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Alumni social networks and hedge fund performance: Evidence from China

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A R T I C L E I N F O

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A B S T R A C T

Based on unique data of Chinese private hedge funds, we first construct the "strong alumni" (alumni of the same school and the same major) social networks of private hedge fund managers, and examine the impact of alumni social networks on the performance of hedge funds in China. We build a series of alumni networks using the educational background information of 4734 private hedge funds, and perform an empirical analysis on a sample of 1115 private hedge funds products from 2010 to 2019. Different from previous findings of mutual funds, we find that more central network positions of hedge fund managers are associated with better risk-adjusted fund performance. Hedge fund managers with more central positions conduct more active investment styles and receive lower fund flows.[1] The results supplement the evidence that information advantages brought by central position in social networks can influence managers' investment styles, thus improve hedge fund performance.

1. Introduction

Studies on social networks in the fund market have grown dramatically and have become a promising field recently. Such networks bring the potential for personal interaction and information exchange, which will influence the behavior of fund managers and then their investment performance (Pool, Stoffman, & Yonker, 2015). Most of the existing research focus on mutual funds in developed markets since reliable and accurate data of hedge funds are often difficult to obtain due to the nature of voluntary reporting in the industry (Hong, Jiang, Yan, & Zhao, 2017). However, hedge funds are different from mutual funds in many ways (Zhao, Li, & Chen, 2018), such as incentive mechanism, investing scope, and information disclosure, leading to different management objectives between hedge fund managers and mutual fund managers. Thus, the impacts of social networks on hedge funds remain unclear. China is a meaningful case for this study not only for the rapid development of Chinese hedge fund industry but also for the Chinese culture that values personal relationship ("Guanxi" in Chinese), which makes social network effects more typical and obvious. Using our unique data which cover more comprehensive types of hedge funds in China, we figure out the alumni social network effects on hedge funds, which is different from the previous conclusions of mutual funds, and we further explore the influencing mechanism.

The social networks of fund managers include several types: college alumni, colleagues, association members, etc. Among these social connections, alumni relationships are more special than other business connections. First, people usually choose schools and majors according to their interests and abilities, thus, schoolmates naturally share the same interests. This identity recognition exists even after graduation (Cohen, Frazzini, & Malloy, 2008; McPherson, Smith-Lovin, & Cook, 2001). Second, for alumni of similar grades, educational connection means common memories of campus life. Beautiful memories can shorten psychological distance and build trust among fund managers, thus providing better opportunities to interact and share information with others. Third, alumni share the same school culture. Each college has its own unique history and culture, such as special school mottos. The experience of immersing in the common school culture will affect the thinking of students, which also makes it easy to form trust and empathy between alumni (Ingram & Zou, 2008; Zou & Ingram, 2007).

Most existing studies about alumni networks in fund markets focus on mutual funds(Liu, Liu, Li, & Li, 2020). Due to the difficulty of data acquisition and the lack of related study, whether the alumni networks of managers have impact on hedge fund performance and, further, how the networks affect hedge funds remain unclear. The following differences between mutual funds and hedge funds motivate our research interest.

First, there are significant differences between hedge funds and mutual funds in terms of raising channels, incentive mechanism, management requirements, asset allocation requirements, redemption, and information disclosure, etc., which leads to different management

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[1] We use the term "fund flow" to refer to the money flow into hedge funds. Please see the detailed definition in Section 5.4.

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objectives of hedge funds and mutual funds. Taking the incentive mechanism as an example, mutual funds do not bind their own money to clients' assets into investment and do not share risks with clients, which are also called OPM (other people's money) contracts. The incomes of mutual fund managers mainly come from fixed management fees without share of excess return. Different from mutual funds, hedge funds adopt a mode of risk sharing and return sharing. Hedge funds typically integrate what is known as a 'two-and-twenty fee' which includes a management fee of 2% and a performance fee of 20%. The incomes of hedge fund managers come from three parts: the first is to charge a fixed management fee of 2% no matter whether the performance is good or not; the second is that when the fund performance exceeds the high-water mark agreed in the contract, the hedge fund manager can get 20% of the income share; the third is the capital gain from the binding investment of the fund manager's own equity with the client's assets. It can be seen that the management objectives of hedge fund managers and mutual fund managers are hugely different. Unlike mutual fund managers whose incomes are linked to asset size, hedge fund managers' incomes are more related to excess returns. Hedge fund managers can be both friends and counterparties. This competitive relationship may make them less willing to share investment ideas through social connections than mutual fund managers.

Second, researchers have found that hedge fund managers are quite different from their mutual fund peers (Goetzmann, Ingersoll, Spiegel, & Welch, 2007; Zhang, Zhang, Li, & Feng, 2021). Compared with market benchmarks, mutual fund managers do not have superior market timing or stock selection ability (Goetzmann et al., 2007), while hedge fund managers usually have good investment performance and professional ability (Agarwal & Meneghetti, 2011; Stulz, 2007). Overall, these differences of information flow and agent abilities imply some surprising effects of alumni network on the hedge fund compared with mutual fund networks.

Our study uses representative samples from China, including more than 4700 hedge funds spanning a decade. China is a meaningful research case because of its strong social-economic environment. In recent years, the hedge funds industry in China develops from near non-existence in 2002 to more than $2.1 trillion assets under management by the end of 2019, which is now comparable with the mutual fund industry in China.[2] The remarkable development of China' hedge fund industry provides us with ample and valuable research samples. Moreover, Chinese culture values personal relationship ("Guanxi" in Chinese) and "Guanxi" is one of the major dynamics in Chinese society (Luo, 1997; Tsang, 2002). Educational connection is a main source to form personal social network. In the Chinese security market, there are several famous alumni groups, such as "Tsinghua Circle", "Fudan Circle" and "Peking Circle", showing that alumni connections play an important role in Chinese financial markets.

The representativeness of our data is more embodied in that it includes more comprehensive types of hedge funds. Researchers have used the data of "sunshine hedge fund", which only invest in stocks and is subject to relatively strict information disclosure requirements, to study the social network effect of hedge funds in China (Li, Li, Wang, & Xiao, 2020). However, hedge funds that investing in stocks only account for 59% of all the hedge fund products in China (Zhao et al., 2018). It means that the social network effects on the other nearly-half of the hedge funds in China is still unknown. Our unique data contains not only stock strategy hedge funds but also hedge funds that invest in other assets such as futures, warrants, currencies, and bonds.

Using the sample of 4734 hedge funds in China, we build a series of alumni networks which evolve over time, and conduct empirical analysis of the impact of social network on the performance of hedge funds. We build "strong alumni networks" among hedge funds which require the fund managers graduating from the same school and majoring in the same directions.[3] We adopt text analyze technology to determine whether two majors with different Chinese names belong to the same research direction. This definition of alumni relationship captures more nuanced differences between majors and filter out weak connections that may not exist in reality. We also aggregate multiple-manager level information into the unified-manager level to better measure the full benefits of multiple managers bringing to the fund.

To measure the network position of hedge funds, we generate four proxies, namely, degree centrality, betweenness centrality, closeness centrality, and clustering coefficient.[4] We find that alumni network position has significant impact on the risk-adjusted investment performance of hedge funds in China. The effects of the three centrality measures on performance are all positive, which are contrary to the network effects found on mutual funds (Qi, Li, Xie, & Ding, 2020). Moreover, we introduce a new proxy of social network position, that is, clustering coefficient, and find its strongly negative effects on risk-adjusted return (significant at the 0.001 level), which is rarely noticed in the previous research. The results are robust to fund fixed effect and to time fixed effect. We then examine the network effects under different abilities and different strategies. The results show that the influence of alumni network on hedge fund managers with different abilities is significant and similar. However, the network effects vary under different strategies. For example, the degree centrality measure has positive effects on stock strategy hedge funds while having a negative effect on fixed income strategy hedge funds, showing that managers who adopt stock strategy benefit more from the width of alumni relationships.

To further specify a channel through which the alumni network can affect fund return performance, we conduct a mediation analysis of investment style. Our results show that investment style is a full mediator of alumni network effect on hedge fund performance. Alumni social network of hedge fund managers exert its positive influence on fund performance by changing the managers' investment styles. Hedge funds of more central network position invest more in the assets of high risk, such as stocks and warrants. It indicates the information advantages of central nodes in the alumni social network, which can improve the fund managers' risk management and enhance their confidence to pursue higher return.

Finally, we analyze whether fund managers' position in the alumni network affects flows of money into the hedge funds they manage. The results show the negative effects of alumni network on hedge fund flows. The width and depth of a fund manager's alumni relationships result in fund size reduction.

Our contributions to the extant literature are three-fold. First, we contribute to the literature of social network effects in financial markets. The most important finding is that we find out the influence path of social networks on the performance of hedge funds, that is, the information advantages brought by social networks affect the investment styles of managers, thus improve the fund performance. Unlike previous studies which only analyze the investment of hedge funds in the stock market, we conduct empirical analysis using the data of specific investment proportion of hedge funds in different assets such as stocks, warrants, futures and so on. Our study provides a deeper insight into the mechanism of how the social network affects hedge fund performance. Specifically, a more central network position leads to a more active investment style. This is supplement evidence that social networks

[2] By the end of 2019, the asset size of China's mutual fund industry was about $2.66 trillion. Data source: China Private Securities Investment Fund Annual Report by the Asset Management Association of China. http://www.amac.org.cn/.

[3] "Majoring in the same directions" means the study fields of these majors are similar. Please see the detailed definition in Section 4.1.

[4] Clustering coefficient is one of the basic properties of networks. This coefficient describes "what proportion of the acquaintances of a vertex know each other". See Bela and Riordan (2003) for a thorough introduction of clustering coefficient.

influence the investment behavior of agents.

Second, we provide empirical evidence for the detailed effects of alumni social networks on hedge fund performance. We find the positive influence of network centralities on hedge fund performance, which is contrary to the findings of mutual funds. Moreover, we find the social network effects on hedge funds vary under different strategies. This is a new finding in the related literature.

Finally, we contribute to the financial network theory by introducing a new construction method of alumni social network and a new proxy variable for financial network position measurement. By defining the "strong alumni relationship" which requires the same graduating school and the same major direction, we can filter out weak connections that may not exist in reality and build social networks that are more realistic. In addition, we find a new proxy variable for network position measurement, that is, clustering coefficient, which is rarely noticed by previous research of social networks in financial and economic systems. We find that the clustering coefficient has significant and different explanatory power compared to the centrality measures.

The rest of the paper is organized as follows. Section 2 reviews related literature and provides hypothesis. Section 3 introduces our data. Section 4 introduces the methodology of network construction and network position measures, and presents empirical evidence on the evolution of the networks. Section 5 presents descriptive statistics and empirical results. Section 6 conducts robustness tests. Section 7 summarizes and concludes.

2. Literature review and hypotheses

Prior research has begun to introduce social networks, as the instrument of social sciences, into the area of finance and corporate governance. It is found that economic agents are influenced by their social ties (Coleman, 1988). One of the most concerned topics is the relationship between social networks and investment behaviors. Hochberg, Ljungqvist, and Lu (2007) establish a network through syndicated investment of venture capital (VC) firms and find that more central VC firms experience significantly better fund performance. Cohen et al. (2008) focus on connections between mutual fund managers and corporate board members via alumni networks and find that social networks may be important mechanisms for information flow into asset prices. Pool et al. (2015) use residence to capture social connections between fund managers and find that socially connected fund managers have more similar holdings and trades. Rossi, Blake, Timmermann, Tonks, and Wermers (2018) investigate the relationship between network centrality and delegated portfolio management performance, and find that better-networked managers take more portfolio risk, receive higher fund flow, and achieve better fund performance.

A possible path through which social networks influence the investment behaviors of economic agents is the information-access hypothesis (Chahine, Fang, Hasan, & Mazboudi, 2019). Personal social connections are deemed to increase access to more valuable information and promote the dissemination of information in social networks (Pool et al., 2015). Information and knowledge can be transmitted through social networks and may have three kinds of impacts on the connected members. First, managers make decisions based on the information and knowledge they have obtained. For example, superior information will lead managers to invest more in companies or stocks they are familiar with (Cohen et al., 2008). Second, information advantage will enhance the confidence of managers and affect investment styles (Rossi et al., 2018). Third, social interactions offer opportunities for a manger to observe competitors' actions, resulting in imitation to excellent peers and similar portfolios (Hong, Kubik, & Stein, 2005).

Moreover, information received by different positions in social networks may vary. A position of centrality is found enjoying greater control of information flow compared to those located on the periphery (Brass, 1992; Brass & Burkhardt, 1992; Burt, 1982). Investors of dominant network positions tend to trade earlier and earn higher returns (Ozsoylev, Walden, Yavuz, & Bildik, 2014). From this perspective, the position of a manager in the social network has an important impact on his investment behavior, which means the characteristic of the relationships between individuals and the overall network is an important issue.

Empirical studies have shown that information benefits brought by central positions of networks can turn into better investment performance. Shen, Zhao, and He (2015) find that investors with larger alumni networks are more likely to get private information about stocks thus achieving better returns in stock market. Liu et al. (2020) find that fund managers' degree of centrality in social networks has a significant positive effect on their information sharing and trading behaviors. Consistent with the perspective of "information benefits", we present our first hypothesis:

H1. Information-benefits hypothesis. Hedge funds with more central network positions have better performance relative to those located on the periphery of their alumni social networks.

Another stream of literature suggests that the information exchange through social networks will lead to imitation and portfolio homogenization, thus having a negative impact on investment performance. Pareek (2012) presents evidence of information linkages between funds with large positions in the same stocks. Kellard, Millo, Simon, and Engel (2017) find that the communication and idea sharing between competing hedge funds will lead to "expertise-based" herding. Qi et al. (2020) study the college network effects on mutual funds in China, and find that mutual fund managers with alumni connection tend to have similar portfolio allocation and the performance of socially connected funds is worsened by the degree of the connection. It seems that social networks are a channel for information leakage and can undermine the vantage of excellent managers. Hence, we present the following hypothesis:

H2. Information-leakage hypothesis. Hedge funds with more central network positions have worse performance relative to those located on the periphery of their alumni social networks.

3. Data

Our empirical analysis is based on data of hedge funds in China from 2010 to 2019. The studied data mainly come from Simuwang database and supplemented by CSMAR database. Different from most previous studies on social network of Chinese hedge funds, our research sample includes not only stock hedge funds, but also hedges funds that invest in other assets, such as futures, warrants, currencies, bonds and so on. The key parts of the data, including managers' educational backgrounds, net value of hedge funds, asset size of hedge funds, fund flows and investment allocation, are provided by Simuwang database. Factor data used to calculate four-factor risk-adjusted performance are obtained from the CSMAR database. In our data set, the frequency of hedge fund managers' changes reporting is quarterly, while the net value data is monthly. In general, the change of fund managers is not very frequent, so it is a reasonable assumption that the managers have not changed within a quarter. Therefore, we sort the sample data into monthly frequency.

We examine the impact of alumni networks of hedge fund managers on investment behaviors and fund performance for the period of January 2010 to December 2019. During this period, we totally collect a data set of 4734 hedge funds which have reported the educational backgrounds of their managers. A series of alumni networks updated over time was built and we compute the network position measures on the basis of this series. In the regression analysis, we exclude the data of hedge funds that had reported monthly net value less than 12 times during the period for the accuracy of estimations. The data of isolated nodes in the networks are also excluded. The data for regression analysis contains 1150 hedge fund products and 202 of the 1150 have reported their asset allocations.

Finally, the data for network construction contains 4734 hedge funds, the data for regression analysis contains 1150 hedge fund products and 20,568 observations, and the data for investment style analysis contains 202 hedge funds with 1654 observations.

4. Methodology

4.1. Network construction

A social network is characterized by its nodes (agents) and edges (social connections). In an alumni network, each node represents a hedge fund, and each edge represents the educational connection between two linked nodes. We built an alumni social network between hedge funds in China through "strong alumni" relationship which requires the connected pairs graduate in the same graduated school and the same major direction.

Thanks to the detailed data, we are able to establish more accurate alumni connections than those in previous literature. In China, many universities have a large number of majors. Not only are the courses varied among majors, but also the time and place of classes are quite different. It is not easy to develop close friendships with students of other majors because of the different schedules. However, students in the same major take common courses together and usually have sports and entertainment together in their spare time, which makes them closer to each other than to those of other majors in the same school. Despite the obvious effects of majors, few researchers have considered it in the alumni networks. Inspired by the previous work, we consider the difference of majors when we built the network. When defining the alumni relationship, we require not only the same school, but also the same major direction. This definition is closer to reality. Alumni from the same school and the same major have more opportunities to know and communicate with each other in the school. They often become friends before graduation. Therefore, we use "strong alumni" relationships to capture more nuanced differences between majors and filter out weak connections that may not exist in reality.

Since different schools have different names for majors (for example, the names of "business administration" and "business management" in Chinese are different, but the contents of these two majors are similar), we use text analysis technology to decompose the majors' names into more refined nouns, which represents the exact content of this major (it is worth noting that the text content processed is all in Chinese). Each major's name is decomposed into a phrase vector. According to the overlapping degree of the phrase vectors, we can judge whether the two majors belong to "the same major direction". As there have been many name changes and mergers of schools and colleges, we use the names of universities and colleges in 2019 to denote schools. For foreign universities, we adopt unified translations to avoid inconsistency.

Using the educational background information of hedge fund managers, we construct the alumni network among hedge funds in China. In the established networks, each node represents a hedge fund and a link (edge) between two nodes is the educational connection between the two hedge funds. We first aggregate manager-level information into the fund-level. In the studied data set, the proportion of fund managers with master's degree or above is 74.8%. It is common for highly educated managers to experience more than one school. In fact, more than 34% of the hedge fund managers in our data set have attended two or more schools. For example, fund manager m_1 of hedge fund f_1 graduated from school A with a bachelor's degree and from school B with a master's degree, manager m_2 of hedge fund f_2 graduated from school C with a bachelor's degree, from school D with a master's degree and school B with a doctor degree. There exists an educational connection between m_1 and m_2 in terms of school since they are all alumni of school B.

Further, we aggregate multiple-manager level information into the unified-manager level. For many hedge funds, there is more than one manager. In our data, about 24% of hedge funds have two or more managers. When dealing with multiple-manager funds, much of the literature builds social networks between fund managers and take the network position of one of the managers to represent the fund's network position (Li et al., 2020). The implication behind this proxy is to use some weighted average of fund managers' social competence (such as the highest, the median, or the lowest network centrality of the managers) to represent the entire fund. In fact, the social competence of a fund should be the aggregate rather than the average of its managers. Every manager's social network can bring information benefits to the fund, not just those with the most extensive social network. Therefore, for fund manager m_1 of a hedge fund f_1, graduated from school A, B, and C, studied in major a, b, and c, and fund manager m_2 of f_1, graduated from school D, and E, studied in major d and e, we then treat the educational background information set of hedge fund f_1 as $\{School; Major: A, B, C, D, E; a, b, c, d, e\}$.

To construct networks, we include all hedge funds present at a given point in time. This allows us to construct a time series of alumni network. The frequency of fund manager changes reporting is quarterly thus we update the alumni network every quarter. During the sample period from January 2010 to December 2019, totally 24 alumni networks are established and analyzed. Fig. 1 shows the alumni networks at three points in time during our sample, namely, the December 2013, December 2016, and December 2020.

4.2. Measuring network position

Network centrality can be used as a measure of node importance and a proxy of network location (Billio, Getmansky, Lo, & Pelizzon, 2012). To capture the different dimensions of network effect, there are several designs of network centrality. Because of such differences, we employ three centrality measures, namely, degree centrality, betweenness centrality, and closeness centrality, to ensure robustness of our empirical analysis.

The first measure of network centrality, degree centrality, measures the number of neighbors of a particular node, relative to the total number of nodes (Freeman, 1978). For a specific network node, i.e., a hedge fund manager, degree centrality can be interpreted as the immediate probability that the node gains information through its alumni. The degree centrality of node j at time t, DE_{jt}, is defined as

$$DE_{jt} = \frac{d_{jt}}{N_t - 1} \tag{1}$$

where d_{jt} is the number of connected neighbors of node j at time t and N_t is the total number of nodes in the network at time t.

The second measure of network centrality, betweenness centrality, is a measure of all the shortest paths in the network through a given node in the fraction form. It measures the degree of control of a node over important paths and captures the importance of a node in connecting other nodes (Freeman, 1977). The betweenness centrality of node j at time t, BE_{jt}, is defined as

$$BE_{jt} = \frac{\sum_{k \neq i; j \neq k; j \neq i} \frac{P_{jt}(k,i)}{P_t(k,i)}}{(N_t - 1)(N_t - 2)/2} \tag{2}$$

where $P_{jt}(k,i)$ is the number of shortest paths between node k and i that pass through node j at time t, and $P_t(k,j)$ is the number of shortest paths between node k and i at time t.

Thirdly, closeness centrality is calculated by taking the reciprocal of the average length of the shortest paths between the relevant node and all others. It measures how central a given node is in the network (Sabidussi, 1966). In particular, the closer a node is to other nodes, the more central it is. The closeness centrality of node j at time t, CE_{jt}, is defined as

$$CE_{jt} = \frac{N_t - 1}{\sum_{i \neq j} l_t(j,i)} \tag{3}$$

where $l_t(j,i)$ is the length of shortest path between node j and i at time t.

Moreover, we consider clustering coefficient into the model. The

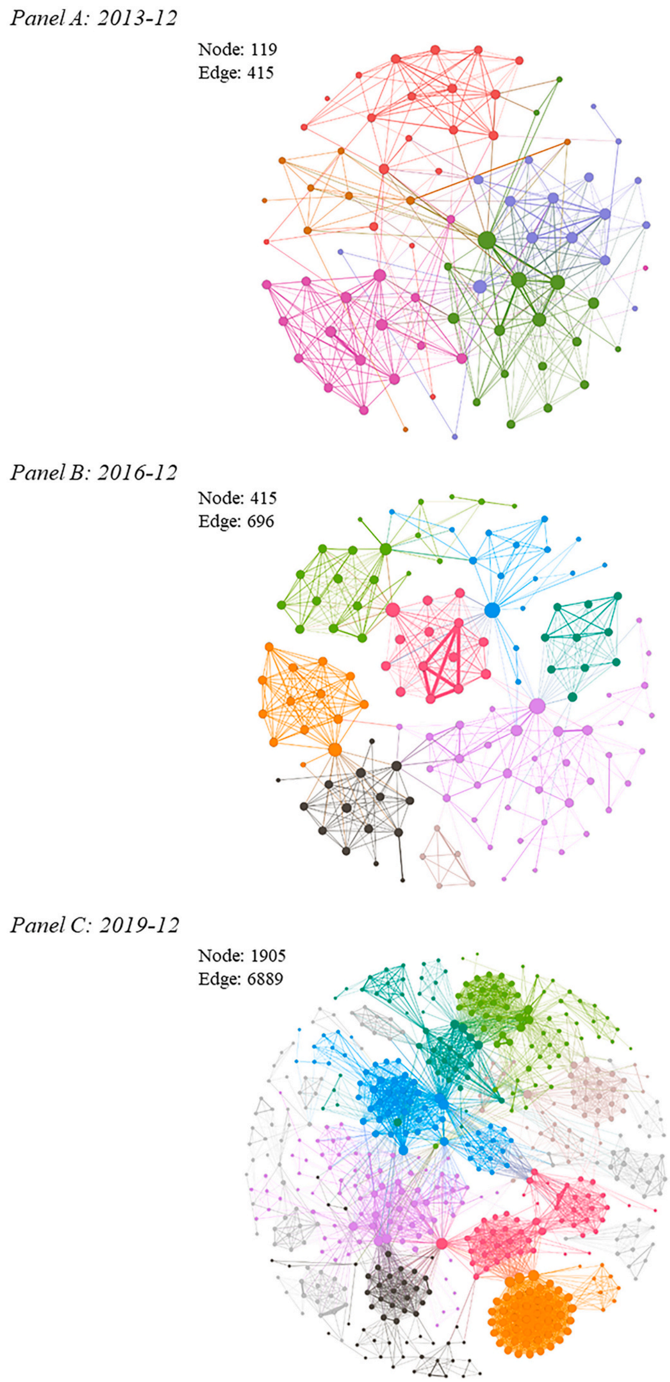

Fig. 1. Alumni networks of hedge funds in China. Each panel shows the giant component of the alumni network. The size of a node represents the degree of the node and the color denotes the community it belongs to.

clustering coefficient of node j at time t, CC_{jt}, is defined as

$$CC_{jt} = \frac{2e_{jt}}{d_{jt}\left(d_{jt}-1\right)} \tag{4}$$

where e_{jt} is number of edges between the neighbors of node j (Bela & Riordan, 2003).

Clustering coefficient is a measure of the closeness of groups in a network. Different from the above three centrality measures which compute the individual importance of the node itself, clustering coefficient is a density measure that focuses on j-centered subnetworks. Considering a subnetwork G_j formed by node j and its directly connected neighbors $j_k^{neighbor}$. The higher the clustering coefficient of fund manager j is, the higher is the density of the subnetwork G_j. In the alumni social network constructed in this study, if CC_{jt} is considerably low, then the probability of the existence of connection between any neighbor $j_k^{neighbor}$ and $j_i^{neighbor}$ is also low, which means that $j_k^{neighbor}$ cannot connect to $j_i^{neighbor}$ without the existence of node j. A low CC_{jt} means that the connections in the j-centered subnetwork G_j is sparse. If we take away node j, the connectivity of G_j would be sharply reduced and the other nodes in G_j would be unconnected (which means node j is important in its directly connected subnetwork). When CC_{jt} is high, G_j is dense and the absence of node j would not have much effect on the connectivity of G_j. The other nodes of G_j can still get in touch with each other without node j (which means node j is not important in its directly connected subnetwork).

4.3. Evolution of the networks

Fig. 1 suggests that the number of funds and connections in the network has changed substantially over time, indicating the structural changes in the alumni network series over time. The evolution of the alumni network of fund managers is mainly caused by three factors: (1) the emergence of new hedge funds; (2) the withdrawal of old hedge funds; (3) the change of fund managers of existing funds.

We next study the time-series of the average network position measures to explore how the alumni social networks of hedge fund managers evolved during our sample. We first standardize each network position measure, that is, the three centrality measures and clustering coefficient, by subtracting its time series average and divided by its standard deviation. Then we get measures with mean zero and unit variance. Let $Net_t = N_t^{-1}\sum_{i=1}^{N_t} Net_{it}$ be the cross-sectional average network position measure at the beginning of quarter t, average across N_t hedge funds in existence. $MEAN(Net_t)$ and $STDEV(NET_t)$ are time series statistics of Net_t computed over the full sample from 2010 to 2019. The standardized network position measure is then computed as:

$$S\_NET_t = \frac{Net_t - MEAN(NET_t)}{STDEV(NET_t)} \tag{5}$$

Fig. 2 plots the time series of the normalized network position measures, S_NET_t, over our sample period. For all four measures, they are relatively stable from 2010 to 2013. However, from 2014 to 2016, all four measures fluctuate violently. In 2014 and 2015, both degree centrality measure and closeness centrality measure decreased sharply and returned to the average level rapidly in the second half of 2016. We use the trading volume of CSI 300 index to represent the dynamics of Chinese security market at the same time. As can be seen from Fig. 2, the trading volume of CSI 300 index from 2014 to 2016 is much higher than that in other periods, which indicates a special state of Chinese financial market at that time.[5] This is consistent with the period when the rapidly structural changes of the network of hedge funds happen. This synchronicity suggests that the particular volatility of Chinese financial market will affect the hedge fund industry and is reflected in the alumni network structure of fund managers, making the structural changes of the fund network a good window to explore financial risks.

Moreover, we find that the volatilities of betweenness centrality measure and clustering coefficient measure lag behind that of the trading market. It indicates not only that the four network position measures share a common trend component, but also that each measure of network position captures somewhat different short-run information.

[5] In 2015, the Chinese stock market experienced a crash of about 40% after reaching its second highest in history. The trading volume curve captures the abnormal activity of the Chinese financial market.

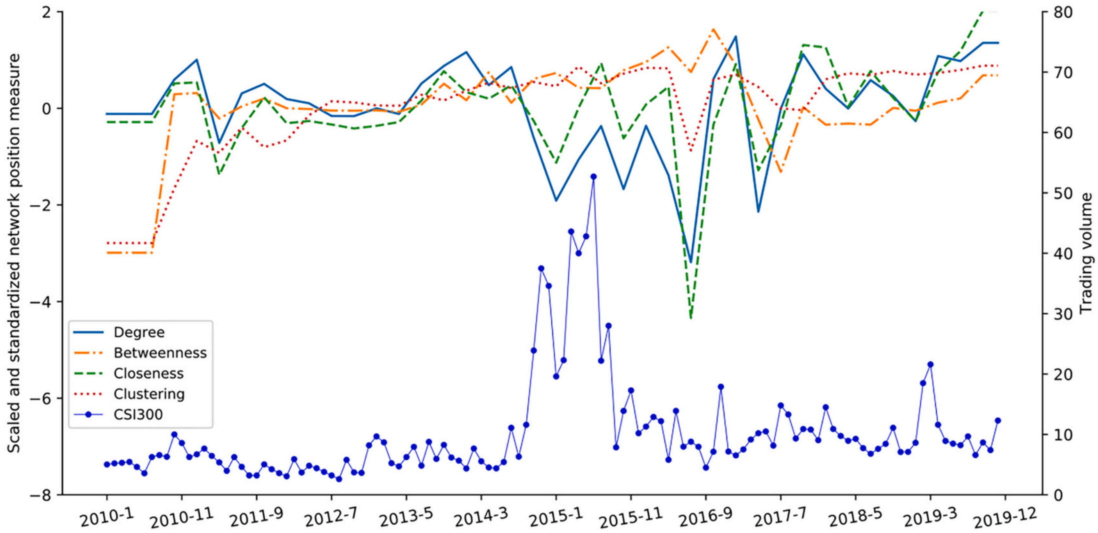

Fig. 2. Average network centralities and clustering coefficient, S_NET_t, over time, comparing with the financial market states which is represented by the changing trading-volume of CSI 300 Index.

5. Empirical results

5.1. Descriptive statistics

Table 1 presents descriptive statistics for the main variables in our analysis. It provides the summary statistics using the mean, standard deviation, minimum and maximum for the entire sample. The total sample includes 1150 hedge fund products and 22,059 observations from January 2010 to December 2019. The centrality measures are converted to relative centrality by dividing them by the cross-sectional average. The size variables are converted to relative size by dividing them by the cross-sectional average and taking the natural log of this quantity.

Table 2 reports the Pearson's correlation coefficient matrix of the key variables. The coefficients are obtained by computing cross-sectional correlations in the first step and then taking the averages of time series. The correlation matrix shows that the correlations between explanatory variables are generally small. It is worth noting that the low correlation between clustering coefficient and degree centrality, as well as the negative correlation between clustering coefficient and betweenness centrality imply clustering coefficient may be a special proxy of social network effect, which is rarely noticed in the previous literature.

Table 3 presents the summary statistics of variables *Doctor* and *School*.[6] The first column "All_sample_average" is calculated based on the total regression samples which contain duplicated fund managers that appear in different periods. Since our experimental sample is an unbalanced panel data, we also compute the time-weighted average by calculating the mean of each period. Lastly, we remove the duplicated managers and keep only one record for each manager. The third column "Unique_sample_average" is based on the unique-manager sample. As Table 3 shows, 10.2% of the hedge fund managers have a doctor's degree and 28.6% of them graduate from famous schools.

It's necessary to examine the collinearity of variable *Doctor* and *School* before we conduct econometric analysis. The Pearson correlation coefficient of these two variables is low, indicating that these two variables are relatively irrelevant.

Table 1
Descriptive statistics. This table reports the descriptive statistics for the main variables used in our analysis. This sample consist of 22,059 observations from Jan. 2010 till Dec. 2019.

Variable	Obs	Mean	Std.Dev.	Min	Max
Degree centrality	22,059	1.028	0.972	0.066	7.221
Betweenness centrality	22,059	1.073	4.542	0.000	90.408
Closeness centrality	22,059	1.034	0.833	0.012	4.484
Clustering coefficient	22,059	0.751	0.376	0.000	1.000
FundSize	22,059	-2.78	2.899	−23.759	6.333
FamilySize	22,059	-2.724	2.946	−25.18	5.007
FundAge	22,059	2.336	1.211	1.000	11.000

5.2. Return performance and network position

5.2.1. The basic model

This section addresses how the location of fund managers in a social network influences their investment performance. To explore the relation between return performance and network location, we construct an estimate of risk-adjusted returns by employing a four-factor model (Carhart, 1997). For each hedge fund, we first compute the monthly cumulative net return on dividend reinvestment, $R_{i,\ t}$, then the excess fund return net of a risk-free rate, $R_{i,\ t} - R_{f,\ t}$. We regress the hedge fund excess return on the excess returns on the Chinese stock market index, $R_{m,\ t} - R_{f,\ t}$, returns on a size factor, SMB_t, a value-growth factor, HML_t, and a momentum factor, MOM_t:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{1,i}\left(R_{m,t} - R_{f,t}\right) + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \beta_{4,i} MOM_t + \varepsilon_{i,t} \tag{6}$$

The data of these factors are supplied by CSMAR database. For each hedge fund and each month, we compute the associated risk-adjusted returns, $\widehat{r}_{i,t}^{adj} = \widehat{\alpha}_i + \widehat{\varepsilon}_{i,t}$. Hedge funds with less than 12 observations are dropped in order to reduce estimate insufficiency.

Using the estimated risk-adjusted returns as the dependent variable, we perform panel regressions that include both fund and time fixed effect. Previous research shows that the network effects may vary under different market conditions (Chen, Ho, & Yang, 2020). In order to avoid the influence of potential structural changes in financial market, we categorize our sample into three periods. As indicated in Fig. 2, the trading volume of CSI300 Index, which is one of the most important stock indices in China, fluctuated significantly around 2015. Thus, we categorize our sample into three parts according to the trading activity

[6] See detailed definitions of variables *Doctor* and *School* in Section 5.2.

Table 2
Correlation between main variables.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Degree centrality	1.000						
(2) Betweenness centrality	0.546	1.000					
(3) Closeness centrality	0.741	0.414	1.000				
(4) Clustering coefficient	0.228	−0.225	0.300	1.000			
(5) FundSize	0.077	0.067	0.055	0.012	1.000		
(6) FamilySize	0.224	0.050	0.140	0.113	0.530	1.000	
(7) FundAge	0.020	0.084	0.037	−0.098	0.039	−0.006	1.000

Table 3
Summary statistics of variables *Doctor* and *School*. We calculate three kinds of average value of these two variables. Taking *Doctor* as an example, the computational methods are as followed. $All\_sample\_average_{Doctor} = k/n$, where k is the num of samples with doctor degrees and n is the num of total regression sample. $Time\_weighted\_average_{Doctor} = (\mathrm{Mean}_{p1} + Mean_{p2} + Mean_{p3})/3$, where $Mean_p$ is the *All_sample_average* of period p. $Unique\_sample\_average_{Doctor} = Unique(k)/Unique(n)$, where the function $Unique(\cdot)$ reserves only one count for each fund.

	All_sample_average	Time_weighted_average	Unique_sample_average	Pearson Corr.
Doctor	0.123	0.168	0.102	
School	0.318	0.368	0.286	
Doctor * School				0.224

of Chinese financial market. The first period is from January 2010 to December 2013, the second period is from January 2014 to September 2016 and the last period is from February 2016 to December 2019. We conduct the time fixed effect analysis on the basis of this divide.

In the model, we also include other relevant variables. Based on prior literature and data availability, we consider FundSize, FamilySize, and FundAge as control variables. Individual fixed effect panel regression can exclude the influence of time invariant factors, so we choose the time varying variables as control variables. We include variables that control for both fund-level and fund-family-level scale economies to control for size effects on performance. First, we compute the size of each hedge fund, $\mathrm{FundSize}_{it}$, measured by net asset size. Second, for each fund company, we compute the size of fund family (hedge funds that belong to the same company) by aggregating $\mathrm{FundSize}_{it}$ into company-level, that is, $FamilySize_{it} = \sum_i FundSize_{it}$. For size control variables, we convert them to relative size measures by taking the log of size variable divided by its cross-sectional average, e.g., $\log(FundSize_{it}/FundSize_t)$, where $FundSize_t = N_t^{-1}\sum_{i=1}^{N_t} FundSize_{it}$ is the cross-sectional average of hedge fund size.

We also normalize the network position measures for manage i by scaling it by the cross-sectional average, i.e., Net_{it}/Net_t. This normalization helps to accounting for time series trends in the overall network structure, which could otherwise affect our econometric estimates. The network position variables are always measured ex ante, i.e., prior to the performance measurement month.

To analyze the impact of alumni network position on hedge fund performance, we construct the following model:

$$\widehat{r}_{i,t}^{adj} = a_i + b_t + \lambda_1 Net_{it} + \lambda_2 FundSize_{it} + \lambda_3 FamilySize_{it} + \lambda_4 FundAge_{it} + \varepsilon_{it} \quad (7)$$

where $\widehat{r}_{i,t}^{adj}$ is the risk-adjusted return of hedge fund i, Net_{it} represents the proxy variables of network position of fund i at time t, $FundSize_{it}$ is the asset size of fund i at time t, $FamilySize_{it}$ is the size of hedge fund family of fund i at time t, $FundAge_{it}$ is the age of fund i at time t.

Table 4 presents the results for panel regressions of hedge fund manager's risk-adjusted investment performance on manager's degree centrality, betweenness centrality, closeness centrality and clustering coefficient. The results show that alumni network position has a significant impact on the risk-adjusted investment performance of hedge funds in China.

The coefficients of degree centrality, betweenness centrality and closeness centrality are all positive, which is in line with the existing studies on private managed portfolios, such as "Sunshine" hedge funds in China (Li et al., 2020) and delegated investment management in UK (Rossi et al., 2018). The positive impacts of central position in social networks on the performance of private asset management are consistent.

Table 4
Network position and return performance. This table reports results for panel regressions of hedge fund manager's risk-adjusted investment performance on manager's degree centrality, betweenness centrality, closeness centrality and clustering coefficient. All specifications use fund and period fixed effects. p-values (reported in parentheses) are computed using standard errors that are clustered at the fund level.

	Degree	Betweenness	Closeness	Clustering
Net	0.185	0.019	0.172	−0.479
	(0.020)	(0.052)	(0.037)	(0.001)
FundSize	−0.080	−0.087	−0.082	−0.090
	(0.003)	(0.001)	(0.002)	(0.001)
FamilySize	0.037	0.042	0.040	0.047
	(0.233)	(0.169)	(0.193)	(0.129)
FundAge	−0.025	−0.022	−0.027	0.00
	(0.671)	(0.704)	(0.646)	(0.997)
Period	Control	Control	Control	Control
Fund	Control	Control	Control	Control
N	22,059	22,059	22,059	22,059

Moreover, we find that the clustering coefficient has a strongly negative effect on risk-adjusted return (significant at the 0.001 level), which is rarely noticed in previous research. Clustering coefficient measures the unimportance of the manager in his close subnetwork. A high clustering coefficient indicates the manager is dispensable to his socially connected neighbors since the information exchange in the social network would not be affected by the absence of him. The manager with low clustering coefficient has less access to important information and is more difficult to get comparable performance with the central peers.

Though the signals of regression coefficients of network proxies are different, they all point to the same conclusion: the more central the network position of the manager is, and the more important the manager is, no matter in the global network or in the local network, the better is the manager's hedge fund performance. However, the degree of influence of each network position measure is different. From the absolute value of the coefficient, the clustering coefficient has the greatest impact on the hedge fund performance and is about 2.6 times of the degree centrality. Among the three centrality measures, the influence of betweenness centrality is the smallest while degree centrality and closeness centrality are almost the same, about 10 times of that of the betweenness.

From the perspective of economic meanings, clustering coefficient represent the unimportance of the manager in his directly connected social circle. The results show that the impact of directly connected alumni network is much more significant than indirectly connected network since the importance in directly connected network contributes most to the fund performance. Looking back to the other centrality measures, degree centrality represents the width of the alumni relationships of the fund manager while closeness centrality represents the depth. The nearly equal coefficients of these two variables indicate their equal importance when we evaluate the quality of alumni social relationships of the hedge fund manager. Betweenness centrality represents the manager's control over the information flow in the alumni network. As a proxy of impact of indirectly connected alumni network, the explaining contribution of betweenness centrality is much smaller than the proxies of directly connected network (degree centrality and clustering coefficient).

The results in terms of centrality measures are contrary to those in the literature of mutual funds which finds negative effects of degree centrality, betweenness centrality and closeness centrality on mutual fund performance (Qi et al., 2020). The difference of alumni network effect between hedge funds and mutual funds may be caused by the following two factors. The first factor is the different requirements of information disclosure. The private information that mutual fund managers obtain from alumni social networks will be public soon due to the regular disclosure of mutual funds. Managers outside the social network can also be informed through the portfolio information of mutual funds, which reduce the value of private information brought by personal alumni networks. Eventually, the debuff of imitation and herding caused by information leakage outweigh the information benefits, resulting in negative network effect on mutual fund performance. The second factor is the different incentive mechanism. Mutual fund managers take a fixed proportion of management fees as income and do not share excess returns. Compared with hedge fund managers, mutual fund managers may be more conservative and less willing to make major changes in their investments based on newly acquired information. Therefore, the utilization efficiency of information is not as high as that of hedge fund managers.

5.2.2. *Network effects and abilities*

The return performance of a hedge fund depends on the ability of its fund manager. Fund managers' ability not only refers to their understanding of financial instruments and markets and investment skills, but also includes the ability of information searching and processing. One consideration is that the effects of alumni network on fund performance will be affected by the informational ability of fund managers. We thus examine the impact of alumni network on fund performance under different abilities. We extracted two variables from the graduation information that best represented individual abilities: degree and school. We first consider whether the hedge fund manager has a doctorate.

$$\begin{aligned}\widehat{r}_{i,t}^{adj} =& a_i + b_t + \lambda_1 Net_{it} + \lambda_2 FundSize_{it} + \lambda_3 FamilySize_{it} + \lambda_4 FundAge \\ &+ \lambda_5 Doctor_{it} + \varepsilon_{it}\end{aligned} \tag{8}$$

where $Doctor_{it}$ denotes if the manager of fund i at time t has a doctorate (including doctoral and postdoctoral degree). We also test whether the fund manager graduated from the top four universities in China, that is, Tsinghua University, Peking University, Fudan University and Shanghai Jiao Tong University. These four universities are the most famous and recognized school in financial industry in China.

$$\begin{aligned}\widehat{r}_{i,t}^{adj} =& a_i + b_t + \lambda_1 Net_{it} + \lambda_2 FundSize_{it} + \lambda_3 FamilySize_{it} + \lambda_4 FundAge \\ &+ \lambda_5 School_{it} + \varepsilon_{it}\end{aligned} \tag{9}$$

The explanatory variable $School_{it}$ denotes if the manager of fund i at time t graduates from the top four. Table 4 reports the results of the above regression.

Table 5 shows that the impact of alumni network on hedge fund performance is still significant after excluding the influence of fund managers' personal ability differences. The conclusions from Table 5 are consistent with those of the basic model. It indicates that alumni network will affect managers' investment performance regardless of their abilities. It is worth noting that the variable $School_{it}$ has a significant impact on risk-adjusted return (at the 0.01 level) while the doctoral degree is not statistically significant. This reflects the value of Chinese famous schools and the recognition of them by Chinese financial market, which is in line with the reality.

5.2.3. *Network effects under different strategies*

Most previous studies of hedge funds in China use the data of stock hedge funds, which is also called "Sunshine Hedge Fund" in China. This kind of hedge funds is between mutual funds and hedge funds in form, and only invest in stocks. However, our unique data contains not only stock strategy hedge funds but also hedge funds that hire other strategies and invest in other assets. Specifically, our samples totally hire nine kinds of strategies, that is, stock strategy, macro strategy, managed future strategy, event driven strategy, relative value strategy, fixed income strategy, fund portfolio strategy, composite strategy, and others strategy. According to the main invested assets, we divide the samples into four categories: (1) stock strategy, (2) managed future strategy, (3) fixed income strategy, and (4) others strategy. We then conduct regression analysis of the impact of alumni network on fund performance under different strategies base on this division. For the sample subset of each category, we do panel regression on the form of eq. (7) respectively.

The results in Table 6 show that the impact of alumni network position on the risk-adjusted return of hedge funds is different among fund strategies. For the stock strategy hedge funds, the result is basically consistent with the conclusions in basic model. For the managed future strategy hedge funds, only clustering coefficient has a significant impact on fund performance. Moreover, different from the stock strategy hedge funds, the effects of network position measured by clustering coefficient on the risk-adjusted return of managed future strategy hedge fund is positive. For fixed income strategy hedge funds, the three centrality measures all have significant influence, and clustering coefficient is borderline significant. Different from stock strategy hedge funds, degree centrality measure and closeness centrality measure have negative effects on the risk-adjusted return of fixed income strategy hedge funds.

In summary, the results of this section prove that alumni network has a significant impact on hedge funds under different strategies. Moreover, the network effects are different under different fund strategies, which may be related to the investment characteristics of different types of asset markets.

5.3. *Possible path: Investment style and network position*

Previous researchers believe that social network realizes its effects on fund managers by influencing their information processing (Chahine et al., 2019). A more central network position brings fund manager more advantages in information searching and processing. Such a central network position helps managers to gather information and learn from counterparts that which investment strategy works or not. However, we cannot observe direct proxies of the information flow in networks. Thanks to our unique data which provides asset allocation of hedge funds in China, we can observe the result of information exchange, that is, the change of investment styles of hedge fund managers. We address the significant effects of alumni network position on the risk-adjusted return of hedge funds in the previous section, however, the channel through which the social network can affect fund return performance is still unknown. Therefore, we conduct regression of investment styles on

Table 5
Network effects on fund performance under different manager abilities. *p*-values (reported in parentheses) are computed using standard errors that are clustered at the fund level.

	Degree		Betweenness		Closeness		Clustering	
Net	0.187	0.174	0.019	0.017	0.171	0.169	−0.479	−0.476
	(0.018)	(0.032)	(0.051)	(0.081)	(0.038)	(0.042)	(0.001)	(0.001)
FundSize	−0.080	−0.081	−0.086	−0.087	−0.082	−0.082	−0.090	−0.090
	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
FamilySize	0.038	0.037	0.043	0.042	0.041	0.040	0.047	0.047
	(0.228)	(0.229)	(0.164)	(0.168)	(0.188)	(0.191)	(0.126)	(0.129)
FundAge	−0.028	−0.027	−0.025	−0.025	−0.030	−0.030	−0.004	−0.004
	(0.624)	(0.645)	(0.661)	(0.669)	(0.609)	(0.607)	(0.950)	(0.945)
Doctor	−0.533		−0.491		−0.460		−0.481	
	(0.124)		(0.116)		(0.147)		(0.115)	
School		0.703		0.884		0.930		0.942
		(0.008)		(0.000)		(0.000)		(0.000)
Period	Control	Control	Control	Control	Control	Control	Control	Control
Fund	Control	Control	Control	Control	Control	Control	Control	Control
N	22,059	22,059	22,059	22,059	22,059	22,059	22,059	22,059

network position measures to examine how alumni network affects managers' investment behavior.

In the data of this study, part of hedge funds report their asset allocations. In our database, assets held by hedge funds are divided into six categories, namely, stock, warrants, funds, bonds, currencies, and others. These hedge funds report their proportion of investments in each category every quarter. We generate a proxy variable for investment styles, which is obtained by the sum of the proportion of stocks and the proportion of warrants, $Style_{it} = Prop_{it}^{stock} + Prop_{it}^{warrant}$.

In the end, we get 202 hedge funds with a total of 1654 observations. The limited number of samples within individual fund will interfere with the estimation accuracy of individual fixed effects. Therefore, we consider the period fixed effect in the regression.

$$Style_{it} = a_t + \lambda_1 Net_{it} + \lambda_2 FundSize_{it} + \lambda_3 FamilySize_{it} + \lambda_4 FundAge_{it} + \varepsilon_{it} \tag{10}$$

The results, reported in Table 7, suggest that fund managers' positions in the alumni networks have significant impact on managers' investment styles. The coefficients of three centrality measures of network position are significantly positive. The positive coefficients of centrality measures indicate that managers of more central network position invest more in the assets of high risk. It is reasonable that the information advantages brought by central network positions enhance their confidence in the face of market risk.

To further confirm the influencing path of alumni network effect, we conduct mediation analysis for the independent variable Net_{it} and the possible mediator $Style_{it}$. We use the causal step approach proposed by Baron and Kenny (1986). The basic causal chain involved in the mediation is diagrammed in Fig. 3. The mediation test includes three regressions(Baron & Kenny, 1986): first, regressing the mediator on the independent variable (Eq. 11); second, regressing the dependent variable on the independent variable (Eq. 7); and third, regressing the dependent variable on both the independent variable and on the mediator. We propose the following equation for the third step:

$$\begin{aligned}\widehat{r}_{i,t}^{adj} = & a_i + b_t + \lambda_1 Net_{it} + \lambda_2 Style_{it} + \lambda_3 FundSize_{it} + \lambda_4 FamilySize_{it} \\ & + \lambda_5 FundAge_{it} + \varepsilon_{it}\end{aligned} \tag{11}$$

As depicted in Table 8, mediation analysis shows that investment style is a significant mediator of the impact of alumni social network on hedge fund performance [λ=0.012, p<0.024 in all specifications]. Moreover, after controlling the mediator $Style_{it}$, the direct effect of alumni networks on hedge fund performance becomes nonsignificant (see the first row in Table 8), indicating full mediation.

For the three centrality measures that are statistically significant in Table 8, the coefficient of the independent variable in mediated path $X \rightarrow M$ (*Network* → *Style*) and the coefficient of the mediator variable in path $M \rightarrow Y$ (*Style* → *Performance*) are both positive, joining up to a positive indirect impact of alumni network on hedge fund performance. This is consistent with the direct impact found in Table 4.

The empirical results above prove that investment style is a full mediator of alumni social network effects on hedge fund performance. The alumni network of hedge fund managers exerts its impact on the fund performance by influencing the manager's investment style. From the perspective of information processing, a more central network position will bring the manager more information. The financial market in China is weak-form efficient (Lim, Huang, Yun, & Zhao, 2013) thus additional fundamental information can help investors to obtain excess returns. Hedge fund managers with information advantage tend to be more aggressive in their investment style and invest more in risky assets, as evidenced by the positive impact of *Network* → *Style*. From the positive correlation between mediator *Style* and outcome variable *Performance*, it can be seen that the more aggressive the investment style of the hedge fund manager, the better the fund performance. Alumni social networks ostensibly "raise the courage of managers" but actually improve hedge fund managers' risk management abilities, allowing them to take control of riskier targets and make more profits. This mediation finding supports our information-benefit hypothesis.

5.4. Further investigation: fund flow and network position

We next analyze whether fund managers' position in the alumni network affects flows of money into the hedge funds they manage. We estimate the flow of fund i at time $t+1$ as:

$$Flow_{i,t+1} = \left(\frac{FundSize_{i,t+1} - FundSize_{i,t}}{FundSize_{i,t}} - R_{i,t}\right) FundSize_{i,t} \tag{12}$$

where $FundSize_{i,\ t}$ and $FundSize_{i,\ t+1}$ are the market value of assets of hedge fund i at quarter t and $t+1$ and $R_{i,\ t}$ is the return generated over quarter t.

For the reason of asset reporting frequency, we calculate the quarterly flows of hedge funds and conduct panel regression at quarter frequency. We regress the fund flow variable on lagged flow, $Flow_{i,\ t}$, and network position measure, $Net_{i,\ t}$. We also include control variables to control the size effect and age effect. Finally, the regression includes time and fund fixed effects:

$$Flow_{i,t+1} = a_i + c_t + \beta_1 Net_{i,t} + \beta_2 Flow_{i,t} + \beta_3 FundSize_{i,t} + \beta_4 FamilySize_{i,t} + \varepsilon_{i,t+1} \tag{13}$$

Table 9 shows that degree centrality and closeness centrality are negatively and significantly related to hedge fund flows. It indicates the diseconomies of alumni social relationships on attracting money flows. The width and depth of a fund manager's alumni relationships result in fund size reduction. As for the remaining coefficients, all the control variables have significant coefficients while their impact are quite

Table 6
Network effects on fund performance under different strategy. For the sample subset of each strategy, we do panel regression on the form of eq. (7). Strategy categories are as follows: (1) stock strategy, (2) managed future strategy, (3) fixed income strategy, and (4) others strategy. All specifications use fund and period fixed effects. *p*-values (reported in parentheses) are computed using standard errors that are clustered at the fund level.

	Degree				Betweenness				Closeness				Clustering			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Net	0.211	0.061	−0.165	0.310	0.019	−0.026	0.056	0.023	0.272	0.119	−0.328	−0.034	−0.491	0.618	−0.979	−0.240
	(0.032)	(0.903)	(0.050)	(0.153)	(0.128)	(0.409)	(0.049)	(0.329)	(0.006)	(0.806)	(0.059)	(0.850)	(0.013)	(0.077)	(0.102)	(0.342)
FundSize	−0.084	0.139	−0.042	−0.195	−0.093	0.139	−0.039	−0.207	−0.083	0.137	−0.041	−0.210	−0.096	0.134	−0.052	−0.211
	(0.008)	(0.026)	(0.248)	(0.026)	(0.004)	(0.024)	(0.305)	(0.013)	(0.008)	(0.027)	(0.272)	(0.010)	(0.002)	(0.023)	(0.185)	(0.011)
FamilySize	0.033	−0.302	0.109	0.149	0.040	−0.313	0.118	0.161	0.034	−0.298	0.111	0.160	0.046	−0.290	0.114	0.159
	(0.338)	(0.004)	(0.297)	(0.117)	(0.240)	(0.003)	(0.263)	(0.079)	(0.312)	(0.003)	(0.282)	(0.079)	(0.180)	(0.006)	(0.245)	(0.082)
FundAge	0.047	0.164	−0.065	−0.120	0.055	0.191	−0.100	−0.118	0.044	0.163	−0.051	−0.108	0.082	0.178	−0.099	−0.100
	(0.430)	(0.523)	(0.531)	(0.561)	(0.356)	(0.421)	(0.333)	(0.566)	(0.459)	(0.517)	(0.612)	(0.612)	(0.172)	(0.494)	(0.356)	(0.616)
N	13,923	1638	2223	4275	13,923	1638	2223	4275	13,923	1638	2223	4275	13,923	1638	2223	4275

Table 7
Investment style and network position. All specifications use period fixed effects. *p*-values (reported in parentheses) are computed using standard errors that are clustered at the fund level.

	Degree	Betweenness	Closeness	Clustering
Net	2.071	0.814	4.947	−0.514
	(0.048)	(0.001)	(0.002)	(0.822)
FundSize	0.070	0.036	0.098	0.081
	(0.880)	(0.939)	(0.834)	(0.863)
FamilySize	5.900	6.080	5.962	6.150
	(0.000)	(0.000)	(0.000)	(0.000)
FundAge	4.209	4.036	4.023	4.276
	(0.000)	(0.000)	(0.000)	(0.000)
Period	Control	Control	Control	Control
N	1654	1654	1654	1654

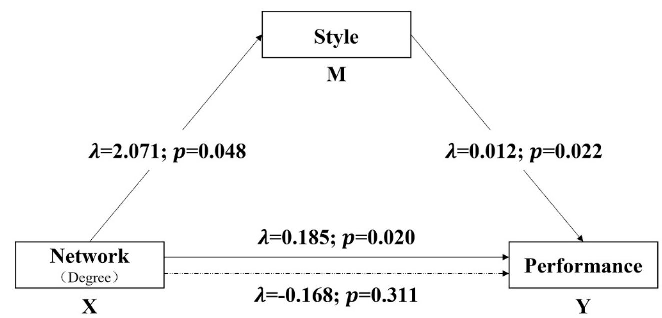

Fig. 3. Path diagrams for the alumni social network effect on hedge fund performance. X represents the independent variables, M represents the mediator, and Y represents the dependent variable. The solid line represents the total effect of the independent variable on the dependent variable and the dashed line represents the indirect effect of independent variable on the dependent variable through the mediator variable. We use the result of specification of Degree Centrality as an example in the diagram.

Table 8
Regression results of mediator and independent variables. All specifications use period fixed effects. *p*-values (reported in parentheses) are computed using standard errors that are clustered at the fund level.

	Degree	Betweenness	Closeness	Clustering
Net	−0.168	0.023	−0.474	−0.052
	(0.311)	(0.474)	(0.085)	(0.915)
Style	0.012	0.012	0.012	0.012
	(0.022)	(0.024)	(0.023)	(0.024)
FundSize	−0.083	−0.081	−0.088	−0.081
	(0.173)	(0.185)	(0.152)	(0.186)
FamilySize	0.054	0.047	0.051	0.047
	(0.698)	(0.733)	(0.717)	(0.734)
FundAge	0.136	0.123	0.169	0.132
	(0.315)	(0.366)	(0.212)	(0.316)
Period	Control	Control	Control	Control
N	1654	1654	1654	1654

different. The lagged flows have a negative and significant impact on future flows. The size control variables are negatively related to fund flow while the coefficient of fund age is positive. Taken together, the results in this section show the negative effects of alumni network on hedge fund flows.

Empirical studies have found diseconomies of scale in the hedge fund industry. For example, Agarwal, Daniel, and Naik (2009) find that both fund size and fund flows have negative effects on hedge fund performance. Getmansky (2012) studies competition in the hedge fund industry and also finds decreasing returns to scale. They interpret this as evidence of limits to growth in hedge funds. Our empirical results are in line with existing studies. The negative effect of central network position on hedge fund flows found in our study is consistent with the positive

Table 9
Network position and fund flows. The size variables are converted to relative size by dividing it them by the cross-sectional average and then taking the natural log of this quantity. The network position measures are also converted by dividing them by the cross-sectional average. *p*-values (reported in parentheses) are computed using standard errors that are clustered at the fund level.

	Degree	Betweenness	Closeness	Clustering
Net	−0.632	−0.001	−0.760	0.044
	(0.000)	(0.967)	(0.000)	(0.826)
$Flow_t$	−0.218	−0.217	−0.222	−0.217
	(0.000)	(0.000)	(0.000)	(0.000)
FundSize	−0.190	−0.173	−0.191	−0.173
	(0.010)	(0.018)	(0.008)	(0.018)
FamilySize	−0.103	−0.110	−0.105	−0.110
	(0.100)	(0.082)	(0.081)	(0.083)
FundAge	0.390	0.376	0.412	0.374
	(0.002)	(0.003)	(0.001)	(0.003)
Period	Control	Control	Control	Control
Fund	Control	Control	Control	Control
N	4896	4896	4896	4896

effect on fund returns.

6. Robustness tests

We examine robustness of our results using several different alternative specifications.[7] To test the robustness of the fund performance, we use the monthly return of net value, return adjusted by three-factor model of Fama and French (1993), and return adjusted by Capital Asset Pricing Model (CAPM) as explained variables, respectively. The results are consistent with those using the four-factor model of Carhart (1997).

We divide the studied period into three parts according to the different states of Chinese financial market. Now we remove this model setting and conduct regression analysis using year fixed effect. The findings remain consistent with the main regressions.

In the regression of risk-adjusted return on network position measures, we assume the alumni network stay unchanged within one quarter and extend the quarterly data of network structure to monthly frequency to meet the frequency of return. As a robustness check, we relax this assumption and repeat the basic model on the data of quarterly frequency. The results are proved to be robust.

7. Conclusion

Our purpose is to explore the effects of alumni network on hedge fund performance. We focus on the hedge funds in China and construct the college alumni networks of hedge funds using the data of 4734 hedge fund products existing from January 2010 to December 2019. We perform empirical analysis on the relationship between network position measures and fund return performance, investment styles and fund flows.

We find strong and robust evidence that alumni network position can affect the risk-adjusted performance of hedge funds. The alumni network effects remain positive under different abilities of fund managers, which supports our "Information-benefits hypothesis". We further find that the investment style is the mediator of the alumni network effect on hedge funds' performance. The more central a hedge fund is in the network, the more active is its investment style. Finally, we find the negative effect of alumni network on hedge fund flows.

We contribute to the literature of social network effects in financial markets by providing a deeper insight into the mechanism of how the social networks influence the investment behavior of agents, and adding new evidence on the relationship between alumni social network and hedge fund performance. We also contribute to the financial network theory by introducing a new construction method of alumni social network and a new important proxy variable for network position measurement.

We conduct our research based on samples from China. China is a meaningful research case and our study also has implications for international finance. The economic effects of social relationships are concerned in global financial markets and researchers have long been interested in this topic. This study provides empirical evidence of the economic effects of social relationships in the background of eastern cultures, which complements relevant theories. It also provides an instructive methodology for studies on other developing countries. Moreover, our study explores the economic effects of social relationships in the background of Chinese culture, which may be very different from the western. The social network effect of Chinese hedge funds and its influencing mechanism found in this study can help international investors better understand the Chinese financial market thus properly evaluate the funds' potential.

Our research is particularly timely in the Fintech era. With the development of Fintech, the speed and form of information dissemination have changed greatly. In recent years, universities have begun to build alumni databases using information technology and construct larger alumni networks in order to better maintain alumni relationships. Besides, communication between alumni has become more convenient and private, through instant message/video chat services and real-time online meetings. Fintech can accelerate the information processing and make the social network effect on investment performance even more pronounced than before.

There are a number of extensions for future research. One of the limitations of this study is that we do not consider the year of graduation when computing alumni connections due to the lack of relative data. This may be an important factor in the alumni network. In addition, we are not able to analyze the alumni network effects on detailed fund portfolio. Future studies could shed light on these aspects.

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