Good versus Bad Networking in Private Equity Pension Fund Investment[1]

Da Li
University of Wisconsin – Madison

Timothy J. Riddiough
University of Wisconsin – Madison

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Abstract

We investigate how pension fund networks influence private equity investment performance, and further explore the mechanisms behind network formation. Pension funds with access to parts of the overall network that others do not have (stronger networks) generate superior performance relative to pension funds that simply have more network connections or have connections with influential fund managers (weaker networks). Strong networking correlates positively with less fund manager lock-in, better first-time fund manager selection, and lower risk investments that ultimately deliver better performance. Pension funds that target high expected returns, generate lower past returns, require higher employee retirement contributions, and experience higher CEO and board turnover rates form weaker networks that impair their performance. Those pension funds get locked into the pre-existing GP networks, and a vicious cycle forms with weaker-networked pension funds adopting riskier investment strategies that fail to perform well. This results in greater funding gaps that lead to more aggressive investment strategies. These effects are attenuated somewhat if pension funds link to well-connected consultants that improve access to better-performing GPs. In contrast, pension funds that are well-connected across the whole network structure experience a more virtuous cycle that results in a more solvent fund.

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Good versus Bad Networking in Private Equity Pension Fund Investment

This paper examines the role of networks in Private Equity fund selection, and raises the research questions: How do networks influence pension fund investment performance? What are the mechanisms behind network formation? Do pension funds through their networks get locked into vicious or virtuous cycles?

We analyze pension fund network centrality in three different ways. The first way is a degree measurement that simply counts the number of connected participants for each pension fund. The second way is a betweenness measurement that quantifies the extent to which one pension fund accesses the whole network structure. A higher relative betweenness value means that a pension fund has access to parts of networks that other participants do not have. The third way, referred to as eigenvector centrality, quantifies how well pension funds connect to other influential participants in the network.

In our analysis there are three agent types that comprise the whole Private Equity network structure: i) Pension funds, ii) Fund managers, aka GPs, and iii) Consultants. We examine direct networks formed between pension funds and GPs, as well as indirect networking through consultants.

We are interested in assessing how and why investment networks affect investment performance. Networks are measured over the five years preceding the current investment year. Even though the network structure is lagged, joint causality is a concern, since networks are persistent and may be modified in anticipation of adapting particular strategies that eventually translate into investment performance. In response, we introduce an instrument variable – the change in the pension fund's total size (asset value) five years prior to the current investment year. This lagged change in asset value may correlate with lagged network formation, but it is hard to imagine that the five-year lagged change in pension fund asset size will correlate with current investment performance. A battery of standard instrumental variable-identification tests proves this out.

Our 2SLS results show that pension funds' network centralities have important and distinctive roles in pension fund performance. Pension funds that connect to more or more influential participants experience worse performance (the results of "bad" networking). On the other hand, if pension funds have better access to the whole network structure, and hence show a higher betweenness centrality score, their performance improves (the result of "good" networking). Based on "good" and "bad" networking, we build a comprehensive good network index. This index solves the overlapping and skewness issues of the three centralities. A one standard deviation increase in the good network index results in 767 to 917 basis points increase in average performance.

GP and consultant positions in the network also play an important role in pension fund performance. Pension funds connecting to fund managers with central positions in the network experience worse performance. A one standard deviation in GP network index in this case decreases pension fund performance by 180 to 199 basis points. Alternatively, well-connected consultants can improve pension fund performance by anywhere between 559 to 656 basis points given a one standard respective index increase.

Why do pension fund network centralities have distinctive impacts on performance? We answer this question from both the back- and front-end perspectives. The front-end investigates why pension funds form such network structures to begin with. We specifically examine two perspectives: Asset growth rates and CEO and board of trustee turnover rates. From the front end, we find that high fund contributions, low long-term investment returns, and high expected returns adversely incentivize pension funds to form weaker networks. Turnovers of CEOs and the board of trustees lead pension funds to enter weaker networks. In order to address the issue of centrality distribution, we continue to utilize the comprehensive good network index to measure the extent of influence. Our findings indicate that substantial fund contributions, lower long-term investment returns, and the composition of the board of trustees continue to have a significant impact. Specifically, a one standard deviation increase in each of these factors leads to a decrease in performance ranging from 109 to 130 basis points, 88 to 106 basis points, and 61 to 73 basis points, respectively.

We then analyze the back end by exploring the broader consequences of network formation. To address this, we first examine the relationship between investor networks and investment characteristics, finding that, in addition to poor investment performance, pension funds that form weak networks exhibit greater reliance on consultants and manage larger fund as compared to the stronger networked pension plans. Consultants play an important role in enhancing investment performance within the weaker networked plans, as we document that the incremental improvement in investment performance more than pays the typical consultant fee of between $0.50 million and $1.00 million.

We further analyze the relationship between network centrality and fund manager selection. We build four novel fund manager switching rate indexes to assess fund manager lock-in effects and pension fund skill at selecting high-performance fund managers. We find that pension funds with weaker networks get locked into their pre-existing GP relations, experiencing lower switch rates by staying with fund managers whose follow-on funds perform poorly. In contrast, pension funds with stronger networks move switch between fund managers at a higher rate and exhibit superior skill at selecting new fund managers.

The final segment of the back-end analysis focuses on how networks influence pension fund risky investment behaviors. We find that bad networks harm pension fund returns through increasing pension fund risky investment behaviors, which generates lower returns.

Our paper contributes to several strands of documents in the literature. One strand focuses on LP and GP investment performance persistence. Kaplan and Schoar (2005) first empirically show that some GPs perform persistently better than others. Korteweg and Sorensen (2017) further confirmed GP persistence magnitudes by a variance decomposition method and Harris et al. (2020) re-examined the GP persistence based on GP previous fund performance known at the time of fundraising. As for LP performance persistence, using the MCMC method, Cavagnaro et al. (2019) find that some LPs consistently outperform, indicating LP persistence. They attribute such persistence to LP's skill to identify and invest in scarce high-quality GPs. However, few studies have been done on the persistence puzzle. Maurin, Robinson, and Strömberg (2022) build a liquidity model to explain the persistence puzzle in LPs. They argue that LPs with higher tolerance to illiquidity realize better returns. Our paper contributes by providing an empirical explanation for LP performance persistence through a network channel. We find that LPs with strong networks persistently select well-performing funds.

The second strand of literature is about the underfunded issue of pension funds and how the underfunding status influences asset allocations. One possible channel is from the US GASB[2] regulations that require further contributions from underfunded pension funds. Andonov, Bauer,

[2] Governmental Accounting Standards Board.

and Cremers (2017) find that pension funds act on this regulation. Pension funds are likely to be risk-taking to justify a higher expected return used to discount future liabilities. However, such an investment strategy can be dangerous and harmful to performance, especially for risk-averse managers (Bodnaruk and Simonov (2016)). Riddiough (2022) reconfirms the underfunding gaps in pension funds and the underperformance of pension funds' investments in two real estate risky asset classes, i.e., Value-add and Opportunistic funds. He provides another explanation why pension funds are prone to invest in risky assets when they are underfunded, that is, the "volatility veil" that Value-add and Opportunistic fund investment provides. This paper contributes by finding a vicious cycle of pension funds: when they are underfunded, they form weaker networks that lead to risky investments that perform poorly, adding to the underfunded status.

The closest papers to ours are Hochberg, Ljungqvist, and Lu (2007), Krautz and Fuerst (2015), Rossi et al. (2018). Hochberg, Ljungqvist, and Lu (2007) show that better-networked VCs earn higher profits. Krautz and Fuerst (2015) analyze network roles in GP fundraising speeds and find that better-connected GPs can experience a more effortless and faster fundraising process. Finally, Rossi et al. (2018) find that networks help fund managers achieve higher risk-adjusted performance. In contrast to the above three papers, we focus on LPs and examine how pension fund networks influence their performance. We find distinctive roles of networks contrary to the homogenous effects. In addition, we are the first to solve the endogeneity issue of networks in PE by introducing a novel instrumental variable.

I. Networks and the Role of Consultants

Pension fund networks are complex and involve several participants, including pension funds, GPs, and consultants. The network establishment itself is an endogenous process (Matthew O. Jackson Brian W. Rogers and Zenou (2016)). Pension funds and other participants can form networks through former transactions or personal executive relationships. Due to data limitations and the non-public nature of private equity, it is common to back out networks by past transactions (Hochberg, Ljungqvist, and Lu (2007), Krautz and Fuerst (2015)). We build pension fund networks based on the last 5-year transactions[3] and cover all three types of participants. Networks between LPs and GPs formed by past transactions measure formal LPA contracts (transactional) instead of just knowing each other (relational). As we will illustrate in Figure 1, LP transactions proxy their position in networks, and the position in the whole network structure determines how central the LP is from different perspectives. In this sense, the network we are analyzing is not whether LPs know other LPs' investments (the lead and follower model between LPs) but the LP's formal positions in the network.

Figure 1. ABOUT HERE

Figure 1 illustrates a typical network structure of pension funds. We use a few actors as examples to represent and visualize the pension fund network structure without loss of generality. Networks are based on former transactions, and each line represents one investment. In the figure, there are seven pension funds (labeled as LPs), nine GPs, and one consultant (labeled as C). LP_1 has four investments: three direct investments in GP_1, GP_3, and GP_4 and one indirect investment in GP_2 through C_1. LP_2 has the largest GP investment numbers and invests in five GPs (GP_4-GP_8), while GP_9 has the largest LP investments. The investments in GP_9 by LP_3 to LP_7 do not implicate that LP_3 to LP_7 know each other when they make commitments[4]. Pension funds with similar features could invest in the same GPs. In Figure 1, LP_1 and LP_2 invest in GP_4 may just because they have similar investment strategies but not because they share their investment information

[3] We get similar results when constructing networks based on the past 3-, 4-, 6- years transactions. See Appendix for details.
[4] Some pension funds do care whether there are other big or influential LPs investing in the same funds (the lead and follower model).

and invest in a specific GP. However, what is clear is that the positions of LP_1 and LP_2 in the network are different with LP_1 standing between the left and right part of the network and LP_2 investing in the largest number of GPs.

A. Network Measurements

Graph theory is applied to estimate how central the pension funds and other participants' positions are in the whole network, and the key indicator is network centrality. We code pension funds investing in GPs' one specific fund or employing a consultant to support as having a tie and weigh each tie by connection numbers. Again, we construct each year's network matrices based on investments over a trailing 5-year window. We not only include pension funds closed-end fund investments but also incorporate open-end and separate account investments. This guarantees us full coverage of LP investments[5].

Figure 2 shows an example of network structures and ties in 2001. We highlight Blackstone Group (GP) in the figure. It is one of the largest GPs in 2001 and connects to many other market participants. It is located in the US but invests globally in multiple assets, including private equity, real estate, infrastructure, etc. By Q3, 2021, it has \$ 684,000 Mn current assets under management with \$208,000 Mn real estate assets (Preqin, 2021). Blackstone Group has a long history of investments dating back to 1985.

Figure 2. ABOUT HERE

Based on the graph theory, we construct three typical centrality measurements, i.e., degree centrality, betweenness centrality, and eigenvector centrality. Each measure provides one aspect of how central the participants are in the whole structure.

[5] Our results are robust if we just build the network using closed-end funds.

Degree centrality measures how many market participants one pension fund connects to, an indicator of connection frequency. The more participants one pension fund links to, the higher the degree centrality is. Because we code connections based on former transactions, no matter whether pension funds invest in GPs directly or indirectly through consultants, one investment represents one connection. Large pension funds generally invest more and thus have a higher degree centrality. In Figure 1, LP_2 has 5 investments in 5 different GPs and ranks the highest in degree centrality. We further normalize the degree centrality as 0 to 1 by total actor numbers. So, the degree centrality implies the percentage of the total market participants one actor links to. Formally, we define the degree centrality as:

$$DC_i = \frac{d_{it}}{N_t - 1} \tag{1}$$

Where d_{it} is the number of participants actor i connects to in year t. N_t is the total number of actors at time t.

Betweenness centrality assesses the extent to which an actor lies on the shortest path between other participants. A higher betweenness centrality means the participants act as an intermediary that other actors rely on to make connections and are central to different kinds of information (Hochberg, Ljungqvist, and Lu (2007)). Figure 1 shows LP_1 has the highest betweenness centrality. It has the access to LP_2's networks on the left and connects to LP_3's networks on the right. In contrast, LP_2 and LP_3 do not have direct access to each other's network but only indirectly through LP_1. Thus, betweenness centralities in this paper represent access to networks. A higher betweenness centrality means the participant has more access to networks that others do not directly connect to. The calculation of betweenness centrality can be expressed as:

$$BC_{kt} = \sum_{i \neq j \neq k} \frac{\theta_k(i,j)}{\theta(i,j)} \tag{2}$$

where BC_{kt} represents the betweenness centrality of participant k in the year t. $\theta_k(i,j)$ is the number of shortest paths between participant i and participant j through pension fund k. $\theta(i,j)$ is the number of shortest paths between participant i and participant j. This indicator is further normalized by $(N_t - 1)(N_t - 2)/2$.

Eigenvector centrality is an estimate of how participants connect to well-connected participants (Bonacich (1972)). In Figure 1, LP_3 connects to GP_9 who is invested by the other four LPs. Because GP_9 is so influential and attracts the most pension funds, connecting to LP_9 makes LP_3 rank the highest eigenvector centrality. Analytically, the eigenvector centrality is calculated by the eigenvector equation as

$$Ax = \lambda x \tag{3}$$

where A is the adjacency matrix, x is the relative centrality, and λ is the eigenvector centrality. More detailed analytical definitions and formulas of each centrality can be found in Bloch, Jackson, and Tebaldi (2021).

B. The Role of Consultants

TABLE I. ABOUT HERE

Although consultants could play a discretionary role in the fund portfolio selection of some pension funds, they are mostly missing in private equity network analysis. Pension funds employ consultants extensively in their PERE investments. 5,943 out of 10,728 investments are advised by consultants (See Table I for details). There are 145 consultants in our sample, each counseling an average of 40.986 investments. Public pension funds are more likely to use consultants in their PERE investments. There are 97 consultants involved in public pension funds' investments. Each consultant's average advised investment number is about 43.227; however, only 81 consultants participated in private pension funds' investments, with each guiding about 21.605 investments.

There is a vast variance (100.639) in the number of investments advised by each consultant at the investment level. Aon Hewitt investment consulting advised 675 investments, which is the largest. On the other hand, small constantans can advise as small as one PERE investment. There is high skewness of the advertised investments by consultants. The median of the advised investment number by each consultant is only about 7.000, which is much lower than the average level (approximately 40.986). It indicates specific consultants are dominant and constitute a large share of the PERE consultant market. Pension funds stick to specific consultants over several years as the general term of consultant contracts is about 3 to 5 years. Incumbent consultants usually obtain the opportunity to rebid after the contract expires. At the pension fund level, each consultant's average advised pension fund number is around 4.759. Each consultant's average advised private pension fund number is about 3.407 compared to approximately 4.268 for public pension funds. This number also exhibits a massive variation in the number of advised pension funds by different consultants. Prominent consultants can sign contracts with more pension funds. For example, Aon Hewitt investment consulting guided 62 different pension funds.

Panel B of Table I shows five prominent consultants in the PERE investments[6] in our sample. All five consultants have a long operation history, and the earliest firm launch date is 1972 (Wilshire Associates). These five firms are all located in the US and rank in the first quarter of all three centrality measures. Aon Hewitt Investment consulting is the largest one with $ 4,200,000 Mn assets under advisement as of Q3, 2021. Two of the five consultants report real estate asset values under advertisement. NEPC and Callan Associates have $11,5000Mn and $75,000 Mn RE assets under advisements[7].

[6] Consultants are ranked by advised investment numbers.

[7] Consultants advise a wide array of clients, including defined contribution pension plans, hedge funds managers, governmental entities, foundations, endowments, corporations, etc.

Pension funds issue requests for proposals from consultants. A final list usually contains about 3 to 5 consultants, and the decision is generally made within two years. Consultants can provide either discretionary or non-discretionary consulting services to their clients as required. The discretionary service comprises fund selections and selling. In contrast, a non-discretionary service could include due diligence, which pension funds use to guarantee nothing important is missing in board meetings.

II. Sample and Data

The data used for our analysis is sourced from two primary databases: Preqin and the Public Plans Database (PPD). Preqin gathers information on both public and private funds through the utilization of the Freedom of Information Act (FOIA), establishing connections with General Partners (GPs) and Limited Partners (LPs). On the other hand, the PPD comprises plan-level data spanning from 2001 to 2020, encompassing 200 public pension plans that account for approximately 95 percent of public pension membership and assets nationwide. Around 85.50% of pension fund investments are included in the dataset provided by Preqin. Private equity real estate funds typically have a lifespan of 10 years. In the fund marketing stage, which lasts approximately one year, pension funds typically play a role in selecting funds and determining commitment amounts. However, once this stage is concluded, pension funds primarily contribute commitments and receive distributions, relinquishing their involvement in fund management. The administration of funds is typically handled by the GPs, who charge the associated fees.

Preqin begins reporting the net-of-fee internal rate of return (Net IRR) for funds on a quarterly basis starting from the second year after the fund's vintage year. The vintage year refers to the year when General Partners (GPs) commence calling commitments or making investments in projects. The calculation of IRRs is based on the cash flows generated by the funds. Preqin receives and reports the quarterly net-of-fee IRRs provided by either GPs or pension funds. The reported performance data in Preqin exhibits similar characteristics to other prominent private equity data providers such as Burgiss and Cambridge Associates. Given that it is unlikely for the three data providers subject to the same bias, the IRR data in Preqin should be reliable (Harris, Jenkinson, and Kaplan (2014)). We close the sample at the end of 2015 to allow non-liquidated funds at least four years to realize stable IRRs. Q4, 2019 IRRs for each fund are used to exclude the COVID effects on fund performance[8]. Funds are usually composed of multiple investors, so pension funds who invest in the same funds share the same returns. We also run our IRR-based performance results using the net multiplex (TVPI). Results show high similarity.

We concentrate our analysis on pension funds and exclude all other LP categories such as endowments and foundations. Analyzing different types of LPs' network structures as a whole can be misleading because they present different network structures and apply heterogeneous investment strategies. We build pension fund networks with commingled (both closed and open-ended) and separate account funds to cover all pension fund investments[9]. The two typical PERE fund strategies are value-added and opportunistic, and they represent 69.98% of all funds with performance. The value-added strategy does moderate upgrading and enhancement to properties in primary and secondary markets, while the opportunistic strategy possesses lower-quality buildings and significantly enhances properties. Another main difference between value-added and opportunistic is the leverage level. Funds with opportunistic strategies (>60%) have higher leverage than value-added funds (50-70%) on average.

[8] Some funds do not report Q4, 2019 performance, and in those cases, we use the latest IRRs as funds' returns. To address the concern that fund returns are not stabilized with a four-year fund life, we used Q4, 2022 updated returns as robustness tests. The newest funds will have at least 7-year life to realize performance. Results are robust.
[9] Results are robust if we just use closed-end funds to build networks.

We construct time-series consultant data with the combination of Preqin primary data, Preqin news, and PPD data. Preqin primary data provides cross-sectional consultant information for both private and public pension funds. However, pension funds change their consultants frequently. Preqin news gives us a way to assign each consultant to a specific year. The news shows when pension funds request a proposal from consultants, when it hires new consultants, and when the old consultants' contract expires. PPD data is another source of consultant information. It reports yearly consultant information for each public pension fund from 2001. We only keep pension funds with zero or one consultant and delete all pension funds' investment data with two or more consultants to get the precise consultants[10]. The final data set contains 10,733 investments made by 1,443 pension funds with 577 public pension funds and 866 private pension funds.

TABLE II. ABOUT HERE

A. Pension Fund Investment Performance

We estimate pension fund performance by net-of-fee IRRs. Net-of-fee IRRs are returns pension funds receive after management fees, carried interests, and catch-ups charged by GPs. A high gross-of-fee IRR does not guarantee a high net-of-fee IRR, especially when pension funds invest in funds managed by powerful GPs such as Blackstone Group. Blackstone Group can charge as high as 100% catch-up for returns after it pays the preferred returns to pension funds. The catch-up is an additional fee on top of fees and standard carried interest and can largely reduce the return received by pension funds. Only closed-end funds report performance information in Preqin. Table II shows that the size-weighted average pension fund annual return is 8.656% with public pension funds earning a 7.553% average net-of-fee IRR and private pension funds' return at 9.557%[11].

[10] 8.60% (1010) investments are deleted.

[11] The returns here are averaged commitment weighted returns. We replace pension funds without commitment amounts for all its investments with unweighted returns. The unweighted returns are not reported in Table II but show

Public pension funds are more politically driven than private pension funds and focus more on non-pecuniary benefits (Barber, Morse, and Yasuda (2021) and Andonov, Kräussl, and Rauh (2021)).

We further separate pension funds by the median investment number (three) and test whether there is a significant difference in IRRs between different pension fund investment numbers. As shown in Table II, there is about a 161-basis point difference in the IRRs. Surprisingly, pension funds with less than three investments earn slightly more than those with better investment experience. As a measure of pension fund experience, longer investment history could not guarantee a higher return.

B. Pension Fund Investments and Expected Returns

Large pension funds may perform differently from small pension funds. We use two size variables as controls to capture the size effects, i.e., pension fund asset values and commitment amounts. Pension fund assets include PERE investments and all other non-real estate investments, so it is a proxy of pension fund size. The pension fund asset level is only available for public pension funds and is obtained from PPD. Commitment amounts are the money invested in a specific fund by pension funds. Due to data limitations, there are only 4,488 out of all the 10,729 investments with this data. Commitment amount shows significant heterogeneity, with less than \$100,000 as the minimum and more than \$2.8 billion as the maximum. Asset levels among all the public pension funds also show a considerable variation. The smallest public pension funds only have \$898 Mn assets under management, while the largest public pension funds manage more than \$302.418 billion.

similar results. The unweighted return of all investments is 9.449%, with 8.753% for public pension funds and 10.018% for private pension funds.

With the PPD database, we can obtain yearly expected returns for public pension funds. Table II shows that pension funds expect to earn 7.851% annual returns between 2001 and 2019. We further report pension funds' 1-year realized return and 5-year realized return. Pension funds earn lower returns than their expected returns in both 1-year (6.366%) and 5-year (6.308%) windows, i.e., 149 basis points and 154 basis points lower than the expected returns.

C. Fund Level Performance and Characteristics

This section reports the fund level performance and characteristics. Our sample has 1,126 funds[12] with performance data, with the average fund size at $695.157 Mn and 6.940% fund size-weighted annual net-of-fee IRR. North America is the largest PERE market with 859 funds and gains higher fund returns (8.082%) than non-North America funds (4.771%). We also classify funds by their strategies into core/core+, value-added, opportunistic, and others[13]. Funds with other strategies earn more returns (8.319%) than opportunistic strategy funds (7.196%), which in turn gain more returns than value-added funds (6.825%) and Core/Core+ (3.731%). However, the unweighted fund returns show significantly different patterns from the weighted returns. This is consistent with Arnold, Ling, and Naranjo (2019). The unweighted results show that core/core+ funds have the highest returns (11.404%), followed by value-added (10.573%), and Opportunistic funds (8.190%). The fund sequence number by GPs is defined as the rank of each fund sorted by the fund vintage year in each GP. Funds with the same vintage year are sorted by their fund close date, and funds with an earlier one get a lower sequence number. The sequence number of funds by each GP is another measure of GP skills and experience and is important to control the sequence effects. The average fund sequence number in each GP is about 7.040. Details are reported in Table II.

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[12] Pension funds may invest in the same funds. The fund level data drop all the duplicated investments.

[13] Including debt, distressed and fund of funds, secondaries, etc.

D. Pension Fund Networks

From 2001-2015, PERE experienced a substantial variance in network centralities. Therefore, we calculate dynamic centralities for each pension fund. Over each five-year window, we do not distinguish connections with GPs or consultants in earlier or later years. We weigh connections by investment numbers and count each investment as a tie.

Table II reports the results. Pension fund degree centrality averages about 0.4% across the sample periods, which means pension funds connected to an average of about 0.4% of actors in the networks over the sample periods. The results also show that consultants connect to approximately 4.6% of the participants. GPs have a relationship with 10.5% of other actors This is not surprising. PERE needs intensive capital, and GPs need to get enough commitments from multiple pension funds. The fundraising process is difficult for small GPs (Krautz and Fuerst (2015)). The magnitude of betweenness and eigenvector centrality do not have direct intuitions as degree centrality. Pension fund betweenness and eigenvector centralities are 0.10% and 0.9% on average, respectively.

III. Networks and Pension Fund Performance

Section I provides an overview of a typical structure found in pension fund networks, comprising three main participant types: pension funds, general partners (GPs), and consultants. The following section delves into the influence of pension fund networks on performance with the control of GP and consultant networks that pension funds connect to. More specifically, it examines how changes in centralities within a pension fund can influence investment performance.

A. The Basic Network Model

$IRR_{l,g,f} = \alpha_0 + \alpha_1 * LP\ Centrality_{l,t-5:t-1} + \alpha_2 * GP\ Centrality_{l,t-5:t-1} + \alpha_3 *$

$Consultant\ Centrality_{l,t-5:t-1} + \alpha_4 * X_l + \alpha_5 * X_g + \alpha_6 * X_f + Vintage_f + LP_l + GP_g +$

$Consultant_c + \varepsilon_{l,g,f}$

(4)

where $IRR_{l,g,f}$ is the net-of-fee internal rate of return by pension fund l that invests in fund f managed by GP firm g. We use the Q4, 2019 reported IRR as the pension fund performance. The fund's vintage year is t. $Centrality_{l,t-5:t-1}$ are weighted centrality indicators including degree, betweenness, and eigenvector centrality, of pension fund l and are generated by the past five years' transactions before the fund vintage year of t . $GP\ Centrality_{l,t-5:t-1}$ and $Consultant\ Centrality_{l,t-5:t-1}$ in equation (5) investigate whether investing in more central GPs' funds or following the advice of more central consultants would be a strategy for pension funds to gain higher returns.

X_l is the vector of pension fund characteristics which include log(L. pension fund asset value), log(Pension fund commitment amounts), pension fund firm type (Public pension fund=1 and private pension fund=0), pension fund investment sequence, and a dummy variable that identifies when pension funds turn public. Log(L. pension fund asset value) and log(Pension fund commitment) control size effects. Due to data limitation, pension fund assets are only available in public pension funds, and only about half of investments have log(pension fund commitment) available. Pension funds' last investment Net IRR and pension fund investment sequence represent the pension fund's skill and experience.

X_g includes GP fund sequence number and whether GP is a public firm. The GP fund sequence number controls the GP's skills and fund sequencing effects.

X_f are fund characteristics. Variables include log(fund size), fund strategy, and fund primary location. Funds with different sizes, strategies, and locations could have different expected performances and risks.

LP_l and GP_g are pension fund and GP fixed effects, and are used to further control pension fund and GP skills and other time-invariant variables. $Consultant_c$ is the consultant fixed effect to control consultant size effects and time-invariant variables[14]. We also include $Vintage_f$ which is the vintage year fixed effects. It mitigates dynamic market influence. Funds with the same vintage year share similar features because they are exposed to common market conditions (Korteweg and Sorensen, 2017). With the LP fixed effect, α_1 should be interpreted as within effects. This avoids the size concern that large pension funds have higher centralities, especially degree centralities in their nature.

TABLE III ABOUT HERE

Table III reports the results. The results are divided into two sets: columns (1), (3), and (5) present the results without considering pension fund commitment amounts, while columns (2), (4), and (6) include this variable. The analysis reveals diverse network roles in terms of performance outcomes. Regarding degree and eigenvector centrality within a pension fund, the study demonstrates that increases in these measures are associated with relatively lower average returns. These negative effects suggest that pension funds that establish a wide range of connections with multiple GPs through investments or invest in funds managed by influential GPs may experience lower returns. Interestingly, the results for betweenness centrality contrast with those of degree and eigenvector centrality. The study finds that an increase in betweenness centrality leads to a significant improvement in average performance. Higher betweenness centrality indicates greater access to networks, which benefits pension funds in achieving higher returns. On the other hand, the centralities of GPs and consultants generally do not have a significant impact on performance

[14] Introducing consultant fixed effects means only observations with consultants will enter the regression. However, our results remain robust when we do not include them.

outcomes. Table III also shows that when a GP turns public, its fund performance will drop significantly. Immediately after GPs turn public, the return reduces by about 5%-6% on average.

B. Endogeneity and the Instrumental Variable

Hochberg, Ljungqvist, and Lu (2007) present an argument to address concerns about reverse causality between networks and performance. They assert that networks are constructed based on past transactions that occurred before fund vintage years, while fund returns are realized years later. Therefore, there is a time lag of at least five years between the formation of networks and fund performance. However, this argument overlooks the possibility that pension funds may engage in networking with other market participants in the present, aiming to achieve higher returns in the future. These expectation effects are not accounted for in Equation (4) and can potentially introduce endogeneity issues. Another potential source of endogeneity arises from network persistence. The current network structure may persist until the time when funds realize their returns. Consequently, even though lagged 5-year transactions are used to construct network centralities, the network structure at the time of return realization could still bear a resemblance to the current network. This phenomenon is referred to as the persistence effect. Both of these effects necessitate the use of instrumental variables to obtain an unbiased estimate of network effects.[15]

To address the expectation effects, we incorporate expected returns at the pension fund level as part of our analysis. We utilize two variables from PPD (Pension Plan Data), namely pension fund assumed returns and 5-year investment returns. The pension fund assumed returns represent the expected returns, while the 5-year investment returns reflect the average investment returns over the past five years. These variables capture the expectations at the pension fund level. However, it's important to note that public pension funds may have varying expected returns for each

[15] We further confirmed the endogeneity of the network variables by Hausman tests in Table V , and all results reject the exogeneity assumptions.

individual fund they invest in. Additionally, incorporating these variables alone does not fully address the persistence effect that we discussed earlier.

We introduce the lagged 5-year pension fund asset value as an instrumental variable. This lagged asset level serves as a proxy for size and directly influences the network structures of pension funds. Given that the PERE represents only approximately 5% of total asset values and that this instrumental variable is measured at least ten years prior to the realization of fund returns, it is highly unlikely to have any significant impact on the fund returns managed by GPs through error terms. Intuitively, real estate funds are managed by general partners (GPs) and are beyond the control of pension funds. Therefore, changes in pension funds' overall asset levels would not influence the performance of GPs' funds, which are invested by numerous other pension funds, unless through the effects of expectations.

TABLE IV ABOUT HERE

By incorporating the lagged pension fund asset value in our regression analysis, we interpret the lagged 5-year asset level as a measure of changes in asset values. In other words, assuming a fixed one-year lagged asset value, a higher lagged 5-year asset level indicates a smaller increase in assets over the past four years. However, we have a concern regarding this approach as the asset increment over the past four years may be correlated with error terms in performance regressions. Specifically, if asset values rise in anticipation of higher returns, our instrumental variables may not be truly independent. To address this concern, we examine the factors influencing variations in asset increments and assess whether they are influenced by performance expectations. We employ two variables as proxies for pension fund expectations: the reported assumed (expected) returns of pension funds and the pension fund's 5-year average return. In Table IV, we analyze the geometric average asset growth over the lagged 5 to lagged 1 year, treating it as the dependent variable, while considering lagged six-year pension expected returns, payouts, and contributions as independent variables. Column (1) of Table IV solely incorporates the lagged 6-year assumed (expected return), column (2) includes only the lagged 6-year 5-year investment return, and column (3) encompasses both the lagged 6-year assumed (expected return) and the lagged 6-year 5-year investment return. Our findings indicate that lagged expected returns, regardless of whether they are proxied by assumed returns or 5-year investment returns, do not significantly impact asset growth in subsequent years. The primary drivers of asset growth are projected contribution rates and average benefits. Overall, the increase in asset growth predominantly stems from factors related to contributions and payouts, which pertain to fund obligations, rather than expected return factors. Consequently, the asset value of each pension fund does not factor into performance terms and should be considered exogenous to performance, at least a decade later.

C. Two-stage Least Square Results

Figure 3 ABOUT HERE

We conduct Two-Stage Least Square (2SLS) regressions, employing instrumental variables as part of our methodology. Figure 3 provides a visual representation of the empirical strategies employed. To illustrate, let's consider Fund A, which has a vintage year of 2015, and assume that it receives investments from pension fund B. In order to assess performance, we utilize Fund A's return in Q4 of 2019. Furthermore, we construct pension fund B's networks based on its previous transactions spanning from 2009 to 2014. Given that most asset values are reported in the middle of each year, pension fund B’s asset value in the middle of the year 2010 is then used as the instrumental variable. By controlling for the asset value in the middle of 2014, these two asset values capture the changes in assets between the middle of 2009 and 2014. Notably, this asset change coincides with the four-year network formation period, resulting in a correlation with the network formation period.[16]

The 2SLS results are presented in Table V. Columns (1), (3), and (5) display the results without controlling for log(Pension fund commitment), while Columns (2), (4), and (6) include the commitment variables as controls. Due to missing data on some pension fund commitment variables, the sample size is smaller for the columns that include these variables. All the results are consistent with the OLS regressions, but they exhibit increased significance and larger magnitudes of influence. Notably, pension fund degree and eigenvector centrality have a significant negative impact on pension fund performance.

Additionally, it is worth noting that in the case of 2SLS, the impact of betweenness centrality appears to be even more pronounced. The substantial magnitude of the coefficient associated with betweenness centrality is primarily attributed to the inherent skewness and kurtosis of the betweenness variable itself, rather than the instrumental variable. To address the skewness issue, we conducted robustness tests by replacing the original centrality variables with centrality rankings. Our results remained consistent and robust even after this modification. Given the skewed distribution of centrality measures, we defer the detailed analysis of their influential magnitudes to the comparative statics section.

TABLE V ABOUT HERE

Furthermore, GP centrality demonstrates a significant negative effect on pension fund returns, indicating that funds managed by more influential general partners tend to have lower performance. On the other hand, consultant centrality shows a significantly positive influence in all the 2SLS

[16] Due to the data limitations, only public pension funds have such an instrumental variable. Thus, we can only solve the endogeneity issue with public pension funds. In unreported results, we re-run the OLS regressions to show our results are nonrandom with just the public pension funds.

regressions. This suggests that although most public pension funds engage consultants, employing better-connected consultants can yield benefits for pension funds.

In contrast to Hochberg, Ljungqvist, and Lu (2007), our findings suggest that networks are not inherently "good" or "bad". Having access to a broader network can be advantageous as it provides shorter paths to other participants (higher betweenness centrality). This allows pension funds to gather more information and discern which funds have the potential for higher future returns or identify well-performing general partners (GPs). However, it is important to note that blindly connecting to numerous participants, which increases pension fund degree centrality, or haphazardly establishing connections with influential participants, can hinder effective information filtering. In such cases, the quality of information may be compromised, leading to detrimental effects on pension funds' performance.

The endogeneity issue is confirmed by the Hausman tests presented in Table V. To further validate the instrumental variable, we conduct additional tests. Firstly, we perform the Kleibergen-Paap rk test, which serves as an under-identification test. Subsequently, we apply the weak identification test as weak instruments can lead to significantly biased estimates. The results presented in Table V decisively reject the null hypothesis, providing strong evidence against the instrument variable being under-identified or weak. Furthermore, since the endogenous and instrumental variables are of the same size, there are no over-identification concerns, and our regression model is exactly identified.

D. Comparative Statics

Section C presents our analysis of how networks impact pension fund performance. However, we did not quantitatively measure the magnitudes of these effects. This is primarily because network centralities exhibit a highly skewed distribution, and there may be correlations among different centrality measures. For instance, a higher betweenness centrality may be associated with a higher degree centrality.

To address these concerns, we employ a ranking approach for the three centralities, ranging from low to high. We then divide the rankings by the total number of centralities to obtain the network ratio for each centrality measure. This transformation helps address the issue of skewness in the centrality distributions. Additionally, to mitigate the overlapping influence of different centralities, we construct a "good network index" for pension funds by subtracting the degree and eigenvector centrality ratios from the betweenness centrality ratio. This good network index for pension funds accounts for the heterogeneity in the network influence among pension funds. However, when it comes to GP centralities and consultant centralities, their influence on performance exhibits less homogeneity. Therefore, we calculate the simple average of all three centrality ratios to create comprehensive indexes representing GP and consultant network centralities.

TABLE VI ABOUT HERE

The results are presented in Table VI[17]. A one standard deviation change in good network centrality leads to an increase in returns ranging from 767 to 917 basis points. On the other hand, higher GP centrality has a detrimental effect on pension fund performance. A one standard deviation change in the GP network index results in a decrease in returns ranging from 180 to 199 basis points. Conversely, consultants play a positive role in enhancing pension fund performance. A one standard deviation increase in the consultant network index leads to a decrease in returns ranging from 559 to 656 basis points.

[17] The three transformed indexed are close to normal distribution.

E. Robustness Tests

In order to address concerns about the validity of our results, we conducted several robustness tests. The first concern relates to our consultant data, as it is sourced from news and there is a possibility that we may not have captured all consultants hired by pension funds. However, for public pension funds, their consultants are sourced from PPD, which allows us to obtain comprehensive data on consultants, at least for public pension funds. Furthermore, we performed additional regressions by including vintage years starting from 2006. The underlying assumption is that more recent consultant information is likely to be more reliable and complete. Importantly, the results from these robustness tests remain consistent and do not significantly alter our main findings.

Another concern pertains to the construction of network centralities using a 5-year window. It is possible that network characteristics may exhibit varying levels of persistence. To address this concern, we recalculated network centralities using transaction windows of different durations, including 3 years, 4 years, 6 years, and 7 years. These alternative calculations aimed to alleviate any potential issues arising from the chosen window size. Importantly, the results from these robustness tests remained consistent and did not significantly impact our findings. For further details, please refer to the Appendix.

The third concern is that adding $GP\ Centrality_{l,t-5:t-1}$ and $Consultant\ Centrality_{l,t-5:t-1}$ to the model reduces our sample size. Furthermore, pension funds, GPs, and consultants without past transactions will not appear in the sample as we construct networks by past five years' transactions. Thus, the results may be generated by small samples. To alleviate this concern, we first run all the models without these two variables, and the estimation for $LP\ Centrality_{l,t-5:t-1}$ remains robust (See Appendix for details). We then run a separate set of results by replacing the first-time network centrality of pension funds, GPs, and consultants with zero (the minimum value). Our results remain robust (See Appendix for details).

The fourth concerns are the performance measurements. One is that we use IRR as our performance measurement with TVPI as a replacement. These are absolute returns instead of benchmarked returns. However, benchmark methods, including the PME benchmark methods (Index Comparison Method-PME by Long and Nickels (1996)), the PME plus (PME+) method by Rouvinez (2003), KS-PME by Kaplan and Schoar (2005), the modified PME (mPME) method by Cambridge Associates (2013), the direct alpha method by Gredil, Griffiths, and Stucke (2014), and the GPME by Korteweg and Nagel (2016)) or standard asset pricing specifications (Gupta and Van Nieuwerburgh (2021)), all require cash flow data which is highly missing. The focus on PERE and the control of vintage fixed effects partially solves this issue. PEREs have relatively homogenous fundamentals, i.e., real estate, and thus are exposed to relatively similar markets. Another concern is that our newest fund performance data is only based on four-year performance after the vintage. GPs have incentives to manipulate fund performance by changing the net asset values (Brown, Gredil, and Kaplan (2019), Jackson, Ling, and Naranjo (2022)). We re-run all the results with the updated Q4, 2022 performance. This allows at least 7 years for funds to realize returns. Because funds have an average life of 10 years, performance closer to 10 years is more reliable. Again, all results are robust (See Appendix for details).

The final concerns are from centralities. The first is the centrality distribution. In comparative statics, we have used the rankings of centralities as a replacement for the original value. Our results remain robust. Another concern is whether each centrality measurement captures the other two centrality components. Instead of using the comprehensive index in comparative statics, we further test the robustness by regressing each centrality on the other two types by controlling the year-fixed effects. We use the regression residues as the value for each centrality, which eliminates the overlapping effects. The results are consistent with our main results (See Appendix for details).

IV. Mechanisms: Network Formation and Risky Investment

This section delves into the mechanisms behind network effects on performance by investigating what leads to good (bad) network formations (the front end), and how networks influence pension fund behaviors (the back end). We analyze network formations through two channels: asset growth components and CEO and board of trustee turnover rates. The back end is to investigate pension fund investment characteristics and risky investment behaviors.

IV.I. Front End: Network Formation

A. Asset Growth Rates

The first stage of the 2SLS model (Table V) reveals that at the investment level, a faster asset growth rate over the past four years (lower lagged five-year asset values) leads to increases in both degree and eigenvector centrality, but a decrease in betweenness centrality. Subsequently, the higher degree and eigenvector centralities have a negative impact on pension fund returns, while betweenness centrality contributes to increasing pension fund returns. In this section, we focus on decomposing the asset growth components. These components represent the fund sources for investments, which serve as the basis for constructing networks. To investigate the formation of networks, we conduct regressions with network centralities as dependent variables and lagged six-year asset growth components as independent variables. This analysis aims to shed light on how networks are formed.

The annual asset growth into its components:

$$Annual\ asset\ growth = Change\ in\ value\ of\ investment\ portfolio - Investment\ expenses + Pension\ contribution - Pension\ payouts - Operating\ expenses - Other\ revenues/expenses \quad (6)$$

TABLE VII ABOUT HERE

Results are shown in Table VII. We also add expected returns, 1-year investment returns, and 5-year investment returns in the regression to control expectation effects. Results without these variables are largely similar. Regressions are weighted by investment numbers at the pension fund level. Our findings indicate that contributions serve as the primary driver for the increase in both degree and eigenvector centralities. When pension funds make larger contributions, they tend to form worse networks. However, contributions do not exhibit a significant impact on betweenness centralities. This suggests that higher contributions do not necessarily facilitate entry into the right networks, further confirming the notion that building good networks is a challenging task.

Expected returns exhibit a positive effect on the formation of bad networks, but a negative effect on the formation of good networks. This suggests that when pension funds are driven by a desire for higher returns, they are more likely to end up in unfavorable networks. Moreover, the situation can be further exacerbated if pension funds have a poor track record in terms of their past 1-year returns. Changes in 5-year returns, on the other hand, have consistent effects across all types of networks. Notably, while a stronger past 5-year performance may result in stronger connections within networks, it can also limit pension funds' access to other participants, leading to a reduction in network access (betweenness centralities).

B. CEO and Board of Trustee Turnover Rates

Andonov, Hochberg, and Rauh (2018) analyzed how pension fund board of trustee representations influence fund performance. In this section, we analyze how CEO and board of trustee turnovers would influence networks. This examination allows us to directly observe the transition from relational networks to transactional networks and understand the implications for network dynamics.

We conducted a manual collection of data, gathering information on 1,338 CEO names and 14,492 board of trustee names from a total of 111 public pension funds spanning the period between 2001 and 2015. The CEO turnover variable measures whether there was a turnover in the CEO position prior to the formation of the networks. Additionally, the board of trustee turnover rate is calculated by dividing the number of members who left during a given year by the average number of members throughout the period. To examine the influence of CEO and board of trustee turnovers on networks, we regress the network centralities on the lagged 6-year turnover rates. It is worth noting that the network centralities are constructed based on transactions that occurred over the past 5 years. CEO turnovers, on average, occur approximately every 4.5 years, while board of trustee turnovers typically take place within a range of 3 to 5 years, with each member serving different terms.

TABLE VIII ABOUT HERE

Table VIII shows the results. The turnover of CEOs also negatively impacts performance, primarily through its effects on degree and betweenness centralities. When new CEOs take over, they are more inclined to initiate new investments, leading to a decrease in returns. Additionally, our findings indicate that higher board of trustee turnover rates result in weaker networks. The turnovers of trustee board members have a negative influence on networks, significantly increasing the formation of bad networks (as measured by degree and eigenvector centralities) and reducing the formation of good networks. These results highlight the adverse effects of CEO and trustee board member turnovers on network dynamics and ultimately on pension fund performance.

C. Comparative statics

Again, we conduct comparative statics for asset growth rates and turnover rates. We utilize the good network index of pension funds as the dependent variable and perform a regression analysis, considering these two mechanisms as control variables.

TABLE IX ABOUT HERE

Table IX presents the results of our analysis. In Column (1), we present the findings regarding the asset growth mechanism, while Column (2) displays the results for the turnover rate mechanism. As we changed the dependent variable, the significance of certain key variables also changed. Specifically, the expected return, 1-year investment return, and CEO turnover rates are no longer statistically significant. However, the 5-year investment return, pension contribution, and board of trustee turnover rates continue to exhibit significance. Our analysis reveals that a one standard deviation reduction in the 5-year investment return leads to a significant decrease in the good pension fund network index by approximately 0.06. Consequently, this reduction in the network index translates to a performance decline ranging from 88 to 106 basis points, as indicated by the coefficients in Table V. Similarly, a one standard deviation increase in pension contribution significantly contributes to a decrease in the good pension fund network index by about 0.07. This reduction in the network index corresponds to a performance decline ranging from 109 to 130 basis points, based on the coefficients in Table V. Additionally, a one standard deviation increase in the pension board of trustee turnover rate significantly leads to a decrease in the good pension fund network index by approximately 0.04. Consequently, this reduction in the network index corresponds to a performance decline ranging from 61 to 73 basis points, according to the coefficients in Table V.

IV.II. Back end

A. Networks and investment characteristics

TABLE X ABOUT HERE

In this section, we delve deeper into network effects by examining the relationship between investor networks and investment characteristics. We divide each network centrality measure into two groups: the top quantile (Q1) and the remaining (Q2-Q4) for betweenness, and the bottom quantile (Q4) and the remaining (Q1-Q3) for degree and eigenvector. Consequently, based on investor centrality across the three network perspectives, each investor centrality falls into one part of a 2 by 2 by 2 matrix. Panel A of Table X presents summary statistics for investment levels within each group. We focus on several investment metrics, namely: unweighted average returns (IRR), consultant ratios, public firm ratios, risky investment ratios, and average fund size. On average, investments in the worst network group (Degree (Q1-Q3), Eigen (Q1-Q3), and Betweenness (Q2-Q4)) exhibit a 159 basis point reduction in performance compared to investments in the best network group (Degree (Q4), Eigen (Q4), and Betweenness (Q1)). Investments in the worst network group demonstrate the highest reliance on consultants (91.1%), a strong emphasis on risky investment strategies (43.4%), and larger fund sizes ($1,868 million). Public pension funds constitute the largest proportion of investments in this group, accounting for 77.2% of all investments. Conversely, investments in the best network group exhibit lower consultant utilization (22.6%), a lower proportion of risky investments (only 22.6% classified as risky), and more restricted fund sizes ($1,196 million). Public pension funds represent a smaller portion of investments in this group, comprising 67.9% of the total. The significant disparity in consultant usage suggests that external consultants can be highly substitutable when pension funds operate within well-connected networks.

Next, we compare the four groups formed by the 2 by 2 matrix consisting of degree and eigenvector centrality, specifically focusing on investments with Q1 betweenness and Q2-Q4 betweenness. Our analysis reveals that investments made by pension funds with Q1 betweenness exhibit a lower reliance on consultants, lower levels of risk, and primarily consist of smaller fund sizes when compared to investments with Q2-Q4 betweenness. More specifically, investments associated with Q1 betweenness demonstrate a reduced need for external consultants, implying a higher level of internal expertise within pension funds. These investments also exhibit a lower proportion of risky assets, suggesting a more conservative investment strategy. Additionally, the fund sizes associated with Q1 betweenness investments tend to be smaller, indicating a preference for managing relatively modest investment portfolios.

The table shows that the most detrimental impact on performance is attributed to the influential connection. Specifically, investments associated with an investor possessing Q1-Q3 eigenvector centrality (and Q4 degree) exhibit the poorest performance, with average returns ranging from 6.47% to 7.05% in terms of IRR (unweighted average returns).This underperformance is not only influenced by the relatively larger fund size, which falls within the range of $1443 million to $2030 million, but also by the above-average proportion of risky investments. Investments with Q1-Q3 eigenvector centrality have a higher allocation to risky assets, with the proportion ranging from 33.8% to 35.2%. This elevated exposure to riskier investments further contributes to the subpar performance observed.

The significant underperformance of the worst network group, coupled with the substantial involvement of consultants, raises the question of where the positive effects of consultants originate. To investigate this matter, we further dissect the worst network group based on consultant centralities.[18] In line with the findings in Section D, our analysis reveals that consultants play a role in enhancing investment performance. When compared to the bottom

[18] Investments without consultants are not in this analysis. However, investments without consultants earn fewer returns (8.766%) than investments with consultants (9.286%) on average.

consultant centrality group, investments within the Q1 consultant centrality and inter-quantile group generate higher returns. The spread in returns ranges from 102 basis points to 527 basis points, indicating a notable improvement. This suggests that the positive effects of consultants can be observed within the worst network group.

The question of whether consultants are costly arises when considering the benefits they bring. Consultant costs typically range between $500,000 to $1 million. To illustrate the potential impact, let's examine the allocation of public pension funds to real estate in 2015 as an example. In that year, pension funds aimed to allocate 8.88% of their portfolio to real estate on average. Assuming that just 10% of these funds are invested in private equity real estate (PERE), we can explore the effect of a one standard deviation change in consultant centralities on returns. Based on our analysis, a one standard deviation change in consultant centralities can lead to an increase in returns ranging from 5.59% to 6.56%. The average asset level in public pension funds is $18,738 million. By multiplying the target real estate allocation by the total asset level and the consultant centrality effects, we find that the average increase in returns from hiring consultants who are one standard deviation better connected amounts to $9.30 million to $10.92 million. Clearly, these potential increases in returns surpass the cost of hiring consultants, suggesting that the benefits derived from better-connected consultants outweigh their expenses. This analysis indicates that the average gains achieved by engaging consultants who are more well-connected in terms of one standard deviation exceed the associated costs.

B. What do Networks Mean: Locking-in or Fickle?

Do the worse performance of pension funds with a high degree and eigenvector centrality come from locking in bad relationships or because pension fund relationships with GPs are short-lived and pension funds are not skilled enough to find good GPs? In this part, we address this issue by building several novel switching rate indicators, and analyze how networks relate to the pension fund switching rates among GPs and whether pension fund relationships with GPs are locked or short-lived.

Based on whether funds are the first or last fund of a GP and whether the fund is the first and last investment by pension funds in the GP, we build up four switching indicators: the overall turnover or switch rate, the overall switch-in rate, the one-off fund investing rate, and the discretionary one-off investing rate (see Appendix for details). [19] The overall switch rate measures both the switch in and out rates. Those switch in and out could be discretionary and non-discretionary. We define a discretionary switch when a GP still issues at least one follow-on fund, but pension funds decide not to invest in it; on the other hand, one could be non-discretionary or discretionary if a GP does not raise a follow-on fund. One-off fund investing is a one-time investment in a GP's fund and is defined as discretionary when a GP continues to raise a follow-on fund but the pension fund does not commit to it.

TABLE XI ABOUT HERE

With the control of pension fund firm fixed effect and fund year fixed effect, we report the results in Panel A to Panel C in Table XI. We find clear and strong lock-in effects instead of fickle relationships for pension funds with higher degree and eigenvector centrality. The relationships between degree (eigenvector) and overall switch rate (and switch-in rate) are significantly negative. A 0.1 increase in degree and eigenvector centralities could lead to a 1.66% to 34.96% decrease in the overall switch rate. In contrast, betweenness has a positive relationship with the overall switch rate. A 0.1 increase in betweenness leads to about a 22.68% to 28.58% increase in the switch rate. This implies pension funds that gain an increase in betweenness are those that move around the network more between. They are more likely to switch in and out to form new

[19] We also analyzed switch-out and other switching rates but all of them are not significant.

relationships with GPs. Combined with the good performance found in section C, it indicates that they are more skilled to select good GPs. This is further confirmed in Column (2). Pension funds with higher betweenness centralities are more likely to switch to new relationships while those with higher degree and eigenvector centralities are less likely to switch in. In this sense, pension funds with high degree and eigenvector centralities seem to be locked in the relationships with GPs and continue to invest in the follow-on funds of the GP and then experience worse performance.

Columns (3) and (4) of Panel A to C in Table XI report the one-off fund investing rate and the discretionary one-off investing rate. Both degree and betweenness centralities are significantly positively correlated with the one-off fund investing rate but the eigenvector does not have a significant influence. Pension funds with a higher degree and betweenness form more one-time relationships. Given pension funds with high betweenness have better performance, one would suspect that pension funds with a higher betweenness are better at selecting good performance funds than those with a higher degree centrality. To formally test this assumption, we regress the pension fund investment performance of those one-off investments on the spread between betweenness and degree (eigenvector) transformed index of a pension fund with the control of vintage, fund size, and year fixed effects. Panel D of Table XI shows the results. Column (1) and (4) only includes the vintage year fixed effects; Columns (2) and (5) add the strategy fixed effects; Columns (3) and (6) further add the log (fund size). In all the settings, we find that the spread between betweenness and degree centralities of a pension fund has a significantly positive effect on the selected one-off fund performance at the 5% significance level, while the influence of the spread between betweenness and eigenvector centralities also has a significantly positive influence on the performance but at a lower level.

C. *Risky Investments*

We conduct additional tests to explore the factors that contribute to either positive or negative relationships between networks and performance. Our investigation focuses on examining how networks impact the risk-taking behaviors of pension funds. We hypothesize that pension funds might be influenced by their networks to make investments in high-risk assets. Since these assets carry a significant level of risk, the returns may exhibit substantial variability, potentially detrimental to the performance of pension funds.

PERE encompasses various strategies that exhibit heterogeneous levels of risk. We categorize these strategies into three types based on their risk profiles. The strategies with the lowest risk level include real estate debt funds and real estate core/core+ funds. Real estate core/core+ funds employ relatively conservative strategies, primarily focusing on investments in core assets. Real estate debt funds, on the other hand, involve loans secured by real estate, such as B-note, CMBS, preferred equity, and similar instruments. The middle-risk level strategy is known as the value-added fund, while the highest-risk level funds are real estate opportunistic and real estate distressed funds. Value-added funds typically maintain lower leverage and invest in real estate assets with comparatively lower levels of risk compared to opportunistic funds. Real estate distressed funds, on the other hand, specialize in investing in distressed properties. To represent these categories, we assign the lowest-risk level strategies as 1, the middle-risk strategies as 2, and the highest-risk level strategies as 3. We utilize this variable as the dependent variable in our analysis.[20].

TABLE XII ABOUT HERE

[20] Real estate co-investment, fund of funds, and secondary funds cannot be clearly classified to specific risk levels and deleted in the regressions.

The findings are presented in Table XII. When considering all three participants, we observe that connecting with a greater number of participants or those with more influence amplifies risk-taking behaviors. Moreover, when combined with the poor performance of fund strategies in high-risk categories without considering weights, it becomes evident that weaker networks lead pension funds astray in making misguided investments. However, the centralities of consultants can assist in mitigating the risk associated with degree and eigenvector centralities. Interestingly, having more access to the entire network structure, as indicated by higher betweenness centrality, does not significantly impact the propensity for risky investments.

V. Conclusions

This research paper aims to examine the impact of pension fund networks in the private equity real estate (PERE) sector on their performance, as well as uncover the mechanisms underlying network formation. Our study involves constructing pension fund networks by establishing direct and indirect connections, facilitated by consultants, between pension funds and fund managers. We analyze the networks of pension funds, fund managers, and consultants individually. Our findings highlight the crucial and distinct role that networking plays in the performance of pension funds. It is imperative for pension funds to cultivate robust networks. Given the inherent lack of transparency in private equity, pension funds' ability to access a broader range of networks is essential in discerning promising investment projects. However, it is important to note that simply engaging with more or highly influential participants can actually harm pension funds' performance. In essence, the quality of networking is more significant than the quantity.

Furthermore, we conduct a more in-depth analysis of the mechanisms through which networks influence performance, considering both the front and back ends. Our investigation uncovers a perilous pitfall in pension funds' PERE investments: pension funds that set high expectations for returns, but subsequently generate lower short-term returns, require higher employee pension fund contributions, and experience higher CEO and board turnover rates, find themselves caught in a cycle of forming weaker networks that ultimately impair their performance. Pension funds with weaker networks tend to invest in larger funds, relying heavily on pre-existing general partners' follow-on networks, and demonstrate limited proficiency in selecting individual investments. Consequently, these weaker networks incentivize them to take greater risks in poorly performing investments. On the contrary, pension funds with greater access to networks exhibit the ability to switch among general partners and select well-performing funds. They also adopt less risky investments. This strategic maneuvering, facilitated by their extensive network connections, contributes to their overall performance. Furthermore, our research reaffirms the vital role played by consultants in assisting pension funds in accessing favorable investment opportunities. These consultants play a key part in enabling pension funds to tap into networks that provide access to promising investments.

References

Andonov, Aleksandar, Rob M. M. J. Bauer, and K. J. Martijn Cremers, 2017, Pension fund asset allocation and liability discount rates, *The Review of Financial Studies* 30, 2555–2595.

Andonov, Aleksandar, Yael V. Hochberg, and Joshua D. Rauh, 2018, Political representation and governance: Evidence from the investment decisions of public pension funds, *The Journal of Finance* 73, 2041–2086.

Andonov, Aleksandar, Roman Kräussl, and Joshua Rauh, 2021, Institutional Investors and Infrastructure Investing, *The Review of Financial Studies* 34, 3880–3934.

Arnold, Thomas R., David C. Ling, and Andy Naranjo, 2019, Private equity real estate funds: Returns, risk exposures, and persistence, *The Journal of Portfolio Management* 45, 24–42.

Barber, Brad M., Adair Morse, and Ayako Yasuda, 2021, Impact investing, *Journal of Financial Economics* 139, 162–185.

Bloch, Francis, Matthew O. Jackson, and Pietro Tebaldi, 2021, Centrality Measures in Networks, *SSRN Electronic Journal*.

Bodnaruk, Andriy, and Andrei Simonov, 2016, Loss-averse preferences, performance, and career success of institutional investors, *The Review of Financial Studies* 29, 3140–3176.

Bonacich, Phillip, 1972, Factoring and weighting approaches to status scores and clique identification, *The Journal of mathematical sociology* 2, 113–120.

Brown, Gregory W., Oleg R. Gredil, and Steven N. Kaplan, 2019, Do private equity funds manipulate reported returns?, *Journal of Financial Economics* 132, 267–297.

Cavagnaro, Daniel R., Berk A. Sensoy, Yingdi Wang, and Michael S. Weisbach, 2019, Measuring Institutional Investors' Skill at Making Private Equity Investments, *The Journal of Finance* 74, 3089–3134.

Gredil, Oleg, Barry E. Griffiths, and Rüdiger Stucke, 2014, Benchmarking Private Equity: The Direct Alpha Method, *SSRN Electronic Journal*.

Gupta, Arpit, and Stijn Van Nieuwerburgh, 2021, Valuing private equity investments strip by strip, *The Journal of Finance* 76, 3255–3307.

Harris, Robert S., Tim Jenkinson, and Steven N. Kaplan, 2014, Private equity performance: What do we know?, *The Journal of Finance* 69, 1851–1882.

Harris, Robert S., Tim Jenkinson, Steven Neil Kaplan, and Ruediger Stucke, 2020, Has Persistence Persisted in Private Equity? Evidence from Buyout and Venture Capital Funds, *SSRN Electronic Journal*.

Hochberg, Yael V., Alexander Ljungqvist, and Yang Lu, 2007, Whom you know matters:

Venture capital networks and investment performance, *The Journal of Finance* 62, 251–301.

Jackson, Blake, David C. Ling, and Andy Naranjo, 2022, Catering and Return Manipulation in Private Equity, *SSRN*.

Kaplan, Steven N., and Antoinette Schoar, 2005, Private equity performance: Returns, persistence, and capital flows, *The Journal of Finance* 60, 1791–1823.

Korteweg, Arthur, and Stefan Nagel, 2016, Risk-Adjusting the Returns to Venture Capital, *The Journal of finance* 71, 1437–1470.

Korteweg, Arthur, and Morten Sorensen, 2017, Skill and luck in private equity performance, *Journal of Financial Economics* 124, 535–562.

Krautz, Sebastian, and Franz Fuerst, 2015, Size Signals Success: Evidence from Real Estate Private Equity, *The Journal of Portfolio Management* 41, 73–81.

Long, Austin M., and Craig J. Nickels, 1996, A private investment benchmark, *Working paper*.

Matthew O. Jackson Brian W. Rogers, And, and Yves Zenou, 2016, Networks : An Economic Perspective by Why Should We Study Network Structure ?, *SSRN*.

Maurin, Vincent, David T. Robinson, and Per Strömberg, 2022, A Theory of Liquidity in Private Equity, *Management science*.

Riddiough, T. J., 2022, Pension Funds and Private Equity Real Estate: History, Performance, Pathologies, Risks, *Handbook of Real Estate and Macroeconomics* (Edgar).

Riddiough, Timothy J., 2020, Pension Funds and Private Equity Real Estate: History, Performance, Pathologies, Risks, *SSRN Electronic Journal*.

Rossi, Alberto G., David Blake, Allan Timmermann, Ian Tonks, and Russ Wermers, 2018, Network centrality and delegated investment performance, *Journal of Financial Economics* 128, 183–206.

Rouvinez, Christophe, 2003, Private equity benchmarking with PME+, *Venture Capital Journal* 43, 34–39.

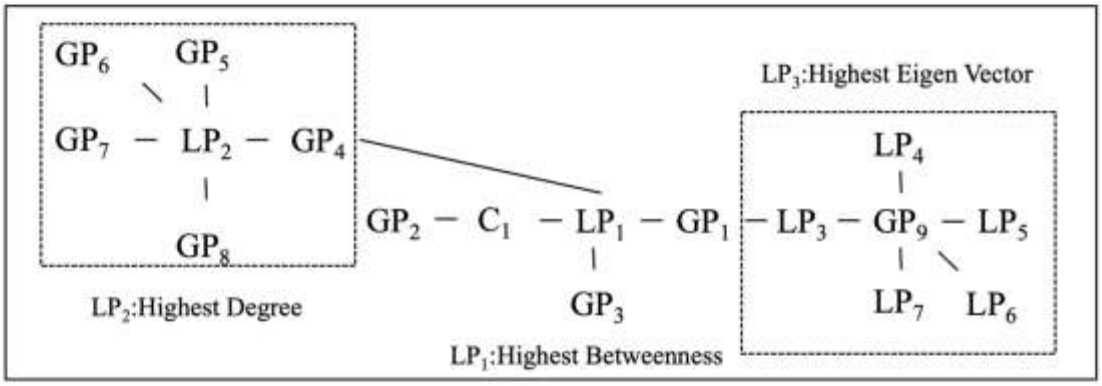


Figure 1. A typical network structure.

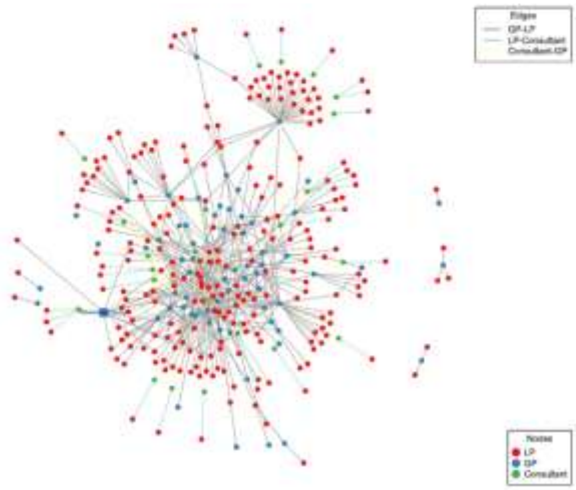


Figure 2. Network graph example: 2001 networks among pension funds, GPs, and consultants.

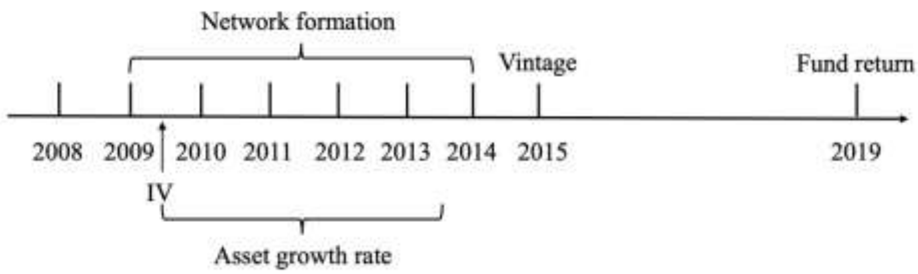


Figure 3. An empirical strategy example.

Table I
Consultants

The first panel in this table shows the summary statistics of consultants in investments and pension funds. The second panel shows the most used five consultants by LPs at the investment level. RE AUA in the table is real estate asset under advisements; AUA in the table is asset under advisements. Network centralities are ranked and classified into four different groups and the first quarter is the highest centrality group. 1st in the parentheses means the first quarter.

	N	Mean	Std. Dev.	Min	Median	Max
Consultant	145					
Consultant advised investments	5943					
Advised investment by each consultant	145	40.986	100.639	1.000	7.000	675.000
Advised public investment by each consultant	97	43.227	101.366	1.000	8.000	539.000
Advised private investment by each consultant	81	21.605	36.794	1.000	5.000	164.000
Advised pension funds by each consultant	145	4.759	9.154	1.000	2.000	62.000
Advised public pension funds by each consultant	97	4.268	6.927	1.000	2.000	34.000
Advised private pension funds by each consultant	81	3.407	5.130	1.000	1.000	33.000

	Advised LPs	Advised Investments	Vintage	Degree	Betweenness	Eigenvector	Country	RE AUA ($ Mn)	All AUA ($ Mn)
Wilshire Associates	25	387	1972	0.170 (1st)	0.058 (1st)	0.154 (1st)	US	-	1,100,000
NEPC	47	425	1986	0.144 (1st)	0.073 (1st)	0.056 (1st)	US	11,500	1,100,000
Pension Consulting Alliance	10	416	1988	0.191 (1st)	0.040 (1st)	0.595 (1st)	US	-	1,374,000
Callan Associates	39	560	1973	0.235 (1st)	0.063 (1st)	0.354 (1st)	US	75,000	2,300,000
Aon Hewitt Investment Consulting	62	675	1974	0.209 (1st)	0.094 (1st)	0.333 (1st)	US	-	4,200,000

Table II
Descriptive Statistics

This table summarizes the variables used in the regressions. * means commitment amount value-weighted value. ** means fund size weighted value.

	No.	Mean	Std. Dev.	Min	Median	Max
Pension fund investment number						
All pension funds	1443	7.435	15.121	1.000	2.000	199.000
Public Pension Funds	577	10.726	20.560	1.000	3.000	199.000
Private Pension Funds	866	5.242	9.363	1.000	2.000	88.000
Pension fund investment performance (as of q4, 2019)						
All pension fund IRRs	827	8.656*	7.868*	-27.200*	8.915*	62.000*
Public Pension Fund IRR	372	7.553*	7.077*	-27.200*	7.753*	37.160*
Private Pension Fund IRR	455	9.557*	8.360*	-17.270*	9.990*	62.000*
Pension funds with ≤ 3 investment IRR	350	9.583*	9.818*	-27.200*	9.930*	62.000*
Pension funds with > 3 investment IRR	477	7.972*	5.973*	-15.280*	8.342*	41.142*
Other pension fund characteristics						
Commitment amount ($Mn)	4488	74.021	134.870	0.010	40.000	2800.000
Investment sequence number by pension funds	10729	1.734	1.323	1.000	1.000	14.000
Pension fund asset values ($Billion)	1861	16.551	30.769	0.090	5.941	302.418
Assumed (Expected) return in percentage	1820	7.851	0.416	5.500	8.000	9.000
1-year return in percentage	1838	6.366	11.469	-30.850	9.100	38.605
5-year return in percentage	1672	6.308	3.953	-1.130	5.200	19.300
Fund performance in percentage (as of q4, 2019)						
All fund IRR	1126	6.940**	12.227	-55.420	10.330	65.400
North America IRR	859	8.082**	12.292	-55.420	10.600	65.400
Non-North America IRR	267	4.771**	12.025	-23.660	9.310	62.000
Core/ Core+	111	3.731**	11.533	-39.900	10.200	63.200
Value-added IRR	440	6.825**	13.337	-55.420	11.375	65.400
Opportunistic IRR	348	7.196**	12.795	-54.700	9.800	53.120
Others IRR	227	8.319**	8.725	-25.800	9.990	47.520
Small fund (≤ median) IRR	548	10.133**	12.857	-55.420	11.000	65.400
Large fund (> median) IRR	548	9.824**	11.410	-50.500	10.000	49.100
Fund Characteristics						
Fund size ($Mn)	1096	695.157	1134.170	7.500	400.735	15800.000
Fund sequence number by GPs	1126	7.040	8.367	1.000	4.000	62.000
Network centrality						
Pension fund						
Degree		0.004	0.006	0.001	0.002	0.084
Betweenness	7665	0.001	0.003	0.000	0.000	0.086
Eigenvector		0.009	0.044	0.000	0.001	0.914
GP						
Degree		0.105	0.016	0.001	0.005	0.172
Betweenness	2859	0.007	0.017	0.000	0.002	0.305
Eigenvector		0.019	0.043	0.000	0.005	1.000
Consultant						
Degree		0.046	0.078	0.001	0.014	0.429
Betweenness	1524	0.019	0.029	0.000	0.006	0.180
Eigenvector		0.039	0.143	0.000	0.004	1.000

Table III
***OLS* Regression Results**

In this table, centrality is formed by transactions between GPs and LPs over a trailing 5-year window. The dependent variable is the net IRR. Centralities in Columns (1) and (2) are degree centralities; Centralities in Columns (3) and (4) are betweenness centralities; Centralities in Columns (5) and (6) are eigenvector centralities. Standard errors are clustered at the fund level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dependent Variable: Net IRR	Degree		Betweenness		Eigenvector	
	(1)	(2)	(3)	(4)	(5)	(6)
Pension fund Centrality	-0.857**	-1.008**	2.837**	3.157**	-0.047**	-0.065**
	(0.350)	(0.413)	(1.207)	(1.377)	(0.023)	(0.025)
GP Centrality	-0.251	-0.374	0.062	-0.166	-0.129	-0.178
	(0.347)	(0.350)	(0.279)	(0.332)	(0.132)	(0.139)
Consultant Centrality	-0.005	0.013	-0.018	0.001	0.019*	0.028**
	(0.040)	(0.046)	(0.094)	(0.116)	(0.010)	(0.013)
log(Pension fund commitment)		-0.000		-0.002		-0.000
		(0.004)		(0.004)		(0.004)
Pension fund firm type(Public pension fund=1)	-0.065	0.065	-0.060	0.088	-0.069	0.054
	(0.066)	(0.080)	(0.066)	(0.079)	(0.066)	(0.078)
Pension fund investment sequence	0.001	0.001	0.001	0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
GP fund sequence	0.004**	0.005**	0.004**	0.005***	0.004**	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
GP listed=1	-0.055*	-0.049	-0.062**	-0.055*	-0.059**	-0.053*
	(0.031)	(0.031)	(0.030)	(0.030)	(0.029)	(0.029)
log(Fund size)	0.001	0.003	0.001	0.003	0.001	0.002
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Constant	0.155**	0.080	0.133**	0.060	0.148**	0.077
	(0.068)	(0.106)	(0.067)	(0.101)	(0.066)	(0.099)
Observations	3,248	2,126	3,248	2,126	3,248	2,126
Adjusted R-squared	0.603	0.611	0.604	0.611	0.603	0.612
Pension fund firm FE	YES	YES	YES	YES	YES	YES
GP firm FE	YES	YES	YES	YES	YES	YES
Consultant FE	YES	YES	YES	YES	YES	YES
Fund strategy FE	YES	YES	YES	YES	YES	YES
Fund vintage FE	YES	YES	YES	YES	YES	YES
Fund primary location FE	YES	YES	YES	YES	YES	YES

Table IV
Exogeneity Test of Instruments

This table shows the exogeneity test of instruments. The total contribution ratio is defined as total contributions over actuarial liabilities. The total deduction ratio is defined as total deductions over actuarial liabilities. Annual asset growth is the annual asset growth between lagged one and five years. All independent variables are lagged by six years. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dependent Variable: Average annual asset growth	(1)	(2)	(3)
L6 Assumed (expected) return	-1.302		-1.496
	(2.860)		(2.996)
L6. 5-year investment return		-0.178	-0.186
		(0.170)	(0.172)
L6. total contribution ratio	-0.164	-0.239	-0.265
	(0.351)	(0.363)	(0.363)
L6. net payout ratio	0.351*	0.415*	0.393*
	(0.213)	(0.212)	(0.210)
L6. projected contribution rate	0.548***	0.554***	0.542***
	(0.126)	(0.128)	(0.130)
L6. average salary	0.002**	0.002**	0.001*
	(0.001)	(0.001)	(0.001)
L6. average benefit	-0.009***	-0.011***	-0.011***
	(0.003)	(0.003)	(0.003)
L6. total membership	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Constant	-0.200	-0.199***	-0.063
	(0.253)	(0.073)	(0.257)
Observations	899	810	804
Adjusted R-squared	0.502	0.524	0.523
LP firm FE	YES	YES	YES
Fund vintage FE	YES	YES	YES

Table V

***2SLS* Regression Results**

In this table, centrality is formed by transactions between GPs and pension funds over a trailing 5-year window. In *2SLS* regressions, the asset value from five years ago is used as the instrument variable. Only public pension funds data are used in this table due to data availability. Centralities in Columns (1) and (2) are degree centralities; Centralities in Columns (3) and (4) are betweenness centralities; Centralities in Columns (5) and (6) are eigenvector centralities. Standard errors are clustered at the fund level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dependent Variable: Net IRR	Degree		Betweenness		Eigenvector	
	(1)	(2)	(3)	(4)	(5)	(6)
Pension fund Centrality	-3.126***	-2.678***	88.418**	61.284**	-0.439***	-0.351***
	(0.946)	(0.979)	(35.045)	(26.866)	(0.141)	(0.129)
GP Centrality	-0.816**	-0.824**	-1.517**	-1.446**	-0.109	-0.161
	(0.370)	(0.375)	(0.655)	(0.604)	(0.133)	(0.129)
Consultant Centrality	0.217***	0.182**	0.271*	0.199	0.192***	0.156***
	(0.071)	(0.077)	(0.163)	(0.144)	(0.061)	(0.056)
log(Pension fund commitment)		0.003		-0.006		0.003
		(0.004)		(0.005)		(0.004)
Pension fund investment sequence	0.001	0.001	0.001	0.002	0.001	0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
L. Pension fund asset values	0.226***	0.206***	0.258***	0.222***	0.246***	0.228***
	(0.066)	(0.050)	(0.070)	(0.052)	(0.070)	(0.057)
L.Assumed (expected) return	-1.833**	-1.584*	-0.884	-1.124	-0.124	-0.328
	(0.733)	(0.882)	(0.919)	(0.933)	(0.888)	(0.965)
L.1-year investment return	0.008	-0.002	-0.150*	-0.139*	0.006	-0.004
	(0.023)	(0.025)	(0.084)	(0.073)	(0.027)	(0.029)
L.5-year investment return	-0.147*	-0.135	0.045	-0.005	-0.101	-0.114
	(0.088)	(0.090)	(0.155)	(0.128)	(0.098)	(0.097)
GP fund sequence	0.004**	0.004**	0.004**	0.004**	0.004***	0.004***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
GP listed=1	-0.028	-0.030	-0.039	-0.033	-0.043*	-0.042*
	(0.024)	(0.023)	(0.027)	(0.025)	(0.025)	(0.024)
log(Fund size)	0.026***	0.026***	0.029***	0.030***	0.025***	0.025***
	(0.008)	(0.007)	(0.009)	(0.008)	(0.008)	(0.007)
Constant	-0.227***	-0.256***	-0.270***	-0.207**	-0.498***	-0.471***
	(0.082)	(0.090)	(0.102)	(0.096)	(0.133)	(0.137)
Observations	1,619	1,450	1,619	1,450	1,619	1,450
Adjusted R-squared	0.697	0.700	0.316	0.492	0.606	0.642
Pension fund firm FE	YES	YES	YES	YES	YES	YES
GP firm FE	YES	YES	YES	YES	YES	YES
Consultant FE	YES	YES	YES	YES	YES	YES
Fund strategy FE	YES	YES	YES	YES	YES	YES
Fund vintage FE	YES	YES	YES	YES	YES	YES
Fund primary location FE	YES	YES	YES	YES	YES	YES
The first stage (Instrument):	-0.053***	-0.054***	0.002***	0.002***	-0.390***	-0.418***
Pension fund asset value lag 5 years	(0.004)	(0.005)	(0.001)	(0.001)	(0.073)	(0.075)
Hausman p-value	0.032	0.111	0.001	0.008	0.004	0.030
Under identification test						

Kleibergen-Paap rk F statistic	58.701***	54.684***	16.834***	21.219***	22.696***	24.606***
Weak identification test						
Cragg-Donald Wald F statistic	259.130	228.923	16.619	21.408	46.953	45.434
Kleibergen-Paap rk Wald F statistic	121.526	107.706	12.854	15.608	28.942	30.854

Table VI

Performance Comparative Statics Results

In this table, all the settings are the same to Table V except that we changed the network centralities to indexes. The good network index for pension funds is constructed by subtracting the degree and eigenvector centrality ratios from the betweenness centrality ratio. GP and consultant network indexes are simple averages of all three centrality ratios. Standard errors are clustered at the fund level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dependent Variable: Net IRR	(1)	(2)
Pension Fund Good Network Index	18.041***	15.087**
	(6.010)	(6.081)
GP Network Index	-7.502*	-8.288**
	(3.875)	(3.823)
Consultant Network Index	32.924***	28.040**
	(10.437)	(11.183)
log(Pension fund commitment)		-0.174
		(0.383)
Pension fund investment sequence	0.075	0.100
	(0.123)	(0.132)
L. Pension fund asset values	25.341***	22.290***
	(6.926)	(5.349)
L.Assumed (expected) return	-76.345	-69.984
	(84.340)	(91.135)
L.1-year investment return	-0.235	-1.679
	(2.545)	(2.802)
L.5-year investment return	0.238	-2.546
	(12.361)	(11.523)
GP fund sequence	0.311**	0.329**
	(0.143)	(0.142)
GP listed=1	-4.243*	-4.159*
	(2.495)	(2.386)
log(Fund size)	2.629***	2.685***
	(0.778)	(0.745)
Constant	-35.701***	-31.945***
	(11.018)	(11.456)
Observations	1,619	1,450
Adjusted R-squared	0.616	0.644
Pension fund firm FE	YES	YES
GP firm FE	YES	YES
Consultant FE	YES	YES
Fund strategy FE	YES	YES
Fund vintage FE	YES	YES
Fund primary location FE	YES	YES
The first stage (Instrument):	0.920***	0.934***
Pension fund asset value lag 5 years	(0.132)	(0.144)
Hausman p-value	0.003	0.025
Under identification test		
Kleibergen-Paap rk F statistic	60.578***	56.640***
Weak identification test		

Cragg-Donald Wald F statistic	59.911	57.652
Kleibergen-Paap rk Wald F statistic	48.228	42.314

Table VII
Network Formation: Asset Growth Rates

In this table, centrality is formed by transactions between GPs and pension funds over a trailing 5-year window. Independent variables are lagged by six years to be non-overlapping with centralities. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	Degree	Betweenness	Eigenvector
	(1)	(2)	(3)
L6. expected return	0.241*	-0.091***	9.701***
	(0.126)	(0.025)	(1.833)
L6. 1-year investment return	-0.005***	-0.000	-0.043
	(0.002)	(0.001)	(0.035)
L6. 5-year investment return	-0.028***	-0.005**	-0.358***
	(0.005)	(0.002)	(0.107)
L6. change in value of investment portfolio	0.003***	0.000***	0.024**
	(0.000)	(0.000)	(0.011)
L6. income, interests, and dividends	-0.034***	0.003*	-1.024***
	(0.006)	(0.001)	(0.159)
L6. investment expenses	-0.171***	-0.005***	-0.876***
	(0.012)	(0.002)	(0.298)
L6. pension contribution	0.019***	0.000	0.514***
	(0.003)	(0.001)	(0.093)
L6. pension payouts	-0.036***	0.002**	-0.585***
	(0.007)	(0.001)	(0.158)
L6. operating expenses	0.043***	0.005	0.343**
	(0.013)	(0.003)	(0.152)
Constant	-0.000	0.007***	-0.537***
	(0.010)	(0.002)	(0.144)
Observations	2,086	2,086	2,086
R-squared	0.893	0.694	0.623
Pension fund firm FE	YES	YES	YES
Fund vintage FE	YES	YES	YES

Table VIII
Network Formation: Turnover Rates

In this table, centrality is formed by transactions between GPs and pension funds over a trailing 5-year window. CEO turnover is a dummy variable and measures whether there is a CEO turnover. Board of trustee turnover rates measure the ratio of left members in a specific year. Both turnover rates are lagged by 6 years. Betweenness is in 1000s. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	Degree	Betweenness	Eigenvector
	(1)	(2)	(3)
L6. CEO turnover	0.002***	-0.294**	0.001
	(0.001)	(0.116)	(0.016)
L6. Board of Trustee turnover rate	0.009***	-0.741***	0.239***
	(0.001)	(0.268)	(0.033)
Constant	0.013***	0.888***	-0.021
	(0.001)	(0.221)	(0.016)
Observations	1,316	1,316	1,316
R-squared	0.847	0.785	0.624
Pension Fund firm FE	YES	YES	YES
Fund vintage FE	YES	YES	YES

Table IX

Front-End Comparative Statics Results

In this table, the independent variables in column (1) are the same to Table VII, while those in Column (2) are the same to TableVIII. The good network index for pension funds is constructed by subtracting the degree and eigenvector centrality ratios from the betweenness centrality ratio. Standard errors are clustered at the fund level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dependent Variable: Good network index for pension funds	(1)	(2)
L6. CEO trunover rate		-0.001
		(0.018)
L6. Board of Trustee trunover rate		-0.255***
		(0.038)
L6. expected return	-7.420	
	(9.817)	
L6. 1-year investment return	-0.133	
	(0.091)	
L6. 5-year investment return	1.490***	
	(0.342)	
L6. change in value of investment portfolio	-0.033***	
	(0.010)	
L6. income, interests, and dividends	0.039	
	(0.240)	
L6. investment expenses	3.126***	
	(0.347)	
L6. pension contribution	-0.485***	
	(0.099)	
L6. pension payouts	0.730***	
	(0.163)	
L6. operating expenses	-1.680***	
	(0.497)	
Constant	-1.520*	-1.069***
	(0.783)	(0.022)
Observations	2,086	1,316
R-squared	0.848	0.874
Pension fund firm FE	YES	YES
Fund vintage FE	YES	YES

Table X
Networks and Investment Characteristics

In this table, each centrality (Degree, Betweenness, and Eigenvector) is divided into two groups: the top 25% quantile group (Q1) and the remaining group (Q2-Q4). Each investment is then classified into eight different categories based on investors' centrally groups. Panel A shows the cross-sectional comparisons of these eight categories. In this panel, IRR is unweighted and in percentile. Panel B further classifies investment performance based on consultant centralities in the investor centrality group of Betweenness (Q2-Q4), Degree (Q1), and Eigenvector (Q1). IRRs are reported in this panel and are unweighted and in percentile.

Panel A: Cross-sectional Comparisons

		Degree (Q1-Q3) & Eigen (Q1-Q3)	Degree (Q1-Q3) & Eigen (Q4)	Degree (Q4) & Eigen (Q1-Q3)	Degree (Q4)& Eigen(Q4)
Betweenness (Q1)	N	476	110	54	53
	IRR	8.826	12.168	6.469	10.828
	Consultant ratio	48.5%	19.1%	25.9%	22.6%
	Public firm ratio	41.6%	47.3%	50.0%	67.9%
	Risky invest ratio	26.1%	31.8%	35.2%	22.6%
	Fund Size ($mn)	1201.930	1177.350	2030.088	1195.781
Betweenness (Q2-Q4)	N	2495	414	470	828
	IRR	9.240	11.063	7.048	10.234
	Consultant ratio	91.1%	91.5%	70.9%	63.0%
	Public firm ratio	77.2%	42.5%	55.5%	46.0%
	Risky invest ratio	43.4%	43.0%	33.8%	34.3%
	Fund Size ($mn)	1868.259	2026.066	1442.563	1472.892

Panel B: Consultant in-group effects on performance (IRR)

	Consultant centralities	Degree	Betweenness	Eigen
Betweenness (Q2-Q4) * Degree (Q1) & Eigen (Q1)	Consultant (Q1)	11.688	10.036	8.879
	Consultant (Q2-Q3)	9.451	10.156	10.224
	Consultant bottom (Q4)	6.422	6.908	7.858

Table XI
Switching Rate and Network Centrality

Panel A to Panel C reports the relationships between switching rates and three centralities. The dependent variables are switch rates. Panel D reports the regression results with Net IRR as the dependent variable and the spread of betweenness and degree (eigenvector) centralities as the independent variables. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	Overall switch rate	Overall switch-in rate	One-off fund investing rate	Discretionary one-off investing rate
Panel A: Degree centrality				
Degree	-3.496***	-1.649*	2.252***	1.864**
	(0.731)	(0.857)	(0.801)	(0.774)
Constant	0.973***	0.816***	0.084*	0.039
	(0.035)	(0.042)	(0.044)	(0.036)
Observations	3,477	3,477	3,477	3,477
Adjusted R-squared	0.458	0.446	0.572	0.565
Pension fund firm FE	YES	YES	YES	YES
Fund vintage FE	YES	YES	YES	YES
Panel B: Betweenness centrality				
Betweenness	2.268***	2.858***	2.414**	2.426**
	(0.873)	(1.017)	(1.103)	(1.017)
Constant	0.949***	0.800***	0.090**	0.042
	(0.035)	(0.043)	(0.044)	(0.036)
Observations	3,477	3,477	3,477	3,477
Adjusted R-squared	0.455	0.446	0.572	0.565
Pension fund firm FE	YES	YES	YES	YES
Fund vintage FE	YES	YES	YES	YES
Panel C: Eigenvector centrality				
Eigen	-0.166***	-0.108*	-0.008	-0.030
	(0.052)	(0.060)	(0.046)	(0.043)
Constant	0.954***	0.806***	0.096**	0.048
	(0.034)	(0.042)	(0.044)	(0.036)
Observations	3,477	3,477	3,477	3,477
Adjusted R-squared	0.455	0.446	0.572	0.564
Pension fund firm FE	YES	YES	YES	YES
Fund vintage FE	YES	YES	YES	YES

Panel D: Networks and Performance

Dependent variable: Net IRR						
Betweenness-Degree	0.023**	0.021**				
	(0.010)	(0.010)				
Betweenness-Eigen			0.021**	0.020**		
			(0.009)	(0.009)		
Betweenness-Degree- Eigen					0.016**	0.014**
					(0.007)	(0.007)
log(Fund size)		0.011		0.010		0.009
		(0.008)		(0.007)		(0.007)
Constant	0.007	-0.053	0.013	-0.044	0.015	-0.040
	(0.034)	(0.054)	(0.034)	(0.053)	(0.035)	(0.053)
Observations	1,531	1,523	1,516	1,508	1,516	1,508

Adjusted R-squared	0.417	0.424	0.418	0.423	0.418	0.424
Vintage FE	YES	YES	YES	YES	YES	YES
Strategy FE	YES	YES	YES	YES	YES	YES

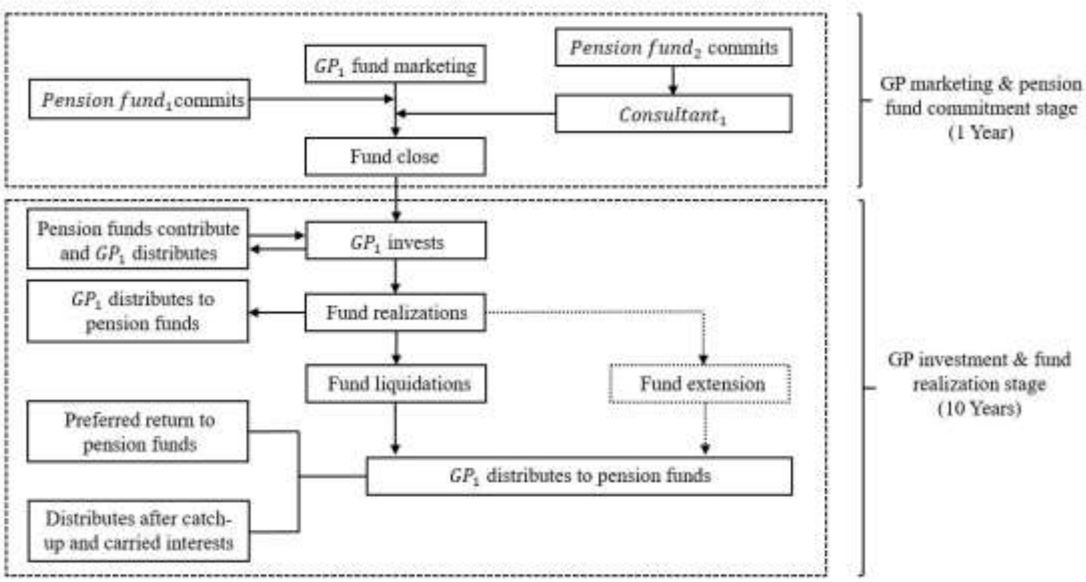
Table XII
Risk Investment Behavior

In this table, centrality is formed by transactions between GPs and pension funds over a trailing 5-year window. The dependent variable is the risk level of the investment ranked by fund strategies. Centralities in Columns (1) and (2) are degree centralities; Centralities in Columns (3) and (4) are betweenness centralities; Centralities in Columns (5) and (6) are eigenvector centralities. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Dependent Variable: Risk levels	Degree		Betweenness		Eigenvector	
	(1)	(2)	(3)	(4)	(5)	(6)
Pension fund Centrality	2.447**	3.374**	3.368	1.799	0.116*	0.230**
	(1.204)	(1.616)	(4.609)	(5.798)	(0.070)	(0.117)
GP Centrality	2.309	3.620**	-0.584	0.542	0.615***	0.571
	(1.650)	(1.817)	(0.595)	(2.120)	(0.226)	(0.838)
Consultant Centrality	0.071	-0.357*	0.371	-0.635	0.022	-0.097*
	(0.131)	(0.184)	(0.390)	(0.427)	(0.046)	(0.059)
log(L. Pension fund asset values)		-0.060**		-0.023		-0.037
		(0.027)		(0.024)		(0.025)
L. Assumed (expected) return		14.597**		14.785**		13.834**
		(6.030)		(6.200)		(6.110)
L.1-year investment return		-0.125		-0.108		-0.116
		(0.337)		(0.326)		(0.325)
L.5-year investment return		-1.649		-1.748		-1.628
		(1.131)		(1.125)		(1.119)
Constant	1.958***	1.402**	2.028***	1.394**	2.000***	1.546**
	(0.206)	(0.653)	(0.123)	(0.669)	(0.119)	(0.631)
Observations	4,039	1,965	4,039	1,965	4,039	1,965
Adjusted R-squared	0.078	0.118	0.070	0.101	0.072	0.103
Fund vintage FE	YES	YES	YES	YES	YES	YES
Fund primary location FE	YES	YES	YES	YES	YES	YES

Appendix

I. PE investment structure



Appendix Figure A1: PE investment structure

Figure A1 shows a typical pension fund investment structure. It includes two stages, i.e., GP marketing & pension fund commitment and GP investment & fund realization. The GP marketing & pension fund commitment stage lasts about one year. In this stage, GP_1, for example, markets its funds. Pension funds may either investigate the fund through in-house consultants ($Penssion\ fund_1$) or external consultants ($Pension\ fund_2$). If they decide on investments, they sign contracts with GPs about commitment amounts. The fund closes after the GP connects enough funds.

The second stage usually lasts 10 years. In this stage, GP_1 invest as planned. Pension funds follow the contract and make committed contributions. If there are any fund realizations, GP_1 distributes them back to pension funds. At the end of the fund life, GP_1 liquidates the fund and distributes the committed preferred returns. If there are any excess returns beyond the preferred returns and management fees (usually about 2%), GPs will get catch-ups if there are such provisions. Catch-ups are the additional fees on top of management fees and carried interests. Carried interests are the standard promotions and are usually 20% of excess profits beyond preferred returns.

II. Switching rate

Consistent with the network, we build up pension fund switching rate based on the past five years' transactions. In each year, we classify each investment by whether the fund is the first- or last-time fund for GP and whether it is the first or last time that the LP invests in this GP. Our ranking of the fund sequence in GPs and LPs are based on all the historical data between 1969 and 2020. We close the sample period in 2020 to allow at least 5 years for GPs to raise another fund. We assume if GPs are not able to raise another fund in 5 years, then the GPs are out of the market. This is quite a long time given the typical time difference between two funds of a GP are just 2 to3 years (Jackson, Ling, and Naranjo (2022)). Based on the fund sequence in LPs and GPs, we are able to analyze how pension funds switch between GPs. We classify pension switching to and from GPs into the following 9 categories. Each category is mutually exclusive and exhaust all of the possibilities.

1. First time LP invests with GP, not the last time LP invests with GP, first GP fund, not the last GP fund (switch in),
2. First time LP invests with GP, not the last time LP invests with GP, not the first GP fund, not the last GP fund (switch in)
3. First and last time LP invests with GP, first GP fund, not the last GP fund (a one off that is discretionary, and qualifies as both switch in and switch out)
4. First and last time LP invests with GP, first GP fund, last GP fund (a one off that may not be discretionary, and qualifies as both switch in and switch out)

5. First and last time LP invests with GP, not the first GP fund, not the last GP fund (a one off that is discretionary, and qualifies as both switch in and switch out)
6. First and last time LP invests with GP, not the first GP fund, last GP fund (a one off that may not be discretionary, and qualifies as both switch in and switch out)
7. Not the first time LP invests with GP, last time investing with GP, last GP fund (may or may not be a discretionary switch out)
8. Not the first time LP invests with GP, last time investing with GP, not the last GP fund (discretionary switch out)
9. Continuation fund – not the first time and not the last time LP invests with GP (not switch in and not switch out)

Whenever the LP invests in a fund, the investment gets put into one of these nine different categories. Then, based on dollars committed or invested in the identified funds, we create 5-year lagged variables just the same as the measures of centrality. Below are different measures of switching rates. In each case the denominator is the sum of all investments made by the LP over the prior five-year period (that is, sum of 1 through 9 above):

1. The overall turnover or switch rate: Sum of 1 through 8.
2. The overall switch-in rate : Sum of 1 through 6.
3. The one-off fund investing rate: Sum of 3 through 6
4. The discretionary one-off investing rate: Sum of 3 and 5.

III. Robustness Tests

A. Empirical results with networks formed by transactions over a trailing 3-year window

Appendix Table A1： Results of Networks Formed by Transactions over A Trailing 3-year Window

In this table, centrality is formed by transactions between GPs and pension funds over a trailing 3-year window. Net IRR in Q4, 2019 is the dependent variable. The basic model does not include GP and consultant centrality, and the full model includes these two variables. Only key variables are reported, and other control variables are the same as the main context. Centralities in Columns (1) and (2) are degree centralities; Centralities in Columns (3) and (4) are betweenness centralities; Centralities in Columns (5) and (6) are eigenvector centralities. Standard errors are clustered at the fund level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

		Degree		Betweenness		Eigenvector	
		(1)	(2)	(3)	(4)	(5)	(6)
OLS-Full Model	Pension fund centrality	-1.416***	-1.583***	1.042	2.395*	-0.065**	-0.075**
		(0.445)	(0.525)	(0.953)	(1.448)	(0.026)	(0.030)
	GP centrality	0.175	0.295	-0.528	-0.467	-0.024	-0.012
		(0.485)	(0.548)	(0.415)	(0.458)	(0.137)	(0.142)
	Consultant centrality	0.014	0.053	0.014	0.049	0.019	0.024
		(0.043)	(0.050)	(0.088)	(0.100)	(0.015)	(0.018)
	Observations	2,656	1,758	2,656	1,758	2,656	1,758
	Adjusted R-squared	0.647	0.656	0.645	0.654	0.645	0.653
OLS-Basic Model	Pension fund centrality	-1.169***	-1.082***	1.595	2.440**	-0.029*	-0.031**
		(0.333)	(0.360)	(1.007)	(1.204)	(0.015)	(0.015)
	Observations	3,773	2,483	3,773	2,483	3,773	2,483
	Adjusted R-squared	0.645	0.657	0.643	0.656	0.642	0.655
2SLS-Full Model	Pension fund centrality	-2.461***	-2.004**	68.202*	42.686	-0.295***	-0.218*
		(0.902)	(0.990)	(38.728)	(31.253)	(0.114)	(0.112)
	GP centrality	0.593	0.480	-0.497	-0.425	0.347**	0.262*
		(0.448)	(0.455)	(0.480)	(0.476)	(0.160)	(0.156)
	Consultant centrality	0.137*	0.111	0.123	0.109	0.116**	0.083
		(0.071)	(0.080)	(0.106)	(0.100)	(0.051)	(0.051)
	Observations	1,353	1,214	1,456	1,302	1,353	1,214
	Adjusted R-squared	0.723	0.721	0.554	0.630	0.693	0.706
2SLS-Basic Model	Pension fund centrality	-1.997***	-1.687**	64.507*	40.085	-0.124***	-0.097**
		(0.641)	(0.696)	(34.330)	(30.697)	(0.041)	(0.041)
	Observations	1,876	1,662	2,040	1,802	1,876	1,672
	Adjusted R-squared	0.736	0.735	0.569	0.640	0.724	0.731

B. Empirical results with networks formed by transactions over a trailing 4-year window

Appendix Table A2： Results of Networks Formed by Transactions over A Trailing 4-year Window

In this table, centrality is formed by transactions between GPs and pension funds over a trailing 3-year window. Consultant relationships are used in the formation of centrality. Net IRR in Q4, 2019 is the dependent variable. The basic model does not include GP and consultant centrality, and the full model includes these two variables. Only key variables are reported, and other control variables are the same as the main context. Centralities in Columns (1) and (2) are degree centralities; Centralities in Columns (3) and (4) are betweenness centralities; Centralities in Columns (5) and (6) are eigenvector centralities. Standard errors are clustered at the fund level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

		Degree		Betweenness		Eigenvector	
		(1)	(2)	(3)	(4)	(5)	(6)
OLS-Full Model	Pension fund centrality	-1.105***	-1.255***	3.502**	3.728**	-0.056**	-0.068***
		(0.392)	(0.463)	(1.403)	(1.570)	(0.023)	(0.025)
	GP centrality	-0.115	-0.154	-0.152	-0.659	-0.082	-0.086
		(0.350)	(0.388)	(0.429)	(0.605)	(0.135)	(0.143)
	Consultant centrality	0.005	0.022	0.044	0.064	0.019	0.024*
		(0.041)	(0.048)	(0.088)	(0.100)	(0.012)	(0.013)
	Observations	3,056	1,998	3,056	1,998	3,056	1,998
	Adjusted R-squared	0.610	0.625	0.612	0.629	0.608	0.624
OLS-Basic Model	Pension fund centrality	-0.868***	-0.857**	2.466**	2.501*	-0.025	-0.024
		(0.297)	(0.333)	(1.174)	(1.333)	(0.015)	(0.015)
	Observations	3,836	2,510	3,836	2,510	3,836	2,510
	Adjusted R-squared	0.643	0.659	0.644	0.660	0.642	0.658
2SLS-Full Model	Pension fund centrality	-2.675***	-2.238***	61.526**	44.534**	-0.346***	-0.268***
		(0.785)	(0.823)	(24.730)	(21.299)	(0.108)	(0.102)
	GP centrality	-0.392	-0.446	-1.297**	-1.434**	0.017	-0.050
		(0.354)	(0.361)	(0.600)	(0.595)	(0.143)	(0.140)
	Consultant centrality	0.144**	0.117*	0.309**	0.216*	0.149***	0.115**
		(0.061)	(0.068)	(0.141)	(0.126)	(0.048)	(0.047)
	Observations	1,569	1,402	1,693	1,507	1,569	1,402
	Adjusted R-squared	0.692	0.692	0.505	0.576	0.637	0.661
2SLS-Basic Model	Pension fund centrality	-1.951***	-1.621**	39.122**	24.418	-0.141***	-0.109**
		(0.621)	(0.662)	(18.005)	(16.322)	(0.047)	(0.046)
	Observations	1,884	1,668	2,055	1,815	1,884	1,678
	Adjusted R-squared	0.735	0.735	0.639	0.670	0.718	0.727

C. *Empirical results with networks formed by transactions over a trailing 6-year window*

Appendix Table A3: Results of Networks Formed by Transactions over A Trailing 6-year Window

In this table, centrality is formed by transactions between GPs and pension funds over a trailing 3-year window. Consultant relationships are used in the formation of centrality. Net IRR in Q4, 2019 is the dependent variable. The basic model does not include GP and consultant centrality, and the full model includes these two variables. Only key variables are reported, and other control variables are the same as the main context. Centralities in Columns (1) and (2) are degree centralities; Centralities in Columns (3) and (4) are betweenness centralities; Centralities in Columns (5) and (6) are eigenvector centralities. Standard errors are clustered at the fund level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

		Degree		Betweenness		Eigenvector	
		(1)	(2)	(3)	(4)	(5)	(6)
OLS-Full Model	Pension fund centrality	-0.492	-0.566	2.616**	2.546*	-0.065***	-0.084***
		(0.331)	(0.384)	(1.166)	(1.330)	(0.022)	(0.024)
	GP centrality	-0.027	-0.205	0.115	-0.071	-0.204	-0.232
		(0.343)	(0.346)	(0.271)	(0.322)	(0.166)	(0.170)
	Consultant centrality	0.001	-0.009	0.091	0.086	0.023**	0.034***
		(0.039)	(0.045)	(0.099)	(0.123)	(0.010)	(0.012)
	Observations	3,333	2,183	3,333	2,183	3,333	2,183
	Adjusted R-squared	0.617	0.623	0.620	0.625	0.620	0.629
OLS-Basic Model	Pension fund centrality	-0.534*	-0.516*	2.051**	1.747*	-0.033**	-0.030**
		(0.273)	(0.298)	(0.946)	(1.051)	(0.015)	(0.015)
	Observations	3,869	2,527	3,869	2,527	3,869	2,527
	Adjusted R-squared	0.643	0.658	0.644	0.659	0.643	0.658
2SLS-Full Model	Pension fund centrality	-4.422***	-3.697***	42.723	42.397	-0.491***	-0.384**
		(1.396)	(1.411)	(30.394)	(27.609)	(0.175)	(0.155)
	GP centrality	-0.816**	-0.811**	-2.481***	-2.529***	-0.012	-0.081
		(0.359)	(0.360)	(0.801)	(0.849)	(0.159)	(0.152)
	Consultant centrality	0.320***	0.263**	0.296**	0.257*	0.202***	0.160**
		(0.100)	(0.105)	(0.148)	(0.149)	(0.071)	(0.064)
	Observations	1,677	1,494	1,493	1,342	1,677	1,494
	Adjusted R-squared	0.702	0.706	0.605	0.582	0.620	0.659
2SLS-Basic Model	Pension fund centrality	-3.445***	-3.445***	42.547	44.175*	-0.229***	-0.173**
		-2.789**	-2.789**	(27.981)	(26.259)	(0.086)	(0.077)
	Observations	1,894	1,676	1,674	1,497	1,894	1,686
	Adjusted R-squared	0.716	0.721	0.624	0.597	0.686	0.707

D. Empirical results with first-time network centralities replaced by zero

Appendix Table A5: Results of Networks with first-time network centralities replaced by zero

In this table, centrality is formed by transactions between GPs and pension funds over a trailing 5-year window and the first-time network centralities are replaced by zero. Consultant relationships are used in the formation of centrality. Net IRR in Q4, 2019 is the dependent variable. The basic model does not include GP and consultant centrality, and the full model includes these two variables. Only key variables are reported, and other control variables are the same as the main context. Centralities in Columns (1) and (2) are degree centralities; Centralities in Columns (3) and (4) are betweenness centralities; Centralities in Columns (5) and (6) are eigenvector centralities. Standard errors are clustered at the fund level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

		Degree		Betweenness		Eigenvector	
		(1)	(2)	(3)	(4)	(5)	(6)
OLS-Full Model	Pension fund centrality	-0.857**	-1.008**	2.837**	3.157**	-0.047**	-0.065**
		(0.350)	(0.413)	(1.207)	(1.377)	(0.023)	(0.025)
	GP centrality	-0.251	-0.374	0.062	-0.166	-0.129	-0.178
		(0.347)	(0.350)	(0.279)	(0.332)	(0.132)	(0.139)
	Consultant centrality	-0.005	0.013	-0.018	0.001	0.019*	0.028**
		(0.040)	(0.046)	(0.094)	(0.116)	(0.010)	(0.013)
	Observations	3,248	2,126	3,248	2,126	3,248	2,126
	Adjusted R-squared	0.603	0.611	0.604	0.611	0.603	0.612
OLS-Basic Model	Pension fund centrality	-0.749***	-0.708**	2.051**	2.104*	-0.020	-0.019
		(0.287)	(0.317)	(0.998)	(1.180)	(0.015)	(0.015)
	Observations	-0.020	-0.019	3,878	2,527	3,878	2,527
	Adjusted R-squared	(0.015)	(0.015)	0.642	0.658	0.641	0.657
2SLS-Full Model	Pension fund centrality	-2.735***	-2.253**	75.860**	51.151**	-0.382***	-0.281**
		(0.852)	(0.887)	(30.120)	(23.740)	(0.125)	(0.109)
	GP centrality	-0.702*	-0.731**	-1.445**	-1.437**	-0.080	-0.132
		(0.364)	(0.371)	(0.620)	(0.575)	(0.127)	(0.126)
	Consultant centrality	0.201***	0.166**	0.292**	0.185	0.171***	0.128***
		(0.066)	(0.072)	(0.143)	(0.122)	(0.054)	(0.048)
	Observations	1,915	1,692	1,915	1,692	1,915	1,692
	Adjusted R-squared	0.734	0.735	0.489	0.611	0.674	0.705
2SLS-Basic Model	Pension fund centrality	-2.407***	-2.127***	68.353**	47.214**	-0.184***	-0.139**
		(0.785)	(0.791)	(27.965)	(22.831)	(0.065)	(0.060)
	Observations	1,891	1,818	1,891	1,673	1,891	1,683
	Adjusted R-squared	0.729	0.723	0.529	0.625	0.700	0.716

E. Empirical results with Q4, 2022 performance

Appendix Table A6: Q4, 2022 Performance Results

In this table, centrality is formed by transactions between GPs and pension funds over a trailing 5-year window. Consultant relationships are used in the formation of centrality. Net IRR in Q4, 2022 is the dependent variable. The basic model does not include GP and consultant centrality, and the full model includes these two variables. Only key variables are reported, and other control variables are the same as the main context. Centralities in Columns (1) and (2) are degree centralities; Centralities in Columns (3) and (4) are betweenness centralities; Centralities in Columns (5) and (6) are eigenvector centralities. Standard errors are clustered at the fund level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

		Degree		Betweenness		Eigenvector	
		(1)	(2)	(3)	(4)	(5)	(6)
OLS-Full Model	Pension fund centrality	-0.804**	-1.026**	3.490***	3.479***	-0.044*	-0.048*
		(0.357)	(0.410)	(0.972)	(1.136)	(0.024)	(0.025)
	GP centrality	0.085	0.031	0.143	0.073	-0.060	-0.110
		(0.113)	(0.136)	(0.118)	(0.148)	(0.054)	(0.068)
	Consultant centrality	0.007	0.041	0.001	0.058	0.011	0.014
		(0.040)	(0.048)	(0.095)	(0.117)	(0.011)	(0.012)
	Observations	3,218	2,085	3,218	2,085	3,218	2,085
	Adjusted R-squared	0.612	0.626	0.616	0.629	0.612	0.626
OLS-Basic Model	Pension fund centrality	-0.526*	-0.456	2.155**	2.334*	-0.017	-0.015
		(0.296)	(0.332)	(0.926)	(1.223)	(0.017)	(0.017)
	Observations	3,659	2,393	3,659	2,393	3,659	2,393
	Adjusted R-squared	0.650	0.661	0.651	0.663	0.650	0.660
2SLS-Full Model	Pension fund centrality	-2.890***	-3.330***	83.806**	79.271**	-0.401***	-0.438***
		(1.056)	(1.055)	(37.260)	(31.506)	(0.153)	(0.144)
	GP centrality	-0.492***	-0.418***	-1.503***	-1.452***	-0.006	-0.056
		(0.157)	(0.158)	(0.533)	(0.521)	(0.086)	(0.094)
	Consultant centrality	0.237***	0.272***	0.360**	0.305*	0.175***	0.198***
		(0.078)	(0.080)	(0.160)	(0.158)	(0.066)	(0.064)
	Observations	1,584	1,413	1,584	1,413	1,584	1,413
	Adjusted R-squared	0.712	0.730	0.424	0.460	0.647	0.649
2SLS-Basic Model	Pension fund centrality	-1.941**	-2.215**	55.639*	54.281**	-0.150**	-0.149**
		(0.889)	(0.916)	(28.538)	(25.381)	(0.071)	(0.063)
	Observations	1,867	1,641	1,867	1,641	1,867	1,641
	Adjusted R-squared	0.701	0.713	0.587	0.604	0.687	0.701

F. *Empirical results with Q4, 2019 TVPI*

Appendix Table A7: Q4, 2019 TVPI Results

In this table, centrality is formed by transactions between GPs and pension funds over a trailing 5-year window. Consultant relationships are used in the formation of centrality. TVPI in Q4, 2019 is the dependent variable. The basic model does not include GP and consultant centrality, and the full model includes these two variables. Only key variables are reported, and other control variables are the same as the main context. Centralities in Columns (1) and (2) are degree centralities; Centralities in Columns (3) and (4) are betweenness centralities; Centralities in Columns (5) and (6) are eigenvector centralities. Standard errors are clustered at the fund level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

		Degree		Betweenness		Eigenvector	
		(1)	(2)	(3)	(4)	(5)	(6)
OLS-Full Model	Pension fund centrality	-2.894*	-2.783	10.073***	9.336**	-0.196*	-0.217*
		(1.507)	(1.785)	(3.362)	(4.174)	(0.106)	(0.114)
	GP centrality	1.751***	1.405**	1.364***	1.459**	0.414**	0.437*
		(0.520)	(0.632)	(0.483)	(0.667)	(0.206)	(0.261)
	Consultant centrality	0.038	0.118	0.581	0.648	0.086**	0.095*
		(0.161)	(0.200)	(0.425)	(0.549)	(0.043)	(0.051)
	Observations	3,128	2,011	3,128	2,011	3,128	2,011
	Adjusted R-squared	0.575	0.581	0.576	0.583	0.573	0.581
OLS-Basic Model	Pension fund centrality	-2.088	-1.589	8.185***	6.535*	-0.058	-0.054
		(1.299)	(1.525)	(3.039)	(3.969)	(0.075)	(0.078)
	Observations	3,803	2,417	3,803	2,417	3,803	2,417
	Adjusted R-squared	0.597	0.606	0.598	0.607	0.597	0.606
2SLS-Full Model	Pension fund centrality	-9.988***	-9.025***	406.924**	287.530**	-1.299***	-1.144**
		(3.404)	(3.481)	(191.925)	(135.717)	(0.470)	(0.447)
	GP centrality	0.048	-0.085	-2.475	-0.163	1.313***	1.156***
		(0.724)	(0.706)	(2.244)	(1.846)	(0.404)	(0.392)
	Consultant centrality	0.931***	0.771***	2.296***	1.839***	0.580***	0.515**
		(0.291)	(0.296)	(0.412)	(0.376)	(0.210)	(0.203)
	Observations	1,505	1,345	1,505	1,345	1,505	1,345
	Adjusted R-squared	0.616	0.626	0.234	0.434	0.580	0.603
2SLS-Basic Model	Pension fund centrality	-7.051**	-6.732**	270.339**	213.956**	-0.526**	-0.454**
		(2.939)	(2.957)	(133.095)	(106.913)	(0.231)	(0.207)
	Observations	1,789	1,574	1,789	1,574	1,789	1,574
	Adjusted R-squared	0.634	0.642	0.483	0.549	0.623	0.636

G. *Empirical results with non-overlapping centralities*

Appendix Table A8: Non-overlapping Centrality Results

In this table, centrality is formed by transactions between GPs and pension funds over a trailing 5-year window. Consultant relationships are used in the formation of centrality. Net IRR in Q4, 2019 is the dependent variable. All centralities are the residue values that regress one type of centralities on the other two types. The basic model does not include GP and consultant centrality, and the full model includes these two variables. Only key variables are reported, and other control variables are the same as the main context. Centralities in Columns (1) and (2) are degree centralities; Centralities in Columns (3) and (4) are betweenness centralities; Centralities in Columns (5) and (6) are eigenvector centralities. Standard errors are clustered at the fund level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

		Degree		Betweenness		Eigenvector	
		(1)	(2)	(3)	(4)	(5)	(6)
OLS-Full Model	Pension fund centrality	-0.249	-0.123	1.903**	1.831*	-0.027	-0.030
		(0.270)	(0.304)	(0.911)	(1.082)	(0.021)	(0.021)
	GP centrality	-0.366*	-0.489**	0.898	1.112*	0.016	0.019
		(0.201)	(0.215)	(0.553)	(0.631)	(0.017)	(0.019)
	Consultant centrality	-0.081	-0.252	0.349	0.054	0.046**	0.056**
		(0.252)	(0.298)	(0.810)	(0.926)	(0.023)	(0.025)
	Observations	3,591	2,355	3,591	2,355	3,634	2,355
	Adjusted R-squared	0.644	0.658	0.646	0.660	0.643	0.658
OLS-Basic Model	Pension fund centrality	-0.405	-0.303	2.102**	2.137**	-0.009	-0.012
		(0.259)	(0.295)	(0.831)	(1.058)	(0.018)	(0.019)
	Observations	3,878	2,527	3,878	2,527	3,878	2,527
	Adjusted R-squared	0.641	0.657	0.643	0.659	0.640	0.656
2SLS-Full Model	Pension fund centrality	-15.799	-33.679	24.627***	23.093**	-0.431***	-0.322***
		(11.097)	(52.402)	(8.308)	(9.435)	(0.153)	(0.117)
	GP centrality	0.166	0.028	-0.856	-0.719	0.039*	0.041**
		(0.480)	(1.025)	(0.710)	(0.770)	(0.023)	(0.020)
	Consultant centrality	3.824	8.212	-4.075***	-4.576***	0.264***	0.207***
		(2.535)	(12.341)	(1.299)	(1.440)	(0.085)	(0.065)
	Observations	1,796	1,589	1,796	1,589	1,796	1,589
	Adjusted R-squared	0.014	-2.866	0.691	0.697	0.613	0.672
2SLS-Basic Model	Pension fund centrality	-30.638	47.906	22.433***	20.117**	-0.302**	-0.205**
		(43.766)	(120.815)	(8.436)	(9.653)	(0.120)	(0.095)
	Observations	1,891	1,673	1,891	1,673	1,891	1,673
	Adjusted R-squared	-2.231	-7.148	0.692	0.696	0.660	0.700