Social Networks, Corporate Governance and Contracting in the Mutual Fund Industry*

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JOB MARKET PAPER

January 4, 2006

Abstract

Do business connections affect hiring, compensation, and performance? This paper presents evidence from the mutual funds industry using a novel panel data set of business connections between fund directors and the advisory firms that manage the funds. I find that fund boards award portfolio management contracts preferentially to advisory firms which have had more business relationships with the funds' directors. A one-standard deviation increase in connections between directors and a candidate advisor increases the odds that the candidate is chosen by 16%. Similarly, when advisory firms create new funds they offer board seats preferentially to directors known from past business relationships. Increasing connections by one standard deviation corresponds to a 28% increase in the odds of a candidate director being nominated. Moreover, advisors receive higher pay when they are more connected to the fund directors. A one standard deviation increase in connections translates into more than $1 billion increase in transfers from mutual fund investors to advisory firms each year. The preferential hiring and pay of connected advisors is not compensated by higher performance. A one standard deviation increase in connections corresponds to a decrease in fund returns (before and after advisory fees) and fund alphas of 1% per year. These findings identify adverse effects of social networks on corporate governance, and support recent initiatives for more disclosure regarding the negotiation of advisory contracts by fund boards.

Keywords: Social networks, influence, mutual funds, corporate governance, contracts

*I would like to thank Ulrike Malmendier, Jeff Zwiebel, Paul Pfleiderer, Steve Grenadier, Ilya Strebulaev, Andrzej Skrzypacz, Denis Gromb, Diane Del Guercio, Jeremy Graveline, Steve Drucker, Stefan Ruenzi, David Jackson and seminar participants at New York University and University of Oregon, as well as participants at the 2005 Financial Research Association and the Northern Finance Association meetings for helpful comments and discussion. All remaining errors are mine.

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I. Introduction

Do business connections of top corporate decision-makers influence the governance, management and performance of firms? Do connections matter when boards of directors of firms select managers, negotiate their pay and choose the intensity of monitoring? If so, is the effect of directors' business networks[1] beneficial or detrimental to shareholders?

To address these questions, I construct a novel data set of business connections of agents in the mutual fund industry. These agents are the fund directors and the advisory firms that manage the funds' money. I develop a new method for analyzing the corporate governance of mutual funds that takes into account the repeated nature of interactions between fund directors and advisory firms. I track the business relationships between directors and advisory firms through time and define measures of connections and influence between these parties using notions from social networks theory.

I find evidence that connections matter for contractual arrangements and for fund performance: directors tend to hire advisory firms that they have worked with in the past, and, when creating new funds, advisory firms tend to offer board seats to directors they have had business relationships with in the past. Moreover, transfers from funds to advisors are higher. At the same time, fund performance — before and after advisory fees — is lower if advisors are more connected to the board of directors.

The mutual fund industry is an ideal environment for studying the role of connections among agents in principal-agent settings, for several reasons. First, the roles of the agents in this industry are very clear: directors negotiate contracts with and monitor the advisors, and advisors manage the money. Second, it is easy to measure the performance of these agents, as contractual arrangements and fund returns are publicly available. Third, the size of the industry is significant. More than $8 trillion are managed by investment advisory firms on behalf of 92 million individual investors, representing 48% of all U.S. households.[2] Hence, connections between agents (fund directors and advisors) may lead to economically significant agency costs born by the principal (the fund investors).

[1] Other types of connections, aside from business interactions, may affect corporate decisions. For instance, political connections of CEO's can impact corporate outcomes such as job creation and destruction, as shown in Bertrand, Kramarz, Schoar, and Thesmar (2004).

[2] 2005 Investment Company Institute Fact Book, online at http://www.ici.org/stats/latest/2005_factbook.pdf

The structure of the asset management industry potentially leads to conflicts of interests between fund directors and investors, as directors are nominated by the same party they have to monitor: the fund advisor. A mutual fund, as regulated by the Investment Company Act of 1940, is simply a pool of money contributed by investors. It has no employees beside the board of directors and several officers. The assets of the fund are managed by one or more investment advisory firms, which are required to be separate legal entities from the fund. In general, a mutual fund is started by an advisory firm, which becomes the primary advisor. It is common for mutual funds to be managed by the primary advisor together with one or more secondary advisors (subadvisors).[3]

When a new fund is created, the primary advisor nominates the board of directors. The fiduciary duty of directors is to protect the interest of investors. Specifically, fund directors contract with and monitor advisors. Section 15 of the 1940 Act stipulates that, after the initial two-year term, an advisory contract can be renewed annually if approved by either the board of directors or by the shareholders of the fund. As the shareholder vote is a costly alternative, typically, the contract is renewed by the fund directors.[4] Hence, directors have the opportunity each year to look for and hire other firms to manage the fund's money, or renegotiate the advisors' pay. No empirical work so far has shown what determines a fund's decision to contract with a particular advisor. However, as shown in Kuhnen (2004), advisory fees do not change much over time and advisors are rarely fired: on average, only about 10% of all U.S. mutual funds renegotiate the management fee or change a subadvisor in any given year between 1993-2002. There are only a handful of cases where the primary advisor was fired by the board.

Given that directors are offered jobs on fund boards by advisory firms when new funds are started, it is possible that they will "return the favor" and offer advisory contracts to these firms based on connections rather than on merit. Favoritism can be manifested when directors negotiate the management fees with the fund's primary advisor (the entity that offered them the board seats) and also when they select a new subadvisor, since candidate subadvisors may have in the past nominated these directors for other funds' boards, or may do so in the future. This

[3] One third of all U.S. mutual funds were managed by more than one advisor in 2002 (Kuhnen (2004)).

[4] *Fund Director's Guidebook*, 2nd ed., published by the American Bar Association, 2003.

potential conflict of interests between fund directors and fund investors is the topic of an on-going debate between the Securities and Exchange Commission (SEC) and the representatives of the asset management industry. Due to concerns that directors may not negotiate advisory contracts in the interests of fund investors, the SEC adopted a new rule in June 2004 whereby directors must state in the funds' shareholder reports why they chose a particular advisor for the fund and how the advisory fee was decided.

In this paper I first analyze whether the business connections of fund directors affect the choice of fund advisors. Given that primary advisors are replaced by the board extremely rarely (and changed mainly because of a takeover by another firm), I study the selection of *subadvisors*, who do the actual portfolio management for the fund. I then examine the role of business connections of directors in the assignment of board seats by primary advisors when new funds are created, and in the negotiation of payments from funds to advisors. Moreover, I study whether the influence of connections on directors' decisions is detrimental to fund performance.

To address these questions I construct a large and unique data set containing information about advisory contracts for all U.S. mutual funds during 1993-2002, as well as information about the identity of the directors of these funds during the same period. This dataset tracks business relationships between individuals who serve as mutual fund directors, and advisory firms, as well as between advisory firms themselves. I identify 303 cases of funds that hired a new advisor between 1996-2002. Of these, 257 hired a new subadvisor, and 46 experienced a change of primary advisor as a result of a takeover of the advisory firm. The first 257 events are used to study which advisors (from a pool of about 1000 firms each year) win contracts from funds[5], and how fund performance evolves after the change, as a function of how connected the newly hired subadvisor is to the board of directors. The remaining 46 events are used to study the influence of connections between fund directors and the new primary advisor on the renegotiation of the management fee. I also study the sample of 216 open-end U.S. mutual funds newly created in 1998 to test whether the connections of candidate directors (3005 individuals) influence the assignment of board seats by the advisors of these new funds. I track these 216 funds from 1998 to 2002 to examine whether the directors-advisor connections play a role in

[5]In some cases, fund directors may use the help of outside consulting firms when selecting a new subadvisor or when setting the management fee. These instances, however, can not be identified in my data set.

negotiation of management fees, loads and expense reimbursements from advisors back to the funds. I do the same analysis regarding the role of director-advisor connections on fund fees and performance using the entire set of U.S. open-end mutual funds during 1996-2002.

I show that when mutual funds choose among candidate advisory firms to help manage the fund together with the primary advisor, the more connected such a firm is to the directors of these funds through past business relationships, the more likely it is to win the portfolio management contract. This effect holds even after controlling for the candidate's reputation, degree of specialization in the investment objective of the fund, cost, and for the connections between the fund's primary advisor and the candidate. A one standard deviation increase in the strength of connections between the fund directors and a candidate advisory firm increases the odds of the candidate winning the subadvisory contract by 4 to 16%, depending on the econometric model used.

Moreover, the more connected are the newly hired subadvisory firms to fund directors, the lower are the net, as well as risk-adjusted returns to shareholders, controlling for fund and advisor characteristics. An increase of one-standard deviation in the strength of connections between directors and the newly hired subadvisor corresponds to a decrease in annual net fund returns of 1.5% and a similar decrease in the funds' alphas. I also analyze the relationship between fund returns and connections between directors and primary advisors in the entire set of open-end U.S. mutual funds during 1996-2002. The relationship is again negative in this large sample consisting of 5936 funds. A one standard deviation increase in the measures of director-advisor connections translates into a 30 to 100 bp decrease in annual net fund returns. The effect is similar for before-fee returns.

The preferential selection of connected advisors by directors is mirrored by the preferential hiring of connected directors by primary advisory firms when these firms create (sponsor) new funds. An increase of one standard deviation in the strength of connections between the primary advisory firm and a candidate director increases the odds of the director winning a board seat by 8 to 28%, depending on the econometric specification.

In the case of newly formed funds, I find that the connections between directors and the primary advisors are positively related to the fund loads, and negatively related to the expenses reimbursements paid back to the fund by advisors, controlling for fund and advisor characteristics. A one standard-deviation increase in connections corresponds to a 12% increase (from 236 bp to 266 bp per year) in the total loads paid by fund investors, and to a 17% decrease (from 82 bp to 68 bp per year) in the expenses reimbursed by the advisor back to the fund. I also find a negative relationship between director-advisor connections and the amount of expenses reimbursed using the entire sample of U.S. open-end mutual funds during 1996-2002.

Lastly, I show that measures of connections between fund directors and primary advisors are positive predictors of the advisory fee paid by funds to their advisors for portfolio management services, controlling for fund and advisor characteristics. For the subsample of mutual funds where the primary advisor was changed as a result of a takeover – an event that requires the renegotiation of advisory fees – a one-standard deviation increase in the measures of connections between fund directors and the new primary advisors translates into a 15% or higher increase in the fee (from an average of 51 bp to 59 bp). In the entire sample of open-end U.S. mutual funds a one standard-deviation increase in the measures of connections between fund directors and the primary advisor corresponds to a 1 bp increase in the advisory fee (from an average of 66 bp to 67 bp). This translates into an increase of $1 billion in the amount transfered from fund investors to advisory firms each year.

The results in this paper indicate that business connections influence the decisions of fund directors. Connections could facilitate the information transfer between parties, or could be channels of influence or persuasion (Wasserman and Faust (1994)). If connections were simply proxies for information transfer, several stories would explain why fund directors select advisors they know from the past. Models of asymmetric information, moral hazard and costly search would predict a positive relationship between the likelihood of an advisor being hired, and the strength of its relationships with the fund board. For instance, directors may be more likely to hire an advisor they know from previous relationships because they have more information about the advisor's skill. Also, it may be easier to monitor the known advisor, since directors already monitor this firm for other funds their are overseeing. Finally, directors may hire a known advisor simply because it it too costly to search for the best alternative among all the possible candidates. These models, however, are difficult to reconcile with the finding that connections are positively related to the pay of advisors, and negatively related to performance.

Thus, connections seem to capture more than information transfers: they could proxy for influence (persuasion) between parties. Directors and advisory firms are part of the same network and have repeated interactions. This may lead to collusion, or side-dealing, manifested thorough favors in the assignment of portfolio management contracts and board seats, and in the negotiation of transfers from funds to advisors. This side-dealing hypothesis is the most plausible explanation for the results in this paper, and is supported by the recent SEC requirement for more disclosure from fund directors as to why advisory firms were awarded the portfolio management contract and how their pay was decided.

The data does not allow, however, for a direct test of the causality between connections and contracting decisions or fund performance. For instance, it is possible that there is no causal relation between hiring connected advisors and lower performance. Instead, poorly performing funds are simply of lower quality, and lower-quality funds are also characterized by higher fees and may have directors who nominate their friends as secondary advisors for other reasons. In other words, it can not be ruled out that other factors drive both corporate governance and the dependent variables studied. Social networks are, at a minimum, one parsimonious explanation for the full set of results presented in this paper. Moreover, even if an unobserved factor drives my findings, the results help to identify funds with poor governance and point to potential channels for efficiency improvements.

The rest of the paper is organized as follows: section II presents the related literature, section III describes the empirical strategy and the measures of connectivity, section IV identifies the data sources, section V presents the results, and section VI concludes.

II. Related literature

The paper contributes to two streams of literature: the first is the literature on the corporate governance of mutual funds, and the second is focused on the role of social influence on the decisions of economic agents.[6] To my knowledge, this is the first empirical paper that studies the *selection* process involved in creating boards of directors, as well as the selection of fund managers.[7] I develop a finer measure of director independence than those previously used in

[6]Wasserman and Faust (1994) summarize the sociology literature on networks and discuss in detail the concepts I use in this paper that refer to connections and influence.

[7]While there exist theoretical models for board creation in the context of *corporate* boards (Hermalin and Weisbach (1998) and Hermalin and Weisbach (2003)), there are no formal models for the se-

the corporate governance literature by analyzing the network of business relationships between directors and advisory firms over a ten-year horizon.

Previous work on mutual funds (Tufano and Sevick (1997), Del Guercio, Dann, and Partch (2003), Almazan, Brown, Carlson, and Chapman (2004)) has shown that corporate governance may play an important role in the way funds are organized. However, most papers[8] that examine the link between board independence and various fund characteristics use the standard SEC rule for classifying directors as independent, based on whether they or members of their family are employees of the advisory firm. This measure does not account for the *repeated* interactions (through time and via multiple funds) between individuals classified as independent directors, and advisory firms, and thus may lead to an understatement of the impact of governance on the welfare of fund investors. The repeated interactions between directors and advisors, and possible resulting side dealings, may compromise the independence of directors and need to be incorporated in governance measures. Thus, in this paper I do not use the SEC rule-based classification. Rather, I use a continuous gradation for the strength of the relationships between directors and advisors, based on their past business interactions.

Tufano and Sevick (1997) examine the relationship between board composition and compensation and the size of fees charged by open-end funds to their shareholders, and find that having lower expense ratios and more independent boards are correlated. Del Guercio, Dann, and Partch (2003) find that having more independent boards leads to more beneficial fund restructuring decisions in a sample of closed-end funds. Khorana, Tufano, and Wedge (2005) find a positive link between board independence and a fund's decision to undergo a merger with another fund after having underperformed. Cremers, Driessen, Maenhout, and Weinbaum (2005) find that funds with high director ownership outperform those with low director ownership, and Almazan, Brown, Carlson, and Chapman (2004) show that funds with a higher proportion of independent directors impose fewer investment constraints on the manager.

The role of social networks, connections and influence in financial markets has only re-

lection of *mutual fund* directors, and no empirical work on the selection of either directors or advisory firms.

[8] An exception is Del Guercio, Dann, and Partch (2003), where the authors compute alternative measures of independence, such as the percentage of independent directors on board since the inception of the fund, the directors' compensation or the existence of staggered boards. None of these measures, however, capture the repeated interactions between directors and advisors over time and through the numerous funds they oversee and manage, respectively.

cently been considered in the finance literature.[9] The influence of social networks on portfolio choices and stock market participation is documented in Hong, Stein, and Kubik (2005) and Hong, Kubik, and Stein (2004). Hochberg, Ljungqvist, and Lu (2005) find a positive role of venture capital networks on investment performance. Larker, Richardson, Seary, and Tuna (2005) and Hallock (1997), among several others, study the role of social networks, such as board interlocks, in monitoring and setting the pay of CEOs. Perez-Gonzales (2005) finds that nepotism is detrimental to firm performance in the context of CEO successions in a sample of publicly traded companies.

The potential link between repeated interactions among agents and collusion (favoritism or side-dealing), has been captured by theoretical models as in Tirole (1986), Prendergast and Topel (1996) and Faure-Grimaud, Laffont, and Martimort (2002). These models study hierarchies comprised of an agent who exerts effort to produce output, a supervisor who gets a signal about the agent's productivity, and a principal who owns or buys the output produced by the agent. The supervisor provides a report to the principal regarding the agent's type; crucially, this report may not be truthful. In this case, the agent and the supervisor have incentives to engage in side-contracts that are Pareto-improving for these two parties and may lead to distorted reports and a lower profit to the principal. Tirole (1986) shows that collusion between an agent and its supervisor is costly for the principal, and suggests that one possible way to mitigate these costs is to keep relationships between agents and supervisors short, as cooperation between two parties at any given time increases with the time horizon of their relationship. Repeated interactions result in mutual blackmail, which makes the breakdown of collusion costly and forces the parties into a coalition to keep on colluding. It is easy to see how one can extend such a model in the setting of mutual funds: the principal are the shareholders, the agent is the advisory firm, and the supervisor is the board of directors. As long as there are gains from collusion between the board and the advisory firm, the fund's shareholders will incur loses as a result of inefficient supervising of the advisor by the board.

While these models imply that favoritism can be caused by economic gains, there also exist a behavioral explanation for favoritism: homophily. This concept from the sociology literature (McPherson, Smith-Lovin, and Cook (2001)) refers to the principle that a contact between

[9] See Jackson (forthcoming) for a survey on the economics of social networks.

similar people occurs at a higher rate than among dissimilar people, that is, "birds of a feather flock together". Patterns of homophily get stronger as more types of relationships exist between two people, and individuals use as a reference group those who are similar to them in various ways, including their position in the network. As a result, people have inherent preferences to associate with like-minded individuals; moreover, they are prone to be influenced most by the individuals that they are connected to.

These homophily-induced biases could lead to favoritism and inefficiencies in economic settings like the one studied here: fund directors more connected to a particular fund advisor will favor and will be more easily influenced by this advisor than by a comparable one that they are less connected to. This influence can translate into less stringent monitoring of the advisor by the board, and less pressure on the advisor to accept a lower pay, without there being any intent side-dealing (collusion) between these parties. Although the empirical results in this paper support the hypothesis that favoritism exists among fund directors and advisors, it cannot distinguish whether it is mainly caused by the homophily or by economics gains from side-contracts, as in models such as Tirole (1986).

III. Empirical Model

I analyze the impact of business connections on the selection of fund subadvisors, on the negotiation of transfers from funds to advisors, and on fund performance. The empirical strategy is described in section A. In section B I define all measures of connections and influence I use in the empirical estimation. All variables are defined in table I.

A. Estimation strategy

A.1. Model of the new subadvisor selection process by fund boards

In the econometric model, I assume that each year advisory firms compete for contracts with funds. I label a fund as "actively looking" to hire an advisor if the fund separated from an existing advisor at that time and has replaced it with another, or added a new advisor to the existing ones.[10] Thus, my results will indicate what characteristics funds value when deciding to contract with a candidate firm, conditional on the fund being actively looking for advisors.

Advisory firms compete with each other based on characteristics such as reputation, performance and specialization in the investment objective of the fund, as well as through the contracts they are willing to accept. Two advisors with equal reputation, past performance and fit with the fund will compete by offering to accept a lower fee — expressed as percentage of the value of assets under management (AUM).[11]

I assume that *advisors* compete for funds and will accept any reasonable offer instead of ranking and selecting funds. A similar methodology is employed in Ljungqvist, Marston, and Wilhelm (2004) in the context of underwriter-issuer matching. Thus, I do not model funds competing for advisory services through a two-sided matching process.[12]

My modeling choice is based on two reasons. First, there is a prevalent belief that the money management business offers large economies of scale. In other words, an advisor may be quite content to work for as many clients as it can get business from. The existence of concave pay schemes for advisory firms — that is, decreasing fees as a function of size of assets under management — supports this hypothesis.

Second, even if the assumption of economies of scale in the asset management industry is incorrect[13] and thus managers of large funds may face an increasing marginal cost of effort (e.g. as a result of increased trading costs), it remains true that the main driver of an advisor's compensation is the fund size, not its performance. An advisor has more to gain from capturing more assets under management (on average, 1% of the AUM) than it has to lose as a result of decreasing economies of scale (equivalent to a lower alpha) experienced after adding these

[10] Note that this definition of actively looking funds does not include the set of funds for which the board is considering hiring a new subadvisor but does not actually achieve this goal, either because no suitable candidate is found or no agreement can be reached between the fund and any candidate. The data do not allow me to identify these cases.

[11] Advisors can also accept an incentive (fulcrum) fee that depends symmetrically on the fund's performance relative to a benchmark. In theoretical models of sorting, agents with better skill are willing to take the compensation scheme that is more strongly linked to performance. In this paper I leave the second mechanism aside, and assume that advisors compete via their characteristics and fit with the fund, and via the fee they are willing to accept.

[12] See, for instance, Fernando, Gatchev, and Spindt (2005). In that paper, which is focused on how firms that issue securities are paired up with underwriters, the underwriters-firms relationships are the result of a process where both sides rank each other and then match accordingly.

[13] For instance, Berk and Green (2004) propose a model of the relationship between fund flows and past performance where it is assumed that there are diseconomies of scale that prevent skilled managers to achieve superior performance as more money flows into their funds.

assets. Thus, in my model advisors will always compete for funds to manage, irrespective of how much money they already have under management.

It is possible, though, that there is endogenous matching: for instance, an advisory firm may only compete for funds in the advisor's area, or for funds with a minimum size. Some of the control variables in my analyses should alleviate this problem.

I model the advisory selection process using the random utility model of McFadden (1974) as it is the most appropriate estimation procedure for settings where only the best alternative is chosen among many.[14] For fund board i, the utility from choosing subadvisor $j \in \{0, ..., J\}$ is $y^*_{ij} = \beta' x_{ij} + \epsilon_{ij}$, where x_{ij} is a vector of observable characteristics of the board and of the candidate subadvisor, while ϵ_{ij} represents unobservable factors that affect utility.

Let j be the choice for board i that maximizes its utility: $y_i = argmax(y^*_{i0}, ..., y^*_{iJ})$. McFadden (1974) shows that if $\{\epsilon_{ij}\}_{j \in 0,1,...J}$ are independently distributed with Weibull distribution $F(\epsilon_{ij}) = exp(-e^{-\epsilon_{ij}})$, then the probability that candidate j is chosen is:

$$Prob(y_i = j|x_i) = \frac{e^{\beta' x_{ij}}}{\sum_{h=0}^{J} e^{\beta' x_{ih}}} \tag{1}$$

I estimate the conditional logit model in equation (1) using a panel dataset containing all possible pairs of advisor j - fund i relationships at the time of hiring τ. The dependent variable is 0 or 1, indicating whether at time τ advisor j and fund i contracted with each other. I shall only consider funds that at time τ are actively looking for an advisor. The potential determinants x_{ij} of the probability that at time τ advisor j is chosen by fund i include advisor j's characteristics ($A_{j\tau}$) and advisor-fund characteristics ($AF_{ji\tau}$). The standard errors[15] of the estimates are adjusted for heteroskedasticity and correlation among error terms within observations belonging to the same fund-year cluster.[16] A limitation of the analysis is that it does not capture the possibility that an advisor's decision to compete for the management contract is endogenous. Ideally, I would instrument for the latent decision variable with a

[14] A simple logit model estimates the probability of an alternative being chosen, without conditioning on the fact that only one alternative can be selected among all, which is the case in the setting I analyze. The McFadden conditional logit solves this problem.

[15] See Froot (1989) and Williams (2000) for the exact form of the robust covariance matrix.

[16] I use fund-year clusters to account for the fact that a few of the funds changed subadvisors in more than one year in my sample, and thus, faced a different set of choices in each year they hired a new firm. Clustering observations by fund yields very similar results.

variable that is independent of the likelihood of winning. The data, however, do not provide such an instrument.

In the empirical model, advisor characteristics ($A_{j\tau}$) include measures of advisor *reputation* (number of portfolios, value of assets under management and past performance across all investment categories), *specialization* (fraction of portfolios and value of assets under management in the specific category of the hiring fund) and its *cost* (i.e. the fee the advisor is willing to accept in exchange for management services). The proxy for the cost characteristic is the average fee paid by the funds that advisor j already has under management.

Advisor - Fund characteristics ($AF_{ji\tau}$) include various measures for the strength of connections between candidate advisor j and fund i's directors from past business relationships, as defined in subsection B.

A.2. Model of the director selection process by primary advisors of new funds

I employ a logit model to find whether previous business connections determine which directors are selected on the boards of new funds by the primary advisors of these funds. The probability of a candidate director d being hired by advisor j in year t is allowed to depend on several characteristics of the director (D_{dt}) and of the director-advisor pair (DA_{djt}). D_{dt} includes measures of the director's prominence in the network, for instance, the number of funds he is overseeing in the year before the selection decision. DA_{djt} includes measures of connections or influence between the advisor and the candidate director - for instance, the number of funds managed by the advisor and overseen by the director, up to the year prior to the selection decision. The standard errors of the estimates are adjusted for heteroskedasticity and correlation among error terms within observations belonging to the same cluster, which is defined by the hiring advisory firm.

I do not use the McFadden conditional logit model for the director selection process, since that model works best for the selection of one alternative among many. When new funds are created, multiple directors win board seats, and thus a logit estimation is more appropriate in this setting.[17]

[17] Another empirical approach would be to use a rank-order logistic model with incomplete rankings for unchosen alternatives and ties among the chosen alternatives.

A.3. Models of fund performance, risk and fund fees

To study the impact of social connections on fund performance, risk and fund fees, I estimate the following models in a pooled OLS setting[18]:

$$FundPerf_t = f(A_{j\tau}, AF_{ji\tau}, F_t), \quad \forall t >= \tau, \tag{2}$$

$$FundRisk_t = f(A_{j\tau}, AF_{ji\tau}, F_t), \quad \forall t >= \tau, \tag{3}$$

$$AMR_t = f(A_{j\tau}, AF_{ji\tau}, F_t), \quad \forall t >= \tau, \tag{4}$$

where τ is the time of hiring, F_t includes fund characteristics, $A_{j\tau}$ and $AF_{ji\tau}$ are advisor characteristics and the connection strength measured at the time of hiring of the new subadvisor, respectively, $FundPerf_t$ is a measure of fund performance, $FundRisk_t$ is a measure of risk factor loadings, and AMR_t is the advisory fee paid by the fund.

When estimating models 2, 3 and 4 I only consider observations from years $t \geq \tau$ when the the advisor hired at τ is still working for the fund. I employ several measures of fund performance: annual net fund returns, and alphas as estimated in a one-factor and also in a four-factor model (Fama and French (1993), Carhart (1997)). For fund risk, the measures I use are the estimated risk factor loadings from the CAPM and Fama-French model: $R_m - R_f$ (market excess return), SMB (excess return on the portfolio long small and short big company stock), HML (excess return on the portfolio long high and short low book-to-market stocks, and UMD (the momentum portfolio).

The same empirical procedure (pooled OLS with robust standard errors adjusted for correlation among observations belonging to the same fund) is used to test the role of board-advisor connections for the setting of transfers between the fund and the advisor for the sample of funds newly created in 1998. I also use the Fama-MacBeth estimation procedure (Fama and MacBeth (1973)) as a robustness check.

[18]Standard errors are adjusted for heteroskedasticity and correlation among error terms within observations belonging to the same fund.

B. Measures of connections and influence

All the measures of connections or influence between a fund's directors and a particular advisory firms are based on the number of times the directors of the fund have sat on boards of any funds managed by the advisor. To start with, I measure connectivity between each individual fund director and the advisor, then I aggregate the individual scores to obtain the board level of connections with the advisory firm. Using notation from the sociology literature on social networks (Wasserman and Faust (1994)), I will use the concept of "degree" to denote the number of links between an individual in a network and the other network participants.

Figure 1 illustrates the director-level connection measures: there I calculate these measures between a director ("Director 1") and an advisory firm ("Advisor 1") knowing which fund boards Director 1 sits on and which funds Advisor 1 manages, in 1996 and 1997.

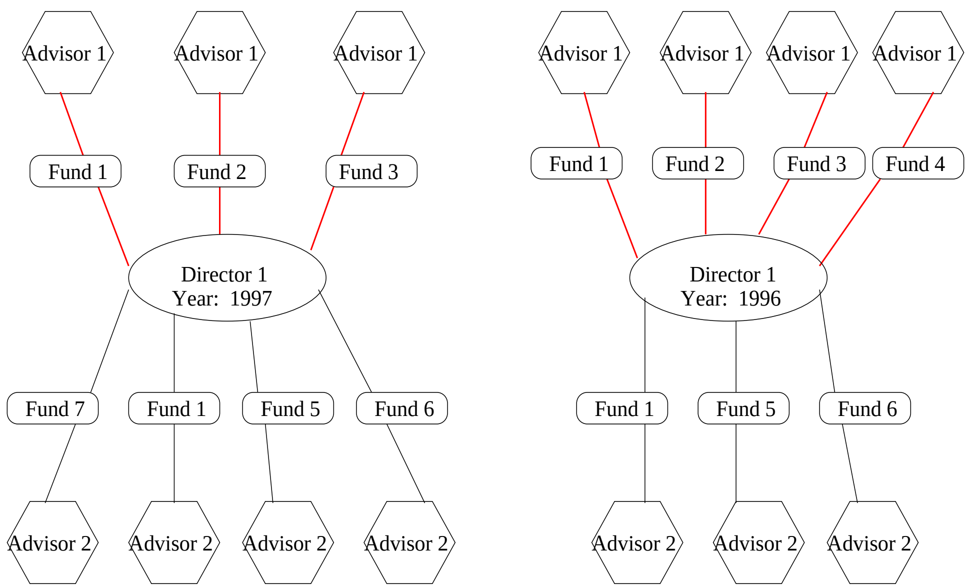

Figure 1
Measures of connections between fund directors and advisory firms.
For the director ("Director 1") in this example, his degree is the number of connections to advisory firms through the funds he oversees in any year: $DirectorDegree_{1996} = 7$ and $DirectorDegree_{1997} = 7$. The number of funds through which the director is linked to advisor 1 ("Advisor 1") is their joint degree: $DirectorAdvisorDegree_{1996} = 4$ and $DirectorAdvisorDegree_{1997} = 3$. The influence of advisor 1 over the director is their joint degree divided by the director's degree that year (this is a proxy for the fraction of the director's income or perks that is received from advisor 1). Hence, for advisor 1, its influence over the director is: $InfluenceAdvisorDirector_{1996} = \frac{4}{7}$ and $InfluenceAdvisorDirector_{1997} = \frac{3}{7}$. Averaging the yearly influence over the years of contact so far between the director and advisor 1 yields another measure of connections: $LongRunInfluenceAdvisorDirector_{1996} = \frac{4}{7}$ and $LongRunInfluenceAdvisorDirector_{1997} = \frac{\frac{3}{7}+\frac{4}{7}}{2} = \frac{1}{2}$. The final measure used is the years of contact so far between the director and the advisor. In this case: $YearsOfContact_{1996} = 1$ and $YearsOfContact_{1997} = 2$.

For Director 1 his *degree* is the number of connections to advisory firms through the funds he oversees in any year: $DirectorDegree_{1996} = 7$ and $DirectorDegree_{1997} = 7$. A director's degree proxies for his prominence in the network, among other directors, and for his income from overseeing funds. The number of funds through which the director is linked to advisor 1 is their *joint degree*: $DirectorAdvisorDegree_{1996} = 4$ and $DirectorAdvisorDegree_{1997} = 3$. The joint degree proxies for the dollar amount of money (or perks) received by the director as compensation from the funds managed by that advisor, as well as for the dollar amount of potential side-payments (or perks) received directly from the advisory firm.

The *influence* of advisor 1 over the director is their joint degree divided by the director's degree that year. This measure is a proxy for the fraction of the director's overall fund-related income[19] or perks that is received from advisor 1. Hence, for advisor 1, its influence over the director is: $InfluenceAdvisorDirector_{1996} = \frac{4}{7}$ and $InfluenceAdvisorDirector_{1997} = \frac{3}{7}$. Averaging the yearly influence over the years of contact so far between the director and advisor 1 yields another, long-run measure of connections: $LongRunInfluenceAdvisorDirector_{1996} = \frac{4}{7}$ and $LongRunInfluenceAdvisorDirector_{1997} = \frac{\frac{3}{7}+\frac{4}{7}}{2} = \frac{1}{2}$. The final individual-level measure used is the years of contact so far between the director and the advisor. In this case: $YearsOfContact_{1996} = 1$ and $YearsOfContact_{1997} = 2$.

I aggregate these individual-level measures to get board-level measures of connections to the advisory firm. The first such measure, $BoardAdvisorDegree_{\tau}$, is obtained by finding who was on the fund board at time τ; for each person in this set, I calculate their $DirectorAdvisorDegree_t, \forall t <= \tau$, then I add up all of these individual scores (over time for each director and then across the board) to obtain $BoardAdvisorDegree_{\tau}$.

For the analysis of the selection of new subadvisory firms by funds, I calculate a measure of connectivity between the hiring fund's continuing advisor and the candidate subadvisor. I do so to test whether the continuing advisor (which is the advisor that formed the fund in the first place) has a say in the decision whether the candidate is hired or not. The measure I calculate, $ContAdvisorCandidateDegree_{\tau}$, equals the number of times in the past that the fund's continuing advisor has managed other mutual funds together with the candidate advisor

[19] It could be that for some individuals the amount of pay or perks they receive for their actions as directors is small relative to their total income, and thus my measure of influence could be biased upward. While it would be useful to control for the directors' total income in my analysis, this data is not available.

in years $t \leq \tau$.

I also aggregate the *influence* measures, by obtaining the mean and the standard deviation of the director-level $InfluenceAdvisorDirector_t$ and $LongRunInfluenceAdvisorDirector_t$ across the members of the fund board. The resulting variables represent the influence of the advisor on the board ($MeanInfluenceAdvisorBoard_t$ and $MeanLongRunInfluenceAdvisorBoard_t$) and the dispersion of the advisor's influence across board members, ($SdInfluenceAdvisorBoard_t$ and $SdLongRunInfluenceAdvisorBoard_t$, where the "Sd" prefix stands for standard deviation). It is possible that, during the decision to hire a new subadvisor, having directors with different levels of connections to a candidate may lead to dissagreement regarding the approval of the candidate. Thus, I include the standard deviation of the influence measures as an additional explanatory variable in my model for subadvisor selection.

In the empirical analysis, I include proxies for the prominence (visibility) of various agents in the network: for each director, this is the total number of relationships with advisors ($DirectorDegree_t$), and for each advisor, this is the total number of directors they are connected to ($AdvisorDegree_t$).

IV. Data

The data come from NSAR-B and N-30D filings filled by mutual funds with the SEC during 1993-2002 (available through the SEC's public Edgar database), and from CRSP. The dataset created from NSAR-B filings provides for each mutual fund and each year the fund's characteristics (investment objective, foreign vs. domestic securites, index vs. actively managed), performance (net asset value per share, total assets under management, dividends and capital gain distributions), the overall advisory fee, and the names of investment advisors (up to three per fund per year).[20]

The second dataset contains the names of all persons affiliated with any mutual fund during 1993-2002. This data can be extracted from the website of EdgarOnline, a company specialized in the processing and sale of information from SEC filings. EdgarOnline provides the names of all persons mentioned in a particular company's SEC reports during 1993-2002. For each

[20] See Kuhnen (2004) for a detailed description of this data.

director name (obtained by concatenating the first, middle and last name) in the list, I conduct an automatic search of all mutual fund year-end shareholder reports (form N-30D) available on the SEC's website. This allows me to find which fund companies (as identified by their CIK, the tag used by the SEC) a particular director was associated with in any year during 1993-2002. The full director name has to match exactly a fragment of the text of the filing.

Ideally, I would like to know for each person and for each year the name of all the fund portfolios this person was a director of. However, the data only provide me with the identity of the *fund company* that the director was associated with. A fund company, or family, may offer multiple funds (portfolios) to investors. Thus, if there are 5 portfolios in a fund family, and I know a director was associated with this family, I do not know how many of the five boards he sat on. However, as found by Tufano and Sevick (1997) and others[21], the same directors tend to sit on the boards of all funds in the same fund company. Hence, I assume that a director works for all portfolios in the fund family if he is mentioned in the shareholder report filed by the fund family.

The set of funds that hired new subadvisors during 1993-2002 is found using the NSAR-B dataset. The names of these funds, as listed in NSAR-B filings, are manually matched with those in CRSP, in order to get monthly fund return data. These are used to compute annual portfolio risk and abnormal returns for each of these funds.[22] For each instance of a fund hiring a new subadvisor, the set of potential candidates includes all the advisory firms active in the market in the year prior to the change. I exclude the fund's continuing advisors from the set of possible choices and eliminate all observations that miss information about the fund's directors or miss returns in the NSAR-B filings for the hiring year.

Table II shows the number of advisors actively managing funds in each year in the sample for each investment objective, as specified in the N-SARB filings and described in the Appendix. These categories include: bond funds (Bond), aggresive capital appreciation and capital appreciation funds (ACA & CA), growth funds (G), growth and income and income funds (GI & I) and total return funds (TR).

[21] See the Independent Directors Council Task Force Report "Director Oversight of Multiple Funds", May 2005

[22] NSAR-B and CRSP do not show a common fund identifier other than the fund's name. Since the name is often spelled or abbreviated slightly differently in NSAR-B filings and in CRSP, it is not possible to automate the matching process.

The advisory firms in Table II constitute the set of potential advisors a fund can pick from the following year. So, for instance, if a fund is looking for an advisory firm in 1999, I assume it can choose from any of the 1047 advisors that were active in 1998, but I allow for the fund to have a preference towards advisors specialized in its own investment objective. I find a total of 257 secondary advisor changes and 46 primary advisor changes. Since many of these events take place late in my sample, there are relatively few post-event years (two, on average) during which I can track fund and advisor characteristics.

To test whether connections influence which directors are given board seats by advisory firms that start new funds, I identify all the open-end mutual funds newly created in 1998 using the CRSP dataset. I manually match these funds (by name) with those in the NSAR-B and N-30D data to track the characteristics and the directors of these newly born funds over time. The final sample contains 216 new funds. I picked the 1998 fund "births" in order to have enough data prior to the creation of the fund to calculate connections between candidate directors and the primary advisors of these new funds (1993-1997), and to have enough observations after the funds' inception to track its contractual agreements with the advisor (1998-2002). The potential candidates for board seats are all the directors who were actively overseeing funds at any time between 1993-1997, were active in at least one year during 1998-2002 and who prior to 1998 did not oversee portfolios belonging to the family that created the new fund.[23]

I also use the set of funds created in 1998 to study the potential role of connections between directors and the funds' primary advisors on the negotiation of several types of transfers between the funds and advisors; these transfers include management fees, 12b-1 (marketing) fees, fund loads (generally used for marketing and distribution), and expense reimbursements, which are voluntary payments from the advisor back to the fund. All fees and loads are obtained from CRSP, while expense reimbursements are calculated using NSAR-B data.

The entire sample of U.S. open-end mutual funds contained in the NSAR-B dataset is also used to test the relationship between connections, fund performance and fees. This analysis is conducted for 1996-2002, since many funds did not file the NSAR-B forms on-line until 1996, and thus the measures of connections are noisy for the intial period of 1993-1995.

[23] The last restriction is due to the limitation of the data: I can only observe whether a director works for a fund family, but not for which specific portfolios in the family.

V. Results

A. Selection of new fund subadvisors

For this part of the analysis I focus on the 257 cases of subadvisor changes. I use this sample to study the determinants (including connections) of an advisor's success at being hired, as well as the effect of connections between the newly hired firm and fund directors on fund performance post-hiring.

Panel A of Table III presents the summary of characteristics of advisory firms that won contracts from the hiring funds. There is much dispersion in these characteristics across firms. The connection measure $BoardAdvisorDegree_{\tau-1}$ is on average about 48, with a standard deviation of 108. The average value can be attained, for instance, if each director sitting on a fund board with eight members has in the past dealt with the winning candidate (in a director-advisor relationship) six different times. The other measures of connectivity are also quite dispersed.

Winning advisors have on average 22% of the portfolios under management in the specific investment category of the fund. Three dimensions define the investment category: (1) the investment objective (aggressive capital appreciation & capital appreciation, growth, growth and income, total return, and bond), as described in the Appendix; (2) whether this is an index fund; (3) whether the fund invests primarily in foreign securities. Across all investment categories, winning advisory firms already have total assets under management of about $3 billion.

The average one-year performance of winning advisors, measured as the simple average of the performance of all portfolios under management, is 5.50. This performance measure assigns funds into deciles each year based on their net returns relative to those of all the other funds with the same investment objective. The best performing funds are in decile 10, and the worst performers are in decile 1. Hence, winning advisors have a portfolio of funds that in the year before the hiring event have done slightly better than average.

The advisory fee paid by the portfolios that winning advisors already have under management is 66 basis points (bp), on average, with a standard deviation of 21 bp. It is the norm in the asset management industry to have the advisory fee be simply a percentage of the total value of the fund. See Kuhnen (2004) for more details on fee structure, and Massa and Patgiri (2005) for an analysis of the effect of compensation on fund risk-taking.

The coefficient estimates from the conditional logit model in equation 1 for the advisor selection process are shown in table IV. In all the specifications I find that the strength of connections between a fund's directors and a candidate advisory firm, or between the continuing primary advisor and the candidate, is a positive and statistically and economically significant predictor of the advisor's success at contracting with the fund. Increasing $BoardAdvisorDegree_{\tau-1}$ by one standard deviation (37.44, see panel B of Table III) increases the odds of an advisor being hired by the fund by 4%. Following the usual nomenclature in a logistic MLE, the odds ratio is defined as $\frac{Prob\{Advisor\ is\ hired\}}{Prob\{Advisor\ is\ not\ hired\}}$. A one-standard deviation (28.25) increase in $BoardAdvisorDegree_{\tau}$ increases the odds of a subadvisory candidate being hired by 6%. Similarly, a standard deviation increase in $MeanInfluenceAdvisorBoard$ (0.006) and in $MeanLongRunInfluenceAdvisorBoard$ (0.007) lead to an increase of 15%, and of 16% respectively, in the odds of the candidate firm being hired.

In the specifications in panels A and B the measure of connections between the fund's continuing (primary) advisor and the candidate subadvisor ($ContAdvisorCandidateDegree$) has a positive and significant effect of the likelihood of the candidate being hired. This shows that indeed, the fund's primary advisor has an impact on which subadvisors are selected.

As hypothesized, the standard deviation of the measures of influence between a candidate subadvisor and a director, calculated across the board, has a negative and significant effect on the likelihood of the candidate getting the contract. A one standard deviation increase in either of the two measures I use to proxy for dispersion in the influence of the candidate over the board, $SdInfluenceAdvisorBoard$ and $SdLongRunInfluenceAdvisorBoard$, leads to a 12% decrease in the odds of the candidate being hired.

In all the specifications in Table IV I include as a control a measure of how overall well-connected the candidate advisor is: $AdvisorDegree_{\tau-1}$. This is the number of directors the candidate is associated with (via the funds network) the year prior to the hiring decision. This measure proxies for the candidate subadvisor's prominence in the network, and thus, for its reputation among all participants. As one would expect, candidates who know more directors are more likely to be hired. The effect is significant in all specifications in table IV.

Advisors are significantly more likely to win contracts if they already have more assets under management across all fund categories ($AdvisorLnAUMOverall$). Increasing the assets by one-standard deviation increases the odds of winning the contract by 65%.

More specialized advisors are also more likely to win contracts: the fraction of the total number of portfolios the candidate already has under management in the specific investment category of the fund ($AdvisorFractionFundsInCategory$) is a positive and significant predictor of the likelihood of obtaining the contract.

Interestingly, controlling for assets under management and performance, older advisory firms are less likely to be hired as subadvisors by mutual funds, as shown by the negative effect of $AdvisorAge$ in all specifications in table IV. This result may simply reflect the self-selection of advisory firms that compete for subadvisory contracts: older firms may decide to start their own funds instead of helping other advisors manage funds.

The average marginal rate charged by an advisor from the portfolios already under its management across all fund categories is a negative predictor for the advisor's likelihood of being chosen. This indicates that fund directors prefer to hire cheaper advisors, all else equal, in accordance with their fiduciary duty.

The average overall short-term past performance of the advisor ($AdvisorPerformanceOverall$) is not a significant predictor for which firm gets hired. This is an indication that fund directors do not "chase returns", as individual investors do. The preference of investors to invest in last year's best performing funds has been documented in the literature (see, for instance, Sirri and Tufano (1998)) and is seen as detrimental, in light of the lack of clear evidence for fund performance persistence.[24] Thus, fund directors seem to be less influenced by short-term performance when choosing an advisor than individual investors are when choosing a fund (manager), and, arguably, this is beneficial for fund shareholders.

[24] There is a large number of papers focused on determining whether fund performance persists. See, for instance, Grinblatt and Titman (1992), Carhart (1997) and Bollen and Busse (2004).

B. The impact of connections between fund directors and newly hired subadvisory firms on the fund's subsequent performance and risk-taking

The relative importance of the characteristics of the newly-hired advisors for subsequent fund performance is shown in Table V. I only use fund-year observations where the newly-hired firm is still among the fund's advisors.

$BoardAdvisorDegree_{\tau-1}$ is a significant and negative predictor of yearly net fund returns (panel A), as well as of risk-adjusted returns calculated from the CAPM and the Fama-French four-factor model (panels B and C). A one-standard deviation (equal to 108, see Table III) increase in this measure of connectivity causes the annual net fund return to drop by 1.51%, and the risk-adjusted returns $alpha^{CAPM}$ and $alpha^{FF}$ to decrease by 1.62% and 0.43%, respectively. To put the size of the effect in perspective, I compute the post-change average performance of these funds that change subadvisors (for the years when the newly-hired advisor is still working for the fund). The average post-change net return, $alpha^{CAPM}$ and $alpha^{FF}$ are: -0.10%, -1.15% and -2.95%. Hence, a one-standard deviation increase in the strength of connections between fund directors and the newly hired subadvisor brings the average net annual fund return from -0.10% to -1.61%. The average risk-adjusted annual return $alpha^{CAPM}$ decreases from -1.15% to -2.77%, and the $alpha^{FF}$ decreases from -2.95% to -3.38%. These numbers demonstrate the significant negative role that social network effects have on fund shareholders' welfare.

The only other advisor characteristic that plays a significant role in fund performance is the dollar-value of the assets the new advisor already has under management at the time of being hired ($AdvisorLnAUMOverall$). As indicated in Table IV, this variable, which is a proxy for the advisor's reputation, is a positive and significant predictor of the likelihood of being selected by the fund. The fact that the same variable also predicts better subsequent fund performance is an indication that there is some truth to the idea that agents with more responsibilities are of better quality (in other words, this validates using $AdvisorLnNAVOverall$ as a measure of reputation.)

In the regressions in Table V I include controls for the fund's portfolio risk (as indicated by the dummies for investment objective, and by dummies indicating index funds and funds investing in foreign securities). I also control for fund size, and for the size of the fund board, to isolate the effect of connectivity from potential effects coming from other potential sources of bad governance, such as having large boards.

Arguably, the directors' preference to hire firms they have worked with in the past can be justified if directors have a preference towards having low volatility in fund returns. This preference can come from simple risk-aversion in directors' utilitity function, or from the shape of their compensation scheme. In general, fund directors are paid a flat fee for being on board. Directors benefit relatively little from funds performing well (some may own shares in the fund and partake in the upside), but have a lot to lose if the fund does very badly: their reputation, and thus future jobs on other boards, are at stake in such bad states. Hence, it is in the directors' best interest to contract with an advisor that is not likely to destroy value by excessive risk-taking. As a result, hiring connected advisors will mechanically lead to lower net fund returns, but it won't necessarily lead to lower alphas.

If this incentive-based explanation for the preferential hiring of connected firms is true, then I should observe that funds that hired more connected advisors have lower risk-factor loadings than the other funds. Table VI shows the estimates of a pooled OLS regression of fund factor risk loadings on fund and advisor characteristics as in eq. 3. The results in panels A, B and D show that there is no significant effect of $BoardAdvisorDegree_{\tau-1}$ on the market risk (β^{CAPM} and β^{Rm-Rf}), nor on the HML factor loading (β^{HML}). Estimates in panels C and E suggest that there is a small effect of the connectivity measure on β^{SMB} (positively related to connection strength) and β^{UMD} (negatively related to connection strength.) The fact that these two effects go in opposite direction and the lack of effect of connectivity on market risk factor loadings across funds do not lend support to the above incentive-based story for advisor selection.

C. The role of connections between directors and primary advisors on fund performance in the entire sample of U.S. open-end funds

I investigate the robustness of the negative relationships between director—*subadvisor* connections and fund performance documented in section B by doing a similar analysis using the entire set of U.S. open-end mutual funds that are in the NSAR-B dataset between 1996-2002. In a panel dataset that tracks 5936 funds during this time frame, I examine whether connections between fund directors and the *primary* advisor matter for fund performance.

Summary statistics for various measures of connectivity between directors and primary advisors for all the fund-year observations in this sample are shown in Table VII. The connections are much stronger in this sample than the connections between directors and newly hired subadvisors refered to in sections A and B. For instance, $MeanInfluenceAdvisorBoard$ is 0.51 on average in the entire sample of U.S. open-end funds, and only 0.033 in the sample used in the subsections refering to newly hired subadvisors. This is expected, as fund directors are much less likely to severe connections with the primary advisor than with subadvisors, which get changed over time.

Due to the large size of this sample, I can not obtain risk-adjusted measures of performance, as doing so would require monthly returns from CRSP, and finding the CRSP identifier for each of these 5936 funds would be too time-consuming. Thus, I have to use as performance measure the fund annual net returns, computed using the raw data in the NSAR-B filings. These returns are calculated as the change in net asset value per share from year to year, and include dividends and other distributions. I include dummies for the fund's investment objective in the performance regression, as a means to control for fund risk.

I estimate the pooled OLS regression in equation (2) using the entire sample of U.S. open-end funds. The results are shown in table VIII. All the three measures of connections between directors and the primary advisor ($BoardAdvisorDegree_t$, $MeanInfluenceAdvisorBoard_t$, or $MeanLongRunInfluenceAdvisorBoard_t$) are significant negative predictors of fund net returns. Increasing either measure by one standard deviation (shown in Table VII) leads to a 30 to 100 bp decrease in the annual net fund return, depending on the measure used. These figures are comparable with the 150bp effect found in section B. With either connectivity measure included as explanatory variables, I find that board size per se is not related to fund performance.

When I repeat these regressions using the fund's before-fee return (defined as the net return plus the advisory fee) as the dependent variable, I find a similar negative impact of connections on performance. The coefficient estimates for the three measures of connectivity are virtually identical to those estimated in Table VIII, and thus I do not report the before-fee return regressions here. These results suggest that the decrease in fund performance implied by stronger board-advisor connections is not simply the result of an increase in the fees paid to advisors. This point is revisited in section E.

Characteristics of the primary advisor are significant predictors of fund returns. Table VIII shows that funds get higher returns if the primary advisor has fewer assets under management, overall and in the specific investment category of the fund. Thus, if an advisory firm oversees too many funds, the performance of these funds will suffer (as implied by the theoretical model of Berk and Green (2004)). The one-year performance of the primary advisor across all the funds it oversees ($AdvisorPerformanceOverall_{t-1}$) has no predictive power for the subsequent one year net return of the fund.

Table VIII also shows that fund characteristics influence returns. Large funds underperform small funds, as also shown by Chen, Hong, Huang, and Kubik (2004). I also find that the family size is a negative predictor of fund performance. Funds investing in foreign securities also underperform their conterparts that invest mainly in U.S. securities.

Thus, in both the sample of funds hiring new subadvisors and in the entire sample of open-end U.S. funds, I find that business connections between directors and advisors or subadvisors are negative predictors of fund performance.

D. Directors-advisor connections and the fee paid to new primary advisors

To find whether directors' connections have any impact on the fee paid to the newly hired advisors, I look at the subsample of new fund-advisor relationships where the primary advisor is changed. In general, the primary advisor, not the secondary ones, negotiates the fee to be received from the fund in exchange for portfolio management services.

I use this subsample to regress the applicable marginal rate (AMR) paid by the fund on advisor and advisor-fund characteristics, controlling for fund characteristics. As found in Deli (2002) and Kuhnen (2004), cross-sectional fund characteristics such as the investment objective, or the fund being an index fund or investing in foreign securities are important determinants of the size of the fee paid to the fund's advisors. Hence, I control for these characteristics when testing the role of connections in determining the AMR.

Table IX shows the determinants of the rate paid to the newly hired primary advisors. Both

$BoardAdvisorDegree_{\tau-1}$ and $BoardAdvisorDegree_{\tau}$ are positively and significantly related to the size of the advisory fee, controlling for advisor's reputation and degree of specialization. Thus, the more connected a firm is to a fund's directors prior to becoming the primary advisor of the fund, the higher is the fee it will receive for its services, expressed as percentage of the fund's assets. A one standard deviation (equal to 61 and 107, respectively, in this subsample) increase in $BoardAdvisorDegree_{\tau-1}$ and $BoardAdvisorDegree_{\tau}$ translates into a change in AMR of 31, and 8 bp respectively. The average AMR for this subsample is 51 bp. Thus, these effects are economically significant: they represent an increase in the advisory fee of at least 15%.

In the regressions in Table IX I control for the size of the fee prior to the advisory change ($AMR_{\tau-1}$), as this variable may also be related to the quality of corporate governance, as suggested by others (Tufano and Sevick (1997), Del Guercio, Dann, and Partch (2003)). It could be that "bad" boards tend to pay advisors more (high $AMR_{\tau-1}$) no matter who the advisors are; the same "bad" boards may also be the ones that tend to hire advisors they are connected to. In my analysis, I need to isolate the effect of networks from the effect of other sources of bad governance. To achieve this goal, I include $AMR_{\tau-1}$ in the models in table IX.

Other advisor characteristics are also significant determinants of the AMR: the more money the advisor already has under management already, the lower is the fee charged from the newly acquired fund. This is an expected result, given that there are economies of scale in the asset management industry. In all specifications in Table IX I find that the more portfolios the advisor already manages in the fund's category, the lower is the rate received from the newly acquired fund, perhaps indicating the economies of scale that characterize the industry.

As found elsewhere (Deli (2002), Kuhnen (2004)), fund characteristics are also important for the size of the AMR: the fee is significantly higher for equity funds relative to bond funds, and is lower for larger funds and for index funds.

E. Directors-advisor connections and the advisory fee for the entire sample of U.S. open-end funds

To test the robustness of the positive relationship between the size of the advisory fee and the strenght of connections between directors and primary advisors documented in section D, I conduct a similar analysis for the entire sample of U.S. open-end mutual funds during 1996-2002. This is the same sample used for the robustness checks in section C.

Table X shows the results of the pooled OLS model in equation 4. All the three measures of connectivity between fund directors and the primary advisor are significant positive predictors of the size of the fee paid to the advisor. Increasing either $BoardAdvisorDegree_t$, $MeanInfluenceAdvisorBoard_t$ or $MeanLongRunInfluenceAdvisorBoard_t$ by one standard deviation (see table VII) increases the fee by 1 bp per year. While this effect is smaller than that founds in the subsample of funds where the primary advisor is changed after a takeover, it is still economically significant given the size of the industry ($8 trillion). Increasing the advisory fee from an average of 66 bp (as indicated by the summary statistics in table VII) to 67 bp would shift almost $1 billion more from the fund investors to advisory firms *each year*.

These results shed light on the finding in section C that the negative effect of connections on fund returns is similar when returns are measured before or after fees. Increasing connectivity measures by one standard deviation in the sample of open-end U.S. funds translates into a decrease of 30 - 100 bp in the fund net returns and only into a 1 bp increase in the advisory fee. Thus, fees can not account for the impact of connections on net returns, as these returns decrease by much more than the increase in fees.

Interestingly, I find that board size is negatively correlated with the advisory fee, a result that seems to run contrary to the finding of Del Guercio, Dann, and Partch (2003) that for closed-end funds, the expense ratios are positively correlated with board size at the fund complex level.

Advisor-specific characteristics influence the fee received from the fund: advisors are more specialized in the objective of the fund (i.e. those which have more portfolios under management that have the same objective) get significantly higher fees. The fee is lower for advisors with higher overall assets under management, indicating that economies of scale are shared with the fund investors. However, the results in Table X also show that advisors that have more portfolios under management across all investment categories receive higher fees. It is possible that these are the older, most reputable advisory firms, which can charge a premium for their services.

As before, I find that fund characteristics matter for the size of the advisory fee. Fees are higher for funds with riskier investment objectives, and for foreign and non-index funds. Larger funds pay a lower percent of assets as fees, and funds belonging to larger families pay higher fees.

Thus, the positive relationship between advisory fees and the strength of connections between the primary advisor and the fund directors holds in both the subsample of funds that have a new primary advisor as a result of a takeover, as well as in the entire sample of open-end U.S. mutual funds.

F. Selection of directors of new mutual funds

As stated by Tirole (1986), for there to exist collusion and favoritism, it has to be that both parties benefit from these activities. So far the results indicate that advisory firms benefit from their connections to fund directors, by being preferentially hired to help manage funds and by not being monitored as intensely by directors.

But do directors benefit from these relationships, too? One way to answer this question is to analyze the process by which directors obtain board seats of newly created funds. The primary advisors of these new funds (their creators, or sponsors) are the entities responsible for putting together the fund board. While having to comply with the legal requirement that a certain proportion of the directors be independent (the required proportion of independent trustees used to be 40%, but was increased to 75% in 2004), the advisor is free to offer board seats to the individuals of their choice. If relationships matter, then advisors of new funds should preferentially hire directors that they are connected to from past business relationships.

I identify 216 cases of newly created open-end U.S. mutual funds whose characteristics and board composition I can track over time. For each of these new funds, I know the identity of the directors that won board seats. I am also able to find the set of all possible director candidates that could have been considered for the job: these are the directors overseeing funds anytime during 1993-1997 and who oversee funds at least one year during 1998-2002. The latter criterion is used to avoid having retired directors in the sample of potential candidates. The resulting set of candidates contains 3005 unique candidate director names. For fund clusters where a new fund was added, and that existed prior to 1998, the directors who are already working for the funds in the cluster are not considered. This allows me to focus on the hiring of new directors, or, equivalently, on board changes. If, for instance, a fund cluster adds a new fund and the board of the cluster does not change at all, then I do not use these observations in my analysis.

The results of the estimation of the logit model of director selection are shown in Table XI. All the specifications used show a significant effect of connections of a candidate director to the new fund's advisor on the likelihood of the candidate winning a board seat.

The results in panel A show that a standard deviation (1.03) increase in the number of funds a director and the advisor of a fund newly created in 1998 have in common in 1997 ($DirectorAdvisorDegree_{1997}$) translates into an 8% increase in the odds of the director being added to the board in 1998. Similarly, using the coefficient estimates in panel C, the effect of a standard deviation (0.053) increase in the long-run measure of influence between the hiring advisor and a candidate director leads to a 28% increase in the odds of the director being added to the board of the newly created fund.

Controlling for the connections between the advisor and the candidate directors, how overall well-connected a candidate is ($DirectorDegree_{1997}$) turns out to be a significant predictor of obtaining a board seat. A standard deviation increase in this variable (44.69) increases the odds of the candidate being added to the board by 25%. Thus, advisors are more likely to hire directors who already oversee more funds, and with whom they have had more business relationships with prior to the creation of the new fund.

G. Director-advisor connections and fund-advisor transfers for funds created in 1998

The preferential hiring on new fund boards of directors that are connected to the fund's advisor suggests that connections may also affect the contracting decisions that are the result of negotiations between the board and the advisor.

In the regressions in Table XII I use the subset of funds created in 1998 to test whether director-advisor connections matter for the setting of advisory fees, fund loads, 12b-1 fees and expense reimbursements. All of these fees have to be negotiated by the board on a yearly basis. In contrast with advisory fees, which are direct transfers from the fund to the advisor, the fund loads and 12b-1 fees (decided in the *beginning* of the year) are not directly paid to the advisor. They are used to pay for the distribution and marketing of fund shares, but indirectly help the advisory firm by attracting flows into the fund. As shown by Christoffersen, Evans, and Musto (2005), flows to load funds are less sensitive to performance than flows to non-load funds. Thus loads benefit advisory firms by making the asset base, and the revenues from managing the fund, more stable. Expense reimbursements are payments from the advisor back to the fund, negotiated by the board (at the *end* of the year). They provide a direct a mechanism for increasing shareholder value, as well as a strategy for the advisor to temporarily increase the fund returns and potentially the fund inflows by forgoing some of the management fee (Christoffersen (2001)).

In all the specifications in Table XII I control for fund characteristics, such as total net assets and the investment objective, and for board size. I also include advisor characteristics as controls (the total number of portfolios, as well as the total value of assets under management) as these may influence the negotiations of various fees paid by the fund to the advisor. In the regression of expense reimbursements, I add the fund annual net return as an additional explanatory variable, as Christoffersen (2001) has shown that performance affects the level of reimbursements.

If connections between directors and advisors lead to less stringent negotiation of the transfers between funds and advisory firms, then one would expect to observe that the connectivity between directors and advisors is positively related to the management fee, loads and 12b-1 fees, and is negative related to expense reimbursements. Table XII shows that some of these implications hold in the sample of funds born in 1998. There is a positive and significant correlation between $BoardAdvisorDegree$ and the total loads charged by the fund, and a negative and significant correlation between $BoardAdvisorDegree$ and the expense reimbursements received by funds from advisors. A standard deviation increase (about 1590 in the sample of observations studied in this subsection) in the strength of connections between the directors of the newly-formed fund and its primary advisor, measured at the end of the previous year ($BoardAdvisorDegree_{t-1}$) translates into a 30 bp increase in the total loads charged by the fund. To put this number in prospective, the mean load is 236 bp. A standard deviation increase in the connections between directors and the advisor measured at the end of the current year ($BoardAdvisorDegree_t$) decreases the expense reimbursements received by the fund by 14 bp, which is about 17% of the average value (82 bp) of the annual reimbursements experienced by the funds born in 1998. Thus, the effect of connections between directors and advisors have an economically significant impact on these two types of transfers.

I do not observe an effect of connections on the level of 12b1 fees. There is an economically and statistically weak negative effect on the advisory fee, but this effect dissapears when the model is estimated using the Fama-MacBeth procedure (Fama and MacBeth (1973)). The economically significant impact of connections on total loads and expense reimbursements passes this robustness check.

H. Director-advisor connections and the expense reimbursements for all U.S. open-end mutual funds

The data I have allows me to test the robustness of the result found in section G that connections between the board and the primary advisor lead to lower expense reimbursements from the advisor, by conducting a similar analysis using the entire sample of U.S. open-end mutual funds during 1996-2002.[25] This is the same sample used for the robustness checks in sections C and E.

I run a pooled OLS regression as in equation (4) where the dependent variable are the annual expense reimbursements. The results are shown in Table XIII. I find that all measures of connections between the fund directors and the primary advisor ($BoardAdvisorDegree_t$, $MeanInfluenceAdvisorBoard_t$ and $MeanLongRunInfluenceAdvisorBoard_t$) are significant negative predictors of the size of expenses reimbursed by the advisor back to the fund. Increasing either of these variables by one standard deviation (see table VII) decreases the annual expense reimbursed by about 1 bp. This is a significant effect, given that the average amount reimbursed in the sample is 15 bp per year. At the industry level, the effect translates into almost $1 billion less to fund shareholders, and more to advisory firms, each year.

VI. Conclusion

The paper uses a unique dataset that tracks characteristics of U.S. open-end mutual funds and investment advisory firms, as well as the business relationships between fund directors and

[25] Unfortunately, I do not have the data on 12b1 fees or on total loads for the entire set of open-end funds in the NSAR-B dataset.

advisory firms during 1993-2002. I find that social connections of fund directors are important for contracting decisions, such as the hiring and pay of fund advisors, and for fund performance.

In the sample of U.S. open-end mutual funds that hired new subadvisory firms to help manage their assets, a candidate advisor is significantly more likely to be offered the portfolio management contract by a fund if it has been more connected in the past to the fund's directors through other business relationships. Also, when advisory firms start new mutual funds they are more likely to offer fund board seats to directors they are more connected to through previous business relationships.

Advisors receive a higher management fee if they are more connected to the directors of the fund through past relationships. The strength of directors-advisors connections is positively correlated with fund loads, and negatively related to expense reimbursements. Moreover, the strength of these connections is a negative predictor of fund performance: returns before and after management fees, as well as risk-adjusted returns, are significantly lower for funds where advisors are more connected to the board of directors.

This evidence suggests that the social networks of agents with important roles in financial markets (such as fund directors) have a significant impact on their decision-making, and may have a negative effect on the quality of actions taken by these agents as part of their fiduciary duty. These results support the recent initiative of the SEC to request more disclosure regarding the approval of investment advisory contracts by mutual fund boards.

Appendix: Classification of funds investing in equity securities

In the empirical analysis in the paper, I_t^x are indicator variables equal to 1 if the fund has the investment objective denoted by x, where x can be: **ACA & CA**=aggressive capital appreciation funds and capital appreciation funds; **G**=growth funds; **GI&I**=growth and income funds, as well as income funds; **TR**=total return funds. See below for a detailed explanation of these categories.

Excerpt from the SEC's General Instructions for filing form NSAR

(http://www.sec.gov/about/forms/formn-sar.pdf)

"A registrant/series with an investment objective of **aggressive capital** appreciation is one that primarily and regularly seeks short-term appreciation through high-risk investment, with little or no concern for receipt of income.

A registrant/series with an investment objective of **capital appreciation** is one that primarily and regularly invests for an intermediate-term return by investing in moderate to high-risk securities, with little or no concern for receipt of income.

A registrant/series with an investment objective of **growth** is one that seeks long-term growth, with a moderate degree of risk. Receipt of income may be considered to some degree in selecting investments.

A registrant/series should place a "Y" beside sub-item 66E, **growth and income**, if it primarily and regularly makes low-risk investments with the objective of capital growth and income production.

A registrant/series should place a "Y" beside sub-item 66F, **income**, if the receipt of income is the primary reason for selecting portfolio securities.

A registrant/series whose portfolio includes a varying mix of equity and debt securities should place a "Y" beside sub-item 66G, **total return**."

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Table I

Description of variables

Variable	Description
$AdvisorDegree_t$	Number of directors a particular advisor is associated with through all the funds managed in year t
$AdvisorAge_t$	Number of years, until t, since a particular advisor entered the dataset
$AdvisorFractionFundsInCategory_t$	The fraction of all funds a particular advisor has under management at t that are in the same investment category as that of the fund of interest
$AdvisorFundsInCategory_t$	Number of portfolios the advisor had under management at t that were in the same category as the fund of interest.
$AdvisorFundsOverall_t$	Total number of funds the advisor had under management at t
$AdvisorLnAUMOverall_t$	The natural logarithm of the dollar amount (in thousands) that the advisor had under management in all investment categories in year t
$AdvisorPerformanceOverall_t$	Advisor's overall peformance in year t. It is the average performance (expressed as deciles 1-10, 1=lowest, 10=highest) of all portfolios it manages.
$AdvisorAMROverall$	Average fee (in basis points) charged by the advisor from the funds it already has under management in all investment categories at t.
AMR_t	The management fee ("applicable marginal rate") paid in year t by the fund to its advisors, expressed as a fraction of the fund size.
$BoardAdvisorDegree_t$	Number of connections between the directors sitting on the fund's board at t and the advisory firm of interest
$BoardSize_t$	Number of directors on the fund board in year t
$ConnStrengthContAdv_t$	Number of connections between a candidate subadvisor and the continuing (primary) advisor of the fund
$DirectorDegree_t$	Number of connections between the director and all advisors in the network in year t
$DirectorAdvisorDegree_t$	Number of connections between the director and the advisor at time t
$ExpenseReimbursements_t$	Amount of expenses reimbursed back to the fund by the advisor at the end of year t, as a fraction of the fund size
$Foreign_t$	Indicator equal to 1 for funds that invest primarily in foreign securities
$FundFamilySize_t$	Number of funds (portfolios) offered by the fund family in year t
$FundLnTNA_t$	Natural logarithm of fund size ("total net assets") at the end of year t Size expressed in \$thousands. In Table XII expressed in \$millions.
$FundTNA_t$	Fund size ("total net assets"), in the units described above.

– Continued on the next page –

– Description of Variables - Continued –

$I_t^{ACA\&CA}$	Indicator equal to 1 if the fund's investment objective is aggressive capital appreciation or capital appreciation (see Appendix)
I_t^{G}	Indicator equal to 1 if the fund's investment objective is growth (see Appendix)
$I_t^{G\&I}$	Indicator equal to 1 if the fund's investment objective is growth and income (see Appendix)
I_t^{TR}	Indicator equal to 1 if the fund's investment objective is total return (see Appendix)
I_t^{Bond}	Indicator equal to 1 if the fund invests primarily in fixed income securities
$Index_t$	Indicator equal to 1 for index funds
$InfluenceAdvisorDirector_t$	The influence of the advisor over the director in year t, calculated by dividing the number of connections between these two parties by the total number of connections of the director at t.
$LongRunInfluenceAdvisorDirector_t$	The time-series average of the yearly influence of the advisor on the director, for all years up to t.
$MeanInfluenceAdvisorBoard_t$	The average, across the members of the fund board, of the measure of influence of the advisor on each director, $InfluenceAdvisorDirector_t$
$MeanLongRunInfluenceAdvisorBoard_t$	The average, across the members of the fund board, of the measure of long run influence of the advisor on each director, $LongRunInfluenceAdvisorDirector_t$
$FundReturn_t$	Net return of the fund in year t.
$SdInfluenceAdvisorBoard$	Standard deviation, across the members of the fund board, of the measure of influence of the advisor on each director, $InfluenceAdvisorDirector_t$
$SdLongRunInfluenceAdvisorBoard_t$	Standard deviation, across the members of the fund board, of the long run influence of the advisor on each director, $LongRunInfluenceAdvisorDirector_t$
$TotalLoads_t$	Total fund loads (front, back and deferred) in year t
$YearsOfContact_t$	Number of years, up to year t, since the first connection between the director and the advisor of interest
$12b1Fees_t$	The fund's 12b-1 (marketing) fees in year t

Table II
Number of advisory firms managing mutual funds, by investment objective

Bond=fixed income funds. All other symbols refer to equity funds, as follows: **ACA & CA**=aggressive capital appreciation funds and capital appreciation funds; **G**=growth funds; **GI&I**=growth and income funds, as well as income funds; **TR**=total return funds. See Appendix for the detailed description of these investment objectives.

	Number of active advisory firms					
Year	Bond	ACA & CA	G	GI & I	TR	Total
1993	134	102	83	73	57	217
1994	299	303	189	199	140	538
1995	430	447	282	297	206	786
1996	468	511	338	346	232	892
1997	493	587	399	351	263	972
1998	525	641	428	388	274	1047
1999	479	656	443	390	303	1055
2000	511	736	491	399	314	1155
2001	481	712	481	374	290	1105
2002	469	735	479	364	318	1100

Table III
Summary of characteristics of advisory firms

Characteristics of advisors which won portfolio management contracts from mutual funds are shown in Panel A, and of all firm-observations used to estimate the conditional logit model of advisor selection are shown in Panel B. All characteristics are measured the year prior to hiring (i.e. at $\tau - 1$). All variables are defined in table I.

	Panel A Firms that won subadvisory contracts			Panel B All firm-observations used to estimate the subadvisor selection model		
Characteristic	Observations	Mean	Std. Dev.	Observations	Mean	Std. Dev.
$BoardAdvisorDegree_{\tau-1}$	257	48.357	108.306	194249	7.141	37.442
$BoardAdvisorDegree_{\tau}$	257	41.883	94.393	194249	5.552	28.257
$MeanInfluenceAdvisorBoard$	257	0.033	0.068	194249	0.001	0.006
$SdInfluenceAdvisorBoard$	257	0.016	0.038	194249	0.001	0.008
$MeanLongRunInfluenceAdvisorBoard$	257	0.036	0.075	194249	0.001	0.007
$SdLongRunInfluenceAdvisorBoard$	257	0.017	0.039	194249	0.001	0.008
$ContAdvisorCandidateDegree$	257	4.540	14.381	194249	0.063	1.503
$AdvisorDegree$	257	38.225	43.022	194249	13.210	22.074
$AdvisorAge$	257	4.797	2.331	194249	4.570	2.155
$AdvisorFractionFundsInCategory$	257	0.222	0.267	194249	0.146	0.269
$AdvisorLnAUMOverall$	257	15.036	2.094	194249	12.833	2.524
$AdvisorPerformanceOverall$	257	5.503	1.792	194249	5.576	2.374
$AdvisorAMROverall$	257	66.0	21.1	194249	76.9	29.1

Table IV

Predictors of advisors' success at winning portfolio management contracts

The Table shows the coefficient estimates from the conditional logit model of subadvisor selection in equation 1. Each fund looking for a subadvisor at time τ can choose among all the firms actively managing funds at $\tau - 1$. The dependent variable is a dummy equal to 1 for the fund — candidate subadvisor pairs that contracted with eachother at τ. All advisor characteristics are measured at time $\tau - 1$. Standard errors are adjusted for correlation among observations belonging to the same fund. All variables are defined in table I.

	Dependent Variable: dummy equal to 1 if the fund hired the candidate subadvisor			
Independent Variables	Panel A	Panel B	Panel C	Panel D
$BoardAdvisorDegree_{\tau-1}$	0.001			
	(1.90)*			
$BoardAdvisorDegree_{\tau}$		0.002		
		(2.76)***		
$MeanInfluenceAdvisorBoard$				22.873
				(11.80)***
$SdInfluenceAdvisorBoard$				-15.333
				(4.09)***
$MeanLongRunInfluenceAdvisorBoard$			21.778	
			(10.99)***	
$SdLongRunInfluenceAdvisorBoard$			-15.670	
			(4.19)***	
$ContAdvisorCandidateDegree$	0.048	0.046	0.006	0.007
	(5.43)***	(5.38)***	(0.88)	(1.16)
$AdvisorDegree$	0.011	0.011	0.011	0.012
	(6.14)***	(6.23)***	(6.37)***	(6.48)***
$AdvisorAge$	-0.131	-0.132	-0.129	-0.127
	(3.38)***	(3.41)***	(3.27)***	(3.21)***
$AdvisorFractionFundsInCategory$	1.322	1.324	1.240	1.199
	(5.41)***	(5.42)***	(4.86)***	(4.68)***
$AdvisorLnAUMOverall$	0.257	0.255	0.226	0.224
	(7.42)***	(7.37)***	(6.34)***	(6.27)***
$AdvisorPerformanceOverall$	-0.019	-0.019	-0.013	-0.020
	(0.56)	(0.56)	(0.38)	(0.58)
$AdvisorAMROverall$	-0.752	-0.752	-0.864	-0.830
	(2.47)**	(2.47)**	(2.74)***	(2.64)***
Observations	194249	194249	194249	194249
Pseudo R-squared	0.10	0.10	0.17	0.17

Absolute value of z statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table V

Determinants of yearly fund performance after the hiring of a new subadvisor

Pooled OLS regressions are estimated to examine the role of connections between fund directors and the newly hired *subadvisor* on subsequent fund performance. The three performance measures used are the fund net returns, alphas estimated from the CAPM and alphas estimated from the Fama-French four factor model, using monthly returns data from CRSP. All three measures are expressed in percentage points. τ denotes the hiring year. Standard errors are adjusted for correlation among observations belonging to the same fund. All variables are defined in table I.

	Dependent Variable		
Independent Variables	r_t	$alpha_t^{CAPM}$	$alpha_t^{FF}$
$BoardAdvisorDegree_{\tau-1}$	-0.014	-0.015	-0.004
	(3.04)***	(2.83)***	(1.84)*
$AdvisorFundsInCategory_{\tau-1}$	-0.026	0.002	-0.106
	(0.20)	(0.02)	(1.26)
$AdvisorFundsOverall_{\tau-1}$	-0.048	-0.031	-0.016
	(1.21)	(1.25)	(0.67)
$AdvisorLnAUMOverall_{\tau-1}$	0.936	0.528	0.870
	(2.52)**	(2.26)**	(3.14)***
$BoardSize_t$	-0.085	-0.133	-0.186
	(0.71)	(1.55)	(1.96)*
$FundLnTNA_{t-1}$	-0.239	-0.100	0.062
	(0.50)	(0.32)	(0.18)
$I_t^{ACA\&CA}$	-4.389	0.133	0.483
	(2.14)**	(0.09)	(0.31)
I_t^{G}	-7.610	-3.705	-1.942
	(3.22)***	(2.16)**	(1.02)
$I_t^{G\&I}$	1.026	0.595	-0.341
	(0.47)	(0.42)	(0.25)
I_t^{TR}	-6.390	-2.785	-2.221
	(2.39)**	(1.66)*	(1.86)*
$Foreign_t$	-4.857	-7.770	-10.789
	(2.74)***	(5.12)***	(6.94)***
$Index_t$	-1.504	1.964	-0.068
	(0.51)	(1.26)	(0.06)
$Constant$	5.642	-4.173	-10.751
	(0.81)	(0.92)	(2.17)**
Year fixed effects	Yes	Yes	Yes
Observations	583	583	583
R-squared	0.32	0.20	0.19

Robust t statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table VI
Determinants of yearly portfolio risk after the hiring of a new secondary advisor

Pooled OLS regressions are estimated to examine the role of connections between fund directors and the newly hired *subadvisor* on subsequent fund risk. The risk measures used are the CAPM beta, and the loadings on the four risk factors in the Fama-French model (Rm-Rf, SMB, HML and momentum). τ denotes the hiring year. Standard errors are adjusted for correlation among observations belonging to the same fund. All variables are defined in table I.

	Dependent Variable				
Independent Variables	β_t^{CAPM}	β_t^{Rm-Rf}	β_t^{SMB}	β_t^{HML}	β_t^{UMD}
$BoardAdvisorDegree_{\tau-1}$	0.0001	-0.0001	0.0009	-0.0001	-0.0004
	(1.43)	(0.50)	(2.07)**	(0.46)	(6.33)***
$AdvisorFundsInCategory_{\tau-1}$	-0.0006	0.0005	0.0025	0.0063	-0.0003
	(0.19)	(0.23)	(0.69)	(1.90)*	(0.14)
$AdvisorFundsOverall_{\tau-1}$	0.0017	0.0016	-0.0033	-0.0030	0.0001
	(1.66)*	(1.75)*	(2.67)***	(2.54)**	(0.11)
$AdvisorLnAUMOverall_{\tau-1}$	-0.0060	-0.0134	0.0098	0.0007	0.0093
	(0.72)	(1.61)	(1.06)	(0.07)	(1.62)
$BoardSize_t$	-0.0077	-0.0011	-0.0024	0.0043	0.0008
	(2.66)***	(0.36)	(0.68)	(1.10)	(0.30)
$FundLnTNA_{t-1}$	0.0036	0.0096	-0.0337	0.0289	-0.0136
	(0.26)	(0.74)	(2.56)**	(1.61)	(1.42)
Investment category dummies	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	583	583	583	583	583
R-squared	0.69	0.69	0.25	0.14	0.12

Robust t statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table VII
Summary statistics for the entire sample of U.S. open-end mutual funds, 1996-2002

Characteristics of all U.S. open-end mutual funds, 1996-2002. The panel data tracks 5936 individual funds. All variables are defined in table I.

Characteristic	Observations	Mean	Std. Dev.
AMR_t	15398	65.89	26.49
$ExpenseReimbursements_t$	15398	14.88	26.01
$FundReturn_t$	15398	4.01	18.23
$BoardAdvisorDegree_t$	15398	677.95	1084.86
$MeanInfluenceAdvisorBoard_t$	15398	0.51	0.31
$MeanLongRunInfluenceAdvisorBoard_t$	15398	0.52	0.30

Table VIII
Director-advisor connections and returns for all open-end U.S. mutual funds

Pooled OLS regressions are estimated to examine the role of connections between fund directors and the *primary* advisor on the fund net returns, for the entire sample of 5936 open-end U.S. mutual funds during 1996-2002. The dependent variable, $FundReturn_t$, is the annual net return (expressed in percentage points) of the fund calculated using data in the N-SARB filings. Standard errors are adjusted for correlation across observations belonging to the same fund. All variables are defined in Table I.

Independent Variables	Panel A	Panel B	Panel C
$BoardAdvisorDegree_t$	-0.001		
	(3.23)***		
$MeanInfluenceAdvisorBoard_t$		-0.973	
		(2.02)**	
$MeanLongRunInfluenceAdvisorBoard_t$			-0.949
			(1.94)*
$BoardSize_t$	0.046	-0.004	-0.004
	(1.82)*	(0.20)	(0.22)
$AdvisorFractionFundsInCategory_{t-1}$	-3.149	-3.141	-3.142
	(4.56)***	(4.57)***	(4.57)***
$AdvisorFundsOverall_{t-1}$	0.011	0.006	0.006
	(1.96)**	(1.17)	(1.15)
$AdvisorLnAUMOverall_{t-1}$	-0.315	-0.302	-0.300
	(2.87)***	(2.74)***	(2.71)***
$AdvisorPerformanceOverall_{t-1}$	0.025	0.036	0.034
	(0.27)	(0.39)	(0.38)
$FundLnTNA_{t-1}$	-0.366	-0.364	-0.364
	(4.32)***	(4.27)***	(4.27)***
$FundFamilySize_t$	-0.025	-0.033	-0.032
	(2.25)**	(2.76)***	(2.73)***
$I_t^{ACA\&CA}$	-1.420	-1.410	-1.410
	(3.89)***	(3.86)***	(3.86)***
I_t^{G}	-1.501	-1.440	-1.439
	(3.58)***	(3.43)***	(3.43)***
$I_t^{G\&I}$	0.277	0.329	0.327
	(0.71)	(0.84)	(0.84)
I_t^{TR}	0.726	0.717	0.723
	(1.63)	(1.61)	(1.63)
$Foreign_t$	-3.826	-3.808	-3.802
	(8.85)***	(8.80)***	(8.79)***
$Index_t$	-0.518	-0.555	-0.560
	(0.67)	(0.72)	(0.73)
$Constant$	23.041	23.616	23.596
	(13.72)***	(13.90)***	(13.91)***
Year fixed effects	Yes	Yes	Yes
Observations	15398	15398	15398
R-squared	0.239	0.239	0.239

Robust t statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table IX
Determinants of the advisory fee paid to new primary advisors

Pooled OLS regressions are estimated to examine the role of connections between fund directors and the new *primary* advisor on the advisory fee AMR_t ("applicable marginal rate") paid by the fund after the management change. The fee is expressed in basis points. τ is the year when the primary advisor was changed as a result of a takeover. Standard errors are adjusted for correlation across observations belonging to the same fund. All variables are defined in Table I.

AMR_t	Panel A	Panel B
$AMR_{\tau-1}$	0.897	0.902
	(12.75)***	(9.62)***
$BoardAdvisorDegree_{\tau-1}$	0.519	
	(7.56)***	
$BoardAdvisorDegree_{\tau}$		0.072
		(2.19)**
$AdvisorFundsOverall$	-1.069	0.019
	(6.67)***	(0.12)
$AdvisorLnAUMOverall$	1.782	-2.751
	(1.20)	(1.36)
$AdvisorFundsInCategory$	-0.536	-0.730
	(1.85)*	(1.27)
$BoardSize_t$	-0.027	-0.157
	(0.18)	(0.81)
$FundLnTNA_{t-1}$	-1.159	-0.891
	(1.91)*	(1.43)
Investment category dummies	Yes	Yes
Year fixed effects	Yes	Yes
Observations	106	106
R-squared	0.95	0.94

Robust t statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table X
Director-advisor connections and the advisory fee for all open-end U.S. mutual funds

Pooled OLS regressions are estimated to examine relationship between directors-advisors connections and the advisory fee, for the entire sample of 5936 open-end U.S. mutual funds during 1996-2002. The dependent variable, AMR_t, is the advisory fee paid by the fund in year t. Standard errors are adjusted for correlation across observations belonging to the same fund. All variables are defined in Table I.

Independent Variables	Panel A	Panel B	Panel C
$BoardAdvisorDegree_t$	0.001		
	(1.65)*		
$MeanInfluenceAdvisorBoard_t$		3.694	
		(3.49)***	
$MeanLongRunInfluenceAdvisorBoard_t$			3.109
			(2.84)***
$BoardSize_t$	-0.135	-0.109	-0.104
	(2.27)**	(2.31)**	(2.22)**
$AdvisorFractionFundsInCategory_{t-1}$	4.726	4.482	4.528
	(3.02)***	(2.88)***	(2.91)***
$AdvisorFundsOverall_{t-1}$	0.068	0.068	0.069
	(6.17)***	(6.40)***	(6.52)***
$AdvisorLnAUMOverall_{t-1}$	-2.534	-2.588	-2.587
	(9.94)***	(10.07)***	(10.02)***
$AdvisorPerformanceOverall_{t-1}$	0.043	0.021	0.028
	(0.35)	(0.17)	(0.23)
$FundLnTNA_{t-1}$	-1.337	-1.314	-1.319
	(6.95)***	(6.82)***	(6.84)***
$FundFamilySize_t$	0.026	0.061	0.055
	(0.99)	(2.22)**	(1.99)**
$I_t^{ACA\&CA}$	26.903	26.928	26.923
	(30.50)***	(30.62)***	(30.59)***
I_t^{G}	25.903	25.833	25.833
	(25.73)***	(25.60)***	(25.59)***
$I_t^{G\&I}$	13.335	13.213	13.232
	(12.42)***	(12.28)***	(12.31)***
I_t^{TR}	17.492	17.588	17.552
	(14.26)***	(14.31)***	(14.29)***
$Foreign_t$	14.223	14.194	14.176
	(14.13)***	(14.09)***	(14.08)***
$Index_t$	-35.398	-35.155	-35.178
	(26.53)***	(26.38)***	(26.38)***
$Constant$	100.698	99.045	99.315
	(25.93)***	(25.68)***	(25.79)***
Year fixed effects	Yes	Yes	Yes
Observations	15398	15398	15398
R-squared	0.369	0.370	0.370

Robust t statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table XI
Predictors of directors' success at winning the board seats of the funds newly created in 1998

The Table shows the coefficient estimates from the logit model of director selection in subsection A.2. For each new fund "born" in 1998, the potential candidate directors the fund advisor can choose from are all the directors actively overseeing funds anytime between 1993-1997, and who are also active at some time during 1998-2002. Directors already working for the fund company (cluster) that the newly born fund is a part of are not included. The dependent variable is equal to 1 for the fund-director pairs that successfully contracted with eachother in 1998, and 0 for all the other pairs. Standard errors are adjusted for correlation among observations belonging to the same fund. All variables are defined in table I.

	All newly created funds in 1998			Funds created by new fund companies		
Independent Variables	Panel A	Panel B	Panel C	Panel D	Panel E	Panel F
$DirectorAdvisorDegree_{1997}$	0.074			0.110		
	(1.99)**			(3.81)***		
$YearsOfContact_{1997}$	1.399	0.620	0.549	1.226	0.579	0.553
	(12.79)***	(3.19)***	(3.16)***	(8.38)***	(1.81)*	(1.84)*
$DirectorDegree_{1997}$	0.004	0.006	0.006	0.004	0.006	0.006
	(6.65)***	(18.22)***	(19.33)***	(3.65)***	(13.27)***	(13.42)***
$InfluenceAdvisorDirector_{1997}$		4.504			4.674	
		(8.19)***			(4.45)***	
$LongRunInfluence$ $AdvisorDirector_{1997}$			4.736			4.787
			(9.68)***			(4.97)***
$Constant$	-7.099	-7.288	-7.297	-6.912	-7.191	-7.187
	(60.08)***	(60.95)***	(60.21)***	(32.13)***	(30.41)***	(30.60)***
Observations	514855	514855	514855	133940	133940	133940
Pseudo R-squared	0.22	0.26	0.27	0.33	0.38	0.38

Robust z statistics in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table XII

Director-advisor connections and fund-advisor transfers for funds created in 1998

Pooled OLS regressions are estimated to examine the role of directors-advisors connections for the setting of fund-advisor transfers for the sample of funds created in 1998. AMR_t is the advisory fee the fund pays to its advisors (from NSAR-B data), $TotalLoads_t$ is the sum of front, back and deferred loads (from CRSP), $12b1Fees_t$ are the 12b-1 fees charged by the fund (from CRSP), while $ExpenseReimbursements_t$ represents the amount reimbursed by the advisor back to the fund (from NSAR-B data). All of these quantities are expressed in basis points. Standard errors are adjusted for correlation across observations belonging to the same fund. All variables are defined in Table I.

	Dependent Variable			
Independent Variables	AMR_t	$Total$ $Loads_t$	$12b1$ $Fees_t$	$Expense$ $Reimbursements_t$
$BoardAdvisorDegree_{t-1}$	-0.002	0.019	-0.000	
	(1.71)*	(1.91)*	(0.21)	
$BoardAdvisorDegree_t$				-0.007
				(1.83)*
$BoardSize_t$	0.418	3.978	-0.000	0.841
	(1.94)*	(1.82)*	(0.25)	(0.71)
$FundTNA_t$	-0.018			
	(2.64)***			
$FundLnTNA_t$		-20.058	-0.038	-36.694
		(2.54)**	(3.96)***	(6.72)***
$FundReturn_t$				-0.664
				(3.75)***
$AdvisorFundsOverall_t$	0.084	-0.588	-0.000	0.478
	(1.77)*	(1.17)	(0.58)	(1.53)
$AdvisorLnAUMOverall_t$	-3.104	27.805	0.019	-3.897
	(3.36)***	(2.91)***	(1.98)**	(0.61)
$I_t^{ACA\&CA}$	31.905	11.050	-0.006	-44.696
	(9.11)***	(0.25)	(0.10)	(1.78)*
I_t^G	23.715	-23.066	-0.084	-54.878
	(5.43)***	(0.47)	(1.41)	(2.19)**
$I_t^{G\&I}$	17.590	56.018	-0.003	-66.846
	(4.17)***	(1.00)	(0.05)	(2.37)**
I_t^{TR}	18.952	-31.734	0.013	-45.931
	(3.10)***	(0.45)	(0.15)	(1.62)
$Foreign_t$	10.425	11.878	0.003	-20.603
	(2.27)**	(0.27)	(0.06)	(1.15)
$Index_t$	-33.318	-43.287	-0.108	-15.921
	(6.46)***	(0.46)	(1.52)	(0.84)
$Constant$	99.570	-140.382	0.131	296.486
	(7.66)***	(1.05)	(0.95)	(3.40)***
Year fixed effects	Yes	Yes	Yes	Yes
Observations	586	638	638	638
R-squared	0.401	0.135	0.105	0.224

Robust t statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table XIII

Director-advisor connections and expense reimbursements for all open-end U.S. mutual funds

Pooled OLS regressions are estimated to examine relationship between directors-advisors connections and the expense reimbursements, for the entire sample of 5936 open-end U.S. mutual funds during 1996-2002. The dependent variable, $ExpenseReimbursements_t$ represents the expenses reimbursed back to the fund (according to NSAR-B data) by the advisor at the end of year t, expressed as a fraction of the fund's total net assets (in basis points). Standard errors are adjusted for correlation across observations belonging to the same fund. All variables are defined in Table I.

Independent Variables	Panel A	Panel B	Panel C
$BoardAdvisorDegree_t$	-0.001		
	(3.33)***		
$MeanInfluenceAdvisorBoard_t$		-1.996	
		(1.87)*	
$MeanLongRunInfluenceAdvisorBoard_t$			-2.839
			(2.56)**
$BoardSize_t$	0.164	0.065	0.070
	(3.16)***	(1.66)*	(1.81)*
$AdvisorFractionFundsInCategory_{t-1}$	2.637	2.659	2.733
	(1.68)*	(1.69)*	(1.74)*
$AdvisorFundsOverall_{t-1}$	0.015	0.006	0.007
	(1.27)	(0.49)	(0.60)
$AdvisorLnAUMOverall_{t-1}$	0.136	0.165	0.184
	(0.46)	(0.55)	(0.62)
$AdvisorPerformanceOverall_{t-1}$	0.013	0.036	0.035
	(0.10)	(0.27)	(0.26)
$FundReturn_t$	-0.135	-0.134	-0.135
	(10.45)***	(10.40)***	(10.41)***
$FundLnTNA_{t-1}$	-6.390	-6.385	-6.393
	(29.67)***	(29.63)***	(29.65)***
$FundFamilySize_t$	-0.040	-0.056	-0.065
	(1.95)*	(2.59)***	(2.95)***
Investment category dummies	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	15398	15398	15398
R-squared	0.196	0.195	0.196

Robust t statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%