed, 0 otherwise. *Number_Fund_Managers* is an indicator variable counting the number of fund managers.

Team_Managed	Freq.	Percent
0	827	30.52%
1	1,883	69.48%
Total	2,710	100.00%

Number_Fund_Managers	Freq.	Percent
1	827	30.52%
2	1,136	41.92%
3	747	27.56%
Total	2,710	100.00%

APPENDIX C

CORRELATION MATRIX

Correlation Matrix

	Expense Ratio	Management Fee	Turnover Ratio	Net Asset Value	Total Net Asset	Fund Age	Fund Flow	Return Volatility	Annual Return
Expense Ratio	1								
Management Fee	0.48	1							
Turnover Ratio	0.01	-0.06	1						
Net Asset Value	-0.10	0.13	-0.14	1					
Total Net Asset	-0.39	0.05	-0.05	0.25	1				
Fund Age	-0.03	0.10	-0.03	0.11	0.50	1			
Fund Flow	-0.02	0.01	-0.01	-0.01	0.02	-0.16	1		
Return Volatility	0.32	0.32	-0.08	0.05	-0.07	0.10	-0.05	1	
Annual Return	0.02	0.12	-0.09	0.24	0.04	0.04	-0.01	-0.01	1