Network Centrality and Pension Fund Performance

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Abstract

We analyze the relation between the location of a pension fund in its network and the investment performance, risk taking, and flows of the fund. Our approach analyzes the centrality of the fund's management company by examining the number of connections it has with other management companies through their commonality in managing for the same fund sponsors or through the same fund consultants. Network centrality is found to be positively associated with risk-adjusted return performance and growth in assets under management, after controlling for size and past performance, for domestic asset classes; however, we do not find this relation for international equity managers. These findings indicate that local information advantages, which are much stronger among managers holding locally-based stocks, exhibit positive externalities among connected managers. Of particular note is that we do not find that the centrality of a manager within one asset class (e.g., domestic bonds) helps the performance of the manager in another asset class (e.g., domestic equity), further indicating that our network analysis uncovers information diffusion effects. Network connections established through consultants are found to be particularly significant in explaining performance and fund flows, consistent with consultants acting as an important information conduit through which managers learn about the effectiveness of each other's strategies. Moreover, the importance of network centrality is strongest for larger funds, controlling for any economic scale effects. Better connected funds also attract higher net inflows for a given level of past return performance. Finally, more centrally placed fund managers are less likely to be fired after spells of low performance. Our results indicate that networks in asset management are one key source of the dissemination of private information about the efficacy of investment strategies.

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1 Introduction

Money management, in its essence, involves a large and costly search across a wide scope of potential investment strategies in an attempt to provide an attractive risk-reward profile to investing clients. One need only look at the large number of management companies, not to mention the multiplicity of funds that each company offers, to infer that many different strategies are being applied in pursuit of superior returns in the investment management sector. Compounding the search problem, for these fund managers, is that particular strategies can become overused ("crowded"), or even stop working altogether as macroeconomic and market conditions evolve.[1] Indeed, the fact that many funds fail each year, while many others are born, indicates that the search for successful strategies is an ongoing challenge, and that funds must "reinvent" themselves and evolve as market conditions, as well as the characteristics of the fund (e.g., fund size and clientele) evolve.

Consider, for instance, an equity fund manager searching for a strategy. Such a manager must choose among literally hundreds of potential strategies, each of which, in turn, have several potential implementation approaches. Suppose that the manager decides to pursue a value strategy in picking equities. Next, this manager must choose among deep-value, growth-at-a-reasonable price, accrual-based, neglected stock, price contrarian, and many other top-level strategies within the value category. Within each of these top-level strategies, there are numerous sub-strategies. For instance, deep-value can be based on purely quantitative signals, such as price-to-earnings or book-to-market, or can be based on qualitative signals, such as companies whose assets are undervalued because of problems with the current management team. Further, each of these sub-strategies can be formed differently–price-to-earnings, e.g., can be based on backward-looking accounting earnings or forward-looking analyst forecasts, or even on the earnings of peer companies. And, the potential combinations of sub-strategies is, itself, overwhelming.[2]

How do fund managers and management companies decide on their strategies? Clearly, one ap-

[1] Take, for example, the so-called "Quant Crisis" of August 2007. During a short period of time, stocks that exhibited attractive characteristics to quantitative equity hedge funds–such as deep value and momentum–suffered large negative returns. Another example is the financial crisis of 2008/2009, where common strategies of active equity mutual funds generated very poor returns–resulting in a large underperformance, relative to equity index funds.

[2] Consider a strategy that has 10 potential sub-strategies. The number of combinations of these sub-strategies is $2^{10} - 1 = 1,023$. In addition, there are an infinite number of ways to weight these combinations of strategies. For example, one manager may decide to use four strategies, weighing each equally, while another may decide to weight one of the four much more heavily than the other three.

proach for a quantitative manager is to monitor the academic and practitioner literature, and to conduct backtests of the more promising proposed strategies. Or, the qualitative manager may try the "country-club" approach, where the manager attempts to gain personal connections with corporate managers. However, the "quant" faces the large problem of papers published with tests that have been "data-mined," either wittingly or not by their authors. And, the "qual" faces hurdles such as Regulation FD in the U.S., which carries penalties for dissemination of private information to preferred investors.

In this paper, we provide evidence of another avenue through which fund managers collect information on potential investment strategies. In our setting, investment managers oversee only a portion of an overall pension portfolio, with potentially many other managers overseeing the remainder. These investment managers are hired, by the pension fund sponsor, from different investment management houses, each of which brings a set of strategies that have evolved within that house. Key to our setting is that an investment consultant is hired to locate the investment managers, and to monitor their performance and strategies closely over time. As a result, these consultants gain intimate knowledge of each manager's strategy, how well it works, and how it compares with the strategies used by other fund managers.[3] And, if the consultant oversees several pension funds that employ a particular manager, the consultant gains an even keener understanding of the strategy and how well it works under differing conditions with different pension fund sponsor incentive contracts and investment constraints. Importantly, this investment consultant can transmit information about the efficacy of investment strategies from one manager to another, in order to improve the overall performance of the pension fund that the consultant advises – the goal for which he has been hired.

In this paper, we use data on a large set of UK pension fund accounts over the period 1984-2004 to determine the role of network connections in the investment performance, risk-taking behavior, and flows of managers. If our conjecture about the transmission of information is correct, then we should observe managers who are more "central" in a network exhibiting better success in their investing, since they will be exposed to a larger number of competitor strategies, which they can adopt, either partially or fully. Of course, one consideration in this decision is whether joining their competitors

[3] In essence, the investment consultant can observe, in real-time, the testing of a large number of strategies, each of which has presumably been gleaned (by the management company) from a large number of candidate strategies.

may result in overcrowding of a strategy, with the resulting decreasing industry returns-to-scale of that strategy.

Specifically, our unique dataset, also described in Blake et al. (2013), allows us to compute network connections in a very detailed manner.[4] That is, for each calendar quarter from 1984-2004, we have information on the identity of each fund manager employed by each pension fund, the return of the manager, and the sector in which that manager is expected to invest. Our database contains three broad asset classes – UK Equity, UK Bonds, and International Equities – that together account for more than 85% of the pension funds' asset holdings. This breadth of asset classes allows us to compare and contrast findings across investment sectors for which we would expect network effects to be very different – for example, we would not expect network connections within the UK to be as important to performance in foreign markets as in domestic markets, as access to information about one's competitor should yield the biggest benefits in local markets. That is, managers of foreign market investments cover many areas of the world; in such a setting, the benefit of receiving information about the strategy used by one's competitor – which is likely used in a very different market setting – is limited.

Our data represents a large cross-section and time-series of managers, consultants, and sponsors, allowing several dimensions through which we can identify the impact of networks on information diffusion–an important consideration because networks may themselves respond to changes in information flows. Network connections in our dataset arise from two separate sources. First, as described previously, many pension funds use multiple managers (each managing a separate account for the sponsor), and such overlaps, in turn, create a network of connections across fund-manager pairings. For example, UBS might manage a portion of the accounts of each of dozens of pension fund clients, many of whom have also hired Merrill Lynch. This creates a "strong connection" between UBS and Merrill Lynch (we envision this connection as being facilitated by the single consultant to the pension fund sponsor).[5]

As a second source of network connections, pension funds hire consultants to provide advice on which managers to hire, thus creating a network between, say, UBS and Merrill Lynch, through

[4]Blake et al. (2013) focus on the effect of the recent decentralization of pension fund management on investment performance, while we focus on the network connections between fund managers, fund sponsors, and investment consultants.

[5]In the pension fund industry, a single pension fund sponsor retains only one consultant.

having a common consultant in their interactions with several fund sponsors even if the managers do not manage assets for the same pension fund at the same time. Such relationships help reduce the search costs incurred by the pension fund trustees. In addition, the model of Acemoglu, et al. (2011) characterize conditions under which convergence to the right action will occur as a network becomes larger. One condition is that each participant must be able to observe the true actions of others in the network. In our setting, a management company, e.g., UBS, has no incentive to share its strategy with another; in addition, unlike the mutual fund sector, the disclosure of portfolios is not mandated for pension funds. Thus, the investment consultant provides the necessary conduit of information about strategies from one manager to another.

In our setting, both network types play complementary roles; if, say, UBS and Merrill Lynch are "connected" through many different fund sponsors which have a common consultant, we would expect that the information transmission about strategies would be enhanced between the two investment managers.

Our dataset allows us, uniquely, to analyze not only the relation between network centrality and key variables such as investment performance, risk-taking behavior, and fund flows, but also which type of network connection matters–directly through managing money at the same pension fund (and, thus, sharing that fund's consultant), or through a more distant relationship, where two managers are only connected by sharing a common consultant, and do not manage money at the same pension fund – through shared managers or through shared consultants.[6] This is important, since little is known about the specific channels through which information flows in the asset management business. As monitors of the fund management industry, consultants are a natural conduit through which information flows on individual fund manager strategies. In fact, the entire justification for the existence of consultants arises from their ability to identify successful fund-manager matches.

Our empirical analysis uncovers a number of novel findings. First, we find that managers that are better connected (or more central in a network) tend to have higher risk-adjusted performance in both UK equities and UK bonds. Since we control for the manager's average centrality, this effect is identified from variation over time in a manager's network centrality, and the associated time-

[6]To capture network centrality, our analysis focuses on degree centrality, which measures the probability that a node (fund-manager pairing) immediately captures newly released information through its direct contacts with other nodes (fund-managers).

variation in risk-adjusted performance–helping to establish that managers with higher (time-series) average skills do not simply become better connected (i.e., the reverse causality).

Moreover, this result is not explained simply by more central managers being bigger, and, thus, more highly connected. In fact, while there is a positive correlation between manager size and centrality, size is negatively related (consistent with Chen, Hong, Huang, and Kubik, 2004), while centrality is positively related to risk-adjusted performance. We also find an interesting interaction effect between fund-manager size and network centrality, which suggests that large funds use their domestic (UK) network centrality to counteract the negative effect of size on investment performance (diseconomies-of-scale). In contrast, we find little evidence that centrality within our network of UK managers affects the risk-adjusted performance in international equities, consistent with more "localized" benefits associated with network centrality. That is, the international managers appear to cover very different non-UK markets, making the information associated with each manager's investment strategy of limited value to other managers.

Second, across all three asset classes, we find that network connections have a large and significantly positive effect on fund flows–driven entirely by a manager attracting new pension fund assets rather than attracting more assets from existing clients–again after controlling for size. In contrast, fund size has a negative effect on fund flows, whereas past returns and future returns explain flows from existing clients, but not new clients. This suggests that, controlling for size and past returns, the more central a manager is, the greater expected inflows tend to be–consistent with pension fund sponsors (with the assistance of their consultants) understanding and endogenizing the value of a manager having higher network centrality–with its benefits in gathering greater levels of information on the effectiveness of other strategies.

Third, we find that managers with with high centrality take more risk in UK equities, consistent with more central managers having higher levels of private information deriving from their network position and pension fund sponsors (and consultants) tolerating this higher risk level because of better average performance.

Fourth, network centrality may also influence managers' or consultants' behavior through the probability that they are fired by their pension fund clients. To explore if this is the case, we estimate

semi-parametric Cox regressions that relate managers' or consultants' hazard rate (the probability that they are fired next period) to the tenure of the fund-manager relation, manager size, past return performance and network centrality. We find strong evidence that more central managers face a significantly reduced probability of being fired, after controlling for size and past return performance. This finding is consistent with pension sponsors (and their consultants) understanding that more central managers have an information advantage over less-connected managers.

Our results reveal rich dynamic interactions between fund-manager centrality, risk-adjusted performance, fund flows and, ultimately, fund size. Our final empirical contribution addresses whether size drives centrality, or centrality drives size, by conducting panel Granger causality tests. These suggest that network centrality Granger-causes size, while size does not Granger-cause network centrality. In particular, highly centralized fund managers tend to grow faster than more peripheral fund managers, after controlling for past size.

One might be concerned that our results are, in part, driven by a potential "reverse causality," where a manager becomes more central in a network in anticipation of good future performance, rather than the increased centrality being chiefly responsible for the future performance. We address this concern in three different ways. First, we study the average pair-wise correlation between the idiosyncratic returns of connected versus non-connected managers. We find that connected managers' idiosyncratic returns are significantly more positively correlated than those of non-connected managers, which strongly indicates that highly connected managers tend to learn about, and at least partially adopt, each others' strategies.

Second, we use the merger between two large consultants in our data set as a natural experiment that allows us to track the effect of exogenous variation in network centrality on subsequent performance. We use a diff-in-diff estimator that estimates the effect of an increase in network centrality of the treatment group (the fund-manager pairings affected by the merger) relative to the non-treatment group. For UK equity funds, we find a significantly positive effect on the performance of the affected funds (those who end up with a "merged consultant"), consistent with network centrality affecting return performance. Third, we test whether consultants have differential ability to identify funds with superior future performance. Consistent with Jenkinson, Jones and Martinez (2014) we find little

evidence that this holds, again suggesting that the reverse causality is unlikely to be substantially driving our results.

To summarize, our results suggest one significant reason why some pension fund managers are successful, while others are not. Being centrally located in the fund-manager network fosters better risk-adjusted investment performance, higher inflows, and an ability to reduce the negative impact of size that affects most funds as they grow large. Key to these results is that better-networked managers have better access to information on competitors' strategies, and they adapt to use the best of these strategies over time. Our findings are related to studies on networks, such as Cohen, Frazzini, and Malloy (2008), who find that social networks facilitate information transfer in securities markets, and that mutual fund managers' connections with corporate board members (identified through education) help them better identify investment opportunities.

Our paper proceeds as follows. Section 2 introduces our data and presents evidence on both manager- and consultant-based networks at fixed points in time as well as throughout our sample. Sections 3 and 4 explore the relation between risk-adjusted return performance and network centrality. Section 5 considers the dynamic relation between fund flows and network centrality by estimating models that relate fund flows to past flows, size, return performance, and network centrality. Section 6 considers how funds' risk-taking behavior is linked to their network centrality and analyzes if centrality affects managers' incentives through their risk of being fired. Section 7 presents results from a Granger causality analysis of the size-centrality relation. Section 8 concludes.

2 Data and network centrality measure

This section introduces the data on UK pension funds used in our study, and depicts the networks established between funds, managers, and consultants for three asset classes – UK equities, UK bonds and international equities – that are central to the pension funds' portfolio holdings. Next, we describe how we construct the centrality measure used in our analysis (degree centrality) and provide insights into its characteristics, its evolution over time, and its correlation with other variables in our dataset.

2.1 Data

Our dataset comprises quarterly returns and asset holdings of 2,385 occupational defined benefit pension plans between March, 1984 and March 2004. The data, which was provided by BNY Mellon Asset Servicing, has information on seven asset classes, but we concentrate on the three biggest ones– UK Equity, International Equity, and UK Bonds – which together comprise around 85% of asset holdings by market value throughout the sample.[7] For each fund, and within each asset class, we know the identity of the fund manager – or managers in cases with multiple managers – at each point in time. This is important since it is common, especially for large funds, to hire different managers for different asset classes; moreover, funds commonly employ two or more specialized managers within the same asset class, e.g., a large and a small cap equity manager.

Such overlaps create the possibility of network effects as fund sponsors will want to coordinate the investment decisions across different managers so as to minimize the inefficiency loss associated with decentralized decision making (e.g., Sharpe (1981), van Binsbergen et al. (2008), and Blake et al. (2013)). Funds may also indirectly reveal information about other managers' investment strategies by setting up competition among managers, ensuring that the best-performing managers within a particular asset class see their assets under management increased at the expense of the worse-performing competitors.

2.1.1 Managers

Table 1 shows the number of fund-manager pairings–the unit of observation for much of our analysis– at three points in time (1984, 1994, and 2004).[8] Within UK equities the number of fund-manager pairings starts at 1204, increases to 1420, only to decline to 1053 at the end of the sample.[9] A similar pattern emerges for international equities, where the count of fund-manager pairings is 1135, 1354 and 956 in 1984, 1994 and 2004, respectively. UK bonds behave slightly differently as the number of fund-manager pairings decreases from 1165 to 745 during the decade 1984-1994, then increases to 817 in 2004. The increase in the number of fund-manager pairings for UK bonds reflects the increased

[7] The other asset classes are cash, international bonds, index-linked bonds, and property.

[8] Each time a manager manages a portion of a pension fund's assets, a separate account is set up whose assets and return performance are tracked through time.

[9] This decrease is typical in the defined benefit industry, as it has decreased in popularity recently.

prominence of this asset class towards the end of sample as many defined benefit pension schemes switched their assets towards domestic bonds.

Table 1 also reports the number of funds in the dataset at the same three points in our sample. Between 1984 and 1994 the number of UK equity and international equity funds increased slightly, while conversely it decreased for UK bonds. The number of funds then decreased for all asset classes between 1994 and 2004. Comparing the number of fund-manager pairings to the number of funds, it is evident that over our 20-year sample a large number of funds moved from being single-managed to being multi-managed - a change in paradigm analyzed in detail by Blake et al. (2013). For example, the average number of UK equity managers per fund went from 1.26 in 1984 to 1.67 in 2004.

The remaining columns of Table 1 present the number of managers as well as summary statistics for the number of connections per manager. The number of UK equity managers in our sample declined from 113 in 1984 to 82 in 2004. An even sharper decline is observed for UK bond managers (from 109 to 61), while the decline was more modest for international equities (from 108 to 89). At the same time, the number of network connections per manager increased over time, indicating that the pension fund management industry became more concentrated among fewer managers who become more inter-connected over time. For example, the proportion of managers with more than 20 network connections increased from 7% in 1984 to 12% of the managers in 2004. Similar patterns are seen for UK bonds and international equities.

2.1.2 Consultants

The pension funds in our sample are advised by consultants who play a very significant role in the appointment of fund managers and the choice of investment mandates, as well as monitoring managers after they are hired.[10] A total of 12 different consultants performed these services over our sample period. For each consultant, Figure 1 presents time-series plots of the number of clients in UK equities

[10] As of June 2011, $25 trillions of institutional assets worldwide were advised by investment consultants and in certain countries, like the U.K., sponsors are required by law to seek the advice of investment consultants in their investment decisions. As stated by Jenkinson, Jones, and Martinez (2015): "From the perspective of asset managers, investment consultants are key gatekeepers whose opinions determine whether a plan sponsor will even consider a particular fund. Despite a voluminous literature examining whether active managers add value for investors, many plan sponsors continue to search for active managers. Investment consultants play a critical role in both encouraging and guiding this search for winners, and, thus, understanding whether they add value for investors has important implications for investment strategy."

(Panel A), UK bonds (Panel B) and international equities (Panel C). The number of clients advised by individual consultants follows very similar patterns across the three asset classes, indicating that the consultants do not specialize in specific asset classes. This is consistent with the view that consultants provide "full service" advice to their pension fund clients. While such cross-asset-class manager selection and oversight is required when employing a fund manager under a multi-asset class or a balanced investment mandate, this type of full service arrangement has persisted as managers have become more specialized (e.g., to manage only equities or only bonds). Employing a single consultant allows control over the asset allocation decision, as well as overseeing the mix of strategies (managers) within each asset class.

While Figure 1 shows proportions by counts, Figure 2 shows market shares by asset value. Here, we see that the market for consultants was dominated by four large firms whose combined market size did not change much over the sample period.[11]

2.2 Asset-class specific network relations

A network is characterized by its nodes (agents) and edges (connections). To construct networks, we include all agents (fund managers, e.g., UBS) that are present at a given point in time. This allows us to construct a time series of network connections. Consultants act as interlocutors in the network, so we separately consider network connections established either through consultants or managers and networks in which connections are established exclusively through managers (managers only) or exclusively through consultants (consultants only). In the manager-only case, managers are connected only if they co-manage the assets for one or more pension funds either as joint balanced asset managers or as specialist managers within the same or different asset classes. In the consultant-only case, two managers can be connected if any of the clients whose portfolios they manage share the same consultant (e.g., pension fund P uses Manager A, while pension fund Q uses Manager B; both pension funds use the same Consultant C); in this case, the two managers are connected through the common consultant although they do not invest for the same (pension fund) client.

Figure 3 shows network connections in UK equities at three points in time during our sample, namely 1984, 1994, and 2004. Nodes shown as red circles represent individual managers (management

[11] In 1998, consultant no. 11 merged with consultant no. 2; the merger is evident in all panels of Figure 1.

companies), while the black diamonds in the horizontal row represent the twelve consultants. Next to each node is shown the code of the manager or consultant. This is specific to individual managers and consultants, and remains constant throughout the sample. Managers whose nodes are shown above the consultants are only connected to other managers through consultants (i.e., they never manage the same pension fund simultaneously), while managers whose nodes fall below the consultants are connected with at least one other manager though a simultaneous presence in a pension fund. In all cases, we envision the consultant as the main conduit through which strategy information is transmitted from one manager to another.

Specifically, blue lines in Figure 3 track network connections between managers (established through managers' sharing of the same pension fund client, and, thus, being linked through that fund's consultant) while green lines track connections between consultants and managers. While the two are, of course, related–consultants are more likely to favor certain managers over others–the figure, nevertheless, shows how we can separately measure the two types of connections. For instance, for a given manager, we can explore whether a direct network connection with another manager (both managers are involved in managing a portfolio at the same pension fund at the same time) provides a different benefit than a more distant connection with another manager (where the two managers are never at the same fund, but share a consultant). This identification strategy provides us with an opportunity to more precisely determine how information flows through the network–i.e., how the "distance" between two managers affects information transfer.

In 1994, 9 of the 12 UK Equity consultants have multiple connections, while, in 2004, this number decreased to seven consultants, showing the consolidation that took place in the consulting industry over the 20-year sample period.[12] Thus, the number of network connections among managers tells a similar story to that provided by market shares plotted in Figure 2.

Figures 4 and 5 display the corresponding networks for UK Bonds and International Equity. UK bond managers in particular had far fewer network connections than UK Equity managers, with International Equity managers falling in the middle. Moreover, the networks have evolved very differently through time. For example, while the UK Equity network became denser between 1984 and 2004, the

[12]Note that some consultants have no connections to managers; they are shown, however, since they either have connections in other asset classes (including, potentially, the four asset classes that we do not study in this paper) or because they have connections at a different point-in-time.

opposite appears to have happened for UK bonds, where the number of connections actually declined over the sample.

Figure 6 shows a three-dimensional plot of network connections at the end of the sample (2004) for the three asset classes. This figure contains similar information as the bottom plots in Figures 3-5, but presents it in an alternative way. Green balls represent fund managers while the yellow balls represent consultants; the size of each ball is proportional to its centrality in the network.[13] The plots indicate that the UK equities network is populated by both highly connected managers and consultants that are very central to the network as well as a number of much less well-connected peripheral managers. The network in international equities is more dispersed in that the number of managers in the very center of the network is smaller than for the UK equity asset class. Finally, the network for UK bond managers is sparsely populated by managers in the very center, as managers are more distant from each other. Overall, network centrality, itself, is much more concentrated among a subset of managers in UK equities, as compared to UK bonds or international equities.

2.3 Measuring network centrality

We use degree centrality as our measure of network centrality. Degree Centrality measures the number of neighbors a node has relative to the total number of nodes.[14] For a specific network node, this measure can be interpreted as the immediate probability that the node "catches" information flowing through the network. A node can be a manager or a consultant, because we can think of either as conduits for information flows. However, information flows between managers–at the same pension fund–are facilitated by the pension fund's consultant.

In our context, if a particular manager (or consultant) is in possession of some information, the probability that this information gets transferred to another manager (consultant) during the next period is a function of the number of contacts (nodes) the manager (consultant) is adjacent to. Our

[13] The layout of the plot is obtained by using the Fruchterman-Reingold 3D force-directed layout algorithm with a factor of 3. The idea behind the Fruchterman-Reingold 3D algorithm is to represent the nodes as steel rings and the edges as springs between them and consider attractive and repulsive forces between them. The attractive force is analogous to the spring force and the repulsive force is analogous to the electrical force. The algorithm minimizes the energy of the system by moving the nodes and changing the forces between them.

[14] Other measures of network centrality such as betweenness centrality and prestige centrality have also been proposed. However, these are either not appropriate for measuring a node's importance for the flow of information (betweenness) or focus on longer-term effects of information flow (prestige) which are likely to be less relevant to financial networks such as those studied here in which information can be expected to flow fast.

analysis uses this simple centrality measure to capture the tendency of a consultant to inform one manager about another manager's strategy choice and success. Although a more complex flow of strategy information is possible–such as Manager A adopting a strategy used by Manager C, each of whom have different consultants, through communications by Manager B, who is connected to each of the two consultants–we believe this type of information flow is of second-order importance. That is, managers likely have little incentive to communicate directly with each other; consultants are key to this information transfer about strategies.

Formally, the degree centrality "DE_{jt}" of node j at time t is defined as:

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

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

2.4 Evolution in Networks

Figures 3-5 suggest that the number of network connections within each of the three asset classes has changed substantially over time. To get a better sense of how the "average" centrality measure has evolved during our sample, we next study the time-series of average degree centrality. Specifically, we first standardize each centrality measure "CM_t" by subtracting its time-series average and standard deviation over the full sample so as to create a measure with mean zero and unit variance. Specifically, for each asset class the standardized centrality measure is constructed as follows:

$$S\_CM_t = \frac{CM_t - MEAN(CM_t)}{STDEV(CM_t)}, \tag{2}$$

where $CM_t = N_t^{-1} \sum_{j=1}^{N_t} CM_{jt}$ is the cross-sectional average centrality measure at time t, and $Mean(CM_t)$ and $STDEV(CM_t)$ are time-series averages of CM_t computed over the sample 1984-2004.

Figure 7 plots time series of the normalized centrality measure, S_CM_t, over our sample period. We show the total centrality measure based on network connections established across either managers

or consultants ("total," shown as a black line) as well as the separate measures established across managers only (blue dotted line) and consultants only (red dashed line).

For UK equity (upper left corner), we see a distinct upward trend in both the total and manager-only centrality measures after 1990, while the consultant-only centrality measure displays more evidence of mean reversion, particularly during 1998-2002. Almost identical patterns are seen for international equities, while all three centrality measures trend upwards for UK bonds (upper right corner).

Arguably, information across managers is most likely to flow within the same asset class. For example, manager A is likely to learn more from manager B's actions if they both advise the same client on UK equities than if manager A is a domestic equity manager and manager B is a bond manager. Figures 3-6 therefore show results based on the individual asset classes. However, we can also construct networks that allow for connections across asset classes (e.g., if a UK equity manager and a UK bond manager share the same pension fund client). The bottom right window in Figure 7 shows that such network connections trend upwards for the total and manager-only measures but mean-revert for the consultant-only measure.

These plots indicate that the consultant-only and manager-only measures, though clearly sharing a common component, display quite different behavior and so are likely to capture different information. To explore the relation between the centrality measures and other variables, Table 2 uses correlations to summarize the relation between the overall ("total") network centrality measure established across either managers or consultants (NET) versus the two separate centrality measures established across managers-only (NET_M) or consultants-only (NET_C). Across all three asset, we find a correlation near unity (0.985-0.998) between overall and manager-only centrality measures, indicating the two are very strongly related. We find instead a positive, but relatively weaker correlation (0.78-0.81) between the manager-only and consultant-only network centrality measures. As we shall see in subsequent analysis, the far from perfect correlation between the manager-based and consultant-based centrality measures allows us to identify whether changes in manager behavior is induced through manager connections, consultant connections or both.

In turn, all centrality measures are nearly uncorrelated with the fund-manager size but have a

positive correlation (0.48-0.56) with manager size. We would expect larger managers to have more network connections, but the results here suggest that manager size only accounts for a modest proportion of the variation in network centrality, raising the prospects that we can identify the separate effect of network centrality and size on managers' investment performance. We address this question in the next section.

To provide a different perspective on the evolution of network connections, we also compute the average clustering coefficient across time and across asset classes. The clustering coefficient of a given node 'i' computes the fraction of nodes connected to i that are connected to each other and so is bounded between zero and one. Averaging this coefficient across all nodes in a given network, we obtain the average clustering of the network. For each asset class, Figure 8 plots the time-series of average clustering coefficients for networks computed using both managers and consultants (red line) or using only managers (blue line).

If the networks were formed at random, we should expect to observe very small clustering coefficients (close to zero) if the probability of having a network connection is sufficiently low and the network expands over time. Instead the plots in Figure 8 suggest quite high clustering coefficients in the UK pension fund data although the average clustering coefficients appear to be trending down over time.

3 Return performance and network centrality

How does a network influence the performance of fund managers? We explore this question for the three asset classes (UK equities, UK bonds and international equities). We first explain how we construct the dependent variable (risk-adjusted returns) for each asset class, then present results from panel regressions that use centrality as a covariate, while controlling for both fund and fund-manager size effects.

3.1 Risk-adjusted return regressions

To explore the relation between risk-adjusted returns and network centrality, we first construct an estimate of risk-adjusted returns using a procedure similar to that in Blake et al. (2013).[15] Specifically, for each fund-manager pairing, we compute quarterly UK equity returns net of a three-month risk-free rate, r_{ijt}. Here, the subscript 'i' refers to the fund, while 'j' refers to the manager and 't' refers to the time period. We next regress this on the excess returns on the UK stock market portfolio, $r_{mkt,t}$, returns on a UK size factor, SMB_t, a UK value-growth factor, HML_t and a UK momentum factor, MOM_t:[16]

$$r_{ijt} = \alpha_{ij} + \beta_{1ij} r_{mkt,t} + \beta_{2ij} SMB_t + \beta_{3ij} HML_t + \beta_{4ij} MOM_t + \varepsilon_{ijt}. \tag{3}$$

For UK bonds we estimate a two-factor model using excess returns on the FTSE All-Gilts Total Return Index (GOVB) and UK government consol bonds ($CONS$) as regressors:

$$r_{ijt} = \alpha_{ij} + \beta_{1ij} GOVB_t + \beta_{2ij} CONS_t + \varepsilon_{ijt}. \tag{4}$$

Finally, for international equities, we use a four-factor model that includes sterling-denominated excess returns on the MSCI North American (NA) and Europe Australasia Far Eastern ex-U.K. (EAFEX) Total Return Indices, as well as global size (SMB) and value-growth (HML) factors:[17]

$$r_{ijt} = \alpha_{ij} + \beta_{1ij} NA_t + \beta_{2ij} EAFEX_t + \beta_{3ij} SMB_t + \beta_{4ij} HML_t + \varepsilon_{ijt}. \tag{5}$$

To estimate these models, we drop fund-manager pairings that survive for less than 12 quarterly observations. Using the resulting estimates, for each fund-manager and each quarter, we compute the associated risk-adjusted returns, $\widehat{r}_{ijt}^{adj} = \widehat{\alpha}_{ij} + \widehat{\varepsilon}_{ijt}$.

[15] Since we are not interested in studying market timing skills, and since Blake et al. (2013) only found weak evidence that managers have market timing skills, we omit the market timing terms from the performance regressions here.

[16] We use the FTSE All-Share Total Return Index as the UK stock market portfolio, $r_{mkt,t}$. The factors SMB_t, HML_t, and MOM_t are UK versions of the factors commonly used in US Equities. They are supplied by Professor Alan Gregory of Exeter University (http://xfi.exeter.ac.uk/researchandpublications/ portfoliosandfactors/index.php).

[17] We include a North American market return factor separately due to the evidence in Timmermann and Blake (2005) that UK pension funds considerably overweighted this market in their international equity portfolio. As the value factor, we use the sterling return on the MSCI Barra World ex-U.K. Standard Value Index. As the growth factor, we use the sterling return on the MSCI Barra World ex-U.K. Standard Growth Index. We have also experimented with versions of this model that add a momentum factor.

3.2 Risk-adjusted returns and network centrality

Using our estimates of risk-adjusted performance from Equations (3)-(5) as dependent variables, we perform panel regressions that include both fund-manager and time fixed-effects, that control for fund-manager and manager size effects, and that use standard errors that are clustered at the fund-manager level. To control for size effects on performance, we include terms that control for both fund-level and management company-level scale economies (or diseconomies). First, we compute the size for each fund-manager pairing, $size_{ijt}$, and measured as the market value of assets controlled by management company j for fund i at the beginning of quarter t. Second, for each management company, we compute the assets under management in, e.g., UK equities across all funds managed at time t, labeled $M\_SIZE_{jt} = \sum_{i=1}^{N_{it}} SIZE_{ijt}$. Each quarter, we convert these to relative size measures by taking the log of the size variable divided by its cross-sectional average, e.g., $\log(M\_SIZE_{jt}/\overline{M\_SIZE}_t)$, where $\overline{M\_SIZE}_t = N_{jt}^{-1} \sum_{j=1}^{N_{jt}} M\_SIZE_{jt}$ is the cross-sectional average manager size at time t. This normalization helps to control for any time-varying industry-level diseconomies-of-scale, as documented by Pastor, Stambaugh, and Taylor (2015).[18]

Our measure of network centrality for manager j is also cross-sectionally normalized, i.e., $NET_{jt} = N_{jt}/\overline{N}_t$, where N_{jt} is the degree centrality measure for manager j at time t, and $\overline{N}_t$ is the cross-sectional average (across j) at time t. Centrality is always measured ex-ante, i.e., prior to the return measurement period. It is also likely that any advantages conferred by a high level of network centrality are better exploited by larger management companies, since economies-of-scale exist in interpreting and processing information. For instance, a large management company generally has a large pool of analysts, each of which tend to be more specialized in interpreting and gathering information, compared to analysts at a small management company. To capture possible scale effects of network centrality, we add an interaction term between network centrality and manager size, $NET_{jt} \times M\_SIZE_{jt}$. To simplify the comparison of estimated coefficients, we standardize all regressors so that they each have unit variance.

[18] We note that industry-level diseconomies, due to the increasing size of the UK asset management industry relative to, e.g., UK equity markets, are captured through the quarterly time dummies.

For each asset class, Table 3 presents results from panel regressions of the form[19]

$$\widehat{r}_{ijt}^{adj} = a_{ij} + b_t + \lambda_1 SIZE_{ijt} + \lambda_2 M\_SIZE_{jt} + \lambda_3 NET_{jt} + \lambda_4 NET_{jt} \times M\_SIZE_{jt} + \varepsilon_{ijt}. \quad (6)$$

This regression allows us to study the effect of network centrality, NET_{jt} (measured within each asset class), while controlling for variations in fund-manager size or management company size within an asset class, and allowing for fund-manager and time fixed effects. Thus, we use variation *over time* in network centrality for a given fund-manager combination (e.g., Goldman Sachs at Unilever) to identify its effect on risk-adjusted performance. For each asset class, we show results without and with the network-size interaction terms ($NET \times M\_SIZE$ or $NET\_C \times M\_SIZE$) in odd and even columns, respectively, along with regressions based on the total (first two columns in each panel) as well as consultant-only network measures (last two columns).[20]

First, consider the effect of size on risk-adjusted performance, across regression specifications, as shown in the first two rows of Table 3. Across all three asset classes and four model specifications, fund-manager and total management company size, in general, negatively predict performance–consistent with past literature.[21]

Most importantly, consider the effect of network centrality on risk-adjusted performance in UK equities (columns 1-4). The first column, which uses NET, the overall measure of network centrality, shows that there is a positive and significant effect of centrality on risk-adjusted performance. The coefficient is economically significant–a one standard deviation increase in network centrality (controlling for size of mandate and management company) raises the expected risk-adjusted return by 0.20% per annum–as well as being statistically significant. In column two, we find a strongly positive effect of including a centrality-management company size interaction term. The significance of the interaction term confirms that the performance of large managers is more sensitive to network centrality than

[19] For simplicity, we suppress reference to the asset class in this notation.

[20] We do not tabulate the results for manager-only network measures because the very high correlation between NET and NET_M (see Table 2) makes them redundant.

[21] Notably, Chen, Hong, Huang, and Kubik (2004), find negative economies at the fund level but positive economies at the management company level for the U.S. mutual fund industry. Our finding of diseconomies-of-scale at the management company level is likely due to the fact that pension fund management companies comprise a much larger fraction of the total market capitalization in the UK, relative to mutual funds in the U.S. Large management companies in the UK, therefore, face difficulties in trading their positions that outweigh other advantages of being large (such as being able to cross trades within the company or share a large pool of analysts).

that of small managers, which also implies that a central position in the network helps management companies cushion the otherwise strongly negative effect of their aggregated asset class size (under management) on performance. This interaction effect is so important that NET, by itself, is now insignificant–well-connected small management companies are not able to exploit their centrality.

Columns 3 and 4 explore whether the centrality of a manager, with respect to consultants, matters for risk-adjusted investment performance. These models indicate that centrality, measured through consultant connections, appear to be stronger than general centrality (through both same-fund and consultant-only connections, columns 1 and 2).

To more precisely address this point and to shed light on the relative importance of manager and consultant connections, we next undertake a two-step encompassing regression. Specifically, we obtain the residuals from Equation (6) based on the manager-only centrality measure. By construction, these residuals are orthogonal to the manager-only centrality terms. Next, we regress these residuals on the consultant-only network measure (both stand-alone and interacted with manager size) and perform a joint significance test. Rejection of this test (i.e., a low p-value) suggests that the consultant-only centrality measure helps explain part of the risk-adjusted return performance beyond what the manager-based centrality measure explains. For UK equities, we find a p-value of 0.09, suggesting significant evidence (at the 10% level) that centrality obtained through the consultant networks helps explain part of the return performance that is not explained by the manager centrality measure.

Analogously, we obtain the residuals from Equation (6) based on the consultant-only centrality measure, project these residuals on the manager-only network terms and perform a joint significance test. For this case, a low p-value suggests that the manager-based centrality measure helps explain part of the risk-adjusted return performance that the consultant-only centrality measure does not capture. In this case, with a p-value of 0.24 we find no evidence that manager-based centrality helps explain excess return performance not explained by consultant centrality. Thus, consultant centrality is key to gaining information in our network, which indicates that consultants, indeed, pass information about strategies from one manager to another.

Turning to UK bonds, columns 5-8 in Table 3, we see a positive relation between network centrality and risk-adjusted return performance, regardless of which of the two centrality measures (total or

consultant-only) is used (see columns 5 and 7). However, the size of the centrality effect is strongest for the consultant-only network. Note that (columns 6 and 8), in contrast to the results for UK equity, the coefficient on the centrality-size interaction term is negative, and it is significant for the overall NET (column 6) model. Further analysis lends insight into this result. Specifically, adding $NET \times M\_SIZE$ (i.e., moving from column 5 to 6) changes the sign of M_SIZE–indicating that, among bond managers, there is a high degree of correlation between $NET \times M\_SIZE$ and M_SIZE– i.e., only large bond management companies are well-connected, and the interaction effect exhibits the disadvantage of being large and highly networked. (We will return to examine the overall impact of size and centrality in the presence of such correlations in the next subsection.) Among bond fund managers, the prior-described encompassing test again suggests that the consultant centrality measure explains return performance in UK bonds not explained by manager centrality (p-value of 0.00). (On the other hand, there is no evidence to suggest the converse, i.e., that manager centrality explains excess returns over and above that identified through the consultant centrality measure–the associated p-value is 0.80.)

In the case of international equities (columns 9-12), we find little evidence that network centrality matters to investment performance, except for some mild evidence that a larger consultant centrality-size interaction term is associated with better performance (last column). In this case, both of the encompassing tests are insignificant, suggesting that neither the consultant nor manager-based network measures encompasses the other.

Overall, our results suggest a positive relation between the network centrality of a manager and its ability to generate risk-adjusted performance in the UK equity and UK bond markets, i.e., more centrally positioned managers tend to be those with the best investment performance. Conversely, the centrality of our UK network of managers does not appear to matter for the funds' investment performance in international equities.

An explanation for these findings is that, while better UK network connections can be exploited to generate better performance in domestic asset markets, they do not easily translate into information that can be used to achieve better investment performance in foreign markets. UK pension funds are a much smaller fraction of the overall market in international markets than in domestic asset markets.

For example, over our sample, UK pension funds and insurance companies held between 50% and 68% of the outstanding value of government bonds. The stronger effect found for the two domestic asset classes may therefore have do with the knowledge that network centrality provides about the resulting asset market equilibrium. A manager with a central position in the domestic asset market observes the preferred investment strategies of a large part of the market and so should be better able to infer the resulting asset market equilibrium and possibly take advantage of this.

3.2.1 Combined Effect of Manager Size and Centrality on Performance

As indicated by Table 3, there are significant and often an opposing impact on risk-adjusted returns between the size variables, M_SIZE and $SIZE$, and the centrality variables, NET and NET_C. For example, the results in the second column of Panel A in Table 3 show that the coefficients on $SIZE$ and M_SIZE are negative (-0.292 and -0.722, respectively) while the coefficients on NET and $NET \times M\_SIZE$ are positive (0.042 and 0.365, respectively).

We illustrate the combined effect of size and centrality through a simple exercise undertaken for UK equities and UK bonds, the two asset classes for which we find a significant effect of centrality on performance. We focus on the 75-th, 90-th, and 95-th percentiles of the size distributions and compute the combined (marginal) effect of the size and centrality variables on performance. For example, denote the 75-th percentile of $SIZE$ and M_SIZE as $SIZE\_75$ and M_SIZE_75. From Panel A in Table 3, the effect of size and centrality on UK equity fund performance is

$$\begin{aligned} Combined\_Effect = &- 0.292\ SIZE\_75 - 0.722\ M\_SIZE\_75 + 0.042\ NET \\ &+ 0.365\ NET \times M\_SIZE\_75, \end{aligned}$$

where we let NET range over its full support, i.e. from 0.07 to 4.08. This results in the red line in Panel A of Figure 9.

Overall, Figure 9 shows that, even for very large managers and funds (the 95-th percentiles of the size distributions), the joint effect of size and centrality is positive, as long as the centrality measure is greater than 2.5 for UK equities and 1.5 for UK bonds. These centrality values are relatively small, if we consider that large fund managers tend to have large centrality measures. In fact, 2.5 corresponds

to the $75-th$ percentile for the NET distribution in UK equities, while 1.5 corresponds to the $36-th$ percentile for the NET distribution in UK bonds. Note also that, in all cases (all three lines in each graph), increasing centrality is associated with an increasing risk-adjusted return–illustrating that the "$Combined\_Effect$" always results in a positive first-order condition with respect to centrality.

3.2.2 Results Controlling for Centrality in other Asset Classes

To the extent that the benefits from network connections arise due to managers' improved ability to receive and process information on strategies of other managers, we would expect that centrality *within* a specific asset class would matter more than centrality established through other asset classes. For example, a manager's network connections in the UK equity market should be more relevant than the same manager's connections in UK bonds, when it comes to receiving information on strategies that work in UK equity markets.

To assess the impact of asset-class specific centrality on performance, we modify the procedure in Section 3.2 as follows. For UK equities, we run panel regressions that include network centrality in UK equities as well as centrality in UK bonds. Because the two centrality measures are correlated with each other, we orthogonalize the centrality in UK bonds with respect to the centrality in UK equities at the fund-manager level.[22] Our baseline specification includes centrality in UK equities and the orthogonalized centrality measure for UK bonds. An extended specification includes interactions of these terms with manager size. As in Table 3, the analysis is conducted using the overall measure of manager network connection (through consultants or through managers) as well as network connections established through consultants only. For UK bonds, we perform the same analysis, reversing the roles of the centrality measures for UK bonds and UK equities in the orthogonalization procedure described above.

Table 4 reports results for the two asset classes for which we find a significant effect of centrality, i.e., UK equities (Panel A) and UK bonds (Panel B). The results show that, after accounting for network connections within UK equities, the performance of UK equity managers is either negatively affected, or insignificantly affected by additional network connections established through the management of

[22] In particular, we regress — at the fund-manager level — UK bond fund centrality on UK equity fund centrality. We then store the residuals, which represent the portion of UK bond fund centrality that is orthogonal with respect to UK equity fund centrality.

UK bond portfolios (and the coefficient on bond centrality is generally much lower, compared to the coefficient on equity centrality). Conversely, the coefficient on network centrality established in UK equities is significant in each model, either alone or when interacted with size. The results remain the same when we interact the centrality measures with manager size: centrality in UK equities generates positive and significant coefficients for this asset class, while centrality in UK bonds generates either negative or insignificant coefficients.

Turning to UK bonds (Panel B), a similar result emerges. Once we account for network connections within UK bonds, there is little evidence that the performance of UK bond managers is helped by additional network connections established through UK equity mandates. Without the size-centrality interaction terms, centrality in UK bonds is always positive and strongly (or marginally) significant for UK bond manager performance, while the coefficient on UK equity market centrality displays no particular pattern. Allowing for size-centrality interaction terms, only network centrality in UK bonds matters for UK bond manager performance.

These results suggest that asset-class-specific network connections are important in explaining manager performance in both the UK equity and UK bond markets. The results also lend support to the hypothesis that the network centrality measure captures fund managers' ability to gather and process information on strategies of importance to risk-adjusted performance within their asset class, and that the centrality measure is not merely acting as a proxy for an omitted variable.

4 Robustness

Networks are endogenously formed and could potentially be the result of agents' use of forward-looking information about future performance. Thus, it is particularly important to explore alternative explanations of the apparent relation between investment performance and network centrality. We address this issue in this section, first, by analyzing the similarity in returns between connected and non-connected managers. Stronger correlation in the returns of connected managers is indirect evidence that information flows across connected managers. Next, we use the merger between two consultants in our sample to do a difference-in-difference analysis that explores how risk-adjusted performance changes after an exogenous shock to network centrality of some fund managers, relative

to those not experiencing the shock. Throughout this analysis, we focus on the two asset classes for which we have previously found significant network effects on performance, i.e., UK equities and UK bonds.

4.1 Correlation between connected and non-connected managers

To further understand how network connections affect fund performance, we next ask if we can detect information flows between managers that share one or more network connections. If there is significant information flowing through network connections, we would expect the (abnormal) returns of portfolios managed by connected funds to be more highly correlated than the returns of portfolios managed by unconnected funds, due to the flow of information on strategies, and resulting partial convergence, between such connected funds.

We measure performance using three different estimates of returns, namely, total, systematic (factor-induced), and abnormal (residual) returns (these return components are computed using Equations (3) and (4). For each asset class and each measure of returns, we proceed as follows. First, we aggregate returns at the manager level by value-weighting returns across all funds managed by a given manager. We then compute return correlations for all possible pairings of managers in the dataset subject to the manager pairings overlapping for at least 12 quarters, to obtain a reliable estimate of manager-to-manager correlations (within the same asset class). Third, for each manager, we separately average the return correlations for that manager (1) with managers that are connected with that manager, and (2) with managers who are not. Fourth, we compute the median of the average correlations across all connected and non-connected managers in the dataset. Fifth, and finally, we evaluate the differences in medians across the two sets of correlations using two-sided permutation tests with 1,000 iterations.

Table 5 reports the outcome of this analysis. The median correlations between total returns (Panel A) are very similar for portfolios of connected managers compared to portfolios of non-connected managers. Specifically, for UK equities, the return correlation among connected managers is 95.4% compared to 94.9% among non-connected managers. The corresponding correlation estimates for UK bonds is 94.7% for connected managers and 93.6% for non-connected managers. In all cases the

correlations are not statistically different from each other.

Using the systematic return component, Panel B shows that the median correlations computed across connected and non-connected managers are very comparable, with differences equal to 0.000 and -0.001 for UK equities and UK bonds. This result indicates that there is no difference in systematic risk-taking between either connected or non-connected managers, and no difference between these differences.

In sharp contrast, Panel C reveals much greater differences in residual return correlations among connected and non-connected managers. Specifically, for UK equities, the median residual return correlation among connected managers is 17.0% versus 9.6% among non-connected managers. For UK bonds, the median residual return correlation among connected managers is 46.3% versus 34.6% for non-connected managers. In both cases these differences in residual return correlations are statistically and economically different. These findings are consistent with information flowing through network connections affecting fund managers' security and sector selection strategies, although network connections do not appear to affect managers' investment "style".[23]

4.2 The merger of two consultants: A natural experiment

The results presented so far indicate a positive relation between managers' network centrality and their ability to outperform. A potential concern with the results is that of reverse-causality: being well-connected can improve managers' risk-adjusted performance due to the resulting informational advantages, but an alternative explanation is that managers could be centrally placed in the network *because* they possess skills. Under this alternative mechanism, network centrality is the *result* of managers' skills, and not vice-versa.

To test the plausibility of this reverse-causality hypothesis, we use an exogenous shock in the network structure of the UK pension fund industry. On October 1, 1998, it was announced that two consultants (William M. Mercer and Sedgwick, Noble, Lowndes, consultants no. 2 and 11 in our data set), were merging. Mercer had mainly large clients, while Sedgwick, Noble, Lowndes had mainly small clients, so the merger was based on business synergies unrelated to the investment performance

[23] Under an alternative explanation that consultants somehow pick managers based on the correlation in their residual returns, we would expect to find a negative correlation between connected managers, as consultants would presumably attempt to diversify their clients' (idiosyncratic) risk explosures.

of the two consultants.

As it was unrelated to return performance, this merger provides an exogenous shock in the centrality of those managers that were associated with the merged consultants. Before the merger, consultant no. 2 (Mercer) managed 202 mandates, while consultant no. 11 (Sedgwick) managed 213 mandates. After the merger, the number of joint mandates (two managers that manage assets at the same pension fund) jumped to 405, so all managers connected to either of the two separate consultants benefitted from an exogenous increase in their network connections during a single quarter. We use this exogenous event to identify the causal impact of centrality on performance in the two asset classes for which we have evidence of an impact of centrality on performance, i.e., UK equities and UK bonds.

Our analysis adopts a simple diff-in-diff approach that modifies the baseline specification in Equation (6) to include a treatment dummy interacted with the NET measure of centrality for all those managers connected to Consultant no. 2 (the merged consultant) after 1998, the date of the merger. Specifically, we estimate:

$$\widehat{r}_{ijt}^{adj} = a_{ij} + b_t + \lambda_1 SIZE_{ijt} + \lambda_2 M\_SIZE_{jt} + \lambda_3 NET_{jt} + \lambda_4 NET_{jt} \times M\_Dummy_{jt} + \varepsilon_{ijt}.$$

The merger treatment dummy M_Dummy_{jt} is switched on for three years after the merger for all managers involved in the merger. We choose a three-year window to allow the additional connections to have an impact on the managers' performance, but the results are robust to the use of different windows.

The results, reported in Table 6, show that, for UK equities, the interaction between the treatment dummy and centrality has a positive and significant coefficient equal to 0.153, indicating that there a significant and positive relation between being exogenously exposed to a shock to network centrality and risk-adjusted performance. The coefficient is also economically large. The results for UK bonds are similar, but weaker. Although the coefficient on the interaction between the treatment dummy and network centrality remains positive, it is not statistically or economically significant (0.033). This result is in line with our prior finding that network centrality is highly correlated with manager size in UK bonds, and is more weakly associated with abnormal performance, as compared to UK equities. The transfer of information about strategies appears to have limited value in fixed-income markets.

4.3 Can investment consultants pick winners?

Our above tests provide evidence that network centrality leads to superior performance, due to centrally located managers being better-positioned to receive information on the strategies of their competitors. As a final robustness check of this hypothesis vs. the reverse (managers are central because they are skilled), we test whether any of the consultants are able to systematically select successful fund managers. Consultants are the most well-informed entities in the UK pension fund industry, as they are able to closely observe the strategies of the majority of fund managers–which is why they are trusted in advising fund sponsors in their hiring and firing decisions. We conjecture that, if it is possible to identify successful managers in the industry, the consultants should be best-positioned to successfully perform this task. If consultants have the ability to predict which managers will outperform in the future, then they may place such superior managers in a larger network–even before they realize superior performance. Network centrality might, therefore, lead subsequent performance even though the direction of causality might be the reverse.

At the heart of this reverse causality mechanism lies the hypothesis that consultants can pick winners. To test this hypothesis, we estimate consultant fixed-effects in the regressions for risk-adjusted performance. These fixed effects pool information across funds that are advised by the same consultant. Specifically, for UK equities, we adopt the specification,

$$r_{ict} = k + \alpha_c + \beta_{1ic} r_{mkt,t} + \beta_{2ic} SMB_t + \beta_{3ic} HML_t + \beta_{4ic} MOM_t + \epsilon_{ict}, \tag{7}$$

while, for UK bonds, we adopt the model,

$$r_{ict} = k + \alpha_c + \beta_{1ic} GOVB_t + \beta_{2ic} CONS_t + \epsilon_{ict}. \tag{8}$$

In these regressions 'i' refers to the fund, 'c' refers to the consultant, and 't' refers to the time period. Notice that we allow for consultant-fund differences by allowing the betas to differ across consultant-fund pairings.[24] This is an important consideration if consultants operate under different mandates (i.e., different levels of risk) for different funds. The estimated annualized alphas for the

[24] In these models, standard errors are clustered at the fund-consultant level.

individual consultants are reported in Table 7. For UK equities, none of the consultants have alphas that are different from zero at the 95% confidence level (using a two-tailed t-test). In UK bonds, only consultants 2 and 11 generate significant annualized alphas–equal to 18 and 35 bps/year, respectively. These results suggest that consultants are not systematically able to pick superior fund managers, a result consistent with the findings in Jenkinson, Jones, and Martinez (2014).

These results make it unlikely that the managers are central in the network because they are skilled, and suggest that network centrality, in itself, offers certain advantages. Another consideration that renders reverse-causality less plausible is that regression (6) allows for fund-manager and time fixed-effects. The presence of a fund-manager fixed-effect means that we already account for consultants' ability to identify "good matches" between funds and managers. Instead, the estimated effect of network centrality in (6) comes from time-series variation in the relation between network centrality and risk-adjusted performance. Presumably, predicting such time variation can be considered significantly more challenging for a consultant than simply predicting good performance "on average".

5 Fund flows and network centrality

We next address whether managers' centrality in the network affects flows of money into the funds they manage. We consider the results at the manager, rather than the fund-manager level, since defined-benefit flows for managers mainly occur through being hired (or fired) to manage additional (fewer) funds.

We split the analysis by considering inflows from existing mandates as well as inflows from new mandates. This distinction plays an important role for our sample of defined benefit pension schemes. For existing mandates, high past returns may actually result in smaller inflows because they result in the fund generating a surplus, which allows the sponsor to reduce or entirely suspend future contributions for a period of time. This is a unique feature of our data that contrasts starkly with mutual funds for which higher past performance tends to lead to stronger inflows. In our setting of defined benefit pensions, high network centrality is more likely to allow managers to grow assets through new clients, rather than existing ones.

For existing mandates we generate our fund-flow variable for manager j over the course of quarter

t as follows:

$$Flow_{jt+1} = \left(\frac{SMV_{jt+1} - SMV_{jt}}{SMV_{jt}} - R_{jt:t+1} \right) SMV_{jt}, \tag{9}$$

where SMV_{jt} and SMV_{jt+1} are the starting market values (of existing mandates) of manager j's asset holdings at quarter t and $t+1$ and $R_{jt:t+1}$ is the return generated over quarter t. For newly assigned mandates, the fund-flow variable for manager j over quarter t is the value of the newly assigned mandates.

We regress the manager flow variable on the lagged flow, network centrality, NET, and manager size, M_SIZE. We also include $Past\_Risk\_Adj\_Ret$ – constructed by value-weighting the risk-adjusted returns in a given asset class across the various funds managed over the previous year – and $Future\_Risk\_Adj\_Ret$ – constructed by value-weighting the risk-adjusted returns in a given asset class across the various funds managed over the following year. We include this variable so as to discern whether any effects from network centrality on flows arise because of the ability of network centrality to predict future return performance. Finally, the regression includes time and manager fixed effects:

$$\begin{aligned} Flow_{jt+1} = a_j + c_t + \beta_1 NET_{jt} + \beta_2 Flow_{jt} + \beta_3 M\_SIZE_{jt} \\ + \beta_4\ Future\_Risk\_Adj\_Ret_{jt} + \beta_5\ Past\_Risk\_Adj\_Ret_{jt} + \varepsilon_{jt}. \end{aligned} \tag{10}$$

The results for existing mandates are reported in Panel A of Table 8. For all three asset classes, the centrality coefficient NET is insignificant, indicating that more central managers do not attract more flows from existing mandates because of their network position. The results for the remaining coefficients differ across asset classes. For UK equities (first column), past flows are positively correlated with future flows, while manager size is strongly negatively related to future flows – consistent with sponsors understanding the diseconomies-of-scale in asset management. Also, past return performance is related to flows, consistent with sponsors increasing their wealth allocation to managers that perform well. The positive and significant coefficient on future risk-adjusted performance is an indication that sponsors have some ability to predict which UK equity managers are going to perform well in the future–though note that the coefficient on this variable is half the estimate on past performance, reflecting that future performance is difficult to forecast.

The results for UK bonds (second column) suggest that only size and past flows explain current flows. Both coefficients are consistent with the ones we obtain for equities, with size being negatively related to flows and past flows being positively related to flows. Finally, the results for international equities (third column) show that none of the explanatory variables explain flows.

Turning to the results for the newly assigned mandates reported in Panel B of Table 8, our estimates indicate that, for all three asset classes, centrality is positively and significantly related to flows. As for the remaining coefficients, size is negative and significant for domestic and international equities, but not for UK bonds.

Taken together, the results reported in this section show that network centrality does not seem to explain managers' ability to attract greater flows among existing clients, but, notably, it is strongly related to managers' ability to acquire new clients.

6 Risk-Taking and Network Centrality

Section 3 established a positive association between fund-manager centrality and risk-adjusted investment performance for UK equities and UK bonds, but not for international equities. We next address whether centrality affects managers' willingness to take risk, and the consequences of such actions. Network centrality could affect managers' risk-taking for at least two reasons. First, if more centrally placed managers have access to more precise information, they may be willing to take what appears to outsiders to be riskier bets. Second, if more centrally-placed managers are less likely to be fired for a given level of investment performance (as we find subsequently), then they should also be willing to take riskier bets. We also note the importance of controlling for size in measuring risk-taking, as there is likely to be a size effect on managers' risk-taking. Larger managers will find it more difficult to deviate from the market benchmark due to a greater market impact of their trades and less maneuverability, compared with that of smaller managers.

6.1 Idiosyncratic Risk and Network Centrality

We perform our analysis by proxying for the unobserved level of risk-taking by means of the level of idiosyncratic risk taken by a fund manager. Specifically, using equations (3)-(5), we first extract an

estimate of the fund-manager pairing's idiosyncratic risk, $|\widehat{\varepsilon}_{ijt}|$. Note that if these residuals are drawn from a Gaussian distribution, then $E[|\widehat{\varepsilon}_{ijt}|] = \sqrt{2/\pi} stdev(\hat{\varepsilon}_{ijt})$, thus justifying this particular proxy for risk. It should be recognized, however, that this is clearly a noisy measure of risk, as it is based on a single observation for every period.

Because of this limitation, we undertake the following procedure. From $|\widehat{\epsilon}_{ijt}|$, we subtract its cross-sectional average, computed using all the fund-manager pairings available at each point in time. We then compute the time-series average of the de-meaned absolute residuals at the fund-manager level and use this as our measure of risk. We use a similar procedure for managers' centrality and size as well as fund-managers' size. In particular, the size variables are converted to relative size by dividing them by the cross-sectional average and taking the natural log of this quantity. The centrality measures are converted to relative centrality by dividing them by the cross-sectional average. Finally, we regress, at the fund-manager level, the average absolute residual on average centrality, fund-manager size, and manager size.

Results from this regression are presented in Table 9. First, notice that fund-manager size as well as manager size have a strongly negative effect on risk-taking across all three asset classes and across different specifications: larger funds and larger managers take on less active risk and mirror the benchmarks more closely for each of the three asset classes. This makes sense, as it is more difficult for large managers to deviate from the market.

For UK equities, there is strong evidence that funds with higher centrality take on more risk than less central funds. While the coefficient on network centrality remains positive for UK bonds and international equities, it is insignificant for these asset classes.

Our results, therefore, indicate that managers with high centrality take more risk in UK equities, consistent with more central managers having higher levels of private information deriving from their network position and pension fund sponsors (and consultants) tolerating this higher risk level because of better average performance.

6.2 Network Centrality and Hazards of Firing

Network centrality does not only affect the information flowing to and from a particular manager or consultant; it can also affect the manager or consultant's incentives. This can happen through its effect on flows of funds into and out of the funds under the manager's (consultant's) control and, thus, the manager's remuneration, which is likely to depend on the asset base; we analyzed this effect in Section 5. It can also happen through its effect on the probability that the manager or consultant is fired by a client. To address this second channel, we next analyze whether the probability that a manager or consultant is fired is affected by his network centrality.[25]

6.2.1 Modeling the Hazard of Being Fired

To see whether a fund manager's or consultant's probability of being fired is influenced by his position (centrality) in the network, we estimate hazard rate models. The hazard rate (h) measures the probability of being fired next period, conditional on having survived up to the present time. To avoid having to impose restrictions on how the baseline hazard rate depends on the duration (d) of the relation between a manager and the pension fund, we use the Cox semi-parametric regression approach. This allows the effect of the 'age' of the fund-manager relationship–denoted the baseline hazard rate, $h_0(d)$–to be estimated nonparametrically, while the effect of fund-manager variables, x_{ijt}, on the hazard rate is modeled parametrically.

Specifically, letting $h(d_{ijt})$ be the hazard rate for fund-manager i, j at time t and $h_0(d_{ijt})$ be the baseline hazard rate as a function of the duration of the fund-manager's tenure at time t, we estimate the following semiparametric Cox regression model

$$h(d_{ijt}) = h_0(d_{ijt}) \exp(\beta' x_{ijt}). \tag{11}$$

Our model allows the manager's hazard rate to depend on four factors, x_{ijt}. First, we consider the effect of the duration of manager j's relation with pension fund i at time t, d_{ijt}, measured in quarters.

[25] Previous studies have analyzed the factors influencing the likelihood of termination for mutual fund managers. Chevalier and Ellison (1999) report that young managers face a higher risk of being fired following poor risk-adjusted performance. Khorana (1996) finds that underperforming managers with decreasing inflows also face a higher probability of being fired.

This maps into the baseline hazard, $h_0(d_{ijt})$. We present results for this variable graphically. An upward-sloping curve indicates that the manager's risk of getting fired increases as the length of his contract with a pension fund gets extended, while a downward-sloping curve suggests that the manager is less likely to get fired, the longer he has been with a particular pension fund.

Second, we include $Past\_Risk\_Adj\_Ret$ – constructed by value-weighting the risk-adjusted returns in a given asset class across the various funds managed over the previous two quarters. The hypothesis here is that higher past risk-adjusted returns should reduce the chance of a manager getting fired.

Third, we control for manager size, M_SIZE_{jt}, measured at the beginning of each quarter. We found earlier that this matters for both return performance and fund flows and so it is natural to expect this variable also to be important for managers' prospects of getting fired. Here, the hypothesis is that, after controlling for past return performance, large, established managers are less likely to get fired than smaller managers.

Our final covariate is the overall centrality measure, NET_{jt}. The hypothesis is that the more central a manager is within the network, the less likely she is to get fired.

In summary, our regression model for the hazard rate takes the following form:

$$h(d_{ijt}, Past\_Risk\_Adj\_Ret_{ijt}, M\_SIZE_{jt}, NET_{jt}) = \\ h_0(d_{ijt}) \exp(\beta_1 Past\_Risk\_Adj\_Ret_{ijt} + \beta_2 M\_SIZE_{jt} + \beta_3 NET_{jt}) + \varepsilon_{ijt}. \quad (12)$$

6.2.2 Results for Managers

Figure 10 (top panels) plots the (smoothed) baseline hazard rates for the three asset classes. These show how the probability that a manager is fired in the subsequent quarter varies with the duration of the fund-manager contract. For all three asset classes, the hazard rate increases systematically in the duration, quadrupling from around 0.2 - 0.3% per quarter for managers with a tenure of 10 quarters to 0.8% - 1.2% per quarter for managers with a tenure of 70 quarters.

Panel A in Table 10 reports estimation results for the model in (12). The hazard rate, i.e., the risk that the manager is fired by a client, is significantly negatively related to past performance for both UK equities and international equities, but generates an insignificant coefficient for UK bonds. Higher

past (risk-adjusted) performance is, thus, associated with a reduced probability that a manager will be fired by the fund.

We estimate a large negative, and highly significant, coefficient on manager size, suggesting that large managers face a lower probability of being fired. Moreover, the estimated coefficient is largely the same across the three asset classes and is robust to the included measure of centrality.

Turning to network centrality, all specifications generate negative coefficients on this measure. The coefficients are all significant at the 5% level. Thus, more central managers appear to face a greatly reduced chance of being fired, compared with more peripheral managers. The effect is strongest for UK and International equities.

These results establish a strong case that managers' network centrality negatively affects their probability of being fired. Besides the advantages that centrality offers managers in terms of higher inflows and better performance, this suggests that more central managers also are "safer", i.e., they stand a lower chance of being fired.

6.2.3 Results for Consultants

We next undertake a similar hazard rate analysis for the consultants as that undertaken for the managers. Figure 10 (bottom panels) plots the baseline hazard rate for our sample of consultants. The figure again shows broad evidence of a hazard rate that increases in the duration of the fund-consultant relation. Note, however, that the baseline level is somewhat lower than for the managers and ranges from around 0.2% per quarter for newly formed relations to 0.8% per quarter for relations longer than 15 years (60 quarters).

Panel B of Table 10 shows parameter estimates from applying (12) to the consultant data. Past average return performance no longer appears to be a significant predictor of firing events for UK equities and UK bonds, although it generates a negative and significant coefficient for international equities. Consultant size remains strongly negatively related to the firing probability in all three asset classes. Interestingly, consultant centrality is, once again, a negative and highly significantly predictor of future firings in all three asset classes. Thus we find that, for managers and consultants alike, network centrality helps reduce the risks of getting fired–consistent with pension fund sponsors (and

consultants) recognizing that higher expected future performance is associated with a higher level of network centrality.

7 Size and Network Centrality: Granger Causality Tests

Table 2 shows that a manager's size and network centrality are positively connected. Large managers are likely to manage the assets of more clients and so this finding does not come as a surprise. While it can be difficult to formally test if size causes centrality or vice versa, more limited tests of whether one variable precedes the other one are feasible through Granger causality tests.

To implement such Granger causality tests, we first obtain the centrality measure for each manager at each point in time. Similarly, we compute the size of each manager by aggregating investments in all the funds (and asset classes) managed by the manager. We then regress changes in log-size on its own lag and the lag of changes in degree centrality. Because the lagged size and lagged centrality measures are not exogenous, we instrument these variables by using their own lags using instrumental variable estimation.

Specifically, we follow the procedure for Granger causality tests in a panel setting developed by Holtz-Eakin, Newey, and Rosen (1988). To this end, consider the simple panel model:

$$y_{it} = \lambda_0 + \sum_{l=1}^{m} \lambda_l y_{it-l} + \sum_{l=1}^{m} \delta_l x_{it-l} + u_{it}. \tag{13}$$

The model in (13) is a simple pooled OLS that imposes the constraint that the underlying structure is the same for each cross-sectional unit. This assumption can be relaxed either by introducing an individual specific intercept–so as to allow for individual heterogeneity in the levels of x and y–or by allowing the variance of the innovation in (13) to vary with the cross-sectional unit so as to capture individual heterogeneity in the variability of x and y.

Working with a panel of data rather than individual time-series offers key advantages. We can allow the coefficients on the lags to vary over time and the large number of cross-sectional units does not require the vector autoregression to satisfy the usual conditions that rule out unit roots or even explosive roots. Exploiting these advantages, Holtz-Eakin et al. (1988) propose a model that allows

for individual effects and non-stationarities:

$$y_{it} = \lambda_{0t} + \sum_{l=1}^{m} \lambda_{lt} y_{it-l} + \sum_{l=1}^{m} \delta_{lt} x_{it-l} + \Psi_t f_i + u_{it}, \tag{14}$$

where f_i is an unobserved individual effect and the coefficients $\lambda_{0t}, \lambda_{1t}, ..., \lambda_{mt}, \delta_{1t}, ..., \delta_{mt}, \Psi_t$ are the coefficients of the linear projection of y_{it} on a constant, past values of y_{it} and x_{it} and the individual effect f_i. Implicit in equation (14) is that for each period, t, the projection of y_{it} on the entire past depends only on the past m observations.

Our analysis of the relation between fund size and network centrality uses the specification

$$y_{it} = \lambda_0 + \sum_{l=1}^{m} \lambda_l y_{it-l} + \sum_{l=1}^{m} \delta_l x_{it-l} + \Psi_i + u_{it}.$$

First-differencing this model yields

$$y_{it} - y_{it-1} = \sum_{l=1}^{m} \lambda_l (y_{it-l} - y_{it-l-1}) + \sum_{l=1}^{m} \delta_l (x_{it-l} - x_{it-l-1}) + v_{it}, \tag{15}$$

where $v_{it} = u_{it} - u_{it-1}$.

Estimation

To estimate the model, define $N \times 1$ vectors of observations on the various units at a given time period, $\mathbf{Y}_t = (Y_{1t}, ..., Y_{Nt})'$ and $\mathbf{X}_t = (X_{1t}, ..., X_{Nt})'$. Let $\mathbf{W}_t = (\mathbf{e}_N,\ \mathbf{Y}_{t-1}, ...,\ \mathbf{Y}_{t-m},\ \mathbf{X}_{t-1}, ...,\ \mathbf{X}_{t-m})$ be the matrix of regressors, where $\mathbf{e}_N$ is an $N \times 1$ vector of ones. Further, let $\mathbf{V}_t = (v_{1t}, ..., v_{mt})'$ be the vector of transformed disturbance terms and let $\mathbf{B} = (a,\ \lambda_1, ..., \lambda_m, \delta_1, ..., \delta_m)'$ be the vector of coefficients. Then we can write (15) as:

$$\mathbf{Y}_t = \mathbf{W}_t \mathbf{B} + \mathbf{V}_t. \tag{16}$$

Stacking the observations for each time period, we can simplify this to a system

$$\mathbf{Y} = \mathbf{W}\mathbf{B} + \mathbf{V}. \tag{17}$$

Finally, defining a set of instrumental variables, $\mathbf{Z}$, we estimate $\mathbf{B}$ from the equation

$$\mathbf{Z}'\mathbf{Y} = \mathbf{Z}'\mathbf{W}\mathbf{B} + \mathbf{Z}'\mathbf{V}. \tag{18}$$

This specification makes it easy to test whether the coefficients on the $x-$variables are jointly equal to zero by imposing simple linear restrictions and then computing the likelihood ratio test comparing the restricted and unrestricted model.

Our implementation uses one-step GMM estimation and the Arellano-Bond estimator and limits the instruments to a maximum of 16 lags.[26] We separately consider the total, manager- and consultant-based centrality measures.

7.1 Empirical Findings

Table 11 presents the outcome of the Granger causality tests described above as applied to our data. Panel A uses the overall centrality measure as the dependent variable, while lagged size and lagged centrality are used as independent variables. In all instances lagged size fails to significantly predict centrality, leading to the conclusion that size does not Granger-cause network centrality. As expected, lagged centrality predicts current centrality, consistent with the persistence in the centrality measures revealed in plots such as Figure 7.

Panel B of Table 11 performs the reverse regression, regressing current size on lagged centrality and past size. Here we find that centrality strongly (and positively) predicts future size, after controlling for past size. Thus, network centrality Granger-causes size, but not the reverse. This result is consistent across all asset classes. Moreover, the results are robust to the number of lags chosen.

The conclusion from these results is that network centrality adds a novel dimension to our understanding of managers' investment performance, risk-taking behavior, and fund flows. Moreover, network centrality, though positively related to size, is clearly not subsumed by size. In fact, although size and network centrality are positively correlated, size generally has a negative effect on investment performance and fund inflows while conversely network centrality is associated with better

[26] This is due to the fact that we have 81 observations in the time-series and the number of instruments would become unmanageably large otherwise.

risk-adjusted performance and higher inflows.

We also computed panel Granger causality tests for the relation between quarterly return performance, aggregated across asset classes, and network centrality. The procedure adopted is virtually identical to that described above, with the exception that we control for the effect of manager size, $SIZE\_M$, which we found has an important impact on performance. The results suggest that performance does not Granger-cause centrality. Conversely, our results indicate that network centrality NET Granger-causes future performance. A more central position in the network thus seems to precede improvements in managers' return performance, while the opposite relation does not hold.

8 Conclusion

Financial systems are intricate, highly interconnected networks in which the relations between institutional clients, fund managers, and investment advisors (consultants) evolve dynamically in a way that reflects past performance which, in turn, will affect future performance. How information flows between clients and investment managers is important for both investment performance, flows of funds, and the incentives and risk-taking behavior of fund managers. No prior study has been able to address this question empirically.

This paper uses a unique data set to shed light on these questions. First, we document how managers and fund-managers are connected and how such connections evolve over time. We distinguish between network connections established only through managers versus connections established only through consultants. Next, we show that a manager's (relative) degree of centrality in a network positively affects risk-adjusted returns and growth in assets under management and that this effect is particularly strong for large fund managers. Finally, we show that more centrally placed managers are more likely to take on risk and less likely to be fired after spells of low performance.

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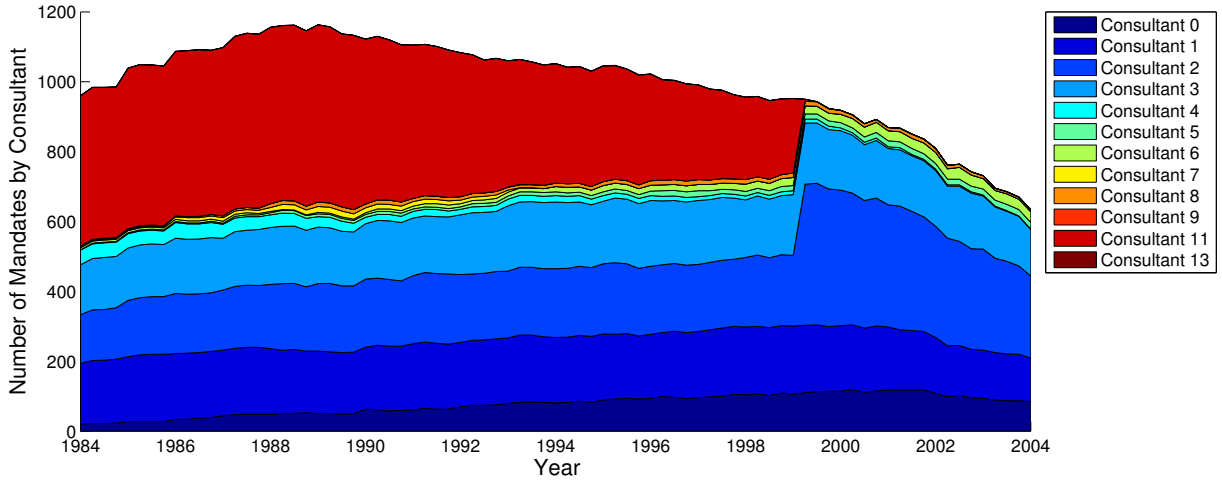
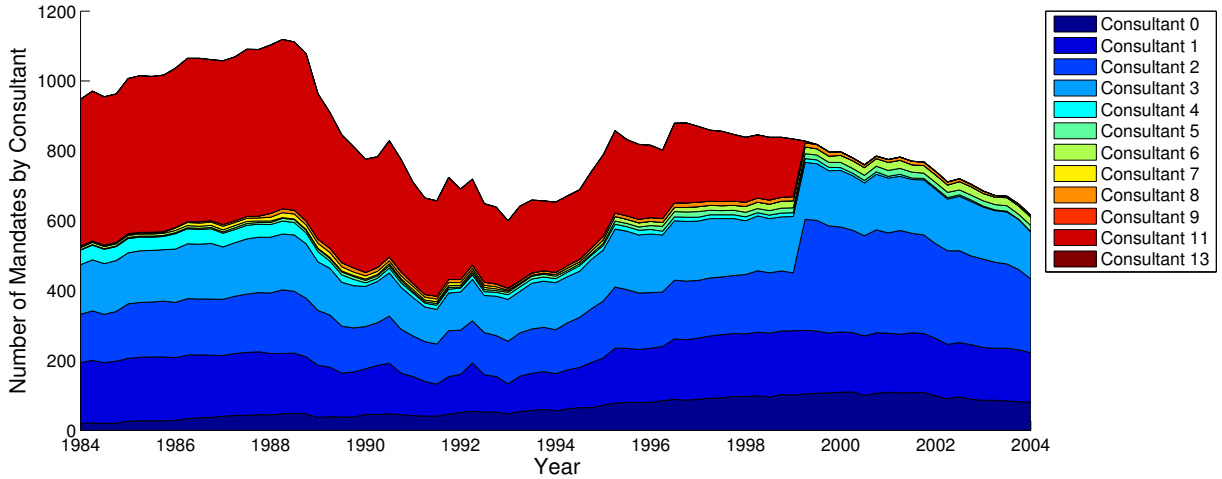
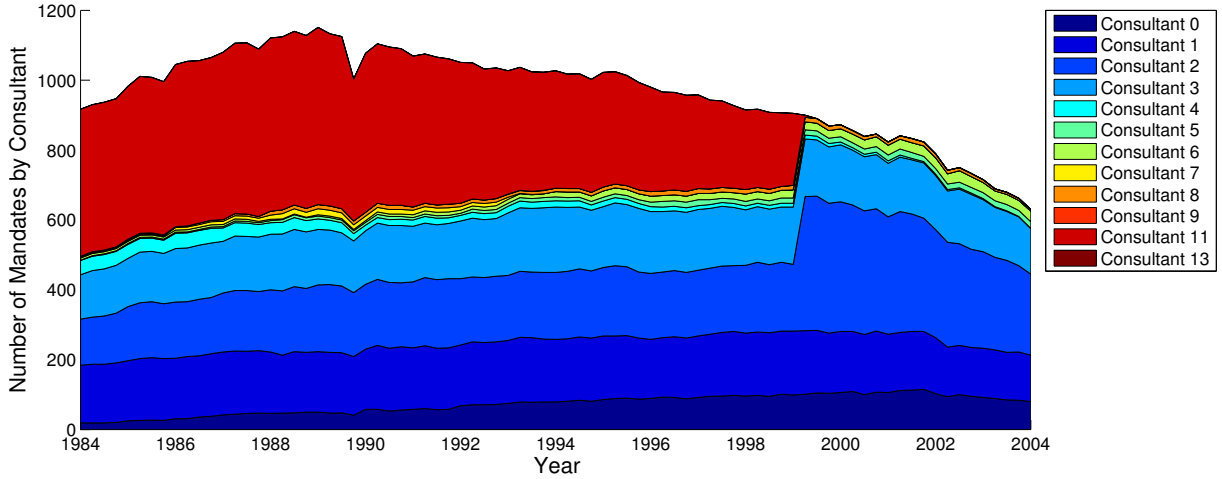
Figure 1. Evolution of the Number of Mandates by Consultants.



(A) UK equities



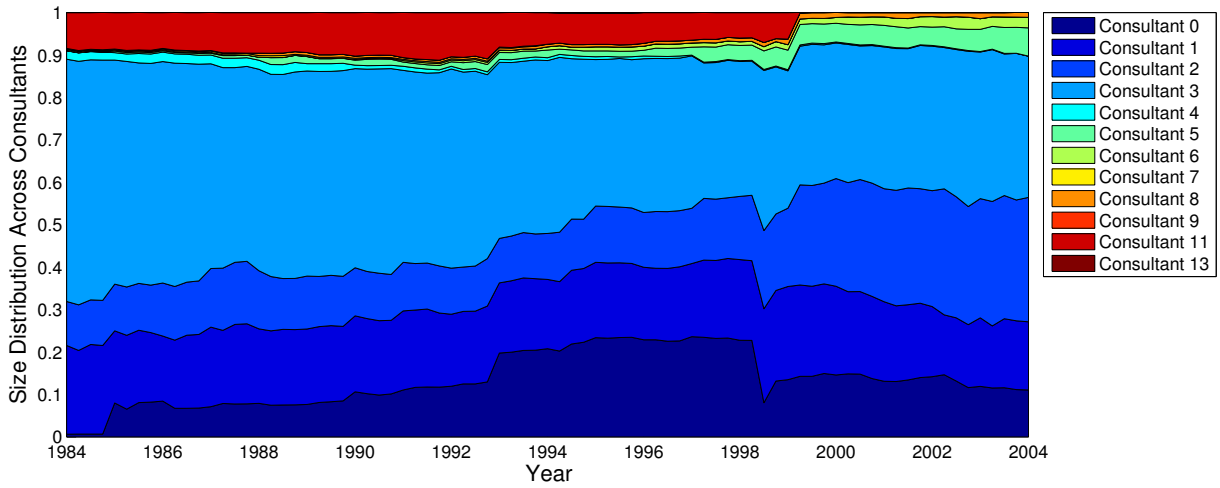
(B) UK bonds



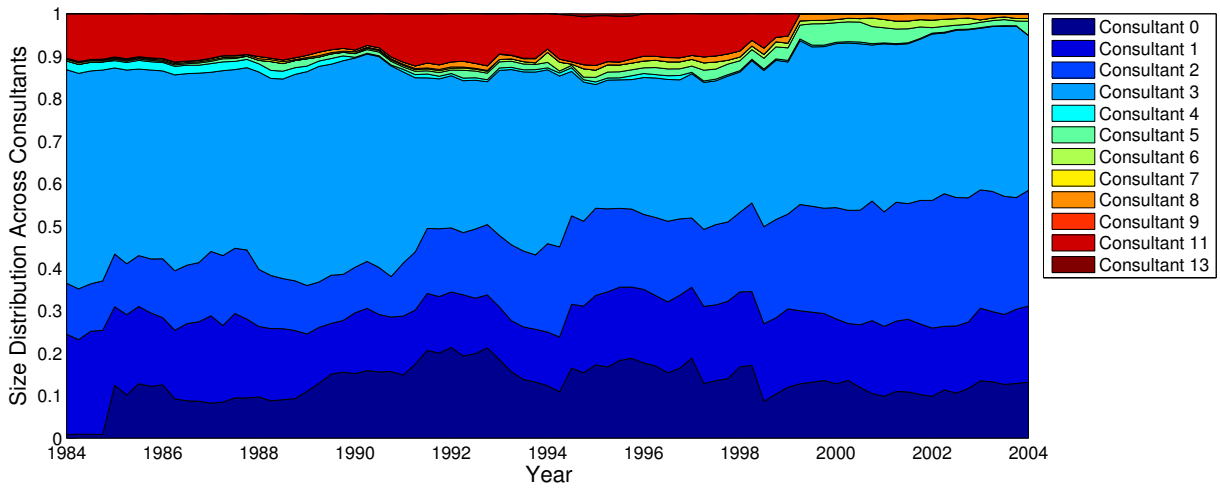
(C) International equities

This figure plots the number of mandates by consultants over the period 1984 to 2004. The results for UK equities are reported in Panel A, the results for UK bonds are reported in Panel B and the results for international equities are reported in Panel C.

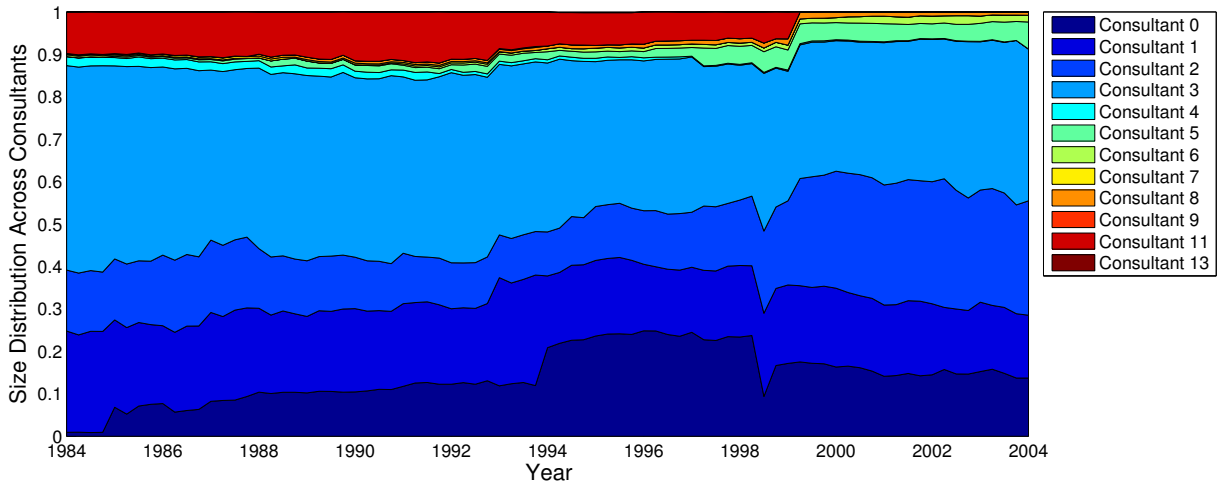
Figure 2. Relative Size of Consultants over Time.



(A) UK equities



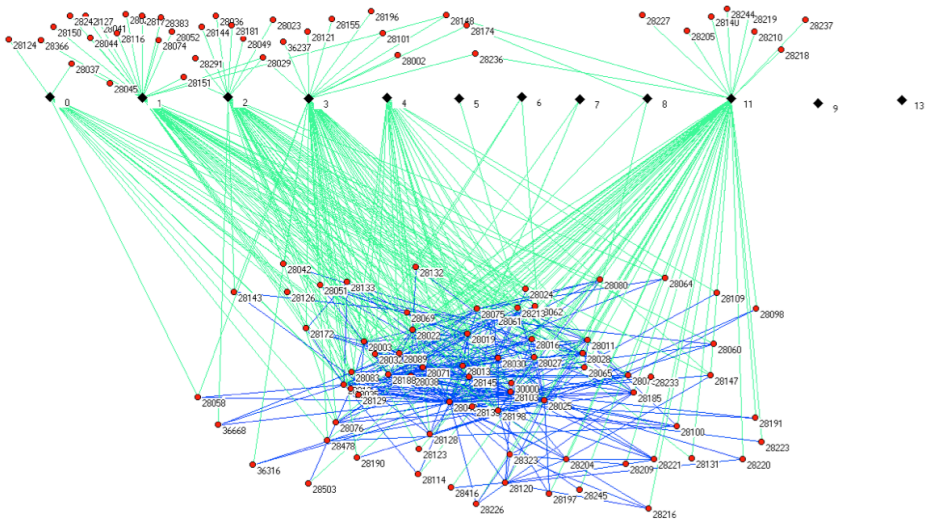
(B) UK bonds



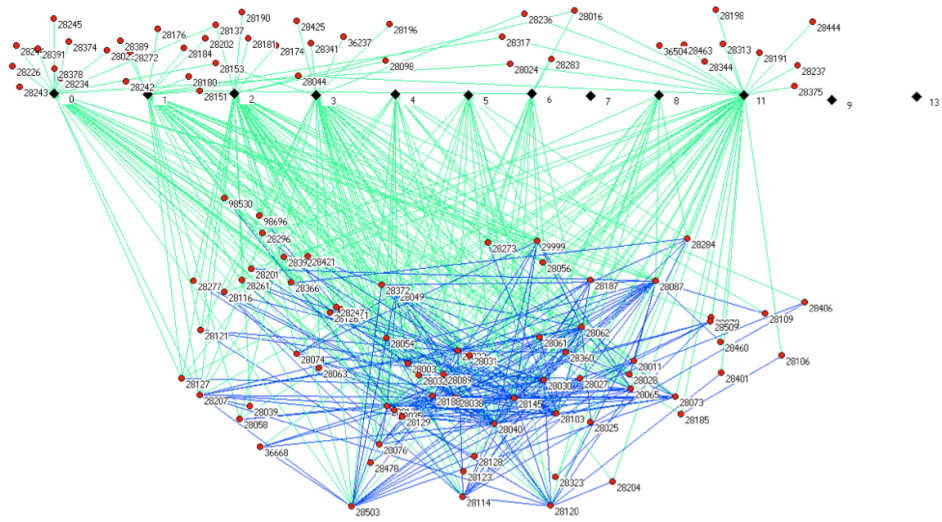
(C) International equities

This figure plots the relative size of consultants over the period 1984 to 2004. The total size of each asset class is normalized to one in every period and for each consultant we report the proportion of assets managed relative to the total size of the asset class. The analysis is conducted for UK equities in Panel A, for UK bonds in Panel B and for international equities in Panel C.

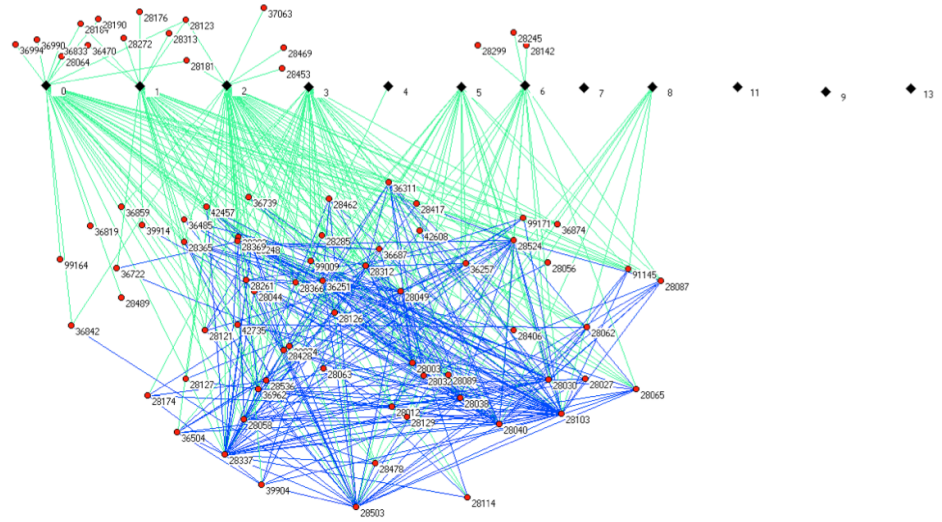
Figure 3. Network connections in UK equities asset class in the UK pension fund industry



(A) year : 1984



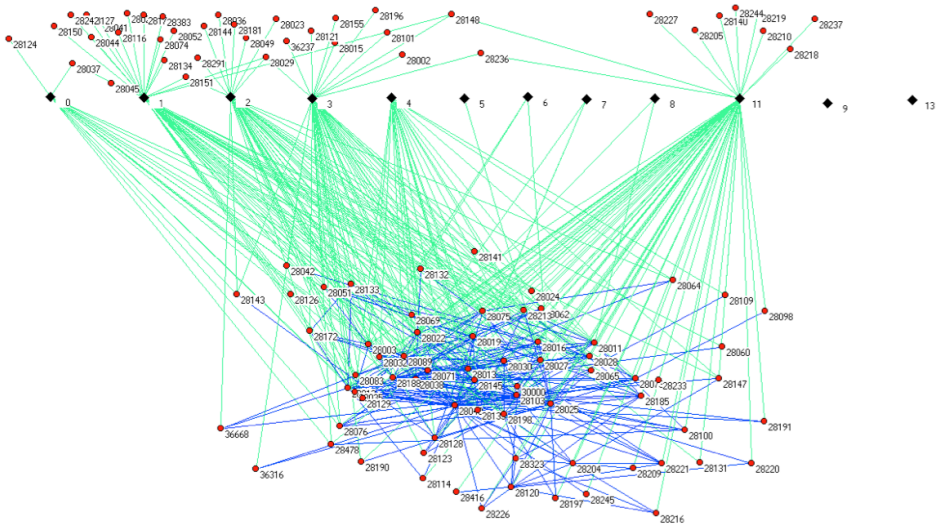
(B) year : 1994



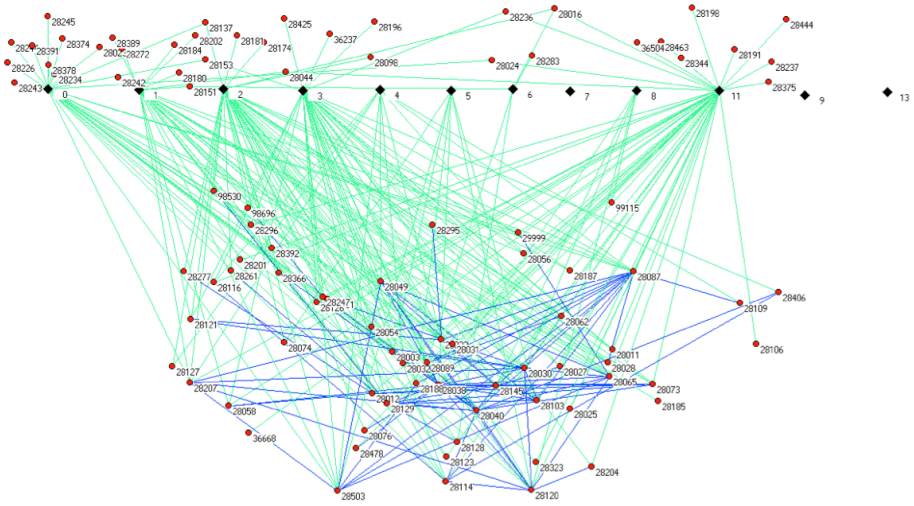
(C) year : 2004

This figure plots the network connections in UK equities at three points in time during our sample, namely 1984, 1994, and 2004. The red circles represent individual managers, while the black diamonds in the horizontal row represent the 12 consultants. Next to each node is shown the code of the manager or consultant. Managers whose nodes are shown above the consultants are only connected through the consultants, while the managers whose nodes fall below the consultants are connected with at least one other manager.

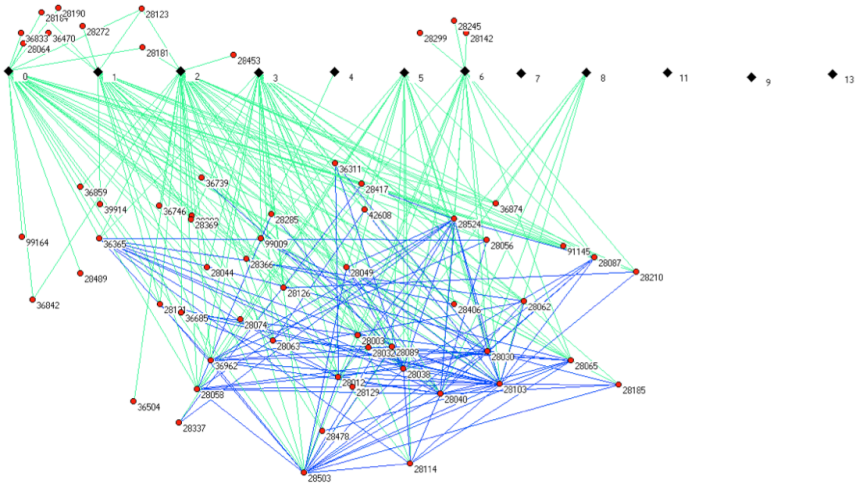
Figure 4. Network connections in UK bonds asset class in the UK pension fund industry



(A) year : 1984



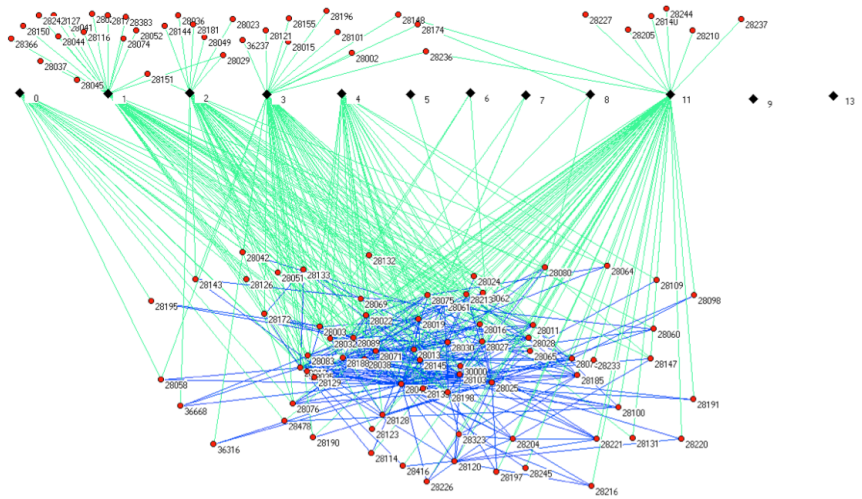
(B) year : 1994



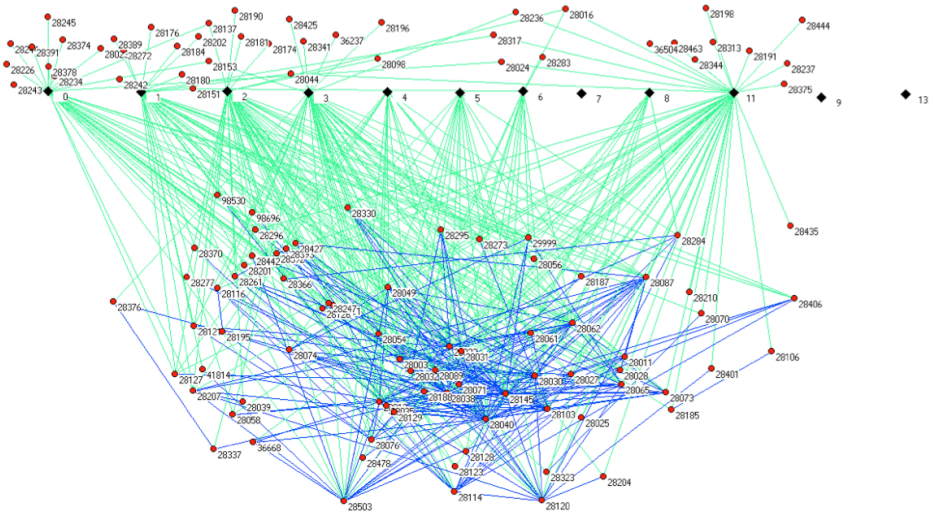
(C) year : 2004

This figure plots the network connections in UK bonds at three points in time during our sample, namely 1984, 1994, and 2004. The red circles represent individual managers, while the black diamonds in the horizontal row represent the 12 consultants. Next to each node is shown the code of the manager or consultant. Managers whose nodes are shown above the consultants are only connected through the consultants, while the managers whose nodes fall below the consultants are connected with at least one other manager.

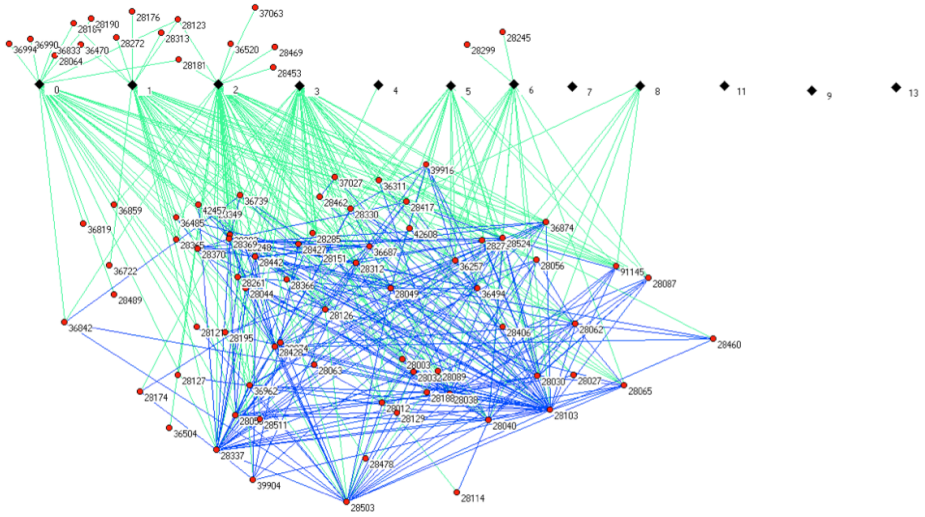
Figure 5. Network connections in international equities asset class in the UK pension fund industry



(A) year : 1984



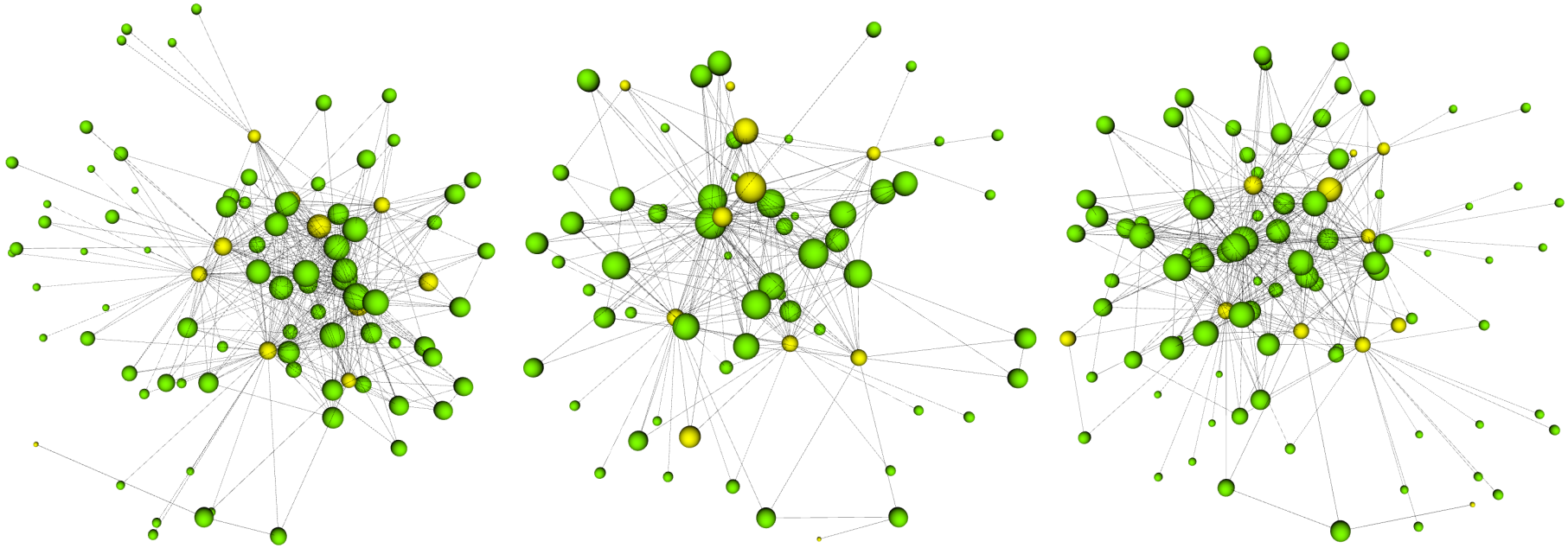
(B) year : 1994



(C) year : 2004

This figure plots the network connections in international equities at three points in time during our sample, namely 1984, 1994, and 2004. The red circles represent individual managers, while the black diamonds in the horizontal row represent the 12 consultants. Next to each node is shown the code of the manager or consultant. Managers whose nodes are shown above the consultants are only connected through the consultants, while the managers whose nodes fall below the consultants are connected with at least one other manager.

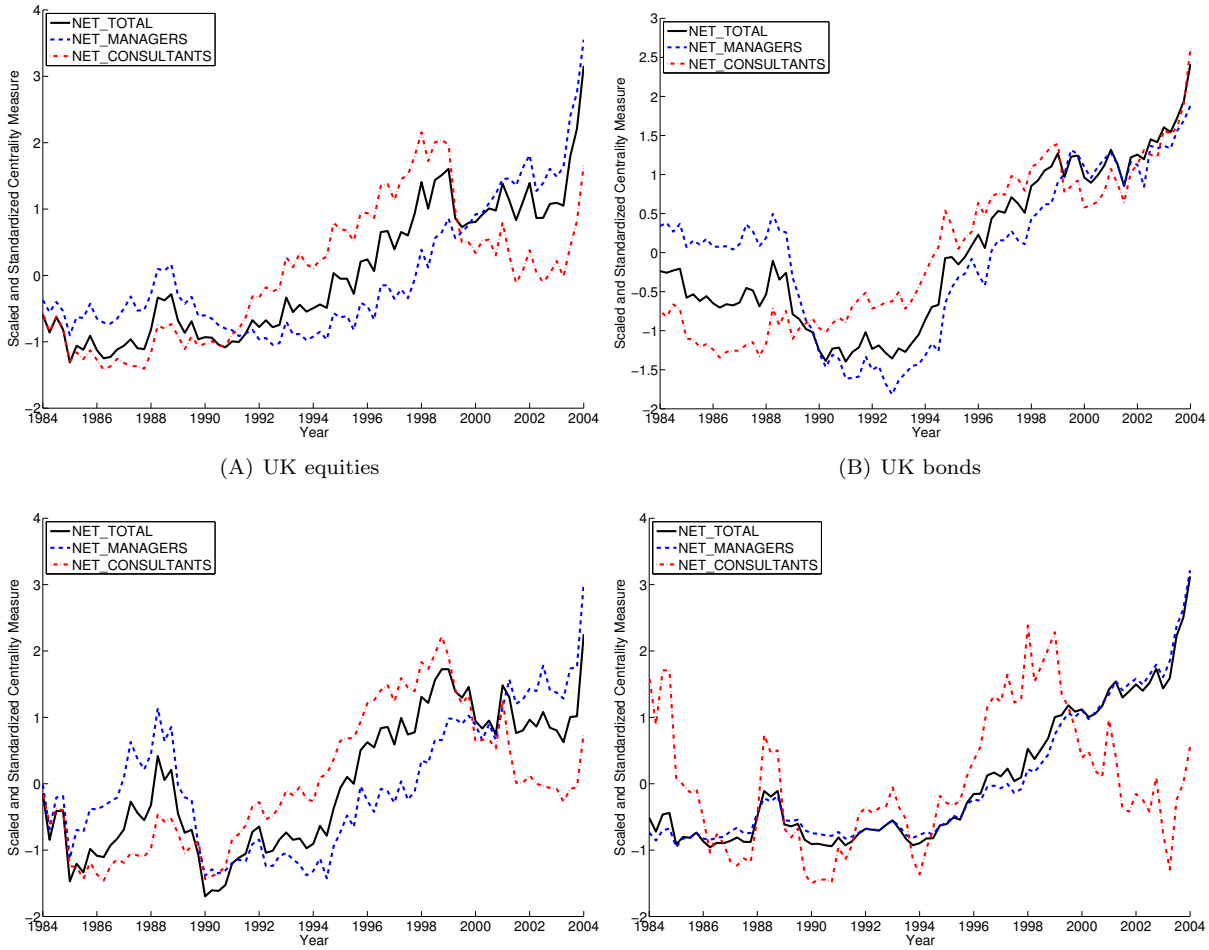
Figure 6. 3-D Representation of the Network Connections across managers and consultants in UK Equities, UK bonds and International equities for the year 2004.



(A) UK equities (B) UK bonds (C) International equities

This figure plots the network connections between consultants and managers in 2004 for UK equities (Panel A), UK bonds (Panel B) and international equities (Panel C). Each green sphere represents a manager and each yellow sphere represents a consultant. The size of the spheres is a function of the relative degree centrality of the manager or the consultants. The lines connecting the various spheres represent manager-to-manager connections and manager-to-consultant connections.

Figure 7. Average network centrality in the UK pension fund industry



(A) UK equities

(B) UK bonds

(C) International equities

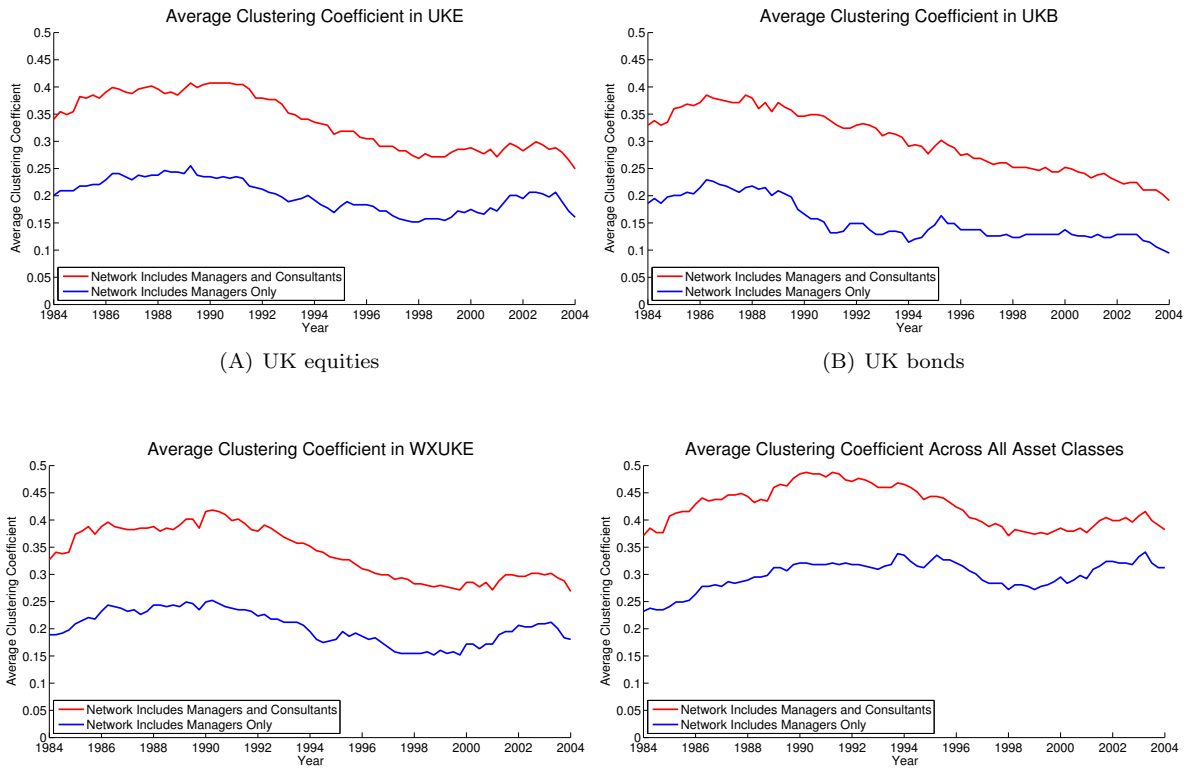
(D) Across all Asset Classes

This figure plots the time series of the average degree centrality, the average degree centrality computed using the managers' network only and the average degree centrality computed using the consultants' network only. The centrality measures are computed using network connections in UK equities only in Panel (A), network connections in UK bonds only in Panel (B) and network connections in international equities only in Panel (C) and network connections across all asset classes in Panel (D). In each panel, each average centrality measure "CM_t" is standardized as follows

$$S\_CM_t = \frac{CM_t - MEAN(CM_t)}{STDEV(CM_t)},$$

where $MEAN(CM_t)$ is the time-series mean of the average centrality measure CM_t and $STDEV(CM_t)$ is its standard deviation.

Figure 8. Evolution of Clustering Coefficients



(A) UK equities

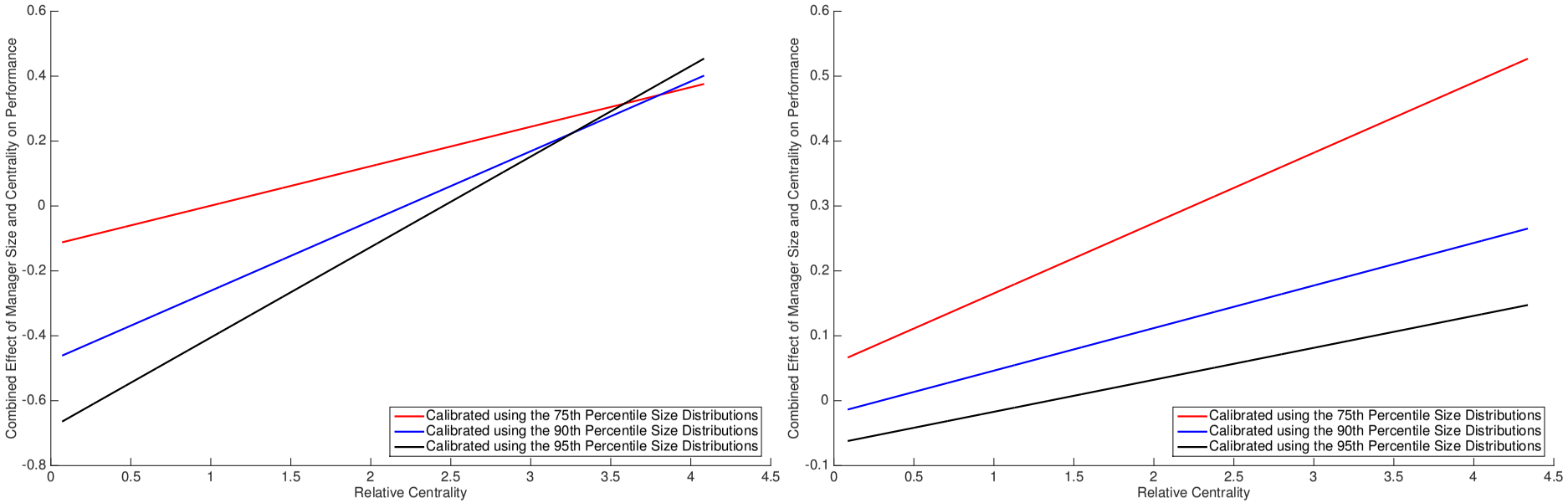
(B) UK bonds

(C) International Equities

(D) All Asset Classes

This figure reports the evolution of the average clustering associated with network connections in UK equities (Panel A), UK bonds (Panel B), international equities (Panel C) as well as network connections across all asset classes (Panel D). The networks considered are the ones generated by both managers and consultants connections (red lines) as well as the ones generated by managers-only connections (blue lines). The clustering coefficient of a given node 'i' is computed as the fraction of nodes connected to 'i' that are connected among each other. It is therefore bounded between 0 and 1. The average clustering of a network is obtained by averaging the clustering coefficients of all the nodes in the network.

Figure 9. Combined Effect of Manager Size and Centrality on Performance



(A) UK equities (B) UK bonds

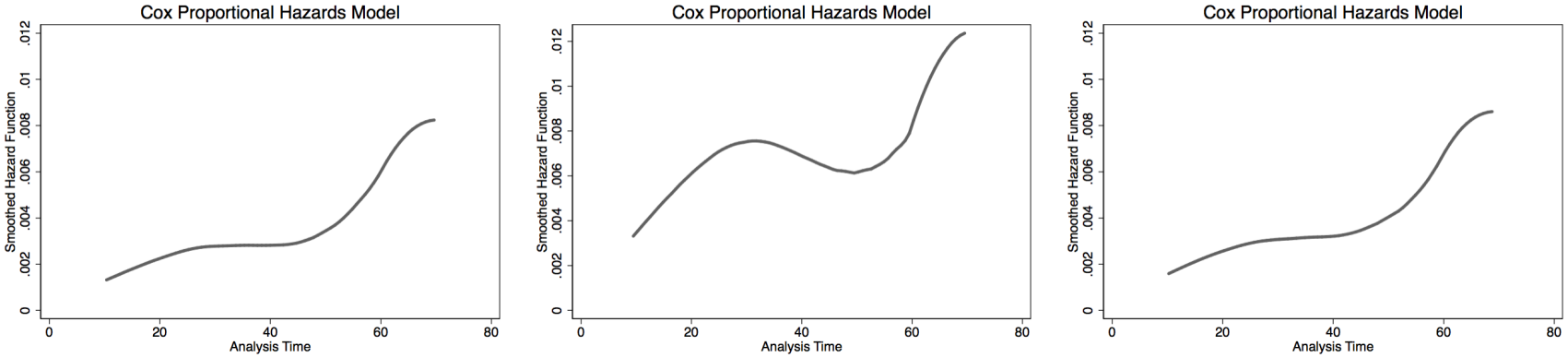
This figure plots the combined effect of manager size and centrality on performance. To compute these quantities, we focus on particular percentiles of the fund-manager size $SIZE$ and manager size M_SIZE: we use, alternatively, the 75th, 90th or 95th percentiles of the size distributions, while we allow the centrality measure NET to vary across its full support. The coefficients used are the ones reported in Table 3. As an example, consider the case of the 75-th percentile of $SIZE$ and M_SIZE and denote them as $SIZE\_75$ and M_SIZE_75. We report the results of the following calculation:

$$Combined\_Effect\_of\_Manager\_Size\_and\_Centrality = -0.292 \times SIZE\_75 - 0.722 \times M\_SIZE\_75 + 0.42 \times NET + 0.365 \times NET \times M\_SIZE\_75,$$

where we let NET range 0.07 through 4.08. The results for UK equities are reported in Panel A, while the results for UK bonds are reported in Panel B.

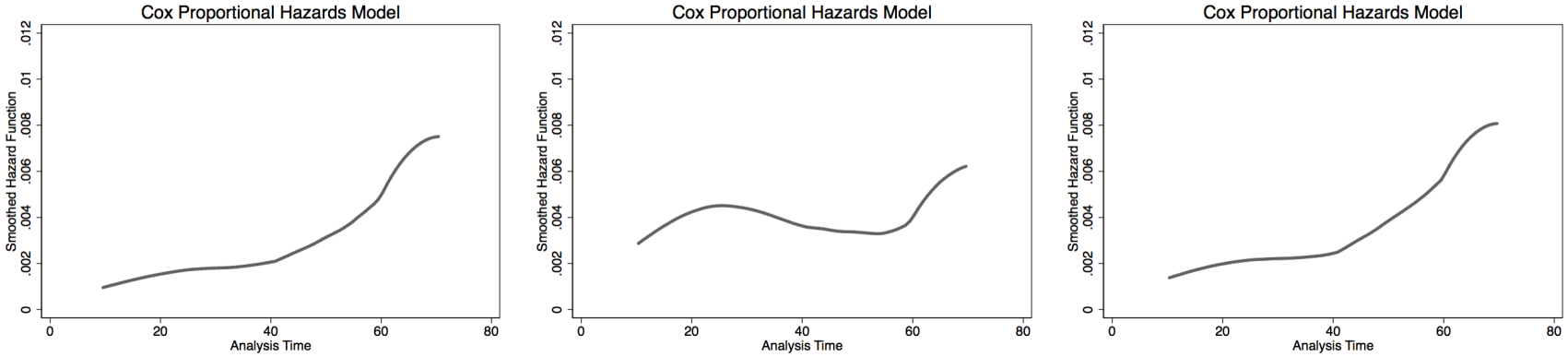
Figure 10. Baseline Hazard Rates for Managers' and Consultants' Survival Analysis

Managers' Baseline Hazard Rates



(A) UK Equities (B) UK Bonds (C) International Equities

Consultants' Baseline Hazard Rates



(D) UK Equities (E) UK Bonds (F) International Equities

This figure plots baseline hazard functions for fund-managers in Panels A through C and consultants in Panels D through F. Panel A and D display the results for UK equities, panels B and E display the results for UK bonds and panels C and F display the results for international equities. All hazard functions are estimated non-parametrically.

Table 1. Number of Funds, Managers and their Connections Across Time and Asset Classes

Panel A. UK Equities

Year	N. of Fund-Managers	N. of Funds	N. of Managers	$Net = 1$	$2 \leq Net \leq 5$	$6 \leq Net \leq 10$	$11 \leq Net \leq 20$	$Net \geq 21$
1984	1204	955	113	35	35	15	20	8
1994	1420	1044	112	34	42	14	12	10
2004	1053	630	82	22	23	17	10	10

Panel B. UK Bonds

Year	N. of Fund-Managers	N. of Funds	N. of Managers	$Net = 1$	$2 \leq Net \leq 5$	$6 \leq Net \leq 10$	$11 \leq Net \leq 20$	$Net \geq 21$
1984	1165	943	109	37	32	15	20	5
1994	745	652	96	36	41	8	10	1
2004	817	612	61	19	22	6	10	4

Panel C. International Equities

Year	N. of Fund-Managers	N. of Funds	N. of Managers	$Net = 1$	$2 \leq Net \leq 5$	$6 \leq Net \leq 10$	$11 \leq Net \leq 20$	$Net \geq 21$
1984	1135	911	108	34	35	11	21	7
1994	1354	1019	118	37	42	17	21	7
2004	956	627	89	22	32	14	12	9

This table presents summary statistics for the number of fund-manager pairings, number of funds, and number of managers in 1984, 1994 and 2004. For the same years, it also reports the number of managers with one network connection ($Net = 1$), the number of managers with number with network connections between 2 and 5 ($2 \leq Net \leq 5$), the number of managers with number with network connections between 6 and 10 ($6 \leq Net \leq 10$), the number of managers with number with network connections between 11 and 20 ($11 \leq Net \leq 21$), and the number of managers with number with network connections greater than 20 ($Net \geq 21$). The analysis is conducted for UK equities in Panel A, UK bonds in Panel B and international equities in Panel C.

Table 2. Correlation between centrality and size measures

Panel A. Results Across Asset Classes

	NET	NET_M	NET_C	$SIZE$	M_SIZE
NET	1.000				
NET_M	0.998	1.000			
NET_C	0.840	0.802	1.000		
$SIZE$	-0.008	-0.008	-0.014	1.000	
M_SIZE	0.653	0.647	0.552	0.092	1.000

Panel B. Results for UK Equities

	NET	NET_M	NET_C	$SIZE$	M_SIZE
NET	1.000				
NET_M	0.996	1.000			
NET_C	0.866	0.817	1.000		
$SIZE$	-0.017	-0.018	-0.012	1.000	
M_SIZE	0.637	0.634	0.564	0.092	1.000

Panel C. Results for UK Bonds

	NET	NET_M	NET_C	$SIZE$	M_SIZE
NET	1.000				
NET_M	0.985	1.000			
NET_C	0.872	0.787	1.000		
$SIZE$	-0.018	-0.021	-0.005	1.000	
M_SIZE	0.542	0.533	0.478	0.092	1.000

Panel D. Results for International Equities

	NET	NET_M	NET_C	$SIZE$	M_SIZE
NET	1.000				
NET_M	0.995	1.000			
NET_C	0.839	0.780	1.000		
$SIZE$	-0.019	-0.019	-0.013	1.000	
M_SIZE	0.625	0.619	0.551	0.092	1.000

This table reports the correlation between the degree centrality measures and the size measures in our dataset. The centrality measures of interest are degree centrality (NET), degree centrality computed using the managers' network only (NET_M) and degree centrality computed using the consultants' network only (NET_C). The centrality measures are computed across all asset classes in Panel A, in UK equities in Panel B, in UK bonds in Panel C and in international equities in Panel D. $SIZE$ denotes the assets under management of each fund-manager pairing, while M_SIZE denotes each manager's assets under management across all funds managed. The size variables are converted to relative size by dividing them by the cross-sectional average and taking the natural log of this quantity. The centrality measures are converted to relative centrality by dividing them by the cross-sectional average. All correlations are computed in the time-series as well as the cross-section dimensions.

Table 3. Centrality and Fund-Manager Performance

	Panel A. UK Equities				Panel B. UK Bonds				Panel C. Int. Equities			
$SIZE$	-0.284	-0.292	-0.294	-0.291	-0.187	-0.166	-0.175	-0.173	-0.915	-0.919	-0.911	-0.921
	(0.14)	(0.13)	(0.13)	(0.13)	(0.05)	(0.08)	(0.06)	(0.06)	(0.00)	(0.00)	(0.00)	(0.00)
M_SIZE	-0.631	-0.722	-0.610	-0.871	-0.047	0.115	-0.150	-0.084	-0.291	-0.310	-0.337	-0.725
	(0.00)	(0.00)	(0.00)	(0.00)	(0.52)	(0.14)	(0.03)	(0.39)	(0.23)	(0.20)	(0.13)	(0.02)
NET	0.197	0.042			0.098	0.160			-0.061	-0.093		
	(0.04)	(0.68)			(0.06)	(0.00)			(0.65)	(0.57)		
$NET \times M\_SIZE$		0.365				-0.229				0.056		
		(0.00)				(0.00)				(0.69)		
NET_C			0.157	0.220			0.270	0.260			0.008	0.094
			(0.03)	(0.01)			(0.00)	(0.00)			(0.95)	(0.47)
$NET\_C \times M\_SIZE$				0.298				-0.063				0.389
				(0.01)				(0.32)				(0.02)
Between R^2	0.014	0.009	0.017	0.011	0.061	0.057	0.053	0.053	0.024	0.024	0.026	0.030
Joint-Significance	0.038	0.000	0.032	0.005	0.064	0.000	0.000	0.000	0.652	0.849	0.947	0.075

This table reports results for panel regressions of fund-managers' risk-adjusted performance in UK equities (Panel A), UK bonds (Panel B) and International equities (Panel C) and managers' centrality. The risk-adjusted return of manager i in fund j at time t is computed as $\widehat{r}_{ijt}^{adj} = \widehat{\alpha}_{ij} + \widehat{\epsilon}_{ijt}$, where $\widehat{\alpha}_{ij}$ is estimated using the full set of observations available for manager i in fund j. We adopt a four-factor model for UK Equities:

$$r_{ijt} = \alpha_{ij} + \beta_{1ij}\ r_{mkt,t} + \beta_{2ij}\ SMB_t + \beta_{3ij}\ HML_t + \beta_{4ij}\ MOM_t + \epsilon_{ijt},$$

where $r_{mkt,t}$ is the excess return on the UK market portfolio, SMB_t is a size factor, HML_t is a value-growth factor and MOM_t is a momentum factor. We adopt a two-factor model for UK bonds:

$$r_{ijt} = \alpha_{ij} + \beta_{1ij} GOVB_t + \beta_{2ij} CONS_t + \epsilon_{ijt},$$

where $GOVB_t$ is the excess return on the FTSE All-Gilts Total Return Index and $CONS_t$ is the excess return on the UK government consol bonds. Finally, we adopt a four-factor model for international equities:

$$r_{ijt} = \alpha_{ij} + \beta_{1ij}\ NA_t + \beta_{2ij}\ EAFEX_t + \beta_{3ij}\ SMB_t + \beta_{4ij}\ HML_t + \epsilon_{ijt},$$

where NA_t is the sterling-denominated excess return on the MSCI North American Total Return Index, $EAFEX_t$ is the sterling-denominated excess return on the MSCI Europe Australasia Far Eastern ex-UK Total Return Index, SMB_t is a global size factor and HML_t is a global value-growth factor. We drop from the sample the fund-manager pairings that have less than 12 observations. The panel regressions use as control variables the assets under management of each fund-manager pairing (denoted by $SIZE$), as well as each manager's assets under management in UK equities (in Panel A), UK bonds (in Panel B) and international equities (in Panel C) across all funds managed (denoted by M_SIZE). The centrality measures of interest are degree centrality (NET) and degree centrality computed using the consultants' network only (NET_C), computed in UK equities (Panel A), UK bonds (Panel B) or international equities (Panel C). The size variables are converted to relative size by dividing them by the cross-sectional average and taking the natural log of this quantity. The centrality measures are converted to relative centrality by dividing them by the cross-sectional average. Each covariate series has been standardized using its own unconditional standard deviation to ease the interpretation of the coefficients. For each centrality measure we adopt two specifications. In the first we include the centrality measure. In the second we include the centrality measure and its interaction with manager size. All the specifications use fund-manager and time fixed effects. The p-values are reported in parentheses and are computed using standard errors that are clustered at the fund-manager level.

Table 4. Effect of Centrality on Performance Controlling for Centrality in Other Asset Classes

Panel A. Performance in UK Equities				
$SIZE$	-0.285	-0.291	-0.294	-0.292
	(0.14)	(0.13)	(0.13)	(0.13)
M_SIZE	-0.619	-0.709	-0.609	-0.865
	(0.00)	(0.00)	(0.00)	(0.00)
NET_BONDS	-0.070	-0.084		
	(0.00)	(0.00)		
$NET\_EQUITIES$	0.179	0.022		
	(0.06)	(0.83)		
$NET\_BONDS \times M\_SIZE$		-0.053		
		(0.00)		
$NET\_EQUITIES \times M\_SIZE$		0.363		
		(0.00)		
NET_C_BONDS			0.011	0.021
			(0.55)	(0.25)
$NET\_C\_EQUITIES$			0.157	0.217
			(0.03)	(0.01)
$NET\_C\_BONDS \times M\_SIZE$				0.045
				(0.06)
$NET\_C\_EQUITIES \times M\_SIZE$				0.294
				(0.01)
Between R^2	0.014	0.010	0.017	0.010
Panel B. Performance in UK Bonds				
$SIZE$	-0.188	-0.167	-0.175	-0.172
	(0.04)	(0.08)	(0.06)	(0.07)
M_SIZE	-0.044	0.121	-0.150	-0.084
	(0.53)	(0.12)	(0.03)	(0.39)
$NET\_EQUITIES$	0.020	0.002		
	(0.06)	(0.86)		
NET_BONDS	0.098	0.164		
	(0.07)	(0.00)		
$NET\_EQUITIES \times M\_SIZE$		-0.056		
		(0.00)		
$NET\_BONDS \times M\_SIZE$		-0.228		
		(0.00)		
$NET\_C\_EQUITIES$			0.025	0.031
			(0.13)	(0.05)
NET_C_BONDS			0.271	0.260
			(0.00)	(0.00)
$NET\_C\_EQUITIES \times M\_SIZE$				0.022
				(0.38)
$NET\_C\_BONDS \times M\_SIZE$				-0.063
				(0.31)
Between R^2	0.060	0.057	0.053	0.052

This table reports results for panel regressions of fund-managers' risk-adjusted performance in UK equities (Panel A) and UK bonds (Panel B) managers' centrality. The risk-adjusted return of manager i in fund j at time t is computed as $\widehat{r}_{ijt}^{adj} = \widehat{\alpha}_{ij} + \widehat{\epsilon}_{ijt}$, where $\widehat{\alpha}_{ij}$ is estimated using the full set of observations available for manager i in fund j. We adopt a four-factor model for UK Equities:

$$r_{ijt} = \alpha_{ij} + \beta_{1ij}\ r_{mkt,t} + \beta_{2ij}\ SMB_t + \beta_{3ij}\ HML_t + \beta_{4ij}\ MOM_t + \epsilon_{ijt},$$

where $r_{mkt,t}$ is the excess return on the UK market portfolio, SMB_t is a size factor, HML_t is a value-growth factor and MOM_t is a momentum factor. We adopt a two-factor model for UK bonds:

$$r_{ijt} = \alpha_{ij} + \beta_{1ij} GOVB_t + \beta_{2ij} CONS_t + \epsilon_{ijt},$$

where $GOVB_t$ is the excess return on the FTSE All-Gilts Total Return Index and $CONS_t$ is the excess return on the UK government consol bonds. We drop from the sample the fund-manager pairings that have less than 12 observations. In Panel A, the centrality measures of interest are degree centrality ($NET\_EQUITIES$) and degree centrality computed using the consultants' network only ($NET\_C\_EQUITIES$), computed in UK equities (Panel A). The centrality measures (NET_BONDS) and (NET_C_BONDS) are used as control and are orthogonalized with respect to corresponding centrality measures in equities at the fund-manager level. The opposite holds true in Panel B. In both panels, we use as additional control variables the assets under management of each fund-manager pairing (denoted by $SIZE$), as well as each manager's assets under management in UK equities (in Panel A) and UK bonds (in Panel B) across all funds managed (denoted by M_SIZE). The size variables are converted to relative size by dividing them by the cross-sectional average and taking the natural log of this quantity. The centrality measures are converted to relative centrality by dividing them by the cross-sectional average. Each covariate series has been standardized using its own unconditional standard deviation to ease the interpretation of the coefficients. For each centrality measure we adopt two specifications. In the first we include the centrality measure. In the second we include the centrality measure and its interaction with manager size. All the specifications use fund-manager and time fixed effects. The p-values are reported in parentheses and are computed using standard errors that are clustered at the fund-manager level.

Table 5. Performance Correlation between Connected and Non-Connected Managers

Panel A. Correlation of Returns

Asset Class	Connections	Non-Connections	Diff.	P-val.	Obs
UK Equities	0.954	0.949	0.005	0.649	139
UK Bonds	0.947	0.936	0.011	0.285	111

Panel B. Correlation of Factor-Explained Returns

Asset Class	Connections	Non-Connections	Diff.	P-val.	Obs
UK Equities	0.978	0.978	0.000	0.968	139
UK Bonds	0.982	0.983	-0.001	0.771	111

Panel C. Correlation for Returns' Residuals

Asset Class	Connections	Non-Connections	Diff.	P-val.	Obs
UK Equities	0.170	0.096	0.074	0.000	139
UK Bonds	0.463	0.346	0.117	0.000	111

This table compares the performance correlation between managers that are connected to each other and managers that are not connected to each other. Performance is measured as returns (Panel A), factor-explained returns (Panel B), and returns residuals (Panel C). The results for returns in UK equities are computed as follows. We first compute returns at the manager level by value-weighting the returns in each fund managed by a given manager. We then compute returns correlations between each manager and every other manager contained in the dataset, making sure to use only manager-pairings that overlap for at least 12 quarters. Third, for each manager, we average the returns correlations associated with connected and non-connected managers. Fourth, for connections and non-connections, we compute the median of the average correlations across all the managers in the dataset. Finally, we compute tests of differences in medians across the two sets of correlations using two-sided permutation tests that use 1,000 iterations. The procedure is repeated for UK bonds and for the other measures of performance, i.e., factor-explained returns and returns residuals.

Table 6. The Causal Effect of Network Connections on Performance

	UK Equities	UK Bonds
Treatment×NET	0.153	0.033
	(0.02)	(0.33)
NET	0.193	0.010
	(0.04)	(0.86)
$SIZE$	-0.281	-0.160
	(0.14)	(0.09)
M_SIZE	-0.646	-0.231
	(0.00)	(0.00)
Between R^2	0.015	0.068

This table reports results for the causal effect of network connections on performance in UK equities and UK bonds. In the first step we compute the risk-adjusted return of manager i in fund j at time t as $\widehat{r}_{ijt}^{adj} = \widehat{\alpha}_{ij} + \widehat{\epsilon}_{ijt}$, where $\widehat{\alpha}_{ij}$ is estimated using the full set of observations available for manager i in fund j. We adopt a four-factor model for UK Equities:

$$r_{ijt} = \alpha_{ij} + \beta_{1ij}\ r_{mkt,t} + \beta_{2ij}\ SMB_t + \beta_{3ij}\ HML_t + \beta_{4ij}\ MOM_t + \epsilon_{ijt},$$

where $r_{mkt,t}$ is the excess return on the UK market portfolio, SMB_t is a size factor, HML_t is a value-growth factor and MOM_t is a momentum factor. We adopt a two-factor model for UK bonds:

$$r_{ijt} = \alpha_{ij} + \beta_{1ij} GOVB_t + \beta_{2ij} CONS_t + \epsilon_{ijt},$$

where $GOVB_t$ is the excess return on the FTSE All-Gilts Total Return Index and $CONS_t$ is the excess return on the UK government consol bonds. We drop from the sample the fund-manager pairings that have less than 12 observations.
In the second step, we estimate:

$$\widehat{r}_{ijt}^{adj} = a_{ij} + b_t + \lambda_1 SIZE_{ijt} + \lambda_2 M\_SIZE_{jt} + \lambda_4 NET_{jt} \times M\_Dummy_{jt} + \varepsilon_{ijt},$$

where the merger treatment dummy $Merger\_Dummy_{jt}$ is switched on for 3 years after the merger for all the managers involved in the merger. The panel regressions use as control variables the assets under management of each fund-manager pairing (denoted by $SIZE$), as well as each manager's assets under management in UK equities (first column), UK bonds (second column) across all funds managed (denoted by M_SIZE). The centrality measure of interest is degree centrality (NET), computed in UK equities (first column) and UK bonds (second column). The size variables are converted to relative size by dividing them by the cross-sectional average and taking the natural log of this quantity. The centrality measure NET is converted to relative centrality by dividing each entry by the cross-sectional average. Each covariate series has been standardized using its own unconditional standard deviation to ease the interpretation of the coefficients. All the specifications use fund-manager and time fixed effects. The p-values are reported in parentheses and are computed using standard errors that are clustered at the fund-manager level.

Table 7. Annualized Consultants' Alphas in UK equities and UK bonds

	UK Equities	UK Bonds
	Annualized Alphas	Annualized Alphas
Consultant 1	0.091	0.124
	(0.51)	(0.13)
Consultant 2	0.071	0.182
	(0.58)	(0.03)
Consultant 3	0.006	0.121
	(0.96)	(0.15)
Consultant 4	-0.645	0.184
	(0.06)	(0.29)
Consultant 5	0.075	0.086
	(0.69)	(0.64)
Consultant 6	-0.070	-0.071
	(0.74)	(0.65)
Consultant 7	-0.019	0.230
	(0.97)	(0.36)
Consultant 8	-0.035	-0.057
	(0.91)	(0.85)
Consultant 11	-0.202	0.355
	(0.11)	(0.00)
Constant	0.200	0.462
	(0.08)	(0.00)

This table reports the annualized consultants' alphas in UK equities and UK bonds. In particular, it reports the α_c coefficients associated with the following regression in UK equities:

$$r_{ict} = k + \alpha_c + \beta_{1ic}\, r_{mkt,t} + \beta_{2ic}\, SMB_t + \beta_{3ic}\, HML_t + \beta_{4ic}\, MOM_t + \epsilon_{ict}$$

and the following regression in UK bonds:

$$r_{ict} = k + \alpha_c + \beta_{1ic} GOVB_t + \beta_{2ic}\, CONS_t + \epsilon_{ict}$$

where 'i' refers to the fund, 'c' refers to the consultant and 't' refers to the time period. Notice that we allow for consultant-fund differences by allowing the betas to differ across consultant-fund pairings. The standard errors are clustered at the fund-consultant level.

Table 8. Fund-Flows and Managers' Centrality

	Panel A. Flows Coming from Existing Mandates		
	UK Equities	**UK Bonds**	**Int. Equities**
NET	12.399	2.668	8.598
	(0.34)	(0.33)	(0.11)
Lag_Flow	0.095	0.119	0.029
	(0.02)	(0.00)	(0.66)
M_SIZE	-20.919	-6.123	-6.484
	(0.08)	(0.02)	(0.09)
$Future\_Risk\_Adj\_Ret$	1.273	-0.031	0.151
	(0.05)	(0.97)	(0.86)
$Past\_Risk\_Adj\_Ret$	2.563	0.323	-0.655
	(0.05)	(0.48)	(0.38)
Between R^2	0.065	0.082	0.000

	Panel B. Flows Coming from Newly Assigned Mandates		
	UK Equities	**UK Bonds**	**Int. Equities**
NET	16.725	3.040	6.089
	(0.00)	(0.01)	(0.00)
Lag_Flow	0.075	0.058	0.074
	(0.10)	(0.23)	(0.12)
M_SIZE	-7.534	-0.206	-2.600
	(0.00)	(0.87)	(0.02)
$Future\_Risk\_Adj\_Ret$	0.376	0.128	0.594
	(0.44)	(0.48)	(0.10)
$Past\_Risk\_Adj\_Ret$	0.630	0.320	0.125
	(0.29)	(0.17)	(0.70)
Between R^2	0.529	0.382	0.467

This table reports panel regression results for the effect of managers' centrality, size and past performance on fund inflows and outflows from existing mandates and newly assigned mandates. For existing mandates (Panel A), the fund-flow variable for manager i over quarter t is defined as:

$$Flow_{jt:t+1} = \left(\frac{SMV_{jt+1} - SMV_{jt}}{SMV_{jt}} - R_{jt:t+1} \right) * SMV_{jt},$$

where SMV_{jt} and SMV_{jt+1} are the starting market value (of existing mandates) of manager j's asset holdings at quarter t and $R_{jt:t+1}$ is the return generated over quarter t. The analysis is performed separately in UK equities (first column), UK bonds (second column) and international equities (third column). The centrality measure of interest is degree centrality (NET), computed in UK equities (first column), UK bonds (second column) or international equities (third column). The size variable M_SIZE denotes the total assets under management (across all funds managed) of each manager at each point in time. For each manager, $Past\_Risk\_Adj\_Ret$ is constructed by value-weighting the risk-adjusted returns in a given asset class across the various funds managed over the previous year, while $Future\_Risk\_Adj\_Ret$ is constructed by value-weighting the risk-adjusted returns in a given asset class across the various funds managed over the following year. Risk-adjusted returns are computed using the models described in the caption of Table 3. We convert the size variable to relative size by dividing it by the cross-sectional average and taking the natural log of this quantity. The centrality measures are converted to relative centrality by dividing them by the cross- sectional average. Each covariate series – with the exception of lagged-flows – has been standardized using its own unconditional standard deviation to ease the interpretation of the coefficients. All results are computed using manager and time fixed effects. The p-values are reported in parentheses and are computed using standard errors that are clustered at the manager level.

Table 9. Centrality and Fund-Manager Risk

	UK Equities	UK Bonds	Int. Equities
NET	0.258	0.011	0.106
	(0.00)	(0.82)	(0.35)
$SIZE$	-0.375	-0.092	-0.193
	(0.00)	(0.01)	(0.00)
M_SIZE	-0.567	-0.128	-0.570
	(0.00)	(0.02)	(0.00)
R^2	0.049	0.012	0.027

This table reports results for cross-sectional regressions of fund-managers' risk in UK equities (first column), UK bonds (second column) and international equities (third column) and managers' centrality. The results are computed by regressing the average risk of each fund-manager pairing on average fund-manager size, average manager centrality, and average manager size. We take $|\widehat{\epsilon}_{ijt}|$ as the measure of risk for manager i in fund j at time t. We then subtract the cross-sectional average, computed using all the fund-manager pairings available at each point in time. Third, we compute the time-series average of the de-meaned absolute residuals at the fund-manager level and use it as our average risk variable. We repeat a similar procedure for managers' centrality, managers' size, and fund-managers' size. In particular, the size variables are converted to relative size by dividing them by the cross-sectional average and taking the natural log of this quantity. The centrality measures are converted to relative centrality by dividing them by the cross-sectional average. Finally, we regress, at the fund-manager level, the average absolute residual on average centrality (denoted by NET), fund-manager size (denoted by $SIZE$), manager size (denoted by M_SIZE). Each covariate series has been standardized using its own unconditional standard deviation to ease the interpretation of the coefficients. The p-values are reported in parentheses. To compute $|\widehat{\epsilon}_{ijt}|$, we use a four-factor model for UK Equities:

$$r_{ijt} = \alpha_{ij} + \beta_{1ij}\ r_{mkt,t} + \beta_{2ij}\ SMB_t + \beta_{3ij}\ HML_t + \beta_{4ij}\ MOM_t + \epsilon_{ijt},$$

where $r_{mkt,t}$ is the excess return on the UK market portfolio, SMB_t is a size factor, HML_t is a value-growth factor and MOM_t is a momentum factor. We adopt a two-factor model for UK bonds:

$$r_{ijt} = \alpha_{ij} + \beta_{1ij} GOVB_t + \beta_{2ij} CONS_t + \epsilon_{ijt},$$

where $GOVB_t$ is the excess return on the FTSE All-Gilts Total Return Index and $CONS_t$ is the excess return on the UK government consol bonds. Finally, we adopt a four-factor model for international equities:

$$r_{ijt} = \alpha_{ij} + \beta_{1ij}\ NA_t + \beta_{2ij}\ EAFEX_t + \beta_{3ij}\ SMB_t + \beta_{4ij}\ HML_t + \epsilon_{ijt},$$

where NA_t is the sterling-denominated excess return on the MSCI North American Total Return Index, $EAFEX_t$ is the sterling-denominated excess return on the MSCI Europe Australasia Far Eastern ex-UK Total Return Index, SMB_t is a global size factor and HML_t is a global value-growth factor. We drop from the sample the fund-manager pairings that have less than 12 observations.

Table 10. Survival Analysis for Managers and Consultants

Panel A. Analysis at the Managers' Level

	UK Equities	UK Bonds	Int. Equities
Past_Risk_Adj_Ret	-0.079	-0.013	-0.099
	(0.00)	(0.50)	(0.00)
SIZE	-0.196	-0.214	-0.247
	(0.00)	(0.00)	(0.00)
NET	-0.345	-0.036	-0.346
	(0.00)	(0.04)	(0.00)

Panel B. Analysis at the Consultants' Level

	UK Equities	UK Bonds	Int. Equities
Past_Risk_Adj_Ret	0.003	-0.033	-0.082
	(0.89)	(0.14)	(0.00)
SIZE	-0.327	-0.303	-0.385
	(0.00)	(0.00)	(0.00)
NET	-0.220	-0.160	-0.162
	(0.00)	(0.00)	(0.00)

This table reports in Panel A (Panel B) the coefficients of a Cox proportional hazard rate model relating the probability of managers' (consultants') contracts being terminated in UK equities, UK bonds and international equities asset classes to their past performance, their size, as well as their network centrality. In Panel A, $SIZE$ denotes the assets under management of each fund-manager pairing. In Panel B, $SIZE$ denotes the assets under management of each fund-consultant pairing. Past performance ($Past\_Risk\_Adj\_Ret$) is computed as the average abnormal returns in UK equities, UK bonds or international equities over the previous two quarters for each fund-manager pairing in Panel A and for each fund-consultant pairing in Panel B. In Panel A the centrality measure of interest is overall managers' degree centrality (NET) computed in UK equities, UK bonds or international equities. In Panel B the centrality measure of interest are consultants' degree centrality (NET). The size variables are converted to relative size by dividing them by the cross-sectional average and taking the natural log of this quantity. The centrality measures are converted to relative centrality by dividing them by the cross-sectional average. Each covariate series has been standardized using its own unconditional standard deviation to ease the interpretation of the coefficients. The p-values are reported in parentheses.

Table 11. Granger Causality Tests of Size versus Network Centrality

Panel A. Dependent Variable: Centrality Measure

	A.I. All Asset Classes	A.II. UK Equities	A.III. UK Bonds	A.IV. Int. Equities
M_SIZE	-0.001 (0.39)	0.001 (0.12)	0.000 (0.48)	-0.000 (0.44)
NET	0.885 (0.00)	0.865 (0.00)	0.874 (0.00)	0.890 (0.00)

Panel B. Dependent Variable: Size

	B.I. All Asset Classes	B.II. UK Equities	B.III. UK Bonds	B.IV. Int. Equities
M_SIZE	0.619 (0.00)	0.829 (0.00)	0.798 (0.00)	0.780 (0.00)
NET	2.321 (0.00)	1.278 (0.01)	2.221 (0.00)	0.973 (0.02)

This table reports the results of panel Granger causality tests for managers' size and centrality. Managers' centrality is computed as the overall degree centrality (NET). Managers' size is computed as the log of the total assets under management across funds and asset classes managed. The dependent variable is managers' centrality in Panel A and managers' size in Panel B. Centrality is computed across asset classes in Panels A.I. and B.I, in UK equities in Panels A.II. and B.II., in UK bonds in Panels A.III. and B.III. and in international equities in Panels A.IV. and B.IV. The parameters are estimated using one-step GMM that use up to 16 lags of the dependent variable as instruments. The details of the procedure are reported in Section 6 of the paper. The p-values are reported in parentheses and are computed using robust standard errors.