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The Dark Side of Alternative Asset Markets:

Networks, Performance and Risk Taking

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Abstract

When actors invest in making strong network ties (relationships) with other actors, such ties can potentially influence behavior and subsequent financial performance, but the strength and direction of these effects is debated. Using original fine-grained data that documents the nature and extent of the relationships between Hedge Funds through their Prime Brokers (banks that provide leverage, issue credit lines and serve as bridges between Hedge Funds) we probe the social topology of Hedge Fund to Hedge Fund relationships that shapes this global alternative asset market. Contrasting much recent research that tends to stress the positive effects of network relationships, we find that investing in network relationships in this industry appears to have a "dark side" in terms of both performance and risk taking; where we probe various measures of both performance and risk in line with recent finance literature. We explore the reasons for these effects, and conclude that investing in Hedge Fund to Hedge Fund network ties can lead to inferior performance and increased risks that may not benefit the investor.

1. INTRODUCTION

Building a network of relationships at either the personal or institution level is an investment decision that carries both downside risk and upside potential. In recent years the literature has increasingly recognized that financial markets have network dimensions; and until now researchers have explored some of the upside potential of these relationships. For example, Cornelli and Goldreich (2003) show that bulge-bracket investment banks benefit from use of their ties with institutional investors when pricing and distributing corporate securities before information about these assets becomes freely available; Hochberg, Ljungqvist and Li (2007) suggest those ties can improve the quality of deals that flow to venture capital firms, and can allow venture capitalists to pool correlated signals so as to achieve superior information possibilities; and Cohen and Frazzini (2010) explore why markets should look more closely at supplier-customer relationships to predict performance. The positive performance effects of networks in financial markets have also been noted in the management and sociology literatures: for instance, Uzzi (1999) shows that the costs of a firm's capital varies positively with the degree to which its commercial transactions with a bank are embedded in social attachments, and Sorenson and Stuart (2001) show that better networked venture capitalists experience better performance[1].

However, the possibility that investments in networks might increase risk and have negative effects on performance is much less attended. Anticipating our study is the work of Guner, Malmendier and Tate (2008), who noted that when bankers sit on firms' boards, such connections may lead firms to over-invest in projects and be more likely to engage in risky mergers. More robustly, Guedj and Barnea (2009), studying Fortune 1,500 companies, find that

[1]The connections discussed here are not the same as direct investment linkages caused by linking the asset side of one balance sheet to the liability sides of the counter-party; see for instance the discussion of Allen and Babus, 2009.

greater network centrality of their directors can be associated with some negative performance effects for the firms involved, but they did not consider risk explicitly. In other contexts such as the movie industry, a few recent studies have suggested that ‘over-tight’ networks can create high costs due to ‘over-crowding’ and ‘cognitive dissonance’ effects, leading to inferior decision making (Ferriani, Cattani and Baden-Fuller, 2010). But until now there does not appear to have been any serious exploration of the possibility of increased risk and decreased performance when investing in network relationships in financial markets generally, and more particularly in alternative asset markets; by focusing on the Hedge Fund industry, this paper aims to address all of those deficiencies.

Networks feature prominently in the Hedge Fund industry. Recent ethnographic evidence suggests that a Hedge Fund is seldom an entity that confronts a market ‘on its own’. More typically, it is part of a rich network of interpersonal and inter-organizational connections, through which support is channeled and information circulates, including research reports, news, prices, as well as information about the behavior of other market actors (Beunza D.; I. Hardie and D. MacKenzie. 2006 Hardie and MacKenzie, 2007). Some of this flow is at the level of individuals who typically work for Hedge-Funds (see Simon, Millo, Kellard and Engel, 2010 and Figueiredo, Meyer and Rawley, 2010), but much of it passes through the firm to firm connections that are orchestrated by prime brokers. We know that almost all Hedge Funds rely on Prime Brokers to assist them executing their trades; but some choose to nurture the relationship with their Prime Brokers to gain information about what other Hedge Funds are doing in terms of trading (Danielsson, Taylor and Zigrand, 2005: 531; Simon et al. 2010). For example, it is not uncommon for a Prime Broker to pass information on whether a certain stock is being shorted by other Hedge Funds, and to what extent, without naming any particular fund. In addition there is anecdotal evidence that Prime Brokers perform bridging between their clients; that is they inform some of their Hedge Fund clients about selective trades made by others knowing that this information could be a source of competitive advantage. This is vividly illustrated by the comments of one of the Prime Broker managers we interviewed for this research:

> *"We at …. have a large desk dealing with Hedge Funds". I talk to all my clients every day, asking them what they are doing and answering their questions. Of course I do not know (everything about) what they are doing, but the questions they ask are very revealing. Such as "how do we do this particular trade for this stock". And when several people ask the same question in the same day, then one has a sense that things are happening" .. "yes of course we have Chinese walls, but I agree some information inevitably leaks." (interview evidence from prime broker manager, 2009).*

Not all Hedge Fund managers believe that this Hedge Fund to Hedge Fund information circulation adds value. Just as Griffin, Shu and Topaloglu (2010) showed that "market information" on corporate announcements are not perceived to add value by all participants, when they examined detailed trading data for the NASDAQ over a 6 year period; so too in this alternative asset market, some Hedge Fund managers caution against valuing the gossip about other Hedge Fund activity that comes from talking to prime brokers:

> *"Prime brokers carry gossip and the value of this is often over-estimated. Their information can tell you about the herd, but such information is typically too late and unreliable. Sorting out the good gossip from the bad takes a lot of time and effort. We here (in our Hedge Fund) undertake original modeling and research, we believe we make market trends not follow them, and our performance outcomes are superior giving force to our beliefs..." (interview evidence from owner-manager of Hedge Fund, 2010)*

In summary, some Hedge Funds have chosen their Prime Brokers to make connections with other Hedge Funds (and a few may choose multiple well-connected Prime Brokers such as Goldman Sachs, UBS, Bear Stearns or Morgan Stanley each with several hundred Hedge Funds in their direct network - to maximize this exposure); where as some Hedge Funds may deliberately choose Prime Brokers that have few connections (such as JP Morgan or Barclay Capital or Fidelity with less than 50 Hedge Funds in their direct network)[2]. Critically for our study, the choice of which Prime Broker to use is always viewed as being crucial for the Hedge Fund, and almost always this decision is made when the Hedge Fund is first formed; and once taken this decision is rarely changed (at least before the financial crisis of 2007)[3]. This means that any analysis of the relationship between Hedge Fund network connectivity and Hedge Fund risk taking and performance is unlikely to suffer from 'reverse causality', because the connectivity was known and set at the moment of the Hedge Fund formation.

To explore the effect of these "network choices" on the risk behavior of Fund managers and Fund performance we selected a sample of more than 2,000 active Hedge Funds listed in the TASS database for the period up to 2006; a period of relative tranquility in financial markets. The Tass data base is the only reliable data base that contains data on both Hedge Fund performance and Hedge Fund connectivity. Noting the fact that Hedge Funds do not form direct links with other Hedge Funds, we mapped the connections among Hedge Funds that exist on account of Prime Brokerage connections. Figure One shows a partial view of these connections; and it can be seen that some Hedge Funds are not well connected with other Hedge Funds, where as some are very well connected because their Prime Brokers have many links; and that some Hedge Funds (7% of the sample) choose to be connected to more than one prime broker and these typically have an even more extended set of direct and indirect connections. This crude picture is illustrative; our analysis uses well established, sophisticated measures for capturing network centrality (including the eigenvalue, closeness and betweenness measures).

Figure One about Here

In our work, we measure the risk taking and the performance for each Fund in our sample; we utilize the last 5 years of monthly returns data provided by Tass[4]. Taking into account some of

[2] Since 2007, several Hedge Funds have started to consider multiple prime brokers is to alleviate counter-party risk.

[3] According to industry sources; and Justin Miller, expert on Hedge Funds, has undertaken a longitudinal analysis of Prime Broker connections and orally confirms this fact.

[4] Where a fund has been in existence for less than 5 years but more than one, we also include it in our dataset, as we will explain below.

the most recent developments in Hedge Fund Industry measurement approaches particularly as they relate to risk (e.g. Bollen and Whaley, 2009; Patton, 2009) we then estimated a robust (to outliers) linear regression model where the dependent variables were: performance (absolute returns), performance adjusted for risk (Sharpe and Sortino), and risk taking behavior (negative skew and positive kurtosis; market risk exposure; and market risk exposure on the downside), and the independent variable – network centrality along with appropriate controls.

Summarizing our results we found that network centrality measures had a negative and statistically significant influence on all three major measures of Hedge Fund performance, and a positive and statistically significant impact on all three major measures of risk taking. In the paper we explore the possible meanings of our results and explain our very extensive robustness tests that extended our measurement set of performance, risk taking and centrality measures.

Our paper makes several contributions to the literature. First, we show that the relationship structure of the Hedge Fund industry has an important influence on Fund risk taking and Fund performance, which suggests that for a better understanding of the industry, future studies of Hedge Fund behavior need to take account of this dimension. In this respect, our findings give support to the claims of Abolafia (1997) and Mizruchi and Stearns (1994) on the need to include sociological variables to finance studies. Second, our results advance a better appreciation that investing in network relationships can have a "dark side" (Gargiulo and Benassi, 2000): Networks have costs as well as benefits and it is not obvious whether one side always offsets the other. Third, our analysis suggests that rearchers should examine risk taking dynamics when they look at performance effects; risk taking is a variable largely disregarded in prior studies of network effects.

In the following sections we briefly review the contrasting lines of argument concerning the performance-related consequences of network centrality. We begin with findings suggesting that networking is beneficial to Hedge Fund performance, and next turn to research highlighting the downsides of networks. We continue by discussing the relationship between network centrality and risk. We then describe data, measurement strategy and present the results. We conclude by highlighting the implications of the findings, their limitations and topics for future research.

Theory-Context

We combine the rich research tradition on the role of social networks in economics with the extensive finance literature on risk-taking and performance in Hedge Funds to explore novel links between risk-taking and performance. We focus on the hedge fund industry for both theoretical and substantive reasons. In theory terms, this is an important industry for studying risk taking behavior, because most of its actors claim their skills and expertise give them a deep understanding of the drivers of risk that allows them to divorce risk from return: in short, they claim to have the highly prized answer to the ‘search for absolute returns’. In terms of substance, Fung and Hsieh (1999) have deepened our understanding of this issue by exploring the limited extent to which Hedge Funds actually succeed in gaining ‘absolute returns’ rather than merely tracking the overall market, and paved the way for many others to explore particular this and other dimensions fund behavior and performance (e.g. Brown, Goetzmann and Park, 2001; Fung, Hsieh, Naik and Ramadorai, 2009). One of the most important recent contributions comes from Patton (2009) who carefully unpicked the meaning of risk in the risk-return metrics. He noted that the sophisticated investor does not mind risk on the upside, but is averse to down-side risk, especially when it is correlated with market down-turns. Patton developed and refined risk measures for Hedge Funds; and using these metrics he noted that only a few hedge fund managers were able to avoid risk. His results confirm that the hedge fund industry is a ripe site for investigating what factors make for better or worse risk-return, and we use some of his measures in this paper

Theory-The upside of centrality

The network literature proffers a well developed body of published work that provides robust theoretical and empirical approaches to support the intuitive idea that connections between actors involved in an industry will lead to advantages (including the management of risk). We begin our theory section by revisiting these arguments about the *positive* effect of networks on performance, although only – since the arguments are both well known and intuitively clear - summarizing the more important themes which have a long antecedence in the literature. The argument goes like this: direct ties - as well as their indirect 'ties-of-ties' - shape information flows (Uzzi, 1996): direct ties potentially yielding many benefits including knowledge sharing and complementarities (Arora and Gambardella, 1990; Powell, Koput, and Smith-Doerr, 1996; Ahuja, 2000, Sorenson and Stuart, 2001), while indirect ties can also represent channels for communication, transferring information and facilitating knowledge exchange (Gulati and Gargiulo, 1999). Writers such as Podolny (1994) and Gulati (1995 and 1998) have explained how actors (firms) benefit both from favorable network positions as well as from the resources they can access from their *alters*. Through their direct and indirect partners, firms can get access to the knowledge and experience that come from their interactions with their partners. Hence the access to information, resources, knowledge, contacts, and so on can vary according to the firms heterogeneous positions in their networks and - to the degree that better access to fine-grained information and resources facilitates superior knowledge exchange and generates greater awareness of available opportunities - differences in network position can at least partly explain the better performance of some actors.

When we apply these traditional ideas to our chosen industry, we can hypothesize that Hedge Funds that occupy central positions within their social structures are likely to see performance benefits. Centrality allows the Hedge Funds access to flows of information that circulate selectively within their networks, thus enhancing their ability to tap resources and contacts dispersed in the field, resulting in higher performance.

Hypothesis 1A (White side of networks): For a given level of risk-taking, the performance of Hedge Funds will be better when they are more centrally connected

To finish with the positive considerations, we need to examine risk-taking. The literature on an individual's risk taking behavior is extensive, but generally focused on psychological factors (e.g. Kowenburg and Ziemba, 2007). Here we are concerned with a positional explanation of the phenomenon for firms, and we begin with the premise that behavioral phenomena, such as risk taking, are driven in large part by the opportunities linked to a firm's position in its external environment (Burt, 1982; Mizruchi and Galaskiewicz, 1993). A firm that has a more central position in the network of actors should have better access to information and so be able to avoid risks more easily. In contrast, those on the periphery not only face informational difficulties in assessing risks, but (if their performance is poor) may face strong incentives to engage in risk taking (Bromiley 1991). This logic of the powerless - where those on the periphery have less to lose by taking risks - would also appear to be consistent with prospect theory (Kahneman and Tversky 1979), which states that being in the 'domain of losses' produces risk-seeking behavior. If the lack of power puts actors in the domain of losses, and possessing power puts actors into the domain of gains, then we can hypothesize that power has a negative relationship with risk taking. Such arguments can easily be seen as potentially relevant to the context where being close to other Hedge Funds can give better information about risks

Hypothesis 2a (White side of networks): Hedge funds that are more centrally located can achieve a given level of return with lower risk taking on account of superior information.

Hypotheses 1a and 2a can be explained mathematically as follows: if (π, σ) represent the return and variance of the fund respectively, and N the measure of the closeness of the fund to the centre of the network, then H1a and H2a mean that:

$$\frac{\partial(\pi)}{\partial N} > 0 \; and \frac{\partial(\sigma)}{\partial N} < 0$$

Theory - The downside of centrality

Whilst the positive dynamics of network centrality are well known, the negative dynamics have been less commonly explored. Fracassi and Tate (2010) explore the network effects of CEOs and Boards of Directors in a study of S&P 1,500 companies, and find that CEO-Director ties can reduce firm value, which lends further support to Guner, Melmendier and Tate's (2008) novel results that direct connections with experts do not always yield valuable information. And there may be other factors at work: maintaining an increasing number of relationships implies the higher coordination costs of the greater time and energy needed to managing these relationships; and it is plausible to assume that the costs incurred in negotiating and monitoring increasing numbers of relationships will eventually outweigh their information benefits (Ferriani, Cattani and Baden-Fuller, 2009). What may be true for individuals; may also be true for firms. The time, effort and attention required in managing both direct and indirect relationships may starve activities that have more value for the firm (McFayden and Cannella 2004), again meaning that too many relationships make additional benefits from shared experience difficult to attain (Berman, Down and Hill, 2002). Put in the context of the Hedge Fund industry, having more social relationships with other Hedge Funds may not be cost-efficient in certain situations or at certain levels (Adler and Kwon, 2002).

Second, cognitive research points to the dysfunctional behavior that can arise from overexposure to information (Simon, 1971; McFadyen and Cannella, 2004; Sutcliffe and Weick, 2007). There are opportunity costs of inspecting each alternative opportunity, so increasing the number can cause information overload and lead to dysfunctional behavior such as lack of perspective, difficulty in selecting relevant information, and unproductive scrutiny of new ideas or knowledge (Schwartz, 2004). Schneider (1987) demonstrates that when economic actors (individuals or organizations) are overloaded, primary and secondary symptoms become manifest: the former including a lack of perspective and inability to select out irrelevant information, leading to cognitive strain that adversely affects the timeliness and quality of decisions (Eppler and Mengis, 2004), while secondary symptoms include reduced scanning ability, narrowed attention, and a desire for increased control. Together they compound both the mental effort and the time required to make sense of the information, exacerbating those problems the actors (individuals or firms) are trying to solve (Sutcliffe and Weick, 2007). This speculation is consistent with theorizing by Hansen, Poldolny and Pfeffer (2001) who suggest that large networks might prove counter-productive as they compound the problem of assimilating diverse suggestions, solutions and ideas, which is also consistent with Ferriani et al.'s (2009) findings (in studying the Hollywood film industry) that despite the informational benefits of centrality, project entrepreneurs can suffer downsides arising from overexposure. Project entrepreneurs are also limited in their ability to take full advantage of such positions, if faced with the added complexity of managing and monitoring a large network.

When these ideas are put in the context of Hedge Funds that have strong connections with other Hedge Funds, we can speculate that, far from simplifying the problem of how to analyze market information, centrality may amplify the amount information their managers have to assimilate, causing negative effects.

Hypothesis 1b (Dark Side): Hedge Funds that are more central to the industry will exhibit inferior returns for a given risk profile

Just as being centrally connected in a network of ties can lower returns, it can also promote perverse risk taking effects. Inefficient information processing in overly connected networks may not just cause poor decisions to be made, but may make risky decisions appear to be safe. Guner et al. (2008) explain how connections can also bring biased and misleading information, which may be inadequately sorted and screened. Both these factors suggest that Hedge Funds that are more central may engage in unnecessary risk taking, and the management literature reinforces these arguments. Being central in a network may give rise to feelings of power (even for an organization), and that power can have negative effects. According to Anderson and Galisnky (2006), for instance, possessing power leads actors (that could include firms) to pay more attention to the positive potential payoffs inherent in risky actions and devote less to the potential dangers, since power makes people (or organizations) suppresses their behavioral inhibition system and give more credence to reward-laden information. This focusing on rewards and being less aware of dangers is clearly likely to be associated with risky behavior that ignores the negative potential consequences).

We amplify the point by referring back to individual behaviors, and speculating that these may be relevant for firms. It is argued that powerful individuals would be more likely to engage in gambling because they would be more focused on the money they could win, and less on the possibility of losing the bet. Furthermore, power might also lead actors to be more optimistic of their chances of winning, and also in their estimates of risk, since power induces a reduction in the perceived probability of experiencing the downside of risk. The accumulated rewards associated with past successes can also lead to over-optimism and risky behavior. In the stock market arena, previous capital gains have been shown to increase investors' optimism and risk-taking, and previous market losses to increase their risk aversion, by exacerbating their fear of incurring further losses (Barberis, Huang, & Santos, 2001). Finally, power can increase the propensity to take risks by leading actors to be over-confident in their abilities to capture the upside of risk or to deal with negative consequences should their risky behavior fail to pay off. Whilst all these last arguments related to individuals, we suggest that they may also be relevant for firms. To illustrate this point, consider that Julian Robertson and his prominent Tiger hedge fund was openly criticized by Business Week on April 1, 1996 for excessive risk taking. Yet these comments appear to have been ignored for Tiger fund continued to woo investors and although it reached a peak value of around $22 billion in 1998, a series of high risk moves (that some have argued was the continuation of what was long evidenced by past behavior) caused the value of these funds to collapse, and Robertson closed his funds in 2000. One would think that Robertson with his connections would have heeded the warnings and not have needed to take unnecessary risks. But this does not appear to be the case. And one might also think that, after the collapse of the Tiger funds, the actors in the market would wish to avoid Robertson and those associated with him, to punish him for making those mistakes. But subsequent to these events several of the managers who worked with Robertson in his fund (and so associated with the risk taking) went on to form their own companies, typically labeled as the Tiger Cubs; and paradoxically they found strong support from many parts of the finance community. The suggestion of commentators is that because Robertson was so central to the industry, that centrality continued to hold sway, and these Tiger Cubs used the connections they made with influential actors when working for Robertson, to overcome the Robertson *opprobrium* and obtain valuable resources in their subsequent careers.

Thus, since centrality increases power and insofar as perception of power accentuates risk-taking behavior, we should observe an increase in risk taking behaviour for those hedge funds that move towards more central positions.

Hypothesis 2b (Dark Side): Hedge Funds that are more central to the network will take more risks than those located on the periphery.

Going back to our mathematical notation, we can portray hypotheses 1b and 2b as follows:

$$\frac{\partial(\pi)}{\partial N} < 0 \; and \frac{\partial(\sigma)}{\partial N} > 0$$

Visualizing the results

We can visualize our 'dark side' predictions against the 'white side' using the traditional risk-return map shown as Figure 2 below, where the X axis represents risk taking and the Y axis returns, and the heavy line indicates the usual optimal portfolio trade-off of risk and return. The points to the North and West represent areas where increases in centrality yield superior returns and the possibility of less risk taking (for a given return); whereas the South and East portrays the area where centrality in the network has negative effects on returns and risk-taking. The figure can be thought of as a graphical representation of different scenarios of what happens when an actor starts with a market based portfolio and uses its network connections to shift position, above the line representing positive network effects and below the line representing negative network effects.

Insert Figure 2 Near Here -

2. Data and Methods

2.1. Setting and sample

Although dating from the 1940s, Hedge Funds developed into their current form in the late 80s since when their number has increased dramatically from a few hundred in the early 1980s to a peak of about 11,000 in 2007-8. They have become significant actors in global capital markets, with paid-in capital peaking in mid-2008 at approximately $1.9 trillion (Hedge Fund Research Inc, HFR, 2008). This study used the 2006 TASS database, which is well known to industry experts who generally consider it as very representative of the industry (Miller, 2009; Fung and Hsieh, 1999)[5]. It contains data about 4,158 Hedge Funds operating all over the world, and is the only generally available dataset that contains a reliable measure of prime-broker hedge-fund connections (Miller, 2009). To calculate our connectivity measures, we eliminated those funds that did not state whether they had a prime broker (perhaps because they lacked a formal prime broker relationship) or who listed as their prime broker an institution that did not appear to be part of the investment banking community (in technical network parlance, this meant we eliminated funds that were not part of the 'main component'), thus reducing our dataset to 3,435 funds with 25 prime brokers; that individually had a wide variation in number of Hedge Fund customers: in particular, Morgan Stanley, Goldman Sachs, Bear Stearns, and UBS each had more than 300 Fund connections, whereas at the other extreme Fidelity, AIG, ING, and Prudential had fewer

[5] According to Miller: The largest industry data base as of 2007 was HFR with about 44% coverage of the industry, the next largest data base is TASS with 33% coverage and the third largest is CISDM (formerly MARS) with 23% coverage; and there is some overlap between the data-bases.

than 20 direct connections[6]. In our actual estimations, on account of missing data, we had to further reduce our data set to 2,116 funds with on average 40 monthly observations for each fund[7]. The year 2006 was deliberately chosen as representing a period of relative stability in markets, where concepts of risk were not 'stretched' by outside events.

2.3 Variable and measures

Dependent variables

Our dependent variables are performance and risk-taking using the monthly valuation data in the five year window from 2001 to 2006. Where a fund has been in existence for less than 5 years but more than one year, we also include it into our analysis. Regarding the measures of performance, we define and report results for the absolute return and for the standard Sharpe and Sortino measures, the later being the two most commonly used in the financial literature. We note that Eling and Schuhmacher (2007) show how adding further, different performance cross-sectional measures does not change the rankings of different funds: and we too checked our data and found similar results - that adding more measures does not add more information.

As far as risk-taking is concerned, we utilize Patton's (2009) suggestions, which build on earlier work on Hedge Funds. This means that for the second, third, and fourth moment of the distribution of the funds' returns we adopt measures that look to down-side risks, and the extent to which they are correlated (or are uncorrelated) with market risks. To identify the market risk, we follow again Patton in using the MSCI World Market Index (Source: Datastream). We explain everything in more detail below.

[6] In computing the network statistics, where a fund manager had two funds one in euro and one in US dollars, the network data were computed as if this were one fund in line; doing the computation the other way would make no difference, as centrality measures are all normalized in our estimation procedures. Note also, in 2006 Bear Stearns was independent of JP Morgan.

[7] The most common missing data was fund size, an important control variable; we undertook robustness checks on the missing observations.

Performance Measures: Absolute Return, Sharpe, and Sortino

Our first measure is the absolute return of the fund without regard to risk. Our other two reported measures take account of risk: the second measure examines risk adjusted performance using the *Sharpe Ratio*, developed by Nobel prize laureate William F. Sharpe, which is widely used in the Hedge Funds industry and is defined as:

$$\text{Sharpe Ratio}_i = \frac{\frac{\sum_{t=1}^{T}(r_{t,i}-r_{t,f})}{T}}{\sigma}$$

where $r_{t,i}$ identifies the monthly return series for the individual hedge fund i at month t; r_f the monthly risk free rate at month t; and σ the standard deviation of the excess return series (and we use the yield on US Treasury bonds as proxy of the risk free rate).

As the Sharpe Ratio is based on strong assumptions about the underlining return generating process, we also employ as our third measure the Sortino Ratio. In fact, it is well known that the wide use of derivative instruments in the hedge fund industry generates both asymmetric return distributions and 'fat tails' (see among others Geman and Kharoubi, 2003), and we compute the Sortino Ratio (developed by Frank A. Sortino) that deals with negative and positive returns differently when computing volatility (standard deviation). Its definition is:

$$\text{Sortino Ratio}_i = \frac{\frac{\sum_{t=1}^{T}\left(r_{t,i}-r_{t,f}\right)}{T}}{\sigma*}$$

Comparing the Sortino and Sharpe Ratios, the only difference is the divisor - $\sigma*$ -which in the Sortino case refers to the standard deviation of the 'only negative' returns. It follows that this formula emphasizes the highest negative rather than highest positive returns to compute volatility, reflecting the stance of the risk-averse investor.

We further checked the robustness of our results using other performance measures including: the Omega ratio, the Calmar ratio, the excess return on the Conditional Value at Risk, and the excess return on the Modified Value at Risk using the Cornish-Fisher expansion. As noted above, like Eling and Schuhmacher (2007) we found that all ratios give similar results, so are again not reported here (although they are available on request).

Risk Measures: Skew, Kurtosis, and Co-movements with Market Indices

Most hedge fund managers claim that they look to avoid risk by utilizing complex trading strategies; yet they are unable to achieve high returns without taking some risks (such as the risk that the market will not price the assets correctly in line with their judgments, even in the longer term, as explained by Beunza and Stark, 2004). In line with previous work, when estimating risk we employ several measures, taking at first the main moments of the distribution of hedge fund returns, such as standard deviation, skewness and kurtosis. Standard deviation is a well known measure that places equal weight to upside and downside risks; in contrast skewness measures the extent of asymmetry between the two, while the kurtosis gives the extent to which the returns feature 'fat tails'.[8] Putting this in context means that a hedge fund which shows both negative skewness (more left tails) and high kurtosis (fat tails - leptokurtosis) is considered more unattractive than a normally distributed return by a risk averse investor. To control for the risk-averse investor we employ a logit model using a dummy variable that equals one where a fund presents both negative skewness and positive kurtosis and zero otherwise.

Thus far, our risk taking measures are rather simple, and consider risk from the perspective of the investor that is not diversified. The reality for the sophisticated investors who deal in Hedge Funds is different; they have other ways to combat risk that involve market portfolios. To overcome this potential limitation, we need to consider risk in terms of co-movement respect to

[8] In lay person terms, a fat tailed distribution has extreme events occuring more frequently than implied by the 'normal' distribution.

the market index, so, moving from a concept of idiosyncratic risk to a systematic one.[9] Few researchers have taken this approach until recently for both conceptual and technical reasons, due partly to the non-linearity of Hedge Funds returns. However Patton (2009) has explained how to resolve this challenge. Our second measure of risk is risk matched to market movements (Patton, 2009). For those who unacquainted with his approach, we explain that computationally the first step is to find the correlation between the portfolio return and the market return, and we estimate (for each fund) a polynomial approximation to the conditional function-polynomial regression, as follows:

$$r_{t,i} = \sum_{n=0}^{\infty} \beta_n (r_{t,MSCI})^n + \varepsilon.$$

where $r_{t,i}$ and $r_{t,MSCI}$ are the returns of the hedge fund *i* and the *MSCI World Index,* respectively, at time *t*. Whilst theoretically one should consider all moments of the equation, we consider only the first and second order terms as we found little significance to the higher orders, so this paper reports the results (for each fund) of the following model:

$$r_{t,i} = \beta_0 + \beta_1 r_{t,MSCI} + \beta_2 r_{t,MSCI}^{\ 2} + \varepsilon .$$

We then test the 'neutrality'(to the risk) of each hedge fund to the market index by testing the null hypothesis that β_1 and β_2 both equal zero and use the p-value of the test (Wald test) as a primary proxy of the systematic hedge fund risk exposure to the market. Here, a low p-value indicates that the fund is not 'neutral' to the main source(s) of market risk, and translates into a signal that the fund is suffering from high systematic risk exposure.

Our third approach recognizes that some (but not all) investors such as the pension funds are quite risk averse. These risk-averse investors are concerned with the potentially asymmetric preference of investors to the co-movement of the fund to the market index (see Patton, 2009). Again, considering only the second order of the polynomial MacLaurin expansion, we run a

[9] Systematic risk, sometimes called market risk, aggregate risk, or undiversifiable risk, is the risk associated with aggregate market returns. By contrast, unsystematic risk, sometimes called specific risk, idiosyncratic risk, residual risk, or diversifiable risk, is the specific risk in a portfolio, which is uncorrelated with aggregate market returns.

second battery of regressions that take the following form

$$r_{t,i} = \gamma_0 + \gamma_{1,neg}\, r_{t,MSCI}\delta + \gamma_{2,neg} r_{t,MSCI}{}^2\delta + \gamma_{1,pos}\, r_{t,MSCI}(1-\delta) + \gamma_{2,pos} r_{t,MSCI}{}^2\,(1-\delta)\ \varepsilon\ .$$

where δ is a dummy variable that equals one whether the return of the *MSCI World Index* ($r_{t,MSCI}$) at time t is less than zero, and zero otherwise. In our equation, $\gamma_{1,neg}$ and $\gamma_{2,neg}$ capture the co-movement of the hedge fund with the market risk conditionally to negative returns of the market index, while $\gamma_{1,pos}$ and $\gamma_{2,pos}$ capture the co-movement of the hedge fund to the market risk conditionally to positive returns of the market index. To compute the *"neutrality on the downside"* (Patton, 2009) we test whether the first derivative of the equation is **not** positive when the market is **negative** - in other words:

$$\frac{\partial(r_{i,t})}{\partial(r_{MSCI,t})} = \gamma_{1,neg} + 2\,\gamma_{2,neg}(r_{t,MSCI} |\ r_{t,MSCI} \leq 0)$$

As before, we use the Wald test to examine if the equation is not just different from zero, but also that it is positive. Consequently, a low p-value of the test indicates neutrality (to the risk) of the hedge fund on the downside. For instance, a p-value below 10 percent means a rejection of the null hypothesis that the hedge fund is positively affected by the market when the latter is negative: this being a situation where the hedge fund's return does not follow the market going down, something potentially attractive to sophisticated risk averse investors.

Network variables

The Hedge Fund industry has a sparsely connected structure, since Funds are not formally linked with others, except via the intermediary of the prime brokers. (In this respect, this industry is quite unlike many others, where many firms have formal alliances with competitors to collaborate on specific issues). Investigation of the data reveals that 93% of Hedge Funds are connected to only one prime broker, and it is the few funds (7% of total) with multiple prime brokers that makes the connections between the groups. As Figure 1 showed, the network structure of the industry is characterized by the presence of a main component (where funds are connected either directly or distantly) plus a few isolated funds, typically smaller specialist funds perhaps having no prime broker or being connected to only a few others using an unconnected investment bank[10]. In our network analysis we remove these isolates and analyze only those funds in the main component of this large network[11].

We utilize four standard measures to capture the centrality of the fund in the network, explained below, and their differences visually illustrated in Figure 3.

Insert Figure 3 Near Here

The first such measure is *Degree centrality* which is the simplest because it just counts the number of connections of an actor-firm, stressing the local viewpoint. (Technically it measures 'transaction activity' or 'capacity' of each actor of a given network.) The second network centrality measure is *betweenness centrality;* this measures the capacity of the paths or geodesics (i.e. minimal length paths) that connect a focal point to two other points in the network. Hedge Funds that occur on many shortest paths between other Hedge Funds have higher betweenness, and are hypothesized to be the most able to control flows of communication across the whole network, which depends on their relationships with all members of the network, and not necessarily on their number of direct connections. But a high betweenness score is not the same as being well connected, as Figure 3 illustrates.

The third centrality measure is *closeness centrality*, which is defined as the mean geodesic distance (i.e. the shortest path) between a hedge fund and all other Hedge Funds reachable from it. Funds that are closer to all network members are seen as more central. This measure is often used to show that, as an actor's (i.e. hedge fund) closeness to others increases, so does its access to

[10] The main component is the largest connected cluster in the network. It eliminates isolates and small disconnected clusters. In substantive terms, the main component is the largest subset of organizations that can reach each other through indirect paths of finite length. The percentage of organizations connected to the main component is close to 90%.
[11] Most network measures are based on the main component, which is a connected graph for which measures can be generated.

information (Leavitt, 1951), power (Coleman, 1973), prestige (Burt, 1982), and influence (Bavelas, 1950; and Friedkin 1991). It follows that those hedge funds closest to others are also nearest to sources of information, power, prestige or influence (Degenne and Forse', 1994).

All the centrality measures so far presented evaluate the centrality of the actor-fund without regard for the centrality of the actors to whom they are connected. But we need a distinction between an outlying local centre and a core centre, because being the centre of a group of relatively isolated funds is very different from being the centre of a set of highly integrated funds. So our fourth measure, the *Eigenvector centrality* assigns relative scores to all Hedge Funds in the network based on the principle that connections to high-scoring nodes (i.e., here, prime brokers connected to many Hedge Funds) contribute more to the score of the node in question than connections to low-scoring nodes. Bonacich (1972) asserts this index is particularly well suited to gauge an actor's power.

Once again, we stress that the different network measures try to capture the position of the actor in the network in different ways, and whilst they are generally correlated, they do not always move together as we pass through the data set. Theory does not say whether one measure is superior to the others; rather each has a slightly different role, measuring slightly different dimensions of the concept of network centrality: degree and betweenness emphasize direct connections whereas closeness and eigenvector centrality give more weight to indirect connections.

2.4 Specifications

Our two sets of dependent variables are the performance and the risk taking behavior of the hedge funds, and our cross-section equation specification takes the following form:

Performance = Φ_i (Network features) + $\Sigma\ \gamma_y$ (dummy strategy)

+ γ_1 (Ln(Age)) + γ_2 (Ln(Asset Under Management)

$$\text{Risk} = \Phi_i \text{ (Network features)} + \Sigma\, \gamma_y \text{ (dummy strategy)}$$

$$+ \gamma_1 \text{ (Ln(Age))} + \gamma_2 \text{ (Ln(Asset Under Management)}$$

where Φ_i is a vector of the *i*-coefficients of the variables of theoretical interest (betweenness centrality, closeness centrality, eigenvalue), and γs are the coefficients of control variables. In these models, we control for the hedge fund's investment style (as defined by Fung and Hseigh, 1999, and used by all other analysts of Hedge Funds) using the coefficients $\gamma_{y;}$ and standard errors are computed using Huber-White sandwich estimators making the statistical tests on the parameters robust to outliers. In line with previous research (see for instance Fung and Hsieh, 1999; Titman and Tiu, 2010), we control for other Hedge Funds characteristics that may affect funds' performance and the shape of their return distributions. We use *Age* and *Assets under Management* as a proxy of the longevity and size of the fund, respectively: and because of their strong positive asymmetric distributions, we use the natural logarithms of the variables.

3. Results

Before we explore the network effects on risk and performance, we stress tested our data set to ascertain the nature of risk taking and returns in our industry sample. Our results highlight how risk taking in Hedge Funds differs from that of regular index investing; those knowledgeable of this aspect of the industry may wish to skip this section, as it will not surprise Hedge Fund industry experts.

Risk Management by Hedge Funds

As the first row of Table 1 shows, the median hedge fund was less profitable than the World Market Index (MSCI World) throughout the period under investigation, In fact, while the funds have shown a monthly median return of 0.8 percent, which translates into a median yearly continuously compound return of 10 percent, the MSCI World's slightly higher 0.88 percent monthly median return translates into a yearly continuously compound median return of 11.13 percent. However, the lower median return seems to be correlated to the lower risk of the median fund measured by its volatility (standard deviation), skewness and kurtosis. In fact, Table 1 shows that returns for the median hedge fund are less volatile, less right-tailed, and less fat-tailed than the market index over the sample time window. This evidence is corroborated by the fact that the market index shows a wider returns gap, recording both the smallest (minus 11 percent) and the highest (8.23 percent) monthly returns. Not surprisingly, the Shapiro-Wilk test for normality, reported in the last rows of Table 1, rejects the hypotheses of normal distribution for the MSCI World Index monthly return distributions. We can conclude, therefore, that over our study period, Hedge Funds delivered lower performance (returns) because of their implementation of risk-averse strategies.

Insert Table 1 near here

Hedge funds follow many different strategies, and we categorize funds by investment style and give summary statistics for each strategy of the variables used in the multivariate analysis (Table 2). In the top part of the table, we report in the last two columns the statistical tests that indicate a statistically significant difference for all moments of the return distributions among investment style using both a parametric test (F-test) and a non-parametric one (χ^2-test). As expected, all but two of the styles have heavy tailed distributions (kurtosis greater than 3). However, negative skewness seems not to have been widespread during the study period, as evidenced by the fact that the median maximum for all styles is greater than (the absolute value) of the median minimum. (Further probing of the data reveals that only the Event Driven style funds have a distribution that approximates the normal distribution of returns, and then only just at the 10 percent level, as shown by the normality statistic and the corresponding p-value of the Shapiro-Wilk test reported in Table 2.)

Insert Table 2 near here

The middle part of Table 2 probes the nature of the returns more deeply and explores the extent to which the funds associated with different strategies are exposed to systemic factors. First of all, we report the median linear correlation of the funds and the market index $\rho(r_i;r_{MSCI})$. This term is negative (as expected) for the two styles labeled Dedicated Short Bias and Managed Futures; and it is approximately zero for Equity Market Neutral and Fixed Income Arb(itrage) strategies (again as expected). On the other hand, as many other writers have noted, the highest correlation between the median fund and the market index is detected for the 'Fund of Funds' and Long-Short Equity styles, which between them represent the largest part of the Hedge Fund industry by both number and size of funds.

The coefficients β_1 and β_2 show the causal relationship of the funds with the MSCI market index: and thus constitute measures of systematic risk. The Wald test rejects (at the 10% level) the null hypothesis that β_1 and β_2 are conjointly different from zero for 9 styles out of 11, a result that suggests that funds are correlated with the market index. Again, only the median Equity Market Neutral and the Fixed Income Arb(itrage) funds are risk neutral to the market. As direct consequence, the percentage of non-neutral Hedge Funds in each style follows the same pattern. Our findings are quite similar to those of Patton (2009) and others, who note that a large percentage of funds in each style category are non-neutral to the market.

The bottom part of table two probes other dimensions of returns, and focuses on whether the funds achieve downside market neutrality, as discussed by Patton (2009) and elaborated above. We report the conditional sign of the market index returns and test for the positive sign of the first derivatives, and find that only the Dedicated Short Bias and Managed Futures funds pass the test (at least at the 10 percent statistical level). Put technically, they are (in median) statistically significant in rejecting the null hypothesis of neutrality conditionally to a non-positive market movement, and so should be preferred by risk-averse investors in economy downturn as they tend to move in the opposite direction to the market. As noted in our discussion above, this concept of neutrality is much more stringent than the more traditional metrics; and like Patton we find that most funds perform badly on this test. In particular, 77% of the Equity Market Neutral funds - that by definition should be neutral to downside market moves - failed this test. Looking at the last two columns of Table 2, which report the parametric and the non-parametric tests, we conclude there is a great dispersion among style classes for the neutrality on the downside.

As far as our indicators of risk-adjusted performance -the Sharpe and Sortino ratios - we reach quite similar conclusions. When we compare the average (F-test) and the median (χ^2-test) of the different fund styles, we can the null hypothesis that they are equal (last two columns of Table 2). In particular, note that the funds which (risk-adjusted) perform better are the Event Driven ones, and those which (risk-adjusted) perform worse are the Dedicated Short Bias ones.

In summary, our stress testing of the Hedge Funds in our sample reveals that many have great difficulty in fully controlling risk. And in making this statement, we stress that we engaged in a wide variety of tests about risk that are sophisticated to take account of the complexity of this industry. In our network analysis that follows, we preserve this level of sophistication, maintaining an awareness of the multi-dimensional nature of testing and controlling for the style of the fund in order to avoid any chance of finding spurious relationships between our variables of interest.

Risk and Performance

Correlation matrix of variables

Table 3 reports the correlation matrix of the variables used in the multivariate analysis; that has three parts. The top left hand corner deals with performance measures; the middle part deals with risk measures; and the bottom section deals with the network-centrality measures.

Insert Table 3 near here

When we look at the correlations between the performance measures, we detect strong and statistically positive correlations at the 1% level between the absolute returns, and the Sharpe and Sortino ratios that are risk adjusted return measures. These high correlations as expected (see for instance Eling and Schuhmacher, 2007), and we discuss our stress testing for other measures further on.

Regarding risk measures, as might be expected in view of our previous comments, the first three variables used to measure idiosyncratic risk (standard deviation, skewness and kurtosis) are positively correlated, at least at the one percent level. If we add considerations of systematic risk, we see that funds that are risky - in terms of their neutrality to market risk (1-p-value high) - show low volatility, high skewness and high kurtosis, while funds with high systematic risk, that is 1-p-value high, tend to present asymmetric positive (positive skewness) fat tails (positive kurtosis). The reverse is true when we look at the definition of neutrality on the downside. This result introduces the evidence that the correlation between the two measures of neutrality (1-p-value and p-value of neutrality) is negative and equal to minus 0.23 (statistically significant at at least the 1 percent level): it seems that avoiding market risk is very different from avoiding market risk on the downside.

The four measures of network-centrality are also highly correlated. For computational reasons, we divide the closeness and eigenvalue variables into "deciles" that make easy interpretation of the results: and note that closeness and eigenvalue are very closely correlated (0.79) which is as expected because they both place strong weights on distant connections. The betweennees and degree variables put strong weight on local connections and so they have a limited range and a distribution that is highly skewed, because most Hedge Funds have only one direct connection to a node of other Hedge Funds through its prime brokers. So for computational reasons, like others before us, we restrict these to take on integer values: in our case the betweenness variable takes on the integer values of 1 to 4; and betweenness is either zero or one. These measures are also very closely correlated (0.89), and we discuss our robustness checks to these restrictions later.

Network Effects on Performance

This section discusses our results on the effects of the network variables on Hedge Funds' performance (Table 4), and on their risk taking behavior (Table 5 and 6) using the full multivariate analysis.

Table 4 shows that, controlling for other variables, network centrality has a negative effect on Hedge Funds' returns measured in the crudest manner - as the 'early mean' of each fund. We used separate models to assess the effect of each measure of centrality separately to avoid the correlation problems that usually occur among centrality measures. The results that use the *Eigenvalue* or *Degree* measures show significant and negative effect on Hedge Funds' returns (respectively $p<0.01$, $p<0.05$), strongly suggesting that using or being connected to many Prime Brokers is not beneficial for the Hedge Funds' returns. The reader is reminded that the *Eigenvalue* places strong weight on distant connections whereas *Degree* places strong weight on local connections. The results for the control variables are as expected: younger (*ln(Age)*) Hedge Funds display negative and significant performance ($p<0.01$) and bigger Hedge Funds (*ln(size)*) positive and significant performance ($p<0.01$). We stress that we do not place undue emphasis on these results, as the measure of returns is quite crude.

Insert Table 4 about here

When we look at the effect of Hedge Funds centrality on their risk-adjusted performance, we see strong effects for both the Sharpe Ratio (Model 5,6,7 and 8) and the Sortino Ratio (Model 9, 10, 11, and 12): the impact of centrality on Hedge Funds risk-adjusted performance is strongly and significantly negative using three of the four network metrics at the 5% levels (and some are also significant at the 1% level). In particular, Degree and Betweenness (measures of local connectivity) are important (negative) moderators of performance (see models 7, 8, 11, and 12). The models also show strong results for the Eigenvalue measures of centrality (significant and negative) – a measure that captures both distant and local connections. In all cases, our control variables have expected signs: younger (Ln(*age)* negative and significant*,* p<.01) and bigger (*Ln(Size)* positive and significant, p<.01) Hedge Funds have better risk-adjusted performance.

Taking the results together we see strong support for the notion that networks bring a dark side to performance: Hedge Funds that are more central to the network of Prime Brokers along two of the possible dimensions show consistently inferior returns. And it should be emphasized that we do not need **all** the centrality measures to be significant for the results to hold, for as Figure 3 shows, different measures measure different kinds of centrality.

The size of the effects is quite large. Taking the eigenvalue effect first, we can see that moving 10% closer to the centre reduces the absolute return by 2% (0.25 a year on a typical *long-short equity hedge fund return of* 11.2%)*;* and the Sharpe ratio by 2.9% (0.008 on an average of 0.276 for the same fund) and the Sortino by 0.014 (on an average of 0.000). These are large effects. And if we take the measure of *degree*, we can see that for the typical *long-short equity hedge fund connecting to another set of funds via an* extra prime broker depresses the Sharpe ratio from 0.276 to 0.250 (9.41%), and the Sortino ratio from 0.00 to -0.06 – both very significant changes.[12]

Network Effects on Risk Taking

The Long-Short Equity hedge is the most frequently observed investment style of hedge fund, with a typical fund size of about $58.8 million, and average age (5 years). Using our data we can see that this typical fund has a Sharpe ratio of 0.276, with just one Prime Broker connecting to an average of 120 funds, and it is forecasted to move to a Sharpe ratio of 0.25 for an additional Prime Broker. For example referring to the first computation, and following the rank of Model 4 of Table 5 figures are as follow for one Prime Broker 0.276 = -0.026 [1] - 0.06 [ln(5)] + 0.02 [ln(58791039)] + 0.40 [1] – 0.36 [1] and for two Prime Broker 0.250 = -0.026 [2] - 0.06 [ln(5)] + 0.02 [ln(58791039)] + 0.40 [1] – 0.36 [1]

But what of risk taking behavior: is inferior performance correlated with taking fewer risks – or of taking more? Table 5 sheds light on this (very) relevant issue by showing the regression coefficient of logit models where the endogenous variable is a compound indicator that accounts for both skewness and kurtosis. The dependent variable is a dummy variable that takes the value one when the fund's return presents both negative skewness and positive kurtosis – that is when the returns can be considered risky - and zero otherwise. Model 3 and 4 show that the more central Hedge Funds are, the more risks they take (*Betweenness* and *Degree* significant and positive, at $p<.05$ and $p<.01$ respectively). These results lend further support to the view that Networks can have a dark-side: centrality seems to increases risk-taking behavior as well as diminishing performance.

The control variable *size* is not significant, but the *age* variable suggests that older Hedge Funds take more risks (*age* positive and significant at 1% level). Patton (2009) suggests that this last result about the effect of age might be the result of a 'drift' in fund style.

Insert Table 6 about here –

We interpret the size of the effect as follows. Again, using the regression logit regression coefficients of model (4) in Table 6, and applying them to the median fund in line with the methodology previous discussed gives a change in the likelihood of having both left and fat tails from 45.3% for the typical fund using one prime broker to connect with typically 70 funds to 53.7% for adding another prime broker making an additional set of connections to other Hedge Funds. That is a change of 18% in the likelihood percentage.

To continue our tests of risk-taking behavior, we utilize the more sophisticated measures of risk-taking related to 'market risk exposure'. By this measure, both the eigenvalue and the closeness measures are positive and significant. Interpreting the results we see that moving 10% closer to the centre changes the probability of market risk exposure by 1%. We note that this measure is likely to be the one accepted by institutional investors that have a market based portfolio.

Finally, in line with Patton (2009) we look at ‘market risk exposure on the downside’- as noted before, this is a demanding criterion, and not necessarily correlated with other measures of risk taking. Table 6 presents the results of the *eigenvector* and *closeness centrality* metrics (which measure both direct and indirect ties, from different perspectives) confirm our finding that centrality is highly correlated with risk taking, with closeness being consistently significant across both. Again, it seems that moving 10% closer to the centre increases the probability of market risk exposure by 1%.

We noted earlier that Market Risk exposure is negatively correlated with Market Risk Exposure on the Downside, so it is surprising but pleasing to see that centrality measured by *closeness* still plays a role with the latter measure. And again, we see that moving 10% closer to the centre of the network increases the change of the fund taking risks on the downside by 1%. As explained below, both sets of results seem to support the theorizing that the forces that increase risk-taking are related to the eigenvector and closeness measures of centrality - power and hubris - rather different from the argument about the factors that depress returns - the costs of information overload. It is likely that there are multiple factors at work in the network, and that high costs and information overload *act together* with a sense of power and hubris to yield these results.

4. Discussion & Conclusion

Taking a significant section of the Hedge Fund industry as our sample, we have mapped the network that existed between Hedge Funds and Prime Brokers in 2006, when industry conditions were relatively benign. Controlling for several determinants of hedge-fund performance - such us fund age, size, strategy and prime broker(s) - we find that an increase in network centrality has a negative effect on performance and a positive effect on risk-taking (where these were measured in a five year window). These results are robust across many metrics of performance, especially the commonly reported absolute returns, Sharpe and Sortino metrics, as well as various measures of risk including skewness and kurtosis, risk of co-movements with market indicators, as well as risk on the downside. The magnitude of all these effects was shown to be significant

Our paper makes several contributions. First, it advances the value of including network variables in finance studies in general and in the study of Hedge Funds in particular. Until now, most of work on the structure of the Hedge Fund industry has focused on the personal background of the managers (see for instance: Haitao Li , Rui Zhao and Xiaoyan Zhang (2008); or Maxam, C. L., Nikbakht, E., Petrova, M., Spieler, A C. (2006)): few authors have looked at the institutional arrangements that permit Hedge Funds to connect with each other. Our approach shows the value of factoring network variables - largely disregarded in previous Hedge Funds performance models - into the performance equation. In this respect, our findings answer the calls to integrate sociological theory more fully into finance made by such as Abolafia (1997) and Mizruchi and Stearns (1994). And the results are practical, showing that understanding these connections may be important for investors choosing which hedge fund to invest in, as highly central funds not only appear to perform worse but also to take more risks.

Second, we believe our paper is the first to connect risk-taking to networks. Until recently, most of the literature in finance (and indeed in management) has stressed the positive influence of network relationships on performance, and has avoided explicitly discussing risk and risk-taking. We fill this important gap, by trying to unpick more fully what drives risk-taking behavior. This study advances knowledge about the 'dark side' of networks (Gargiulo and Benassi, 2000), suggesting that there are downsides to broadening one's network position (at least, if one is a Hedge Fund). These findings should add a note of caution to those studies that overly emphasize the informational properties of networks: networks have costs as well as benefits, and it is by no means a given that one side will always outweigh the other.

Our findings about risk taking are especially intriguing. First, the strongest network correlations of risk-taking (when measured with respect to market co-movements) in our study are global centrality metrics that measure both direct and indirect Hedge Funds connections. In network theory, such global measures are often associated with an actor's perception of 'being in the midst of the action': intuitively correlated with the sense of power. If our speculation is correct, it would seem that risk-taking is more often an irrational than rational decision - one driven by hubris and the power effects, rather than just simply by costs. Second, if we map our finding on risk-taking onto the finance literature's traditional view about risk-taking being driven by the divergence between principals and agents, we see some similarities. The usual argument about hedge fund managers taking risks links the possibility of opportunism to the hedge fund managers' contracts which, with their typically large payments for superior performance, work like a call option in rewarding risk-taking at the possible expense of wealth creation for the investor, a problem that even the inclusion of 'high water marks' does not entirely remove (e.g. Goetzmann, Ingersoll and Ross 2003). However, proponents of such contracts argue that the managers' ability to 'cheat' – by engaging in opportunistic behavior - is limited by the attendant loss of status and reputation (see for instance the arguments of Roberts and Dowling, 2002, applied in another context). Our insight adds another layer of argument: that being centrally located in their networks (as measured by both direct and indirect ties) may encourage actors to believe the penalty for taking 'excessive' risks will be lessened, or can even give them a sense of 'immunity' from punishment. And this may have some reality - network ties can not only create a sense of power in 'central' actors - they can also create a sense of obligation from other actors that does indeed make the central player impervious to the adverse consequences of external events (Pffeffer and Salanik, 1978; Anderson and Galinsky, 2006). The other (less central) actors may conspire to cover up cheating and provide resources to assist centrally-placed cheaters to re-establish themselves. Where such tie-dependency exists, the central player can engage in repeated opportunistic behavior that would be caught out in a normal market with good information mechanisms. Put bluntly, a hedge fund manager who is central in their network may be able to exploit that position to take unjustified risks, creaming profits from the 'upside' (as agent) and leaving the investor (the principal) holding the risks, and do so repeatedly, and without being punished. Our opening story hinted at this possibility, but to test these ideas scientifically would require a new approach - possibly involving identifying actors that are central in their sets of direct and indirect connections, and seeing if their behaviors are consistent with our speculation.

Finally, it is worth restating that our work is an attempt to build bridges between the work of finance scholars and those involved in strategy and organization theory. There is a long history of work by sociologists on the nature of financial markets - important in this respect is the contribution of Baker (1984) on the behavior of traders in the Chicago exchange markets, which documented the dynamics of actors' behaviors, and how they were influenced by changes in markets and in turn how this influenced the efficiency of trading. We also recognize the work of Buenza and Stark (2004) and Buenza, Hardie and MacKenzie (2006); they looked at how arbitrage actually works, and why prices sometimes do not converge in markets. Both these studies have inspired our social network perspective of risk and performance in the hedge fund industry. We believe these kinds of approaches are important to guide the development of new theories that can help us understand such events as the recent financial crisis, as well as to design new regulations that can better meet the challenges of an increasingly networked world.

References

Adler P.S., Kwon S., 2002. Social capital: Prospects for a new concept. *Academy of Management Review* 27(1): 17-40.

Ahuja G., 2000. Collaboration networks, structural holes, and innovation: A longitudinal study. *Administrative Science Quarterly* 45(3): 425-455.

Anderson C.A., Galinsky A.D., 2006.Power, optimism, and the proclivity for risk. *European Journal of Social Psychology* 36: 511-536.

Arora A., Gambardella A., 1990. Complementarity and External Linkages: The Strategies of the Large Firms in Biotechnology. *Journal of Industrial Economics* Vol.XXXVIII(4): 361-379.

Baker W.E., 1984. The Social Structure of a National Securities Market. *The American Journal of Sociology* 89(4): 775-811

Barberis N., Huang M., Santos T., 2001.Prospect Theory and Asset Prices. *Quarterly Journal of Economics* 116: 1-53.

Bavelas A., 1950. Comunication Patterns in Task Oriented Groups. Journal of the Acoustical Society of America 22: 271-82.

Berman S.L., Down J., Hill C.W.H., 2002. Tacit Knowledge As A Source Of Competitive Advantage In The National Basketball Association. *The Academy of Management Journal* 45: 13-31.

Beunza D., Stark D., 2004. Tools of the Trade: The Socio-Technology of Arbitrage in a Wall Street. *Industrial and Corporate Change* 13: 369-400.

Beunza D.; I. Hardie and D. MacKenzie. 2006 “Price is a Social Thing: Towards a Material Sociology of Arbitrage. *Organization Studies* 27: 721-748

Bollen N.P.B., Whaley R.E.,, 2009. Hedge Fund Risk Dynamics: Implications for Performance Appraisal *Journal of Finance* 64(2) 985-1035

Bonacich P., 1972. Factoring and weighing approaches to clique identification. *Journal of Mathematical Sociology* 2:113–120.

Boyson N.M., 2003., Why do experienced hedge fund managers have lower returns. Working Paper, Purdue University.

Bromiley, P (1991) Testing a causal model of corporate risk taking and performance. *Academy of Management Journal*, 34 (1):37-59

Brown S., Goetzmann W. N., Park, J. 2009. Careers and Survival: Competition and Risk in the Hedge Fund Industry. *Journal of Finance* 56 (5): 1869-1886

Burt R.S. ,1982. *Toward a structural theory of action*. Academic Press: New York.

Coleman J., 1973. *The Mathematics of Collective Action*. Chicago: Aldine.

Cornelli F., Goldreich D., 2003.Bookbuilding: How Informative is the Order Book? *Journal of Finance* 58: 1415-44.

Danielsson J., Taylor A., Zigrand J.P., 2005. Highwaymen or heroes: Should hedge funds be regulated?: A survey. *Journal of Financial Stability*, Elsevier, vol. 1(4): 522-543.

Rui J.P. de Figeiredo, P. Meyer and E. Rawley (2010) ‘Exploring pre-founding determinants of new venture performance: Agglomeration effects and the performance of entrepreneurial spawns” Unpublished Working Paper: Wharton School, U. Penn.

Degenne A., Forsé M., 1994. *Les RéseauxSociaux.* Paris: Armand Colin.

Eling, M. &Schuhmacher, F. (2007). Does the choice of performance measure influence the evaluation of hedge funds?, *Journal of Banking & Finance*, 31 (9), 2632-2647.

Eppler M.J., Mengis J., 2004. The concept of information overload: a review of literature from organization science, accounting, marketing, MIS, and related disciplines. *The Information Society* 20: 325–344.

Ferriani S., Cattani G., Baden-Fuller C., 2009. The relational antecedents of project-entrepreneurship: Network centrality,Team composition and project performance. *Research Policy* 38: 1545–1558.

Fracassi, C.; Tate, G.A., (2000) External Networking and Internal Firm Governance *SSRN* Working Paper

Friedkin N.E., 1991. Theoretical Foundations for Centrality Measures. American Journal of Sociology, 96(6), 1478-1504.

Fung W., Hsieh D.A., 1999. A Primer on Hedge Funds. *Journal of Empirical Finance* 6: 309-331.

Fung W.K.H., Hsieh D.,Naik, N.Y., Ramadori, T.; 2004.Hedge Funds: Performance, Risk and Capitalizaation. *Journal of Finance* 63 (4): 1777-1803

Geman, H., Kharoubi, C., 2003. Hedge funds revisited: Distributional characteristics, dependence structure and diversification. Journal of Risk 5 (4), 55–73.

Griffin, J.M.; Tao Shu; Topaloglu, S., (2010) Examining the Dark Side of Financial Markets: Who Trades Ahead of Major Announcements? SSRN: 1363756

Goetzmann W.N., Ingersoll J.E., Ross S.A., 2003. High-Water Marks and Hedge Fund Management Contracts.*Journal of Finance* 58: 1685- 1718.

Guedj, I.; Barnea, A. (2009) Director Networks SSRN Working Paper

Gulati R, Gargiulo M., 1999. Where do interorganizational networks come from? *American Journal of Sociology* 104(5): 1439-1493.

Gulati R., 1995. Social structure and alliance formation pattern: A longitudinal analysis. *Administrative Science Quarterly* 40(4): 619-642.

Güner, A.B.; Malmendier, U.; Tate, G., (2008) Financial expertise of directors *Journal of Financial Economics* 88 (2) 323-354

Haitao Li , Rui Zhao and Xiaoyan Zhang (2008) Investing in Talents: Manager Characteristics and Hedge Fund Performances; SSRN Working Paper Series

Hansen M., Podolny J.M., Pfeffer J., 2001. So many ties, so little time: a task contingency perspective on the value of social capital in organizations. *Research in the Sociology of Organizations* 18, 21–57.

Hardie, I. and D. MacKenzie, 2007. Assembling an economic actor: the *agencement* of a Hedge Fund *Sociological Review* 55: 1-27

Hochberg Y. V., Ljungqvist A., Lu Y., 2007. Whom You Know Matters: Venture Capital Networks and Investment Performance, *Journal of Finance* 62 (1), 251–301.

Kahneman D., Tversky A., 1979. Prospect theory: An analysis of decisions under risk. *Econometrica*, 47: 313–327

Keating and William F. Shadwick, A Universal Performance Measure The Finance Development Centre 2002.

Kouwenberg, Roy; *Ziemba*, William T. (2007), Incentives and risk taking in *hedge funds*. Journal of Banking & Finance,31 (11): 3291-3310.

Leavitt H., 1951. Some effects of certain communication patterns on group performance. *Journal of Abnormal and Social Psychology* 46:38-50.

McFadyen M.A., Cannella Jr., A.A., 2004. Social capital and knowledge creation: Diminishing returns of the number and strength of exchange relationships. *Academy of Management Journal* 47(5): 735–746.

Maxam, C. L., Nikbakht, E., Petrova, M., Spieler, A C. (2006) Manager Characteristics and Hedge Fund Performance. *Journal of Applied Finance*; 16 (2) 57-70

Miller J. L., 2009. Dying to be Legitimate: The Survival impact of mimetic practices in the Emerging Field of U.S. Hedge Fund Management Companies (Revise & Resubmit).

Mizruchi M., Galaskiewicz J., 1993. Networks of Interorganization Relations. *Sociological Methods and Research* 22:46-70.

Pfeffer J., Salancik G., 1978*. The external control of organizations: A resource dependence perspective*, New York, Harper & Row.

Patton, A.J. 2009. Are “Market Neutral” hedge Funds really Market Neutral? *Review of Financial Studies* 22(7): 2495-2530

Podolny J.M., 1994. Market uncertainty and the social character of economic exchange. *Administrative Science Quarterly* 39(3): 458-483.

Powell, W.W., Koput K.W., Smith-Doerr L., 1996.Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. *Administrative Science Quarterly 41*(1): 116–145.

Roberts, Peter W.; Dowling, Grahame R..(2002) Corporate Reputation And Sustained Superior Financial Performance *Strategic Management Journal* 23 (12) 1077-94

Schneider, S.C., 1987. Information overload: causes and consequences. *Human Systems Management* 7: 143–153.

Schwartz B., 2004. *The Paradox of Choice. Why More Is Less*. Harper, Perennial.

Shaver, J. M.; Flyer, F.. (2000) Agglomeration Economies, Firm Heterogeneity, And Foreign Direct Investment In The United States *Strategic Management Journal*, 21 (12), 1175-84

Simon, J.; Millo, Y.; Kellard, N.; and Engel, O. (2010) Dangerous connections: Hedge Funds, Brokers, and the Construction of a Market Crisis *Working Paper at IESE Business School, London School of Economics and Essex University*

Simon H., 1971. Designing organizations for an information-rich world.In *Computers, communications and the public interest*, Greenberger M. (ed.), 37-72. Johns Hopkins Press: Baltimore, MD.

Sorenson O., Stuart T.E., 2001. Syndication networks and the spatial distribution ofventure capital investments.*American Journal of Sociology* 106: 1546-1588.

Sutcliffe K.M., Weick K.E., 2007. Information overload revisited. In: Starbuck, W., Hodgkinson, G. (Eds.), *Handbook of Organizational Decision Making*. Oxford University Press, Oxford, UK.

Titman S., Tiu C., 2010. Do the best hedge funds hedge? Review of Financial Studies, Jan2011, Vol. 24 Issue 1, p123-168, 46p

Uzzi B., 1996. The Sources and Consequences of Embeddedness for the Economic Performance of Organizations: The Network Effect. *American Sociological Review 61*(August), 674–698.

Uzzi, B., 1999. Embeddedness and the Making of Financial Capital: How Social Relations and Networks Benefit Firms Seeking Financing. *American Sociological Review 64*: 481-505.

Figure 1 – Hedge Fund Industry network

This Figure shows the hedge fund industry network as at the end of 2006. Hedge Funds are represented by blue dots while Prime Brokers are represented by yellow squares. Lines represent the link between Hedge Funds and Prime Brokers. Names for the main Prime Brokers are also reported.

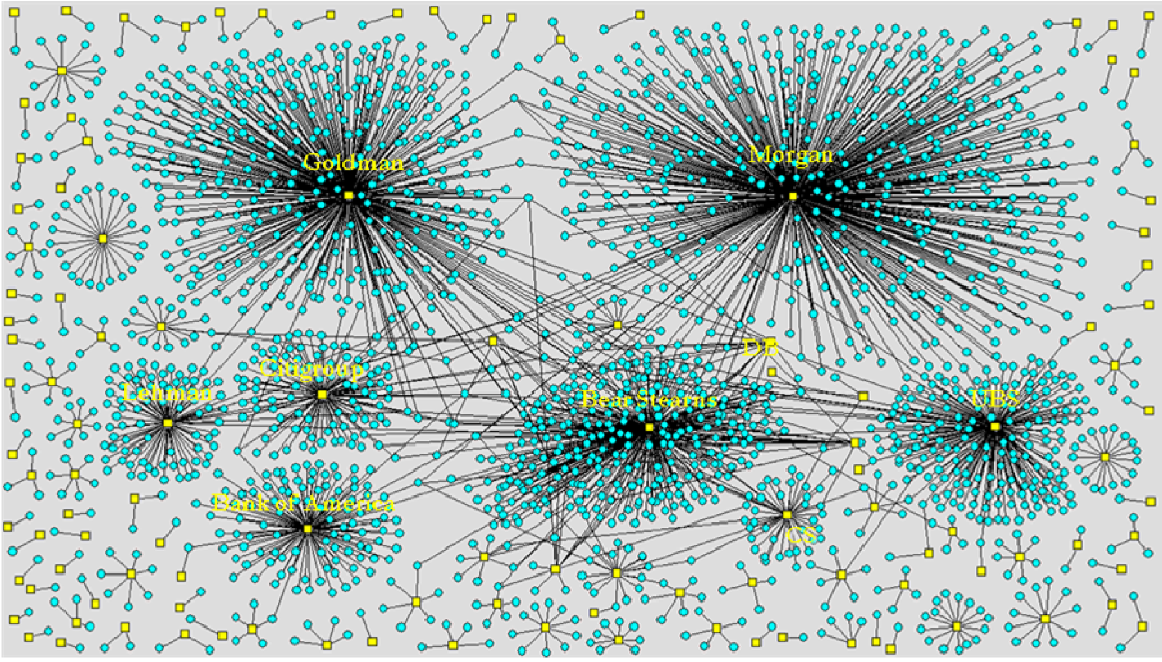


Figure 2 - Centrality effects on Portfolio Risk-Return

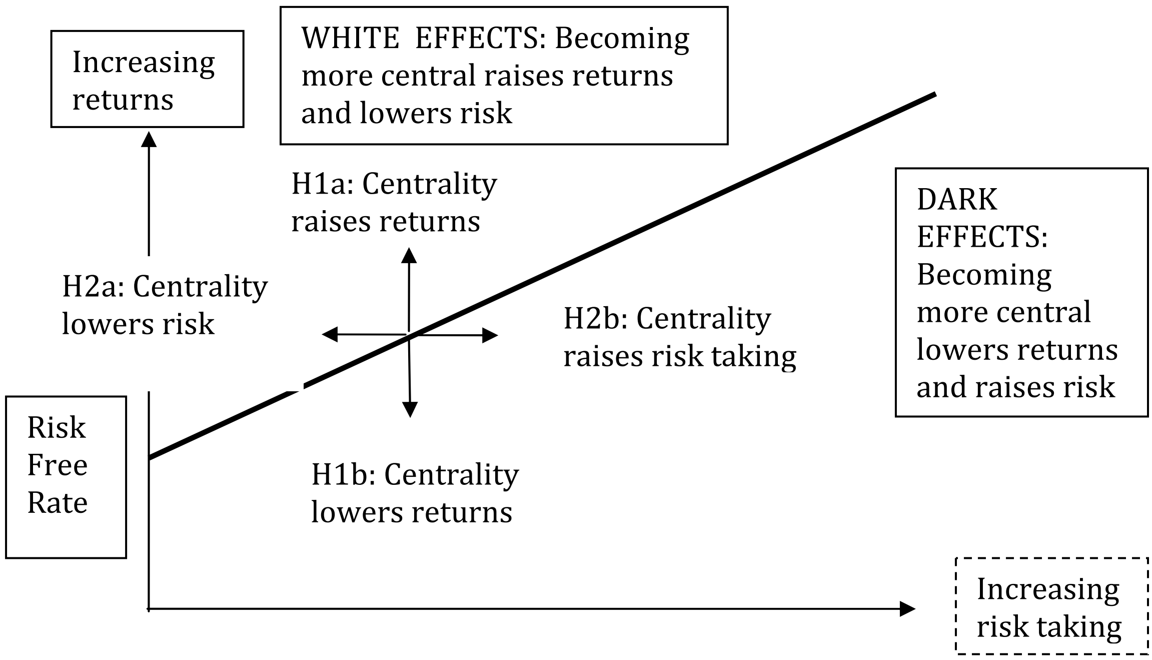
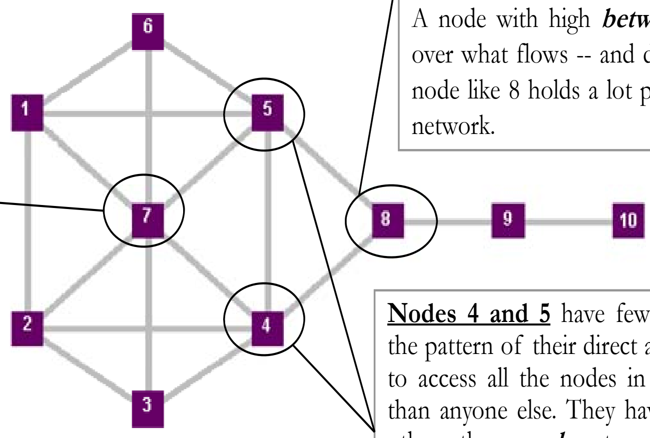


Figure 3 - Graphical Illustration of Network Measures of Degree, Closeness, Betwenness and Eigenvalue using Krackhardt's Kite network example



<u>Node 8</u> has few direct connections but it has one of the best locations in the network. It is between two important constituencies. It plays a 'broker' role in the network which means a powerful role in the network, but also a point of failure. Without it, 9 and 10 would be cut off from information in 7's cluster.
A node with high ***betweenness*** has great influence over what flows -- and does not -- in the network. A node like 8 holds a lot power over the outcomes in a network.

<u>Node 7</u> has the highest ***Degree*** centrality because it has the greatest number of direct connection.
But it has connections only to others in its immediate cluster – its clique. It connects only those who are already connected to each other.

<u>Node 7</u> also has the highest ***eigenvalue***, because it has the highest number of direct and indirect connections.

<u>Nodes 4 and 5</u> have fewer connections than 7, yet the pattern of their direct and indirect ties allow them to access all the nodes in the network more quickly than anyone else. They have the shortest paths to all others, they are ***close*** to everyone else. They are in an excellent position to monitor the information flow in the network, they have the best visibility into what is happening in the network

Table 1 – Summary statistics of Funds included in the sample and the MSCI World Market Index used as benchmark

This table reports the median of the descriptive statistics on monthly hedge funds returns across all funds included in the sample with at least twelve observations. Using the same methodology, the column headed "MSCI World Index" reports same statistics but referring to the MSCI World market index used as benchmark computed only if the referred fund was reported. The "Shapiro-Wilk" refers to the Shapiro-Wilk test of normality. The p-value for this test is also reported.

	Median Hedge Fund	Median MSCI World Index
Mean	0.008014	0.008871
Standard Deviation	0.020713	0.03282
Skewness	-0.072590	-0.90596
Kurtosis	3.302066	4.764936
Min	-0.041000	-0.11794
Max	0.056404	0.08286
Number of obs	56	56
Shapiro-Wilk normality test	0.661	2.183
Shapiro-Wilk p-value	0.254	0.015
Sharpe ratio	0 .222415	
Sortino ratio	0 .357724	

Table 2 – Summary statistics of risk and performance of funds split by investment style category

This table reports the median statistics using the monthly funds returns over the sample period split by investment style. Funds included are those with at least twelve observations. Shapiro-Wilk and the below p-value refer to the Shapiro-Wilk test of normality and the relative p-value, respectively. $\rho(r_i;r_{MSCI})$ refers to the median linear correlation between funds and the MSCI World Market Index. β_1 and $\beta_2$are the coefficients of the following regressions $r_{hf} = \alpha + \beta_1 r_{MSCI} + \beta_2 r_{MSCI}^2 + \varepsilon$. Neutrality test (Wald test) is used to test whether β_1 and β_2 are conjointly equal zero. Consequently, a p-value under 10 percent indicates that the market risk affects the fund performance. % of neutrality indicates the percentage of funds which reject the null hypothesis of neutrality. $\gamma_{1,neg}$, $\gamma_{2,neg}$, $\gamma_{1,pos}$, and $\gamma_{2,pos}$, are the coefficients of the following regressions $r_i = \alpha + \gamma_{1,neg} r_{MSCI}\delta + \gamma_{2,neg} r_{MSCI}^2\,\delta + \gamma_{1,pos} r_{MSCI}(1-\delta) + \gamma_{2,pos} r_{MSCI}^2\,(1-\delta) + \varepsilon$ where δ is one whether the r_{MSCI} is less than zero and zero otherwise. Like Patton (2009), the neutrality test of the Downside (Wald test) tests whether the first derivative $\gamma_{1,neg} + 2\,\gamma_{2,neg}$is higher than 0. A p-value below 10 percent rejects the hypothesis of market risk exposure for a risk-adverse investor. Sharpe ratio, Sortino ratio, and Omega ratio indicate the three risk-adjusted fund performance measures used in this study.

	Convertible Arbitrage	Dedicated Short Bias	Emerging Markets	Equity Market Neutral	Event Driven	Fixed Income Arb	Fund of Funds	Global Macro	Long Short Equity	Managed Futures	Multi Strategy	F-test	χ2-test
Mean	0.0064	-0.0028	0.0127	0.0054	0.0100	0.0075	0.0066	0.0060	0.0093	0.0076	0.0085	25.10	313.31
Standard Deviation	0.0147	0.0363	0.0270	0.0143	0.0152	0.0125	0.0134	0.0243	0.0262	0.0462	0.0129	54.76	664.75
Skewness	-0.1276	0.2883	-0.0437	0.0500	0.0168	-0.1230	-0.3469	0.2236	-0.0541	0.1296	-0.0356	8.00	162.52
Kurtosis	3.5893	2.8119	3.2002	3.2679	4.0384	3.7021	3.0683	3.3406	3.3469	2.8743	3.5478	8.49	122.81
Min	-0.0290	-0.0812	-0.0488	-0.0296	-0.0272	-0.0230	-0.0269	-0.0497	-0.0546	-0.0914	-0.0255	39.78	503.12
Max	0.0376	0.0851	0.0757	0.0383	0.0480	0.0337	0.0343	0.0736	0.0708	0.1174	0.0397	27.83	591.32
Number of obs	60	60	49	52	60	43	46	42	59	60	50		
Shapiro-Wilk normality test	1.2067	-0.2391	0.3296	0.5821	1.5641	0.9108	0.6691	0.7579	0.4815	0.2939	0.8811	10.57	85.37
Shapiro-Wilk p-value	**0.1138**	**0.5945**	**0.3709**	**0.2803**	**0.0589**	**0.1829**	**0.2517**	**0.2243**	**0.3151**	**0.3844**	**0.1891**	**5.16**	**85.37**
$\rho(r_i;r_{MSCI})$	0.1899	-0.769	0.486	0.0757	0.4422	0.0617	0.5713	0.2308	0.4807	-0.0097	0.3566	99.31	611.66
β_1	0.0868	-0.9147	0.5116	0.0413	0.1921	0.0194	0.2767	0.2236	0.423	0.0339	0.1241	43.14	519.38
β_2	1.0366	-1.4220	0.9490	-0.1169	0.0496	0.1301	0.1335	1.8394	0.3281	4.6808	0.5756	7.81	159.58
p-value of neutrality test (Wald test)	0.06	0.00	0.00	0.16	0.01	0.20	0.00	0.03	0.00	0.07	0.03	21.09	386.60
% of Non Neutrality (cutoff 10%)	**0.59**	**1.00**	**0.85**	**0.41**	**0.81**	**0.40**	**0.88**	**0.62**	**0.80**	**0.58**	**0.67**		
$\gamma_{1,\ neg}$	0.1506	-1.0031	0.1692	0.1286	0.2407	0.0131	0.1666	0.1423	0.3373	-0.6458	0.1717	2.25	89.26
$\gamma_{2,\ neg}$	1.5912	-3.8269	0.3153	1.28	0.7789	-0.3821	0.3013	-0.7876	1.2254	-0.6054	0.853	1.15	32.38
$\gamma_{1,\ pos}$	-0.0862	-1.3104	0.6581	0.0558	0.3108	0.0667	0.634	0.487	0.8524	1.6314	0.2204	26.63	371.17
$\gamma_{2,\ pos}$	4.9579	10.6058	-5.9989	-0.9724	-2.5992	1.147	-5.8296	-3.6239	-7.0537	-18.6923	-0.5142	6.95	207.84
p-value of Non Neutrality on the Downside (Wald)	0.51	0.00	0.91	0.47	0.73	0.48	0.86	0.52	0.90	0.08	0.59	49.01	411.82
% of Neutrality on the Downside (cutoff 10%)	**0.15**	**0.71**	**0.04**	**0.23**	**0.10**	**0.23**	**0.07**	**0.20**	**0.06**	**0.50**	**0.11**		
Sharpe ratio	0.1979	-0.1946	0.3550	0.1424	0.3893	0.2896	0.2123	0.0932	0.2171	0.0875	0.3461	24.32	369.72
Sortino ratio	0.2821	-0.3499	0.5447	0.2079	0.6380	0.3999	0.3142	0.1601	0.3570	0.1638	0.5044	13.05	297.41
# of funds	71	14	120	148	213	102	365	92	826	139	97		

Table 3 – Correlation matrix of the risk and risk-performance measures

This Table reports the pairwise correlation coefficients of the risk and risk-adjusted performance measured. Funds included are those with at least twelve observations. All variables are those reported in Table 2. All correlations are significant at 1% level

Correlations of Performance Measures

	Absolute return	Sharpe ratio	Sortino ratio
Absolute return	1.00	0.58	0.30
Sharpe ratio	0.58	1.00	0.59
Sortino ratio	0.30	0.59	1.00

Corrrelation of Risk Measures

	Standard Deviation	Skewness	Kurtosis	1 - p-value(Neutrality Risk test)	p-value of Neutrality Risk on Downside test
Standard Deviation	1.00	0.17	0.09	-0.07	-0.05
Skewness	0.17	1.00	0.17	0.12	-0.11
Kurtosis	0.09	0.17	1.00	0.11	-0.01
1 - p-value(Neutrality Risk test)	-0.07	0.12	0.11	1.00	-0.23
p-value of Neutrality Risk on Downside test	-0.05	-0.11	-0.01	-0.23	1.00

Correlation of Centrality Measures

	10 quantiles of eigenvalue	10 quantiles of closeness	betweenness	degree
10 quantiles of eigenvalue	1.00	0.79	0.29	0.27
10 quantiles of closeness	0.79	1.00	0.39	0.37
betweenness	0.29	0.39	1.00	0.89
degree	0.27	0.37	0.89	1.00

Table 4 – Hedge Funds performance regressed against network indicators

This Table reports coefficients of the Performance measures of each fund with at least twelve observations and the network variable indicators. Control variables are the natural logarithm of the life (Ln(Age)) and the net asset under management Ln(Size) of the fund, respectively. All specifications also consider eleven dummies based on the investment style of the fund. Robust t-statistics in parentheses ***, **, and * denotes significance at least at the 0.01, 0.05,0.10 percent level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	Y = return of the hedge fund (yearly based)				Sharpe ratio				Sortino ratio			
10 quantiles of eigenvalue	-0.256***				-0.008***				-0.014**			
	(-2.75)				(-3.14)				(-2.57)			
10 quantiles of closeness		-0.075				-0.003				-0.005		
		(-0.75)				(-1.35)				(-0.96)		
betweenness			-1.416*				-0.053**				-0.118***	
			(-1.77)				(-2.47)				(-2.81)	
nbroker_degree				-1.025**				-0.026**				-0.065***
				(-2.58)				(-2.07)				(-2.88)
ln(age)	-1.426***	-1.387***	-1.360***	-1.370***	-0.07***	-0.06***	-0.06***	-0.06***	-0.14***	-0.13***	-0.13***	-0.13***
	(-3.45)	(-3.39)	(-3.27)	(-3.29)	(-5.09)	(-4.98)	(-4.87)	(-4.89)	(-4.81)	(-4.71)	(-4.60)	(-4.62)
ln(size)	0.870***	0.823***	0.819***	0.823***	0.03***	0.02***	0.02***	0.02***	0.05***	0.04***	0.04***	0.04***
	(4.69)	(4.46)	(4.20)	(4.22)	(7.21)	(6.63)	(6.76)	(6.72)	(6.31)	(5.74)	(5.97)	(5.95)
Constant	-0.01***	-0.01***	-0.01***	-0.01***	-0.37***	-0.37***	-0.39***	-0.36***	-0.68***	-0.68***	-0.71***	-0.64***
	(-3.41)	(-3.41)	(-3.50)	(-3.31)	(-4.29)	(-4.28)	(-4.41)	(-4.10)	(-4.12)	(-4.13)	(-4.24)	(-3.87)
DUMMY STRATEGY	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2116	2116	2116	2116	2116	2116	2116	2116	2116	2116	2116	2116
R-squared	0.08	0.07	0.07	0.07	0.10	0.09	0.09	0.09	0.08	0.07	0.08	0.08
Adj. R-squared	0.07	0.06	0.07	0.07	0.09	0.09	0.09	0.09	0.07	0.07	0.07	0.07

Table 5 – Hedge Funds risk taking behaviour regressed against network indicators (Logit model)

This Table reports coefficients of Logit models where the dependent variable is one whether the fund present both negative skewness and positive kurtosis and zero otherwise. Control variables are the natural logarithm of the life (Ln(Age)) and the net asset under management Ln(Size) of the fund, respectively. All specifications also consider eleven dummies based on the investment style of the fund. Robust t-statistics in parentheses. ***, **, and * denotes significance at least at the 0.01, 0.05, and 0.10 percent level, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	**Y = (0/1; 1 if negative skewness combined with positive kurtosis)**			
eigenvalue (10 deciles)	-0.016			
	(-0.65)			
closeness (10 deciles)		-0.003		
		(-0.12)		
Dummy positive betweenness			0.451**	
			(2.12)	
nbroker (degree)				0.335***
				(2.66)
ln(age)	0.28***	0.28***	0.29***	0.29***
	(2.78)	(2.81)	(2.82)	(2.87)
ln(size)	0.02	0.02	0.01	0.01
	(0.59)	(0.50)	(0.28)	(0.23)
Constant	-2.61***	-1.18*	-1.17*	-1.47**
	(-2.74)	(-1.83)	(-1.80)	(-2.25)
DUMMY STRATEGY	YES	YES	YES	YES
Observations	2116	2116	2116	2116
Pseudo R-squared	0.03	0.03	0.03	0.03

Table 6 – Hedge Funds market risk exposure taking behaviour regressed against network indicators

This Table reports coefficients of the regression where the dependent variables are the Neutrality risk exposure (Model 1, 2, 3, and 4) and neutrality risk on the downside exposure (5, 6, 7, and 8) of each fund with at least twelve observations. The first dependent is computed firstly regressing $r_{i,t} = \alpha + \beta_1 r_{MSCI} + \beta_2 r_{MSCI}^2 + \varepsilon$ and then computing the neutrality test (Wald test) to test whether β_1 and β_2 are conjointly equal zero. Finally, we consider 1- p-value of the test as a proxy for the neutrality risk exposure of the fund to the market risk. The second dependent is computed firstly regressing $r_i = \alpha + \gamma_{1,neg} r_{MSCI}\delta + \gamma_{2,neg}\, r_{MSCI}^2\, \delta + \gamma_{1,pos} r_{MSCI}(1-\delta) + \gamma_{2,pos}\, r_{MSCI}^2\, (1-\delta) + \varepsilon$ where δ is one whether the r_{MSCI} is less than zero and zero otherwise. Then, we test the neutrality on the Downside (Wald test) computing the first derivative $\gamma_{1,neg} + 2\,\gamma_{2,neg}$ conditionally to negative return of the market index and then test that is higher than 0. A p-value below 10 percent rejects the hypothesis of market risk exposure for a risk-adverse investor. Control variables are the natural logarithm of the life (Ln(Age)) and the net asset under management Ln(Size) of the fund, respectively. All specifications also consider eleven dummies based on the investment style of the fund. Robust t-statistics in parentheses ***, **, and * denotes significance at least at the 0.01, 0.05, and 0.10 percent level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Y = Market risk exposure				Y = Market risk exposure on the downside			
eigenvalue (10 deciles)	0.01***				0.01*			
	(3.23)				(1.68)			
closeness (10 deciles)		0.01***				0.01**		
		(2.97)				(1.99)		
Dummy positive betweenness			0.01				0.03	
			(0.31)				(0.78)	
nbroker (degree)				0.00				0.03
				(0.22)				(1.10)
ln(age)	0.05***	0.04***	0.05***	0.04***	0.05***	0.05***	0.05***	0.06***
	(4.53)	(4.38)	(4.59)	(4.39)	(3.51)	(3.60)	(3.47)	(4.46)
ln(size)	0.00	0.00	0.00	0.00	0.01	0.01	0.01	0.01
	(0.83)	(0.79)	(1.20)	(1.04)	(1.33)	(1.23)	(1.64)	(1.25)
Constant	0.01	0.01	0.02	0.02	-0.12	-0.13	-0.12	-0.03
	(0.16)	(0.10)	(0.30)	(0.30)	(-1.15)	(-1.21)	(-1.14)	(-0.29)
DUMMY STRATEGY	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2116	2116	2116	2116	2116	2116	2116	2116
R-squared	0.107	0.106	0.100	0.102	0.262	0.262	0.260	0.245
Adj. R-squared	0.0977	0.0970	0.0906	0.0939	0.254	0.255	0.253	0.238