THE IMPACT OF MANAGEMENT STRUCTURE ON HEDGE FUNDS' PERFORMANCE AND MISREPORTING

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The Impact of Management Structure on Hedge Funds' Performance and Misreporting

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CERTIFICATE OF ORIGINALITY

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Abstract

This study investigates the association of management structure with hedge fund performance and misreporting. Much management literature supports the belief that teams enjoy several advantages over their individual peers in collecting and integrating information and correcting errors. Since hedge fund managers are strongly incentivized and flexible to implement risky investment strategies, the performance implication of management structure should be more easily observable in hedge funds than in mutual funds and other industrial firms. Using hedge fund data over the period 2001 to 2011, I find that team-managed hedge funds exhibit higher future returns than individual-managed funds, which is consistent with theoretical predictions. The correlation between team management and hedge fund performance is present most strongly among funds with long team tenure, or funds that adopt relatively innovation-oriented investment styles such as global macro and multi-strategy. The association is particularly pronounced during bullish market periods.

Next, I focus on team-managed funds and explore how school-ties within a team is related team performance. Cohen et al. (2008) supports the role of shared school ties as an influential information channel between mutual fund managers and company boards. It is therefore reasonable to conjecture that the more connections a fund team has through its alumni network, the more private information the fund can obtain from senior officers of firms. Such groups should enjoy access to a wider information set and be able to generate superior returns. This assertion is consistent with the information and decision-making hypothesis. However, similarity and social-categorization hypotheses have emphasized an increase in interpersonal liking, and communication in homo-groups due to shared background among members. My results show a negative implication of within-fund school ties on fund performance, especially in volatile periods or in two-manager teams.

Risk-taking behavior may also be influenced by management structure and composition. Findings in this study are in line with group shift theory according to which teams conform to the opinions of dominating members and converge to take risky decisions ultimately. The association is pronounced among teams with strong intra-team school-ties. Furthermore, unlike the result from mutual funds, hedge funds with single-manager are found to attract more capital flows and display a lower probability to fail.

Lastly, I examine return manipulation behaviors across hedge funds with different management structures. My findings support a mitigation role of team management in unethical behavior. Multi-manager funds are found to be less likely to engage in misreporting. Meanwhile, my results show no evidence of an enhancement of such association in teams with highly coherent members. My findings also have implications for practitioners. It may be of help to regulators while they target funds with a higher likelihood of engaging in fraud; investors can incorporate the widely available biographical information into their decision-making process while picking funds to invest in.

Keywords: **Management structure, Fund performance, Deception, Team diversity**

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Chapter 1 Introduction

A hedge fund is an investment vehicle that pools capital from qualified investors and invest the money into diverse range of markets to actively seek returns for their investors. Hedge funds have grown substantially for decades and aroused great interests from investors and academics. However, the public in general still acquire very limited information about the people who are managing the hedge funds and the variety of assets they invest in, let alone the complex investment and risk management strategies adopted by them. Large information asymmetry exists also between funds and their accredited investors. My study focuses on the elite who are running these arcane profit-making engines, the hedge funds managers. As the assets under management grows, new investors will start investigating the target fund in greater detail. In addition to basic information like fund strategy and past performance, investors want to know more about the hedge fund team itself. My research seeks to help investors better understand their target funds' management structures and their association with future performance as well as deception risk.

1.1 Objectives and Motivations

The hedge fund industry has low entry barriers as well as loose regulation. To start a hedge fund, the first decision is to run the fund by an individual or a group of people. Launching a hedge fund may require just one talented investment manager. However, institutional investors would like to see a more comprehensive infrastructure before they can make big bets on the fund. A relatively basic strategy like long-short equity may need only one analyst. However, the more complex strategy a fund adopts, the more manpower it requires. According to these views of industry experts, hedge funds are often seen to be more reliable and sustainable to investors if they have management teams rather than sole managers. And institutional investors prefer "bigger" teams without vacancies in key roles. Here, "sustainable" means the fund can continuously generate superior returns while "reliable" means the fund should be able to shield itself from any fraud. However, there has not been much empirical research on hedge funds that has supported this conjecture.

To test the above conjecture by professionals, my thesis firstly focuses on the association of team structure and composition with hedge fund returns. Looking at the hedge fund industry has allowed me to reassess the conventional topic in management—the performance implications of management structure. My initial suspicion was that management literature may not be providing complete evidence, since results from experiments on weakly incentivized and temporarily formed groups are probably biased. For instance, qualitative performance measures are usually constructed based on subjective judgements like team leaders' ratings (Bar et al., 2007). Even for the quantitative performance measures such as profitability and sales growth (Murray, 1989; Smith et al., 1994; Simons et al., 1999), the results are not that convincing. These profitability measures are relatively noisy as they can be affected by various extraneous factors; it is difficult to rule out all the other factors and specifically look at the relationship between the team structure and performance of large corporations. Also, these studies are conducted mostly on small sample of firms around 200.

Unlike with large corporations, the performance of management teams in the fund industry are easily quantifiable and comparable based on fund returns. Further, hedge funds have several advantages over mutual funds in exploring structural impacts. Li et al. (2011, p.61) claim that "the entrepreneurial nature of hedge fund operations suggests that hedge fund performance should depend more significantly on managers". Hedge funds enjoy more flexibility in investment strategies. Whenever they detect investment opportunities, they are free to implement them with even risky derivatives or short selling strategies which are forbidden for mutual funds. In addition to management fees, which are also received by mutual fund managers, hedge fund managers are further motivated by high incentive fees. Many hedge fund managers have their own wealth invested in the funds. Hence, they will exert effort to maximize the absolute returns to get the best payoffs without limitation. Therefore, a hedge fund's performance, which can be easily observed, functions as a direct reflection of the team's ability. Second, there is a relatively constant proportion of multiple-manager-funds within the hedge fund industry. The evenly distributed sample of single- versus multi-manager funds make my results from hedge funds more convincing than those from mutual funds in a statistical view. And unlike mutual funds or other large institutions, hedge funds managers have exclusive recruiting power. If it's true that hedge fund managers tend to hire other team members from the same school, then sufficient samples of homogeneous groups are expected to be observed in my data that allows me to further explore the influence by team cohesiveness. This argument has been supported by the common observation of funds consisting of alumni from the same school (e.g., Harvard Business School). All this makes me believe that hedge funds provide a better setting to study the association between management structure and performance.

I start by comparing hedge funds managed by individuals and groups. The discipline of psychology has a long tradition of studying the effectiveness of group decision-making. Classical utility theory believes that the decisions made by groups and individuals should be similar since they have been based on the same profit maximizing objective (Arrow, 1986). On the other hand, Simon (1982) posits a bounded rationality model that provides a theoretical base for behavioral decision-making. Behavioral scholars argue that groups have several advantages such as in information gathering and recalling, as well as errors correction.

In contrast to individuals with a single information channel, groups benefit from pooling and integrating disparate pieces of information from multiple sources (Hill, 1982). In addition to reduced cost of information gathering, collective memory is superior in terms of recalling information accurately, which leads to better-informed decisions by groups (Vollrath et al., 1989). Another benefit of group is mitigation of bias and correction of errors. Biases, such as herding or overconfidence, make decision-making to depart from a rational choice model. But multiple sources of random errors made by individuals in the team counteract each other, thus reducing the likelihood of persisting with a wrong question set. Further, people are usually much more aware of others' mistakes than their own so that they can reject incorrect ideas of each other and help the whole team to reduce potential loss by mistakes (Shaw, 1932).

However, although several scholars have highlighted the advantages of team management, empirical results so far have not been consistent across several mutual funds literature and other TMT studies in general firm setting. Most studies (Prather and Middleton, 2002; Chen et al., 2004; Bliss et al., 2008) have documented similar levels of risk-adjusted returns from single- versus multi-manager mutual funds, or even inferior performance by team-managed funds. Patel and Sarkissian (2013a) is the only research on mutual fund so far that has found higher risk-adjusted returns from team-managed funds in comparison to their individual-managed counterparts. To provide more empirical evidence of team benefit by hedge funds, my initial step is to test whether team-managed funds outperform individual-managed funds.

My next focus is on the team composition of hedge funds that are managed by a group of people. "The desire and ability to improve infrastructure should drive hiring decisions. Each successful job candidate's skill set and prior experience must be a fit for the corporate culture you're building and the strategies you're pursuing," said Howard Eisen, co-founder and managing director of a New York-based hedge fund capital raising and consulting firm named FletcherBennett[1]. I look at the background information on fund team members, as

[1] "How to Assemble Your Hedge Fund Team," Jan 27, 2011, Hedge Fund Marketing Association (http://www.hedgefundmarketing.org/how-to-assemble-your-hedge-fund-team/)

what the hedge fund managers do in the recruitment process. In finance literature, Chevalier and Ellison (1999) find that funds managed by graduates from high quality programs (measured by SAT) achieve better performance. High intelligence of fund manager is not the only underlying reason for the outperformance. Cohen et al. (2008) suggest that portfolio managers often put concentrated bets on stocks they are connected to, via their respective alumni networks and generate more profits from such connected holdings than unconnected ones. This observation underscores the role of shared school ties as an influential information channel between mutual fund managers and company boards. Based on this finding, I may conjecture that a diversified group should be enjoying a larger information set from multiple connections with firm senior officers in firms through its alumni network and hence generate superior returns. This assertion is consistent with the information and decision-making hypothesis made by several top management team (TMT) scholars. For instance, Ancona and Caldwell (1992) argue that diverse backgrounds of members in a heterogeneous team will bring advantageous information set and innovative ideas to the team.

Nonetheless, several other theories in management hold the opposite view on the association of team congruence level with performance. For instance, similarity hypothesis states that members with similar demographic attributes like gender or ethnicity tend to treat each other as someone who shares common values. Additionally, according to self- and social-categorization theory, the larger proportion of such “similar” teammates a team has, the more commitment the members will show to the team. Homogeneous groups are, therefore, expected to experience high social-integration, efficient communication, less conflict and more efforts exerted from group members to achieve a better team outcome.

According to the above theories, team diversity can be classified into informational diversity, social category diversity and value diversity. (Williams and O'Reilly, 1998). Informational diversity such as the heterogeneity in education or work experience are related to the size of information set available to the team and potential alternatives members can raise and evaluate. Social category diversity and value diversity affect communication and commitment to the team. Examples are the differences in terms of gender, race or age. Based on the theories mentioned above, Jehn et al. (1999) expect that informational (social category/value) diversity has clear positive (negative) performance implication subsequently. Bar et al. (2007) look at gender, age, tenure and educational diversity, and find empirical evidence consistent with this prediction. Tan and Sen (2017) propose two measures of educational diversity—final educational degree and field of educational specialization—as informational diversity proxy and document a positive association between their measures and mutual fund performance.

However, no one has yet shed light on homogeneity measures based on within group social ties such as the proportion of members who graduated from the same university or had worked in the same company before. I chose intra-group school ties as a proxy for group diversity for several reasons. First, since there is significant information transfer from corporate boards to fund managers via college-based networks (Cohen et al., 2008), diversity of group members' educational backgrounds should be related directly to the information diversity in the entire team. Second, in work places like a hedge fund management team, members tend to categorize themselves and others based on job-related attributes (e.g., industry experience or education) rather than demographic characteristics (e.g., gender, age or race). Third, school-ties build the most homophilous relationships compared to other forms of similarity in terms of professional or geographical backgrounds (Flap and Kalmijn, 2001; Massa et al., 2005). People attending the same school interact with each other over time on campus or through alumni associations. Furthermore, graduates of a specific school receive education of a certain type and quality. This unique imprinting bonds them together (Massa et al., 2011; Guan et al., 2016). Lastly, in my case, I got a relatively complete dataset on managers' educational background.

As previously stated, my measure of intra-group school ties relates to both information diversity and similarity/social-category diversity. On one hand, groups with concentrated backgrounds can be expected to have limited information flowing in through relatively narrow channels of alumni network. On the other hand, strong school-ties induce high level of team cohesiveness which facilitates formal and informal interpersonal communication among members and increase their commitment to the group outcome. As a result, no clear, a priori conclusion can be arrived at about the overall impact of team congruence on the group's overall performance. Nevertheless, the intra-group school-ties seems to provide a very representative proxy for social category diversity and value diversity in view of the strong relationship built among alumni. But, since there are other information channels, it is probably only a partial measure of informational diversity. Given this, if the result still shows an outperformance by heterogeneous hedge fund teams, I can conclude that the informational benefit of diversified team does play a critical role in volatile environments that hedge funds face. In summary, the first research question of my thesis is to test whether teams, especially those with weak intra-group school-ties, indeed perform better.

Another objective of my research is to explore the mechanism through which a fund's management structure can relate to its performance. Several researchers have noted a link between team congruence and performance but have left the underlying mechanism unexplored. Psychology theories attribute it to the congruence's impact on decision-making of a group. With the help of managerial ability measures proposed by previous literature, I will provide partial evidence for such an impact via tests on market timing and strategy distinctiveness.

In addition, Bliss et al (2008) and Bar et al. (2005) confirm the different risk-taking behaviors of single-managed versus team-managed firms and mutual funds. Loose regulations allow hedge funds to engage in riskier investments. Hence, the risk taken by hedge funds with different management structure is expected to be more different from each other. My study represents an initial investigation of the risk-taking strategies being adopted by individually- versus team-managed hedge funds to see whether groups adopt more extreme investment strategy as the group shift theory predicts or make moderate decisions after securing a compromise among group members in accordance with the diversification of opinion hypothesis. Furthermore, I compare the crash risk in funds across different management structure. This thesis also explores relationship between team structure and fund flow to see whether, in accordance with literature, team-managed hedge funds indeed attract more inflows as mutual funds do (Bar et al., 2005). Since hedge funds cannot promote themselves in mass media, they often rely on the social network of management team to attract capital, which should amplify the association of management structure with fund flow. Also, my thesis looks at the differences in fund failure rates.

The other research question is about the relationship between fund management structure and fund "reliability". Teams can be assumed to engage less in deceptive behavior because of the greater peer monitoring, reduced monetary incentives for team members, and reinforced feelings of guilt. But other studies, e.g., Wiltermuth (2011) and Conrads et al. (2013), point out that sharing with others the benefits of dishonest behavior increase the likelihood of engagement in such behavior. Moreover, a contagion of unethical behavior makes teams more vulnerable to deceptions than individuals (Gino et al., 2009).

Another study by Patel and Sarkissian (2013b) investigates the team structural effect on mutual funds' managerial deceptions. Being full of restrictions and monitoring from board of directors, regulatory departments and the public in general, mutual funds rarely engage in earnings manipulation. By contrast, hedge funds enjoy relaxed regulation and monitoring. Since the probability to be detected is quite low, it is easy for hedge fund managers to develop a mindset prone to engaging in fraud. Whether the mitigation role of management structure still holds in the unique environment hedge funds face, is well worth testing. Further, there is no widely acceptable evidence or measure of misreporting by mutual funds, but there is for hedge funds. Also, the hedge fund industry has more balanced and constant sample of funds with single versus multiple managers than the mutual funds industry does. I therefore expect to see clearer results from hedge funds than mutual funds on the variation in misreporting behavior across different team structures.

Regarding the influence of team congruence level on deceptive behavior, Danilov et al. (2013) reveal that the dishonest behavior under team incentives are even more serious than those under individual incentives when strong group affiliation exists. In my case, a higher level of intra-group school ties makes team members behave more cohesively with each other. I'll test whether the high cohesiveness is associated with a higher probability of hedge funds behaving unethically.

1.2 Overview of Research Method and Major Findings

The primary objective of this study is to investigate the association between management structure and hedge fund performance. The collection of fund managers' background information therefore serves as a core part of this research. Since hedge funds are usually not required to disclose details of their management team, existing databases do not contain ready-to-use data on such information. I therefore resort to extracting managerial data from the biographies reported by each fund to the Lipper TASS database, including the basic demographic information on each manager as well as his/her educational background. I further supplement the data with information collected from online resources such as *Linkedin*, *Zoominfor* and *CapitalIQ*. Other data about funds like the fund characteristics and fund performance also come from TASS. The sample period is 2001–2011; owing to the missing biographies of dead funds in TASS prior to 2011.

First, predictive panel regressions with time-fixed effect and fund clustered errors as well as Fama-Macbeth models are adopted to test whether multi-manager hedge funds generate superior returns than single-manager funds. Consistent with mutual fund results presented in Patel and Sarkissian (2013a), my study points to an outperformance by team-managed funds compared to individual-managed funds. Moreover, the added value of team is more salient for relatively basic strategies, which supports industry professionals' belief that complex strategies require a group of people to execute. While groups seem to show more wisdom, they often attract lower fund flow and take higher risk compared to sole managers. Further, single-manager funds usually survive longer; maybe due to a star manager effect. Next, I repeat the same analysis in two market conditions, bull market and bear market, separately. Team management exhibits superior ability in bullish periods while sole-manager structure takes more advantageous positions in a down market because of the special need of information diversity in complex environment. In addition, a subsample analysis by tenure shows that teams only start to outperform individuals after a period of time of working together; they need time to learn from each other.

Secondly, as for team-managed funds, previous literature in management raise team cohesiveness as one key factor relating to team performance. To examine the performance implications of group cohesiveness, a measure of team congruence level is developed based on two related studies — Ahn et al. (2012) and Cohen et al. (2008). I construct my measure of team congruence as the average percentage of connected colleagues for each manager within a fund. Two managers are defined as being connected if they graduate from the same university. The congruence level changes over time as some mangers quit or new members join in. Following Cohen et al. (2008), I also consider an alternative measure which further requires a connection to have two managers attend the same school and receive the same type of degree. Degrees are classified into 6 categories as Undergraduate, Business School, Graduate, Law, Medical and PhD.

I employ the same multi-variate regressions to exploit the association of team cohesiveness with fund performance. The result shows a negative relationship between a team's congruence level and its performance. It confirms the dominant significance of information diversity in volatile environment that hedge fund teams face. Additionally, consistent with the group shift theory, homogeneous teams are found to adopt more extreme strategies than their heterogeneous counterparts. Meanwhile, cohesive groups attract more investments flow in. A possible explanation is the strengthened confidence of investors in funds with predominantly alumni from the same school. People graduating from the same college are believed to have similar investment attitudes. Further, college-based interactions could help reduce information asymmetry between investors and fund managers.

By conducting a subsample analysis on the team size, I conclude that two managers with similar educational background is the worst choice in terms of performance, but the high congruence level might add value to teams consisting of more members. However, the most fundamental reason might be the tradeoff between information adequacy and coordination cost among team members. In a two-manager team, high congruence level can hurt since there is relatively low communication cost but high requirement for knowledge base. But in a larger group with multiple information channels and views, team cohesiveness can help augment the overall efficiency of decision making.

Furthermore, I explore the mechanism through which the management structure could influence the decision-making and the final outcomes as revealed by two existing measures of manager skill, namely market timing and strategy distinctiveness. The findings imply that heterogeneous teams have a significant advantage in developing a distinctive strategy while homogeneous teams reach consensus and react quicker to any changes in the market. However, such differences diminish after members work in the team together for a number of years.

To assess the robustness of my results, I perform several additional tests. First, to differentiate my research from Tan and Sen (2017), I include the informational measure of team members' educational background as a control variable and still find significant results supporting my congruence measure. This implies that my measure captures the additional effect of educational congruence better than the informational advantage of knowledge. Second, I employ an alternative measure of congruence level to different extent and obtain similar result when requiring the two connected members to attend the same university and get the same degree. Next, I exclude observations during the pre- and post-12-month periods that funds experience any changes in fund management to rule out the effect of manager turnover on performance. The results are even more significant than those with the full sample. Lastly, to address the concern about endogeneity problem, I develop an instrumental variable for management structure and conduct subsample analysis on funds with a shift in management structure. It turns out that my primary conclusion still holds.

Finally, I construct a set of measures to proxy a hedge fund's misreporting behavior including six data-quality indicators, two measures of correlation between funds' return and style factors, and unconditional as well as conditional serial correlations following Bollen and Pool (2012) and two flags of December spike following Agarwal et al. (2001). To explore possible correlations between management structure and hedge funds' deceptive behavior, I apply a Probit model that regresses misreporting flags on a team dummy and team congruence level. The results from this cross-sectional analysis support a mitigation role of team management in unethical behavior. However, I find no evidence to show that highly cohesive teams are more likely to engage in immoral activities.

1.3 Contribution

My study serves as a possible first attempt to look at the association between the management structure of a hedge fund and fund performance. contributes to the small number of hedge fund studies exploiting biographic information by looking at the biography of the entire hedge fund management team. In addition to funds' past return, managers' background information also serves as an indicator of managers' talent which helps predict future returns. Although there is some literature looking at managers' background information, its focus was on the talents of individual fund managers, largely ignoring other members in the team. A fund is usually not managed by a single person. Hill (1982) and Bainbridge (2002) suggest that groups, on average, make better decisions than individuals. Bliss et al. (2008) confirm differences in the risk-taking behaviors of single-managed and team-managed firms. Hence, choosing a single manager to represent the overall team may not be appropriate. Instead, a close scrutiny of team characteristics inspires a new branch of research questions.

Secondly, the external connection between mutual fund manager and board members via school ties has been studied, the internal connections within a fund team haven't received enough academic attention. The most relevant study is Patel and Sarkissian (2013a) which observes significant negative impacts of age and SAT but not of tenure diversity on fund performance as revealed by mutual fund data. However, the relationship has not been studied thoroughly enough in that paper as the correlation between team diversity and team outcome does not serve as its main research question. Tan and Sen (2017) look at the performance implications of educational diversity but still in the context of mutual funds. In this sense, my study also provides some initial evidence for the effect of internal cohesion in hedge funds.

My thesis should also contribute to psychological and management literature about top management team (TMT) by providing additional empirical evidence. Although extensive management studies have been done on the effect of TMT homogeneity/heterogeneity, most of them have been essentially theoretical. Even for the limited number of empirical work (e.g., impacts of TMT diversity on corporate performance), the results have been mixed. Smith et al. (1994) document a positive association between TMT educational diversity and company financial performance but a negative relationship between experience diversity and performance while no results for TMT diversity and performance are found in West and Schwenk (1996). In addition, the existing evidence from management literature may not be that convincing since their measure of performance is either too noisy or biased. A majority of the related papers in finance have been conducted on mutual funds but not on hedge funds. However, as mentioned in the motivation part, hedge funds differ from mutual funds in several ways. Different from such literature, my unique dataset provides more direct and convincing empirical evidence on this issue from the viewpoint of hedge fund returns.

Next, since team members' biographic information is found to be highly related to fund performance, my results have some implications for practitioners as well. Investors can incorporate the widely available biographical information into their decision-making process when selecting particular funds to invest in. Existing managers should however take the current team congruence level into consideration before recruiting a new employee.

Finally, recent scandals such as the failure of Bayou Hedge Fund Group and Madoff's Ponzi scheme raises more concerns about fraud in the hedge fund industry. Investors have suffered substantial economic loss from these fraudulent investments. But they usually don't possess useful information to differentiate the "problem fund" until a violation of legal or regulatory rules has occurred. A possible consequence is a lack of confidence in the hedge industry. Some investors may even choose to forego investment opportunities in the whole market (Giannetti and Wang, 2014; Guiso et al., 2008). While investors will be harmed seriously in case of a fraud episode, hedge funds still face weak regulations and little oversight. They are allowed to implement highly risky strategies without disclosing many details. Regulators like SEC have been widely criticized by failing to monitor and deter fraudulent activity. A significant reduction in misreporting by team-managed funds compared to their individual-managed counterparty can help regulators to have closer scrutiny on firms that potentially have higher chance to commit a fraud. Also, this helps investors to better avoid funds with relatively higher deception risk using this easily accessible data.

1.4 Thesis Structure

The remainder of the thesis proceeds as follows. Chapter 2 reviews the literature related to this study. Chapter 3 investigates the association between team structure, team composition and hedge fund performance. Chapter 4 examines deceptive behavior of hedge funds with different management structure. Chapter 5 concludes the thesis.

Chapter 2 Literature Review

This chapter reviews literature on the relationship between management structure and hedge fund performance as well as its misreporting. Section 2.1 reviews literature on team structural effect on performance outcomes. Section 2.2 reviews literature on correlation between management structure and risk-taking behavior. Section 2.3 reviews literature on the impact of top management team. Section 2.4 reviews literature on the impact of fund manager characteristics. Section 2.5 reviews literature on the management structure's effect on the team's deceptive behavior. Section 2.6 summarizes this chapter.

2.1 Team Structure and Performance

Classical decision-making theory is grounded on rational choice models assuming 1) steady and known market states, 2) continuous allocation of resources, 3) clear alternatives and corresponding outcomes, and 4) pricing taking on goods that is subjective to arbitrage (Zeckhauser, 1986). Under this circumstance, the same profit maximizing objective often leads to an indifferent decision no matter such decision is made by an individual person or a group (Arrow, 1987).

On the contrary, the bounded rationality model (Simon, 1982) allows behavioral decision-making theory to further define the model in a manner that takes into account 1) unique and changing market state that need to be adapted, 2) discrete allocation of resources, 3) alternatives that need to be identified, and 4) behavioral factors like personal values, ethics, and culture that may affect the perceptions of risk (Zeckhauser, 1986; Prather and Middleton, 2002). In a decision-making process, the use of scarce resources is mainly directed at gathering, storage, manipulation and transmission of information. Compared to individual decision makers, teams can take advantage of multiple channels of information which makes it less costly to collect information. Additionally, Vollrath et al. (1989) have conducted experiments corroborating that groups have a sort of superior collective memory over individuals. It helps teams to recall and recognize relevant information more accurately and with a larger volume. Another benefit of multimember teams is a balancing of individual biases and detection of errors by groupmates. The initial proponents are less likely to reject their own incorrect ideas, more than other group members do (Shaw, 1932). Having companions thus, can attenuate the likelihood of errors and avoid certain biases that appear while working alone. Hinsz et al. (1997) contend that teams pool and integrate disparate pieces of information and correct each other's errors and biases.

While theoretical arguments keep highlighting the advantages of team management, there is still sparse empirical evidence supporting the outperformance of teams, especially in the fund industry. Prather and Middleton (2002) document insignificant difference between the outcome of team- versus individually-managed mutual funds. Similar risk-adjusted returns between these two are reported in Bliss et al. (2008). Chen et al. (2004) even find inferior performance by team-managed fund. The only supportive result is found by the recent working paper of Patel and Sarkissian (2013a) which report higher risk-adjusted returns from team-managed funds than their single-managed counterparts using a superior mutual fund database. Dass et al. (2013) make additional contribution by decomposing the overall performance into market-timing and asset allocation performance and find that sole-manager funds exhibit greater market-timing ability while multi-manager generate superior returns from specialization.

2.2 Team Structure and Risk-Taking Behavior

Other than average outcomes, the risk-taking behavior of single- versus team-managed funds arose the interest of several scholars. Two competing theories exist on this issue, namely diversification of opinions theory and group polarization/risky shift theory.

The diversification of opinions hypothesis assumes that members within a team hold naturally different opinions. After presenting their own ideas, they will discuss and compromise and eventually reach a consensus (Sah and Stiglitz, 1986). The moderate decision made by teams reflects the average of all members' opinions, which can be expected to result in less extreme outcomes (Sah and Stiglitz, 1991). Adams and Ferreira (2009) on iceberg breakup betting and Bar et al. (2011) on mutual funds, provide evidence in support of this theory. Bar et al.'s (2011), a study which is closely related to my hedge fund research, finds that single-manager-funds are more likely to follow extreme investment styles, bet on certain industries and achieve either extremely good or bad performance. Such impact of opinion diversification is more pronounced among heterogeneous teams where members show diverse preferences (Bar et al., 2009).

In contrast, the group shift hypothesis based on social comparison theory assumes that every individual evaluates himself/herself relative to others around. They identify dominating groupmates and consider their ideas to represent the socially preferred opinions in the group. Then they conform to those preferred opinions in the interest of a positive self-image, thus making the team's final decisions to converge to extremes (Suls et al., 2002). This is because high status confident members often achieve support for their more extreme views. And others shift their opinion further towards those preferred extreme opinions and lead to even higher extremity. Turner et al. (1987) proposed the self-categorization theory and reached the same conclusion. They find that members identify themselves with their group and show loyalty by favoring distinct opinions to other groups. The higher congruence level the group has, the more commitment and loyalty the groupmates will show to the group. A large number of experimental investigators like Wallach et al. (1961), Stoner (1968), and Pruitt and Teger (1969) also support this group shift view.

2.3 TMT Study in Management Literature

In 1984, Hambrick and Mason first introduced the upper echelons theory. Their argument is that the characteristics of top management team (e.g. CEO and executives) has predictive power in organizational outcome; demography reflect the value, knowledge base, and other surface or underlying attributes of people who have influential power in corporate decision-making. As one of the several characteristics, team diversity keeps arousing attention from academics. Researchers have looked at several aspects such as age difference (Wagner et al., 1984), tenure diversity (Tihanyi et al., 2000), diversity in educational specialization (Bantel and Jackson, 1989) and so on. Existing literature show mixed results on the overall effect of TMT demographic diversity on performance. Smith et al. (1994), for example, find that heterogeneity in experience negatively affects sales growth and return on investment (ROI) while diversity in years of education is positively related to performance. Increasing association between diversity in nationality and return on assets (ROA) is found by Nielsen and Nielsen (2013). By developing a heterogeneity index score across several demographic variables like gender and education. West and Schwenk (1996) detect a positive impact of homogeneity on firm performance (sales growth and ROA) and display an even stronger correlation in stable environments.

Though empirical results range from positive through non-significant to negative, the underlying arguments are quite consistent. Advocates of homogeneous group claim that similarity in background facilitates impersonal liking and reinforces attachment to the organization, thereby reducing costs of communication and coordination to improve the outcome. According to one psychological theory, people are more likely to be attracted to and have less difficulty in communicating with someone who shares attributes similar to what they have─the similarity-attraction paradigm (Newcomb, 1961, 1968). Shared attributes (e.g., beliefs, values, or perceptions) will be assumed when people find commonality in their personal backgrounds, for example, study at the same university.

Another relevant theoretical view is the social identity and self-categorization hypothesis which seeks to predict human behavior in groups. Self-categorization (Turner, 1985) refers to the process by which people define themselves as members of groups. Social-identity theory (Hogg and Abrams, 1988; Tajfel, 1981), on the other hand, talks more about the cause and consequence of group identification. Stroessner (1996) points to a stronger tendency among members to categorize themselves and other groupmates based on demographic characteristics in heterogeneous team. Such "us-them" distinction biases people's judgment on each other with favoritism (stereotyping) towards in-(out-) subgroup members (Brewer, 1979, 1995; Schopler and Insko, 1992), which is more likely to induce conflicts within a team. By contrast, the reinforced sense of belongings in a homogeneous team makes members care more about the collective interests. As a result, members of a homogeneous group display stronger psychological attachment to each other, more commitment to the team outcome, less conflict, and lower absenteeism and lower turnover rate.

By contrast, others hold an optimistic view on diversity by emphasizing on its added value and benefits to team outcomes. Hoffman (1959) suggests that diversified groups can be expected to have a broader range of perceptions, knowledge and expertise than their homogeneous counterparts. Furthermore, members with diversified background have access to more others with different experience and networks, thus making the information set even larger (Ancona and Caldwell, 1992). Such advantageous information set in turn enhances the group's capacity for creative problem solving. Rather than quickly converge to a dominant viewpoint, a heterogeneous group will review fundamental assumptions, generate more alternatives, and engage in deeper discussion and debate before making a deliberate decision. This improves the firm's profitability.

All in all, a homogeneous group of people with similar backgrounds is usually expected to enjoy high effectiveness and efficiency of communication and coordination among team members but end up with a smaller information set and lower chance to take significant strategic change. Researchers keep discussing the benefit and cost of team homogeneity under different conditions. I can't conjecture which side will unconditionally outweigh the other.

2.4 Fund Manager Characteristics

As mentioned above, there have been some studies discussing the performance implications of fund manager characteristics. Golec (1996) argues that, all else being equal, younger managers with MBA degrees and longer tenures at their funds generate higher risk-adjusted returns for investors. Chevalier and Ellison (1999) contributes by relating the managerial skills to the quality of the education program they had gone through. This paper concludes that younger mutual fund managers who had attended higher SAT undergraduate institutions achieve better performance. Following it, Gottesman and Morey (2006) dig more into the relationship between mutual fund performance and fund managers' educational background in terms of the quality of MBA program. In their study, the average GMAT score of the MBA program and top Business week rankings are found to have significant positive explanatory power in fund performance.

While all the studies mentioned above focus on mutual funds, Li et al. (2011) extend Chevalier and Ellison's research to hedge funds and reach a similar conclusion that managers from higher-SAT institutions tend to have higher raw and risk-adjusted excess return, take fewer risks (overall, systematic and firm-specific risk) and attract more capital inflows. All these studies only look at the characteristics of one representative in each fund and fail to consider the whole management team. One exception is the recent paper by Tan and Sen (2017), which examines the performance implications of educational diversity among mutual fund teams and detects a positive impact on performance. Tan and Sen (2017) propose measures of educational diversity in terms of team members' educational degree and field of educational specialization. Their paper focuses more on the diversification of knowledge and skills needed for problem solving that different subject learnings bring, but sheds limited light on the other informational advantages that are often gained through alumni networks. My thesis will take a more comprehensive view on the association of team cohesiveness in terms of educational backgrounds with team outcome.

2.5 Management Structure and Deceptive Behavior

Hinsz et al. (1997) and Bainbridge (2002) suggest that one of the group benefits is a mitigation of bias and correction of errors. Going beyond the unintentional behavioral bias individuals have, some scholars also believe that adoption of teams could deter agents from engaging in unethical and illegal behaviors. Their assertions come from both the cost and benefit perspectives.

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On the benefit side, compensation based on the team's overall output weakens incentives by obscuring information about each member's contribution, thus reducing individual workers' willingness to signal through unethical behavior (Acemoglu et al., 2008). This way of transforming high-powered incentives into low-powered ones is particularly meaningful for financial services firms where individuals have too many monetary incentives to exaggerate their performance.

On the other hand, individuals are often in a better position to monitor their groupmates rather than their employers. Acemoglu et al. (2008) state that such teams enjoy the advantage of interdependence among members, which means a dependence of one member 's utility on others' effort. Triggers to such interdependence encourage peer monitoring.

Moreover, Mas and Moretti (2009) find that members in groups care about how they are perceived by their peers. This kind of social pressure together with peer monitoring can build up a mutual supervision relationship, which can largely reduce the opportunity of deviating from the “right” behavior.

Another relevant study (Charness and Dufwenberg, 2006) notes an impact of communication on behavior. There exists a variety of partnerships where one’s guilt aversion can be influenced via communications between each other, including co-owners of firms, employer and employee and co-workers. With such influence, members in a team tend to behave in consonance with others’ expectation and reach a consensus. Hence the guilt-averse individuals will reinforce each other’s feeling of guilt aversion so as to enhance their trustworthy behavior.

All the literature cited above holds a positive view on team’s effect on preventing deceptive behavior. But some other studies have argued that an individual’s engagement in unethical behavior does not solely depend on simple cost-benefit analyses. Individuals cite other peoples’ influence as another influential factor. For instance, several scholars have conducted experiments showing that people are more likely to cheat when they split the benefits of doing so with another person (Wiltermuth, 2011). First, team incentives may make people justify their self-serving unethical actions and treat such dishonest behaviors as morally acceptable with a feeling of “helping the team members”. Second, Conrads et al. (2013) point out that deceit in teams can induce a feeling of diffused responsibility and higher probability to hide their misdeeds. Lastly, people are especially willing to break rules when they have a prior relationship with the beneficiary of their unethical action (Brass et al., 1998; Gino et al., 2009).

Moreover, there is a contagion of unethical behavior that can be called “one bad apple affects others” (Gino et al., 2009). When people are exposed to other’s dishonesty, they change their estimation of the likelihood of negative consequences caused by the unethical behavior. It’s like a man who sees a peer cheating on his wife without being caught and lowers his own estimation of the consequence of cheating. This can influence the magnitude of deceit an individual decides to engage in.

Another possible influence of observing other people’s unethicality is that it may change one's understanding of the social norms related to deceptive behavior (Gino et al., 2009). The more frequent and empathic the communication is with the dishonest person, the greater is the likelihood of adopting such person’s attitudes or values. According to social-identity theory, the impact of the social norm is based on categorization of the actor as whether an in-group or out- group member. If it is an in-group member who is observed to be behaving unethically, other groupmates will conform their standards for descriptive norms and may then increase unethical behavior by themselves. In contrast, if it is an out-group member who engages in unethical behavior, non-groupmates will distance themselves from the “bad apple” and display a reduced likelihood of engaging in unethical behavior (Brewer, 1993).

To my knowledge, there have been not many studies shedding light on the management's effect on funds' deception behavior. The most related study seems to be Patel and Sarkissian (2013b) which investigates team structure effect on managerial deception by looking at the likelihood of mutual funds to engage in two specific unethical or illegal practices, portfolio pumping and window dressing. Their results provide the only empirical evidence supporting the view that multi-manager funds deceive significantly less than sole-manager funds.

2.6 Summary

Whereas theoretical arguments keep highlighting the advantages of team management such as less costly information gathering, superior collective memory and mitigation of errors, few empirical studies have supported the outperformance by teams. Unlike the team effect, theories do not provide a clear prediction on the performance implication of the team cohesiveness level. Similarity and social-categorization hypotheses emphasize an increase in interpersonal attraction, liking, and communication in homogeneous groups because of their similar background. However, the information and decision-making hypothesis stresses the larger information sets that heterogeneous groups enjoy.

Regarding management structural impacts on funds' unethical behavior, a simple cost-benefit analysis supports a "moral team" conclusion due to the greater peer monitoring, reduced monetary incentives for team members, and a reinforced feeling of guilt within the team. Yet, several studies have taken other members' influence into account and have contended that team incentives and observation of other groupmates' dishonesty raises the likelihood of engaging in unethical behavior, especially when the members have close relations among themselves.

Chapter 3 Management Structure and Fund Performance

In this chapter, I examine whether a team's structure and composition can make a difference in hedge fund performance. Section 3.1 presents the theory and its predictions. Section 3.2 describes the data sources I use and the sample selection procedure. Section 3.3 presents the model and methodology. Section 3.4 reports the results. Section 3.5 summarizes this chapter.

3.1 Theory and Prediction

Effectiveness of group decision-making has been a conventional topic in psychology and management literature. According to classical utility theory, groups and individuals should make indifferent decisions based on the same profit maximizing objective (Arrow, 1986). On the contrary, groups are believed by behavioural scholars to have advantages in information gathering and recalling, as well as errors correction. Compared to individuals, groups collect information from multiple sources at a lower cost (Hill, 1982). Furthermore, they have collective memory that recalls information more accurately. It could help the team to make better-informed decisions (Vollrath et al., 1989). Another advantage of groups is the mitigation of bias and correction of errors. Multiple sources of random errors made by individuals in the team counteract each other. And since people are more aware of others' mistakes than their own (Shaw, 1932), groups are more efficient in rejecting incorrect ideas. All these substantially reduce the likelihood of departing from a rational choice model by teams.

Despite theoretical literature emphasizing the outperformance of team structure, many empirical studies have not been able to come up with strong evidence supporting this conclusion. Although Patel and Sarkissian (2013a) find higher risk-adjusted returns from team-managed funds than their single-managed counterparts, some other relevant research into the fund industry has documented similar or inferior returns of multi-manager funds (Prather and Middleton, 2002). Further, all these sources studied mutual funds.

To test whether teams have superior decision-making ability, this study compares the performance of team-managed and individual-managed hedge funds. Higher returns are supposed to be an outcome of a wise decision by the manager/management team. My research will provide further evidence firstly by studying hedge fund data. I have already argued that hedge fund is a better target to study. Hedge fund returns are supposed to be directly reflecting the managers' ability and efficiency arising from the fact that they are better motivated and free to implement risky strategies to achieve superior payoffs. Also, hedge funds have more even samples of single-manager versus multi-manager funds than mutual funds do. Less exposure to mass media makes hedge funds to determine their respective management compositions more depending on whether the structure does indeed bring the best management efficiencies and highest returns rather than other considerations. I expect that these factors will make my results more convincing than the many previous studies cited above.

Professionals working in the hedge fund industry believe in the need for team structures that are capable of conceiving and implementing more complex strategies. This belief is also supported by theories that informational diversity is especially beneficial when innovations are needed for more complex tasks (Jehn et al., 1999; Deszo and Ross, 2012). To test this assertion, I study subsamples according to the investment strategies hedge funds adopted. Additionally, based on the same theory, I do the same analysis for different market conditions following Tan and Sen (2017) to see whether team outperformance is attenuated in bearish periods in comparison to bullish periods.

Going beyond average outcomes, Bar et al. (2011) look at the extremity of outcomes and find that single-manager-funds are more likely to achieve either extremely good or bad performance. This may be due to the different risk level of decisions made by individually- and team-managed funds. There are two competing theories on this issue, namely the diversification of opinions theory and the group polarization/risky shift theory. The former hypothesis assumes that teams naturally achieve consensus through compromise to reach an ultimate decision reflecting the average opinion of each member. The moderation of the decisions made by teams will then lead to relatively less extreme performance. By contrast, group shift theory states that members identify dominant group members, perceive their opinions to be correct and then try to conform to such opinion. Consequently, adjustment toward the opinion of the dominant person often results in a convergence of team's opinion towards extremes. However, there is still a lack of evidence to support either one of the two theories.

Hence, in addition to the average outcome, I conduct an initial investigation on hedge fund risk-taking behavior of single-manager and multi-manager teams to check whether groups adopt more extreme investment strategies as the group shift theory predicts or make moderate decisions after reaching a compromise among group members as stated in the diversification of opinion hypothesis. Furthermore, I compare the crash risk in funds across different management structure to check the mitigation role of team structure in avoiding more extreme negative performance. Hedge funds face loose regulations and enjoy more flexibility in investment strategies. Whenever they detect investment opportunities, they are free to pursue them using risky strategies such as derivatives or short selling which are forbidden for mutual funds. As a result, extremes in the managers' investment decision should differentiate more from each other in my hedge fund data.

I also study the correlation between team structure and fund flow as well as failure rate. As hedge funds cannot advertise and promote themselves publicly, networking of management team should serve as an important channel for attracting fund flows. According to Bar et al. (2005), the advantage of team-managed funds lies in attracting capital inflows. But it's also possible that investors trust "star" managers who are confident enough to run a hedge fund by themselves more than they trust a group of people.

Second, I focus on team-managed fund only and find that hedge funds tend to be homogeneous in terms of managers' alma maters. In a typical hedge fund, managers, on average, share at least one school tie with about 12% of their colleagues. A simple simulation confirms that the observed level of congruence is not being driven by a relatively concentrated universe of alma maters in the hedge fund industry[2]. The underlying reason of this phenomenon may be clarified by Cohen et al. (2008). They had found that portfolio managers place concentrated bets on stocks that they are connected through the alumni network and generate more profits from such connected holdings than unconnected ones. This finding supports the beneficial role of shared school ties that act as an information channel between mutual fund managers and company boards. Based on this logic, the more connection a fund team has, the more private information a hedge fund can obtain from firm senior officers through its alumni network. Does it mean that diversified groups should be enjoying larger information sets and hence always perform better? I investigate whether within-fund school ties have positive implications on hedge fund performance in addition to a team factor,

[2] In my dataset, I have a total of 4436 unique managers. Excluding single-manager funds, there are 6852 positions in these funds. I randomly draw (with replacement) and assign one of the 4436 managers to each position. I first compute the average percentage of connected colleagues who share the same alma maters across managers in each fund and then get the proportion of non-fully-diversified fund (which means at least two members in the fund team are connected via school ties). By repeating this procedure 5000 times, I find that the observed percentage of non-fully-diversified fund in my sample is 31.1%, which is significantly high compared to the same value from a random process (6.8% to 32.0%) with a p-value of 0.0016.

The psychology and management literature have also provided theoretical guidance on the performance implication of group homogeneity. First, the similarity paradigm states that people with similar backgrounds assume they share common values, beliefs, and perceptions. Such a feeling facilitates interpersonal attraction, liking, and communication (Krauss and Fussell, 1990). Second, the self- and social-categorization hypothesis state that team members self-categorize themselves and others into subgroups based on some attributes like race, education or values and; members of a less diversified group will show more commitment to the group and more attachment to others in the organizations (Harrison et al., 1998). These views support the expectation that homogeneous groups experience high social-integration, efficient communication, and less conflict. On the other hand, in a heterogeneous group where members cannot communicate easily and efficiently, information will not be integrated deeply within the group, so a timely decision can be made only rarely. Hostility to other subgroups may make group members reluctant to share or listen to each other's potentially useful ideas or information. For these reasons, some scholars have expressed a positive view on homogeneity and found empirical evidence showing that homogeneity in experience positively affects sales growth and return on investment (ROI) via enhancing informal communication and social integration (Smith et al., 1994).

In contrast, the information and decision-making hypothesis states that, as individuals in a heterogeneous group have access to others with different experience, background and network, diversified teams can be expected to enjoy more advantageous information sets when compared to the homogeneous counterparts (Ancona and Caldwell, 1992). Added information might improve the team outcome. Consistent with information and decision-making hypothesis, funds with diverse school ties may help gather larger amounts of information covering a larger number of firms at low cost. For instance, a connected manager needs only one call to collect information whereas an unconnected one may still get nothing after three calls. This can be inferred from Cohen et al. (2008)'s finding mentioned above. Assisted by information inflow via a variety of school ties, diversified groups are more likely to reach a wise investment decision, thereby generating better returns. Empirically, unlike the findings in Smith et al. (1994), a negative correlation between racial homogeneity and several performance measures (e.g., productivity, return on equity and market performance) has been detected by Richard (2000). While there are other papers studying the group homogeneity effect empirically (e.g. Nielsen and Nielsen, 2013; West and Schwenk, 1996), there still are few consistent results reported.

Williams and O'Reilly (1998) identify three categories of team diversity corresponding to the three theories mentioned above, namely informational diversity, social category diversity and value diversity. I choose intra-group school-ties as the measure of group homogeneity in view of its relevance to all the three diversities. Cohen et al. (2008, 2010) find information transfer through college-based networks between economic agents such as mutual fund managers, corporate boards, sell-side analysts and corporate senior officers. And the superior information transferred are statistically and economically significant. Since a team's information collecting ability through school relationships depends on its members' alumni network, the composition of group members' educational backgrounds should be related to the hedge fund's information diversity. Second, the theory of social categorization holds that attributes like experience and education are easier to become a self-categorizing factor than visible demographic characteristics such as gender, age and race because of their high job-relatedness at the working place (Williams and O'Reilly, 1998). Further, among various forms of similarity such as common professional, educational and geographical experiences, school-ties build the most homophilous relationships (Flap and Kalmijn, 2001; Massa et al., 2005). Schools not only offer people attending the same school a unique imprinting via different types and qualities of education that bond them together, but also facilitate interactions between individuals over time on the campus or through alumni associations (Massa et al., 2011; Guan et al., 2016). In this sense, homogeneity in terms of school-ties can be taken to be relatively more representative proxies of social and value diversities than for informational diversity. If the result still shows an outperformance by a heterogeneous team in my observations of hedge fund, I can conclude that the informational benefit of diversified team plays a critical role in volatile environments like the ones hedge funds face. Next, I conduct a sub-sample analysis based on team size to look for optimal level of team cohesiveness in teams with different magnitude.

Furthermore, hedge funds managers cannot promote themselves through mass media such as TV channels or newspapers, they may highly rely on the social network developed among graduates from same alma maters to attract investments. On the other hand, Massa et al. (2005, 2011) conclude that portfolio choices of individual investors are affected significantly by other investors from the same school via college-based interactions. It may therefore be assumed that their investments in a specific fund will more likely be influenced by fund managers with school-ties. For these reasons, I expect diversified teams to be able to attract more fund flows from various connections. Also, both diversification of opinion and group shift theory may be applicable to risk-taking decision of homo- and hetero-teams. I therefore compare their volatility and idiosyncratic volatility to see which theory is supported by my results.

To further shed light on the mechanism through which the team's congruence level can relates to fund performance, I examine the association between intra-group school ties and measures of hedge fund skill proposed by previous literature, market liquidity timing (Cao et al., 2013) and strategy distinctiveness (Sun et al., 2012). My expectation is that homogeneous teams would be able to make quicker decisions and therefore be more successful in timing the market whereas hetero-teams adopt significantly more distinctive strategies as they evaluate various alternatives and involve in deeper discussions before reaching a conclusion.

3.2 Data Sources and Sample Selection

My data on fund managers' background information came from the biographies reported by each fund in the Lipper TASS database. I included any person that appeared in the self-reported biographies as a member of the fund team. TASS already provides very detailed educational information about everyone in a fund team including the name of the institution, the degree received and sometimes the date granted. The dataset is further supplemented with information offered by some online resources such as *Linkedin, Zoominfor* and *CapitalIQ*. Besides some missing data about educational background, I also obtained from these websites, the specific time the manager in question had joined and left the company; with the help of which, I could make my diversity measures more accurate. This time varying measure is different from the one in the simulation process mentioned earlier which accounts for all the people who have ever worked for the fund at the same time.

Different campuses of a university are assumed to be distinct schools because of the differences in their reputation and quality of the program. Sometimes, the biographies don't clarify which university campus the person belongs to. If the particular campus can't be figured out after searching online, I assumed the person to have attended the main campus.

Other fund data like the fund characteristics and fund performance also come from TASS. Instead of updating the fund characteristics every year, I used the 2012 snapshot of ProductDetail since such characteristics don't change frequently over time. Lastly, to control the quality of the school one graduated from, I got the SAT (Scholastic Aptitude Test) scores of their undergraduate institutions from the U.S. News and World Report.

Regarding sample selection, I implement the following restrictions.

a. Exclude funds that do not provide information on affiliated management company;
b. Exclude funds that do not report net returns (GrossNett ≠ N);

c. Exclude funds that do not report to TASS on a monthly basis (TrackingFrequency ≠Monthly);

d. Exclude funds whose investment strategy is not known (PrimaryCategory = Undefined or NaN);

e. Exclude funds whose investment strategy is others (PrimaryCategory = Other);

f. Exclude funds that do not report USD denominated returns (CurrencyCode≠USD);

g. Exclude funds whose management firm is a non-US company;

h. Exclude duplicate funds following Aggarwal and Jorion (2010, JFE);

i. Exclude funds within which no education information about any team member can be found;

j. Exclude funds that either only have one manager or only the education information of one manager is available throughout the fund.

To avoid backfilling bias, I made separate adjustments on hedge funds with or without adding the date reported in TASS. For funds having an accurate adding date, the observations prior to that day were excluded. For funds without a specific adding date, the first 18 monthly returns since fund inception day were dropped. Another possible concern is survivorship bias. The TASS database excludes all dead funds prior to 1994. Therefore, the sample period is set to be 2001 to 2011.

3.3 Model and Methodology

3.3.1 Measurement of Team Congruence

Ahn et al. (2012) records the proportion of non-CEO executives that share the same educational background (high school) using the CEO as a proxy for the congruence level. Following this measure, I constructed my measure of team congruence as the average percentage of connected colleagues for each manager within a fund. The value changes over time as some mangers quit while new members join in. A pair of managers is defined to be connected via school ties (Cohen et al., 2008). Specifically, congruence level equals mean ((number of connected colleague)/(total number of managers within fund-1)). For example, the educational backgrounds of all the 3 managers within a fund are available. A comes from Stanford University; B is a graduate of Harvard; C holds a bachelor from Yale and a MBA from Harvard., The proportion of team members sharing their alma maters with A is 0/(3-1)=0, while for B and C, it is 1/(3-1)=0.5 Then the congruence level for this fund equals to (0+0.5+0.5)/3=33.3%. More examples can be seen in Appendix I. Since I recorded the year in which a team member starts and ends to work, my congruence measures got updated annually.

I chose this measure for several reasons. 1) It can handle the multi-degree problem which cannot be solved by a traditional Blau/Herfindahl index. When some managers hold more than one degree from different schools, the sum of school share (number of members from this school/team size) no longer equals to 1. Under this circumstance, the index measure cannot be applied to my case. 2) It accounts for the educational background of every team member to facilitate differentiation between similar team composition like a 3 Harvard + 1 Stanford + 1 Chicago fund and a 3 Harvard + 2 Stanford fund. This cannot obviously be achieved by only recording the percentage of team members from the largest-alumni-school.

3.3.2 Model Specification

Multivariate regression analysis is conducted to test the predictive power of a team structure and group cohesiveness in future performance. I first developed a team dummy and calculated the level of congruence for each fund in each year and then used it to estimate fund's performance in subsequent 12 months following Titman and Tiu (2011) and Sun et al. (2012). The following regression model is adopted.

$$Performance_{i,t+1,t+12} = a_i + b_i Team_{i,t} + c_i\, Controli,_{t-23,\mathrm{t}} + e_{i,t} \quad (1)$$

Where *Performance* represents several widely-accepted measures of hedge fund's risk-adjusted return as follows

a) r: average monthly excess return over subsequent 12 months;

b) Alpha: alpha from Fung and Hsieh (2001) 7-factor model[3] which includes two equity-oriented, two bond-oriented and three trend-following risk factors;

c) Sharpe ratio (SR), the ratio of average monthly return during t+1 to t+12 to the corresponding standard deviation of return during the same period;

d) Appraisal ratio (AR), alpha from Fung and Hsieh 7-factor model over the standard deviation of residuals in the same model;

e) MPPM [4] (MPPM3 & MPPM4), manipulation–proof measure developed by Goetzmann et al. (2007). "t" refers to month.

I also include several control variables from prior studies about fund characteristics and

f) logarithm of team-tenure, number of years a team has been working together which is proxied by the average number of years each member has worked with other members in the fund (Smith et al., 1994; Nielsen and Nielsen, 2013);

g) logarithm of number of managers within a fund;

h) logarithm of fund size which is the assets under management in millions;

i) logarithm of fund age in terms of year;

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[3] The FH 7-factor model consists of factors as an equity market factor, a size spread factor, a bond market factor, a credit spread factor, and three trend-following factors for bonds, currency, and commodities. More details can be seen at https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm

[4] MPPM can be obtained through the following equation.

$$\hat{\theta} = \frac{1}{(1-\rho)\Delta t} \ln \frac{1}{T} \left(\sum_{t=1}^{T} [(1 + r_t)/(1 + r_f)]^{1-\rho} \right)$$

Where Δt is the time period between observations, which equals 1/12 in my case; T is the total number of observations within the evaluation period; r_t and r_f. are monthly returns of hedge funds and risk-free assets; ρ is the selected coefficient which make holding the benchmark optimal for an uninformed manager. I try both $\rho = 3$ and $\rho = 4$.

j) SAT, average admission score from Scholastic Aptitude Test of every undergraduate institutions that the team members graduated from;

k) corresponding lagged performance during t-23 to t or fund flow for the previous 12 months;

l) lockup periods, window of time in which investors of a hedge fund are not allowed to redeem or sell shares;

m) management fees, amount of money hedge fund manager charged managing the investments;

n) incentive fees, amount of money paid as an incentive to the general partner of a hedge fund depending on their performance over a certain period of time;

o) offshore dummy, dummy variable which equals to 1 if the hedge fund is outside the United States and 0 otherwise;

p) fund style dummies classified by TASS database including Long/Short Equity Hedge, Convertible Arbitrage, Event Driven, Fixed Income Arbitrage, Global Macro, Managed Futures, Multi-Strategy, Fund of Funds, Dedicated Short Bias, Emerging Markets, Equity Market Neutral, and Options Strategy.

Panel regressions with time-fixed effect and fund clustered errors and Fama-Macbeth model were adopted.

Next, to study the relationship between team cohesion and fund performance, I restricted the sample to team-managed hedge funds only and ran the following model.

$$Performance_{i,t+1,t+12} = a_i + b_i Congruence_{i,t} + c_i\, Control_{i,t-23,\mathrm{t}} + e_{i,t} \quad (2)$$

Where I replaced the team dummy variable in model (1) by a team congruence level in terms of intra-group school ties. I next constructed my measure of intra-group school ties as the average percentage of connected colleagues for each manager within a fund. Detailed definitions have already been given in Section 3.3.1. Two types of model were adopted again, namely panel regressions with time-fixed effect and fund clustered errors according to the Fama-Macbeth model.

3.4 Empirical Result

3.4.1 Team- versus Individual- Managed Funds

Overall, literature on top management teams (TMT) believes that teams have several advantages over their individual peers. First, teams enjoy diversification benefits from multiple information channels through team members. Second, a group of people is supposed to have superior collective memory compared to individuals. Each member has limited memory of the different aspects involved and will complement others' memory to arrive at a collective team perception. Third, team members will monitor each other, and correct potential errors made by their group mates. Since these team benefits can be expected to lead to better decision-making by group of people, my prediction is that team-managed funds have superior performance than single-managed funds.

3.4.1.1 Descriptive Statistics

Panel A of Table 1 presents the cross-sectional summary statistics of my sample. In my sample, nearly 70% of the hedge funds are managed by a team instead of an individual manager. A team consists of roughly 3 members on average. The mean age of funds in the dataset is about 5 years. Panel B presents the correlations between a team dummy and several fund characteristics.

(INSERT TABLE 1 HERE)

Table 2 compares fund characteristics across single- and team-managed funds via a t-test. Funds with smaller sizes, longer times since establishment, shorter redemption notice periods, personal capital invested in the fund, lower requirements on the minimum investment amount and consisting of members from more qualified institutions tend to be managed by a sole manager instead of a management team.

(INSERT TABLE 2 HERE)

Panel A of Table 3 presents the time trends of hedge funds managed by single manager and by teams. During the sample period, while the number of funds kept raising till 2006 and declined gradually afterwards, the proportion of team-managed funds had remained relatively constant by plateauing at approximately 69% every year. This is distinct to a clear increasing pattern in mutual fund industry noted in Patel and Sarkissian (2013a). The more evenly distributed hedge fund sample makes my findings more convincing than those reported in literature while studying mutual funds. Panel B lists the distribution of funds across management structure by investment strategies. Funds with relatively more complex strategies like multi-strategy or funds of funds are more likely to be managed by team, compared to fundamental strategies like long/short. This is consistent with industry professionals' conjecture mentioned in Chapter 1.

(INSERT TABLE 3 HERE)

3.4.1.2 Main Regression Results

A multivariate regression analysis is conducted to test the performance implication of a team structure. Results in Table 4 clearly indicate a positive association between team structure and future performance. On average, a multi-manager fund outperforms a sole-manager fund by roughly 1.2% in excess return annually. It means that management structure has marginal predictive power in performance in addition to the set of control variables of fund and manager characteristics. Consistently increasing relationships with all the performance measures provides strong supportive evidence of the outperformance by management team compared to individuals.

(INSERT TABLE 4 HERE)

Groups can capture larger amounts of information from multiple channels. A collective memory could help to recall and integrate information more accurately (Vollrath et al., 1989). These advantages are particularly important in the hedge fund industry where managers need to have in-depth understanding of multiple markets and develop complex strategies. Meanwhile, hedge funds face fierce competition and a volatile environment. Many hedge funds are shutting down while new funds are starting every day. Any mistakes or errors in decision-making can make a fund collapse within a short period of time. The ability of teams to correct errors and reject impropriate ideas is thus indispensable for hedge funds. All this makes the implementation of a proper team structure important while running a hedge fund.

3.4.1.3 Subsample Analysis by Tenure

Tenure is supposed to be a special managerial characteristic in view of its moderating role. Initially, a group is vulnerable to the drawbacks of team structure such as conflict and difficulty in communication. But after members spend time working together, team members become familiar with the different perspectives prevailing in the group and start to learn from each other (Nielsen and Nielsen, 2013). Correspondingly, communication and cooperation are improved, which substantially weakens the tendency to engage in conflict. These group advantages get reflected eventually in fund returns.

(INSERT TABLE 5 HERE)

To provide evidence supporting this theoretical prediction, I divided my dataset into two subsamples based on the median team tenure across funds in the preceding year and ran model (1). As expected, Table 5 shows a mixed result in terms of the difference between the performances of individual- and team-fund during the early times. In an early stage, the high communication costs hinder groups from enjoying its advantageous information set and network. Nevertheless, the situation may change along with an increase in team tenure. After working together for a number of years, teams generate significantly higher returns than individuals. All the six performance measures show a strong result in a high-tenure subsample. However, such outperformance by groups cannot be observed in the low-tenure group. It implies that teams learn to make good use of its beneficial information set with reduced communication cost over time. Provided the benefits outweigh costs, teams may turn to outperform the individuals since the team can make better investment decisions after involving in deeper discussions about multiple alternatives.

3.4.1.4 Cross-sectional Analysis by Investment Style

Lipper TASS classifies hedge funds investment strategies into 13 categories. Each hedge fund defines itself as belonging to a certain category while reporting to the database. I construct subsamples based on these styles and rerun the main model. Industry experts have suggested that team management structures in funds enable development of more complex strategies. This conclusion is consistent with the assertions in Jehn et al. (1999) and Deszo and Ross (2012), who claim that informational diversity is especially beneficial when innovations are needed for more complex tasks. While complexity of investment styles is hard to be quantified, the innovativeness of hedge fund investment strategies can be measured by the strategy distinctiveness (SDI) from Sun et al. (2012). I sort all the investment styles according to the average SDI value of funds adopting such strategy. Then four representative styles are picked up due to their sufficient number of observations available in my sample. Compare to funds adopting event-driven or long/short strategies, there is relative higher requirements of creativeness for managers in funds with global macro or multi-strategy since they are expected to conduct relatively complicated analysis on multiple markets or asset classes.

(INSERT TABLE 6 HERE)

Results of four typical fund strategies are presented in Table 6. Note that single managers are suitable for relatively basic strategies like long/short or even-driven whereas teams display an outstanding ability while conceiving and implementing complex strategies such as global macro and multi-strategy. It is clear that single-manager structure is preferable for diluted tasks. These results are consistent with predictions by both management theorists and professionals

3.4.1.5 Bullish and Bearish Periods

As noted in the above section, Jehn et al. (1999) and Deszo and Ross (2012) suggest a superior role of teams in dealing with complex tasks. Based on this theory, multi-manager funds are expected to do a better job in a down market. Funds face a variety of complex and uncertain information during bearish periods. Further, groups can deal with ambiguity much better than single managers. Tan and Sen (2017) provide empirical evidence to this argument. Following Tan and Sen (2017), I define market conditions based on the CRSP market factor and label 1994, 2000, 2001, 2002 and 2008 as bearish periods and the other years as bullish periods. Then the main model is rerun on the two subsamples.

(INSERT TABLE 7 HERE)

Table 7 illustrate the superior returns obtainable by groups in bull market, which is in line with literature. Nonetheless, a slightly inferior performance of team-managed funds is found during recession. The reason may be that teams need to reach consensus before making decisions. Hence, they will spend much time in the discussion process and ultimately make a moderate choice. By contrast, a sole manager can quickly react to new information obtained and adopt a riskier but probably more efficient strategy to survive in difficult times.

3.4.1.6 Hazard Model of Fund Failure

In addition, I evaluated team performance from yet another perspective by looking at the fund failure rate. I adopted the hazard model of Aragon and Strahan (2012) while running survival regressions. Specifically, I regressed the time to hedge fund failure against team congruence and several other control variables such as fund size, lengths of the redemption notice, lockup periods, management fees, incentive fees, offshore dummy, return, volatility, flow, team size and average SAT. A fund is defined to be a dead fund once it stops to report performance to TASS. Despite the possibility of some of the funds quitting TASS for other reasons, Getmansky et al. (2004) postulate that it's safe to make such an assumption in hedge fund studies. I measure volatility by the standard deviation of excess returns. The time variable here is the number of days since a fund's first observation in TASS database.

(INSERT TABLE 8 HERE)

As the return of a single-manager-fund solely depends on the success of the only manager's investment strategy, I naturally expect individually-managed fund to suffer from higher probability to fail. However, result in Table 8 consistently suggests a decreasing relationship between team structure and survival probability as indicated by a coefficient around 1.2 which is less than 1. Possible explanation may be implied in subsample analysis by tenure. Newly formed funds under team management generate similar or even lower profits but bear higher cost in manpower. Teams may not be lucky enough to keep alive till the benefit start to outweigh costs. There is a high chance for these funds to die along the way.

3.4.2 Team Cohesiveness and Performance

I next focused on team-managed hedge funds only. Table 9 presents the top 30 schools which have the largest number of alumni in my sample. Not surprisingly, they are either high-quality schools like members of the Ivy League or those enjoying advantageous locations in the financial center ─ New York. Although hedge fund managers tend to be smart guys educated in top universities, they are actually distributed across universities quite evenly. Except for the top five schools in the list, other institutions have graduates of around 1% to 2% of the population. However, the managers are found to have connections with 12% of their teammates on average in my sample. A simple simulation process has confirmed this abnormally high level of intra-group school ties in my hedge fund dataset than the level from a random selection.

In this section, I looked further into the homogeneity of team members' educational backgrounds and assess its relationship with fund performance. Although several previous studies have documented an outperformance of funds managed by graduates from high quality programs (as measured by SAT), a group of people from one popular school may not always function as the optimal team for a fund. On one hand, high level of school ties can improve performance through efficient communication and integration of information.

And the stronger sense of belongings will better motivate people to make full efforts for the team's outcome. On the other hand, homo-groups don't enjoy the advantageous information set and the abundance of innovative ideas hetero-groups enjoy (Ancona and Caldwell, 1992).

(INSERT TABLE 9 HERE)

3.4.2.1 Determinants of the Congruence Level

Table 10 presents the cross-sectional determinants of team congruence by regressing level of congruence on other fund characteristics as well as lagged fund performance, volatility and capital flow. Overall, these two tables indicate that funds with smaller fund and team size, low capital flow, a high-water-mark, larger team, lower management fee and members from more qualified institutions tend to form a relatively homogeneous team. To some extent, the statistically insignificant impacts of past performance allay my worries about the endogeneity problem. Otherwise, someone could attribute the positive association to the situation where homogenous team with talent managers generate superior returns and continue to outperform with a low level of congruence whereas homogeneous teams experiencing big loss probably will seek new members with the same background to form even more cohesive teams.

(INSERT TABLE 10 HERE)

3.4.2.2 Main Regression Results

I applied Model (2) on the restricted sample of hedge funds managed by teams. The results (see Table 11) show that high school ties within a team predicts negative future fund performance. While no significant differences are found in the raw excess return and alpha from FH 7-factor model, all the other performance measures show statistically significant results after considering for the risk taken (Sharp Ratio and Information Ratio) or adjusting for possible manipulation by managers. A 10% rise in congruence level, for instance, induces a reduction in the Sharp Ratio by about 0.27%. It supports the optimistic view of group diversity.

(INSERT TABLE 11 HERE)

When people with heterogeneous backgrounds first cooperate with each other, they are likely to suffer from a difficulty in communication induced by dissimilarities among them. Teams appear to be vulnerable to conflicts among members. Under this circumstance, people may simply ignore or even act against others' opinion in an irrational way. However, the members get used to different perspectives in the group after spending time working together. They can then clearly present their own opinions and, at the same time, think rationally about others' viewpoints. As the communication efficiency keeps improving, hetero-groups learn to make better use of the abundant information available from diversified knowledge and networks of members. This advantage of collecting as well integrating information can be expected to be especially pivotal in the hedge fund industry where managers need to deal with complicated information drawn from multiple markets. That may explain why hedge funds with diversified teams substantially outperform their homogeneous counterparts on average.

3.4.2.3 Subperiod Analysis by Market Conditions

Main results above confirm the dominant significance of information diversity in volatile environment that hedge fund teams face. In this section, I conducted a subsample analysis by different market condition to provide further evidence to this argument. Market condition is proxied by Cboe Volatility Index (VIX Index)[5]. I divided my dataset into two subsamples based on the median VIX value across the whole sample periods and reran model (2).

(INSERT TABLE 12 HERE)

As can be seen in Table 12, while congruence level has slightly positive performance implication in low VIX periods, it turns to hurt the performance in high VIX results. This

[5] I also try other proxies for market condition such as Economic Policy Uncertainty Index (EPU), sentiment and bull & bear market periods. The subsample results based on these measures are similar with the listed results by VIX but relatively weaker.

finding is consistent with that from Tan and Sen (2017). It supports my previous assertion that team diversity is especially beneficial when dealing with complex and uncertain information.

3.4.2.4 Subsample Analysis by Team Size

Subsequently I have a question: Does team cohesiveness always hurt performance? Will the negative correlation change along with group size? To answer this question, I conducted a subsample analysis based on the number of managers in a hedge fund team. Since majority of the funds have 2 to 3 members in the team, I take a team size with 2 as the base line. Next, I divided my dataset into subsamples of funds with exactly and more than two members within the management team and ran Model (2).

(INSERT TABLE 13 HERE)

Table 13 reports the subsample results on congruence level and performance. A clear distinction can be detected in funds with only two managers versus those with larger team. In a 2-manager fund, it’s not difficult for the two members to develop an efficient way of communication and coordination even if they share few similarities between them. However, a fully homogenous team indicated by the high level of congruence provides the team with concentrated and repeated information from a single channel. Consistent results from all the measures clearly illustrate a statistically significant underperformance of homogenous groups due to an insufficiency in the knowledge and information required. On the other hand, there are considerably less worries about a lack of information in groups with larger size. In this case, some level of congruence might increase the teams' cohesiveness, and alleviate conflicts and communication problems to certain extent.

3.4.3 Team Structure and Risk-taking Behavior

Another objective of my research is to have an initial investigation on the influence of management structure and composition on the hedge funds' risk-taking behaviors. I proxied the risk taken by the total and idiosyncratic volatility of hedge fund returns in the subsequent 12 months' period. To simplify modeling, I included the two variables of interests into the same model—the team dummy and congruence level, so that the overall association of management structure with risk-taking can be seen from a single result. Since a single-managed fund can be expected to exhibit full homogeneity, I set the missing values in the congruence level of sole-manager funds to be 1 while running Model (3) on my full sample of observations.

$$Volatility/IdioVol/NCSkew_{i,t+1,t+12} = a_i + b_i Team_{i,t} + c_i Congruence_{i,t} + d_i\, Control_{i,t-23,t} + e_{i,t} \quad (3)$$

In columns (1) and (2) of Table 14, a significantly positive explanatory power of a team dummy can be seen in the figures for both total and idiosyncratic volatility. This finding is in line with literature supporting a group shift theory. Both group polarization and risky shift theories hold a view that team members identify dominating individuals (e.g., founders or "star" managers) and regard their opinions as preferred ideas in the group (Suls et al., 2002). For example, if these dominating members overweigh stocks in the automobiles industry, others are likely to shift their opinion and conform with proposals to concentrate on this industry and even increase betting on such stocks further on their own, thereby leading to a high extremity.

On the other hand, congruence level is found to be positively related to total volatility at a significance level of 5% and the idiosyncratic volatility at 1%. With the same numbers of managers, homogeneous groups will take relatively more risks in their portfolio. A possible explanation can be drawn from the self-categorization theory. Turner et al. (1987) contend that members identify themselves with their group and show loyalty by favoring the currently salient opinion to other groups. Such behavior is reinforced in teams with higher congruence level where the groupmates will show more commitment and loyalty to the group.

The most relevant study in this context is that from Bar et al. (2011) which finds that single-manager-funds follow more extreme investment styles and achieve either extremely good or bad performance. Such association is more pronounced among heterogeneous teams where members show more different preferences (Bar et al., 2009). My results indicate a completely opposite conclusion that teams adopt more extreme investment strategy than individuals, especially in highly cohesive teams where it's easy to converge to an extreme view.

In addition to total and idiosyncratic volatility, I look at the correlation between management structure, its composition and risk-taking in terms of the crash risk. Following Chen et al. (2001), I adopt the "negative coefficient of skewness" as my measure of fund crash risk, which is computed by taking the negative of the third moment of fund monthly returns for 12 months and normalizing it by the standard deviation of fund monthly returns raised to the third power[6].

Result in columns (3) of Table 14 demonstrates that greater crash risk is associated with a sole-management structure and high level of school-ties within the team. As expected, there is a higher probability for single-manager funds or cohesive multi-manager funds to achieve larger negative returns than their counterparts. This conclusion is consistent with aforementioned theory that team management structure are more efficient in detecting and rejecting incorrect ideas, especially for teams with diversified mindsets. By contrast, funds

[6] Specially, NCSkew for each fund in month t can be calculated through the following equation.

$$NCSkew_{i,t} = -\left(n(n-1)^{\frac{3}{2}} \sum R_{i,t}^{3}\right) / ((n-1)(n-2)\left(\sum R_{i,t}^{2}\right)^{\frac{3}{2}})$$

Where $R_{i,t}$ represents the sequence of de-meaned monthly returns to fund i during period t and n is the number of observations on monthly returns during the period.

managed by sole managers or highly cohesive teams where people follow opinions from dominant member(s) are more likely to generate stronger negative returns.

(INSERT TABLE 14 HERE)

3.4.4 Team Structure and Fund Flow

Next, I explored the relationship between management structure and fund flow. Li et al. (2011) conclude that managers from higher-SAT institutions tend to attract more capital inflows. But after controlling the school quality, will investors like to see their money being managed by a group of people as professionals predict? If this is true, will they prefer management teams with similar backgrounds? Following Model (3), I developed model (4) to examine these research questions. I calculated flow as the percentage change in assets under the management in the subsequent year which equals to ($AUM_{i,t+12}$ - $AUM_{i,t+1}$*(1+$Return_{i,t+1,t+12}$)) / $AUM_{i,t+12.}$

$$Flow_{i,t+1,t+12} = a_i + b_i Team_{i,t} + c_i Congruence_{i,t} + d_i\, Control_{\,i,t-23,t} + e_{i,t} \quad (4)$$

According to my results from regressions presented in column (4) of Table 14, funds managed by single managers or cohesive teams attract substantially more capital flows from investors. Investors seem to trust “star” managers who are confident enough to run a hedge fund by themselves more than a group of people. By putting money in these individually managed funds, they clearly know whose investment wisdom they are betting on. In addition, investors prefer homogeneous teams more than heterogeneous ones. They put larger bets on connected funds with predominantly same school alumni. A plausible reason for this may be that similar investment attitudes are shared by graduates from the same college. Second, the superior information transmitted via college-based interactions might be helping to reduce information asymmetry between investors and fund managers.

3.4.5 Managerial Skill

The above results confirm a link between team congruence and fund performance. Based on certain theories of psychology, I can say that this link exists because the congruence level can impact on decision-making of a group. Using measures of hedge fund ability proposed in literature, in this section, I will provide partial evidence for the underlying mechanism by testing the correlation among team congruence level and different aspects of managerial ability. While Dass et al. (2013) have related the management structure to the decomposed fund performance, market timing and asset allocation, my study serve as a first attempt to look at the association between managerial skill and team congruence level.

Cao et al. (2013) show that an equity-oriented fund which can successfully time the market generates better returns. Compared to their heterogenous counterparts, members of homoteams who share common educational experiences tend to make similar judgments (about future market liquidity conditions in this case). It's also easier for members of a homogenous team to communicate and reach agreement among each other. A timely decision on portfolio adjustment, therefore, can then be made within the group. I therefore expect a better market timing ability of hedge fund team with high school-ties. Following the model described below, I measure the liquidity-timing skills of equity-oriented funds using the coefficient of the interaction term of change in market liquidity with the equity market returns, α.

$$Return_{i,t} = \alpha MKT_t \Delta MLIQ_t + \sum_{j=1}^{7} \beta_j FH7_t + \gamma + e_{i,t} \quad (5)$$

where return is excess return of individual funds. MKT_t is market excess return. $\Delta MLIQ_t$ is measured using the Pastor-Stambaugh market liquidity innovation series. And FH7 denotes Fung and Hsieh seven factors.

Sun et al. (2012) document a superior fund returns of hedge fund endowed with high innovation skills. They use the correlation between the return of a fund and return of its peer funds to proxy a fund's Strategy Distinctiveness (SDI). Specifically, it equals 1 minus the correlation between the fund's return and the average return of all funds adopting the same style. As discussed earlier, heterogeneous teams enjoy a larger information set coming from diversified members. Before adopting an investment strategy, members in heterogenous groups are more likely to come up with different ideas, involve in deeper debate and discussion, and eventually develop unique strategies. Hence, heterogeneity is supposed to be positively related to SDI.

(INSERT TABLE 15 HERE)

I regressed the measures of strategy distinctiveness and liquidity-timing skills against Level_1 and Level_2 team congruence[7] on full sample and subsamples based on team tenure. Fama-Macbeth model and Panel regressions with time-fixed effect and fund clustered errors are adopted. As expected, homogenous teams have superior timing skills (Panel A of Table 15) though the difference is not that significant statistically. Further, heterogenous teams substantially outperform their counterpart in pursuing innovative investment strategies at a significance level of 1%. The results from the subsample presented in Panel B illustrate the diminishing marginal impacts of team congruence on both managerial skills along with an increase in team tenure. This is consistent with Pelled et al. (1999)'s assertion that any positive or negative association between congruence and firm performance are expected to be weakened by group longevity. However, while hetero-teams show diminished but still outstanding abilities in strategy innovation, the advantages of homogenous teams in liquidity timing seem to disappear. This implies that

[7] Construction of Level_2 congruence is specified in Section 3.4.6.3 Alternative Measure of Congruence Level.

communication costs can be reduced as members start to have common working experience in the existing team after certain time, but not much improvement can be made on the lack of innovation skill. This result supports my explanation that significant outperformance of team managed funds in the high-tenure subsamples (Table 5); teams need time to learn to make good use of their advantageous information set.

3.4.6 Robustness Tests

3.4.6.1 Causality

If I conclude my results as strong evidence of the team management effect on performance, then my findings may be challenged by an endogeneity concern. A reasonable conjecture is that sole hedge fund manager would only bring in another manager when they believe that the new member's experiences, expertise, and connections are beneficial to the fund future performance. Hence, it is possible that the outperformance of team-managed over individual-managed funds is a not result of the team management structure, but the skill set of the additional member that are particularly beneficial to the fund.

An ideal setting to test this problem is to have an exogenous change in the management structure. However, the difficulty of implementing the test arose from a lack of proper event that could result in exogenous changes in hedge fund team. A merge between two funds may be an example. But it seems that such change in management structure are still endogenous as the new structure are pre-determined by managers via discussion before the merge. Another exogenous event may be an unexpected death of manager. Nevertheless, no dataset is available for such test. To partially address this problem with what I have, I provide the following theoretical and empirical evidence.

In theory, increased performance may not be the only reason to hire new members. Otherwise, the following puzzle concerning the increasing popularity of the team management structure in the mutual fund industry would not exist. Most papers (Prather and Middleton, 2002; Chen et al., 2004; Bliss et al., 2008; Dass et al., 2013) have found no empirical evidence of superior performance by team-managed funds compared with solely managed funds. Given their similar outcomes, there should be an even distribution of the numbers of solo-managers and teams if the management structure depends fully on the returns generated. However, this expectation is inconsistent with the general observation that mutual funds shift gradually from sole- to team-management over time. One possible reason for the prevalence of a team approach is to avoid loss when star managers leave and reduce the costs associated with the rising bargaining power of named managers (Kovaleski, 2000; Massa et al., 2010). Another reason may be to appease investor preference for funds with comprehensive infrastructure and management stability.

I also conduct empirical tests to address the endogeneity problem. Following Bar et al. (2011), I adopt the 2SLS model to solve the endogeneity problem. Hedge funds with the same management company usually have a dominant management strategy to choose between a sole- or team-management structure. In my sample, more than 90% of funds with the same management company followed strategies already dominating their companies. Therefore, I constructed the instrumental variable for team dummy as the proportion of team-managed funds among all the funds the management company had with the respective fund (excluding the respective fund itself). On one hand, such instrument variable is highly related to the management structure of a particular fund. It does not suffer from weak instruments problems. On the other hand, the management structure of other funds in the same company is not expected to be related to the fund's own performance outcome significantly. Hence, the structural policy dominating a management company can only correlate with fund performance through its management structure. I therefore ran the 2SLS model with instrumental variables. This led to results consistent with those from the main regression (see Section 3.4.1). The estimated coefficient on team dummy was still positively significant across different performance measures.

(INSERT TABLE 16 HERE)

Next, I construct subsample of funds that had experienced changes in management structure during the sample period. Firstly, I investigated on whether their fund performance had been significantly affected. Based on the conjecture that single-managers choose to hire the additional member only if the new member was beneficial to the fund future performance, I expected to see a rise in fund performance after a switch from sole- to team-management. I conducted t-tests on these funds over a period of two years before and after each change. However, following the change, the results showed no significant increase in performance. To further study switching funds, I panel-regressed the team dummy on fund performance with fund and year fixed effects over the entire sample period. On average, funds outperformed during years in which the fund was team-managed (Panel B in Table 17). These results are consistent with my previous conclusion from main regression and subsample analysis by team tenure. It takes certain amount of time for a team to learn how to take advantage of its management structure. If the sole-managers believe that the benefit of a switch to team management comes from the new expertise or connection the additional member brought in rather than the team management structure itself, they will expect an immediate increase in their fund's performance in the short-run rather than a steady improvement in the long-run. Owing to concerns about the cost of sharing profits, the solo manager won't wait for such a long time. Overall, there is no evidence that is strong enough to conclude a causal relationship.

(INSERT TABLE 17 HERE)

3.4.6.2 Additional Contribution to Informational Diversity of Education

Tan and Sen (2017), the most relevant study to my own investigation of the association of congruence with fund performance, proposes two measures of educational diversity, namely final educational degree and field of educational specialization and claim that their measures can proxy informational diversity regarding managers' educational background. They also find a positive performance implication in their measures. To differentiate my research from their paper and illustrate that my measure of intra-group school ties captures more potential impacts from similar educational backgrounds of members, I added their diversity measure of manager's educational degree into my Model (2) and reruned the model. Since information about managers' education field are not available in my dataset, I only added a control of diversity in the final degree.

(INSERT TABLE 18 HERE)

Consistent with the findings of Tan and Sen (2017) with respect to mutual funds, their measure of diversity in education positively predicts hedge fund performance as well. However, my measure of congruence in terms of school-ties is able to explain fund performance too. Since these two measures are naturally related to each other, to a large extent, the significances of both measures reduce slightly in my results (Table 18).

Going beyond the knowledge and skills needed for problem solving, contacts serve as another channel to obtain the information needed for decision-making. Informational advantage through social network has been proved in both management and finance literature (Cohen et al., 2008). My measure of congruence thereby captures the marginally informational benefit derivable by diversified teams. Heterogeneous educational backgrounds of team members encourage groups to abandon networking resources. Contacts with senior corporate officers or board of directors or anyone who possess superior information of the firm will certainly increase information availability of the group. Also, different colleges and universities have their own unique cultures and special trainings. These equip their graduates with certain problem-solving abilities and perspectives in addition to the standard knowledge learned while studying each curricular subject, and largely affect the associated decision-making processes.

3.4.6.3 Alternative Measure of Congruence Level

Since the main regression results demonstrate a positive association between team cohesiveness and fund performance, following Cohen et al. (2008), I compute an alternative measure of team congruence level to different extent. As for Level_1 congruence, two people are defined to have common educational background provided they have ever studied in and obtained a degree from the same university. As an alternative measure, Level_2 congruence further requires the two to have attended the same school and received the same type of degree. Degrees are classified into 6 categories: Undergraduate, Business School, Graduate, Law, Medical and PhD. I didn't include Level_ 3 or Level_4 congruence due to the large amount of missing data in granted date. After running the main model (2) again by L2_congruence, I obtained the results presented in Table 19. Despite the observation that L2_congruence always has lower value in coefficients than L1_congruence does, the results are basically the same with those from L1_ measure.

(INSERT TABLE 19 HERE)

3.4.6.4 Changes in Management Structure

As already mentioned, my measure of intra-group school ties is updated annually while the panel regressions are run on monthly basis. Any change in management structure over the 12-month horizon in which performance is being evaluated may have affected my findings with respect to association of management structure with performance. To rule out this alternative explanation, I restrict my sample to observations on funds that have not experienced any turnover of fund managers over the pre- and post-12 months periods. Again, I put team dummy and team cohesiveness into the model, e.g., Model (3), to have an overview on any possible change in my results and set the congruence level of individually managed fund to 1. Table 20 presents the results from my restricted sample. It shows a consistent positive (negative) correlation between team management structure (team cohesiveness) and hedge fund performance.

(INSERT TABLE 20 HERE)

3.5 Chapter Summary

All in all, empirical results from my regression analysis provide further evidence in support of the benefits derivable from a team management structure in generating superior performance. The positive association is pronounced 1) for a mature team, 2) in funds with relatively innovation-oriented investment strategies and 3) during bullish market periods. Within multi-manager funds, those with high levels of congruence in terms of intra-group school ties underperform in an average manner, especially during volatile periods or in teams consisting of only two members. The underlying mechanism may lie in the advantage enjoyed by diversified groups in terms of developing distinctive strategies.

In addition, my findings regarding fund risk-taking behavior are in line with the group shift theory that teams conform to the opinions of the dominating members and converge ultimately risky decisions. Such association is present most strongly in homogeneous teams. I also document that funds managed by sole managers or highly cohesive teams where people follow opinions from dominant member(s) are more likely to generate stronger negative returns than their counterparts. Lastly, unlike the results in mutual funds, single-manager funds are found to attract more capital flows from investors and display a lower probability to fail.

Chapter 4 Management Structure and Funds' Misreporting

In this chapter, I investigated the deceptive behaviours displayed by hedge funds with different management structures. Section 4.1 presents the theory and predictions. Section 4.2 describes data and methodology. Section 4.3 reports the results. Section 4.5 summarizes this chapter.

4.1 Theory and Prediction

As stated already, one of the group benefits is mitigation of bias and correction of errors. Biases, such as herding or overconfidence, lead decision-making to depart from the model of rational choice. But multiple sources of random error made by individuals in the team often counteract each other, thus reducing the likelihood of persisting in a wrong questioning set. Other than the unintentional behavioral bias individuals have, team structure may also deter agents from engaging in unethical and illegal behavior. People usually behave in certain ways to fit the expectations of others to avoid feelings of guilt. Such "guilt aversion" is found to be reinforced in teams via communication among guilt-averse individuals as others' concerns enhance their own trustworthy behavior (Charness and Dufwenberg, 2006).

Additional reasons why teams may differ from individuals in the probability of involving in deceptive behaviors are the greater peer monitoring and reduced monetary incentives among team members. No matter who the agents are, an individual or a team, they choose to deceive only if the benefits of such behavior outweigh the costs. On the cost side, members in a team naturally feel pressures arising from peer monitoring. Such mutual supervision largely reduces the opportunity for deviating from the "right" behavior and increase the cost of deception. On the benefit side, sharing profits among all members results in lower monetary incentives to cheat. Studies have shown that high powered incentives often induce agents to put in good efforts but may also encourage them to use bad efforts to artificially improve their observed performance just to maximize payoffs. Further, compensation contracts based on the whole team's output help to transform individuals' high-powered incentives into low-powered ones (Acemoglu et al., 2008).

Though the above cost-benefit analysis holds a positive view on the team's effect on preventing deceptive behavior, there are other studies proposing other peoples' influence as another influential factor in individual's engagement in unethical behavior. Splitting the benefits of unethical behavior with another person is often found to increase one's own probability of cheating (Wiltermuth, 2011; Conrads et al., 2013; Gino et al.,2013). The perceived immorality of the self is reduced by a feeling of "helping the team members" under team incentive scheme. Furthermore, "hiding" behind the team lowers the probability of being caught by inducing a feeling of diffused responsibility (Conrads et al., 2013).

Also, one member's unethical behavior can turn contagious just as one bad apple affects others (Gino et al., 2009). First, observing other's dishonesty may change people's estimation of the likelihood of negative consequences caused by the deceptions. Think about a poor man who sees his poor friend stealing others' money several times without being caught. This may lower his estimation of being caught as a thief and thereby increase the magnitude of deceit this man decides to engage in. Second, exposure to other people's unethicality can change one's understanding of the social norms related to deception behavior (Gino et al., 2009). It can change one's belief in ethics itself and encourage the adoption of unethical groupmates' low moral standards.

Brass et al. (1998) and Gino et al. (2009) argue that people are especially willing to break rules for the benefit of people with whom they have prior relationships. The more frequent and empathic the communication is with the dishonest person, the greater is the likelihood of adopting such person's attitudes or values. According to social-identity theory, people categorize themselves and other team members into groups. An actor of deceptive behavior often classifies others into whether they belong to the in-group or an out-group. In the former case, other groupmates will conform their standards for descriptive norm and may then step up unethical behavior on their own part. In contrast, if it is an out-group member, non-groupmates will distance themselves from the "bad apple" and display a reduced likelihood of engaging in unethical behavior (Brewer, 1993). Therefore, homogeneous teams are expected to be more likely to unite with each other and get involved in misreporting as team than their heterogeneous peers.

The most relevant study of managerial influence on funds' unethicality is Patel and Sarkissian (2013b). It investigates the effect of team structure on managerial deception by looking at mutual funds' likelihood to engage in two specific unethical or illegal practices, namely, portfolio pumping and window dressing. I believe that hedge funds provide better setting for this research question as there is more developed literature on managerial deception behavior in hedge funds than in mutual funds. Given the fuller restrictions and monitoring from board of directors, regulatory departments and the public in general, mutual funds are believed to be engaging only rarely in manipulating their earnings. There is no widely acceptable evidence or measure of mutual funds' misreporting but there is for hedge fund. In addition to that, the hedge fund industry has more balanced and stable samples with nearly 69% being team, whereas the proportion of individually managed funds in the mutual funds industry has kept decreasing in recent years.

By examining the reporting qualities of individual- versus team- managed as well as homogeneous versus heterogenous hedge funds, I examined how a team structure and its composition can change hedge funds' unethical and illegal behavior. As noted earlier, hedge funds enjoy relaxed regulation and monitoring. The probability that negative consequence will result from misreporting, is quite low. And the time span to detect unethical behavior is considerably long. Under such circumstances, people become prone to developing fluke minds and engage in immoral actions. Therefore, whether the mitigation role of management structure still holds in this unique environment hedge funds face is worth testing.

4.2 Data and Modeling

The dataset used in this section is essentially the same as that described in Chapter 3. I collected background information about fund managers from the biographies reported by each fund to the Lipper TASS database and further supplemented the dataset with the information offered by some online resources such as *Linkedin*, *Zoominfor* and *CapitalIQ*. Everyone that appeared in the self-reported biographies was regarded as a member of the fund team. Data about fund net returns, asset under management, inception date, adding date and investment style are again drawn from TASS.

The same selection procedure as described in Chapter 3 is applied to the sample. However, I restricted the sample to funds that have at least 24 contiguous monthly observations of returns that overlapped with the sample period following Bollen and Pool (2012) for the construction of misreporting measures. To avoid backfilling bias, I dropped the observations before adding the day to TASS database or the first 18 monthly returns since the inception day. Again, the sample period was still set to be 2001 to 2011 while considering survivorship bias.

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A set of misreporting flags were set following prior literature to proxy funds with deceptive behavior, including the six data-quality indicators, the two measures of correlation between funds' return and style factors, and unconditional as well as conditional serial correlations (Bollen and Pool, 2012). I also included the two flags of December spike recommended by Agarwal et al. (2001) and an aggregate dummy variable of the measures above. However, I excluded the Kink flag Bollen and Pool (2012) because Jorion and Schwarz (2014) rejected the role of discontinuity at zero in the distribution of a hedge fund's net return treated as an implication of return manipulation. Jorion and Schwarz (2014) explain the kink by asymmetrically applying incentive fees on positive and negative returns.

December spike flags have been developed by Agarwal et al. (2011). They argue that hedge funds manage December returns upward for incentive fees which is usually calculated at the year-end. Abnormally high raw returns and residuals from FH 7-factor model can be seen in suspicious funds, especially those with greater incentives and more opportunities to manipulate returns.

I included the other 10 misreporting flags following Bollen and Pool (2012). I first conjectured that low correlation with funds in the same category and low explanatory power of hedge fund style factors than random dataset could be a predictor of abnormal performance. Second, managers often purposely smooth returns by reporting moving averages of current and lagged returns. Such smoothing can be indicated by a significant high serial correlation. Taking the magnitudes of lagged returns into consideration, I also incorporated a measure as conditional serial correlation. Lastly, I detected the six specific suspicious patterns in hedge fund returns history to proxy a data quality of he reported returns.

These flags of suspicious patterns function as dependent variables in my model; they only have dummy values, viz., 0 or 1. Therefore, I adopted the Probit model for the main regression. In the following models (6) and (7), misreporting flags are regressed by managerial variables including team dummy and a cohesiveness measure in terms of managers' educational backgrounds as well as several controls.

$$Misreporting\_Flag_i = a_i + b_i Fund\_team_i + d_i\,Control_i + e_i \quad (6)$$

$$Misreporting\_Flag_i = a_i + c_i Mean\_congruence_i + d_i\,Control_i + e_i \quad (7)$$

Where *Misreporting_Flag* represent 13 flags of suspicious pattern in hedge fund returns that proxy for fund managers' deceptions.

i. December Return flag (*Dec_flag*), when the fund's returns are regressed by an indicator variable for the month of December, the flag equals to 1 if the coefficient of the December dummy is significantly positive and 0 otherwise;

ii. December Residual flag (*RDec_flag*), when the residual from Fung and Hsieh's (2001) seven-factor model are regressed by an indicator variable for the month of December, the flag equals to 1 if the coefficient of the December dummy is significantly positive and 0 otherwise;

iii. *Indexsq_flag*, when fund's returns are regress by the adjusted style index which is the equal-weighted return of all the other funds with the same investment style, the flag equals to 1 if the coefficient on the adjusted style index return is not significantly positive and 0 otherwise;

iv. *Maxsq_flag*, equals to 1 if the fund's maximum adjusted-R^2 from model with FH 7 factors as well as Fama-French 4 factors is below the 95th percentile of a fund-specific bootstrap simulation and 0 otherwise;

v. *AR_flag*, equals to 1 if the coefficient of lagged return in a AR (1) model is significantly positive and 0 otherwise;

vi. *CAR_flag*, equals to 1 if the incremental serial correlation following poor returns is significantly positive and 0 otherwise;

vii. *Zero_flag*, equals to 1 if there are too many returns exactly equal to zero in a fund history compared to a random sample and 0 otherwise;

viii. *Nega_flag*, equals to 1 if there are too few negative returns in a fund history compared to a random sample and 0 otherwise;

ix. *Uniform_flag*, equals to 1 if the fund has a distribution of the last digit that rejects the null of uniform and 0 otherwise;

x. *No_Repeated_flag*, equals to 1 if there are too few unique returns in a fund history compared to a random sample and 0 otherwise;

xi. *Recurring_flag*, equals to 1 if there are too many recurring blocks of length two in a fund history compared to a random sample and 0 otherwise;

xii. *Max_Repeated_flag*, equals to 1 if there are too long a string of identical returns in a fund history compared to a random sample and 0 otherwise

xiii. *Any_flag,* equals to 1 if the fund triggers one or more of the above flags just described.

My key variables of interests are the following two measure of management structure

xiv. *Fund_team*, equals to 1 if particular fund is managed by a management team for more than half of the observations and 0 otherwise;

xv. *Mean_congruence*, the average congruence level of a particular fund during its returns history.

And control variables include the follows.

xvi. *lnAUM,* logarithm of fund size which is the assets under management in millions;

xvii. *lnfund_age,* logarithm of fund age in terms of year;

xviii. *fund_ret,* the average returns of a particular fund during its returns history;

xix. *Vol,* the standard deviation of a particular fund’s return during its returns history.

Since the misreporting measures are computed based on the fund level, the regression I had run represents a cross-sectional analysis rather than a panel regression as described in Chapter 3.

4.3 Empirical Results

4.3.1 Descriptive Statistics

Table 21 presents the summary statistics on the misreporting flags conducted based on prior studies and the correlation among them. In my sample, most funds report too many repeated values than random samples. Also, as indicated by a high serial correlation, more than 40% of the funds are suspected to have smoothened returns. By contrast, very few sample funds are found to have December spikes or abnormally high conditional serial correlations, or report too many returns equaling exactly t zero. As for Panel B, not all the measures make consistent prediction on fund's misreporting behavior. *AR_flag*, *CAR_flag* and *Maxsq_flag* do not have very significant positive associations with the other measures.

(INSERT TABLE 21 HERE)

Next, Table 22 lists the results from a t-test on the performance flags of individual- versus team-managed funds. *Maxsq_flag*, *Uniform_flag* and the aggregate flag are triggered at a substantially higher rate for sole-manager funds than they do for multi-manager funds. The largest difference lies in the flag of uneven distribution of last digit. These results can be interpreted as providing some initial evidence supporting the reduction in unethical behavior in a team structure.

(INSERT TABLE 22 HERE)

4.3.2 Main Regression Results for Team Structure and Misreporting

Some experimental studies (Wiltermuth, 2011; Conrads et al., 2013; Gino et al.,2013) have argued that sharing the benefits of unethical behavior with other members in the team reduces the perceived immorality of the self and thereby increase the likelihood of unethical behavior such as returns manipulation. Second, if a single manger chooses to overstate fund returns and is caught by SEC, the reputational cost is supposed to be substantial. But if a team of managers is being suspected to misreport returns, a group member can defend himself/herself from such immoral behavior. Even if the hedge funds are charged with a legal or regulatory violation, team members do not take full responsibility of the violation. And the loss of reputation for one member of the team will be smaller than for a sole-manager.

Nevertheless, a considerably increasing proportion of mutual funds are continuing to choose to recruit a group of managers to reduce the fraud risk based on a cost-benefit analysis. People are reluctant to behave unethically while being monitored by other team members. It is difficult to misreport returns without being detected by other members. Since groups involve a continuing relationship, dishonest members face a threat of expulsion or punishment in future interactions. Secondly, people care about how they are perceived by other groupmates. They comfort themselves in accordance with communal norms in the team and become more guilt averse via communication with other moral members. Groups of managers are less motivated to manipulate fund returns for additional payoffs as they are forced to share it with the other members.

(INSERT TABLE 23 HERE)

I ran a Probit model to study whether the team structure has any correlation with a fund's deceptive behavior. The results presented in Table 23 support the team benefit in reducing the likelihood of engaging in dishonesty activity. About half of the misreporting flags are trigged at significantly lower rate in team managed funds than individually managed funds. Groups are exhibiting a 15% to 30% reduction in the probability to report performance with low data quality. The reported returns by multi-manager funds are more closely related to peer performance with the same investment style and hedge fund style factors relating to standard assets (FH 7 factors and FF 4 factors).

(INSERT TABLE 24 HERE)

Although not all the misreporting measures show consistent decreasing relationships with a team structure, Table 24 presents negative results at a significance level of 1% from an aggregate measure of all the flags mentioned above. My significant results imply a lower probability for hedge funds to commit a fraud under teams, which is consistent with the mutual fund results from the Patel and Sarkissian (2013b).

4.3.3 Team Cohesiveness and Misreporting

The second variable of interest is team cohesiveness. Shared school ties probably imply the existence of prior relationships amongst team members. Brass et al. (1998) and Gino et al. (2009) predict that people are especially willing to break rules for members of familiar background. When members observe other in-group members with similar educational background behaving unethically, frequent and empathic communication between them makes them to conform more easily with the offender's standards for descriptive norm. These members may then increase unethical behavior by themselves. Nonetheless, I find no supporting evidence for the above theoretical prediction in the results presented in Table 25. None of the misreporting flags are significantly positively related to the team average congruence level.

(INSERT TABLE 25 HERE)

4.3.4 Additional Analysis by Team Size

A negative relationship between team structure and fund deceptions has been detected above. In this section, I apply the following model to compare misreporting behaviors across funds with different team sizes—following Patel and Sarkissian (2013b). In model (8), mger2, mger3, mger4 and mger5 are dummy variables each equaling 1, if the fund is managed by a management team and 2, 3 or 4 or more than 4 managers, and 0 otherwise.

$$Misreporting\_Flag_i = a_i + bimger2_i + cimger3_i + dimger4_i + fimger5_i + gi\ Control_i + e_{i.} \quad (8)$$

As can be seen from Table 26, the difference between team-managed and single-managed funds increases with team size. The differences are most economically and statistically significant among funds with five or more managers but attenuate in 3-manager funds.

(INSERT TABLE 26 HERE)

4.4 Chapter Summary

This chapter has examined return manipulation behaviors across hedge funds with different management structures. My results support the theoretical prediction that teams reduce deceptions through greater peer monitoring, reduced monetary incentives, and reinforced feeling of guilt. Also, the reduction in misreporting versus single-managed funds is increasing with team size. On the other hand, no evidence has been found for an increase in the likelihood of engaging in misreporting when members in the team highly cohere with each other.

Chapter 5 Conclusions

5.1 Summary

In the highly competitive hedge fund industry, superior returns mainly come from the distinctive and innovative investment strategies developed by smart individuals or well-functioning fund teams. Majority of existing literature has held a positive view on the effect of team structure on fund performance. Teams enjoy multiple channels of information and superior collective memory over individuals. This helps teams to collect, combine and recognize relevant information more efficiently and accurately. Also, teams can balance individual biases and detect each other's errors. My study has documented the positive associations of team structure with fund performance and provided empirical evidence of teams benefit in performance firstly by hedge funds data. This association is present most strongly among funds with high team tenure or relatively innovation-oriented investment styles such as global macro and multi-strategy. This association is also more pronounced during bullish market periods.

My next focus has been on team-managed funds. Although several previous studies have documented outperformance by funds managed by graduates from high quality programs (as measured by SAT), a group of people from one popular school may not always function as the optimal team for a fund. On one hand, a high level of school ties can improve performance by promoting efficient communication and integration of information. Further, the stronger sense of belongings will better motivate people to make full efforts towards the team's outcome targets. On the other hand, homogenous groups don't enjoy the advantageous information sets and abundant innovative ideas heterogenous groups enjoy (Ancona and Caldwell, 1992). Using a sample of hedge funds with biographic information provided by TASS, I have found empirical evidence showing a negative correlation of within-fund school ties with fund performance. Such association is present most strongly among funds with two managers or during volatile periods.

I have also conducted an initial investigation of the risk-taking behaviors of single-manager and multi-manager funds to check whether groups do adopt more extreme investment strategy as group shift theory predicts, or make moderate decisions after a compromise among group members as implied by the diversification of opinion hypothesis. and documented that more risk taken by teams which is in line with group shift theory. Such association is pronounced in teams with high level of congruence. I also document that funds managed by sole managers or highly cohesive teams where people follow opinions from dominant member(s) are more likely to generate stronger negative returns than their counterparts. Furthermore, inconsistent with the findings in mutual funds, single-managers are found to attract more capital flows from investors and suffer from a lower probability to fail in my data.

Lastly, I have explored the influence of management structure on hedge fund misreporting. Previous theories assumed that teams have greater peer monitoring, reduced monetary incentives for team members, and reinforced feeling of guilt. My results support the mitigation role of team management on unethical behavior. However, I have not found that cohesive teams are more likely to engage in misreporting.

Other than identifying the implications pertaining to helping investors to identify profitable hedge fund management teams and assisting regulators to target funds with higher chance to commit a fraud, my study has also contributed to TMT diversity research which so far has produced mixed results exist regarding managerial impacts on corporate performance. My unique sample of hedge funds with more direct reflection of managerial ability on observable performance provides convincing empirical evidence to this traditional topic in management and psychology literature.

5.2 Limitations and Future Research

One of my major limitations lies in the endogenous management structure determined by the current manager/team itself. As stated in Section 3.4.6.1 Causality, there is no strong evidence to conclude a causal relationship. An ideal setting to test the endogeneity problem is to have an exogenous shift in the management structure. However, my research did not figure out a proper event that could result in such exogenous changes in hedge fund team. Future studies should keep exploring for such events.

Following the management theory that sole-managers enjoy more advantageous positions in solving routine and novel problems while groups are superior in dealing with complex tasks, I side on the view that teams will underperform in stable economic environments (/during expansion) while they outperform in turbulent environments (during recession). However, my study has obtained a contradicting result regarding this problem. Future research could be done to explain this confusing result.

Moreover, whereas team-managed funds often generate superior returns than individually managed fund on average, sole managers are found to attract substantially more capital flows from investors and survive longer. The same situation is faced by homogeneous teams. This phenomenon deserves more attention from future academics. In addition, there should be more studies investigating the underlying mechanisms through which the management structure and team composition may affect performance.

Finally, management literature has predicted that the more cohesive team members are, the higher probability the team will engage in returns manipulation. In highly cohesive groups, members show more trust and thereby less monitoring on their groupmates. Even if they detect other's unethicality, they are more likely to be persuaded to engage in the same immoral behavior together than their heterogeneous counterparts. However, there is no finding in my results supporting the role of team cohesiveness. I would like to explore the underlying reasons in future research.

Appendices

Appendix I Examples of construction of team congruence level

Case I

Member	University	Degree	Connected	ConnectedMates%	Congruence Level
A	University of Toronto	Undergraduate	B;C;D	3/(4-1)= 1	(1+0.67+1+0.67)/4=0.835
	Harvard University	PhD			
B	Stanford University	Undergraduate	A;C	2/(4-1)= 0.67	
	University of Toronto	MA			
C	Stanford University	Undergraduate	A;B;D	3/(4-1)= 1	
	Harvard University	MBA			
D	Harvard University	Undergraduate	A;C	2/(4-1)=0.67	

Case II

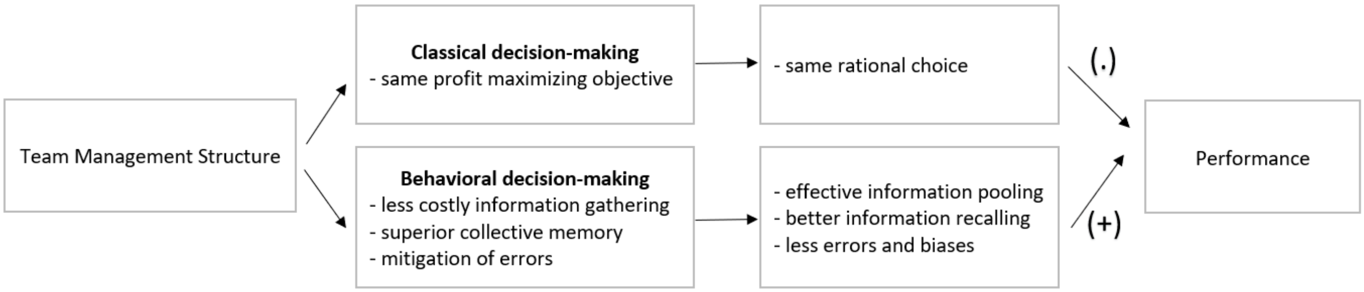
Member	University	Degree	Connected	ConnectedMates%	Congruence Level
A	Harvard University	Undergraduate	C	1/(4-1)= 0.33	(0.33+0.33+0.67+0)/4=0.333
B	Stanford University	Undergraduate	C	1/(4-1)= 0.33	
	University of Toronto	PhD			
C	Stanford University	Undergraduate	A;B	2/(4-1)= 0.67	
	Harvard University	MBA			
D	Princeton University	Undergraduate	N/A	0/(4-1)=0	

Case III

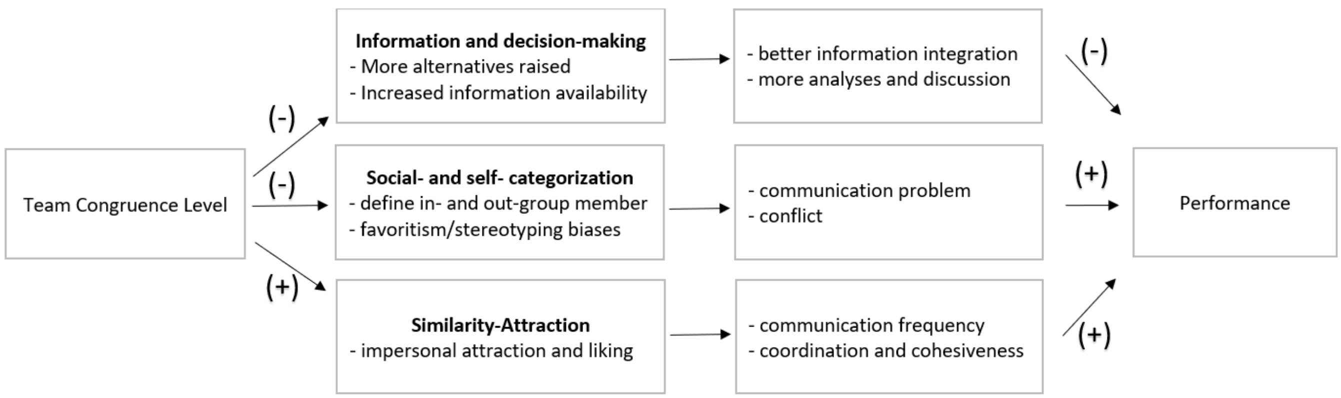
Member	University	Degree	Connected	ConnectedMates%	Congruence Level
A	University of Michigan	Undergraduate	N/A	0/(4-1)=0	(0+0.33+0.33+0)/4=0.165
B	Stanford University	Undergraduate	C	1/(4-1)= 0.33	
	University of Toronto	PhD			
C	Stanford University	Undergraduate	B	1/(4-1)= 0.33	
	New York University	MBA			
	Princeton University	PhD			
D	Northwestern University	Undergraduate	N/A	0/(4-1)=0	

Appendix II Summary of competing hypothesis for main research questions

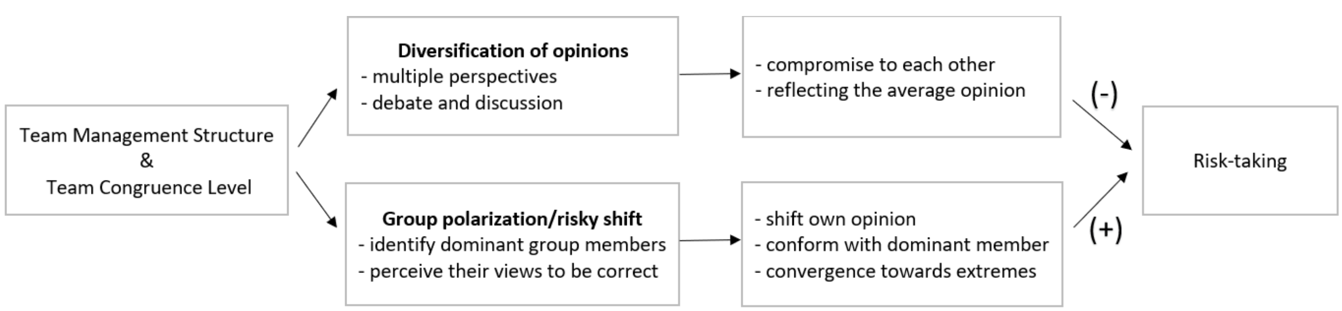
a. Team Management Structure and Performance



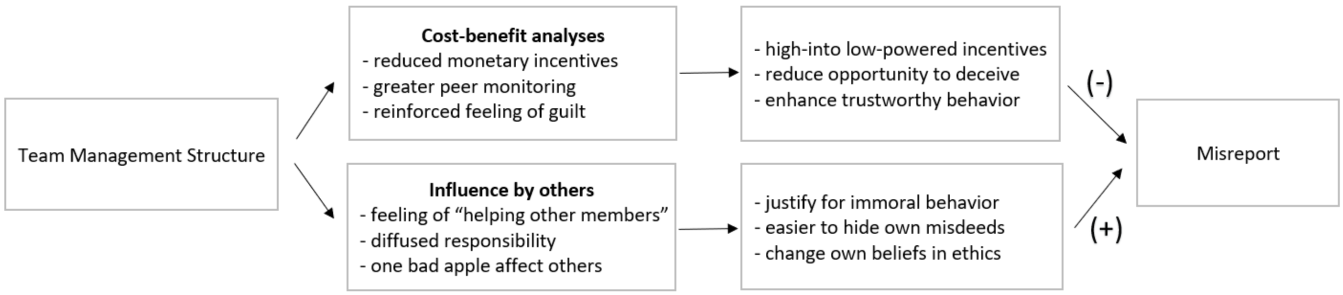
b. Team Congruence Level and Performance



c. Team Management Structure, Congruence Level and Risk-Taking



d. Team Management Structure and Misreport



Reference

Acemoglu, D., Kremer, M., & Mian, A. (2007). Incentives in markets, firms, and governments. *The Journal of Law, Economics, & Organization*, *24*(2), 273-306.

Adams, R., & Ferreira, D. (2010). Moderation in groups: Evidence from betting on ice break-ups in Alaska. *The Review of Economic Studies*, *77*(3), 882-913.

Agarwal, V., Daniel, N. D., & Naik, N. Y. (2011). Do hedge funds manage their reported returns? *The Review of Financial Studies*, *24*(10), 3281-3320.

Ahn, D., Kim, W., Lee, E. J., & Park, K. S. (2012). Congruence within the top management: How "Old boy network" affects executive appointment and performance. *Working Paper*.

Ancona, D. G., & Caldwell, D. F. (1992). Demography and design: Predictors of new product team performance. *Organization Science, 3*(3), 321-341.

Aragon, G. O., & Strahan, P. E. (2012). Hedge funds as liquidity providers: Evidence from the Lehman bankruptcy. *Journal of Financial Economics, 103*(3), 570-587.

Arrow, K. J. (1986). Rationality of self and others in an economic system. *Journal of Business*, S385-S399.

Bainbridge, S. (2002). Why a board? Group decision-making in corporate governance. *Vanderbilt Law Review*, *55*, 1-55.

Bantel, K. A., & Jackson, S. E. (1989). Top management and innovations in banking: Does the composition of the top team make a difference? *Strategic Management Journal, 10*(S1), 107-124.

Bär, M., Kempf, A., & Ruenzi, S. (2005). Team management and mutual funds. *Working Paper*.

Bär, M., Niessen-Ruenzi, A., & Ruenzi, S. (2007). The impact of work group diversity on performance: Large sample evidence from the mutual fund industry, *CFR Working Paper*, No. 07-16.

Bär, M., Kempf, A., & Ruenzi, S. (2011). Is a team different from the sum of its parts? Evidence from mutual fund managers. *Review of Finance*, *15*(2), 359-396.

Bliss, R. T., Potter, M. E., & Schwarz, C. (2008). Performance characteristics of individually-managed versus team-managed mutual funds. *The Journal of Portfolio Management, 34*(3), 110-119.

Bollen, N. P., & Pool, V. K. (2012). Suspicious patterns in hedge fund returns and the risk of fraud. *The Review of Financial Studies, 25*(9), 2673-2702.

Brass, D. J., Butterfield, K. D., & Skaggs, B. C. (1998). Relationships and unethical behavior: A social network perspective. *Academy of Management Review*, *23*(1), 14-31.

Brewer, M. B. (1979). In-group bias in the minimal intergroup situation: A cognitive-motivational analysis. *Psychological Bulletin, 86*(2), 307.

Brewer, M. B. (1993). The role of distinctiveness in social identity and group behavior. In M.A. Hogg & D. Abrams (Eds.), *Group motivation: Social psychological perspectives* (pp. 1-16). New York: Harvester Wheatsheaf.

Brewer, M.B. (1995). Managing diversity: The role of social identities. In S. Jackson & M. Ruderman (Eds.), Diversity in workteams (pp.131-159). Washington, DC: APA Books

Cao, C., Chen, Y., Liang, B., and Lo, A. (2013). Can Hedge Funds Time Market Liquidity? *Journal of Financial Economics,* 109: 493-516.

Charness, G., & Dufwenberg, M. (2006). Promises and partnership. *Econometrica*, *74*(6), 1579-1601.

Chen, J., Hong, H., & Stein, J. C. (2001). Forecasting crashes: trading volume, past returns, and conditional skewness in stock prices. *Journal of Financial Economics, 61*(3), 345-381.

Chen, J., Hong, H., Huang, M., & Kubik, J. D. (2004). Does fund size erode mutual fund performance? The role of liquidity and organization. *The American Economic Review*, *94*(5), 1276-1302.

Chevalier, J., & Ellison, G. (1999). Are some mutual fund managers better than others? Cross-Sectional patterns in behavior and performance. *The Journal of Finance*, *54*(3), 875-899.

Cohen, L., Frazzini, A., & Malloy, C. (2008). The small world of investing: Board connections and mutual fund returns. *Journal of Political Economy, 116*(5), 951-979.

Conrads, J., Irlenbusch, B., Rilke, R. M., & Walkowitz, G. (2013). Lying and team incentives. *Journal of Economic Psychology*, *34*, 1-7.

Danilov, A., Biemann, T., Kring, T., & Sliwka, D. (2013). The dark side of team incentives: Experimental evidence on advice quality from financial service professionals. *Journal of Economic Behavior & Organization*, *93*, 266-272.

Dass, N., Nanda, V., & Wang, Q. (2013). Allocation of decision rights and the investment strategy of mutual funds. *Journal of Financial Economics, 110(1),* 254-277.

Dezsö, C. L., & Ross, D. G. (2012). Does female representation in top management improve firm performance? A panel data investigation. *Strategic Management Journal*, *33*(9), 1072-1089.

Fung, W., & Hsieh, D. A. (2001). The risk in hedge fund strategies: Theory and evidence from trend followers. *The Review of Financial Studies*, *14*(2), 313-341.

Getmansky, M., Lo, A., & Mei, S. (2004). Sifting through the wreckage: Lessons from recent hedge-fund liquidations. *Journal of Investment Management, 4th Quarter,* Giannetti, M., and Wang, TY. (2014). Corporate Scandals and Household Stock Market Participation. *C.E.P.R. Discussion Papers*.

Gino, F., Ayal, S., & Ariely, D. (2009). Contagion and differentiation in unethical behavior: The effect of one bad apple on the barrel. *Psychological science*, *20*(3), 393-398.

Gino, F., Ayal, S., & Ariely, D. (2013). Self-serving altruism? The lure of unethical actions that benefit others. *Journal of economic behavior & organization*, *93*, 285-292.

Goetzmann, W., Ingersoll, J., Spiegel, M., & Welch, I. (2007). Portfolio performance manipulation and manipulation-proof performance measures. *Review of Financial Studies, 20*(5), 1503-1546.

Golec, J. H. (1996). The effects of mutual fund managers' characteristics on their portfolio performance, risk and fees. *Financial Services Review, 5*(2), 133-147.

Gottesman, A. A., & Morey, M. R. (2006). Manager education and mutual fund performance. *Journal of Empirical Finance, 13*(2), 145-182.

Guan, Y., Su, L., Wu, D., & Yang, Z. (2015). Do school ties between auditors and client executives influence audit outcomes? ☆. Journal of Accounting & Economics, 61(2–3), 506-525.

Guiso, L., Sapienza, P., & Zingales, L. (2008). Trusting the stock market. *Journal of Finance*, 63(6), 2557-2600.

Hambrick, D. C., & Mason, P. A. (1984). Upper echelons: The organization as a reflection of its top managers. *Academy of Management Review*, *9*(2), 193-206.

Harrison, D. A., Price, K. H., & Bell, M. P. (1998). Beyond relational demography: Time and the effects of surface-and deep-level diversity on work group cohesion. *Academy of Management Journal*, *41*(1), 96-107.

Hill, G. W. (1982). Group versus individual performance: Are N 1 heads better than one? *Psychological Bulletin, 91*(3), 517.

Hinsz, V. B., Tindale, R. S., & Vollrath, D. A. (1997). The emerging conceptualization of groups as information processors. *Psychological bulletin*, *121*(1), 43.

Hoffman, L. R. (1959). Homogeneity of member personality and its effect on group problem-solving. *The Journal of Abnormal and Social Psychology*,*58*(1), 27.

Hogg, M. A., & Abrams, D. (1988). *Social identifications*. London: Routledge

Jehn, K. A., Northcraft, G. B., & Neale, M. A. (1999). Why differences make a difference: A field study of diversity, conflict and performance in workgroups. *Administrative science quarterly*, *44*(4), 741-763.

Jorion, P., & Schwarz, C. (2014). Are hedge fund managers systematically misreporting? Or not? *Journal of Financial Economics*, *111*(2), 311-327.

Kalmijn, M., & Flap, H. (2001). Assortative meeting and mating: unintended consequences of organized settings for partner choices. *Social Forces*, *79*(4), 1289-1312.

Kovaleski, D. (2000). More mutual fund companies take a team approach. *Pensions & Investments*. *28*(15), 32.

Krauss, R. M., & Fussell, S. R. (1990). Mutual knowledge and communicative effectiveness. *Intellectual teamwork: Social and technological foundations of cooperative work*, 111-146.

Li, H., Zhang, X., & Zhao, R. (2011). Investing in talents: Manager characteristics and hedge fund performances. *Journal of Financial and Quantitative Analysis*, *46*(1), 59.

Mannix, E., & Neale, M. A. (2005). What differences make a difference? the promise and reality of diverse teams in organizations. *Psychological Science in the Public Interest, 6*(2), 31-55.

Mas, A., & Moretti, E. (2009). Peers at work. *The American economic review*, *99*(1), 112-145.

Massa, M., & Simonov, A. (2005). History versus geography: the role of college interaction in portfolio choice and stock market prices. SSRN Electronic Journal, 19(4815), 169-189.

Massa, M., Reuter, J., & Zitzewitz, E. (2010). When should firms share credit with employees? Evidence from anonymously managed mutual funds. *Journal of Financial Economics*. *95*(3), 400–424.

Massa, M., & Simonov, A. (2011). Is college a focal point of investor life?. Review of Finance, 15(4). Mello, A. S., & Ruckes, M. E. (2006). Team composition. *The Journal of Business*, *79*(3), 1019-1039.

Murray, A. I. (1989). Top management group heterogeneity and firm performance. *Strategic Management Journal, 10*(S1), 125-141.

Newcomb, T. M. (1961). The acquaintance process. New York: Holt, Rinehart & Winston.

Newcomb, T. M. (1968). Interpersonal balance. *Theories of Cognitive Consistency: A Sourcebook.Chicago: Rand McNally, 196*(8)

Nielsen, B. B., & Nielsen, S. (2013). Top management team nationality diversity and firm performance: A multilevel study. *Strategic Management Journal, 34*(3), 373-382.

Patel, S., & Sarkissian, S. (2013a). To group or not to group? Evidence from mutual funds. *Working Paper.*

Patel, S., & Sarkissian, S. (2013b). Deception and managerial structure: A joint study of portfolio pumping and window dressing practices. *Unpublished working paper. University of Western Ontario*.

Pelled, L. H., Eisenhardt, K. M., & Xin, K. R. (1999). Exploring the black box: An analysis of work group diversity, conflict and performance. *Administrative Science Quarterly*, *44*(1), 1-28.

Prather, L. J., & Middleton, K. L. (2002). Are N+ 1 heads better than one?: The case of mutual fund managers. *Journal of Economic Behavior & Organization*, *47*(1), 103-120.

Pruitt, D. G., & Teger, A. I. (1969). The risky shift in group betting. *Journal of Experimental Social Psychology*, *5*(2), 115-126.

Richard, O. C. (2000). Racial diversity, business strategy, and firm performance: A resource-based view. *Academy of Management Journal*, *43*(2), 164-177.

Sah, R. K., & Stiglitz, J. E. (1986). The Architecture of Economic Systems: Hierarchies and Polyarchies. *The American Economic Review*, *76*(4), 716-727.

Sah, R. K., & Stiglitz, J. E. (1991). The quality of managers in centralized versus decentralized organizations. *The Quarterly Journal of Economics*,*106*(1), 289-295.

Schopler, J., & Insko, C. A. (1992). The discontinuity effect in interpersonal and intergroup relations: Generality and mediation. *European Review of Social Psychology*, *3*(1), 121-151.

Shaw, M. E. (1932). A comparison of individuals and small groups in the rational solution of complex problems. *The American Journal of Psychology*,*44*(3), 491-504.

Simon, H. A. (1982). *Models of bounded rationality: Empirically grounded economic reason* (Vol. 2). MIT Press, Cambridge, MA.

Simons, T., Pelled, L. H., & Smith, K. A. (1999). Making use of difference: Diversity, debate, and decision comprehensiveness in top management teams. *Academy of Management Journal*, *42*(6), 662-673.

Smith, K. G., Smith, K. A., Olian, J. D., Sims Jr, H. P., O'Bannon, D. P., & Scully, J. A. (1994). Top management team demography and process: The role of social integration and communication. *Administrative Science Quarterly*, 412-438.

Stoner, J. A. (1968). Risky and cautious shifts in group decisions: The influence of widely held values. *Journal of Experimental Social Psychology*,*4*(4), 442-459.

Stroessner, S. J. (1996). Social categorization by race or sex: Effects of perceived non-normalcy on response times. *Social Cognition, 14*(3), 247-276.

Suls, J., Martin, R., & Wheeler, L. (2000). Three kinds of opinion comparison: The triadic model. *Personality and Social Psychology Review*, *4*(3), 219-237.

Sun, Z., Wang, A., & Zheng, L. (2012). The road less traveled: Strategy distinctiveness and hedge fund performance. *Review of Financial Studies*, *25*(1), 96-143.

Tajfel, H. (1981). *Human groups and social categories: Studies in social psychology*. CUP Archive.

Tan, E. K., & Sen, A. (2017). Does educational diversity of managers matter for the performance of team-managed funds? *Accounting & Finance*.

Tihanyi, L., Ellstrand, A. E., Daily, C. M., & Dalton, D. R. (2000). Composition of the top management team and firm international diversification. *Journal of Management, 26*(6), 1157-1177.

Titman, S., & Tiu, C. (2011). Do the best hedge funds hedge? *Review of Financial Studies, 24*(1), 123-168.

Tsui, A. S., Egan, T., & O'Reilly, C. (1991). Being different: Relational demography and organizational attachment. *Academy of Management Proceedings*, *1991*(1) 183-187.

Turner, J. C. (1985). Social categorization and the self-concept: A social cognitive theory of group behavior. *Advances in Group Processes: Theory and Research, 2*, 77-122.

Turner, J. C., Hogg, M. A., Oakes, P. J., Reicher, S. D., & Wetherell, M. S. (1987). *Rediscovering the social group: A self-categorization theory*. Basil Blackwell.

Vollrath, D. A., Sheppard, B. H., Hinsz, V. B., & Davis, J. H. (1989). Memory performance by decision-making groups and individuals. *Organizational Behavior and Human Decision Processes, 43*(3), 289-300.

Wagner, W. G., Pfeffer, J., & O'Reilly III, C. A. (1984). Organizational demography and turnover in top-management group. *Administrative Science Quarterly, 29*(1) , 74-92.

Wallach, M. A., Kogan, N., & Bem, D. J. (1962). Group influence on individual risk taking. *ETS Research Report Series*, *1962*(1).

West, C. T. & Schwenk, C. R. (1996). Top management team strategic consensus, demographic homogeneity and firm performance: A report of resounding nonfindings. *Strategic Management Journal, 17*(7), 571-576.

Williams, K., and C. A. O'Reilly, 1998, Demography and diversity in organizations: a review of 40 years of research, Research in Organizational Behavior 20, 77–140.

Wiltermuth, S. S. (2011). Cheating more when the spoils are split. *Organizational Behavior and Human Decision Processes, 115*(2), 157-168.

Winquist, J. R., & Larson Jr, J. R. (1998). Information pooling: When it impacts group decision-making. *Journal of Personality and Social Psychology, 74*(2), 371.

Wittenbaum, G. M., & Stasser, G. (1996). Management of information in small groups.

Zeckhauser, R. (1986). Comments: behavioral versus rational economics: what you see is what you conquer. *The Journal of Business*, *59*(4), S435-S449.

Table 1 Summary statistics (2001-2011)

Panel A presents summary statistics for main variables: a team dummy variable which equals to 1 for funds managed by multi-manager and 0 otherwise, and other variables includes 1) sat, average score of every undergraduate institutions that the team members graduated from; 2) number of managers within a fund; 3) fund age in years; 4) fund size in millions 5) excess return; 6) alpha from FH 7 factor model; 7) Information ratio; 8) Sharpe ratio; 9) manipulation proof measure with ρ=3 or 4;.10) Vol, volatility of returns; 11) average fund annual flow; 12) other characteristics such as the lengths of the redemption notice, lockup periods, personal capital dummy and high-water-mark dummy, management fees, incentive fees, , minimum investment, and an offshore dummy. Panel B presents the cross-sectional correlation between team dummy variable and other fund and manager characteristics as well as fund performance and flow. The star implies a significant association at a 95% confidence level.

Panel A: Fund Performance and Characteristics

variable	mean	p50	min	p25	p75	max	sd
	Manager Characteristics						
Team	0.69	1.00	0.00	0.00	1.00	1.00	0.46
SAT	1306.94	1320.00	935.00	1245.00	1386.67	1490.00	106.00
No of managers	2.70	2.00	1.00	1.00	3.10	26.36	1.91
Team_tenure	6.18	4.89	0.00	2.71	8.00	38.47	5.03
	Fund Returns						
Excess-return	0.15	0.22	-37.90	-0.16	0.62	10.75	1.58
alpha	0.24	0.17	-91.80	-0.20	0.58	115.22	4.09
AR	0.13	0.10	-4.74	-0.06	0.28	6.88	0.52
SR	0.14	0.08	-29.70	-0.06	0.26	67.88	1.70
MPPM3	-2.81	-1.10	-224.33	-6.51	3.40	78.11	15.41
MPPM4	-3.70	-1.67	-224.24	-7.53	2.98	77.09	15.73
	Fund Characteristics						
fund_age	4.66	3.50	0.08	2.08	6.13	29.38	3.74
AUM (million)	139.88	36.48	0.21	11.71	109.52	3141.78	319.29
RedemptionNotice (days)	46.31	45.00	0.00	30.00	60.00	180.00	27.60
Lockup (months)	6.00	0.00	0.00	0.00	12.00	180.00	8.43
PersonalCap	0.32	0.00	0.00	0.00	1.00	1.00	0.47
HighWaterMark	0.84	1.00	0.00	1.00	1.00	1.00	0.36
MgmtFee	1.40	1.50	0.00	1.00	2.00	20.00	0.66
IncentiveFee	17.26	20.00	0.00	20.00	20.00	100.00	6.61
MinInvestment	1.78	1.00	0.00	0.25	1.00	1000.00	20.64
Leveraged	0.57	1.00	0.00	0.00	1.00	1.00	0.49
Offshore	0.35	0.00	0.00	0.00	1.00	1.00	0.48

Panel B: Correlations

	Team	SAT	no of mgers	tenure	Age	AUM	exret	alpha	AR	SR	MPPM3	MPPM4	Vol
Team	1.00												
SAT	-0.06*	1.00											
ln(no of managers)	0.80*	-0.05*	1.00										
ln(team_tenure)	-0.17*	0.00	-0.14*	1.00									
ln(fund_age)	-0.05*	0.04*	0.01	0.38*	1.00								
lnAUM	0.10*	0.13*	0.17*	0.17*	0.35*	1.00							
avg_exret	0.00	0.04	0.01	0.01	0.11*	0.14*	1.00						
avg_alpha	0.02	-0.02	0.03	-0.03	0.00	0.04	0.14*	1.00					
AR	0.03	-0.03	0.04	0.01	0.02	0.19*	0.43*	0.54*	1.00				
SR	-0.03	-0.01	-0.01	0.00	0.00	0.04*	0.17*	0.04	0.85*	1.00			
MPPM3	-0.02	0.06*	-0.03	0.02	0.00	-0.02	0.15*	0.01	0.03	0.02	1.00		
MPPM4	0.04*	0.03	0.05*	0.01	0.08*	0.12*	0.53*	0.04	0.14*	0.08*	0.99*	1.00	
Vol	-0.10*	-0.02	-0.10*	0.03	0.02	-0.15*	0.02	0.12*	-0.13*	-0.06*	-0.21*	-0.37*	1.00
avg_flow	0.01	0.04	-0.03	-0.15*	-0.18*	0.01	0.19*	0.09*	0.13*	0.15*	0.01	0.06*	-0.01
RedemptionNotice (days)	0.09*	0.03	0.10*	-0.03	-0.03	0.20*	0.01	0.06*	0.10*	0.01	0.01	0.03	-0.13*
Lockup (months)	0.02	0.02	0.02	-0.06*	-0.05*	0.04*	0.03	0.01	0.06*	0.08*	0.02	-0.01	0.03
PersonalCap	-0.06*	0.00	-0.08*	-0.04*	0.08*	-0.05*	0.07*	0.04*	-0.01	0.03	-0.02	0.03	0.09*
HighWaterMark	0.00	0.04	-0.03	-0.08*	-0.11*	-0.03	0.01	0.06*	0.03	0.01	0.08*	-0.01	-0.03
MgmtFee	-0.01	0.03	-0.01	-0.12*	-0.08*	0.03	0.03	0.06*	0.00	-0.01	0.03	-0.02	0.09*
IncentiveFee	-0.03	0.09*	-0.06*	-0.04	-0.07*	-0.09*	0.03	0.06*	0.04	-0.01	0.09*	-0.04	0.17*
MinInvestment	0.02	-0.01	0.05*	0.01	-0.01	0.01	0.01	0.01	0.04	0.01	0.00	0.01	-0.01
leveraged	0.00	0.03	-0.03	-0.07*	0.00	-0.04	0.03	0.03	-0.03	-0.03	0.02	0.02	0.07*
offshore	0.06*	0.08*	0.06*	0.03	-0.07*	0.23*	-0.02	-0.04	-0.014	-0.02	0.00	0.01	-0.09*

	flow	RN (days)	Lp (mon)	PCap	HWM	MFee	IFee	MI	levged	offshore
avg_flow	1.00									
RedemptionNotice (days)	0.02	1.00								
Lockup (months)	0.02	0.27*	1.00							
PersonalCap	0.01	-0.01	0.03	1.00						
HighWaterMark	0.02	0.08*	0.08*	0.09*	1.00					
MgmtFee	0.09*	-0.05*	0.02	0.00	0.03	1.00				
IncentiveFee	0.05*	-0.18*	0.03	0.07*	0.29*	0.08*	1.00			
MinInvestment	0.00	0.02	-0.01	0.02	-0.04*	0.00	0.00	1.00		
leveraged	0.01	-0.13*	-0.03	0.12*	0.08*	0.10*	0.18*	-0.03	1.00	
offshore	0.01	0.03	-0.07*	-0.10*	0.02	0.08*	0.01	0.04	0.03	1.00

Table 2 Descriptive statistics of team- versus individual-managed hedge funds

This table presents descriptive statistics of team- and individual-managed hedge funds and a t-test on their difference. Descriptive variables includes 1) sat, average score of every undergraduate institutions that the team members graduated from; 2) number of managers within a fund; 3) fund age in years; 4) fund size in millions 5) excess return; 6) alpha from FH 7 factor model; 7) Information ratio; 8) Sharpe ratio; 9) manipulation proof measure with ρ=3 or 4;.10) Vol, volatility of returns; 11) average fund annual flow; 12) other characteristics such as the lengths of the redemption notice, lockup periods, personal capital dummy and high-water-mark dummy, management fees, incentive fees, , minimum investment, and an offshore dummy. Panel B presents the cross-sectional correlation between team dummy variable and other fund and manager characteristics as well as fund performance and flow. Panel C lists the top ten schools with largest number of alumni. *** p<0.01, ** p<0.05, * p<0.1

	Single-Managed		Team-Managed		
Variables	No. of Funds	Mean	No. of Funds	Mean	Diff in Mean
lnAUM	643	16.98	1512	17.38	-0.404***
lnfund_age	700	1.24	1668	1.15	0.087**
lnteam_tenure	674	1.73	1648	1.43	0.295***
SAT	630	13.17	1635	13.03	0.141***
RedemptionNotice (days)	700	1.42	1668	1.60	-0.178***
Lockup (months)	700	5.75	1668	6.11	-0.36
PersonalCap	700	0.37	1668	0.30	0.063***
HighWaterMark	697	0.84	1665	0.84	-0.001
MgmtFee	697	1.41	1665	1.40	0.01
IncentiveFee	697	17.54	1665	17.13	0.41
MinInvestment	700	0.58	1667	0.66	-0.080***
Leveraged	700	0.57	1668	0.58	0.00
Offshore	700	0.31	1668	0.37	-0.059***
Excess-return	700	0.14	1668	0.15	-0.005
alpha	692	0.07	1650	0.28	-0.211
AR	592	0.11	1362	0.14	-0.037
SR	692	0.21	1650	0.11	0.102
MPPM3	700	-3.24	1668	-2.68	-0.56
MPPM4	700	-4.33	1668	-3.48	-0.849
Vol	692	3.89	1650	3.27	0.626***
Avg_flow	526	0.27	1199	0.27	0.002

Table 3 Distribution of team- and single-managed funds by year and style

This table presents number of single-managed versus team-managed hedge funds and the corresponding proportion of team-funds by different year from 2001 to 2011 (Panel A) and investment style classified by TASS database (Panel B).

Panel A: Proportion of Team-Managed Hedge Funds Each Year

	No of funds			
Year	Single	Team	Total	Team%
2001	95	180	275	65.45%
2002	163	339	502	67.53%
2003	203	503	706	71.25%
2004	263	666	929	71.69%
2005	348	806	1154	69.84%
2006	383	871	1254	69.46%
2007	375	860	1235	69.64%
2008	350	793	1143	69.38%
2009	304	640	944	67.80%
2010	335	663	998	66.43%
2011	299	582	881	66.06%
			Average	68.59%

Panel B: Proportion of Team-Managed Hedge Funds by Style

Primary Category	No. of funds	Single-Managed No. of funds	Team-Managed No. of funds	Team%
Convertible Arbitrage	76	17	59	77.63%
Fund of Funds	459	106	353	76.91%
Equity Market Neutral	156	37	119	76.28%
Multi-Strategy	143	34	109	76.22%
Emerging Markets	112	30	82	73.21%
Options Strategy	18	5	13	72.22%
Event Driven	261	75	186	71.26%
Global Macro	99	30	69	69.70%
Managed Futures	154	50	104	67.53%
Fixed Income Arbitrage	72	25	47	65.28%
Long/Short Equity Hedge	800	283	517	64.63%
Dedicated Short Bias	18	8	10	55.56%

Table 4: Team structure and fund performance

The model applied to test the association between team structure and fund performance is as follows: $Performance_{i,t+1,t+12} = a_i + b_i Team_{i,t} + c_i\ Control_{i,t-23,t} + e_{i,t.}$. *Team* is a dummy variable which equals to 1 for funds managed by a team and 0 otherwise. Dependent variables are performance in subsequent 1 year. Control variables includes 1) logarithm of team-tenure, no of years a team has been working together which is proxied by the average number of years each member has worked for the fund; 2) logarithm of number of managers within a fund; 3) logarithm of fund size; 4) logarithm of fund age in terms of year; 5) sat, average score of every undergraduate institutions that the team members graduated from; 6) corresponding lagged performance during t-23 to t or fund flow for the previous 12 months; 7) other fund characteristics such as lockup periods, management fees, incentive fees, and an offshore dummy; and 8) fund style dummies classified by TASS. Panel regressions with time-fixed effect and fund clustered errors and Fama-Macbeth model are adopted. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	Excess Return		Alpha		AR	
	Time fixed Fund Clustered	Fama Macbeth	Time fixed Fund Clustered	Fama Macbeth	Time fixed Fund Clustered	Fama Macbeth
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	win_return	win_return	win_alpha	win_alpha	win_AR	win_AR
Team	0.101	**0.104*** **	0.049	**0.065***	**0.145** **	**0.121*** **
	(0.065)	(0.021)	(0.069)	(0.039)	(0.065)	(0.030)
sat	-0.008	0.014*	0.014	0.020**	0.009	0.018**
	(0.019)	(0.008)	(0.019)	(0.009)	(0.021)	(0.009)
lnfund_tenure	0.012	0.016	0.034	0.046***	0.068**	0.057***
	(0.028)	(0.011)	(0.028)	(0.012)	(0.029)	(0.011)
lnAge	0.123***	0.110***	0.078**	0.070***	0.056*	0.047***
	(0.033)	(0.012)	(0.034)	(0.022)	(0.030)	(0.016)
lnAUM	-0.052***	-0.049***	-0.012	-0.011**	0.016	0.017***
	(0.012)	(0.006)	(0.013)	(0.006)	(0.011)	(0.006)
ln_nomger	-0.055	-0.048***	-0.059	-0.054**	-0.111**	-0.109***
	(0.046)	(0.015)	(0.049)	(0.023)	(0.045)	(0.020)
Lockup	0.005**	0.003**	0.008***	0.008***	0.006*	0.004***
	(0.002)	(0.001)	(0.003)	(0.002)	(0.003)	(0.001)
MgmtFee	0.061	0.057***	0.024	0.027	0.043	0.046***
	(0.047)	(0.012)	(0.045)	(0.020)	(0.034)	(0.016)
IncentiveFee	0.006	0.007***	0.005	0.005***	-0.001	0.000
	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)
off	-0.025	-0.036**	-0.093**	-0.108***	-0.073*	-0.079***
	(0.038)	(0.014)	(0.042)	(0.017)	(0.039)	(0.016)
convertible	-0.187	-0.119	-0.641***	-0.495***	-0.362*	-0.248**
	(0.168)	(0.103)	(0.202)	(0.091)	(0.213)	(0.107)
dedicated	-1.246***	-0.736***	-0.958***	-0.625***	-0.898***	-0.553***
	(0.257)	(0.144)	(0.278)	(0.110)	(0.192)	(0.141)
emerging	0.651***	0.416***	0.080	0.254*	-0.333*	-0.178
	(0.193)	(0.158)	(0.235)	(0.131)	(0.177)	(0.129)

equity	-0.057	-0.070	-0.580***	-0.443***	-0.399**	-0.275**
	(0.169)	(0.056)	(0.213)	(0.091)	(0.199)	(0.117)
event	0.207	0.092	-0.334*	-0.208**	-0.220	-0.071
	(0.151)	(0.087)	(0.199)	(0.097)	(0.176)	(0.116)
fixedincome	0.290	0.379***	-0.206	0.055	0.170	0.278***
	(0.219)	(0.094)	(0.243)	(0.107)	(0.292)	(0.084)
fof	0.014	-0.041	-0.503**	-0.392***	-0.358**	-0.203
	(0.155)	(0.059)	(0.201)	(0.095)	(0.175)	(0.130)
global	0.364*	0.317***	-0.256	-0.147	-0.643***	-0.406***
	(0.187)	(0.060)	(0.239)	(0.102)	(0.180)	(0.105)
longshort	0.155	0.043	-0.512***	-0.402***	-0.611***	-0.447***
	(0.148)	(0.092)	(0.197)	(0.093)	(0.169)	(0.107)
mged_futures	0.131	0.095	-0.495**	-0.405***	-0.692***	-0.553***
	(0.170)	(0.071)	(0.214)	(0.123)	(0.170)	(0.109)
multi	0.112	0.057	-0.413**	-0.339***	-0.236	-0.171*
	(0.169)	(0.067)	(0.204)	(0.082)	(0.188)	(0.094)
win_return2Y	-0.066**	0.096***				
	(0.030)	(0.030)				
win_alpha2Y			0.065**	0.096***		
			(0.031)	(0.020)		
win_AR2Y					0.622***	0.664***
					(0.098)	(0.046)
Constant	0.971***	0.602***	0.551	0.342**	0.202	-0.065
	(0.369)	(0.143)	(0.395)	(0.153)	(0.371)	(0.209)
Observations	45,614	45,614	45,614	45,614	45,614	45,614
R-squared	0.278	0.275	0.074	0.140	0.155	0.235

	SR		MPPM3		MPPM4	
	Time fixed Fund Clustered	Fama Macbeth	Time fixed Fund Clustered	Fama Macbeth	Time fixed Fund Clustered	Fama Macbeth
	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES						
team	**0.052****	**0.030*****	0.865	**0.827*****	0.815	**0.769*****
	(0.025)	(0.006)	(0.818)	(0.243)	(0.868)	(0.243)
sat	-0.002	0.006**	0.363	0.588***	0.473*	0.670***
	(0.008)	(0.002)	(0.252)	(0.099)	(0.275)	(0.098)
lnfund_tenure	0.028**	0.024***	0.152	0.172	0.178	0.220
	(0.012)	(0.003)	(0.343)	(0.141)	(0.359)	(0.145)
lnAge	0.032***	0.030***	1.216***	1.154***	1.216***	1.183***
	(0.011)	(0.003)	(0.434)	(0.150)	(0.466)	(0.155)
lnAUM	-0.002	-0.004**	-0.130	-0.201***	-0.029	-0.137
	(0.005)	(0.002)	(0.147)	(0.076)	(0.157)	(0.085)
ln_nomger	-0.037**	-0.026***	-0.167	-0.061	-0.021	0.083

	(0.017)	(0.005)	(0.582)	(0.188)	(0.607)	(0.194)
Lockup	0.002	0.001**	0.012	-0.003	-0.004	-0.012
	(0.001)	(0.000)	(0.032)	(0.018)	(0.036)	(0.018)
MgmtFee	0.008	0.009*	0.123	0.188	-0.108	0.035
	(0.013)	(0.005)	(0.627)	(0.181)	(0.678)	(0.198)
IncentiveFee	-0.002	-0.000	0.053	0.065**	0.036	0.050*
	(0.002)	(0.001)	(0.052)	(0.028)	(0.053)	(0.028)
off	-0.003	-0.003	-0.185	-0.345*	-0.086	-0.257
	(0.016)	(0.004)	(0.499)	(0.186)	(0.533)	(0.193)
convertible	0.001	-0.022	-2.563	-1.096	-2.578	-1.112
	(0.095)	(0.047)	(2.273)	(1.439)	(2.406)	(1.520)
dedicated	-0.368***	-0.250***	-17.520***	-11.403***	-17.802***	-11.766***
	(0.092)	(0.048)	(3.792)	(1.794)	(4.038)	(1.875)
emerging	0.044	-0.013	4.219*	2.654	2.921	1.876
	(0.081)	(0.046)	(2.383)	(2.135)	(2.474)	(2.229)
equity	0.039	0.013	0.609	0.526	1.168	1.042
	(0.096)	(0.037)	(2.202)	(0.678)	(2.292)	(0.688)
event	0.100	0.063	2.320	1.770*	2.282	2.000*
	(0.082)	(0.044)	(1.980)	(1.061)	(2.082)	(1.073)
fixedincome	0.255**	0.205***	1.931	2.995***	1.419	2.384**
	(0.119)	(0.035)	(2.950)	(1.114)	(3.132)	(1.143)
fof	-0.005	-0.025	0.878	0.770	1.099	1.150
	(0.080)	(0.041)	(2.022)	(0.711)	(2.122)	(0.736)
global	-0.091	-0.070**	2.902	3.114***	2.413	2.881***
	(0.082)	(0.029)	(2.289)	(0.777)	(2.348)	(0.808)
longshort	-0.065	-0.078**	-0.444	-0.908	-1.071	-1.221
	(0.079)	(0.037)	(1.950)	(1.154)	(2.057)	(1.180)
mged_futures	-0.132*	-0.129***	-0.579	-0.572	-1.224	-1.068
	(0.079)	(0.029)	(2.209)	(0.946)	(2.323)	(0.997)
multi	0.079	0.021	1.578	1.270	1.657	1.453*
	(0.085)	(0.035)	(2.249)	(0.818)	(2.358)	(0.832)
win_SR2Y	0.377***	0.463***				
	(0.063)	(0.035)				
win_MPPM32Y			-0.095***	0.094***		
			(0.029)	(0.034)		
win_MPPM42Y					-0.059**	0.134***
					(0.028)	(0.037)
Constant	0.186	0.077	-6.058	-8.025***	-9.570*	-10.731***
	(0.153)	(0.065)	(4.761)	(1.289)	(5.158)	(1.234)
Observations	45,614	45,614	45,614	45,614	45,611	45,611
R-squared	0.322	0.381	0.305	0.269	0.302	0.267

Table 5: Subsample analysis by team tenure

Divide the dataset into two subsamples based on the median team tenure across funds in the preceding year and run the following regression on each subsample: $Performance_{i,t+1,t+12} = a_i + b_i Team_{i,t} + c_i\, Control_{i,t-23,t} + e_{i,t}$. Team is a dummy variable which equals to 1 for funds managed by a team and 0 otherwise. Dependent variables are performance in subsequent 1 year. Control variables includes 1) logarithm of team-tenure, no of years a team has been working together which is proxied by the average number of years each member has worked for the fund; 2) logarithm of number of managers within a fund; 3) logarithm of fund size; 4) logarithm of fund age in terms of year; 5) sat, average score of every undergraduate institutions that the team members graduated from; 6) corresponding lagged performance during t-23 to t or fund flow for the previous 12 months; 7) other fund characteristics such as lockup periods, management fees, incentive fees, and an offshore dummy; and 8) fund style dummies classified by TASS. Panel regressions with time-fixed effect and fund clustered errors and Fama-Macbeth model are adopted.

Low Tenure Sample

	Excess Return		Alpha		AR	
	Time fixed Fund Clustered	Fama Macbeth	Time fixed Fund Clustered	Fama Macbeth	Time fixed Fund Clustered	Fama Macbeth
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Team	-0.071	**-0.051***	-0.012	0.070	**0.186****	**0.230*****
	(0.089)	(0.026)	(0.100)	(0.066)	(0.089)	(0.059)
Obs	24,327	24,327	24,327	24,327	24,327	24,327
R-squared	0.291	0.350	0.094	0.196	0.183	0.295

High Tenure Sample

	Excess Return		Alpha		AR	
	Time fixed Fund Clustered	Fama Macbeth	Time fixed Fund Clustered	Fama Macbeth	Time fixed Fund Clustered	Fama Macbeth
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Team	**0.238****	**0.233*****	**0.167***	**0.135*****	**0.171***	**0.117*****
	(0.097)	(0.025)	(0.099)	(0.040)	(0.089)	(0.031)
Obs	21,565	21,565	21,565	21,565	21,565	21,565
R-squared	0.277	0.303	0.070	0.194	0.143	0.273

Low Tenure Sample

	SR		MPPM3		MPPM4	
	Time fixed Fund Clustered	Fama Macbeth	Time fixed Fund Clustered	Fama Macbeth	Time fixed Fund Clustered	Fama Macbeth
VARIABLES	(7)	(8)	(9)	(10)	(11)	(12)
Team	0.042	**0.030****	-0.683	-0.433	-0.426	-0.233
	(0.032)	(0.012)	(1.173)	(0.298)	(1.271)	(0.307)
Obs	24,327	24,327	24,327	24,327	24,327	24,327
R-squared	0.347	0.461	0.324	0.349	0.322	0.347

High Tenure Sample

	SR		MPPM3		MPPM4	
	Time fixed Fund Clustered	Fama Macbeth	Time fixed Fund Clustered	Fama Macbeth	Time fixed Fund Clustered	Fama Macbeth
VARIABLES	(7)	(8)	(9)	(10)	(11)	(12)
Team	**0.076****	**0.059*****	**2.557****	**2.074*****	**2.393****	**1.805*****
	(0.035)	(0.006)	(1.155)	(0.264)	(1.190)	(0.259)
Obs	21,565	21,565	21,565	21,565	21,562	21,562
R-squared	0.313	0.389	0.299	0.303	0.293	0.302

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Cross-sectional analysis by investment style

Construct subsamples based on investment style of hedge fund reported to TASS and run the following regression on each subsample: $Performance_{i,t+1,t+12} = a_i + b_i Team_{i,t} + c_i\, Control_{i,t-23,t} + e_{i,t}$. Team is a dummy variable which equals to 1 for funds managed by a team and 0 otherwise. Dependent variables are performance in subsequent 1 year. Control variables includes 1) logarithm of team-tenure, no of years a team has been working together which is proxied by the average number of years each member has worked for the fund; 2) logarithm of number of managers within a fund; 3) logarithm of fund size; 4) logarithm of fund age in terms of year; 5) sat, average score of every undergraduate institutions that the team members graduated from; 6) corresponding lagged performance during t-23 to t or fund flow for the previous 12 months; 7) other fund characteristics such as lockup periods, management fees, incentive fees, and an offshore dummy; and 8) fund style dummies classified by TASS. Only the result from Fama-Macbeth model are presented.

	Excess Return	Alpha	IR	SR	MPPM3	MPPM4
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES						
	Long/short					
Team	0.007	-0.093	**-0.143*** **	**-0.040*** **	**-0.922***	**-1.178** **
	(0.043)	(0.066)	(0.048)	(0.010)	(0.543)	(0.573)
Obs	15,515	15,515	15,515	15,515	15,515	15,515
R-squared	0.182	0.133	0.110	0.150	0.182	0.177
	Event Driven					
Team	**-0.124** **	**-0.324*** **	**-0.304*** **	**-0.061** **	**-2.071*** **	**-2.226*** **
	(0.049)	(0.069)	(0.084)	(0.030)	(0.638)	(0.672)
Obs	5,574	5,574	5,574	5,574	5,574	5,574
R-squared	0.375	0.298	0.366	0.465	0.378	0.375
	Global Macro					
Team	**1.229***	**0.755** **	**1.071*** **	**0.186***	**8.949*** **	**10.028*** **
	(0.696)	(0.315)	(0.274)	(0.111)	(2.344)	(2.312)
Obs	1,783	1,783	1,783	1,783	1,783	1,783
R-squared	0.716	0.674	0.666	0.737	0.728	0.731
	Multi-Strategy					
Team	**1.506*** **	**1.099** **	**0.580***	**0.524*** **	**26.572*** **	**27.687*** **
	(0.346)	(0.431)	(0.339)	(0.114)	(6.626)	(7.381)
Obs	2,066	2,066	2,066	2,066	2,066	2,066
R-squared	0.743	0.703	0.656	0.643	0.727	0.721

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 7: Subsample analysis during bullish and bearish periods

Divide the dataset into two subsamples based on different market conditions. 1994, 2000, 2001, 2002 and 2008 are labeled as bear market periods while the other years are labeled as bull market periods. The following regression is run on each subsample: $Performance_{i,t+1,t+12} = a_i + b_i Team_{i,t} + c_i\ Control_{i,t-23,t} + e_{i,t}$. Team is a dummy variable which equals to 1 for funds managed by a team and 0 otherwise. Dependent variables are performance in subsequent 1 year. Control variables includes 1) logarithm of team-tenure, no of years a team has been working together which is proxied by the average number of years each member has worked for the fund; 2) logarithm of number of managers within a fund; 3) logarithm of fund size; 4) logarithm of fund age in terms of year; 5) sat, average score of every undergraduate institutions that the team members graduated from; 6) corresponding lagged performance during t-23 to t or fund flow for the previous 12 months; 7) other fund characteristics such as lockup periods, management fees, incentive fees, and an offshore dummy; and 8) fund style dummies classified by TASS. Panel regressions with time-fixed effect and fund clustered errors and Fama-Macbeth model are adopted.

Bullish Period

	Excess Return		Alpha		AR	
	Time fixed Fund Clustered	Fama Macbeth	Time fixed Fund Clustered	Fama Macbeth	Time fixed Fund Clustered	Fama Macbeth
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES						
Team	**0.121***	**0.125*****	0.068	**0.087****	**0.202*****	**0.173*****
	(0.064)	(0.020)	(0.071)	(0.042)	(0.070)	(0.028)
Obs	39,682	39,682	39,682	39,682	39,682	39,682
R-squared	0.240	0.268	0.073	0.138	0.157	0.238

Bearish Period

	Excess Return		Alpha		AR	
	Time fixed Fund Clustered	Fama Macbeth	Time fixed Fund Clustered	Fama Macbeth	Time fixed Fund Clustered	Fama Macbeth
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES						
Team	-0.041	-0.032	-0.045	-0.076	-0.199	**-0.216****
	(0.175)	(0.079)	(0.177)	(0.095)	(0.121)	(0.087)
Obs	5,932	5,932	5,932	5,932	5,932	5,932
R-squared	0.392	0.323	0.112	0.151	0.175	0.212

Bullish Period

VARIABLES	SR Time fixed Fund Clustered (7)	 Fama Macbeth (8)	MPPM3 Time fixed Fund Clustered (9)	 Fama Macbeth (10)	MPPM4 Time fixed Fund Clustered (11)	 Fama Macbeth (12)
Team	**0.065****	**0.042*****	1.110	**1.083*****	1.051	**1.000*****
	(0.026)	(0.005)	(0.744)	(0.232)	(0.763)	(0.235)
Obs	39,682	39,682	39,682	39,682	39,679	39,679
R-squared	0.296	0.386	0.278	0.263	0.274	0.261

Bearish Period

VARIABLES	SR Time fixed Fund Clustered (7)	 Fama Macbeth (8)	MPPM3 Time fixed Fund Clustered (9)	 Fama Macbeth (10)	MPPM4 Time fixed Fund Clustered (11)	 Fama Macbeth (12)
Team	-0.040	**-0.045****	-1.021	-0.824	-0.972	-0.725
	(0.042)	(0.016)	(2.730)	(0.920)	(2.994)	(0.927)
Obs	5,932	5,932	5,932	5,932	5,932	5,932
R-squared	0.410	0.347	0.343	0.313	0.325	0.312

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 8: Hazard Model of Fund Failure

Hazard model is adopted as a survival regression on the time to hedge fund failure by team dummy and several other control variables such as fund size, lengths of the redemption notice, lockup periods, return, volatility and flow, Time variable here is the number of days since a fund's inception day. Robust standard errors are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
team	1.076	1.091	1.084	1.188**	1.169*	1.169*	1.188**	1.188**	1.207**	1.354**
	(0.0775)	(0.0775)	(0.0830)	(0.0963)	(0.0955)	(0.0955)	(0.0972)	(0.0974)	(0.0993)	(0.184)
mrret		0.875***	0.854***	0.849***	0.796***	0.796***	0.798***	0.798***	0.803***	0.794***
		(0.0101)	(0.00893)	(0.00886)	(0.0149)	(0.0149)	(0.0151)	(0.0150)	(0.0151)	(0.0143)
mrmon_flow			1.000***	1.002	1.001	1.001	1.001	1.002	1.001	1.000
			(9.91e-06)	(0.00607)	(0.00613)	(0.00613)	(0.00616)	(0.00600)	(0.00629)	(0.00674)
lnAUM				0.788***	0.782***	0.782***	0.776***	0.775***	0.774***	0.768***
				(0.0200)	(0.0203)	(0.0203)	(0.0201)	(0.0207)	(0.0204)	(0.0199)
mvol					0.924***	0.924***	0.921***	0.923***	0.933***	0.920***
					(0.0149)	(0.0149)	(0.0150)	(0.0152)	(0.0150)	(0.0153)
lnLockup							1.133***	1.123***	1.123***	1.127***
							(0.0320)	(0.0340)	(0.0342)	(0.0358)
lnRedempNotice								1.043	1.011	1.053
								(0.0548)	(0.0589)	(0.0676)
sat										0.939*
										(0.0314)
fund_tenure										0.920***
										(0.00795)
ln_nomger										0.709***
										(0.0743)
MgmtFee										1.261***
										(0.109)
IncentiveFee										1.004
										(0.00940)
off										1.625***
										(0.138)
Strategy dummies	No	No	No	No	No	No	No	No	Yes	Yes
Observations	9,584	9,584	8,288	8,094	8,037	8,037	8,037	8,037	8,037	7,336

Table 9: Top 30 universities with most hedge fund managers

This table lists the top thirty schools with largest number of alumni as hedge fund managers in my sample.

	Institutions	Percentage
1	University of Pennsylvania	6.06%
2	Harvard University	5.16%
3	New York University	4.89%
4	Columbia University	4.58%
5	University of Chicago	3.38%
6	Cornell University	2.34%
7	Stanford University	1.96%
8	Yale University	1.89%
9	Northwestern University	1.80%
10	Princeton University	1.78%
11	University of Michigan	1.76%
12	University of Virginia	1.71%
13	University of California--Berkeley	1.69%
14	Massachusetts Institute of Technology	1.56%
15	Duke University	1.51%

	Institutions	Percentage
16	Georgetown University	1.33%
17	Fordham University	1.26%
18	Boston University	1.22%
19	University of Wisconsin--Madison	1.22%
20	University of Texas--Austin	1.13%
21	Dartmouth College	1.10%
22	University of Illinois--Urbana-Champaign	1.06%
23	University of California--Los Angeles?	1.01%
24	Brown University	0.97%
25	University of Southern California	0.95%
26	Boston College	0.92%
27	Indiana University--Bloomington	0.88%
28	Johns Hopkins University	0.86%
29	University of California--Los Angeles	0.86%
30	University of North Carolina--Chapel Hill	0.83%

Table 10: Determinants of Congruence

Dependent variables are the average fund congruence levels for each fund. Explanatory variables are all on a fund base. They are 1) average score of every undergraduate institutions that the team members graduated from; 2) logarithm of number of managers within a fund; 3) logarithm of average no of years each member has worked for the fund; 4} average lagged logarithm of fund size; 5) average lagged standard deviation of returns which is measured over a rolling window of past 24 months; 6) logarithm of average lagged fund age in terms of year; 6) fund alpha for the whole sample period;.7) average fund's flow during previous 1 year 8) other characteristics such as the lengths of the redemption notice, lockup periods, personal capital dummy and high-water mark dummy, management fees, incentive fees, , minimum investment, and an offshore dummy, Cross-sectional panel regression model with time-fixed effect and fund clustered errors is used. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

VARIABLES	L1_ congruence	L2_ congruence
fund_sat	**0.047*** **	**0.032*** **
	(0.010)	(0.009)
fund_lnomger	**-0.045*** **	**-0.049*** **
	(0.015)	(0.013)
ffund_lntenure	0.003	0.009
	(0.012)	(0.011)
fund_lnage	0.019	**0.020***
	(0.012)	(0.011)
fund_lnAUM	**-0.014*** **	**-0.013*** **
	(0.005)	(0.005)
fund_sd	0.005	0.005
	(0.004)	(0.003)
fund_alpha	0.001	0.003
	(0.011)	(0.010)
fund_flow	**-0.000*** **	**-0.000*** **
	(0.000)	(0.000)
Redemption_30	0.000	0.000
	(0.010)	(0.010)
Lockup	0.001	0.001
	(0.001)	(0.001)
PersonalCap	-0.003	-0.005
	(0.017)	(0.015)
HighWaterMark	**0.059*** **	**0.035***
	(0.022)	(0.020)
MgmtFee	**-0.049*** **	**-0.032** **
	(0.017)	(0.016)
IncentiveFee	-0.003	-0.002
	(0.002)	(0.002)
lnMiniInvestment	0.016	0.023
	(0.017)	(0.016)
leveraged	-0.003	-0.019
	(0.017)	(0.015)
Strategy dummies	Yes	Yes
Constant	-0.182	-0.069
	(0.159)	(0.154)
Observations	1,171	1,171
R-squared	0.084	0.071

Table 11: Team congruence level and fund performance

The model applied to test the relationship between team cohesiveness and fund performance is as follows: $Performance_{i,t+1,t+12} = a_i + b_i Congruence_{i,t} + c_i\, Control_{i,t-23,t} + e_{i,t}$. L1_congruence is measured by the mean of (no. of connected colleagues)/(total no. of managers within fund - 1) across managers in a fund. Dependent variables are performance in subsequent 1 year. Control variables includes 1) logarithm of team-tenure, no of years a team has been working together which is proxied by the average number of years each member has worked for the fund; 2) logarithm of number of managers within a fund; 3) logarithm of fund size; 4) logarithm of fund age in terms of year; 5) sat, average score of every undergraduate institutions that the team members graduated from; 6) corresponding lagged performance during t-23 to t or fund flow for the previous 12 months; 7) other fund characteristics such as lockup periods, management fees, incentive fees, and an offshore dummy; and 8) fund style dummies classified by TASS. Results from Fama-Macbeth model are presented.

	Excess Return	Alpha	IR	SR	MPPM3	MPPM4
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES						
L1_congruence	-0.042	-0.008	**-0.055***	**-0.027*****	**-1.002****	**-1.221****
	(0.037)	(0.034)	(0.031)	(0.009)	(0.496)	(0.520)
sat	0.008	0.023*	0.033**	0.010***	0.574***	0.662***
	(0.009)	(0.012)	(0.014)	(0.004)	(0.115)	(0.112)
lnfund_tenure	0.042***	0.041***	0.027**	0.023***	0.249	0.221
	(0.014)	(0.013)	(0.012)	(0.004)	(0.184)	(0.191)
lnAge	0.135***	0.097***	0.072***	0.038***	1.406***	1.412***
	(0.014)	(0.023)	(0.016)	(0.004)	(0.148)	(0.143)
lnAUM	-0.056***	-0.008	0.022***	-0.006***	-0.341***	-0.275***
	(0.007)	(0.005)	(0.006)	(0.002)	(0.089)	(0.094)
ln_nomger	-0.032**	-0.047**	-0.115***	-0.024***	0.065	0.182
	(0.015)	(0.023)	(0.023)	(0.006)	(0.182)	(0.185)
Lockup	0.008***	0.010***	0.005***	0.002***	0.055***	0.047**
	(0.001)	(0.002)	(0.002)	(0.001)	(0.017)	(0.018)
MgmtFee	0.086***	0.019	0.050***	0.021***	0.514*	0.366
	(0.016)	(0.021)	(0.017)	(0.005)	(0.261)	(0.289)
IncentiveFee	0.006**	0.005**	0.000	-0.001	0.050*	0.037
	(0.002)	(0.002)	(0.002)	(0.001)	(0.027)	(0.025)
off	-0.046***	-0.098***	-0.091***	-0.015***	-0.739***	-0.746***
	(0.013)	(0.020)	(0.020)	(0.004)	(0.169)	(0.173)
convertible	-0.001	-0.400***	-0.067	0.078	0.552	0.575
	(0.079)	(0.088)	(0.107)	(0.048)	(1.065)	(1.125)
dedicated	-0.655***	-0.706***	-0.523***	-0.177***	-9.398***	-9.540***
	(0.171)	(0.120)	(0.158)	(0.048)	(2.175)	(2.250)
emerging	0.589***	0.455***	-0.000	0.081*	4.467**	3.548*
	(0.145)	(0.136)	(0.153)	(0.045)	(1.922)	(2.010)
equity	0.099*	-0.286***	-0.009	0.149***	2.314***	2.788***
	(0.057)	(0.097)	(0.122)	(0.030)	(0.699)	(0.741)
event	0.221***	-0.073	0.084	0.133***	2.900***	3.004***
	(0.077)	(0.095)	(0.125)	(0.044)	(0.908)	(0.928)
fixedincome	0.461***	0.103	0.435***	0.324***	4.761***	4.554***

	(0.096)	(0.100)	(0.120)	(0.044)	(1.024)	(1.024)
fof	0.089	-0.245**	0.014	0.094**	2.224***	2.539***
	(0.054)	(0.102)	(0.139)	(0.043)	(0.681)	(0.712)
global	0.353***	-0.107	-0.133	0.014	4.075***	3.953***
	(0.074)	(0.113)	(0.130)	(0.033)	(0.926)	(0.971)
longshort	0.213***	-0.232**	-0.223*	0.035	1.135	0.792
	(0.080)	(0.099)	(0.117)	(0.037)	(0.929)	(0.945)
mged_futures	0.272***	-0.298**	-0.377***	-0.035	1.179	0.554
	(0.087)	(0.124)	(0.119)	(0.028)	(1.107)	(1.163)
multi	0.160***	-0.233***	0.015	0.127***	1.943***	1.945***
	(0.058)	(0.075)	(0.093)	(0.033)	(0.688)	(0.707)
win_return2Y	0.140***					
	(0.031)					
win_alpha2Y		0.115***				
		(0.023)				
win_AR2Y			0.663***			
			(0.047)			
win_SR2Y				0.445***		
				(0.035)		
win_MPPM32Y					0.163***	
					(0.036)	
win_MPPM42Y						0.202***
						(0.039)
Constant	0.508***	0.054	-0.525*	-0.074	-7.981***	-10.516***
	(0.188)	(0.242)	(0.272)	(0.076)	(1.772)	(1.625)
Observations	32,505	32,505	32,505	32,505	32,505	32,502
R-squared	0.320	0.167	0.261	0.411	0.314	0.312

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 12: Subperiod analysis by market condition

Construct subsamples based on the median VIX value across the whole sample periods and run the following regression on each subsample: $Performance_{i,t+1,t+12} = a_i + b_i Congruence_{i,t} + c_i\, Control_{i,t-23,t} + e_{i,t}$. L1_congruence is measured by the mean of (no. of connected colleagues)/(total no. of managers within fund - 1) across managers in a fund. Dependent variables are performance in subsequent 1 year. Control variables includes 1) logarithm of team-tenure, no of years a team has been working together which is proxied by the average number of years each member has worked for the fund; 2) logarithm of number of managers within a fund; 3) logarithm of fund size; 4) logarithm of fund age in terms of year; 5) sat, average score of every undergraduate institutions that the team members graduated from; 6) corresponding lagged performance during t-23 to t or fund flow for the previous 12 months; 7) other fund characteristics such as lockup periods, management fees, incentive fees, and an offshore dummy; and 8) fund style dummies classified by TASS. Only the result from Fama-Macbeth model are presented.

	Excess Return	Alpha	IR	SR	MPPM3	MPPM4
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES						
			Low VIX Period			
L1_congruence	-0.053	0.045	**0.089****	0.000	-1.217	-1.474
	(0.067)	(0.064)	(0.044)	(0.015)	(0.902)	(0.946)
Obs	12,343	12,343	12,343	12,343	12,343	12,340
R-squared	0.334	0.172	0.237	0.385	0.341	0.339
			High VIX Period			
L1_congruence	-0.034	-0.046	**-0.156*****	**-0.047*****	-1.275	**-1.043***
	(0.041)	(0.037)	(0.038)	(0.011)	(1.015)	(0.593)
Obs	20,162	20,162	20,162	20,162	20,162	20,162
R-squared	0.311	0.164	0.277	0.430	0.234	0.293

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Subsample analysis by team size

Construct subsamples based on number of managers in a hedge fund and run the following regression on each subsample: $Performance_{i,t+1,t+12} = a_i + b_i Congruence_{i,t} + c_i\, Control_{i,t-23,t} + e_{i,t}$. L1_congruence is measured by the mean of (no. of connected colleagues)/(total no. of managers within fund - 1) across managers in a fund. Dependent variables are performance in subsequent 1 year. Control variables includes 1) logarithm of team-tenure, no of years a team has been working together which is proxied by the average number of years each member has worked for the fund; 2) logarithm of number of managers within a fund; 3) logarithm of fund size; 4) logarithm of fund age in terms of year; 5) sat, average score of every undergraduate institutions that the team members graduated from; 6) corresponding lagged performance during t-23 to t or fund flow for the previous 12 months; 7) other fund characteristics such as lockup periods, management fees, incentive fees, and an offshore dummy; and 8) fund style dummies classified by TASS. Only the result from Fama-Macbeth model are presented.

	Excess Return	Alpha	IR	SR	MPPM3	MPPM4
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES						
	No of manager = 2					
L1_congruence	**-0.190*** **	**-0.080***	**-0.093** **	**-0.040*** **	**-2.334*** **	**-2.404*** **
	(0.032)	(0.044)	(0.046)	(0.010)	(0.494)	(0.543)
Obs	13,369	13,369	13,369	13,369	13,369	13,369
R-squared	0.396	0.260	0.362	0.518	0.392	0.392
	No of manager ≥ 3					
L1_congruence	**0.178*** **	0.046	0.062	0.024	**1.441** **	1.156
	(0.056)	(0.066)	(0.057)	(0.016)	(0.715)	(0.728)
Obs	19,136	19,136	19,136	19,136	19,136	19,133
R-squared	0.362	0.230	0.293	0.423	0.357	0.357

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Management structure, fund risk-taking and fund flow

The model applied to test the association between team structure, team cohesiveness and fund risk-taking as well as fund flow is as follows: $Volatility/idioVol/NCSkew/Flow_{i,t+1,t+12} = a_i + b_i Team_{i,t} + c_i Congruence_{i,t} + d_i\, Control_{i,t-23,t} + e_{i,t}$. Team is a dummy variable which equals to 1 for funds managed by a team and 0 otherwise. L1_congruence is measured by the mean of (no. of connected colleagues)/(total no. of managers within fund - 1) across managers in a fund. Dependent variables are total volatility/idiosyncratic volatility/negative coefficient of skewness/fund flow in subsequent 1 year. Control variables includes 1) logarithm of team-tenure, no of years a team has been working together which is proxied by the average number of years each member has worked for the fund; 2) logarithm of number of managers within a fund; 3) logarithm of fund size; 4) logarithm of fund age in terms of year; 5) sat, average score of every undergraduate institutions that the team members graduated from; 6) corresponding lagged volatility/negative coefficient of skewness/fund flow during t-23 to t or fund return for the current or previous 12 months; 7) other fund characteristics such as lockup periods, management fees, incentive fees, and an offshore dummy; and 8) fund style dummies classified by TASS. Results from Fama-Macbeth model are presented.

	Volatility	IdioVol	NCSkew	Flow
	(1)	(2)	(3)	(4)
VARIABLES	win_Vol	win_idVol	win_nega_skew	win_anu_flow
Team	**0.205*** **	**0.063** **	**-0.027** **	**-0.044** **
	(0.058)	(0.029)	(0.013)	(0.020)
L1_congruence	**0.105** **	**0.076*** **	**0.054*** **	**0.039* **
	(0.043)	(0.021)	(0.012)	(0.023)
sat	-0.027***	-0.008*	-0.006*	0.029***
	(0.009)	(0.005)	(0.003)	(0.003)
lnfund_tenure	0.013	-0.015***	-0.018***	0.001
	(0.012)	(0.006)	(0.005)	(0.008)
lnAge	0.044***	0.021**	-0.036***	0.034***
	(0.015)	(0.009)	(0.005)	(0.007)
lnAUM	-0.067***	-0.037***	0.012***	-0.096***
	(0.009)	(0.004)	(0.003)	(0.006)
ln_nomger	-0.052***	0.011	0.061***	0.087***
	(0.017)	(0.013)	(0.010)	(0.020)
Lockup	0.003**	0.003***	-0.002***	0.001***
	(0.001)	(0.001)	(0.001)	(0.000)
MgmtFee	0.103**	0.062***	0.003	0.056***
	(0.048)	(0.016)	(0.006)	(0.010)
IncentiveFee	0.005**	0.007***	-0.007***	-0.004***
	(0.002)	(0.001)	(0.001)	(0.001)
off	-0.127***	-0.004	-0.006	0.146***
	(0.014)	(0.007)	(0.007)	(0.017)
convertible	0.009	0.014	0.146**	-0.306***
	(0.195)	(0.069)	(0.059)	(0.049)
dedicated	0.636***	0.094	-0.004	-0.065
	(0.115)	(0.065)	(0.039)	(0.058)
emerging	0.611***	0.341***	0.023	-0.369***

	(0.138)	(0.065)	(0.043)	(0.060)
equity	-0.237**	0.007	-0.169***	-0.177***
	(0.094)	(0.060)	(0.038)	(0.055)
event	-0.102	-0.026	0.009	-0.122**
	(0.096)	(0.054)	(0.047)	(0.054)
fixedincome	0.127	0.118	0.024	-0.196***
	(0.188)	(0.084)	(0.056)	(0.056)
fof	-0.210*	-0.031	0.056	-0.195***
	(0.107)	(0.059)	(0.036)	(0.050)
global	0.041	0.189***	-0.052	-0.064
	(0.150)	(0.070)	(0.040)	(0.064)
longshort	0.400***	0.146**	0.002	-0.198***
	(0.096)	(0.057)	(0.041)	(0.053)
mged_futures	0.339***	0.281***	-0.019	-0.258***
	(0.104)	(0.062)	(0.040)	(0.045)
multi	-0.158**	-0.056	-0.041	-0.096*
	(0.077)	(0.051)	(0.048)	(0.054)
win_Vol2Y	0.684***			
	(0.022)			
win_idVol2Y		0.436***		
		(0.010)		
win_nega_skew2Y			0.052***	
			(0.012)	
win_anu_flow2Y				0.009***
				(0.002)
RetYear				0.866***
				(0.065)
RetPastYear				0.354***
				(0.046)
Constant	2.124***	0.878***	0.080	1.340***
	(0.232)	(0.128)	(0.063)	(0.096)
R-squared	0.604	0.512	0.151	0.145

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15: Congruence level and managerial ability

This table summarizes the relationship between team congruence level and a fund team's managerial ability in different aspects, strategy distinctiveness (SDI) and market liquidity timing. L1_ and L2_congruence are first and second level of team congruence. Liquidity-timing skills are measured as coefficient β of the following model: $Return_{i,t} = \alpha MKT_t \Delta MLIQ_t + \sum_{j=1}^{7} \beta_j FH7_t + \gamma + e_{i,t}$ where return is excess return of individual funds. MKTt is market excess return. ΔMLIQt is measured using the Pastor-Stambaugh market liquidity innovation series. And FH7 denotes Fung and Hsieh seven factors. SDI equals to 1 minus the correlation between a fund's return and the average return of all funds belonging to the same style. Panel A is the test on full sample while Panel B is on low-tenure and high-tenure subsamples. Results from Fama-Macbeth model are presented. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Panel A: **Full Sample**

	Market Liquidity Timing		Strategy Distinctiveness	
	(1)	(2)	(3)	(4)
VARIABLES				
L1_congruence	**0.515***		**-0.114*****	
	(0.295)		(0.012)	
L2_congruence		0.461		**-0.131*****
		(0.311)		(0.010)
Obs	23,205	23,205	12,648	12,648
R-squared	0.019	0.017	0.013	0.012

Panel B: **Low- and High-Tenure Subsample**

Low Tenure Sample

	Market Liquidity Timing		Strategy Distinctiveness	
	(1)	(2)	(3)	(4)
VARIABLES				
L1_congruence	**0.999****		**-0.264*****	
	(0.476)		(0.027)	
L2_congruence		**2.312*****		**-0.192*****
		(0.539)		(0.016)
Obs	9,743	9,743	5,283	5,283
R-squared	0.028	0.029	0.027	0.015

High Tenure Sample

	Market Liquidity Timing		Strategy Distinctiveness	
	(1)	(2)	(3)	(4)
VARIABLES				
L1_congruence	**0.589***		**-0.062*****	
	(0.337)		(0.009)	
L2_congruence		0.204		**-0.108*****
		(0.328)		(0.009)
Obs	12,803	12,803	7,051	7,051
R-squared	0.032	0.029	0.010	0.013

Table 16: 2SLS result for team management structure

This table presents the result of 2SLS model to test the relationship between team structure and fund performance using an instrumental variable. *Team* is a dummy variable which equals to 1 for funds managed by a team and 0 otherwise. The instrumental variable for team dummy, *percen_team_cp*, is calculated as the proportion of team-managed hedge funds for funds with the same management company (exclude the respective fund itself). Dependent variables are performance in subsequent 1 year. Control variables includes 1) logarithm of team-tenure, no of years a team has been working together which is proxied by the average number of years each member has worked for the fund; 2) logarithm of number of managers within a fund; 3) logarithm of fund size; 4) logarithm of fund age in terms of year; 5) sat, average score of every undergraduate institutions that the team members graduated from; 6) corresponding lagged performance during t-23 to t or fund flow for the previous 12 months; 7) other fund characteristics such as lockup periods, management fees, incentive fees, and an offshore dummy; and 8) fund style dummies classified by TASS. For brevity, I only report the coefficient for some controls.

	First Stage	Second Stage					
Variables	Team Dummy	Excess Return	Alpha	AR	SR	MPPM3	MPPM4
percen_team_cp	0.303***						
	(0.0379)						
Team		0.194	0.187	0.462*	0.176*	5.894*	6.916*
		(0.247)	(0.226)	(0.236)	(0.095)	(3.568)	(3.906)
sat	-0.002	-0.014	0.030	0.009	-0.005	0.549*	0.719**
	(0.010)	(0.022)	(0.021)	(0.026)	(0.011)	(0.319)	(0.359)
lnfund_tenure	0.002	-0.013	0.009	0.086**	0.034**	0.100	0.176
	(0.015)	(0.033)	(0.030)	(0.034)	(0.0145)	(0.415)	(0.435)
lnAge	-0.016	0.137***	0.127***	0.090**	0.039***	1.493***	1.533***
	(0.017)	(0.040)	(0.038)	(0.037)	(0.015)	(0.540)	(0.588)
lnAUM	-0.003	-0.049***	-0.011	0.012	-0.004	-0.123	-0.0382
	(0.006)	(0.013)	(0.012)	(0.014)	(0.006)	(0.177)	(0.198)
Lockup	0.000	0.006*	0.006**	0.006	0.002	0.0158	0.000291
	(0.002)	(0.003)	(0.003)	(0.005)	(0.002)	(0.050)	(0.0575)
MgmtFee	0.007	0.053	0.037	0.093**	0.018	-0.059	-0.274
	(0.021)	(0.053)	(0.044)	(0.044)	(0.017)	(0.843)	(0.943)
IncentiveFee	0.001	0.007	0.002	-0.003	-0.002	0.041	0.0161
	(0.002)	(0.004)	(0.003)	(0.004)	(0.002)	(0.054)	(0.0572)
R-squared	0.679	0.164	0.039	0.141	0.231	0.177	0.169

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 17: Management structural changes and performance

This table presents the result of the change in fund performance for a sample of funds that experienced a change in their management structure (single-manager to multi-manager funds, or multi-manager to single-manager funds). Panel A compares the fund performance during the two-year periods before and after the year of management structure change. In Panel B, I run panel regression on the performance of the sample funds throughout their whole sample period. Team is a dummy variable which equals to 1 for the year in which the funds is managed by a team and 0 otherwise. A set of measures 1) excess return; 2) alpha from FH 7 factor model; 3) Information ratio; 4) Sharpe ratio; 5) manipulation proof measure with ρ=3 or 4; are used to measure the fund performance. Control variables includes 1) logarithm of team-tenure, no of years a team has been working together which is proxied by the average number of years each member has worked for the fund; 2) logarithm of fund size; 3) logarithm of fund age in terms of year; 6) corresponding lagged performance during t-23 to t or fund flow for the previous 12 months; 7) other fund characteristics such as lockup periods, management fees and incentive fees. Panel regressions with time-fixed effect and fund clustered errors are adopted. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Panel A: T-test

	Team to Single				Single to Team			
Variables	No. of funds	Team	Single	Diff in Mean	No. of funds	Single	Team	Diff in Mean
win_ret_2Y	13	0.294	0.288	0.005	28	0.646	0.518	0.128
win_alpha_2Y	13	0.119	0.429	-0.31	28	0.576	0.594	-0.018
win_AR2Y	13	0.002	0.002	0	28	0.004	0.002	0.002**
win_SR2Y	13	0.758	0.497	0.261	28	0.736	0.744	-0.008
win_MPPM3_2Y	13	-0.419	-1.606	1.187	28	3.401	1.707	1.694
win_MPPM4_2Y	13	-0.874	-2.352	1.478	28	2.884	0.92	1.964

Panel B: Panel Regression over the Whole Sample Period

	Excess Return	Alpha	AR	SR	MPPM3	MPPM4
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
team	**0.294*** **	**0.329***	**0.213** **	0.080	**6.074** **	**5.979** **
	(0.112)	(0.168)	(0.089)	(0.077)	(2.405)	(2.394)
_mean24_lnAUM	-0.142**	-0.006	0.086*	-0.030	-1.003	-1.171
	(0.067)	(0.095)	(0.050)	(0.043)	(1.365)	(1.359)
lnAge	-0.041	0.995	0.236	0.685**	19.001**	19.442**
	(0.200)	(0.632)	(0.334)	(0.288)	(9.054)	(9.011)
Year dummy	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.713**	1.001	-0.011***	-1.052**	9.691*	6.073
	(0.694)	(0.713)	(0.003)	(0.405)	(5.339)	(5.395)
Observations	192	192	192	192	192	192
R-squared	0.426	0.312	0.353	0.254	0.370	0.383

Table 18: Additional Contribution to Informational Diversity of Education

This table presents regression result by controlling for effect of informational diversity of education. Run the following model by adding the diversity measure of final educational degree as additional control: $Performance_{i,t+1,t+12} = a_i + b_i Congruence_{i,t} + c_i\ Control_{i,t-23,t} + e_{i,t}$. L1_congruence is measured by the mean of (no. of connected colleagues)/(total no. of managers within fund - 1) across managers in a fund. Dependent variables are performance in subsequent 1 year. Control variables includes 1) logarithm of team-tenure, no of years a team has been working together which is proxied by the average number of years each member has worked for the fund; 2) logarithm of number of managers within a fund; 3) logarithm of fund size; 4) logarithm of fund age in terms of year; 5) sat, average score of every undergraduate institutions that the team members graduated from; 6) corresponding lagged performance during t-23 to t or fund flow for the previous 12 months; 7) other fund characteristics such as lockup periods, management fees, incentive fees, and an offshore dummy; and 8) fund style dummies classified by TASS. Results from Fama-Macbeth model are presented. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

	Excess Return	Alpha	IR	SR	MPPM3	MPPM4
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES						
L1_congruence	-0.044	-0.010	-0.049	**-0.025*** **	**-1.012** **	**-1.226** **
	(0.037)	(0.034)	(0.032)	(0.009)	(0.495)	(0.519)
norm_gentropy	**0.036** **	-0.035	-0.042	0.008	**0.800*** **	**0.907*** **
	(0.017)	(0.038)	(0.033)	(0.007)	(0.191)	(0.190)
sat	0.007	0.022*	0.030**	0.009**	0.554***	0.639***
	(0.009)	(0.012)	(0.014)	(0.004)	(0.114)	(0.111)
lnfund_tenure	0.043***	0.044***	0.027**	0.022***	0.261	0.231
	(0.014)	(0.013)	(0.013)	(0.004)	(0.186)	(0.194)
lnAge	0.135***	0.098***	0.072***	0.038***	1.396***	1.399***
	(0.014)	(0.023)	(0.016)	(0.004)	(0.146)	(0.141)
lnAUM	-0.057***	-0.006	0.024***	-0.006***	-0.377***	-0.315***
	(0.007)	(0.006)	(0.007)	(0.002)	(0.092)	(0.097)
ln_nomger	-0.029*	-0.051**	-0.118***	-0.023***	0.136	0.261
	(0.015)	(0.023)	(0.023)	(0.006)	(0.188)	(0.190)
Lockup	0.008***	0.010***	0.005***	0.002***	0.058***	0.050***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.017)	(0.018)
MgmtFee	0.086***	0.019	0.049***	0.021***	0.522**	0.376
	(0.016)	(0.020)	(0.017)	(0.005)	(0.255)	(0.283)
IncentiveFee	0.005**	0.005**	0.000	-0.001	0.045*	0.031
	(0.002)	(0.002)	(0.002)	(0.001)	(0.026)	(0.025)
off	-0.045***	-0.099***	-0.095***	-0.016***	-0.708***	-0.709***
	(0.013)	(0.020)	(0.020)	(0.004)	(0.168)	(0.172)
Lagged performance	Yes	Yes	Yes	Yes	Yes	Yes
Strategy dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.524***	0.049	-0.503*	-0.068	-7.581***	-10.064***
	(0.186)	(0.240)	(0.269)	(0.075)	(1.763)	(1.623)
Observations	32,505	32,505	32,505	32,505	32,505	32,502
R-squared	0.323	0.171	0.266	0.414	0.316	0.314

Table 19: Alternative congruence level and fund performance

This table presents regression result by replacing L1_congruence by L2_congruence. The model applied to test the relationship between team cohesiveness and fund performance is as follows: $Performance_{i,t+1,t+12} = a_i + b_i Congruence_{i,t} + c_i\, Control_{i,t-23,t} + e_{i,t}$. L2_congruence is measured by the mean of (no. of connected colleagues)/(total no. of managers within fund - 1) across managers in a fund. Dependent variables are performance in subsequent 1 year. Control variables includes 1) logarithm of team-tenure, no of years a team has been working together which is proxied by the average number of years each member has worked for the fund; 2) logarithm of number of managers within a fund; 3) logarithm of fund size; 4) logarithm of fund age in terms of year; 5) sat, average score of every undergraduate institutions that the team members graduated from; 6) corresponding lagged performance during t-23 to t or fund flow for the previous 12 months; 7) other fund characteristics such as lockup periods, management fees, incentive fees, and an offshore dummy; and 8) fund style dummies classified by TASS. Results from Fama-Macbeth model are presented.

	Excess Return	Alpha	IR	SR	MPPM3	MPPM4
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES						
L2_congruence	-0.028	0.029	-0.039	**-0.031*** **	**-1.069** **	**-1.376** **
	(0.036)	(0.047)	(0.037)	(0.010)	(0.496)	(0.528)
sat	0.006	0.020*	0.031**	0.009**	0.553***	0.643***
	(0.009)	(0.012)	(0.014)	(0.004)	(0.115)	(0.111)
lnfund_tenure	0.041***	0.042***	0.028**	0.023***	0.246	0.218
	(0.014)	(0.013)	(0.012)	(0.004)	(0.188)	(0.196)
lnAge	0.135***	0.095***	0.071***	0.039***	1.419***	1.428***
	(0.014)	(0.023)	(0.016)	(0.004)	(0.147)	(0.143)
lnAUM	-0.056***	-0.007	0.022***	-0.006***	-0.343***	-0.278***
	(0.007)	(0.005)	(0.006)	(0.002)	(0.089)	(0.094)
ln_nomger	-0.032**	-0.043*	-0.113***	-0.024***	0.048	0.156
	(0.014)	(0.023)	(0.023)	(0.006)	(0.178)	(0.179)
Lockup	0.008***	0.009***	0.005***	0.002***	0.055***	0.047**
	(0.001)	(0.002)	(0.002)	(0.001)	(0.018)	(0.018)
MgmtFee	0.088***	0.024	0.055***	0.022***	0.532**	0.383
	(0.017)	(0.021)	(0.017)	(0.005)	(0.264)	(0.292)
IncentiveFee	0.006**	0.005**	0.000	-0.000	0.048*	0.034
	(0.002)	(0.002)	(0.002)	(0.001)	(0.026)	(0.024)
off	-0.044***	-0.101***	-0.093***	-0.014***	-0.710***	-0.713***
	(0.013)	(0.020)	(0.020)	(0.004)	(0.171)	(0.175)
Lagged performance	Yes	Yes	Yes	Yes	Yes	Yes
Strategy dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.523***	0.048	-0.516*	-0.068	-7.709***	-10.211***
	(0.189)	(0.243)	(0.275)	(0.077)	(1.768)	(1.622)
Observations	32,505	32,505	32,505	32,505	32,505	32,502
R-squared	0.319	0.168	0.261	0.411	0.313	0.312

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 20: Changes in management structure

Restrict the sample to team-managed funds without any changes in management structure in the pre- and post-1 year periods and run the following model: $Performance_{i,t+1,t+12} = a_i + b_i Team_{i,t} + c_i Congruence_{i,t} + d_i\, Control_{i,t-23,t} + e_{i,t}$. L1_congruence is measured by the mean of (no. of connected colleagues)/(total no. of managers within fund - 1) across managers in a fund. Dependent variables are performance in subsequent 1 year. Control variables includes 1) logarithm of team-tenure, no of years a team has been working together which is proxied by the average number of years each member has worked for the fund; 2) logarithm of number of managers within a fund; 3) logarithm of fund size; 4) logarithm of fund age in terms of year; 5) sat, average score of every undergraduate institutions that the team members graduated from; 6) corresponding lagged performance during t-23 to t or fund flow for the previous 12 months; 7) other fund characteristics such as lockup periods, management fees, incentive fees, and an offshore dummy; and 8) fund style dummies classified by TASS. Results from Fama-Macbeth model are presented.

	Excess Return	Alpha	IR	SR	MPPM3	MPPM4
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES						
Team	**0.063****	0.079	**0.103*****	**0.025*****	**1.093*****	**1.180*****
	(0.030)	(0.056)	(0.037)	(0.008)	(0.333)	(0.347)
L1_congruence	**-0.078****	**-0.056***	**-0.051****	**-0.017****	**-0.776***	**-0.786***
	(0.033)	(0.028)	(0.023)	(0.008)	(0.392)	(0.409)
sat	0.018**	0.027***	0.023**	0.006***	0.632***	0.712***
	(0.008)	(0.009)	(0.010)	(0.002)	(0.105)	(0.105)
lnfund_tenure	0.028***	0.058***	0.084***	0.030***	0.380***	0.422***
	(0.010)	(0.013)	(0.011)	(0.003)	(0.136)	(0.145)
lnAge	0.125***	0.085***	0.050***	0.032***	1.323***	1.366***
	(0.012)	(0.022)	(0.016)	(0.004)	(0.166)	(0.177)
lnAUM	-0.053***	-0.013*	0.016**	-0.004**	-0.209***	-0.140
	(0.006)	(0.007)	(0.007)	(0.002)	(0.076)	(0.085)
ln_nomger	-0.097***	-0.139***	-0.134***	-0.036***	-1.033***	-0.972***
	(0.017)	(0.032)	(0.027)	(0.005)	(0.214)	(0.222)
Lockup	0.002*	0.007***	0.003**	0.001**	-0.013	-0.021
	(0.001)	(0.002)	(0.001)	(0.000)	(0.018)	(0.018)
MgmtFee	0.075***	0.041*	0.059***	0.010**	0.588***	0.486***
	(0.011)	(0.023)	(0.017)	(0.004)	(0.138)	(0.149)
IncentiveFee	0.010***	0.009***	0.005***	0.001	0.100***	0.086***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.029)	(0.028)
off	-0.054***	-0.127***	-0.102***	-0.009**	-0.668***	-0.600***
	(0.014)	(0.018)	(0.019)	(0.004)	(0.179)	(0.184)
Lagged performance	Yes	Yes	Yes	Yes	Yes	Yes
Strategy dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.565***	0.231	-0.266	0.036	-9.239***	-12.041***
	(0.155)	(0.169)	(0.213)	(0.060)	(1.625)	(1.626)
Observations	40,487	40,487	40,487	40,487	40,487	40,484
R-squared	0.282	0.148	0.247	0.398	0.281	0.279

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 21: Summary statistics of misreporting measures

Panel A presents descriptive statistics on 13 misreporting measures including 1) Dec_flag, flag of a December spike; 2) RDec_flag, flag of a December residual spike; 3) AR_flag, flag of high unconditional serial correlation; 4) CAR_flag, flag of high conditional serial correlation based on magnitude of lagged returns; 5) Maxsq_flag, flag of low maximum adjusted-R2 from factor model; 6) Indexsq_flag, flag of low correlation with funds in the same category; 7) Zero_flag, flag of too many returns with a value as exactly zero; 8) Nega_flag, flag of too few negative returns; 9) Uniform_flag, flag of rejection on null of uniform distribution of last digit; 10) No_Repeated_flag, flag of too few unique returns; 11) Recurring_flag, flag too many recurring blocks of length two; 12) Max_Repeated_flag, flag of too long a string of identical returns; 13) Any_flag, an aggregate measure of above flags. Panel B presents the cross-sectional correlation between fund_team dummy variable and misreporting flags. The star implies a significant association at a 95% confidence level.

Panel A: Descriptive statistics

variable	N	mean	p50	min	p25	p75	max	sd
Dec_flag	1398	0.07	0	0	0	0	1	0.26
RDec_flag	1398	0.09	0	0	0	0	1	0.28
AR_flag	1398	0.42	0	0	0	1	1	0.49
CAR_flag	1398	0.05	0	0	0	0	1	0.23
Maxsq_flag	1398	0.12	0	0	0	0	1	0.33
Indexsq_flag	1398	0.19	0	0	0	0	1	0.39
Zero_flag	1398	0.06	0	0	0	0	1	0.24
Nega_flag	1398	0.17	0	0	0	0	1	0.38
Uniform_flag	1398	0.07	0	0	0	0	1	0.26
No_Repeated_flag	1398	0.66	1	0	0	1	1	0.47
Recurring_flag	1398	0.20	0	0	0	0	1	0.40
Max_Repeated_flag	1398	0.20	0	0	0	0	1	0.40
Any_flag	1398	0.88	1	0	1	1	1	0.33

Panel B: Correlations

	fund_team	Any	AR	CAR	Maxsq	Indexsq	Dec	RDec	Zero	Nega	Uniform	No_Repeated	Recur	Max_Repeated
fund_team	1													
Any_flag	-0.06*	1												
AR_flag	0.01	0.31*	1											
CAR_flag	0.01	0.09*	0.51*	1										
Maxsq_flag	0.05	0.14*	-0.04	-0.07*	1									
Indexsq_flag	0.04	0.18*	-0.02	0.01	0.12*	1								
Dec_flag	-0.05	0.10*	0.05	0.07*	-0.11*	-0.05	1							
RDec_flag	-0.03	0.11*	-0.01	-0.02	-0.18*	-0.04	0.39*	1						
Zero_flag	0.01	0.09*	-0.02	-0.05*	0.00	0.01	0.03	0.01	1					
Nega_flag	0.00	0.17*	-0.04	-0.09*	0.32*	0.08*	-0.02	-0.06*	0.02	1				
Uniform_flag	-0.09*	0.10*	-0.02	-0.01	-0.05	0.03	-0.02	-0.04	0.17*	-0.04	1			
No_Repeated_flag	-0.03	0.52*	0.22	0.04	0.09*	-0.06*	0.00	-0.04	0.08	0.28*	0.08*	1		
Recurring_flag	-0.04	0.18*	0.02	-0.04	0.12*	0.05	0.00	0.01	0.11*	0.11*	0.20*	0.19*	1	
Max_Repeated_flag	-0.04	0.18*	0.02	-0.04	0.12*	0.05	0.00	0.01	0.11*	0.11*	0.20*	0.19*	1.00*	1

Table 22: Misreporting flags in single- versus team-managed hedge funds

This table presents a result of t-test in single- versus team-managed hedge funds on their misreporting measures including 1) Dec_flag, flag of a december spike; 2) RDec_flag, flag of a december residual spike; 3) AR_flag, flag of high unconditional serial correlation; 4) CAR_flag, flag of high conditional serial correlation based on magnitude of lagged returns; 5) Maxsq_flag, flag of low maximum adjusted-R2 from factor model; 6) Indexsq_flag, flag of low correlation with funds in the same category; 7) Zero_flag, flag of too many returns with a value as exactly zero; 8) Nega_flag, flag of too few negative returns; 9) Uniform_flag, flag of rejection on null of uniform distribution of last digit; 10) No_Repeated_flag, flag of too few unique returns; 11) Recurring_flag, flag too many recurring blocks of length two; 12) Max_Repeated_flag, flag of too long a string of identical returns; 13) Any_flag, an aggregate measure of above flags.

Variables	Single-Managed Mean	Team-Managed Mean	Diff in Mean
Dec_flag	0.07	0.08	-0.007
RDec_flag	0.08	0.09	-0.006
AR_flag	0.39	0.44	-0.049*
CAR_flag	0.04	0.06	-0.017
Maxsq_flag	0.14	0.11	0.031*
Indexsq_flag	0.20	0.18	0.027
Zero_flag	0.05	0.06	-0.007
Nega_flag	0.17	0.17	-0.004
Uniform_flag	0.11	0.06	0.048***
No_Repeated_flag	0.68	0.65	0.027
Recurring_flag	0.22	0.19	0.032
Max_Repeated_flag	0.22	0.19	0.032
Any_flag	0.91	0.86	0.043**

*** p<0.01, ** p<0.05, * p<0.1

Table 23: Team structure and misreporting flags

This table presents regression result of the relationship between team structure and fund misreporting behavior. The Probit model applied is as follows: *$Misreporting\_Flag_i = a_i + b_i\, Fund\_team_i + d_i\, Control_i + e_i$ fund_team$_i$ is a dummy variable which equals to 1 if it is managed by a management team for more than half of the observations and 0 otherwise.* Dependent variables are misreporting flags from literature. Control variables includes 1) lnAUM, logarithm of fund size which is the assets under management in millions; 2) lnfund_age, logarithm of fund age in terms of year; 3) fund_ret, the average returns of a particular fund during its returns history; 4) Vol, the standard deviation of a particular fund's return during its returns history.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dec_team_L1	RDec_team_L1	AR_team_L1	CAR_team_L1	Indexsq_team_L1	Maxsq_team_L1
VARIABLES	Dec_flag	RDec_flag	AR_flag	CAR_flag	Indexsq_flag	Maxsq_flag
fund_team	0.034	0.010	0.069	0.141	**-0.160***	**-0.170***
	(0.106)	(0.101)	(0.072)	(0.120)	(0.082)	(0.093)
lnAUM	-0.032	-0.041	0.127***	0.006	-0.022	-0.027
	(0.032)	(0.031)	(0.023)	(0.035)	(0.027)	(0.031)
lnfund_age	0.051	0.025	0.236***	0.146*	-0.293***	-0.282***
	(0.079)	(0.074)	(0.053)	(0.079)	(0.060)	(0.076)
Vol	-0.087***	-0.092***	-0.006	-0.016	-0.088***	-0.101***
	(0.029)	(0.029)	(0.015)	(0.025)	(0.021)	(0.024)
fund_ret	24.696***	27.578***	-14.540**	-17.133**	3.309	11.397
	(7.254)	(7.866)	(6.837)	(7.376)	(6.649)	(7.676)
Constant	-0.830	-0.565	-2.735***	-1.902***	0.264	0.012
	(0.565)	(0.555)	(0.398)	(0.625)	(0.477)	(0.539)
Observations	1,398	1,398	1,398	1,398	1,398	1,398

VARIABLES	(7) Uniform_team_L1 Uniform_flag	(8) Zero_team_L1 Zero_flag	(9) Nega_team_L1 Nega_flag	(10) No_Repeated_team_L1 No_Repeated_flag	(11) Recurring_team_L1 Recurring_flag	(12) Max_Repeated_team_L1 Max_Repeated_flag
fund_team	**-0.309*** **	0.079	-0.062	**-0.170** **	**-0.151* **	**-0.151* **
	(0.103)	(0.115)	(0.085)	(0.075)	(0.081)	(0.081)
lnAUM	-0.010	-0.016	0.097***	0.068***	0.022	0.022
	(0.033)	(0.034)	(0.027)	(0.024)	(0.026)	(0.026)
lnfund_age	0.046	0.032	0.231***	0.458***	0.189***	0.189***
	(0.077)	(0.081)	(0.060)	(0.058)	(0.057)	(0.057)
Vol	0.021	0.021	-0.047**	-0.084***	-0.057***	-0.057***
	(0.019)	(0.018)	(0.019)	(0.014)	(0.018)	(0.018)
fund_ret	2.908	-2.833	-36.183***	-1.353	3.706	3.706
	(7.107)	(6.215)	(6.666)	(5.199)	(7.392)	(7.392)
Constant	-1.255**	-1.445**	-2.648***	-0.987**	-1.245***	-1.245***
	(0.575)	(0.589)	(0.467)	(0.409)	(0.447)	(0.447)
Observations	1,398	1,398	1,398	1,398	1,398	1,398

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 24: Team structure and aggregate misreporting flag

This table presents regression result of the relationship between management structure and an aggregate measure of the aforementioned misreporting flags with or without controls. The Probit model applied is as follows: $Misreporting\_Flag_i = a_i + b_i\ Fund\_team_i + d_i\ Control_i + e_i\ \ fund\_team_i$. *fund_team is a dummy variable which equals to 1 if it is managed by a management team for more than half of the observations and 0 otherwise.* Control variables includes 1) lnAUM, logarithm of fund size which is the assets under management in millions; 2) lnfund_age, logarithm of fund age in terms of year; 3) fund_ret, the average returns of a particular fund during its returns history; 4) Vol, the standard deviation of a particular fund's return during its returns history.

	(1)	(2)
	Any_team_L1	Any_fund_team_L1_con
VARIABLES	Any_flag	Any_flag
fund_team	**-0.160***	**-0.275*****
	(0.090)	(0.096)
lnAUM		0.063**
		(0.028)
lnfund_age		0.225***
		(0.073)
Vol		-0.081***
		(0.015)
fund_ret		-6.035
		(5.939)
Constant	1.233***	0.249
	(0.074)	(0.476)
Observations	1,398	1,398

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 25: Team congruence and misreporting flags

This table presents regression result of the relationship between team congruence level and fund misreporting behavior. The Probit model applied is as follows: $Misreporting\_Flag_i = a_i + c_i Mean\_congruence_i + d_i Control_i + e_i$. Mean_L1_congruence is the average team congruence level in terms of educational background during the fund's history. Dependent variables are misreporting flags from literature. Control variables includes 1) lnAUM, logarithm of fund size which is the assets under management in millions; 2) lnfund_age, logarithm of fund age in terms of year; 3) fund_ret, the average returns of a particular fund during its returns history; 4) Vol, the standard deviation of a particular fund's return during its returns history.

VARIABLES	(1) Dec_team_L1 Dec_flag	(2) RDec_team_L1 RDec_flag	(3) AR_team_L1 AR_flag	(4) CAR_team_L1 CAR_flag	(5) Indexsq_team_L1 Indexsq_flag	(6) Maxsq_team_L1 Maxsq_flag
Mean_congruence	**-0.655***	0.124	0.223	-0.039	-0.129	0.038
	(0.358)	(0.240)	(0.170)	(0.209)	(0.274)	(0.249)
lnAUM	-0.026	-0.051	0.158***	0.015	-0.005	0.018
	(0.042)	(0.043)	(0.030)	(0.037)	(0.042)	(0.045)
lnfund_age	0.068	0.036	0.206***	-0.299***	-0.262***	0.221**
	(0.102)	(0.100)	(0.067)	(0.078)	(0.101)	(0.102)
Vol	-0.089**	-0.159***	-0.011	-0.125***	-0.184***	-0.029
	(0.036)	(0.039)	(0.019)	(0.033)	(0.042)	(0.030)
fund_ret	25.359**	39.842***	-20.414***	14.695	15.148	-24.301**
	(11.103)	(11.795)	(6.818)	(9.417)	(12.766)	(9.964)
Constant	-0.868	-0.295	-3.142***	-0.481	-0.372	-2.014**
	(0.723)	(0.741)	(0.521)	(0.645)	(0.747)	(0.792)
Observations	882	882	882	882	882	882

VARIABLES	(7) Uniform_team_L1 Uniform_flag	(8) Zero_team_L1 Zero_flag	(9) Nega_team_L1 Nega_flag	(10) No_Repeated_team_L1 No_Repeated_flag	(11) Recurring_team_L1 Recurring_flag	(12) Max_Repeated_team_L1 Max_Repeated_flag
Mean_congruence	0.285	0.188	-0.187	-0.189	0.202	0.202
	(0.243)	(0.230)	(0.212)	(0.176)	(0.194)	(0.194)
lnAUM	0.004	-0.032	0.116***	0.064**	0.014	0.014
	(0.047)	(0.044)	(0.034)	(0.031)	(0.035)	(0.035)
lnfund_age	-0.022	0.081	0.256***	0.400***	0.198***	0.198***
	(0.107)	(0.101)	(0.076)	(0.073)	(0.074)	(0.074)
Vol	0.047**	0.031	-0.031	-0.075***	-0.070***	-0.070***
	(0.024)	(0.022)	(0.022)	(0.019)	(0.026)	(0.026)
fund_ret	6.586	4.945	-39.915***	-3.998	-5.642	-5.642
	(10.573)	(7.979)	(8.600)	(6.888)	(8.788)	(8.788)
Constant	-1.858**	-1.258*	-3.106***	-1.006*	-1.209**	-1.209**
	(0.818)	(0.763)	(0.592)	(0.530)	(0.603)	(0.603)
Observations	882	882	882	882	882	882

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 26: Team size and misreporting flags

This table presents regression result of the association between team structure and fund misreporting behavior. The Probit model applied is as follows: $Misreporting\_Flag_i = a_i + bimger2_i + cimger3_i + dimger4_i + fimger5_i + gi\ Control_i + e_i$. mger2/mger3/mger4/mger5 are dummy variables which equals to 1 if the fund is managed by a management team with 2 or 3 or 4 or more than 4 managers and 0 otherwise. Dependent variables are misreporting flags from literature. Control variables includes 1) lnAUM, logarithm of fund size which is the assets under management in millions; 2) lnfund_age, logarithm of fund age in terms of year; 3) fund_ret, the average returns of a particular fund during its returns history; 4) Vol, the standard deviation of a particular fund's return during its returns history. Panel A show results of misreporting measures from previous studies while Panel B exhibit results by an aggregate measure.

Panel A: Misreporting measures from previous literature

	(1)	(2)	(3)	(4)	(5)	(6)
	Dec_team_L1	RDec_team_L1	AR_team_L1	CAR_team_L1	Indexsq_team_L1	Maxsq_team_L1
VARIABLES	Dec_flag	RDec_flag	AR_flag	CAR_flag	Indexsq_flag	Maxsq_flag
mger2	0.024	-0.042	0.061	-0.019	**-0.180***	-0.149
	(0.131)	(0.123)	(0.086)	(0.150)	(0.099)	(0.113)
mger3	-0.027	-0.120	0.077	0.142	**-0.236****	-0.210
	(0.157)	(0.150)	(0.101)	(0.165)	(0.120)	(0.136)
mger4	**0.435****	0.203	0.135	0.181	**-0.323***	**-0.541****
	(0.177)	(0.179)	(0.135)	(0.213)	(0.167)	(0.217)
mger5	0.165	0.016	-0.165	**0.462*****	0.058	-0.234
	(0.177)	(0.174)	(0.127)	(0.178)	(0.137)	(0.169)
lnAUM	-0.040	-0.044	0.131***	-0.002	-0.025	-0.024
	(0.034)	(0.032)	(0.023)	(0.037)	(0.025)	(0.029)
lnfund_age	0.044	0.017	0.237***	0.145*	-0.297***	-0.289***
	(0.078)	(0.075)	(0.053)	(0.087)	(0.063)	(0.071)
Vol	-0.087***	-0.093***	-0.008	-0.014	-0.086***	-0.101***
	(0.026)	(0.025)	(0.014)	(0.024)	(0.019)	(0.023)
fund_ret	25.002***	27.754***	-14.623***	-16.655*	3.301	10.997
	(7.883)	(7.383)	(4.870)	(9.180)	(6.017)	(7.056)
Constant	-0.736	-0.470	-2.777***	-1.764***	0.325	-0.005
	(0.584)	(0.556)	(0.401)	(0.643)	(0.442)	(0.514)
Observations	1,398	1,398	1,398	1,398	1,398	1,398

VARIABLES	(7) Uniform_team_L1 Uniform_flag	(8) Zero_team_L1 Zero_flag	(9) Nega_team_L1 Nega_flag	(10) No_Repeated_team_L1 No_Repeated_flag	(11) Recurring_team_L1 Recurring_flag	(12) Max_Repeated_team_L1 Max_Repeated_flag
mger2	**-0.467*** **	-0.058	-0.061	-0.123	-0.085	-0.085
	(0.137)	(0.139)	(0.101)	(0.090)	(0.097)	(0.097)
mger3	-0.122	**0.243***	-0.031	-0.014	-0.025	-0.025
	(0.141)	(0.147)	(0.118)	(0.107)	(0.112)	(0.112)
mger4	0.239	-0.002	-0.124	-0.199	-0.206	-0.206
	(0.167)	(0.216)	(0.160)	(0.142)	(0.158)	(0.158)
mger5	**-1.142*** **	-0.092	**-0.394** **	**-0.466*** **	-0.197	-0.197
	(0.372)	(0.212)	(0.159)	(0.128)	(0.144)	(0.144)
lnAUM	-0.011	-0.013	0.104***	0.073***	0.023	0.023
	(0.033)	(0.036)	(0.027)	(0.023)	(0.025)	(0.025)
lnfund_age	0.055	0.027	0.230***	0.460***	0.189***	0.189***
	(0.080)	(0.084)	(0.064)	(0.056)	(0.060)	(0.060)
Vol	0.017	0.019	-0.050***	-0.086***	-0.056***	-0.056***
	(0.020)	(0.021)	(0.019)	(0.015)	(0.018)	(0.018)
fund_ret	4.434	-3.592	-36.684***	-1.488	3.843	3.843
	(6.824)	(7.834)	(6.949)	(5.060)	(5.521)	(5.521)
Constant	-1.248**	-1.459**	-2.732***	-1.082***	-1.296***	-1.296***
	(0.575)	(0.616)	(0.481)	(0.406)	(0.442)	(0.442)
Observations	1,398	1,398	1,398	1,398	1,398	1,398

Panel B: Aggregate measure

	(1)	(2)
	Any_team_L1	Any_fund_team_L1_con
VARIABLES	Any_flag	Any_flag
mger2	**-0.198***	**-0.280****
	(0.106)	(0.110)
mger3	0.002	-0.089
	(0.131)	(0.136)
mger4	-0.173	**-0.279***
	(0.165)	(0.169)
mger5	-0.241	**-0.455*****
	(0.148)	(0.157)
lnAUM		0.065**
		(0.028)
lnfund_age		0.227***
		(0.073)
Vol		-0.082***
		(0.015)
fund_ret		-5.896
		(5.964)
Constant	1.229***	0.210
	(0.074)	(0.473)
Observations	1,398	1,398

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1