CFR Working Paper NO. 15-16

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A.G. Rossi • D. Blake • A. Timmermann • I. Tonks • R. Wermers

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Alberto G. Rossi[†] David Blake[‡] Allan Timmermann[§] Ian Tonks[¶]

Russ Wermers[‖]

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 foreign equity holdings. 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 each other's actions. Moreover, the importance of network centrality is strongest for larger funds, controlling for any economic scale effects. Better connected funds are also better able to 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 security values.

[†]Smith School of Business, University of Maryland-College Park; Email: arossi@rhsmith.umd.edu.
[‡]Cass Business School, City University of London; Email: d.blake@city.ac.uk.
[§]Rady School of Management, University of California at San Diego; Email: atimmermann@ucsd.edu.
[¶]University of Bath School of Management; Email: it237@management.bath.ac.uk.
[‖]Smith School of Business, University of Maryland-College Park; Email: rwermers@rhsmith.umd.edu.

1 Introduction

The efficient dissemination and processing of information is central to the success of professional money management. The best money managers must both be well-connected to sources of private information on stock values, and be able to quickly interpret and apply the information that they receive from their connections to their portfolio choices. That is, access to information, including information derived from knowledge of competitors' investment strategies, is a likely mechanism though which funds may achieve abnormal performance.

While the econometrician cannot observe the private information that flows to individual fund managers–let alone how managers process such information–the centrality of managers in a network of institutional investors may plausibly be expected to be associated with the breadth of a manager's information on investment strategies and opportunities. Even if better connections do not translate into specific information about "stock picks," better connected managers are more likely to be aware of fund flows into specific asset classes and individual stocks, and, so, can strategically position themselves to take advantage of this, reducing the liquidity effects of redemptions or withdrawals.

In this paper, we use data on a large set of UK pension fund accounts over the period 1984-2004 to ask whether network centrality explains managers' investment performance, risk-taking behavior, and flows. The dataset, also described in Blake et al. (2013), allows us to compute network connections in a unique manner.[1] Moreover, we have data on investment performance and network connections within three asset classes–UK Equity, UK Bonds, and International Equity–that together account for more than 85% of the funds' asset holdings. This allows us to compare and contrast findings across asset classes 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. As such, our large cross-section and time-series of managers, consultants, and sponsors provides several dimensions through which we can identify the impact of networks on information diffusion (since networks can respond to, and not simply predict changes in the information setting).

[1] 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.

Network connections in our dataset arise from two separate sources. First, many of the 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. 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 having a common consultant in their interactions with several fund sponsors. Such relationships help reduce the search costs incurred by the pension fund trustees. In summary, individual pension fund accounts can be connected by their sharing of the same consultant and/or the same manager.

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 connections–through shared managers or through shared consultants–matter most.[2] This is important since little is known about the specific channels through which information flows in the fund management business. One possibility is that information flows through the "overlap" of individual managers. By sharing the same large institutional clients, managers can expect to learn valuable information about their competitors' investment strategies, industry preferences, and resulting investment performance. Alternatively, consultants play a key role in advising fund trustees in selecting, reappointing and firing fund managers. As monitors of the fund management industry, consultants are a natural conduit through which information flows on individual fund manager performance and investment style. 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 fund-managers that are better connected (or more central in the network) tend to have higher risk-adjusted performance in both UK equities and UK bonds. This result is not explained simply by more central managers being bigger. 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

[2]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).

related to risk-adjusted performance. We also find an interesting interaction effect between fund-manager size and network centrality which suggests that large funds have a particular advantage when it comes to benefitting from network centrality. While large funds tend to underperform, large funds that are also well connected manage to reduce the negative effect of fund size. 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.

Second, across all three asset classes, we find that network connections have a large and significantly positive effect on fund flows, again after controlling for size. In contrast, fund size has a negative effect on fund flows, whereas past returns fail to significantly impact fund flows. This suggests that, controlling for size and past returns, the more central a manager is, the greater the expected inflows tends to be. Moreover, interaction terms between centrality and past returns are strongly positively associated with fund flows, even though the separate effect of past return is insignificant. This suggests that being centrally placed in the network allows a fund to positively exploit its past performance record to grow its assets under management. Conversely, large and poorly connected fund managers feel the full negative impact of their size and experience smaller inflows.

Network centrality may influence funds' risk-taking behavior through managers' (or consultants') incentives. Specifically, network centrality could affect managers' risk-taking behavior through its effect on fund flows and, thus, via assets under management, their remuneration. Our third main empirical results establishes evidence that better connected funds tend to reduce their idiosyncratic risk taking within domestic equities and bonds relative to less central funds. This effect is attenuated by fund size: an interaction term between fund-manager size and centrality has a strongly negative effect on idiosyncratic risk taking, suggesting that large, centrally placed managers hold portfolios with less idiosyncratic risk. For international equities we find the opposite effect: better-connected managers increase their idiosyncratic risk levels compared with less central managers, and the effect is particularly strong for the largest managers through the interaction term.[3]

Fourth, network centrality may also influence managers' or consultants' behavior through the

[3]Previous studies (e.g., Kang and Stulz (1997)) have found that foreign investors act as if they are at an informational disadvantage abroad. Our finding is consistent with the larger, more central managers–who are likely to have international offices and networks of their own–being less cautious when investing abroad than the smaller managers.

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 reveals another incentive for managers to establish network connections: it makes them more immune towards being dismissed by their institutional clients.

Fifth, to the best of our knowledge, no previous academic research paper has analyzed the role of consultants in the investment decisions of institutional clients and estimated its effect on investment outcomes. Consultants introduce an extra layer of agency with their own incentives and are subject to the same process of hiring and firing as the managers whom they monitor. For many of our models we find that the consultant-based networks add information over and above the information contained in the networks established solely through manager connections. Thus consultants' role in the investment process is not subsumed by that of the managers.

Our results reveal rich dynamic interactions between fund-manager centrality, risk-adjusted performance, fund flows and thus, 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, central fund managers tend to grow larger faster than more peripheral fund managers, after controlling for past size.

Our results suggest a new mechanism for why some fund managers are successful, while others are not. Being centrally located in the fund-manager network appears to foster 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.

The plan of the paper is 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. Section 3 explores the relation between risk-adjusted return performance and network centrality, while Section 4 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 5 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 6 presents results from a Granger causality analysis of the size-centrality relation, while Section 7 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 equity, UK bonds and International equity–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.[4] 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 partic-

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

ular 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).[5] 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. 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 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 details in 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.[6]

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 equities 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 inter-connected over the sample. For example, the proportion of managers with more than 20 network connections increased from 7% in 1984 to 12%

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

[6]Namely, from 1204/955 to 1053/630.

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 assist in the appointment of fund managers and the choice of investment mandates. A total of 12 different consultants performed these services over our sample period. For each consultant Figure 1 shows time-series plots of the number of clients in UK equities (Panel A), UK bonds (Panel B) and international equities (Panel C). The number of clients advised by the individual consultants appears to follow very similar patterns across the three asset classes, indicating that the consultants did not specialize in specific asset classes. This is consistent with the view that consultants provide 'full service" advice to their pension fund clients, as is required when selecting managers with multi-asset class or so-called balanced investment mandates.

Figure 2 shows the proportion of total assets in UK equities, UK bonds and international equities advised by each of the consultants, i.e., their market shares by asset value. This figure suggests that the market for consultants was dominated by four large firms whose combined market size did not change much over the sample period.[7]

2.2 Networks In different asset classes

A network is characterized by its nodes (agents) and edges (connections). To construct networks we include all agents that are present at a given point in time. This allows us to construct time series of network connections. Consultants act as interlocutors in the network, so we consider separately network connections established either through consultants or managers as well as 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 of separate 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

[7] In 1998, consultant no. 11 merged with consultant no. 2; the merger is evident in all panels in Figure 1. However, the effect of this merger on (consulting) industry concentration was not very pronounced. In fact, while Figure 1 shows that consultant no. 11 was responsible for advising a relatively large number of funds, Figure 2 shows that these funds were typically of small size.

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 share 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, 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 through the consultants, while the managers whose nodes fall below the consultants are connected with at least one other manager.

Network connections can be established either through manager or through consultants. Specifically, blue lines in Figure 3 track network connections between managers (established through managers' sharing of the same pension fund client) while green lines track connections between consultants and managers (established through consultants advising the same pension funds). 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.

Figure 3 reflects that there are far more managers than consultants–although consultants generally have many more connections than the typical manager. In 1984, six consultants had far more connections than the remaining ones; In 1994, nine of the 12 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. 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 also appear to have evolved very differently through time. For example, while the UK Equity network became more dense between 1984 and 2004, the 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 the same 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.[8] 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 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 UK equity. Finally, the network in UK bonds does not seem to be populated by managers in the very center as the managers are more distant from each other.

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. 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.

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) next period is a function of the number of contacts (nodes) the manager (consultant) is adjacent to. The degree measure focuses on short-term information spillover since there is no notion of connectedness through a chain of nodes−only direct connections count for this measure. As such, the measure captures more localized information flows; these are likely to be more strongly correlated with investment performance than more global measures of centrality such as closeness centrality.[9]

[8] 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 represents 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.

[9] 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.

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.

Figure 7 provides a simple example showing how closeness and degree centrality are computed in a simple network with 7 nodes. Node 1 has one connected neighbor (node 2), leading to a degree centrality measure (using equation 1) of $\frac{1}{7-1} = 0.17$. The same degree centrality characterizes nodes 2, 6 and 7. Nodes 3 and 5 have degree centrality of $\frac{3}{7-1} = 0.5$ because they are each connected to three nodes. Finally, node 4 is connected to 2 nodes and so has a degree centrality of $\frac{2}{7-1} = 0.33$.

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 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:

$$\widetilde{CM}_t = \frac{CM_t - MEAN(CM_t)}{STDEV(CM_t)}, \tag{2}$$

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 8 plots time series of the normalized centrality measures over our sample. 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 8 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 classes we find a strongly positive (0.78-0.81) correlation 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 allow us to identify whether changes in manager behavior is induced through manager/consultant connections or through both.

In turn, the manager/consultant 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 next address this question.

3 Return performance and network centrality

This section relates the network centrality measures introduced in the previous section to risk-adjusted return performance in the three asset classes (UK equities, UK bonds and International equities) that we study. We first explain how we construct the dependent variable (risk-adjusted returns) for each asset class and then present results from panel regressions that use centrality as a covariate, while controlling for fund/manager size and other variables. Finally, we also present non-parametric tests based on portfolio sorts using centrality or centrality and size as sorting variables.

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).[10] 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 an intercept, excess returns on the UK stock market portfolio, $r_{mkt,t}$, returns on a size factor, SMB_t, a value-growth factor, HML_t and a momentum factor, MOM_t:

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

For UK bonds we estimate a two-factor model using an intercept and 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 an intercept, sterling-denominated excess returns on the MSCI North American (NA) and Europe Australasia Far Eastern

[10]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.

ex-U.K. (EAFEX) Total Return Indices as well as global size (SMB) and value-growth (HML) factors:[11]

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

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

3.2 Risk-adjusted returns and network centrality

We next perform panel regressions using the risk-adjusted returns, computed as described above, as our dependent variable. To control for size effects in the risk-adjusted return regressions, we include two terms. First, we compute the size for each fund-manager pairing, labeled $size_{ijt}$ and measured as the market value of the assets managed by manager j for fund i at the beginning of quarter t. Second, for each manager we compute the assets under management in UK equities across all funds managed at time t, labeled $Msize_{jt} = \sum_{i=1}^{N_{it}} size_{ijt}$. 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., $\log(Msize_{jt}/\overline{Msize}_t)$, where $\overline{Msize}_t = N_{jt}^{-1} \sum_{j=1}^{N_{jt}} Msize_{jt}$ is the cross-sectional average manager size at time t.

Using our estimates of risk-adjusted performance from equations (3)-(5), we perform panel regressions that allow for both fund-manager and time fixed effects, control for fund-manager and manager size effects and use standard errors that are clustered at the fund-manager level. Our measure of network centrality for manager j is again normalized relative to the cross-sectional mean in the same period, 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 i and j) at time t. Centrality is always measured ex-ante, i.e., prior to the return measurement period. To capture possible scale effects of network centrality, we also consider an interaction term between network centrality and manager size, $NET_{jt}Msize_{jt}$. Notice that it is the variation *over time* in network centrality that identifies its effect on risk-adjusted performance.

[11]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.

For each asset class, Table 3 presents results from panel regressions of the form[12]

$$r_{ijt}^{adj} = a_{ij} + b_t + \lambda_1 size_{ijt} + \lambda_2 Msize_{jt} + \lambda_3 NET_{jt} + \lambda_4 NET_{jt} Msize_{jt} + \varepsilon_{ijt}. \tag{6}$$

This regression allows us to study the effect of network centrality, NET_{ijt}, (measured within each asset class) while controlling for variations in fund-manager or manager size and allowing for fund-manager and time fixed effects. The fund-manager effect controls for abnormal performance due to skills in matching manager j with fund i. For each asset class we show results with the network-size interaction term switched off and on (odd and even columns, respectively), along with regressions based on the total, manager-only and consultant-only network measures.

First consider the effect of size on risk-adjusted performance shown in rows 1 and 2 in Table 3. This varies quite a bit across the three asset classes. For UK equities (columns 1-6), manager size is significantly negatively correlated with risk-adjusted returns, while fund-manager size does not appear to matter. For UK bonds (columns 7-12), fund-manager as well as manager size are both negatively correlated with performance, though only the former is borderline significant. Finally, for international equities (columns 13-18) we find that fund-manager size is strongly negatively correlated with performance while the manager size does not matter.

Next, consider the effect of network centrality on risk-adjusted performance in UK equities (columns 1-6). The first column, which is based on both manager- and consultant centrality, shows that there is a positive and significant effect of centrality on risk-adjusted performance. The coefficient is quite large, suggesting that a one-unit increase in centrality raises expected risk-adjusted returns by 0.35% per annum. Note that this result holds after controlling for both fund size and manager size. In column two we find a strongly positive effect of including a centrality-manager size interaction term. The significance of the interaction term suggests that the performance of large managers is more sensitive to network centrality than that of small managers and that a central position in the network helps managers cushion the otherwise strongly negative effect of size on performance. The interaction term weakens the direct effect of the network term but strengthens the results in the sense that the joint significance of the two network terms is now significant with a p-value less than one percent.

[12] For simplicity we suppress reference to the asset class in the notation.

Columns three and four show results for regressions that use the manager-only network centrality measure. We find borderline evidence that manager centrality is related to risk-adjusted performance (column three) with a p-value of 6%. However, the centrality-manager size interaction term is once again highly significant. The results are even stronger for the consultant-only centrality measure which generates a positive and significant (p-value of 0.03) coefficient that remains significant once the centrality-size interaction term is included.

These results do not reveal whether network connections established through managers, through consultants, or through both, matter most for risk-adjusted investment performance. To address this point, we next undertake a two-step encompassing regression. Specifically, we obtain the residuals from (6) based on the manager-only centrality measure. By construction, these residuals are orthogonal to the manager-only centrality terms. We then regress these residuals on the consultant-only network terms 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 that the manager-based centrality measure does not explain. 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 (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.

Turning to UK bonds, results for which are reported in columns 7-12 in Table 3, the evidence strongly suggests a positive relation between network centrality and risk-adjusted return performance, regardless of which of the three centrality measures (total, manager-only, or consultant-only) is used. Interestingly, the size of the centrality effect is strongest for the consultant-only network. In contrast to the results for UK equity, for UK bonds the coefficient on the centrality-size interaction term is negative and significant in two out of three cases. For all three centrality measures the (marginal) effect of centrality continues to be positive and significant even after including the size-centrality interaction term. This suggests that centrality is always associated with better investment performance for UK bond managers, although the ability to take advantage of a central network position is reduced for the largest UK bond managers. With a p-value of 0.00, the encompassing test strongly suggests that the consultant centrality measure helps explain return performance in UK bonds not explained by manager centrality. Conversely, 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 13-18), we find little evidence that network centrality matters to investment performance, except perhaps 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 come out insignificantly suggesting that neither of the consultant or manager-based network measures encompasses the other.

Overall, these results suggest a positive relation between a fund's network centrality and its ability to generate risk-adjusted performance in the UK equity and 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.

A plausible 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.

3.3 Role of investment consultants

The vast financial literature on investment performance focuses either on the performance of individual funds–mostly mutual funds, but also hedge funds and pension funds–or on fund managers.[13]

To our knowledge, no prior study has considered the role investment consultants play in the

[13] Chevalier and Ellison (1999), Baks (2001) and Ding and Wermers (2012) are examples of studies focusing on the relation between portfolio manager characteristics and investment performance.

investment process, let alone how they influence outcomes. This is an important omission since consultants play an important role in pension funds' choice of investment manager. A key issue is, therefore, whether they actually affect the funds' investment performance.

To address this question, we focus on the four largest consultants for which we have a sufficient number of observations to be able to compute, and compare, investment performance. Specifically, for each fund-consultant pairing we compute the mean return in UK equities in excess of the associated benchmark and divide this by the standard deviation of the associated residual so as to get an estimate of the information ratio (IR).[14] Thus, if a fund is initially advised by consultant 2 followed by a switch to consultant 11, the fund's performance record during the first period will be allocated to consultant 2, while the record during the latter period is assigned to consultant 11.

Figure 9 shows kernel density plots of the distribution of IR estimates for the four largest consultants. The figure indicates notable differences in the distribution of information ratios across consultants. For example, consultant 11 has a distribution that is further to the left–indicating worse performance–than that of the other consultants. Consultant one and two also appear to have higher "upside" performance, marked by slightly heavier right tails. Consultants one and two have average information ratios of 0.11, consultant three has an IR of 0.051 while consultant 11 has an IR of -0.07.

To test if these impressions translate into statistically significant differences, we next undertake a non-parametric permutation test which provides pairwise comparisons of the population of funds advised by different consultants.[15] Table 4 presents the results from this test. Small p-values indicate significant evidence that one manager is better than the other. Consultants 1, 2, and 3 all produce higher mean IRs than consultant 11, while consultants 1 and 2 also better the performance of consultant 3 (at the 10% significance level). There is little to distinguish the performance of consultants 1 and 2. These results suggest that consultants influence the performance of the funds they advise.

[14]This is a more reliable measure than the Sharpe ratio–mean excess return relative to the T-bill rate, divided by the volatility of excess returns–which is sensitive to the period over which the fund-consultants are in existence. For example, consultant 11 has a high average Sharpe ratio for UK equities simply because it is dominated by observations prior to 2000–a period during which UK equity returns were unusually high.

[15]The test pools the populations of funds across two consultants and then reassigns them, at random and without replacement, to the two consultants. It then computes the difference between the mean information ratios for the two consultants and compares this to the difference observed for the funds actually advised by the consultants. The p-value of the test is the proportion of permutations with a difference at least as large as the actual difference.

4 Fund flows and network centrality

We next ask whether managers' centrality in the network affects flows of money into the funds that they manage. In this analysis we aggregate assets under management across all asset classes so as to avoid that the results are contaminated by any shifts in asset allocation undertaken by the manager for reasons unrelated to network centrality. Moreover, we consider the results at the manager, rather than the fund-manager level. Because we are analyzing defined-benefit pension fund accounts, the flows into a given fund-manager account is likely to be determined by factors extraneous to the pairing's centrality in the network such as numbers of employees and their contributions. Conversely, managers may get new client accounts if they are perceived as being capable of delivering superior investment performance.

Specifically, in this analysis we first generate a fund-flow variable for manager i over the course of quarter t as follows:

$$Flow_{jt+1} = \left(\frac{SMV_{j,t+1} - SMV_{j,t}}{SMV_{j,t}} - R_{jt+1} \right) SMV_{j,t}, \tag{7}$$

where $SMV_{j,t}$ is the starting market value of manager j's total asset holdings at the end of quarter t and R_{jt+1} is the return generated by the manager during quarter $t+1$.

We regress the manager flow variable defined in (7) on the lagged flow, manager size, $Msize_{jt}$, past returns over the previous year, $\bar{R}_{jt}$, network centrality, NET_{jt}, along with centrality-size and centrality-return interaction terms, allowing for time and manager fixed effects:

$$\begin{aligned} Flow_{jt+1} &= a_j + c_t + \beta_1 Flow_{jt} + \beta_2 Msize_{jt} + \beta_3 \bar{R}_{jt} + \beta_4 NET_{jt} \\ &\quad + \beta_5 Msize_{jt} NET_{jt} + \beta_5 \bar{R}_{jt} NET_{jt} + \varepsilon_{jt}. \end{aligned} \tag{8}$$

Results from this regression are shown in panels A-C in Table 5. For UK equities (Panel A), past flows appear to be uncorrelated with future flows, while manager size is strongly negatively related to future flows. Past return performance does not appear to matter on its own. However, there is clear evidence that more central managers attract larger inflows of funds, regardless of whether we use the total, manager-only or consultant-only centrality measures. The effect of centrality on fund flows seems unrelated to manager size (columns 6 and 8) but is boosted by consultant size as shown by the positive and significant interaction terms (columns 10 and 12.) Moreover, we also find positive and significant coefficients on the centrality-past return interaction terms, suggesting that higher past returns are exploited by the most central managers to generate larger inflows.

For UK bonds (Panel B), again we find positive and borderline significant coefficients on the centrality measures in the flow regressions that use the manager-only or total centrality measures, though not for the consultant-based centrality measure. Manager size continues to be negatively associated with fund flows and the centrality interaction terms are mostly insignificant, the one exception being the consultant-only centrality-size interaction coefficient which is small but positive.

Results for International equity are similar to those obtained for UK equity fund flows: fund flows are negatively associated with manager size, but positively related to manager and consultant centrality. Moreover, the centrality-past returns and centrality-size interaction terms are positive and predominantly significant, suggesting that network centrality provides the greatest benefits to the largest funds with the highest past returns.

5 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 separate 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 in a later section), then they should also be willing to take riskier bets. There is likely to be a size effect on managers' risk taking as well, however, as 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.

5.1 Idiosyncratic Risk and Network Centrality

We perform our analysis by proxying for the unobserved level of risk 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, $|\hat{\varepsilon}_{ijt}|$. Note that if these residuals are drawn from a Gaussian distribution, then $E[|\hat{\varepsilon}_{ijt}|] = \sqrt{2/\pi} stdev(\hat{\varepsilon}_{ijt})$, 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.

To estimate how funds' idiosyncratic risk taking is affected by network centrality, we next estimate panel regressions similar to (6):

$$|\hat{\varepsilon}_{ijt}| = a_i + b_j + c_t + \lambda_1 size_{ijt} + \lambda_2 Msize_{jt} + \lambda_3 NET_{ijt} + \lambda_4 NET_{ijt} Msize_{jt} + \varepsilon_{ijt}. \tag{9}$$

Results from this regression are presented in Table 6 which uses the same layout as Table 3. 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.

For UK equities (columns 1-6) there is modest evidence that funds with higher consultant-only centrality take on more risk than less central funds. Conversely, the corresponding coefficients for the total and manager-only centrality measures are negative and insignificant. Across the three centrality measures, the centrality-size interaction term generates a negative and highly significant coefficient, however. This suggests that large and centrally placed managers are even less willing to take on idiosyncratic risk than what is explained by size alone.

Similar results are found for UK bond managers–again the centrality-size interaction term is negative and strongly significant while the centrality measure on its own is only significant for one of three cases, this time generating a negative coefficient for the consultant-only network centrality measure.

For International equities we find very different results. For this asset class, the coefficient on network centrality is now positive and statistically significant in two of three cases and the results are now weakest for the consultant-based centrality network. Similarly, the centrality-size interaction term now generates a positive coefficient that remains significant across all three centrality measures.

Whereas large, centrally connected UK equity and UK bond managers tend to take on less risk, we thus find that centrally positioned international managers are willing to take riskier bets.

A possible explanation of this evidence is the finding in previous studies such as Kang and Stulz (1997) that foreign investors act as if they are at an informational disadvantage when investing abroad. Our finding is consistent with more central managers–who are likely to have international offices and networks of their own–being less cautious when investing abroad than the managers who are less well connected.

5.2 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 4. 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.[16]

5.2.1 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.

[16]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.

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

$$h(d_{ijt}) = h_0(d_{ijt}) \exp(\beta' x_{ijt}). \tag{10}$$

Our model allows the manager's hazard rate to depend on four factors, x_{it}. 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. 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, past risk-adjusted returns could affect the probability that the manager is fired and so we include a return measure, $\bar{R}_{it}^{adj}$, which measures the manager's return over the previous four quarters. Returns are risk-adjusted, i.e., adjusted for a fund-manager's exposure to the Fama-French (1993) size and value common risk factors, augmented by the Carhart (1997) momentum factor (SMB_t, HML_t, and MOM_t, respectively). The hypothesis here is that higher past risk-adjusted returns should reduce the chance of getting fired.

Third, we control for manager size, $MSIZE_{jt}$, 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 centrality measure, NET_{jt}. To see if it matters whether network centrality is established through consultants or directly between managers, we also consider these centrality measures separately. The hypothesis is that the more central a manager is within the network, the less likely he is to get fired.

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

$$h(d_{ijt}, \bar{R}_{ijt}, Msize_{ijt}, NET_{ijt}) = h_0(d_{ijt}) \exp(\beta_1 \bar{R}_{ijt} + \beta_2 Msize_{ijt} + \beta_3 NET_{ijt}) + \varepsilon_{ijt}. \tag{11}$$

5.2.2 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 7 reports estimation results for the model in (11). 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 significant at the 5% apart from one case (UK bonds, manager-only centrality) that is significant at the 10% 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 past performance, this suggests that more central managers also are "safer", i.e., they stand a lower chance of being fired.

5.2.3 Results for Consultants

We next undertake a similar hazard rate analysis for the consultants as that undertaken for the managers. Note, however, that once we use consultants' firing as the dependent variable, we can only construct the overall degree measure and so omit two of the three centrality measures.

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 7 shows parameter estimates from applying (11) 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.

6 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:

$$y_{it} = \lambda_0 + \sum_{l=1}^{m} \lambda_l y_{it-l} + \sum_{l=1}^{m} \delta_l x_{it-l} + u_{it}. \tag{12}$$

The model in (12) 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 (12) 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:

$$y_{it} = \lambda_{0t} + \sum_{l=1}^{m} \lambda_{lt} y_{it-l} + \sum_{l=1}^{m} \delta_{lt} x_{it-l} + \Psi_t f_i + u_{it}, \tag{13}$$

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 (13) 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

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

First-differencing this model yields

$$y_{it} - y_{it-1} = \sum_{l=1}^{m} \lambda_l (y_{it-l} - y_{it-l-1}) + \sum_{l=1}^{m} \delta_l (x_{it-l} - x_{it-l-1}) + v_{it}, \tag{14}$$

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 (14) as:

$$\mathbf{Y}_t = \mathbf{W}_t\mathbf{B} + \mathbf{V}_t. \tag{15}$$

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

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

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

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

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.[17] We separately consider the total, manager- and consultant-based centrality measures.

6.1 Empirical Findings

Table 8 presents the outcome of the Granger causality tests described above as applied to our data. Panel A uses the centrality measure as the dependent variable, while lagged size and lagged centrality

[17]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.

is used as independent variables. In all but one instance the 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 8.

Panel B of Table 8 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 our three different measures of network centrality and across asset classes and so are very strong. 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 risk-adjusted performance and higher inflows.

7 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 funds and fund-managers are connected and how such connections evolve over time. We distinguish between network connections established through managers versus connections established through consultants. Next, we show that a fund-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, even after controlling for size. In fact, a central position in the network seems to be important for reducing the large negative effect a manager's size ordinarily has on his return performance and future growth.

These results suggest that there is path dependence in fund managers' performance: the ability of a manager to establish a central position in the network of institutional investors matters to his future success as measured by risk-adjusted returns and growth in assets under management. In turn these measures of performance affect the managers' ability to exploit their central position in the network. Once a central position has been established and the manager has grown large, the manager tends to reduce risk-taking behavior and reduces the chances of getting fired by institutional clients.

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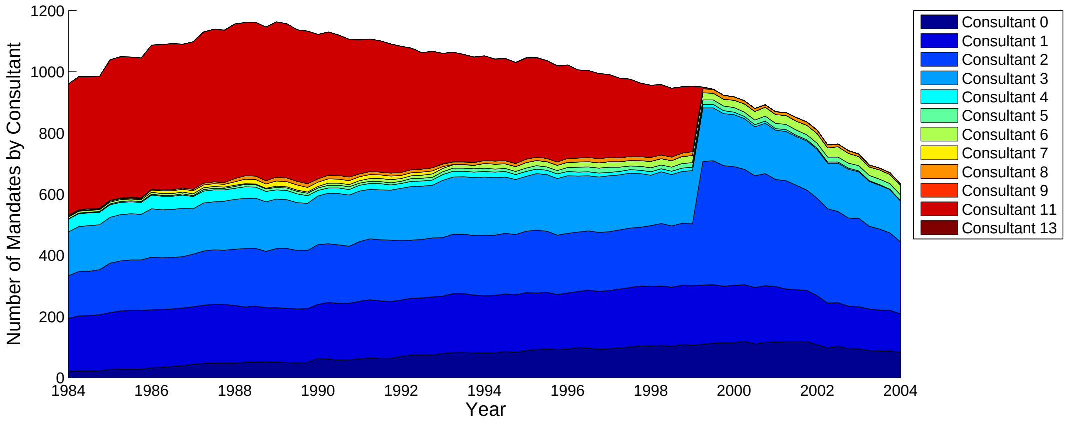
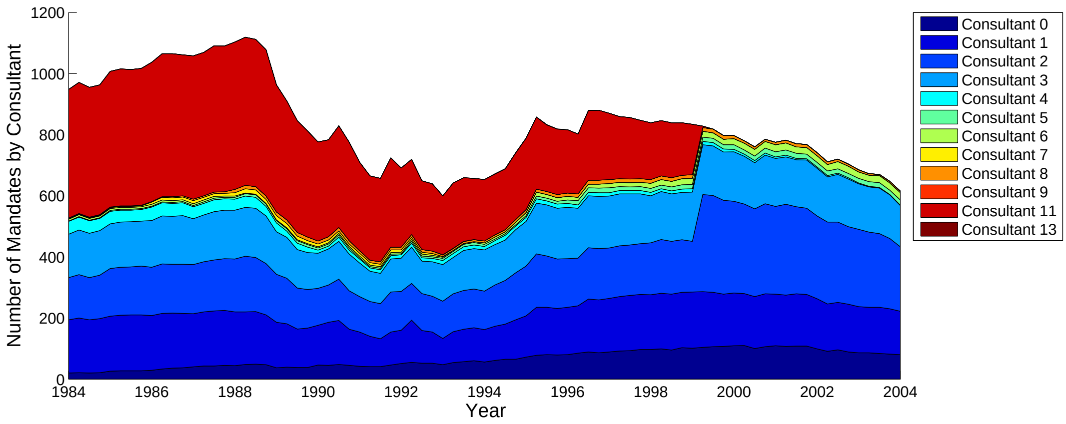
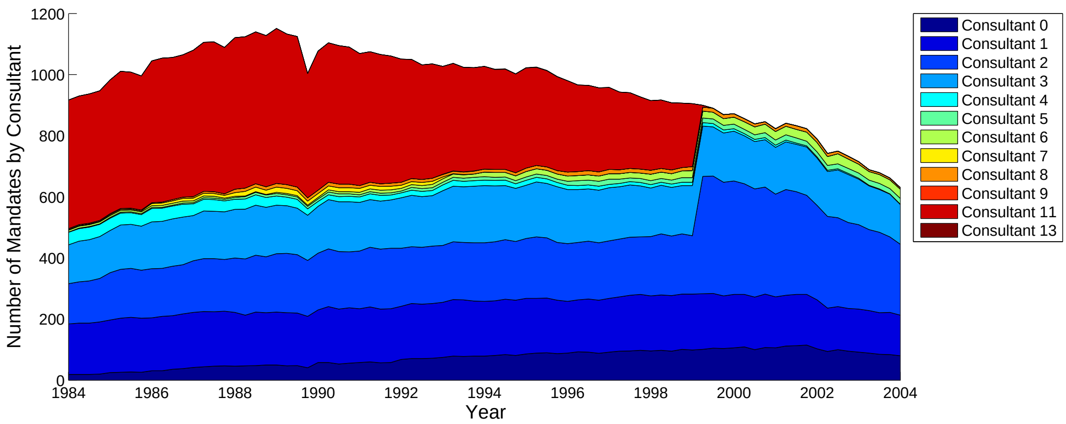
Figure 1. Evolution of the Number of Mandates by Consultants.



(A) UK equities



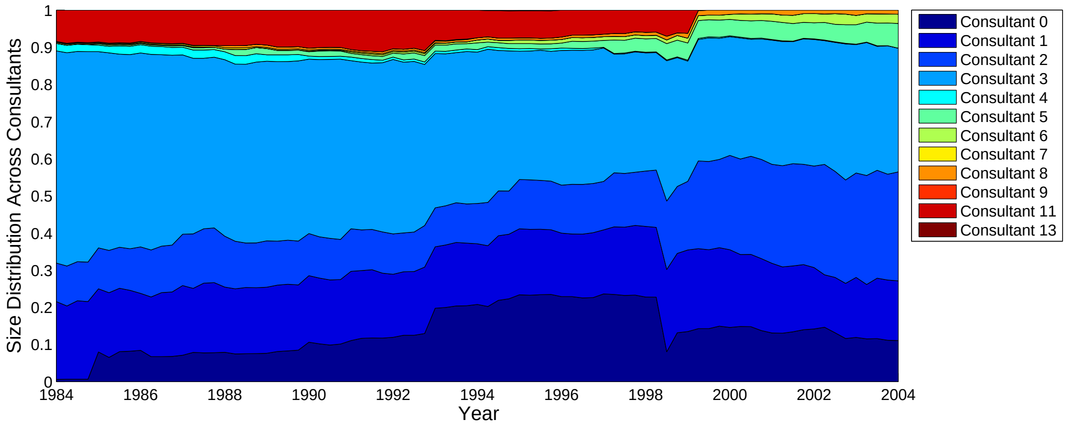
(B) UK bonds



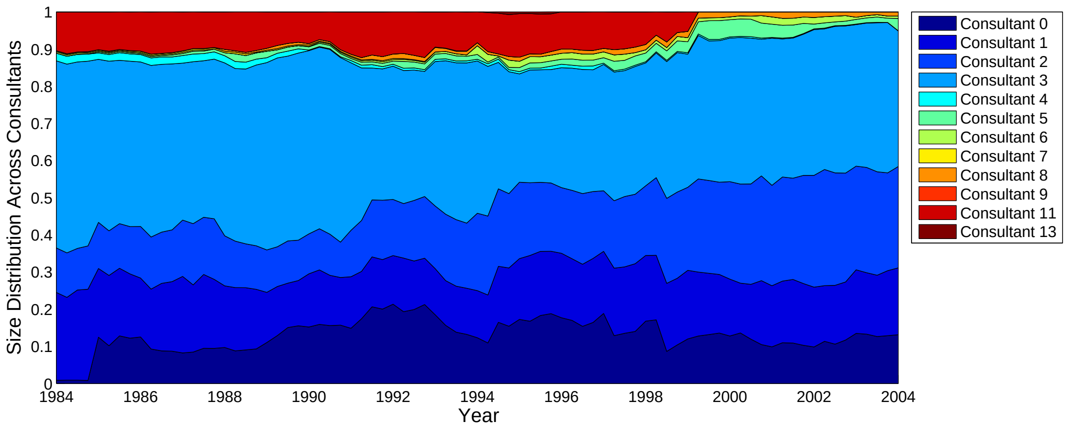
(C) International equities

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.

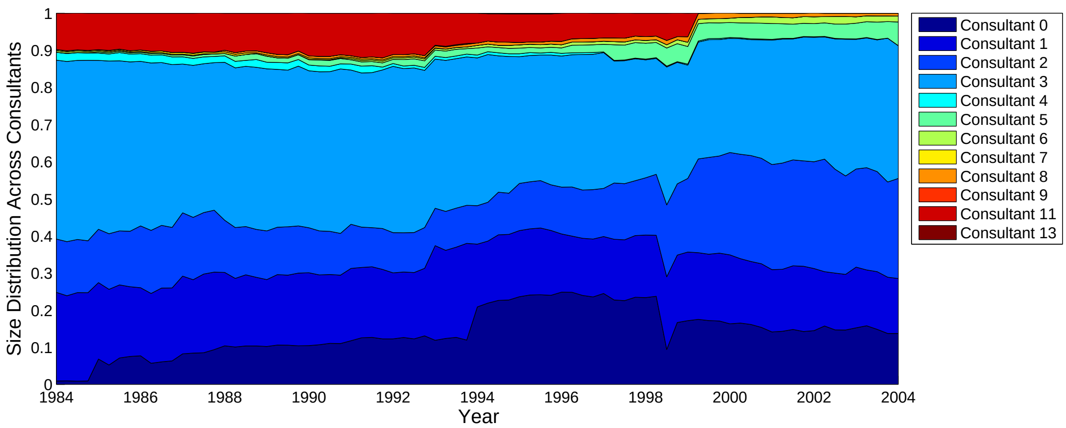
Figure 2. Relative Size of Consultants over Time.



(A) UK equities



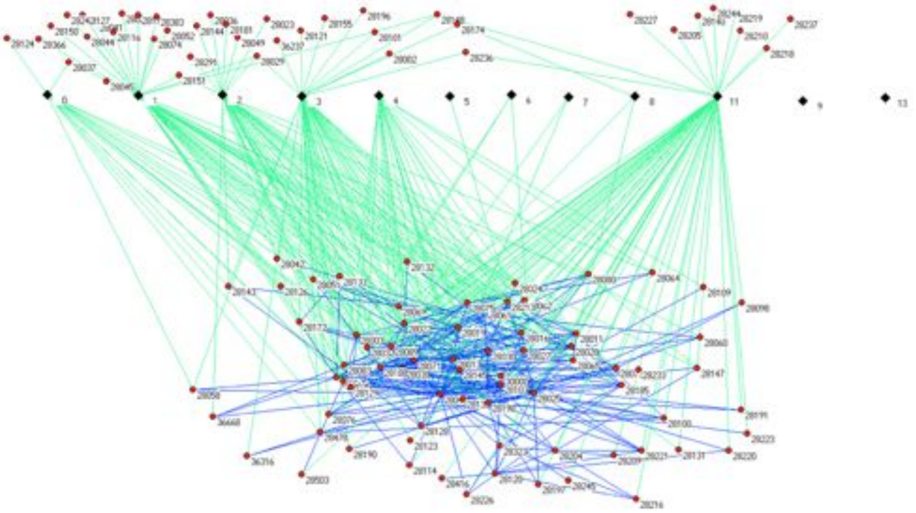
(B) UK bonds



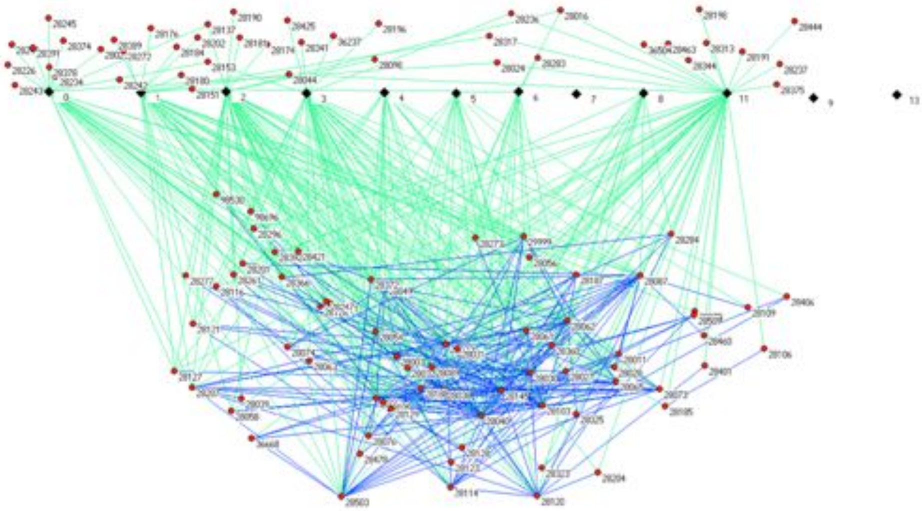
(C) International equities

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.

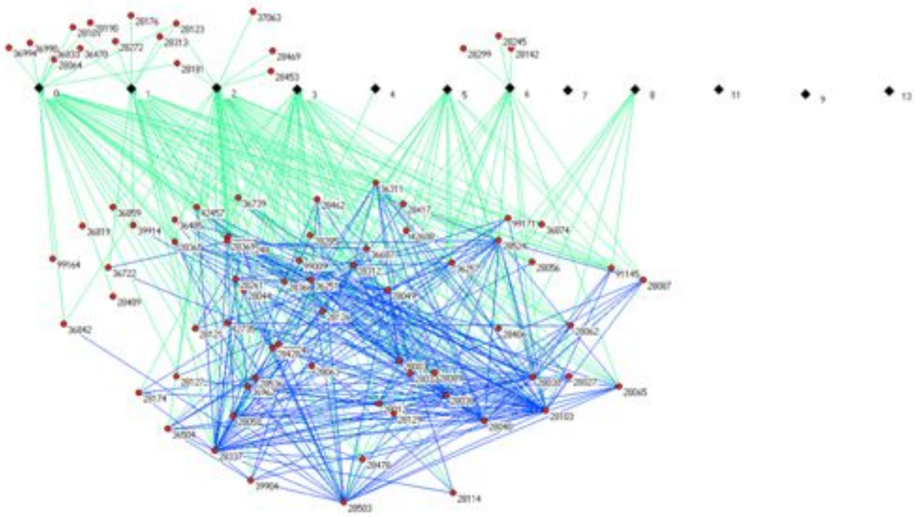
Figure 3. Network connections in UK equities asset class in the UK pension fund industry



(A) year : 1984



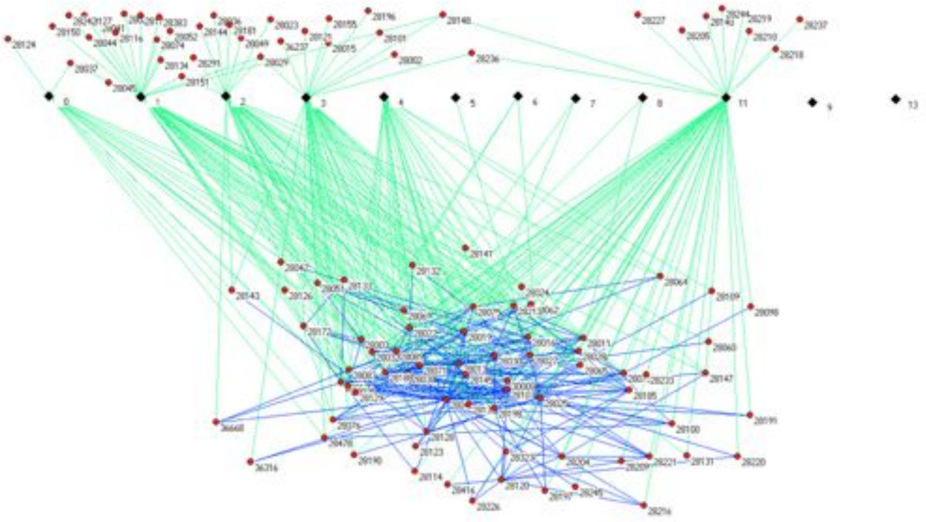
(B) year : 1994



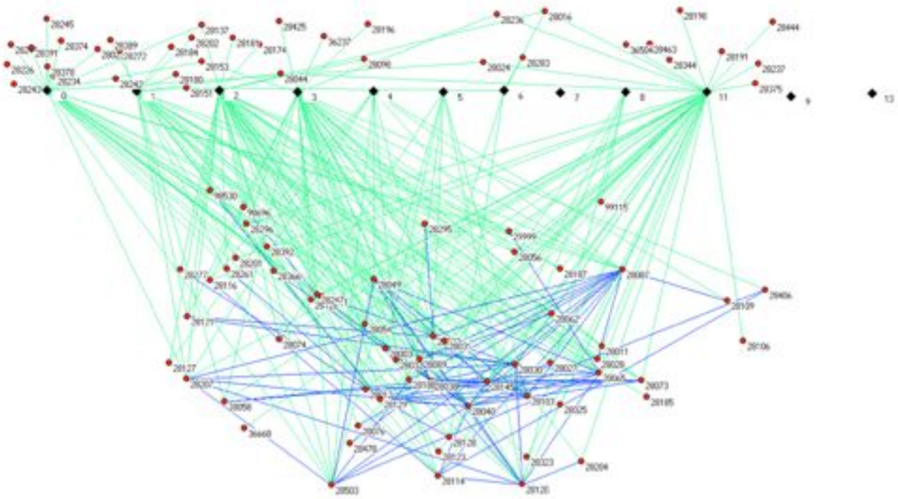
(C) year : 2004

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.

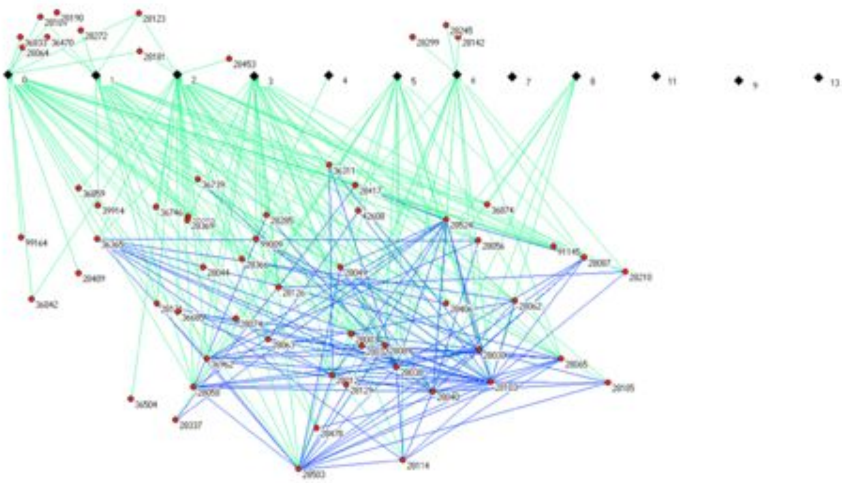
Figure 4. Network connections in UK bonds asset class in the UK pension fund industry



(A) year : 1984



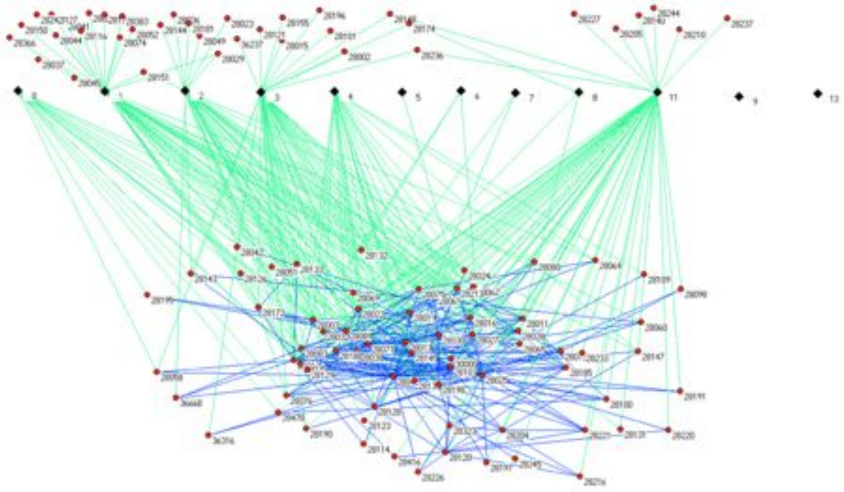
(B) year : 1994



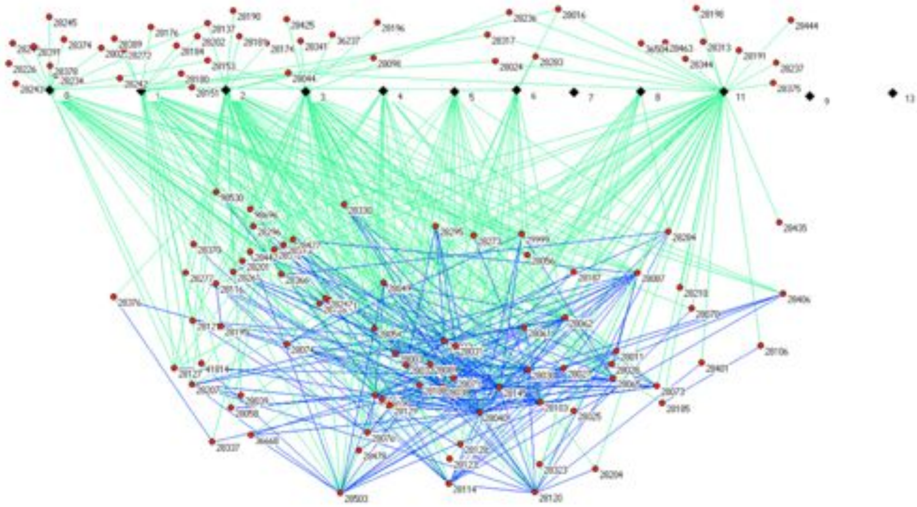
(C) year : 2004

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.

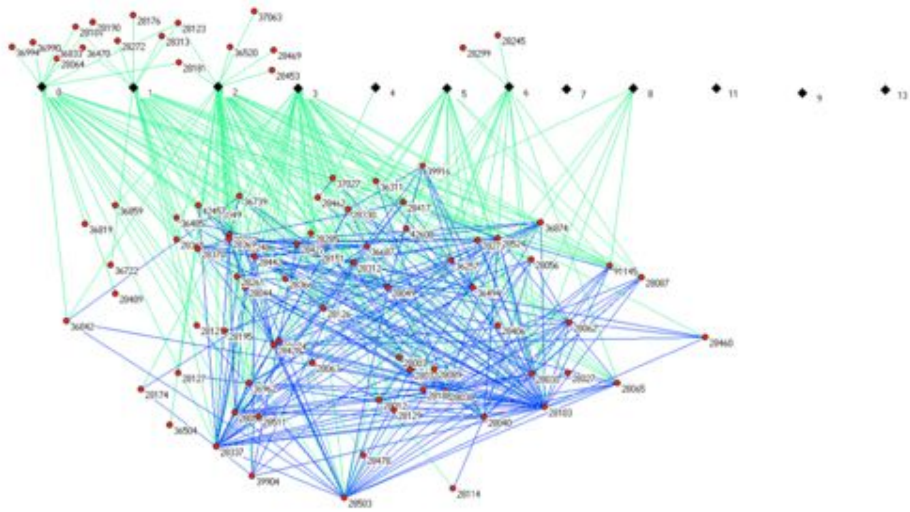
Figure 5. Network connections in international equities asset class in the UK pension fund industry



(A) year : 1984



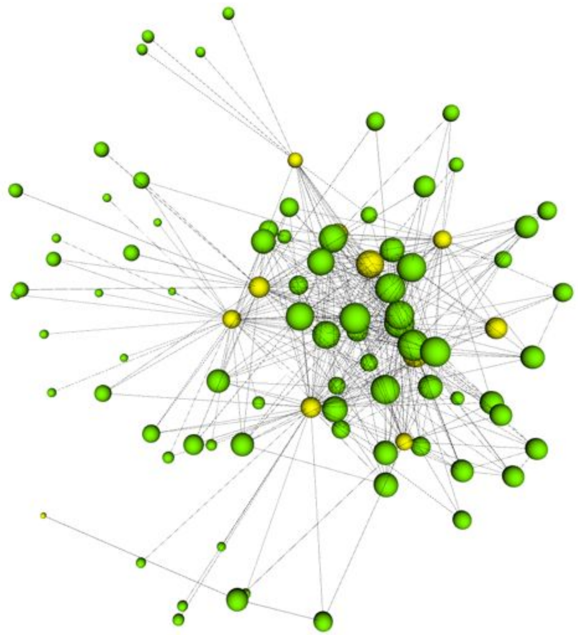
(B) year : 1994



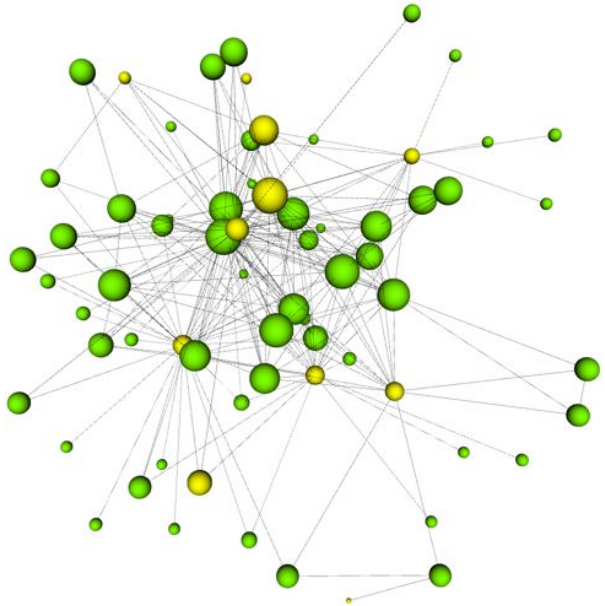
(C) year : 2004

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.

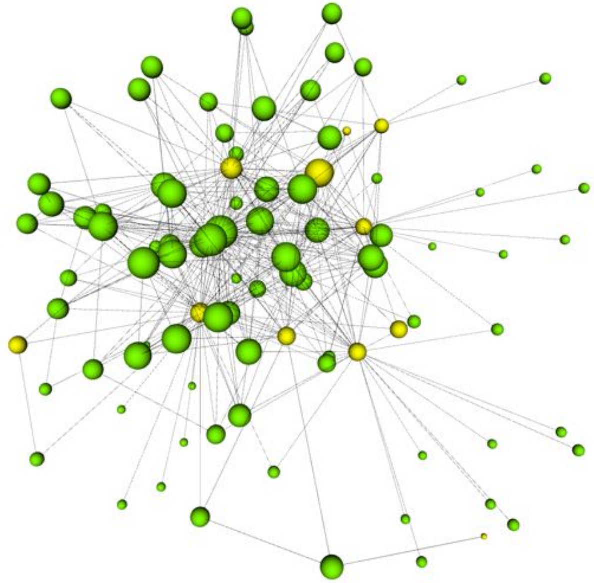
Figure 6. 3-D Representation of the Network Connections across managers and consultants in UK Equities, UK bonds and International equities for the year 2004.



(A) UK equities



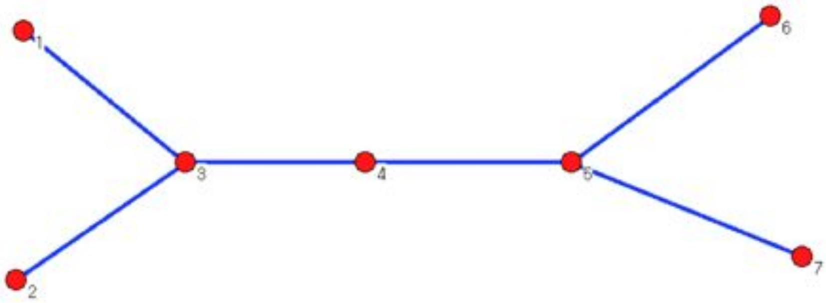
(B) UK bonds



(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.

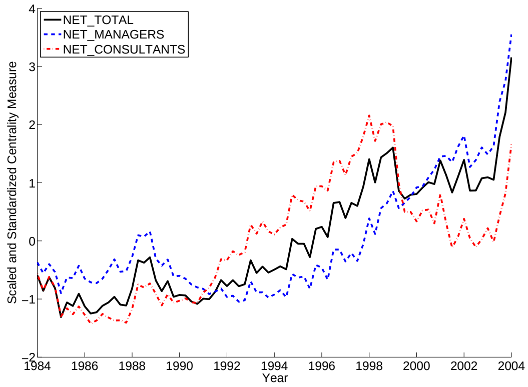
Figure 7. Degree measure of connectedness



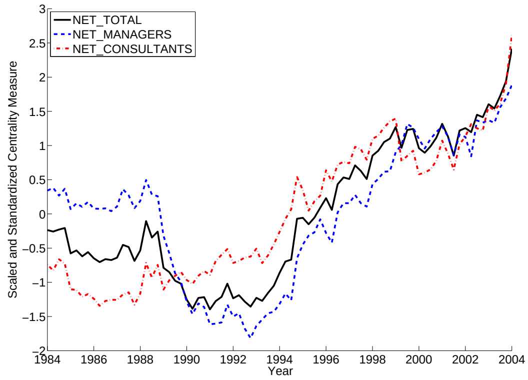
	Nodes 1, 2, 6 and 7	Nodes 3 and 5	Node 4
Degree Centrality	0.17	0.50	0.33

This figure plots a simple example of a network with 7 nodes and reports the degree centrality values for each node in the network. Degree centrality values are computed using equation (1) in the main body of the paper.

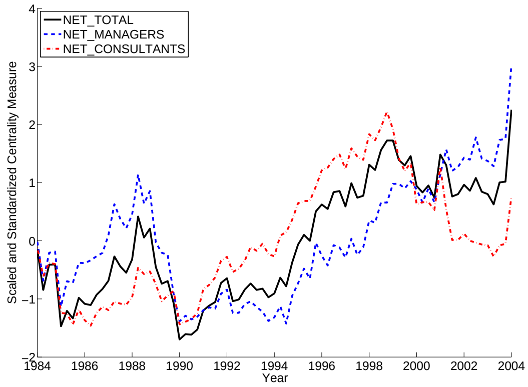
Figure 8. Average network centrality in the UK pension fund industry



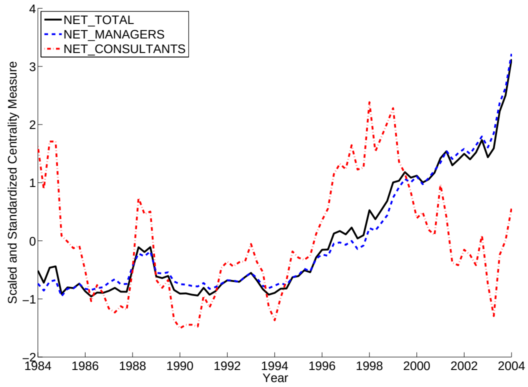
(A) UK equities



(B) UK bonds



(C) International equities



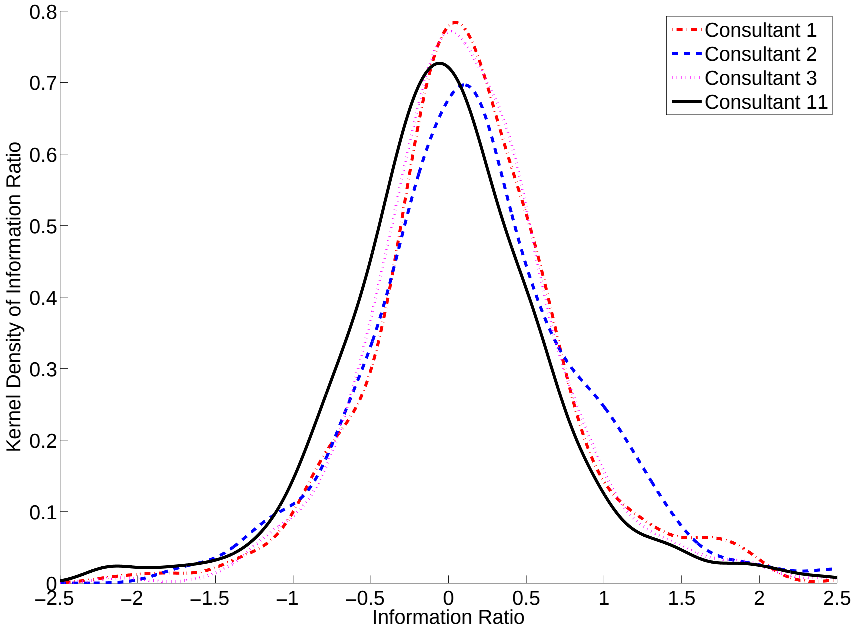
(D) Across all Asset Classes

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 9. Information Ratios of Consultants Across Funds Managed



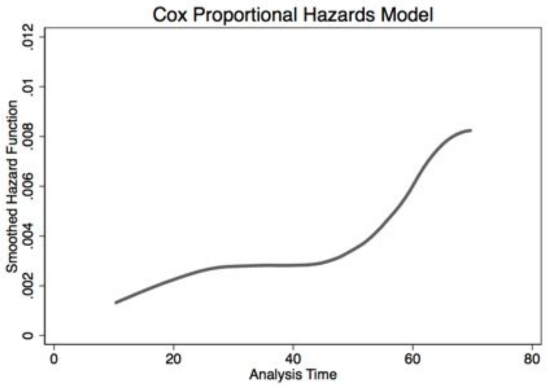
This figure plots the kernel density estimates of the information ratios in UK equities associated with the four consultants with the largest number of mandates, i.e. Consultant 1, Consultant 2, Consultant 3 and Consultant 11. The information ratio of consultant i in fund j is computed as

$$IR_{i,j} = \frac{\frac{1}{(t_{max}-t_{min}+1)} \sum_{t_{min}}^{t_{max}} (r_{i,j,t} - r_{m,t})}{\sqrt{\frac{1}{(t_{max}-t_{min})} \sum_{t_{min}}^{t_{max}} \left((r_{i,j,t} - r_{m,t}) - \overline{(r_{i,j,\cdot} - r_{m,\cdot})} \right)^2}}$$

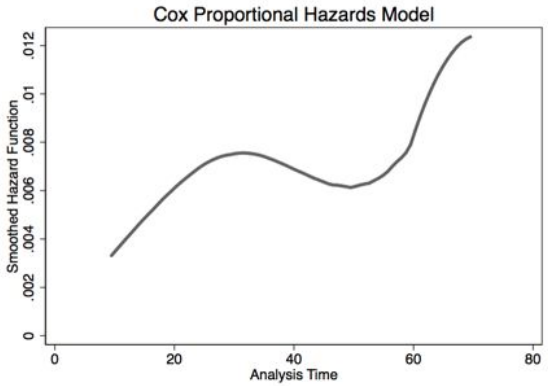
where t_{min} (t_{max}) is the first (last) observation of each consultant-fund pairing, $r_{i,j,t}$ is the excess return of consultant i in fund j at time t and $r_{m,t}$ is the excess return on the UK market portfolio at time t. We drop from the sample the consultant-manager pairings that have less than 12 observations. The information ratios are annualized by multiplying $IR_{i,j}$ by 2.

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

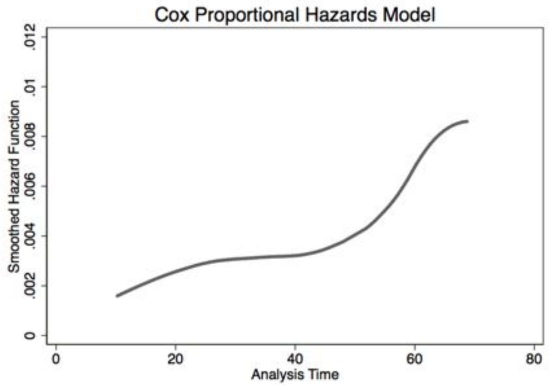
Managers' Baseline Hazard Rates



(A) UK Equities

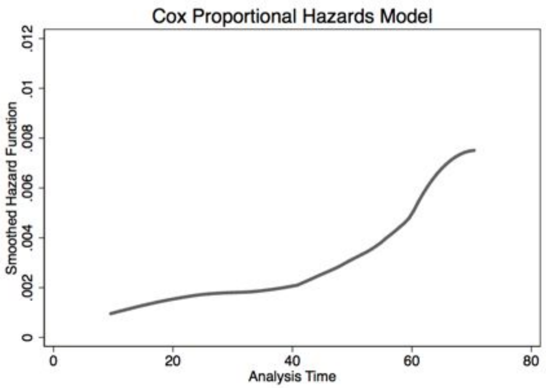


(B) UK Bonds

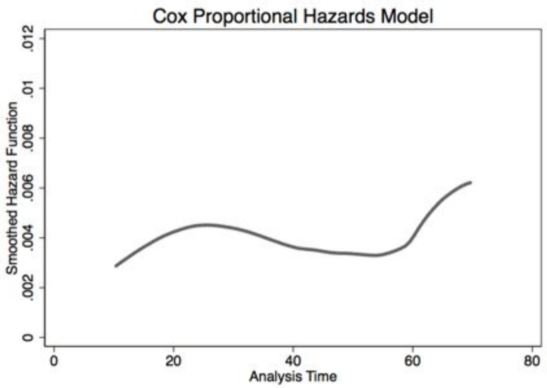


(C) International Equities

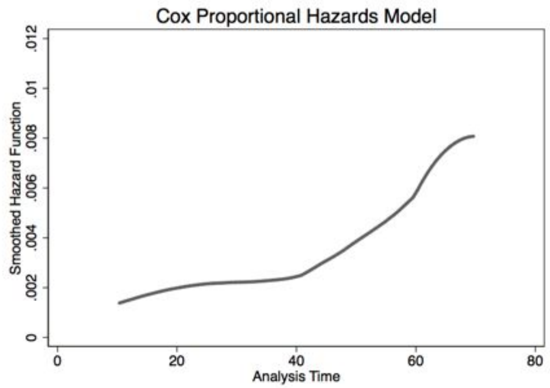
Consultants' Baseline Hazard Rates



(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					
$SIZE$	-0.194	-0.200	-0.195	-0.202	-0.201	-0.200	-0.118	-0.105	-0.119	-0.106	-0.110	-0.109	-0.627	-0.629	-0.629	-0.628	-0.624	-0.631
	(0.14)	(0.13)	(0.14)	(0.12)	(0.13)	(0.13)	(0.05)	(0.08)	(0.04)	(0.07)	(0.06)	(0.06)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M_SIZE	-0.336	-0.384	-0.323	-0.351	-0.325	-0.463	-0.026	0.063	-0.021	0.045	-0.083	-0.046	-0.158	-0.169	-0.140	-0.137	-0.183	-0.394
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.52)	(0.14)	(0.59)	(0.25)	(0.03)	(0.39)	(0.23)	(0.20)	(0.27)	(0.28)	(0.13)	(0.02)
NET	0.357	0.076					0.184	0.301					-0.104	-0.159				
	(0.04)	(0.68)					(0.06)	(0.00)					(0.65)	(0.57)				
$NET \times M\_SIZE$		0.326						-0.230						0.051				
		(0.00)						(0.00)						(0.69)				
NET_M			0.264	-0.008					0.137	0.240					-0.165	-0.145		
			(0.06)	(0.96)					(0.05)	(0.00)					(0.36)	(0.51)		
$NET\_M \times M\_SIZE$				0.317						-0.204						-0.019		
				(0.00)						(0.00)						(0.86)		
NET_C					0.443	0.622					0.754	0.727					0.022	0.256
					(0.03)	(0.01)					(0.00)	(0.00)					(0.95)	(0.47)
$NET\_C \times M\_SIZE$						0.254						-0.056						0.337
						(0.01)						(0.32)						(0.02)
Between R^2	0.014	0.009	0.014	0.010	0.017	0.011	0.061	0.057	0.061	0.061	0.053	0.053	0.024	0.024	0.023	0.023	0.026	0.030
Joint-Significance	0.038	0.000	0.057	0.000	0.032	0.005	0.064	0.000	0.053	0.000	0.000	0.000	0.652	0.849	0.362	0.640	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 $\widehat{r}_{i,j,t}^{adj} = \widehat{\alpha}_{i,j} + \widehat{\epsilon}_{i,j,t}$, where $\hat{\alpha}_{i,j}$ is estimated using the full set of observations available for manager i in fund j. We adopt a four-factor model for UK Equities:

$$r_{i,j,t} = \alpha_{i,j} + \beta_{1,i,j}\ r_{m,t} + \beta_{2,i,j}\ SMB_t + \beta_{3,i,j}\ HML_t + \beta_{4,i,j}\ MOM_t + \epsilon_{i,j,t},$$

where $r_{m,t}$ 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:

$$r_{i,j,t} = \alpha_{i,j} + \beta_{1,i,j} GOVB_t + \beta_{2,i,j} CONS_t + \epsilon_{i,j,t},$$

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:

$$r_{i,j,t} = \alpha_{i,j} + \beta_{1,i,j}\ NA_t + \beta_{2,i,j}\ EAFEX_t + \beta_{3,i,j}\ SMB_t + \beta_{4,i,j}\ HML_t + \epsilon_{i,j,t},$$

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), degree centrality computed using the managers' network only (NET_M) 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. For each centrality measure we adopt two specifications. In the first we include the centrality measure as well as its square. 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. Permutation tests for Consultants' Information Ratios in UK Equities

	Consultant 1	*Consultant* 2	*Consultant* 3	*Consultant* 11
Consultant 1	0	0.008 (0.81)	0.063 (0.08)	0.186 (0.00)
Consultant 2		0	0.055 (0.09)	0.178 (0.00)
Consultant 3			0	0.123 (0.00)
Consultant 11				0

This table reports differences in average Information Ratios across the four consultants with the largest number of mandates, i.e. Consultant 1, Consultant 2, Consultant 3 and Consultant 11. The information ratio of consultant i in fund j is computed as

$$IR_{i,j} = \frac{\frac{1}{(t_{max}-t_{min}+1)} \sum_{t_{min}}^{t_{max}} (r_{i,j,t} - r_{m,t})}{\sqrt{\frac{1}{(t_{max}-t_{min})} \sum_{t_{min}}^{t_{max}} \left((r_{i,j,t} - r_{m,t}) - \overline{(r_{i,j,\cdot} - r_{m,\cdot})}\right)^2}}$$

where t_{min} (t_{max}) is the first (last) observation of each consultant-fund pairing, $r_{i,j,t}$ is the excess return of consultant i in fund j at time t and $r_{m,t}$ is the excess return on the UK market portfolio at time t. We drop from the sample the consultant-manager pairings that have less than 12 observations. Each entry reports the difference average Information Ratio between the row consultant and the column consultant. In parentheses are reported the p-values computed using a permutation test with 10000 iterations. The information ratios are annualized by multiplying $IR_{i,j}$ by 2. The annualized average information ratio for consultant 1 is 0.114, for consultant 2 is 0.106, for consultant 3 is 0.051 and for consultant 4 is -0.072.

Table 5. Fund-Flows and Managers' Centrality

Panel A. Results for UK Equities												
Lag_Flow	-0.024	-0.024	-0.010	-0.010	-0.024	-0.024	-0.012	-0.012	-0.025	-0.025	-0.007	-0.006
	(0.25)	(0.25)	(0.64)	(0.64)	(0.25)	(0.25)	(0.58)	(0.58)	(0.23)	(0.25)	(0.73)	(0.77)
M_SIZE	-0.102	-0.103	-0.102	-0.103	-0.100	-0.100	-0.099	-0.099	-0.095	-0.107	-0.096	-0.108
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Ret	0.260	0.252	-0.073	-0.088	0.245	0.243	0.003	-0.002	0.251	0.235	-0.427	-0.456
	(0.70)	(0.71)	(0.91)	(0.90)	(0.71)	(0.72)	(1.00)	(1.00)	(0.71)	(0.73)	(0.54)	(0.51)
NET	0.046	0.043	0.030	0.026								
	(0.00)	(0.02)	(0.09)	(0.19)								
$NET \times M\_SIZE$		0.003		0.004								
		(0.63)		(0.56)								
$NET \times Ret$			0.505	0.510								
			(0.00)	(0.00)								
NET_M					0.033	0.032	0.019	0.018				
					(0.00)	(0.01)	(0.12)	(0.21)				
$NET\_M \times M\_SIZE$						0.001		0.002				
						(0.89)		(0.79)				
$NET\_M \times Ret$							0.377	0.379				
							(0.00)	(0.00)				
NET_C									0.038	0.044	0.008	0.014
									(0.06)	(0.03)	(0.70)	(0.52)
$NET\_C \times M\_SIZE$										0.019		0.020
										(0.01)		(0.01)
$NET\_C \times Ret$											0.965	0.981
											(0.00)	(0.00)
Joint-Significance	0.002	0.002	0.000	0.000	0.002	0.003	0.000	0.000	0.057	0.003	0.000	0.000
Panel B. Results for UK Bonds												
Lag_Flow	-0.017	-0.017	-0.017	-0.017	-0.018	-0.018	-0.018	-0.018	-0.018	-0.017	-0.017	-0.016
	(0.45)	(0.45)	(0.45)	(0.44)	(0.43)	(0.43)	(0.42)	(0.42)	(0.43)	(0.46)	(0.45)	(0.47)
M_SIZE	-0.129	-0.130	-0.129	-0.130	-0.126	-0.126	-0.126	-0.127	-0.124	-0.140	-0.124	-0.140
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Ret	0.663	0.677	0.689	0.702	0.701	0.700	0.778	0.777	0.589	0.700	0.423	0.559
	(0.58)	(0.57)	(0.56)	(0.56)	(0.55)	(0.55)	(0.51)	(0.51)	(0.62)	(0.56)	(0.73)	(0.65)
NET	0.034	0.031	0.035	0.032								
	(0.05)	(0.12)	(0.08)	(0.15)								
$NET \times M\_SIZE$		0.003		0.003								
		(0.66)		(0.66)								
$NET \times Ret$			-0.029	-0.027								
			(0.89)	(0.90)								
NET_M					0.020	0.019	0.022	0.021				
					(0.06)	(0.14)	(0.09)	(0.15)				
$NET\_M \times M\_SIZE$						0.001		0.001				
						(0.80)		(0.81)				
$NET\_M \times Ret$							-0.081	-0.080				
							(0.61)	(0.62)				
NET_C									0.030	0.035	0.024	0.030
									(0.22)	(0.15)	(0.40)	(0.30)
$NET\_C \times M\_SIZE$										0.020		0.020
										(0.02)		(0.02)
$NET\_C \times Ret$											0.186	0.158
											(0.57)	(0.63)
Joint-Significance	0.046	0.075	0.119	0.115	0.059	0.116	0.160	0.184	0.216	0.022	0.273	0.024

(Table continued on the next page)

(Table continued from the previous page)

Panel C. Results for International Equities

Lag_Flow	-0.039	-0.039	-0.034	-0.035	-0.039	-0.039	-0.035	-0.035	-0.041	-0.039	-0.035	-0.033
	(0.10)	(0.10)	(0.16)	(0.16)	(0.10)	(0.10)	(0.15)	(0.14)	(0.09)	(0.10)	(0.15)	(0.17)
M_SIZE	-0.109	-0.110	-0.109	-0.110	-0.107	-0.107	-0.107	-0.107	-0.102	-0.119	-0.102	-0.119
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Ret	-0.207	-0.228	-0.321	-0.341	-0.218	-0.227	-0.296	-0.304	-0.191	-0.250	-0.439	-0.486
	(0.65)	(0.61)	(0.48)	(0.45)	(0.63)	(0.62)	(0.52)	(0.50)	(0.67)	(0.58)	(0.34)	(0.29)
NET	0.043	0.034	0.039	0.030								
	(0.00)	(0.03)	(0.00)	(0.05)								
$NET \times M\_SIZE$		0.007		0.007								
		(0.20)		(0.21)								
$NET \times Ret$			0.154	0.153								
			(0.03)	(0.02)								
NET_M					0.031	0.026	0.028	0.023				
					(0.00)	(0.02)	(0.00)	(0.03)				
$NET\_M \times M\_SIZE$						0.003		0.003				
						(0.45)		(0.46)				
$NET\_M \times Ret$							0.108	0.109				
							(0.04)	(0.03)				
NET_C									0.035	0.039	0.027	0.031
									(0.04)	(0.02)	(0.12)	(0.06)
$NET\_C \times M\_SIZE$										0.025		0.025
										(0.00)		(0.00)
$NET\_C \times Ret$											0.318	0.304
											(0.01)	(0.01)
Joint-Significance	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.042	0.000	0.006	0.000

This table reports panel regression results for the effect of managers' centrality, size and past performance on fund inflows and outflows. The fund-flow variable for manager i over quarter t is defined as:

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

where $SMV_{i,t}$ is the starting market value of manager i's asset holdings in UK equities (Panel A), UK bonds (Panel B) and international equities (Panel C) at quarter t and $R_{i,t:t+1}$ is the return generated over quarter $t+1$ in the respective asset class. 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), computed in UK equities (Panel A), UK bonds (Panel B) or international equities (Panel C). The size variable M_SIZE denotes the total assets under management (across all asset classes and funds managed) of each manager at each point in time. 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. The past performance of each manager is constructed by value-weighting the returns in a given asset class across the various funds managed over the previous year. 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 6. Centrality and Fund-Manager Risk

	Panel A. UK Equities						Panel B. UK Bonds						Panel C. Int. Equities					
$SIZE$	-1.291	-1.285	-1.292	-1.285	-1.289	-1.291	-0.507	-0.502	-0.501	-0.494	-0.504	-0.502	-1.704	-1.722	-1.703	-1.721	-1.717	-1.723
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
M_SIZE	-0.124	-0.072	-0.117	-0.090	-0.193	-0.014	-0.178	-0.139	-0.198	-0.160	-0.178	-0.141	-0.424	-0.490	-0.424	-0.469	-0.331	-0.519
	(0.09)	(0.33)	(0.10)	(0.21)	(0.00)	(0.86)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
NET	-0.102	0.197					-0.191	-0.139					0.527	0.180				
	(0.64)	(0.36)					(0.10)	(0.23)					(0.02)	(0.47)				
$NET \times M\_SIZE$		-0.347						-0.102						0.321				
		(0.00)						(0.05)						(0.00)				
NET_M			-0.126	0.126					-0.067	-0.007					0.464	0.160		
			(0.48)	(0.48)					(0.42)	(0.93)					(0.01)	(0.42)		
$NET\_M \times M\_SIZE$				-0.293						-0.117						0.292		
				(0.00)						(0.01)						(0.00)		
NET_C					0.365	0.135					-0.281	-0.309					0.148	0.356
					(0.04)	(0.51)					(0.03)	(0.03)					(0.58)	(0.22)
$NET\_C \times M\_SIZE$						-0.327						-0.057						0.301
						(0.00)						(0.34)						(0.02)
Between R^2	0.054	0.050	0.054	0.051	0.053	0.049	0.177	0.177	0.176	0.177	0.178	0.178	0.086	0.088	0.086	0.088	0.089	0.089
Joint-Significance	0.639	0.000	0.484	0.000	0.041	0.000	0.097	0.040	0.417	0.022	0.034	0.083	0.024	0.001	0.013	0.000	0.581	0.067

This table reports results for panel regressions of fund-managers' risk in UK equities (Panel A), UK bonds (Panel B) and International equities (Panel C) and managers' centrality. We adopt a four-factor model for UK Equities:

$$r_{i,j,t} = \alpha_{i,j} + \beta_{1,i,j}\ r_{m,t} + \beta_{2,i,j}\ SMB_t + \beta_{3,i,j}\ HML_t + \beta_{4,i,j}\ MOM_t + \epsilon_{i,j,t},$$

where $r_{m,t}$ 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:

$$r_{i,j,t} = \alpha_{i,j} + \beta_{1,i,j} GOVB_t + \beta_{2,i,j} CONS_t + \epsilon_{i,j,t},$$

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:

$$r_{i,j,t} = \alpha_{i,j} + \beta_{1,i,j}\ NA_t + \beta_{2,i,j}\ EAFEX_t + \beta_{3,i,j}\ SMB_t + \beta_{4,i,j}\ HML_t + \epsilon_{i,j,t},$$

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 risk of manager i in fund j at time t is computed as $\widehat{risk}_{i,j,t} = |\widehat{\epsilon}_{i,j,t}|$. 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), degree centrality computed using the managers' network only (NET_M) 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. For each centrality measure we adopt two specifications. In the first we include the centrality measure as well as its square. 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 7. Survival Analysis for Managers and Consultants

Panel A. Analysis at the Managers' Level

	UK Equities			UK Bonds			Int. Equities		
Risk_Adj_Ret	-0.016	-0.016	-0.017	-0.004	-0.004	-0.004	-0.009	-0.009	-0.010
	(0.00)	(0.00)	(0.00)	(0.50)	(0.51)	(0.46)	(0.00)	(0.00)	(0.00)
SIZE	-0.131	-0.135	-0.122	-0.126	-0.127	-0.123	-0.160	-0.164	-0.153
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
NET	-0.627			-0.063			-0.599		
	(0.00)			(0.04)			(0.00)		
NET_M		-0.537			-0.041			-0.513	
		(0.00)			(0.09)			(0.00)	
NET_C			-0.911			-0.149			-0.825
			(0.00)			(0.00)			(0.00)

Panel B. Analysis at the Consultants' Level

	UK Equities	UK Bonds	Int. Equities
Risk_Adj_Ret	0.001	-0.010	-0.008
	(0.89)	(0.14)	(0.00)
SIZE	-0.205	-0.172	-0.237
	(0.00)	(0.00)	(0.00)
NET	-0.696	-0.463	-0.522
	(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 (*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 measures of interest are managers' degree centrality (NET), managers' degree centrality computed using the managers' network only (NET_M) and managers' degree centrality computed using the consultants' network only (NET_C), 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. The p-values are reported in parentheses.

Table 8. 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 (0.39)	-0.000 (0.01)	0.001 (0.12)	0.001 (0.22)	0.000 (0.36)	0.000 (0.48)	0.000 (0.79)	0.000 (0.33)	-0.000 (0.44)	-0.001 (0.29)	0.000 (0.28)
NET	0.885 (0.00)			0.865 (0.00)			0.874 (0.00)			0.890 (0.00)		
NET_M		0.897 (0.00)			0.879 (0.00)			0.897 (0.00)			0.889 (0.00)	
NET_C			0.840 (0.00)			0.838 (0.00)			0.742 (0.00)			0.834 (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)	0.622 (0.00)	0.650 (0.00)	0.829 (0.00)	0.836 (0.00)	0.838 (0.00)	0.798 (0.00)	0.796 (0.00)	0.856 (0.00)	0.780 (0.00)	0.783 (0.00)	0.791 (0.00)
NET	2.321 (0.00)			1.278 (0.01)			2.221 (0.00)			0.973 (0.02)		
NET_M		2.140 (0.00)			0.915 (0.04)			2.086 (0.00)			0.858 (0.07)	
NET_C			7.376 (0.04)			3.510 (0.02)			1.475 (0.33)			1.438 (0.42)

This table reports the results of panel Granger causality tests for managers' size and centrality. Managers' centrality is computed as the degree centrality (NET), degree centrality computed using the managers' network only (NET_M) and degree centrality computed using the consultants' network only (NET_C). Managers' size is computed as the log of the total assets under management across funds and asset classes managed. The dependent variable is one of the centrality measures in Panel A and managers' size in Panel B. Centrality measures are computed across asset classes in Panels A.I. and A.II, 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.

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centre for financial research
cfr/university of cologne
Albertus-Magnus-Platz
D-50923 cologne
fon +49(0)221-470-6995
fax +49(0)221-470-3992
kempf@cfr-cologne.de
www.cfr-cologne.de