

Socially Connected Holding and Stock Return

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ABSTRACT

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I. Introduction

Social networks plays an important role in the financial market. A seminal paper by Cohen, Frazzini, and Malloy (2008) uses social networks between mutual funds and their holding company to identity information transfer in security markets. They find that portfolio managers place larger bets on connected firms and this portfolio allocation behavior have significant impact on fund performance.

Cohen et al. (2008) find a systematic pattern across the entire uinverse of U.S. mutal fund portfolio managers: fund managers place larger concentrated bets on socially connected firms. Moreover, they create calender time portfolios that mimic the aggreate portfolio allocations of the mutual fund sector in connected and nonconnected stocks and show the connoned aggregate portfolio outperform the nonconnected one.

Cohen et al. (2008) mainly ask how information disseminates through agents in financial markets and into security prices. The information flow could move though social networks in multiple ways. The first channel is a direct transfer from senior firm officers to portfolio managers. The second channel is less information gathering effort imposed on portfolio managers. The third channel, which is similar to the second one, is social networks makes it cheaper to access information on managers of the holded firms and to evaluate managerial quality.

What is missing from Cohen et al. (2008) is, as written in their paper, “not able to rule out any of these mechanisms” through which infomation move through social networks. The goal of my paper is to shed light on those missing mechanisms and to provide firm-level return evidence on the impact of social networks.

There are two major differences of my paper from Cohen et al. (2008). First, I provide firm-level evidence of how social networks affect firm’s future stock return. To the best of my knowledge, this is the first paper that investigate the relationship between social networks and individual stock return. Second, I invesigate the the change in socially connected holdings and explore its predictive power on future stock return. While Cohen et al. (2008) assumes constant holdings between report dates and focus on contemporaneous aggregate connected versus nonconnected portfolio performance.

This paper replicates several key results of Cohen et al. (2008) and confirms that mutual fund managers do place larger portolio weights on connected firms copmared with nonconnected ones.

However, I do not find systematic outperformance of the aggregate connected portfolio versus aggregate connected portfolio in the most recent decade sample.

Apart from not being able to find similar pattern of aggregate portfolio performance in the recent decade, most surprisingly, I find contradicting firm-level response compared with Cohen et al. (2008) aggregate portfolio performance. My preliminary tests indicate that an increase in connected holding measure for a specific company negatively predicts future returns. The puzzling observation is worth for further investigation and future research.

One possible explanation of the negative predicting effect of firm level social connection is company directors' slackness. Instead of a direct transfer from company officers to fund portfolio managers, a reverse rent extraction could exist between the two agents (company officers and fund managers). When a company becomes more socially connected, the managers of the company might simply rely on those social connections and reduce privately costly effort that improves firm performance. Social connection serves as a safety net against bad performance and firm manager's incentive to exert costly effort is reduced. Social connection is compared to an insurance mechanism that ensures slightly higher probability (compared with no social connection) of accessing the capital market.

The rest of the paper is organized as follows. Section II gives a brief introduction of related literature. Section III describes the data and the sample. Section IV presents the main results and findings. Section V discusses robustness and future work directions. Section VI concludes.

II. Literature Review

This paper contributes to several strands of the literature. Firstly, it is related to the analysis of social networks on economic outcomes. The importance of social networks, often also referred to as social capital, have been drawing much attention among economists. There is a growing body of research documenting significant correlations between "social capital" variables and important outcome. Bloom, Sadun, and Van Reenen (2012) document that high social capital increases decentralized decision-making within firms. Guiso, Sapienza, and Zingales (2004) show that trust, a measure of social capital, affects stock market participation and international trade. Jackson (2005) provide a survey on the economics of social networks.

There are contradicting views on the impact of social capital in the literature. Some scholars such as Putnam, Leonardi, and Nanetti (1994) argue that social connection within a group induces trusts and cooperative attitude, which helps better communication among individuals and thus reducing information transfer frictions. In contrast, other researchers like Olson (1982) suggest that socially connected individuals tend to foster self-serving interest groups. Such socially connected groups creates informational barriers against outsiders. Cartels, for example, distort market efficiency and usually reduce social economic welfare. One of the key aspects underlying the two views come from information flow. A natural laboratory to ask how information disseminates is the stock market. Information moves security prices. Welfare-increasing social connections reduces information transmission frictions and improves market efficiency. While self-serving interest among socially connected market participants raises the concern of impeding information distribution outside the socially connected group. My paper provide new empirical evidence on the two conflicting view.

The finance literature also document the importance of social networks in mutual fund behavior. Hong, Kubik, and Stein (2005) show mutual fund managers in the same city hold similar portfolio due to word-of-mouth effect. Kuhn (2005) find mutual fund manager connection with advisory firms is correlated with preferential contracting decision.

Secondly, this paper also links to the mutual fund literature. Social connection can be viewed as another channel to explore fund performance and fund manager abilities. Chevalier and Ellison (1999) uses mutual fund managers' biographical data such as Scholastic Aptitude Test (SAT) score to test fund performance. Similar to Cohen et al. (2008), this paper explore social connections between mutual fund managers and holding company directors as measurable characteristic for mutual fund.

Thirdly, the empirical measure is related to a broad network sociology literature. For example, Useem (1984) uses corporate board linkages as a measure of personal network. This paper focuses on direct connections between company directors and mutual fund managers through same academic institutions.

The empirical work on social capital has focused on two types of evidence. The first type of evidence is based on survey questions. Researchers asks respondents questions such as their perception on trusts. However, Glaeser, Laibson, Scheinkman, and Soutter (2000) shows with

laboratory experiments that this survey measure is not reliable. A second empirical approach to social capital investigates organization membership. This paper shared academic institution as proxy for social connection.

Lastly, the paper could potentially contribute to a large literature on firm manager with moral hazard.

III. Data

I collected data from four different sources. A standard database used in mutual fund research literature is the CRSP Survivorship Bias Free Mutual Fund Database. The CRSP Mutual Fund Database includes mainly fund characteristics, such as fund returns, total net assets, expense ratios, investment objectives, fund manager names, and etc. One constraint imposed on researchers using CRSP is that it does not include detailed information about fund holdings. My data on mutual fund holdings come from the Thomson Reuters CDA/Spectrum S12 database, which includes all registered mutual funds filing with the Securities and Exchanges Commission (SEC). The third database I use for this study, Morningstar Direct, provides mutual fund managers' biographical information including educational background. On the holded company side, I obtain data from BoardEx of Management Diagnostic Limited, a research company specialized in social networks data on company officials in U.S. and European public and private companies and other types of organizations. BoardEx provide employment history and educational information of senior company officers (such as Chief Executive Officer, Chief Financial Officer, Chief Technological Officer, Chief Operating Officer and Chairman) and board of directors.

Following Wermers (2000), I merge the CRSP Survivorship Bias Free Mutual Fund database with the Thomson Reuters CDA/Spectrum S12 database using the MFLINKS table. The focus of my analysis is on actively managed U.S. equity funds, with the investment objective of aggressive growth, growth, or growth and income in the Thomson Reuters CDA/Spectrum dataset¹. I apply several filters to form my sample (following Kacperczyk, Sialm, and Zheng (2006)). I remove passive index funds by manually searching through fund name, index fund indicator, and Lipper objective name. I only include common stock² holdings of mutual funds. Education history of mutual fund managers from Morningstar is linked to the combined CRSP/Thomson Reuters data

by matching manager names. My final mutual fund sample includes survivorship-bias-free data on holdings and biographical information for 1,408 funds and 3,220 mutual fund managers and spans the period from 2006 to 2016 ³.

For companies in the mutual fund holding, I map the identities and educational background information of board members and senior directors from BoardEx by firm CUSIP identifier⁴. My final matched company data contains educational background on 52,583 directors for 6,257 stocks between January 2006 and December 2016⁵.

A. *Connection and Connected Holdings*

The social networks examined in Cohen et al. (2008) paper are defined over educational institutions. They link each member of the social network by these institutions. They match institutions and degrees on Morningstar and BoardEx and group degrees into six categories: (1) business school (Master of Business Administration, MBA), (2) medical school (MD), (3) general graduate (Master of Arts, MA or Master of Science, MS), (4) Doctor of Philosophy (PhD), (5) law school (JD), and (6) general undergraduate.

I follow their approach, and define social networks connection in a similar way. However due to data limitation I collapse and pool all six categories and define a *broad* connection dummy variable, which equals 1 if the mutual fund manager had a senior official and/or a board member of the firm was affiliated with the same academic institution.

With my connection dummy variable, I construct a measure that captures the level of connectedness for company i at time t , as follows:

$$ConHold_{i,t} = \frac{\sum_{j=1}^{N_t} \mathbb{1}_{Connected} \times S_{i,j,t}}{TotShare_{i,t}} \quad (1)$$

where $\mathbb{1}_{Connected}$ is a dummy variable that indicates whether company i is connected to mutual fund j at time t . N_t is the total number of mutual fund managers at time t . $S_{i,j,t}$ is the number of company i 's shares held by mutual fund j at time t . $TotShare_{i,t}$ is the total number of shares outstanding for company i at time t .

B. Summary Statistics

Table I reports summary statistics for the matched company-mutual funds sample from January 2006 to December 2016.

This table shows summary statistics as of January of each year of the sample of mutual funds and their common stock holdings between 2006 and 2016. I include in the sample of fund/portfolio managers actively-managed, domestic equity mutual funds from the merged Thomson Reuters - Morningstar data with the investment objective of aggressive growth, growth, or growth-and-income and non missing information on the portfolio manager's identity and educational background. The sample of stocks includes the funds' holdings in common stocks, with CRSP share codes 10 or 11, from the merged CRSP - BoardEx data with non missing information on the educational background of members of the board of directors and senior officers of the firm (CEO, CFO, or Chairman). Board members and senior officers are combined and defined as directors.

Table II list the academic institutions that are most connected to both publicly traded firms and mutual funds. Following Cohen et al. (2008), a connection to a university is defined as follows: (1) for a given company, any of the senior officers (CEO, CFO, or chairman) having attended the institution and received a degree; and (2) for a given fund, any of the portfolio managers having attended the institution for a degree. As a result, a given company (mutual fund) can be connected to multiple academic institutions.

We see from Table II that the university most connected to both publicly traded firms and U.S. equity mutual funds is Harvard. Harvard is connected to approximately 10 percent of U.S. publicly traded firms. These connections are not merely to mid-level managers, but to senior officers in the firm. Similarly, Harvard is also most connected to active equity mutual funds in the United States. My results are very similar to Cohen et al. (2008)'s. The top five most connected five universities are the same, either for publicly traded firms or for U.S. active equity mutual fund, in both of our samples. Interestingly, the relative ranking has shifted. On the firms' side, the most salient difference is that Stanford University dropped from second place to the fifth place. All the remaining schools keep the same relative ranking as they were a decade ago. While on the mutual fund side, Columbia University has the biggest jump, from a ranking of four to the runner-up. And the rest of the schools' relative rankings also remain unchanged. Recall that the sample period of

Table I : Summary statistics: mutual funds and holdings

Panel A: Time series					
VARIABLES	(1) mean	(2) median	(3) min	(4) max	(5) sd
Number of funds per year	343.6	341	193	465	90.6
Number of portfolio managers per year	275	266	163	373	69.7
Number of firms per year	5,385	5,439	4,650	6,156	459.1
Number of directors per year	12,916	13,000	7,939	16,314	2,687
Number of academic institutions per year	179.0	191	124	210	28.4

Panel B: Pooled firm-year and fund-year					
VARIABLES	(1) mean	(2) median	(3) min	(4) max	(5) sd
Number of academic institutions per firm	32.8	23	1	140	29.2
Number of directors per academic institution	2,208	1,686	1	6,155	1,969
Number of academic institution per fund	2.4	2	1	6	1.1
Number of directors per fund	80.1	36	1	633	117.6

Table II : Summary statistics: academic institutions

Firm's directors

		Average number of firms
		<hr/>
1	Harvard University	894
2	University of Pennsylvania	698
3	Columbia University	582
4	University of Chicago	540
5	Stanford University	496

Portfolio managers

		Average number of managers
		<hr/>
1	Harvard University	129
2	Columbia University	93
3	University of Pennsylvania	92
4	University of Chicago	89
5	New York University	88

Cohen et al. (2008) is from January 1990 to December 2006, and my sample is constructed from January 2006 to December 2016. The ranking shift might also indicate changes in career choice among various school graduates and institutional culture across different universities. But this is not the main focus of this paper.

IV. Results

A. Holdings of Connected Securities

B. Returns of Aggregate Connected Portfolio

C. Individual Stock Return Prediction

V. Robustness and Future Work

To start with, my definition of connectedness is related to the broadest categorization proposed by Cohen et al. (2008). However, Cohen et al. (2008) has more refined measures to define “connected” holdings. In their paper, they define four types of connections between the portfolio manager and the firm, based on whether the portfolio manager and a senior official of the firm (CEO, CFO, or chairman) attended the same school (CONNECTED1) and received the same degree (CONNECTED2), attend the same school at the same time (CONNECTED3), and attended the same school at the same time and received the same degree (CONNECTED4). These measures of connectedness are defined in an increasing degree of strength of the link, with CONNECTED1 being the weakest type and CONNECTED4 as the strongest type. In future work, I would like to use those four definitions of connectedness to define various *CONNECT* dummy variables, and apply equation (1) to construct my measure of individual stock’s social connection.

complication: TR holding data: 1. matching (with mflink2) using fdate, fundno 2. prc correspond to fdate (quarter-end) don't use this! since fdate is legacy date no meaning!! 3. shares correspond to rdate (actual (effective) date of the holdings)

Appendix A. An Appendix

Here's an appendix with an equation. Note that equation numbering is quite different in appendices and that the JF wants the word “Appendix” to appear before the letter in the appendix title. This is all handled in `jf.sty`.

$$E = mc^2. \tag{A1}$$

Appendix B. Another Appendix

Here's another appendix with an equation.

$$E = mc^2. \tag{B1}$$

Note that this is quite similar to Equation (A1) in Appendix A.

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Notes

¹These funds have Investment Objective Code (IOC) of 2,3,or 4.

²Stocks with share code 10 or 11 in CRSP.

³A sanity check: The base sample of Cohen et al. (2008) includes survivorship-bias-free data on holdings and biographical information for 1,648 US actively managed equity funds and 2,501 portfolio managers between January 1990 and December 2006. My sample size is comparable to theirs in magnitude

⁴BoardEx use ISIN, which is derived from CUSIP

⁵A sanity check: In Cohen et al. (2008), the matched sample of combining company officials' biographical information to stock return data from CRSP includes educational background on 42,269 board members and 14,122 senior officials (56,391 combined senior directors) for 7,660 CRSP stocks between January 1990 and December 2006. My sample size is comparable to theirs in magnitude



Figure 1. Structure of model: capital can be invested in a bank sector and an equity sector. An intermediary has the expertise to reallocate capital between the sectors and to monitor bank capital against bank crashes.