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Social Networks in Finance

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To those who ran with enthusiasm

and were less fortunate than me.

Abstract

The main purpose of the present thesis is to shed light on the role of social networks in finance. The interest in this subject is motivated by the fact that social networks influence beliefs, choices and behaviors of agents. Moreover, nowadays financial markets are increasingly interdependent and financial actors are highly interconnected. Nevertheless, according with a traditional approach competition is a standard assumption modelling financial markets. Hence, this work was inspired by the scientific curiosity to investigate whether social interactions may be a channel of information exchange even in a financial context, if the financial choices can be influenced by networks and, what are the implications of social networks in finance.

In an attempt to answer these questions, we exploit the investment behaviors of U.S. mutual funds and the networks of their managers (defined using managers' biographical information).

More precisely, the first chapter is an introduction to social network: we briefly review the recent literature about this topic in finance and we discuss some challenges of these applications.

The second chapter explores whether the trading behaviors of fund managers are influenced by the behaviors of other managers belonging to the same social network (managers who have attended the same university). According to our results a manager is more likely to buy/sell a particular stock in any quarter if managers who belong to the same network do that. The effect turns out to be stronger when we restrict the group to managers graduated in the same year. Such results can be interpreted by the "word of mouth effect".

Other explanations such as same training or socio-economic backgrounds are possible.

Finally, the third chapter investigates the effect of social networks on mutual funds performance. We take advantage of the recent advances in the theoretical and methodological tools provided by social network analysis to examine the network properties. We find that managers' network have all the properties of a *small world* (as defined by Watts and Strogatz, 1998). Consistent with this, we provide empirical evidence that performance is higher for fund managers with many connections and if they are in a good network position.

Abstract (in Italian)

Lo scopo principale di questa tesi è quello di approfondire il ruolo dei network sociali in finanza.

L'interesse per questa tematica nasce dal fatto che i network sociali influenzano opinioni, scelte e comportamenti degli agenti. Non solo, i mercati finanziari oggigiorno sono sempre più interdipendenti e gli agenti che vi operano fortemente interconnessi. Tuttavia nell'approcio tradizionale la competizione è sempre stata un'assunzione standard nei modelli di mercati finanziari. Pertanto, questo lavoro è stato ispirato dalla curiosità scientifica di studiare se l'interazione sociale possa essere un canale di scambio di informazioni anche in ambito finaziario, se le scelte finanziarie possano essere influenzate dai network e più in generale quali possano essere le implicazioni dei network sociali in finanza.

Nel tentativo di dare una prima risposta a queste domande si è utilizzato un campione di fondi di investimento americani e i network dei manager che gestiscono tali fondi (definiti in base a informazioni bibliografiche).

Più precisamente nel primo capitolo si è introdotto il tema dei social network, discutendo la recente letteratura che in finanza si è occupata di tale argomento e menzionando alcune difficoltà applicative.

Nel secondo capitolo si è analizzato se le scelte di investimento dei manager dei fondi di investimento siano influenzati dai comportamenti di investimento di altri manager appartenenti allo stesso network sociale (ovvero manager che si sono laureati presso la stessa università). I risultati hanno evidenziato che un manager ha maggior probabilità di comprare/vendere una determinata azione in un determinato trimestre se i manager del suo

stesso network hanno fatto la medesima scelta di investimento. Questo effetto è più marcato quando la definizione di network si riferisce sia all'università frequentata che all'anno di conseguimento della laurea. Questi risultati possono essere spiegati dal fatto che manager dello stesso network si siano scambiati informazioni, oppure dal fatto di aver ricevuto la stessa formazione accaddemica o aver vissuto nel medesimo contesto socio-economico.

Infine, nel terzo capitolo, si è studiato l'effetto del network sociale sulle performance dei fondi di investimento. Lo studio delle proprietà dei network, mediante l'utilizzo della *social network analysis*, mostra che i network dei manager dei fondi di investimento, costruiti mediante le informazioni sulla formazione universitaria, hanno tutte le caratteristiche di un *small world* (secondo la definizione di Watts and Strogatz, 1998). In linea con questo risultato l'analisi empirica ha mostrato come le performance dei fondi sono significativamente più elevate quando i manager dei fondi hanno molte conessioni e una buona posizione nel network.

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Chapter 1

Introduction

Standard economic models do not cover mechanisms such as interaction effects and network ties and, more generally, the Homo Economicus is defined as an isolated individual. On the other hand, sociology *in primis* recognizes that people are essentially *social* creatures thus, nowadays there is a well-developed research on social network. But also other disciplines such as physics, mathematics or computer science, each one with its own peculiar approach, gives important contributions in social network theory. Yet, this does not imply that economic researchers have completely ignored social network.

In economics the attention for the social aspects of economic behavior is quite recent. In general researchers speak about *social interaction effect* every time that the actions of an individual depend on the actions of other individuals despite the absence of specific reasons to coordinate the actions. Hence, to include social interaction in economic models has been very useful in explaining a variety of settings such as job search, crime diffusion, adoption of new technologies, communication of information, consumers choices.

In the last decade also financial researchers start to pay attention to social network. This is due to the increasing interest for this topic in other disciplines but also to the high connectivity of financial markets. Indeed, today individuals, professional investors, companies, financial institutions are highly dependent on networks[1]. Thus, a theory of network can provide innovative, complementary or alternative interpretations to financial phenomena.

1.1 In search of social connections

Generally speaking social network is an interdependent social structure made up of "nodes", which are connected through ties. Nodes can be individuals, firms or other organizations, consequently ties can have different nature.

In finance a variety of actors have been used as nodes: individual investors, households, corporate executives and board members, analysts, companies, venture capitalists and, banks. Yet definition and measurement of links or relationships is always a difficult task (Jackson (2007)). In this field the existing literature adopts different approaches. To create connections among individuals some works emphasize the geographic dimension (Feng and Seasholes (2004), Ivkovic and Weisbenner (2007), Hong, Kubik and Stein (2005)), other works emphasize the existence of ties, created in the past, based on nodes characteristics. Some instances of social connections include sharing current employment position (Fracassi and Tate (2010)) or past employment history (i.e. Ishii and Xuan (2010)). Also, commonalities in education (undergraduate and graduate institutions) have been adopted as

[1]Information technology, globalization and increased mobility played a crucial role on it.

definition for social connections. Fracassi and Tate (2010), and Schimidt (2009) in order to create connections consider membership to the same non-professional organizations (e.g. golf clubs or non-profit organization). Instead, links among institutions are based on balance sheets (i.e. Furfine (2003)), coinvestment (i.e. Hockberg, Ljugquivist and Lu (2007)) or sharing other things (i.e. the same pool of depositors (Castiglionesi and Navarro (2007)).

In the future we think that other financial actors could be studied and new ways to define connections could be more pervasive than the definitions used until now. For example, the definitions of connection mentioned above do not allow to distinguish between *weak* and *small* ties, distinction widely used in social network theory, and to ignore this aspect in some context can lead to underestimate the role of social connections.

1.2 Applications

But what financial experts can learn from social network? Probably the most interesting aspects of this "framework" for researchers in finance, and economics as well, are that social network can first, influence behaviors, generating also contagion effects and, second, favour diffusion of informations. Thus, applications of social networks concepts are been introduced in different issues such as contagion, corporate finance, investment banking, microfinance[2]. In this section we review those studies that are more close to our work, concentrating our attention on the role of social network in investment behavior and the importance of social connections in corporate finance.

[2] Allen and Babus (2008) provide a review of this topics.

1.2.1 Social network in investment decisions

First, there are several works about social networks in investment decisions among *individual investors.* Hong, Kubik and Stein (2004) investigate the link between the households investment behaviors and social interaction and find that when households are socially active (namely whether they know their neighbors or attend church), they invest more frequently in the stock markets. Brown et al. (2008) provide evidences of causal community effect in individual's decisions of whether to own stocks.

Social interaction does not influence just the stock market participation. Feng and Seasholes (2004) find that Chinese individual investors show correlated trading behavior, particularly when they are close to each others[3]. Similarly Ivkovic and Weisbenner (2007) focus on the households' investment choices at industry level, they show that purchases of stocks are correlated among neighbors (households located within 50 miles). The propagation of financial information through social network has been investigated also by Kelly and O'Grada (2000), the authors find that Irish depositors during the two panics of 1954 and 1957 based their decisions of closing their banking accounting on peers' choices[4].

Social interactions may take place also among colleagues. Duflo and Saez (2002) find that university employees in the same department influence other's enrollment choices in savings plan. Similar results suggesting a social network effect are found in a randomized experiment where authors treat some departments and not others (Duflo and Saez (2003)).

Second, the role of social network has been investigated also among *institutional investors.*

[3]They exploit data on brokerage office location.

[4]Here the reference group, those people that had come from the same county in Ireland, is formed in the past.

Hong, Kubik and Stein (2005) analyze the trading behavior of mutual funds when fund managers are in the same city or in other cities. Their evidence suggests a link in the trades of a certain manager with the trades of other managers in the same city. These results are interpreted in term of communication among managers located in the same city. On the other hand, it could be that the communication exchange takes place with local board of directors or that managers herd at city level for carrer-concerns.

Cohen, Frazzini, Malloy (2008) study the social network of mutual fund managers with board members. They find a relation between holdings stocks and social connections, moreover these investment positions have higher returns. They conclude that fund managers have social networks exploited as a learning opportunity.

1.2.2 Social connections in corporate finance

In this subsection, we consider what the social network has to say about corporate governance, capital structure, and merger activity.

The role of social network has been investigated in management *within* firms[5]. Fracassi and Tate (2010) find that, in presence of powerful chief executive officers, new directors are appointed more frequently in case of preexisting social connections with the CEO, moreover the presence of social connections reduce board monitoring in a way that directors, connected by previous ties with CEO, do not oppose to non profitable investment decisions. Similarly, Nguyen-Dang (2005), using French data on some colleges (Grandes

[5]Probably the attention for this topic comes from research on interlocking directors and board independence. Indeed, one of the first work on this topic was Hwang and Kim (2009). They extend the definition of dipendent directors to those directors that have in common with CEO: military service, mutual alma mater, academic discipline, same industry of primary employment, place of birth, indirect connection with a third director. Their evidences show that "socially" connected directors matter for CEOs' compensations, pay-performance conmensation and turnover.

Ecoles), well known for their exclusivity and selectivity, find that connections between CEOs and directors protect a CEO from being fired in case of poor performance and, in case she is fired, connections guarantee better job opportunities.

A clear evidence of the effect of connections on executive appointments is proposed by Berger et al. (2010). They compare the appointments of outsiders and insiders, they find that outsiders are more likely to be hired when they are connected with executives. They also investigate the carrier path and they find that connections in the banking industry increase the probability of repeated appointments.

Interestigly, connections among board of directors and executives are important also *across* companies. Acquisitions are more likely to occur between two firms that are well-connected to each other through social ties between top managers and directors Ishii and Xuan (2010). Similarly, in Fracassi (2009) the presence of social connections among top key executives or directors of two companies lead to more similar investment policy, CEO compensations and other decisions (in particular cash reserves and interest coverage ratios). Presumably, connections are sources of information exchange via word-of-mouth communication.

1.3 The value of social connections

One more important aspects is that some individuals and organizations may take advantage from social connections or networks structure. In principle social ties could seem useful as source of knowledge and information exchange. So some works document a positive effect (Cohen et al. (2008)). Also analysts seem to have an information advantage in their recommendations for connected stocks (Cohen et al., 2010). Connections have a positive effect also in Hockberg, Ljugquivist and Lu (2007), they investigate venture capitalists performances and find a significant and positive impact of VCs network positions.

Yet, social ties in financial decisions are not always profitable: for example Ishii and Xuan (2010) study the role of social ties between the top managers and directors of the two merging firms. The authors find that social connections between an acquirer and a target have a negative impact on merger performance. And the mergers are more frequently bad investments in the presence of strong social connections in time, leading to divestment choices by the acquirer. As we mentioned before also in corporate governance connections between executives and directors are negative because, for example, they can weaken the monitoring role of boards. Instead, Schimidt (2009) documents that this is not always the case: when the advisory role of the board is necessary, connections have a positive impact on firm's performance, on the other hand, when the monitoring role is required, connections destroy value.

Probably the main lesson from these works is that there isn't a univocal answer to the value of social connections but it depends case by case. So more contributions on the goodness of social connections would be interesting.

1.4 Future research

In this chapter we provide a brief introduction to social network and its financial consequences, giving a general flavour on how networks provide useful tools and suggestions to understand the complexity of financial system. In chapter 2 we investigate the presence of social effects in trading behaviors among mutual funds. In chapter 3 we study the network structure and the impact of network positions on fund performance.

Still, we believe that interactions among financial actors are playing new and not completely understood roles. In particular network structure and its implications are not yet fully explored and could be exploited in a variety of settings. A better understanding of the role played by social network can be helpful also in policy intervention. As a matter of fact empirical works on social interaction effects have to face a significant challenge: the social structure is endogenous and peers usually share many characteristics. This introduces significant difficulties in having clear tests of network effect.

At the same time theoretical models in finance could benefit from recent advancement in decision theory and game theory.

Thus more works are needed in this appealing research area.

Chapter 2

Same College Similar Investment Decision

2.1 Introduction

Available information is a crucial factor in economic and financial decisions. Kahneman and Tversky (1979) claimed that humans do not behave rationally when they have to decide between alternatives that involve risk, as, for example, in financial situations. Hence other elements such as education level, cultural factors, social capital, knowledge of an investment's past performance and recent news events, genes, age, gender, and even emotions or feelings can be important in the decision making process. In this paper we focus on investment decisions and investigate the possibility that trading behaviors are influenced by a further element: *social interactions.*

In 1984 Shiller wrote: "investing in speculative assets is a social activity. Investors spend a substantial part of their leisure time discussing investments, reading about investments, or gossiping about others' successes or failures in investing". Our study provides some empirical evidence in this direction. We focus on how mutual funds investment decisions are related to investment decisions of "peer" fund managers. We exploit data on portfolio holdings, in this way we can study both correlation in portfolio holdings and trading behaviors.

Financial market is usually seen as a setting highly competitive where agents just maximize their own utility and most information is conveyed through prices. So why should managers exchange information and opinions?

Fund managers use several sources to collect information and they have the support of research departments, powerful computers and fancy software. Yet, information about assets is disperse and difficult to identify, initial endowment is limited, the acquisition process is costly, and there is a huge number of stocks with similar characteristics among which to select. On top of that human mind is limited, there are several constraints in information processing (Marois and Ivanoff (2005)) and attention is scarce (Kahneman (1973)). The fact that we deal with professional investors, often named as sophisticated investors, with a specific training, does not avoid at all these limitations[1]. Hence, personal contacts and other network activities could be a useful way to exchange information though a direct transfer from a fund manager to another[2]. Social interaction can take place in

[1]For example Frazzini (2006) documents the existence of the "disposition effect" and the under reaction to news among mutual fund managers; Cohen et al. (2008) find that fund managers exhibit limited attention about their holding stocks ignoring news about economically related news.

[2]Evidence of social interactions among mutual fund managers is provided in two surveys: one conducted among U.S. fund managers (Shiller and Pound (1989)), the other one among German fund managers (Dratcher, Kempf, and Wagner (2007)). In both cases the results suggest that traders exchange information with other people and particularly with colleagues in the mutual fund industry.

different ways: traders may differ in the information they have access to, so an exchange would be mutually advantageous. Ozsoylev (2005) considers a theoretical model in which traders interact with the other traders and they exchange and learn information, this process is defined as "social influence". Traders can truthfully reveal their own information or they can diffuse non-perfect information, adding noise to their private signals. Even a simple chatting about companies could be just a way to drive attention on a particular stock company, although no useful information is revealed[3].

Nevertheless word-of-mouth communication is not the only channel for the information transmission. Previous theoretical works point out that "observational learning", the influence resulting from processing information, gained by observing others (Bikhchandani et al. (1998)), induces people to do what others are doing[4]. For example, in Ozsoylev (2004) traders learn from others' actions (asset demands).

In both cases the "goodness" of information transmission among traders will depend on the relation or the proximity of one manager to another. So a crucial point about empirical works on social interactions is how the reference group or the network is defined. Previous studies exploit data on coauthorships, e-mails, webpages, surveys or interviews; these methods cannot fully capture network. As a matter of fact people have hundreds of relationships changing over time and with different importance. Ideally we would like to know who are the people with whom a mutual fund manager exchanges relevant information for her portfolio decisions and investment strategies, but unfortunately we do not have such

[3]Chapter 3 can be seen as an attempt to study this point.

[4]Different models investigate social learning (i.e. Banerjee (1992), Bikhchandani et al. (1992), Ellison and Fudenberg (1993 and 1995)), while empirical evidence is more rare given some difficulties in the identification strategy.

data.

We exploit data on managers biography and the information on education. More precisely we consider that two managers are connected if:

- they attended the same academic institution and gained the same type of degree (*network-a*);
- they attended the same academic institution, gained the same type of degree and they graduated in the same or previous or following year (*network-b*).

Of course fund managers have many relationships that, in different ways, could be useful in their professional activities and the ones created during the college years are just a part of those. Yet, university offers many opportunities to make friends and high levels of time are devoted to social activities, mostly in US where, often young students move away from their families and high-school friends. So college is a good place where to develop social networks and relationships. These connections are created in the past, but after graduation people may maintain direct or indirect relationships, and after years they may still belong to the same "social circle". Moreover, reunions or internet technology are very useful to carry on interpersonal contacts. Wellman et al. (2001) claim that online interactions may supplement or replace in-person interactions. Even the social network sites allow to establish or maintain connections with others, particularly with those in the same college community (i.e. Facebook.com or LinkedIn.com[5]).

Our article is not the first work to consider academic institutions as connections: this

[5]Facebook was initially founded as a college community and also in the current version users can join networks organized by school and college. Instead LinkedIn is mainly a professional network but users often list their education as well.

"type" of tie has been used by the sociology literature and more recently even in finance. Thus, information on education have been used for funds managers (Cohen et al. (2008)), executives and board of directors (i.e. Fracassi (2008)), analysts (Cohen et al. (2008)) and politicians (Cohen and Malloy (2010)).

Our paper contributes to the literature on social interaction in investment behavior. We follow an empirical approach similar to Hong, Kubik and Stein (2005). First, we provide empirical evidence of correlated portfolio holdings among fund managers in the same academic network. Second, we find that the academic connections affect also active buying and selling decisions. We perform a number of robustness checks: in particular we find that this effect is stronger when we consider the more restrictive definition of network (network-b). Third, we investigate social interactions using herding measures.

We explain our results in term of the word of mouth effect, but the particular way in which we define connections among managers and the impossibility to solve the reflection problem suggest other possible interpretations. People, who attended the same university, could have similar investment behaviors because they had the same training or they shared a priori similar preferences.

The rest of the paper is organized as follow. Section 2 explores the literature related to social interaction in investment decisions. Section 3 describes the data and 4 illustrates the econometric methodology and its limitations. Section 5 presents the results and contains alternative explanations for our findings. A brief conclusion follows.

2.2 Related literature

In the following we describe briefly where we see the position of this work within existing fields of research.

First, our work is related to the literature that documents the effect of social interactions on investment decisions: stock market participation (Hong, Kubik and Stein (2004) and Brown et al. (2008)) and stock picking (Ivkovic and Weisbenner (2007) and Feng and Seasholes (2004)). Looking at professional investors Hong, Kubik and Stein (2005) study the investment decisions among manager in the same city using two years of data. Differently, our definition of network is related to education and we use data for twelve years. Investment behaviors are analyzed also in Cohen, Frazzini and Malloy (2008), but they focus on ties between fund managers and board of directors or executives.

Second, our work is close also to the literature of "proximity investment". The anomaly of local bias has been firstly documented by Coval and Moskowitz (1999), they find that US portfolio managers invest mainly in companies whose headquarters are near their cities. Also, Hiraki et al. (2001) show a similar pattern among Japanese institutional investors. Similarly individual investors bias their investment in favour of local securities (Zhu, 2002) or near to corporate headquarters (Grinblatt and Keloharju (2001)[6]). Other works about portfolio allocations focus on "professional proximity". Huberman (2001) find that shareholders of Regional Bell Operating Companies live in the areas that companies serve.

Such behavioral biases in financial decisions have been explained with an easier access to

[6] They find that also the language of communication with stakeholders and the company's CEO's cultural origin contribute to explain Finnish households' stock investments.

information for "close" assets and interpersonal communication.

Finally, a related strand of literature investigates correlated trading. Many works, both theoretical and empirical, focus on herding behavior[7] and such phenomenon have been documented both among institutional and individual investors (i.e. Grinblatt, Titman and Wermers (1995) and Choe, Kho and Stulz (1999)).

2.3 Data

Thompson maintains data of mutual funds equity holdings, originated from mandatory filing of each U.S. registered mutual fund with the Security Exchange Commission. This allows us to identify the portfolio compositions and trading decisions of mutual fund managers. We use the manager profile data to identify: the academic institution, the type of degree, and the year of graduation. We collect those information mainly from Mornigstar Principia CD-Rom, when data were missing we consulted some web sites such as sec.info, funds website, zoom.info.

The data source for funds information is the Survivorship-Bias-Free US Mutual Fund Database provided by the Center for Research in Security Prices (hereafter CRSP). CRSP reports various data about funds; we collect information about fund family and location. We merge Mornigstar data and CRSP data with the Ticker number; for all funds that do not have a match we merge those manually looking at the name (otherwise those funds were deleted).

Data about stocks is obtained from the CRSP data files, accounting data is from

[7] For a comprehensive survey on this topic see Hirshleifer and Teoh (2003). Lately, herding behavior has been tested in laboratory using college students or financial professionals as subjects.

COMPUSTAT, and analysts recommendations from IBES.

We limit our analysis to funds managed by a *unique* manager, in a way that there is just one decision-maker (it is important to test our hypothesis). We further restrict the sample considering just those funds with an active investment style: Growth, Aggressive Growth, Growth & Income, Income. We restrict our period of observation from 1996 to 2007.

Summary statistics are shown in table A. In each quarter we have around 600 funds that correspond to 434 managers, indeed some managers manage more than one fund. Around 70% of managers have also a graduate degree. For graduate studies there is a stronger concentration among a limited number of institutions than for undergraduate studies. Information about the year of graduations is not available for all managers (27%).

<<Table A approximately here>>

2.4 Methodology

In our empirical approach we follow the methodology used by Hong, Kubik and Stein (2005). We begin testing the existence of correlation in holdings and then in holdings changes.

2.4.1 Holdings

We compute the fractional share of fund j invested in stock i in quarter t, $h_{j,i,n,t}$. Each fund is managed by a manager, who belongs to a network n. Then, we define $h_{j,i,NET-m,t}$ as the equally-weighted average across all funds in network n in stock i[8] in

[8]The average output of the group is the usual specification in the literature on peer effects, but other specifications are possible.

quarter t. Of course computing $h_{j,i,NET-m,t}$ we exclude manager m. We need to consider also the behavior of all other funds. We indicate $H_{ALLFUNDS,i,t}$ as the equally-weighted average across all funds of the shares invested in stock i except for the manager herself.

We are now ready to present our empirical specification:

$$h_{j,n,i,t} = \alpha + \beta h_{j,i,NET-m,t} + \zeta H_{ALLFUNDS,i,t} + \varepsilon_{j,n,i,t} \tag{2.1}$$

This regression captures similarities in *holdings* for funds in the same network after controlling for the average trading behavior of the entire mutual funds sample.

The null hypothesis is that network is not an important dimension for stock picking, i.e. $\beta = 0$. Differently, $\beta > 0$ means that managers, who study together, have more similar holdings positions than the rest of the market (among mutual funds).

Equation 2.1 excludes observations for which a given manager m in a quarter t is alone in her own network (namely she does not have any connection both for undergraduate and graduate studies).

2.4.2 Holdings changes

We then investigate the managers trading behavior to see if it is clustered over networks. Equivalently to equation 2.1 we compute the change in a given stock for the average manager in the same network and the average change for all mutual funds in the sample.

First we measure a manager's change in a given stock by the change in its relative weight in her portfolio as

$$\Delta h_{j,i,t} = \frac{(shares_{i,j,t} - shares_{i,j,t-1})p_{j,t}}{\sum shares_{i,j,t}p_{j,t}} \tag{2.2}$$

$shares_{j,i,t}$ and $shares_{j,i,t-1}$ are respectively the number of shares hold by fund j invested in stock i in quarter t and quarter $t-1$; $p_{j,t}$ is the price of stock i in quarter t. So $\Delta h_{j,i,NET-m,t}$ is the fractional share of manager m invested in stock i. Similarly we compute the equally-weighted average across all funds in network n except manager m in stock i as $\Delta h_{j,i,NET-m,t}$. $\Delta H_{ALLFUNDS,i,t}$ is defined as the equally-weighted average across all funds of the shares invested in stock i except for the manager herself. Notice that this measure does not depend on the change in the price of the asset over the considered quarter.

Our econometric regression for changing in holding is defined in this way

$$\Delta h_{j,n,i,t} = \alpha + \beta \Delta h_{j,i,NET-m,t} + \zeta \Delta H_{ALLFUNDS,i,t} + \varepsilon_{j,n,i,t} \tag{2.3}$$

Similarly to the regression for holdings we want to test if $\beta > 0$, namely whether fund managers in the same network exhibits similar *trading behavior* after controlling for the trading of all funds in our sample. The alternative hypothesis, i.e. $\beta = 0$, implies that a manager in network n does not trade in way that is correlated with other managers in the same network.

An observation to be in our sample needs to have shares at least in one of two consecutive quarters (namely we exclude those observations with zero holdings for fund j in stock i in time $t-1$ and time t: $shares_{i,j,t} = shares_{i,j,t-1} = 0$). Running equation 2.3 we exclude those funds that are in the sample in time t but disappear the quarter later.

We run all regressions from March 1996 to December 2007.

Before to move on the empirical results we need to make some remarks about our econometric specification. It suffers from a so called "reflection problem", that we explain in the next paragraph.

2.4.3 Econometric issue

The econometric issue that rises when we estimate social interaction is formally described by Manski (1993). In this section we abandon our notation to follow Manski one's.

The problem can be formalized in the following way:

$$y = \alpha + \beta E(y|x) + E(z|x)'\gamma + z'\eta + u \tag{2.4}$$

where y is a generic outcome, x represents some attributes characterizing an individual's reference group, and z are all other attributes that affect y. $\alpha, \beta, \gamma, \eta$ are the unknown parameters that the researcher will estimate.

Given that $E(u|x) = x'\delta$ we can rewrite eq. 2.4 as

$$E(y|x, z) = \alpha + \beta E(y|x) + E(z|x)'\gamma + z'\eta + x'\delta \tag{2.5}$$

According to this formulation individuals in the same group tend to behave similarly because of:

- *Endogenous* social effect, individual behavior varies with reference group behavior ($\beta \neq 0$);

- *Exogenous* social effect, individual behavior varies with mean group composition, namely exogenous characteristics of the group ($\gamma \neq 0$);

- *Correlated* effect, agents in the same group tend to behave similarly because they have similar individual characteristics or face similar institutional environments ($\delta \neq 0$).

To clarify the reflection problem we prefer to expose this issue with a more intuitive case about peers effect in students achievement. This example is well known and used in many applications as attempt to solve the reflection problem. The object of interest is the propensity of students grades to depend on the average grades of other students in the reference group[9] (endogenous effect). Yet students achievement depends on shared characteristics like ethnicity or economic status of the reference group (exogenous effect). Finally students grades are related to the achievement level of the reference group because they are taught by the same teacher (correlate effect). So other characteristics, not available to the researchers, in part can cause neighborhood effect. Moreover there is a selection problem whenever smart students choose high ability students as peers.

Clearly sources of the exogenous effects and the correlated effects depend mostly on the application. In any case the problem with specification like the one in eq. 4 is that the unknown parameters are not identified, specifically it is not possible to distinguish these three effects (Manski (1993)).

[9]The reference group can be classmates (i.e. Graham, but many other works use this definition), students in the same section (Arcidiacono et al. 2009) or roommates (Sacerdote, 2001).

2.4.4 The identification of social interaction

The challenge of this identification problem in social interaction have been addressed by several empirical studies. One possibility is to exploit randomization, that allows to create independent variation in a key variable. This is the usual approach in field experiments (i.e. Duflo and Saez (2003)), lab experiments (i.e. Falk, Fischabcher, and Gächter (2003)) or, more rarely, whenever data allow that (i.e. Sacerdote (2001)).

An alternative solution is to exploit exogenous shocks that affect some individuals directly and, affects the others only through the endogenous social interaction (Moffitt (2001)); a good example is the application by Cipollone and Rosolia (2006).

A different approach is to use longitudinal data: Arcidiacono et al. (2009) show that is possible to infer parameters of the exogenous effect even in presence of correlated effects when a panel data is available. Yet, this method does not allow to estimate β, namely the endogenous effect.

Moretti (2010) circumvents this problem and, studying box-office sales dynamics, estimates social learning. His model regards the diffusion on information following surprises in movies quality.

Now we go back to our empirical specification (eq. 1 and 2). Remember that we want to investigate how the portfolio holdings (and changes in holdings) of a manager is influenced by her peers trading (pure endogenous effect). The limit of estimation beta is that the similarities in portfolio holdings among managers in the same networks may be due to not only information exchange. Other factors such as sharing some common attributes, relying on similar sources of information, correlation in their preferences could be important.

Moreover our estimation could suffer from confounding effects whenever managers in the same network are exposed to a similar institutional environment (i.e. to work for similar type of fund), or they are subject to the same shocks.

Unfortunately in our data we do not have neither randomization or shocks. The fact that we have a panel data with a long time series is not very helpful as well (Arcidiacono et al. (2008)). Even the methodology to identify social learning proposed by Moretti is not appropriate in our setting. So, given our data, we cannot solve the reflection problem but, as we will point out in the next section, even if we are not able to disentangle the different channels of social interaction, to show that managers, who studied together, trade in a similar way is still an interesting result. We will discuss this point deeply when we will interpret our findings.

2.5 Empirical results

2.5.1 Holdings

Before to focus on our results we need to explain briefly the role of *fund families*. Funds are usually organized and affiliated to a fund family. So funds belonging to the same fund family often share the research department collecting information about the fundamentals of the markets and, exploiting economies of scale. But for fund families is not optimal to follow a specialization strategy: intra-family funds don't have the same portfolios and investment strategies[10]. Nevertheless in the last decade the number of funds increased a lot, usually when a new fund is created in a fund family, it is different from the previous ones

[10]For example Massa, Matos and Gaspar (2006) find that funds in the same family show opposite trades in order to cross-fund subsidization.

(for example the new fund will be in a different investment style and objective category), in order to attract investors with different needs and preferences (Mamaysky and Spiegel (2001)). Even thought the trading strategies in a family fund can be quite different the research information used is in part the same and we are aware that correlation in trading behaviors in a network could be driven by a "family effect". Thus we follow a conservative approach and, creating each manager network, exclude peers belonging to the same fund family.

The results about holdings are presented in table A.2. In the regressions 1 the coefficient β_{NET} is positive and significant after controlling for the holdings of the other funds. Therefore a one percentage point increase in the average weight of a stock within a network leads an increase of 0.13% in the portfolio weight of stock i by manager m.

Some funds could concentrate their investments towards few industries, because managers could expect that some sectors will outperform the market in a specific period or because they have an information advantage for a particular sector[11]. Consequently in regression 2 we control for stock industry (2 digits that implies 70 sectors, controlling for a small numbers of industries does not imply a big difference[12]).

Since people group objects into classes according to some common features, they tend to think and behave using categories (Mullanaithan (2002)). This mechanism is widespread also in financial market where investors need to decide across many assets. Previous literature (i.e. Bernstein (1995)) shows that investors allocate resources following a specific

[11] Actually Kacperczyk, Sialm and Zheng (2005) show that there is a large variation in portfolios' industry concetration across funds. They also provide robust evidences that funds with concetrate portfolios exhibit higher performances than funds with well diversified holdings.

[12] The definition of 12 industry groups based upon SIC codes is obtained from Kenneth French's website. Reg 4 implies $\beta_{NET} = .1362$ SE(0.0010)

investment style. For this reason we add as controls some characteristics of assets: market capitalization, book-to-market ratio and return momentum over the prior twelve months. As in Hong, Kubik and Stein (2005) we create 5 dummies for each characteristic for each quarter. Moreover we control for the investment style of each fund according to the category defined by the Investment Company Data Inc. (ICDI)[13].

Even with all these controls β_{NET} does not show a big change and it is still statistically significant: a one percentage point increase in the average weight of a stock within a network implies an increase of 0.12 for a managers portfolio. As we expect, the portfolio weight of a particular stock in the overall sample of funds is highly statistically significant and it explains a good part of the endogenous variable. In all regression we use as definition network-a in computing $h_{j,i,NET-m,t}$; in regression 6 we calculate the social interaction effect as in network-b (we add as requirement the year of graduation). The coefficient on average network stock ownership is 0.13, which is slightly bigger than the one in regression 5.

<<Table A.2 approximately here>>

So according to our results investors in the same network seem to hold more similar portfolios than the rest of the funds. But our main interest is on trading behavior, that we test in the next paragraph.

[13] This classification is usually considered quite vague to be really informative, for this reasons we compute also the assets characteristics.

2.5.2 Change in holdings

To look at trading behavior, that implies active choices (buy or sell) done by the fund managers, is more informative rather than to use a static measure like the portfolio holdings. Portfolio changes are, or at least should be, information driven, hence such data is a better test for studying the effectiveness of network.

The results are reported in table A.3. In Reg1 we test the simpler version in (2). We find that a one percentage point increases in the average weight of all fund managers in the same education network n of stock i leads to an increase of 0.9% in that stock for a particular manager m. After all controls, that we describe in the previous section, the increase is 0.8%, still positive and statistically significant.

As a robustness check in specification we use the Fama-MacBeth method. In the first stage we run the regression for each quarter then, we compute coefficients and t-statistics by averaging the results across all quarters. This approach gives a similar value for our coefficient β.

Then, in Reg6 we use our alternative definition of network (network-b). We drop observations for which managers have no peers (that is why we have a lower sample for this regression). As for the portfolio holdings we find that the impact of other funds in the same network is higher ($\beta = 0.10$) than when we use network-a.

<<Table A.3 approximately here>>

We provide alternative specification of our baseline, results are shown in table A.4. We do not know to which information an investor has been exposed but we can control for the response to public information. As proxy we use the average analyst stock recommendation (meanrec). Results in Reg1 show that still there are correlated trading behaviors among managers in the same network.

In Reg2 and 3, we run our baseline specification considering respectively the subsample of buys and sells. Given that we show that the portfolio holdings are similar in the same network we would expect that the coefficient for sells than for buy. Instead we find the opposite results: similarities in trading behaviors concern more the buying choices.

It is more likely that analysts and media follow large companies than smaller enterprises. So it is more easy to get common information for large companies. In each quarter we split the stocks in three categories according to the market capitalization, we report results for mid- and large-cap. Results for Reg4 and Reg5 suggest that the coefficients are not very different in the two subgroups.

In the probit regression (Reg6) the dependent variable is equal 1 when a fund purchase a stock i in quarter t (and did not own i in the previous quarter), otherwise it takes the value of zero.

Next, we focus on close stock companies, to take into account the local bias phenomenon. Reg7 and Reg8 suggest that managers rely more on network's opinion and ideas for distant firms[14]. If for local firms the information asymmetry is lower (Coval and Moskowitz (2001)), it might be that exchange of opinions with others is a substitute of private information whenever the searching process is more costly.

To run regression 9 we split the dependent variable $\Delta h_{j,i,NET-m,t}$ in two components.

[14] To classify stock companies we look at the *census region*: a stock i is local (distant) respect to fund f if both are located in the same region.

First, we collect data on funds location, in a such way that each manager belongs to a city. Second, we divide the peers group for manager m in two groups based on their cities. We define $\Delta h_{j,i,NET-m,t,=\mathrm{City}}$ as the equally-weighted average across all funds in network n and in the same city of manager m in stock i. $\Delta h_{j,i,NET-m,t,\neq\mathrm{City}}$ is the equally-weighted average across all funds in network n and in different city of manager m in stock i. In both computations we exclude manager m. Both coefficients are positive and statistically significant but when we consider peers in the same city the magnitude is higher. This finding is consistent with the empirical evidence in Hong, Kubik and Stein (2004).

We also try a different definition to measure the social network effect. We compute $\Delta h_{j,i,NET-m,t}$ as a average, weighted by the assets under management of each managers across all funds in network n. We find that beta is 0.09, this could suggests that managers exchange information with the best colleagues. But it could be just an imitation effect or, maybe, a combination of both explanations.

<<Table A.4 approximately here>>

2.5.3 Herding behavior

To evaluate social interaction we consider also *herding*.

In general herding in this context is defined as the extent to which a group of investors either mostly buys or mostly sells the same stock at the same time (Grinblatt, Titman and Wermers (1995)). We follow Lakonishok, Shleifer and Vishny (1992) to compute the Unsigned Herding Measure (UHM) in order to measure the herding extent of fund managers in period 1996-2007. The UHM measure is defined as follows:

$$UHM_{it} = |p_{it} - \bar{p}_t| - E\,|p_{it} - \bar{p}_t| \tag{2.6}$$

where for each quarter t and each stock i $p_{it} = \frac{B_{it}}{B_{it}+S_{it}}$. B_{it} (S_{it}) is defined as the number of investors in the subset who buy (sell) The the total number of funds who buy or sell stock i in quarter t is defined with N_{it} ($B_{it} + S_{it} = N_{it}$).

$\bar{p}$ is the expected proportion of funds that buy a stock in a specific quarter, namely it is the average of p_{it} over all stock i that were traded in quarter t, mathematically

$$\bar{p}_t = \frac{\sum\limits_{i}^{I} B_{it}}{\sum\limits_{i}^{I} N_{it}}$$

The second term in equation 2.6 is an adjustment factor, and it follows a binomial distribution, so it is computed as

$$E\,|p_{it} - \bar{p}_t| = \sum_{x_{it}=0}^{N_{it}} |p_{it} - \bar{p}_t| * \Pr(X_{it})$$

The subtraction of this term normalizes the UHM measure and it is calculated under the null hypothesis of herding only by random chance:

$$\Pr(X_{it}) = \begin{bmatrix} N_{it} \\ \\ X_{it} \end{bmatrix} * \bar{p}_t^{X_{it}} * (1 - \bar{p}_t)^{(N_{it} - X_{it})}$$

For a more detailed description of this measure see Lakonishok et al. (1992) or Wermers (1996).

We compute this measure for each stock-quarter for the overall measure, $UHM_{Overall}$.

Then we calculate the measure for each stock-quarter and network, defined as UHM_{Net}. This allows as to evaluate how managers that are part of the same network trade in the same direction. As before we consider two managers connected when they attended the same institution and gained the same degree (network-a)[15]. UHM is meaningful only if a certain number of funds trade in a stock during a quarter (in a given network). The cutoff value for the number of trades is 5. If each fund independently sells (or buys) a particular stock at quarter t with probability $\bar{p}_t$, then p_{it} tends to $\bar{p}_t$ and, the first part of eq. 5 will be almost 0. It takes a larger value when funds *together* sells (or buys) a particular stock at quarter t (p_{it} deviates from $\bar{p}_t$).

2.5.3.A Results

Table A.5 shows the average trading behavior by number of trades: for example the value of the forth raw is computed after averaging the value UHM of across all stock-quarters-network having non-zero net trades for at least seven funds.

A larger UHM indicates a greater degree of herding. The average herding measure at network level is 2.76, it is very close to that found by Lakonishok et al. (1992) for a sample of pension fund (2.7 percent), but lower than the 3.4 percent reported by Wermers (1995). Instead the overall mean for UHM is 4.0, this value is quite similar to the value found by Wermers (1999) on mutual funds; even thought he used a different sample[16]. This value is greater than the one computed at network level, so this result would imply that herding is

[15] I could not consider also the year of graduation otherwise I would have too few trades applying the herding measure.

[16] The period is different: from 1974 to1994; plus he included not only funds with a stated investment objective of "Aggressive Growth", "Growth", "Growth & Income" and "Balanced or Income", but also, those classified as "International", "Metals" and "Veture Capital".

lower for funds in the same network than in the market. But analyzing this measure more deeply it is not really possible to compare directly these two measures. Looking at table A.5 the concept is very clear considering the network, in addition to stocks and quarters, the number of trades per subgroup decrease a lot, because there are many small networks while at the overall level is more frequent to have many funds trading on the same stock. It means that is not really possible to compare $UHM_{Overall}$ and UHM_{Net}. The main point here is to notice how the herding behavior is relative high even thought considering such small groups. And UHM_{Net} increases as we consider a higher number of funds trading[17]. The values that we compare are quite small but these results are are in line with U.S. studies, that never show very high value of herding[18].

<<Table A.5 approximately here>>

2.5.3.B Comments

Our results suggest that traders in the same network exhibit a certain level of herding. Previous works suggest several reasons for herding behavior by institutional investors. Traders herd because they imitate financial decisions of others better informed[19]. As well, in our setting herding in the same network could be information driven.

But someone could think that investors' imitation might be a feature of human behavior.

[17]Similarly also the $UHM_{Overall}$ increases as we restrict for a higher number of trading per stoch-quarter (See table in appendix A).

[18]Similar results are found for UK mutual funds; instead German funds seem to herd much more (i.e. Walter and Weber (2006) and Oehler andWendt (2009)). Higher herding levels are found also for Portuguese mutual funds (Lobao and Serra (2007)), Indonesia (Bowe and Domuta (2004)), Korea (Choe, Kho and Stulz (1999)), Poland (Voronkova and Bohl (2005)) and South Africa (Gilmour and Smit (2002)). These contradictory results are explained with the different degree of development of the financial markets and incompleteness of regulation in the emerging markets.

[19]In such case, institutional investors move price toward fundamental valeus, making markets more efficient (Lakonishok, Shleifer, and Vishny (1992)).

Yet a recent laboratory experiment show that traders do not imitate the actions of other traders and they prefer to follow their own private information when both private and public signals are available (Azofra et al. (2006)). Similarly Cipriani and Guarino (2005) find that in a laboratory financial market individuals do not herd when they trade for informational reason. So traders do not want to trade as everyone else in the market, but they decide to imitate just some investors, (those that are smart or with "good" information). And a manager, who met her colleagues in the past at college, could know who are the best managers.

Other explanations are not related to information. Scharfstein and Stein (1990) explain the herding phenomenon as the money managers' intent of signaling in the labor market or reputation concerns. For Admati and Pfleiderer (1997) a possible cause is compensation schemes based on the performance relative to the other managers[20]. Here these reasons seem less important to justify herding in such small networks. Herding behavior may induce by mutual funds' preferences for certain stock characteristics (Falkenstein, (1996)). Finally irrational psychological factors is a frequent argument in the herding by individual investors but Friedman (1984) recall this explanation also for institutional investors.

2.6 Discussion

Overall our results suggest that managers, who gained the same degree in the same academic institution exhibit similar portfolios and trading behaviors. The magnitude of the effect is amplified when we consider a stronger connection: namely the year of graduation.

[20]In mutual fund industry compensation schemes are in this way because of agency problems between fund managers and (it is difficult to evaluate fund managers' performance).

Also the hearding measures provide results towards the same direction.

Altogether our empirical research has been motivated by the hypothesis that managers in the same network exchange directly valuable information or opinions. We think that the diffusion of information and opinions through direct social connections is a plausible story for our evidence. Moreover managers can be informed also indirectly when news or rumors spread across their networks.

On the other hand taking in mind the reflection problem and the specific way in which we define network, some other explanations are plausible.

First, managers in the same network, according with our definition, can be similar in aspects or individual characteristics, not observed by the researcher, that influence the trading behavior. Indeed students share many things during their years at colleges or universities. This explanation refers to what social networks theorists and sociologists called *homophyly* (Lazarsfeld and Merton (1954)), defined as the tendency for similar individuals, in term of their characteristics, to be connected to each others. This concept is important because it can influence behaviors[21].

In particular students who apply and study in the same university might have, on average, similar *preferences*, that, instead, could be quite different from those of students enrolled in another institution (i.e. UCLA versus Boston University). This effect is probably stronger for MBA students: they share many common values and aptitudes. Then, during their academic years they had similar experiences[22]. Thus correlated trading could be explained

[21] In Golub and Jackson (2008) homophily affects diffusion and learning process, Calvo-Armengol and Jackson (2009) show that homophily influences the decisions about education.

[22] How universities can influence beliefs and preferences is an open question.

by similar preferences among managers in the same academic network[23].

Second, students who attend the same universities receive the same type of training, and probably they attend similar courses or even they have the same teacher. This can influence the decision making process: a particular training can influence the process of gathering and decoding information, and financial information as well, leading to the same interpretation and conclusion. For example to receive a rigorous training in classical finance and to study behavioral finance can lead to different investment approaches. Moreover previous experience and old memory are often used as starting point when people make forecasts (Juliusson, Karlsson, and Garling (2005)). And even whether decision makers look for information, they see what they expect to see and ignore news. To some extent the correlation in trading behaviors, that we documented, could be caused by past background among managers in the same network.

These two alternative explanations are in part attenuated by the fact that we consider different levels of networks, for example a manager has some peers from her undergraduate studies and others from her master courses. But unfortunately there is no way to exclude completely these different interpretations.

Our results could be also justified by an exogenous effect: managers with similar level of ability could trade in similar way. We cannot control for it nevertheless we think that this reason can play just a minor role.

[23]For example it could be that money managers graduated at UC invest more on green companies than all other managers.

2.7 Conclusion

The goodness and the timing in financial decisions depend crucially on the information available, especially in the stock market characterized by a high level of ambiguity. So mutual fund managers in their information acquisition process can exploit personal contacts and actively search for useful information through their friends. Our investigation, conducted stock by stock, shows the existence of similar investment behaviors among managers in the same academic network. This preliminary evidence suggests that social network influences the investment decisions of professional money managers. Given the limits of our empirical investigation, we hope to provide more incontrovertible evidence in future works.

Chapter 3

Network and Mutual Fund Performance

3.1 Introduction

Social interactions play a crucial role in everyday life but also can affect financial outcomes in several ways. Firms exchange technical information thanks to managers informal meeting, corporate structures and financial policies are affected by board-to-board connections. In Chapter 2 we find that presumably there is a similar flow of information also in financial markets through social connections. In this chapter we try to investigate if social network may affect fund performance and in which way.

The work of Shiller and Pound (1989) was the first one to study how fund managers develop their portfolio decisions. Their evidence suggests that computers, analyses by analysts, macro-forecasts, personal investigations or newspapers are not the only source of information for managers' decisions. Fund managers formulate their investment choices also speaking with other people. Similarly Dratcher, Kempf and Wagner (2007) conduct a telephone survey among German mutual fund managers, and show that fund managers acquire relevant information from other people (in particular other fund managers and member of the boards of companies). According to these findings fund managers seem to actively exchange information and not just passively herd the others. If social contacts are relevant for the decision process, the ultimate choice, stock selection and timing of trades, to some extent, will be influenced by the others. When people actively share information they can either exchange valuable information or rumors, that usually spread quite fast and travel far away. Consequently interpersonal connections may affect fund performance. In addition, the structure and the properties of social connections are important to understand the process of diffusion of information, and our paper will focus on this point.

We define that two fund managers are socially connected if they graduated from the same universities with the same type of degree. Hence, the network structure is built in the past and it is exogenous. We think that education network can be a good proxy/measure for the goodness of manager's actual network[1]. For example, a manager that attended an MBA at Harvard University is more likely to have good connections (some of their classmates can be in finance industry as well, some others could reach power position in a company or in public institution), than someone who attended an MBA program at University of Tulsa. Moreover, a better "education network", built during undergraduate and graduate studies, can favour valuable endogenous social connections in the future. And, it could be reflected in higher performance.

[1]We justify more deeply this choice in Chapter 2.

In this work we use tools provided by Social Network Analysis (SNA), SNA allows to study and visualize connections, in this way we can relate fund performance to network. First, we investigate the topology of the network. The analysis of network structure is not simply interesting per se, also the architecture of links and its properties matter for economic behavior and decision-making (Jackson, (2007)). As result, we find that fund managers' network has all the characteristics of a *small-world*. Second, we estimate a higher persistence of performance when a fund is managed by a connected manager. Third, we compute different measures of network centrality and we find that funds managed by managers more socially connected have a better performance. This finding suggests that fund managers benefit from being in a better position of the network.

This paper relates to two strands of literature. First, our work is close in the spirit to Hockberg, Ljugquivist and Lu (2007), they analyze the network of venture capitalists and find that better networked VCs exhibit higher performances. Similarly, in Fracassi (2008) corporate finance policies are related to the social network of boards of directors instead, Barnea and Guedj (2007) investigate the importance of board connections on CEO compensation. Houghton and Serafein (2009) consider the social network of security analysts and they find that their position affect both their performance and career outcomes. To quantify the relative importance of each actor in a network those papers use measures of network centrality. We follow the same approach.

Moreover, we address issues of network *topology.* In economics small-world networks have been verified in different settings such as reputation management (Venkatraman et al. (2000)), labor markets (Tassier and Menczer (2001)), wealth distribution (Souma et al.

(2001)), bilateral trade (Wilhite (2001)), scientific networks (Newman, (2001); Barabási et al. (2002)), co-authorship networks of academic economists (Goyal and Van Der Leij (2006)). To our knowledge Baker et al. (2001) is the only paper in finance that studies network topology, but such work concerns members of corporate boards in US during the 1980s and 1990s.

Second, we contribute to the literature that explains the success of a fund with managers' attributes. The mutual fund performance has been the object of investigation of numerous works. Particularly several papers emphasize the role of managers' characteristics on funds' performance. The pioneering work in this field was Golec (1996), with a limited sample of funds he shows that funds managed by younger managers, with an MBA and with a long tenure obtain higher performance. While Chevalier and Ellison (1999) find that none of those characteristics are particularly important but, what really matter, is the mean composite SAT. The quality of the MBA could be important as well (Gottesman and Morey (2006)). Other works investigate the differences in performance based on fund managers sex (Atkinson, Baid, and Frye (2003) and Niessen and Ruenzi (2009)).

Not all funds are managed by a unique manager, frequently team of managers, either named or anonymously, are in charge of mutual funds[2]. Past research, with ambiguous results, investigates the difference in performance between single and team-managed funds (i.e. Prather and Middleton (2002) Chen, Hong, Huang, and Kubik (2004); Baer, Kempf and Ruenzi (2008)). Baer, Niessen and Ruenzi (2009) focus on team diversity (considering as dimension gender, age, tenure and education).

[2]The number of funds managed by teams of managers is grown a lot in the last decade. This phenomenon have been documented by Massa, Reuter and Zitzewitz (2006). In those mutual funds the portfolio decisions are taken by a committe or each manager decides for a part of the portfolio.

A novelty of our paper is that differing from previous literature we focus on a manager's *social network*.

The paper is organized as follows. Section 2 provides a description of social network tools that we use in our analysis. Section 3 illustrates the data and characterizes the fund managers network. Section 4 describes the methodology, while Section 5 presents the results. Section 6 concludes.

3.2 Social Network Analysis

Social Network Analysis (SNA) studies linkages among individuals and takes into account the position of them in a network at individual level. SNA is an interdisciplinary methodology, that employs ideas and methods from graph theory, algebra, and statistics. There are already many applications in social and behavioral sciences.
The aim of this section is to give some notations and definitions for the readers who might be not familiar with social network analysis. We then define fund managers network and we describe the topology. Finally we explain the centrality measures, used later on for the empirical analysis.

3.2.1 Network topology

A network is a set of *nodes* $N = \{1, ..., n\}$. Nodes can be firms, patents, individuals or other organizations. A network is defined as homogenous when there is just one type of nodes, otherwise it is heterogenous. Nodes are connected among each others through *ties*. Ties, defined with $g_{i,j,}$ represent the relation between node i and node j. The total number of ties is $D = \sum_{i \in N} \sum_{j \in N} g_{i,j}$. The nature of a tie can be very different: friendship, affiliation, behavioral interaction, business alliance, physical connection, transfers of material resources and so on. Granovetter (1973) distinguished between strong and weak ties and stressed the importance of the last ones[3].

In our setting nodes are mutual fund managers and ties are based on academic affiliation. More precisely managers are connected if they attend the same institution and they gain the same degree. Network structure is taken as given as in much of the SNA literature. We draw connections for all years. Unfortunately with the available data we cannot "weight" ties, even thought that could be useful and more realistic. Here each link is *undirected*, like in friendship or other relationship, because g is symmetric in a way that $g_{ij} = g_{ji}$. So applying this definition of connection not all managers are connected to someone else. Another important definition is *degree,* it is the number of link from vertex i formally $k_i(g) = \sum_{i \in N} g_{i,j}$.

The most immediate way to see and also to represent formally a network is through graph. Graph theory has been a tool to understand network properties, moreover it allows to quantify and measure those properties, so we borrow some concepts from this approach. A *graph* $\mathcal{G}$ represents nodes joined by lines and it consists of two sets of element (N, G). G is a matrix $n \times n$ (adjacency matrix). In our case, with unweighted linkages, all entries are either 0 or 1.

<<FIGURE 1 approximately here>>

[3]Usually stronger links represent closer friendship and greater frequency of interaction than weak ties that correspond to acquaintances. Yet, this does not mean that weak ties are not important, weak ties can provide more information and new information (for istance, in Granovetter (1974) weak ties are prominent in getting a job).

At a first view from figure 1[4] we can see that our network is not complete and it is neither a random graph nor completely order, as it usually happens with real-world networks. Moreover there are many managers all mutually reachable through paths. Such a big component, represented by the academic institutions where many fund managers graduated, is called weakly connected component[5] (WCC). Formally a WCC is a maximal subgraph in which there is a path from each vertex to any other vertex (and it contains the vast majority of vertices). The other components are very small in compared to the main WCC.

In addition, observing our graph it seems that the number of ties per node is small in compared with the total number of nodes, when a network exhibits such property is said sparse. Formally a network is classified as sparse or dense according with the level of density. Network *density,* defined as $\delta = D/n(n-1)$ is the proportion of the actual number of ties out of all possible ties (Marsden (1990)). While there are only few nodes with a high number of links, those are called hubs.

These two characteristics are typical of small world network. Thus we deepen the study of network topology because usually it affects the flows of information and, motivated by the previous graph, we investigate the existence of small world network.

[4]The figure has been drawn using the Pajek software for large social networks. We used a Kamada-Kawai energy algorithm separating components to draw the network.

[5]The term "weakly" does not refer to the strenght of ties but to the absence of diretion (hence in case of directed paths we would have strongly connected components).

3.2.2 Degree Distribution

Networks are typically very sparse and our network seems to have this property as well. Sparse networks are classified as regular, random or *small world*[6]. Regular networks are characterized by a large value for the average path length and a high degree of clustering. Differently a network with a low average shortest path and small degree of clustering is defined as random. Instead small world networks (SWN) are neither random graph nor completely order. Strogatz and Watts (1998) find that a graph to be classified as a Small World should have the following properties:

1. pairs of vertices have short paths between them;

2. highly clustered or network transitivity.

To assess the first property we need to compute the average path length. The shortest path length $d(i, j)$ between two vertices, i and j, is defined as the minimum number of edges that needs to be traversed to pass from i to j (or vice versa). Then the average path length is simply the average value of the shortest paths over all distinct pairs of vertices, mathematically

$$L = \frac{\sum d(i, j)}{n(n-1)}$$

L is compared with the average path length of a random graphs of the same size and with the same number of vertices $L_{\mathrm{rand}\,om}$ and the property is verified whenever

[6] This term was introduced by Garfield (1979), but it acquires popularity with Watts and Strogatz (1998).

$L \gtrsim L_{\mathrm{rand}\,om}$. Saying it differently, given any two vertices, they can be reached in a small number of steps.

The second property is captured by defining the clustering coefficient. The clustering coefficient C_i for a vertex i is given by the proportion of links between the vertices within its neighborhood divided by the maximum possible number[7]. The clustering coefficient C for the entire graph is then defined to be the average of over all vertices and it is a quantity which varies between 0 and 1. Formally C_i and C are respectively defined as:

$$C_i = \frac{(\text{number of links between neighbors of vertex } i)}{k_i(k_i - 1)/2}$$

$$C = \frac{1}{N}\sum_{i=1}^{N} C_i$$

As a benchmark $C_{\mathrm{rand}\,om}$ represents the clustering coefficient of a random graph of the same size and with the same number of vertices and in SWN $C \gg C_{\mathrm{rand}\,om}$. For example, the probability that two randomly selected people in the population know each other is much lower than that of two of your friends know each other.

One well known type of small world network is scale-free network, where the degree distribution is right skewed (Albert and Barabàsi (1998)). Hence we need to study the *degree distribution*[8]. In a scale free distribution the probability that a randomly selected node has exactly k ties decreases as a *power law.* It has the asymptotic form

$$p(k) \sim k^{-\gamma}$$

[7]The coefficient is computed considering only 1-neighborhood, other measure to characterize clustering includes 2-neighborhood.

[8]The investigation of degree distribution is a description of the relative frequencies of nodes with different degrees.

where $p(k) = \Pr(K = k)$, namely it indicates the probability that a node has degree exactly equal to k, and γ is the degree exponent and it determines the rate of decay.

A power-law distribution is right-skewed and has a fat tail indicating that extremely large events are rare but much more likely than what we would expect in a standard Gaussian model. On a doubly logarithmic scale, a power-law distribution displays a straight line, and this reveals the most distinctive feature of such distribution, namely the property of scale invariance. In other words if we increase the scale or units by which we measure the quantity of interest k by a given factor, the shape of the distribution $p(k)$ remains unchanged, except for an overall multiplicative constant (Newman (2005)).

3.2.3 Hypothesis and Measures of Centrality

We study managers connections because we think that social network can be a source of information. But which kind of information ?

Our conjecture is that networks might be a way either to search for information or to communicate valuable information. So we interpret linkages between fund managers as channels for possible transfer of knowledge. Consequently better connected managers to some extent should have greater performance.

Yet networks could allow to spread unfounded assertions and false rumors as well. For example the development of modern technology and internet seems to favour the diffusion of false and non verifiable information. In a similar way the network among mangers, that we construct via education ties, could be a source of rumors diffusion. Di Fonzo and Bordia (1997), in two experimental simulations, find that rumors affect trading decisions. In this case high number of connections may decrease performance (or have no impact on performance whenever managers recognize and ignore rumors).

In principle performances and network do not have a clear relation. These hypothesis will be tested later on.

To implement this analysis initially we compute some micro measures, well know in the network literature. We introduce three measures of *centrality*, each one captures a different aspect, that allows to compare nodes and to give a meaning at nodes' positions in relation to the overall network.

- *Degree*: it is the sum of all direct links that each node has with others (we define it formally in section 2.1). A higher number of link means a central position in the network and a greater number of contacts. In our setting managers with a higher number of links have greater opportunities of information exchange, and better opportunities to have valuable information.

- *Betweenness*: captures the absolute position of node in a network. It measures the extent to which a particular node lies "between" the various other nodes in the network (Freeman, (1979))

  $$c_B = \sum_{y<z} \frac{\#\text{ shortest paths between } y \text{ and } z \text{ through unit } x}{\#\text{ shortest paths between } y \text{ and } z}$$

  According with the betweenness centrality measure a node is central, if it lies on several shortest paths among other pairs of nodes.

  In our managers' networks that lie on the shortest paths among pairs of other node are those that can "control" the flow of information in the network.

- *Closeness*: is a measure of influence. Differently from degree centrality, closeness takes into account both direct and indirect links (Sabidussi (1966))

$$c_C(x) = \frac{1}{\sum_{y \in U} d(x,y)}$$

U set of units $d(x, y)$ is the shortest path between x and y. The most central unit can reach all the others quickly. A network is highly centralized when c_C has a high variance. In the case of a "communication networks" the possibility to reach/to be reachable from other investors at shorter path lengths is a source of power.

Those measures indicate, in different ways, how well networked a mutual fund manager is.

3.3 Data

Data on managers education comes from Mornigstar Principia CD-Rom. Since this source is not exhaustive we enlarge our sample collecting data from several web sites (sec.info, funds website, zoom.info). Our information about managers are the academic institution, the type of degree and, the year of graduation. We used information from College Board to compute the average SAT[9] at university level. College Board[10] provides the scores of the 25th and 75th percentiles and we compute the average of those values.

The data source for funds information is the Survivorship-Bias-Free US Mutual Fund Database provided by the Center for Research in Security Prices (hereafter CRSP). CRSP reports various data about funds; we collect information about return, assets, expenses, fund age, turnover. Given that CRSP adopts as unit of observation each share

[9] SAT Reasoning Test (Scholastic Aptitude Test and Scholastic Assessment Test) tests reading writing and math; usually colleges and universities use the SAT score to make their admission decisions.

[10] College Board does not report scores for all colleges and universities in our sample. In these cases as in Christoffersen and Sarkissian (2009) we exploit the ACT scores (American College Testing).

class of each fund rather than each fund we add up those data into one observation per fund. (For variables such as expense ratios or returns values are weighted, the weights being the total net assets of each share class). This method, introduced by Grinblatt, Titman, and Wermers (1997), is not problematic in our setting given that the same manager in a fund is responsible for all class shares with a unique portfolio holdings. Hence we have one observation for each fund per year to avoid double counting. We merge Mornigstar data and CRSP data with the Ticker number; for all funds that did not have a match we merge those manually looking at the name (otherwise those funds were deleted). We limit our analysis to funds managed by a *unique* manager, in a way that there is just one decision-maker (it is important to test our hypothesis). We further restrict the sample considering just those funds with an active investment style: Growth, Aggressive Growth, Growth &Income, Equity-Income[11]. We restrict our period of observation from 1996 to 2007.

3.3.1 Fund and Manager Characteristics

Our final sample, after these restrictions and considering only funds managed by manager with valid education information consists of 6001 fund-year observations.

Summary statistics are given in table A.6; the second column shows characteristics for all funds and managers. On average, the turnover ratio is 89.5% and the expense ratio is 1.3%. The average fund age (FUND AGE), defined as the difference between the current year and the year of organization of the fund, is 12 years.

[11]We select all funds that are classified in one of these categories defined by the Investment Company Data Inc. (ICDI).

In addition to SAT, using the education information about fund managers, we have constructed two additional variables: MBA (it is a dummy variable that takes value one if the manager holds a mba, and zero otherwise) and Ph.D. (it is a dummy variable that takes value one if the manager holds a Ph.D., and zero otherwise). The average SAT is approximately 1252 and x managers hold an MBA degree while only 50 managers hold a PhD. The year of graduation allows to infer the manager age. As in Chevalier and Ellison (1998) we assume that managers were 21 years old upon college graduation. This information is not available for all managers (around managers) so we create a dummy variable equal one for managers with missing age (MISSINGAGE), zero otherwise. Managers tenure is computed as the difference between the current year and the first year that the manager took the control of the fund (TENURE). The average manager is 46 years old while their tenure at a fund is about 5 years.

According to our definition of network not all managers belong to a network. We generate a dummy variable called $NET = 1$ if the manager in charge has some connections in that year, 0 otherwise. In our sample there are 1541 funds-years observations without connections. The third and the fourth column show funds and manager characteristics in the two sub-samples. Funds with a networked managers are significantly older, have higher amount of assets, but lower expenses as compared to non-networked funds. Managers, that do not belong to a network, generally attended not very "popular" universities (at least in the finance industry) and they do not hold a MBA[12]. Networked managers are slightly older, have higher tenure and higher SAT score.

[12]Given our to define connections, managers with an MBA have a higher probability to be connected with someonelse.

<<Table A.6 approximately here>>

3.3.2 Network Characteristics

3.3.2.A Small World Network

In this section we provide a brief characterization of our managers network exploiting SNA tools, empirical network analysis and network simulation.

Given the above definitions, managers are mapped onto networks year by year. As a result there are on average 301 vertices and 3031 links. Our network has a sparse topology: density score of 0.033, shown in Table A.7, means that approximately only 3 mangers know each others. Moreover, as we saw from the previous graph there is a giant weakly connected component, covering 75% of the managers. Sparse topology and the presence of a giant component are two characteristics found very frequent in SWN. Yet, the two most important and distictive properties are a small average shortest path between nodes and a high value of the clustering coefficient. To verify these properties, defined formally in section 2, Table A.7 shows the average path length and the clustering coefficient of the actual and a random network. L equal to 3.88 means that on average in less than 4 steps the whole network can be traversed, this is a quite short chain for connecting two people. This implies that distances between vertices are relatively short. At the same time the manager network is highly clustered, with the coefficient C equal to 0.68. In our context the presence of clustering implies that the probability of connections between managers is much higher if they have a common link than in the opposite case. Given that both the requirements for small world are verified in all years ($L \gtrsim L_{\mathrm{rand}\,om}$ and $C \gg C_{\mathrm{rand}\,om}$), we can safely assert that our network has a nature of a small world. This is an important result given the diffusion properties of such network structure.

<<Table A.7 approximately here>>

The existence of a few nodes with very high degree and many others with low degree, a feature not found in standard random graphs, push as to investigate if our network displays a power-law distribution in their node degree. To grasp further details, in Figure 2 we plot on a log-log scale the complementary cumulative degree distribution (CCDD), defined as $P(k) = \Pr(K \geq k)$. At a glance we notice that the plot follows a clear cut negative relation that is stronger after a threshold value. The CCDD of our network has a very unequal pattern, markedly right-skewed and characterized by a heavy or fat tail. But differently from a power law, individuals with very high number of connections are very low, moreover the rate of decade is very different over years. The reader should bear in mind that our object of investigation are managers, connected through education, so the specific "nature" of the network partially explains the reason for the poor goodness of fit with the power law (Figure A.2). Anyway we calculate empirically the goodness-of-fit between the data and a power law (see the appendix for details). Our results suggest that the degree distribution does not follow a power-law distribution.

3.3.2.B Network Measures

The key variables for our investigation are the centrality measures used as proxies for managers' position in the network.

Descriptive statistics of the centrality measures are shown in table A.8.

<<Table A.8 approximately here>>

The overall centralization in term of betweenness is very low (mean is only 0.006); so it means that there is not betweenness power in the network. Correlations between the centrality measures are high because: by construction, a manager with high number of direct degree will have also a high number of direct and indirect degree (correlationwith closeness is 0.69). Correlations with betweenness are quite high but not as much as between degree and closeness. In fact betweenness captures a different aspect of network as it measures the centrality of a manager in absolute and it does not depend strictly on the number of ties. We will run differently regressions for the three different measures, as in Hockberg, Ljugquivist, Lu (2007), so multicollinearity will not be a problem.

3.3.3 Correlation

Correlations are generally quite low, with exception of degree/closeness with MBA and SAT (see table A.9). This means that managers with high number of connections hold an MBA: it follows by construction of our network definition. The high correlation with SAT means that funds select many managers from good universities and so they are highly networked[13].

3.4 Methodology

3.4.1 Measures of performance

In this section we describe the methodology that we implement.

[13]As a robustness check we run all regressions omitting SAT and MBA and we obtain similar results to those in table A.11, A.12.

The first step of our procedure is to compute the fund return. We use different measures of return. First we consider the *gross return* (defined as the difference between the raw return and the risk free), the *abnormal return* (it is the difference between the gross return of the fund and the mean return across all funds in the same market segment for a given year) and the *net return* (the gross return minus the expenses). Those measures do not take into account the riskiness of a fund's strategy therefore we consider other measures of performance already adopted in previous studies.

We calculate the fund's Jensen Alpha, the 3-factor model, the 4-factor model, the Treynor Mazuy model and a model with public information.

The market model or CAPM (Jensen, 1968) is represented as follows

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t} r_{M,t} + e_{i,t} \tag{3.1}$$

where $r_{M,t} = (R_{M,t} - \tau_t)$.

$r_{i,t}$ is the return on the aggregate mutual fund portfolio i at time t minus the riskfree rate of interest (the one-month U.S. T-bill rate for time t, τ_t), and $R_{M,t}$ is the return of the U.S. market portfolio. $\alpha_{i,t}$ is fund alpha for each fund i. This measure of performance is preferred to raw returns because is risk-adjsted. Precisely the Jensen's alpha will *not* be high when low skilled manager took highly risk position (assets with high betas), on the contrary in such case the raw return could appear highly positive.

The second one is the well known Fama and French model (1993) and it has been appraised as a better representation of fund performance. Formally

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t} r_{M,t} + \gamma_{i,t} SMB_t + \delta_{i,t} HML_t + e_{i,t} \tag{3.2}$$

where SMB_t and HML_t are respectively the size and the book-to-market of the three-factor model. I obtain the monthly time-series of the three Fama-French factors and the momentum factor from Professor Kenneth French's data library.[14]

The third one is the four-factor model used by Carhart (1997) defined as

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t} r_{M,t} + \gamma_{i,t} SMB_t + \delta_{i,t} HML_t + \varrho_{i,t} UMD_t + e_{i,t} \tag{3.3}$$

This model is similar to the Fama and French model but adding a further term UMD_t that represents the momentum factor in order to capture the momentum anomaly (Jegadeesh and Titman, 1993).

Treynor and Mazuy (1966) emphasize that α can include market timing ability of fund managers. So they rewrite eq. 3.1 as

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t} r_{M,t} + \gamma_{i,t} r_{M,t}^2 + e_{i,t} \tag{3.4}$$

In this equation $\gamma_{i,t}$ represents the market timing ability.

Indeed Ferson and Schadt (1996) and Christophersen, Ferson and Glassman (1998) point out the importance to separate managers' abilities and private versus public information. Thus we consider the following conditional alpha model:

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t} r_{M,t} + \varphi_{i,t}(Z_{Tbill,t-1} r_{M,t}) + \upsilon_{i,t}(Z_{Term,t-1} r_{M,t}) + e_{i,t} \tag{3.5}$$

$Z_{Tbill,t-1}$ is the one month U.S. Treasury bill rate and $Z_{Term,t-1}$ is a proxy for public information (term-structure spread) and it is calculated as the difference on the 10-years U.S. government bond and three-months U.S. T-bill.

[14] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

In all these methods $\alpha_{i,t}$ can be interpreted as a measure of out or under performance: when it is positive denotes a skilled manager whose investment choices add value to the fund, while a negative $\alpha_{i,t}$ denotes a low skill manager that reduces the fund value. As in previous articles we use one years of data , namely to compute α in 1996 we use return information starting from January 1995. A fund is deleted if there are not return data for 12-months.

3.4.2 Empirical model

The above measures of performance allow us to estimate the importance of network. As second step of our procedure we use the following specification:

$$\alpha_{i,T} = a_{i,T} + \vartheta_{i,T} X_{Fund} + \theta_{i,T} X_{Manager} + \zeta_{i,T} Network + e_{i,T} \tag{3.6}$$

X_{Fund} and $X_{Manager}$ are the set of control variables respectively for fund and manager characteristics. The object of our interest is ζ. For network we use as explanatory variables degree, betweenness and closeness, computed as defined above.

We include a set of control variables for fund characteristics: PERFORMANCE (the performance in the previous period), SIZE (it is the log of the total net assets in millions of dollars), F.AGE (difference in years between the current year and the year starting the fund), TURNOVER_1 (yearly turnover ratio in the previous period), and EXPENSES_1 (the annual total expense ratios in the previous period). Previous empirical works found that these characteristics impact on fund performance (i.e. Chen, Hong, Huang, and Kubik (2004)). Following Chevalier and Ellison (1999), Gottesman and Morey (2006) we add some controls for managers: M.AGE, MISSINGAGE, TENURE, SAT, MBA, Ph.D.

3.5 Empirical results

We begin by exploring the differences in performances when managers belong to a network versus managers that do not belong to a network.

We start sorting all funds in all years according with the value of NET, and we create two different portfolios (one for funds that keep the value NET=1, another for NET=0). For each portfolio we calculate the equally weighted average four-factor alpha. The results of this portfolio analysis suggest that in both cases the returns are negative but in the case of managers without any connections it is slightly worse by 0.06 percentage point on monthly basis. Thus it seems that performance of networked and no-networked manager portfolios are different.

We investigate if different performances are reflected in different level of performance persistences. First, we compute the performance rank, based on the different performance models, for each fund and in each year. Next, we define the performance persistence as the rank standard deviation for each fund over time[15]. We find that the performance is more persistent, namely the performance ranks vary less over years, for funds managed by networked manager, whatever model is used for computing performance, than for those managed by no-networked managers.

Then, we study this difference at micro-level controlling for funds and managers characteristics. We implement the model of eq.3.6 including, instead of a measure of centrality, the dummy variable NET. Our estimate of the network variable is not statistically significant. Results are in table A.10.

[15]Formally $Perf\,Persistence_f = STD(Perf\,Rank_{f,t})$. We require at least 3 years of performance ranks for a fund f in order to compute the performance persistence.

We then focus on impact of centrality measures on performance. The existence of small world structure encourages to expect a positive effect.

As control variable we include segment-fixed effect to compare funds that have the same investment style. In all regressions we add a time fixed effect.

Results about the relationship of global position in the social network with fund performance are shown in table A.11.

<<Table A.11 approximately here>>

In column 2 the dependent variable is gross return. The coefficient 0.00005 (third column of table A.11) for the impact of degree indicates that, for example, a manager with 10 connections outperforms a manager without connection by 0.6%. We obtain similar results from the other models that we estimate[16]. So these results suggest that the direct connections have a positive impact on fund performance.

It is possible that not only the number of direct links are important, also the position on the overall network and the indirect links. Unfortunately our network does not have betweenness power so when we estimate all previous regressions with betweenness we find that this measure is not significant. Table A.12 shows results in which we include as centrality measure closeness. Remember that closeness measures the influence in the network and takes into account also indirect connections. Considering as example results for fund performance measured by the Four Factor Model (column 5), the coefficient 0.0037, for the impact of closeness, indicates that a manager with a value of closeness= 0.15 outperforms a manager with a closeness=0 by 0.7%. The impact estimated with the other models is

[16]For example in the Four Factor model the coefficient 0.00004 implies that a manager with 10 connections outperforms a manager without any connection by 0.5%.

even greater and in all cases statistically significant. Thus it seems profitable to have as social peers other well-connected managers.

As a robustness check we test our hypothesis implementing Gottesman and Morey (2006) models. Results do not vary substantially.

<<Table A.12 approximately here>>

These results suggest that connections are positive and a central position can guarantee some information gains. These findings are consistent with the structure of managers network found in the previous section. Properties of small world are typical for the architecture of social networks, with important implications on dynamic social phenomena in the population. Specifically, physicians and social scientists recognize that SWN is highly efficient for knowledge diffusion and this network architecture influences both the speed and the extent of transmission[17].

Yet, financial market is a special setting because it is highly competitive so such properties are attenuated. Indeed the impact of connections on performances is quite small. Nevertheless direct communication among managers seems a plausible interpretation and it is reasonable that the information exchange is reciprocally profitable. But positive information externalities could arise just imitating proximate professional investors. Whatever is the mechanism of diffusion of information it seems that managers exploit this additional information (centrality measures are positively related to performance).

Beyond our empirical results, we are aware that information dissemination depends

[17] For example Wilhite (2001) studies a trade economy with imperfect information under different network structure. He finds that when agents trade according to a small world network structure the Pareto optimal equilibrium is reached quicker and with lower search and negotiation costs than with three different types of networks (completely connected network, locally disconected network and locally connected network).

on characteristics and intensity of ties that are no captured by our measures of centrality. Moreover, the trading activity is a repeated game and with experiences managers modify their personal networks. A related concern is that our proxy for network is just on education dimension and of course these managers have personal relationships with people working in financial sector that we cannot observe.

Finally, it is important to keep in mind that private information plays a crucial role in financial markets and its quality is probably one of the main determinant for funds performance.

3.6 Conclusion

The notion of small world network is well known, yet, in finance, the properties of this specific network structure, and in general of network topology, have been rarely explored.

In this work we consider fund managers as nodes and managers' education as ties. Such network exhibits small world characteristics. This structure is very frequent in social networks and generally it has an important impact on social interactions and lastly on diffusion of information. Hence, we investigate the network implications for fund performance. We find that connected managers have on average more persistent performances. Consistent with the network structure, we show that performance is higher for manager with many connections or with "good" connections. Thus financial market is a competitive game but to some extent profitable information exchange is possible.

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Appendix A

Power Law

If the probability that a randomly selected node has exactly k ties decreases as a *power law* the corresponding asymptotic probability distribution is

$$p(k) \sim k^{-\gamma}$$

where γ is the degree exponent and it determines the rate of decay. Usually not all values of k follow a power law, but this behavior fit only above a particular threshold $k_{\min} > 0$. The fact that the number of degree are only positive integer implies that

$$p(k) = \Pr(K = k) = \frac{k^{-\gamma}}{\zeta(\gamma, k_{\min})}$$

where the function ζ is the generalized or Hurwitz zeta function of the form

$$\zeta(\gamma, k_{\min}) = \sum_{n=0}^{\infty}(n + k_{\min})^{-\gamma}$$

To test if the degree distribution behaves as a power law we follow the approach proposed by Clauset et al (2009). First, we fit a power law to the empirical data using the method of maximum likelihood and we estimate the scaling parameter γ and the lower bound $k_{\min}$. Second, we test the power law hypothesis and if the p-value is greater than 0.10 we accept the power law hypothesis for our data.

Table below shows results from the fitting of a power-law distribution to network data for year 2001, in any case for all year the p-value is approximately 0 so we can conclude that the degree distribution of managers networks does not behave as power law distribution.

Year	N	$\hat{k}_{\min}$	$\hat{\gamma}$	$k > \hat{k}_{\min}$	$p - value$
2001	347	20	3.5	97	0.00

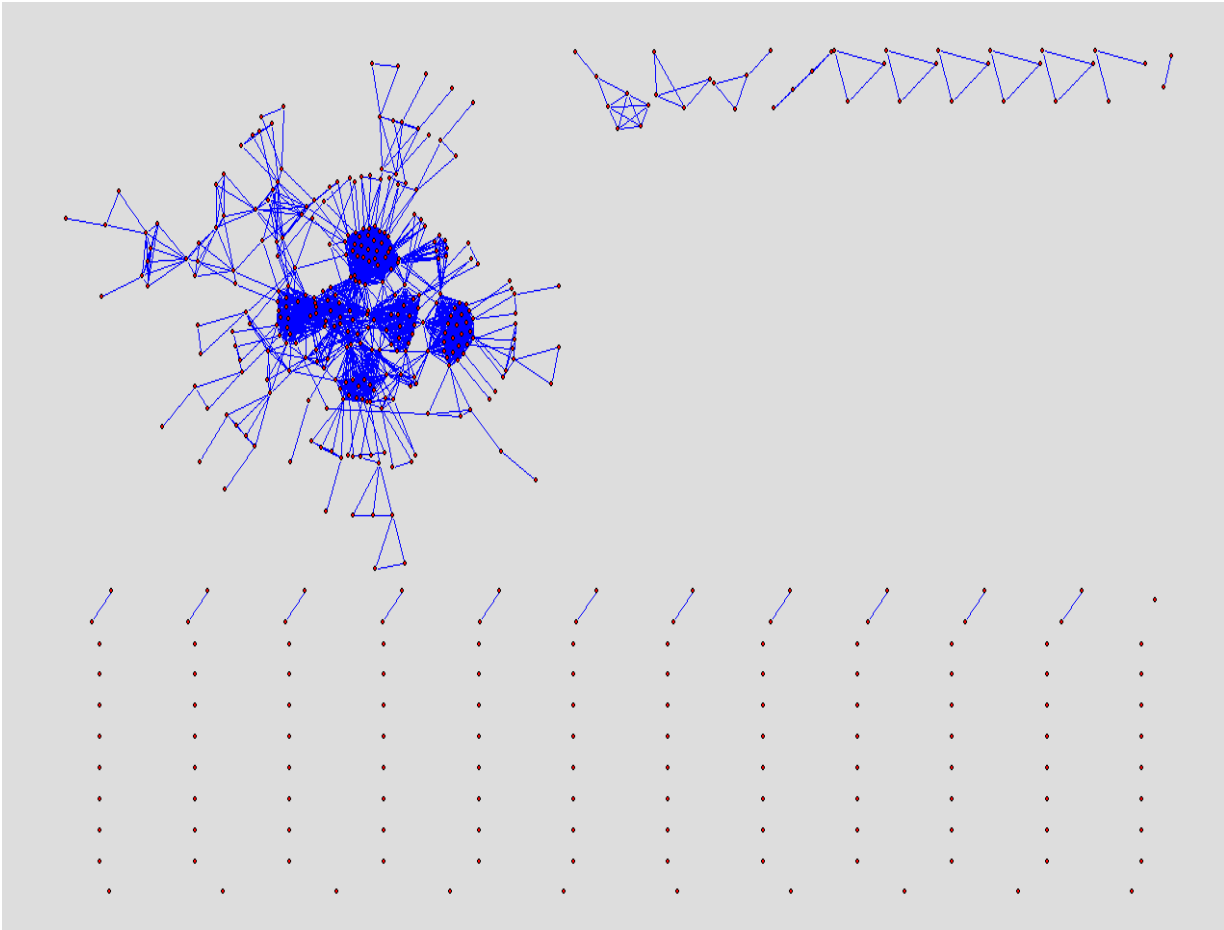

Figure A.1: Social Network (1999).

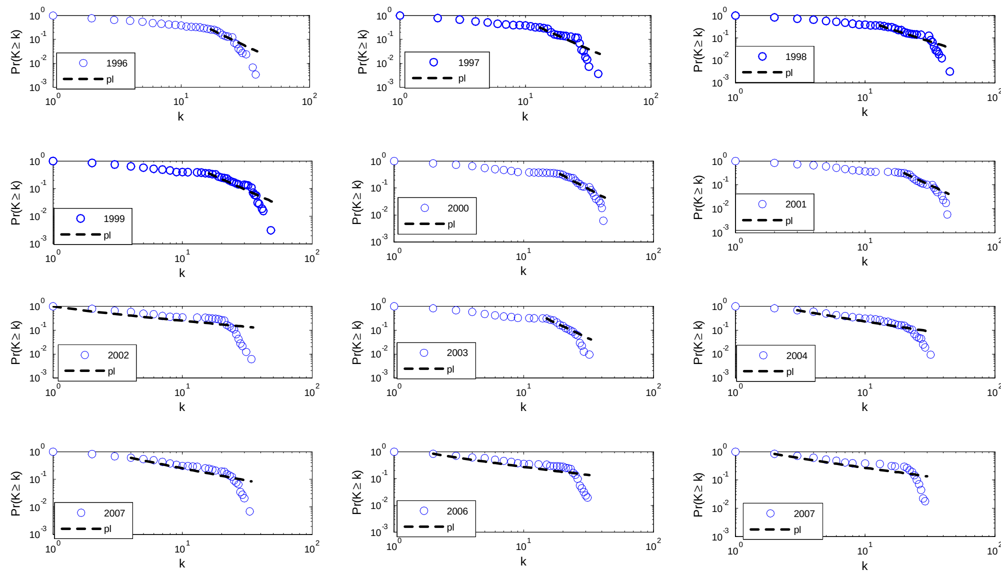

Figure A.2: Complementary cumulative degree distributions and power-law fits

Table A.1: **Summary Statistics.** Part A reports the summary statistics for connections among managers based on the type of degree (Bachelor of Arts, Bachelor of Science, Master of Business Administration, Master of Arts, Master of Scince). Part B shows the average sample that we used for our regressions at quarter level.

A. Connections

	BA	BS	MBA	MS	MA	PHD
Mean	3,51	2,57	5,7	3,15	2,93	2,3
Min	2	2	2	2	2	2
Max	15	11	38	7	6	3
stdev	2,31	1,07	6,52	1,25	1,16	1,1

B. Sample

	Mean
Number of Funds	608
Number of Managers	434
$\ln(\text{mcap}_{t-1})$	12.40
$\ln(\text{B/M}_{t-1})$	-0.784
R.mom_6	0.084

Table A.2: **Portfolio Holdings.**The dependent variable is h (the fractional share of manager m invested in stock i).
h_{NET} is the equally-weighted average across all funds in network n except manager m in stock i. H_{ALL} is the equally-weighted average across all funds of the shares invested in stock i except for the manager herself. Sample size is 1970159. The regression includes 48 quarters from January 1996 to December 2007. We do not report the coefficients of the intercept, time, ioc, industry dummiesn and stock dummies. According with stock characteristics market capitalization, book-to-market ratio and return momentum we define 5 quintiles for each one and we create the dummy variables. Standard errors are in paretheses. In specification 1 to 5 peers are defined as network-a, in specification 6 as network-b. Industry is the stock sector, IOC the style chategory of the fund. Standard errors (cluster at stock level) are in paretheses. Coefficient significant at 1% level are denoted in bold.

	(1)	(2)	(3)	(4)	(5)	(6)
h_{NET}	**.1328**	**.1332**	**.1319**	**.1277**	**.1219**	**.1348**
	(0.010)	(0.010)	(0.011)	(0.012)	(0.011)	(0.009)
$H_{ALLFUNDS}$	**.5407**	**.5231**	**0.5120**	**0.4894**	**0.4754**	**0.4640**
	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)	(0.013)
TIME		Y	Y	Y	Y	Y
INDUSTRY			Y	Y	Y	Y
IOC				Y	Y	Y
15Dummies					Y	Y
R-squared	.12	.12	.14	.15	.16	.15

Table A.3: **Change in Holdings I.** The dependent variable is *deltah* (the fractional share of manager m invested in stock i). $deltah_{NET}$ is the equally-weighted average across all funds in network n except manager m in stock i. $deltaH_{ALL}$ is the equally-weighted average across all funds of the shares invested in stock i except for the manager herself. The other explantory variables are $lnmcap_{t-1}$ (market cap of the previous period), B/M_{t-1} (Book-to-Market ratio), $Rmom_6$ (past 6 moth return), meanrec (average analyst stock recommendation). Industry is the stock sector, IOC is the style chategory of the fund. Sample size is 1762219. The regression includes 47 quarters from March 1996 to December 2007. We do not report the coefficients of the intercept, time, ioc, industry dummies. In specification 1 to 5 peers are defined as network-a, in specification 6 as network-b. Standard errors (cluster at stock level) are in paretheses. Coefficient significant at 1% level are denoted in bold.

	Reg1	Reg2	Reg3	Reg4	Reg5	Reg6	Reg7
Δh_{NET}	**.0967**	**.0877**	**.0875**	**.0842**	**.0810**	**.1049**	**.0843**
	(.0102)	(.0101)	(.0099)	(.0104)	(.010)	(.0093)	(.0123)
$\Delta H_{ALLFUNDS}$	**.2300**	**.2568**	**.2529**	**.2547**	**.2164**	**.2377**	**.2664**
	(.0305)	(.0300)	(.0301)	(.0311)	(.0397)	(.0404)	(.0793)
ln(mcap$_{t-1}$)		**.0001**	**.0001**	**.0001**	**.0001**	**.0001**	
		(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	
ln(B/M$_{t-1}$)		**-.0003**	**-.0003**	**-.0002**	**-.00001**	**-.0003**	
		(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	
R.mom$_6$		**.0003**	**.0003**	**.0003**	**.0004**	**.0003**	
		(.0000)	(.0000)	(.0000)	(.0000)	(.0000)	
IOC			Y	Y	Y	Y	Y
INDUSTRY				Y	Y	Y	Y
TIME					Y	Y	
R-squared	.017	.021	.025	.025	.031	.029	

Table A.4: **Change in Holdings II.** The dependent variable is *deltah* (the fractional share of manager m invested in stock i). $deltah_{NET}$ is the equally-weighted average across all funds in network n except manager m in stock i. $deltaH_{ALL}$ is the equally-weighted average across all funds of the shares invested in stock i except for the manager herself. The other explantory variables are $lnmcap_{t-1}$ (market cap of the previous period), B/M_{t-1} (Book-to-Market ratio), $Rmom_6$ (past 6 moth return), meanrec (average analyst stock recommendation). Industry is the stock sector, IOC is the style chategory of the fund. Sample size is 1762219. The regression includes 47 quarters from March 1996 to December 2007. We do not report the coefficients of the intercept, time, ioc, industry dummies. Standard errors (cluster at stock level) are in paretheses. Coefficient significant at 5% level are denoted in bold.

	Reg1	Reg2 (sell)	Reg3 (buy)	Reg4 (small-cap)	Reg5 (large-cap)	Reg6 (probit)	Reg7 (distant-stock)	Reg8 (lock-stock)	Reg9	Reg10
Δh_{NET}	**.0818**	**.1066**	**.0655**	**.0959**	**.0309**	**1.020**	**.0956**	**.0830**		**.0910**
	(.011)	(.0318)	(.0168)	(.0125)	(.0100)	(.043)	(.0123)	(.0140)		(.0264)
$\Delta H_{ALLFUNDS}$	**.2168**	**-.0761**	**.2527**	**.0769**	**.5755**	**4.697**	**.2479**	**.2251**	**.2335**	**.2401**
	(.0398)	(.0223)	(.0360)	(.0173)	(.0423)	(.1504)	(.0561)	(.0434)	(.0513)	(.0390)
$\Delta h_{NET,=\mathrm{Ci}ty}$									**.0486**	
									(.0090)	
$\Delta h_{NET,\neq\mathrm{Ci}ty}$									**.0410**	
									(.0180)	
ln(mcap$_{t-1}$)	**.0002**	**-.0004**	**.0007**	**.0000**	**.0000**		**.0002**	**.0001**	**.0001**	**.0001**
	(.0000)	(.0001)	(.0000)	(.0000)	(.0000)		(.0000)	(.0000)	(.0000)	(.0000)
ln(B/M$_{t-1}$)	**-.0001**	**-.0005**	**-.0005**	**-.0003**	**-.0001**		**-.0003**	**-.0002**	**-.0001**	**-.0001**
	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)		(.0000)	(.0000)	(.0000)	(.0000)
R.mom$_6$	**.0003**	**.0005**	**.0003**	**.0002**	**.0003**		**.0003**	**.0003**	**.0003**	**.0002**
	(.0000)	(.0000)	(.0000)	(.0000)	(.0000)		(.0000)	(.0000)	(.0000)	(.0000)
Mean Rec	**-0.0002**									
	(.0000)									
IOC	Y									
INDUSTRY	Y									
TIME	Y	Y	Y	Y	Y		Y	Y	Y	Y
R-squared	.028	.024	.045	.027	.039	.031	.024	.022	.026	.028

Table A.5: **Herding measures.** UHM_{Net} is the UHM value computed considering the network dimension. $UHM_{Overall}$ is the UHM measure for the whole sample.

	Number of Trades					
	$\geqslant 5$	$\geqslant 6$	$\geqslant 7$	$\geqslant 8$	$\geqslant 9$	$\geqslant 10$
UHM_{Net}	2.76	3.12	3.3	3.60	3.64	3.26
t	60.66	53.94	45.66	37.64	28.66	19.89
Observations	99939	60598	36427	21617	12283	6840
$UHM_{Overall}$	4.09	4.10	4.09	4.07	4.04	4.03
t	89.52	86.43	83.42	80.50	77.47	75.24
Observations	81031	71716	64289	58382	53386	49302

Table A.6: **Summary statistics of mutual funds and fund managers.** The values shown in brackets are standard deviations. FUND AGE is defined as the difference between the current year and the year of organization of the fund, The tenure of the manager with the fund is the difference in years between the current year and the year when the manager was assigned to the fund; MBA is a dummy variable that takes value one if the manager holds a mba, and zero otherwise; SAT is the average SAT of a manager undergraduate university. AGE is the manager age; MSSINGAGE is a dummy variable that takes value one if we do not have information on the manager's age, and zero otherwise; PHD is a dummy variable that takes value one if the manager holds a PhD, and zero otherwise Column 5 gives the difference between column 3 (subsample of funds with connected managers) and column 4 (subsample of funds with managers without any connection). Statistical significance, based on a two-sided t-test, at the 10%, 5%, and 1% levels is denoted by *, **, ***.

	All	Network=1	Network=0	Difference
FUNDS				
Assets (in million)	1811	2079	994.1	1084.9***
	[6884]	[7472.6]	[4558.1]	
TURNOVER (in %)	88.26	87.98	89.13	1.15
	[1.16]	[1.01]	[1.54]	
EXPENSES (in %)	1.28	1.26	1.34	-0.08***
	[1.07]	[0.61]	[1.87]	
Fund AGE	12.88	13.21	11.86	1.34***
	[14.31]	[14.40]	[14.00]	
MANAGERS				
TENURE	5.12	5.22	4.82	0.39**
	[5.17]	[5.27]	[4.82]	
MBA	0.62	0.71	0.36	0.35***
	[0.48]	[0.45]	[0.48]	
SAT	1252	1280	1165	115***
	[154]	[145]	[150]	
Manager AGE	46.20	46.42	45.42	0.99***
	[9.49]	[9.46]	[9.54]	
MISSINGAGE	0.66	0.69	0.56	0.12***
	[0.47]	[0.46]	[0.49]	
PhD	0.039	0.037	0.044	0.006
	[0.194]	[0.190]	[0.205]	

Table A.7: **Network Statistics.** N is the total number of nodes, D is the total number of links, δ is the network density. We also report the size of giant strongly connected components (SCC), the average path lenght (L) and the clustering coefficient (C) of the actual manager network. As benchmark we use a random network (Erdös and Rényi, 1959) of the same size and with the same number of vertices to compute L_{random} and C_{random}. We compute those measures for all years and the SWN requirements are satisfied in all cases, for brevity in this table we report just the average values.

	Average
N	301
D	3031
δ	0.033
Size of giant WCC (%)	226 (75.3%)
L	3.88
$L_{\text{rand}\,om}$	2.73
C	0.681
$C_{\text{rand}\,om}$	0.034

Table A.8: **Summary statistics: centrality measures.** Degree is the sum of all direct links of a fund manager. Betweenness is the absolute position of node in a network. Closeness is a measure of influence. (see section 3.2.3 for a formal definition)

	DEGREE	BETWEENNESS	CLOSENESS
DEGREE	1.00		
BETWEENNESS	0.47	1.00	
CLOSENESS	0.69	0.40	1.00
Mean	10.3	0.006	0.157
St.dev.	10.2	0.012	0.091
Min	1	0	0.005
Max	48	0.128	0.339

Table A.9: Cross-correlation table

Variables		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18
PERF_1	[1]	1.00																	
SIZE	[2]	0.04	1.00																
F.AGE	[3]	-0.07	0.46	1.00															
TURNOVER_1	[4]	-0.02	-0.09	-0.00	1.00														
EXPENSES_1	[5]	-0.06	-0.27	0.05	0.22	1.00													
AGROWTH	[6]	-0.04	-0.01	0.02	0.18	0.15	1.00												
EQINC	[7]	0.01	0.00	0.02	-0.06	-0.02	-0.07	1.00											
GROWTH	[8]	0.01	-0.13	-0.16	0.05	0.03	-0.35	-0.37	1.00										
GROWTHIN	[9]	0.00	0.16	0.16	-0.12	-0.10	-0.13	-0.14	-0.73	1.00									
M.AGE	[10]	-0.01	0.07	0.12	-0.04	-0.00	-0.04	0.03	0.03	-0.03	1.00								
MISSINGAGE	[11]	0.00	0.10	0.08	-0.02	-0.02	-0.03	0.03	0.02	-0.03	0.97	1.00							
TENURE	[12]	-0.04	0.14	0.41	-0.09	0.07	-0.01	0.02	-0.01	0.01	0.27	0.14	1.00						
SAT	[13]	0.03	0.12	0.04	-0.03	-0.05	0.01	-0.05	0.03	-0.01	0.07	0.07	0.03	1.00					
MBA	[14]	0.01	0.09	-0.00	-0.01	-0.07	-0.06	0.04	-0.01	0.02	-0.25	-0.27	-0.01	0.02	1.00				
PhD	[15]	-0.00	-0.01	0.05	-0.01	0.09	-0.02	0.00	-0.00	0.01	0.05	0.05	0.09	0.09	-0.18	1.00			
DEGREE	[16]	0.03	0.16	-0.00	-0.06	-0.11	-0.01	-0.00	0.01	-0.00	0.04	0.04	0.05	0.34	0.46	-0.09	1.00		
BETWEENESS	[17]	0.00	0.14	-0.03	-0.06	-0.14	-0.04	-0.00	-0.02	0.04	0.03	0.05	0.02	0.25	0.30	-0.05	0.47	1.00	
CLOSENESS	[18]	0.00	0.15	0.03	-0.04	-0.10	0.01	0.00	-0.02	0.01	0.05	0.04	0.02	0.47	0.27	-0.01	0.70	0.40	1.0

Table A.10: **Performance and Network.** Part A reports the monthly returns computed with the four factor model. We divide the sample into two portfolios one for managers within a network and one for managers without any connections and we calculate the equally weighted average. Part B shows the standard deviation in performance ranks for funds managed by managers with NET=1 and for those with NET=0. Part C shows results from regression 6 (the intercept, all controls, year and style fixed effects are included in allregressions but their coefficients are not shown). Standard errors (cluster at manager level) are shown in parentheses. Statistical significance at the 10%, 5% and 1% levels is denoted by *, **, *** respectively.

A. Performance-Portfolio Analysis

	Returns
Network=1	-0.000569***
Network=0	-0.00116***
Difference	0.00060

B. Performance Persistence

	$\alpha_{i,t}(MKT)$	$\alpha_{i,t}(4F)$
Network=1	0.240	0.249
Network=0	0.272	0.275
Difference	0.028***	0.026***

C. Regression (eq. 6)

	$Gross\,\mathrm{Re}\,t$	$Abn.\,\mathrm{Re}\,t$	$\alpha_{i,t}(MKT)$	$\alpha_{i,t}(3F)$	$\alpha_{i,t}(4F)$	$\alpha_{i,t}(TF)$	$\alpha_{i,t}(Cond)$
Network	0.0004	0.0004	0.0003	0.0003	0.0002	0.0004	0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0004)	(0.0003)

Table A.11: **Fund Performance and Degree**.The intercept, year and style fixed effects are included in all regressions but their coefficients are not shown. $PERFORMANCE_1$ is the performance of the fund in the prevoius period; The size of the fund is the logarithm of its total net assets.; FUND AGE is defined as the difference between the current year and the year of organization of the fund; $EXPENSES_1$ is the expenses of the fund in the previous period; $TURNOVER_1$ is the turnover of the fund in the previous period.
The tenure of the manager with the fund is the difference in years between the current year and the year when the manager was assigned to the fund; MBA is a dummy variable that takes value one if the manager holds a mba, and zero otherwise; SAT is the average SAT of a manager undergraduate university. AGE is the manager age; MSSINGAGE is a dummy variable that takes value one if we do not have information on the manager's age, and zero otherwise; PHD is a dummy variable that takes value one if the manager holds a PhD, and zero otherwise. DEGREE is the sum of all direct links of a fund manager. Statistical significance at the 10%, 5% and 1% levels is denoted by *, **, *** respectively. Standard errors (cluster at manager level) are shown in parentheses.

	$Gross\,\mathrm{Re}\,t$	$Abn.\,\mathrm{Re}\,t$	$Net\,\mathrm{Re}\,t$	$\alpha_{i,t}(MKT)$	$\alpha_{i,t}(3F)$	$\alpha_{i,t}(4F)$	$\alpha_{i,t}(TF)$	$\alpha_{i,t}(Cond)$
PERFORMANCE_1	0.1600***	0.1754***	0.1328***	0.2109***	0.1613***	0.1512***	0.1514***	.1503***
	(0.0238)	(0.0247)	(0.0238)	(0.0221)	(0.0425)	(0.0284)	(0.0248)	(0.0227)
SIZE	-0.0003***	-0.0003***	-0.0001	-0.0030***	-0.0002***	-0.0001***	-0.0002**	-0.0003***
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
FUND AGE	-0.0000	0.0000	0.0000	-0.0000	-0.0002	-0.0002*	-0.0003	-0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0007)
EXPENSES_1	-0.0466	-0.0458	-0.8176***	-0.1054***	-0.0860***	-0.0809**	-0.1017***	-0.0388
	(0.0510)	(0.0505)	(0.0780)	(0.0332)	(0.0328)	(0.0373)	(0.0346)	(0.0585)
TURNOVER_1	0.0001	0.0001	0.0000	0.0002	-0.0001	-0.0002	-0.0006	0.0003
	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0001)	(0.0007)	(0.0003)
MANAGER AGE	-0.0000	-0.0000	-0.000	-0.0000*	-0.0001***	-0.0000***	-0.0000	-0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.000)	(0.0000)	(0.0000)	(0.0000)
MISSINGAGE	-0.0015**	0.0014	0.0016	0.0018**	0.0030***	-0.0026***	-0.0014	-0.0026***
	(0.0010)	(0.0010)	(0.0014)	(0.0009)	(0.0008)	(0.0008)	(0.0013)	(0.0009)
TENURE	-0.0000	-0.0000	-0.0000	-0.0000	-0.0000	0.0000	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
SAT	0.0001	0.0001	0.0002	0.0004	-0.0003	-0.0003	0.0006	0.0001
	(0.0001)	(0.0001)	(0.0000)	(0.0009)	(0.0004)	(0.0009)	(0.0001)	(0.0001)
MBA	-0.0004	-0.0004	-0.0005	-0.0007**	-0.0009**	-0.0008**	-0.0014**	-0.0004
	(0.0003)	(0.0003)	(0.0005)	(0.0003)	(0.0004)	(0.0003)	(0.0005)	(0.0003)
PhD	0.0004	0.0000	0.0008	0.0001	-0.0000	0.0000	0.0003**	0.0000
	(0.0007)	(0.0007)	(0.0010)	(0.0006)	(0.0004)	(0.0005)	(0.0009)	(0.0006)
DEGREE	0.00005***	0.00005***	.00005*	0.00004***	0.00004**	0.00004**	0.00004**	0.00003**
	(0.00001)	(0.0000)	(0.0000)	(0.00001)	(0.0000)	(0.00001)	(0.00002)	(0.00001)
Obs.	4058	4058	4058	3893	3893	3893	3893	3893
R^2	0.64	0.65	0.75	0.15	0.13	0.13	0.11	0.13

Table A.12: **Fund Performance and Closeness**.The intercept, year and style fixed effects are included in all regressions but their coefficients are not shown. $PERFORMANCE_1$ is the performance of the fund in the prevoius period; The size of the fund is the logarithm of its total net assets.; FUND AGE is defined as the difference between the current year and the year of organization of the fund; $EXPENSES_1$ is the expenses of the fund in the previous period; $TURNOVER_1$ is the turnover of the fund in the previous period.
The tenure of the manager with the fund is the difference in years between the current year and the year when the manager was assigned to the fund; MBA is a dummy variable that takes value one if the manager holds a mba, and zero otherwise; SAT is the average SAT of a manager undergraduate university. AGE is the manager age; MSSINGAGE is a dummy variable that takes value one if we do not have information on the manager's age, and zero otherwise; PHD is a dummy variable that takes value one if the manager holds a PhD, and zero otherwise. CLOSENESS is a measure of influence (see section 3.2.3 for a formal definition). Statistical significance at the 10%, 5% and 1% levels is denoted by *, **, *** respectively. Standard errors (cluster at manager level) are shown in parentheses.

	$Gross\,\mathrm{Ret}$	$Abn\,\mathrm{Ret}$	$Net\,\mathrm{Ret}$	$\alpha_{i,t}(MKT)$	$\alpha_{i,t}(3F)$	$\alpha_{i,t}(4F)$	$\alpha_{i,t}(TM)$	$\alpha_{i,t}(Cond)$
PERFORMANCE_1	0.1597***	0.1750***	0.1327***	0.2108***	0.1609***	0.1512***	0.1516***	0.1504***
	(0.0238)	(0.0246)	(0.0238)	(0.0221)	(0.0423)	(0.0284)	(0.0249)	(0.0227)
SIZE	-0.0003***	-0.0003***	-0.0001	-0.0002***	-0.0002***	-0.0001***	-0.0002**	-0.0003**
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
FUND AGE	-0.0000	0.0000	0.0000	-0.0001	-0.0002	-0.0002*	-0.0003	-0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
EXPENSES_1	-0.0481	-0.0474	-0.8186***	-0.1060***	-0.0862***	-0.0809**	-0.1019***	-0.0390
	(0.0515)	(0.0510)	(0.0783)	(0.0335)	(0.0330)	(0.0373)	(0.0348)	(0.0587)
TURNOVER_1	0.0001	0.0001	0.0000	0.0002	-0.0001	-0.0002	-0.0006	0.0003
	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0001)	(0.0007)	(0.0003)
MANAGER AGE	-0.0000	-0.0000	-0.0000	-0.0000*	-0.0001***	-0.0000***	-0.0000	-0.0000**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.000)	(0.0000)	(0.0000)	(0.0000)
MISSINGAGE	-0.0016	0.0015	0.0017	0.0018**	0.0030***	-0.0027***	-0.0015	0.0026***
	(0.0010)	(0.0010)	(0.0014)	(0.0009)	(0.0008)	(0.0008)	(0.00013)	(0.0009)
TENURE	-0.0000	-0.0000	-0.0000	-0.0000	0.0000	0.0000	-0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
SAT	0.0001	0.0001	0.0002	0.0004	-0.0003	-0.0003	0.0000	0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0009)	(0.0004)	(0.0009)	(0.0001)	(0.0007)
MBA	-0.0002	-0.0001	-0.0003	-0.0004	-0.0007**	-0.0005**	-0.0013*	-0.0003
	(0.0003)	(0.0003)	(0.0005)	(0.0003)	(0.0003)	(0.0003)	(0.0006)	(0.0003)
PhD	0.0002	0.0002	0.0007	-0.0000	-0.0001	0.0000	0.0004	0.0001
	(0.0007)	(0.0007)	(0.0010)	(0.0006)	(0.0004)	(0.0005)	(0.0009)	(0.0006)
CLOSENESS	0.0061***	0.0059***	.0066***	0.0045***	0.0049***	0.0037**	0.0055**	0.0046***
	(0.0018)	(0.0018)	(0.0024)	(0.0016)	(0.0018)	(0.0017)	(0.0024)	(0.0016)
Obs.	4058	4058	4058	3893	3893	3893	3893	3893
R^2	0.64	0.65	0.75	0.15	0.13	0.13	0.11	0.13