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

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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 and better first-time fund manager selection. Pension funds that target high expected returns, generate lower short-term returns, implement more aggressive performance benchmarking standards, 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 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

Pension funds and Commercial Real Estate (CRE) have long and interactive relationships (Riddiough (2020)). Pension funds invest in CRE as part of their alternative strategy, and such an alternative strategy is called Private Equity Real Estate (PERE). The allocation to CRE by pension funds ranges from less than 1% to more than 15% (Preqin (2021)). PERE is becoming an increasingly crucial risky alternative as its allocation to it helps justify higher liability discount rates for pension funds to lower the present value of their liabilities (Andonov, Bauer, and Cremers (2017)), and it provides a "volatility veil" for pension funds (Riddiough (2020)). Pension funds follow the classical Private Equity (PE) investment structures[2] and only have the right to decide whether to invest in a specific fund and the commitment amount. However, they are not involved in fund management, which General Partners (GPs) charge. This structure stresses the role of networks in fund selections and raises the research question: how do networks influence pension fund investment performance? What are the mechanisms behind network formation?

We analyze pension fund network centrality through three distinctive dimensions. The first dimension is a degree measurement and simply counts the number of connected participants for each pension fund. The second dimension is a betweenness measurement which quantifies the extent to which one pension fund accesses the whole network structure. A higher value means pension funds access parts of networks that other participants do not have. The last network dimension quantifies how well pension funds connect to other influential participants and is called

[2] See Appendix for details.

eigenvector measurement. Three types of participants comprise the whole PERE network structure: i) pension funds, ii) GPs, and iii) consultants. We incorporate direct networks between pension funds and GPs, as well as indirect networking through consultants and explicitly distinguish pension fund networks from connected GPs' and consultants' networks.

We introduce a novel instrument variable (pension fund asset value) to solve the endogeneity issue of networks. Both our OLS and 2SLS results show that pension funds' network centralities have important and distinctive roles in pension fund performance. After controlling the connected GP and consultant network centralities, pension funds that connect to more or more influential participants experience worse performance (the results of "bad" networks). A one standard deviation increase in degree (eigenvector) centralities causes a 429 (566) basis point drop in their average performance; on the other hand, if pension funds have better access to the whole structure, and hence show a higher betweenness centrality score, their performance improves (the results of "good" networks). A one standard deviation increase in the betweenness centrality score results in a substantially 1107 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 a GP with central positions in the network experience worse performance. A one standard deviation respective centrality increase worse pension fund performance by 193 to 234 basis point. Alternatively, consultants can improve pension fund performance by 127 to 458 basis points with one standard respective centrality increase.

The distinctive role of networks in pension fund performance begs the question of what it implies to have a high centrality for pension funds and how it translates to performance. We analyze this issue by looking into the relationships between network centrality and fund manager selection. We build four novel switching rate indexes to capture different aspects of pension fund and GP relations. It is found that pension funds with weaker networks are locked in their pre-existing GP relations, experiencing lower switch rates and investing in pre-existing GP's follow-on funds which perform poorly. In contrast, pension funds with stronger networks move around the network more. We also find that pension funds with stronger networks hold more one-off investments that perform well, while pension funds with weaker networks experience worse one-off investment performance.

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 fund forms such network structures and what factors influence the three dimensions of networks. We examine three perspectives: asset growth rates, benchmark standards, and CEO and board of trustee turnover rates. The back end analyzes how networks affect pension fund investment strategies. From the front end, we find that high fund contributions, low short-term investment returns, and high expected returns adversely incentivize pension funds to form weaker networks. One standard deviation changes in each variable cause 292, 18, and 279 basis point return decreases, respectively. A pension fund with strong (median) benchmarks averages 779 (424) basis points lower returns with better connections compared to when indexes are not identified. Turnovers of CEOs and the board of trustees lead pension funds to enter weaker networks. On the one hand, turnovers of CEOs cause pension funds to invest more (higher degree centralities) and this causes a 163-basis point return decrease. On the other hand, board of trustee turnovers lead to bad network formations and suppress good networks. One standard deviation increase in the turnover rates causes a 254-basis point decrease in returns. We then analyze the back end by exploring 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[3] regulations that require further contributions from underfunded pension funds. Andonov, Bauer, 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

[3] Governmental Accounting Standards Board.

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[4] 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[5]. 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 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.

[4] We get similar results when constructing networks based on the past 3-, 4-, 6-, 7-years transactions. See Appendix for details.

[5] Some pension funds do care whether there are other big or influential LPs investing in the same funds (the lead and follower model).

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[6].

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.

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

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

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[7] 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[8].

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

[7] Consultants are ranked by advised investment numbers.

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

could include due diligence, which pension funds use to guarantee nothing important is missing in board meetings.

II. Sample and Data

The data for our analysis is from Preqin and Public Plans Database (PPD). Preqin collects information on public and private funds based on the Freedom of Information Act (FOIA) and its relationships with GPs and LPs. PPD contains plan-level data from 2001 through 2020 for 200 public pension plans covering about 95 percent of public pension membership and assets nationwide. About 85.50% of pension funds' investments are covered in Preqin. The typical private equity real estate has a fund life of 10 years. Pension funds usually only have a role in selecting funds and deciding commitment amounts in the fund marketing stage, which is about one year, after which, pension funds can merely contribute commitments and receive distributes. They do not play a role in fund management, and GPs charge the administration.

Preqin starts to report funds' net-of-fee internal rate of return (Net IRR) quarterly from the second year after the fund vintage. Vintage is the year when GPs start to call commitments or invest in projects. IRRs are calculated by cash flows generated by funds. Preqin reports the quarterly net-of-fee IRRs provided by GPs or pension funds. The reported performance in Preqin shares similar features as other main private equity data providers, Burgiss and Cambridge Associates, for example. 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[9].

[9] 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.

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[10]. 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.

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

[10] Results are robust if we just use closed-end funds to build networks.

consultants to get the precise consultants[11]. 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%[12]. 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

[11] 8.60% (1010) investments are deleted.

[12] 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 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.

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.

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[13] with performance data, with the average fund size at $695.157 Mn and 6.940% fund size-

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

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[14]. 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.

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

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

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 has described a typical pension fund network structure which includes three participant types: pension funds, GPs, and consultants. This section explores how pension fund networks influence performance with the control of GP and consultant networks that pension funds connect to. Specifically, within a pension fund, how the change in centralities would influence investment performance?

A. The Basic Network Model

$$IRR_{l,g,f} = \alpha_0 + \alpha_1 * LP\ Centrality_{l,t-5:t-1} + \alpha_2 * GP\ Centrality_{l,t-5:t-1} + \alpha_3 * Consultant\ Centrality_{l,t-5:t-1} + \alpha_4 * X_l + \alpha_5 * X_g + \alpha_6 * X_f + Vintage_f + LP_l + GP_g + \varepsilon_{l,g,f} \quad (4)$$

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), and pension fund investment sequence. 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. 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. Columns (1), (3), and (5) are results without pension fund commitment amounts, while columns (2), (4), and (6) include this variable. We find heterogeneous network roles in the performance. One standard deviation increases in degree and eigenvector centrality within a pension fund relatively lower average returns by 7.482 to 12.675 percent. Those amounts to 72 basis points to 121 basis points decrease in returns based on the average fund returns in Table II. The negative effects indicate pension funds that diversely connect to many GPs through investments or invest in influential GPs' funds potentially get a lower return. The betweenness centrality results are contrary to those in degree and eigenvector centrality. One standard deviation increase in betweenness centrality causes a relative 9.341 to 12.408 percent increase in average performance, which equals a 90 to 118 basis points increase in returns. A higher betweenness centrality means more access to networks and benefits pension funds in gaining higher returns. GP and consultant centralities are mostly insignificant.

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) argue that reverse causality between networks and performance should not be a concern. Networks are constructed based on past transactions before fund vintage years, and fund returns are realized years later. Thus, there is at least a five-year spread between networks and fund performance. However, this argument ignores the possibility that pension funds may network with other market participants now to achieve higher returns in the future. Such expectation effects are ignored in Equation (4) and can potentially cause endogeneity issues. Another source of endogeneity comes from network persistence. The current network may persist until the time when funds realize returns. If this happens, even though we used lagged 5-year transactions to build network centralities, the network structure may be quite similar to the one when returns are realized. We call this the persistence effect. These two effects require instrumental variables to get an unbiased estimate of network effects.[15]

We first include expected returns at the pension fund level to address the expectation effects. Two variables are used from PPD, i.e., pension fund assumed returns and 5-year investment returns. Pension fund assumed returns are expected returns, and 5-year investment returns are the mean investment returns over the past five years. These two variables capture pension fund-level expectations. However, public pension funds might have different expected returns for each fund they invest in. Furthermore, it still does not address the persistence effect.

We introduce the lagged 5-year pension fund asset value as an instrument for the endogenous network variables. The lagged 5-year asset level is a size variable that can directly influence pension fund network structures. Because the PERE only represents about 5% of total asset values, and this variable is at least ten years before funds realize returns, it is unlikely to affect fund returns managed by GPs through error terms.

TABLE IV ABOUT HERE

By controlling the lagged pension fund asset value in regressions, we interpret the lagged 5-year asset level as changes in asset values. This means that conditional on a fixed one-year lagged asset value, a higher lagged 5-year asset level suggests a lower asset increment over the past four years. One concern with this instrument, however, is that the increment in assets over the past four years correlates to error terms in performance regressions. Especially, if asset values increase in expectation to achieve higher returns, then our instrumental variables would not be exogenous. To address this concern, we analyze where asset increment variations come, and whether it increases (or decreases) due to performance expectations. We use two variables to proxy for pension fund

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

expectations: the reported assumed (expected) returns of pension funds and the pension fund 5-year average return. Table IV treats geometric average asset growth[16] over the lagged 5 to lagged 1 year as the dependent variable and lagged six-year pension expected returns, payouts, and contributions as independent variables. Column (1) of Table IV only includes the L6. assumed (expected return); Column (2) only includes the L6. 5-year investment return; Column (3) includes both the L6. assumed (expected return) and the L6. 5-year investment return. We find that lagged expected returns (no matter proxied by assumed returns or 5-year investment returns) do not significantly influence asset growth in the following years. The primary asset growth sources are projected contribution rates and average benefits. Overall, the increment of asset growth is mainly due to contribution and payout factors (fund obligations) instead of expected return factors. Thus, the asset value of each pension fund does not enter performance terms and should be exogenous to the performance at least ten years later. Intuitionally, real estate funds are managed by GPs and are out of pension fund controls. Pension funds' overall level asset changes could not influence the performance of GPs' funds that are invested by many other pension funds if not through expectation effects.

C. Two-stage Least Square Results

Figure 3 ABOUT HERE

We carry out the Two-Stage Least Square (2SLS) regressions based on the instrumental variable. Figure 3 illustrates the empirical strategies. Take Fund A with the vintage year of 2015 for example and assume this fund gains pension fund B's investment. We use Fund A' s return in Q4, 2019 as the performance and construct pension fund B's networks by its previous transactions from 2009

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[16] The geometric average asset growth rate is calculated by dividing the lagged 1-year asset value by the lagged 5-year asset value, and then taking that ratio to the 1/4 power.

to 2014. Because most asset values are reported in the middle of each year, pension fund B's asset value is then used in the middle of the year 2010 as the instrumental variable. With the control of the asset value in the middle of 2014, these two asset values measure the asset change between the middle of 2009 and 2014. The asset change overlaps with the network formation periods by four years, so it correlates with the network formation period.[17]

Table V presents the 2SLS results. Columns (1), (3), and (5) are the results without the control of log(Pension fund commitment), while Columns (2), (4), and (6) are the ones with the commitment variables. Because some pension fund commitment variables are missing, the ones with this variable have fewer samples. All results are consistent with the OLS regressions but with more significance and larger influence magnitudes. Pension fund degree and eigenvector centrality significantly and negatively affect pension fund performance. One standard deviation increase in pension fund degree centrality causes a 39.570 to 46.622 percent relative decrease (429 to 493 basis points) in average performance. One standard deviation increase in pension fund eigenvector centrality causes 52.202 to 63.102 percent relative decreases (566 to 667 basis points) in average returns. The betweenness centrality effect is even stronger in 2SLS. One standard deviation increase in pension fund betweenness centrality could bring 76.648 to 104.775 percent higher returns relatively. These amount to 831 to 1107 basis points.

TABLE V ABOUT HERE

The negative effect of GP centrality on pension fund returns still holds. One standard deviation increase in GP centrality would cause an 18.253 to 21.549 percent relative drop (193 to 234 basis points) in average performance. However, the consultant centrality influence is positive in all the

[17] 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.

2SLS regressions, and the effects are 10.881 to 43.308 percent relative increases (127 to 458 basis points) in pension fund average returns. This means that although most public pension funds use consultants, employing better-connected consultants benefits pension funds.

In contrast to Hochberg, Ljungqvist, and Lu (2007), we find networks are not always "good" or "bad". Having access to more networks is a good strategy because it has the shortest paths to all other participants (higher betweenness centrality). Pension funds may get enough information to distinguish which funds can generate higher returns in the future or distinguish good-performing GPs. However, if pension funds blindly connect to many participants, which increases the pension fund degree centrality, or they carelessly connect to other influential participants, the information is not well filtered. Such kinds of networks harm pension funds' performance.

Again, Hausman tests in Table V confirm the endogeneity issue. We further test validations of the instrumental variable. First, we perform the Kleibergen-Paap rk test, which is an under-identification test. Then, we apply the weak identification test because weak instruments lead to severely biased estimates. Our results in Table V strongly reject the null hypothesis that our instrument variable is under-identified or weak. Finally, because the endogenous and instrumental variables are of the same size, there are no over-identification issues, and our regression is exactly identified.

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

We found the distinctive roles of networks in performance. However, what are the implications behind a high network centrality? 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). [18] 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 VI 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 VI. 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

[18] 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 VI 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) of a pension fund with the control of vintage, fund size, and year fixed effects. We first normalize pension fund three centrality measurements by mean and standard deviation before getting the spread. Panel D of Table VI 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.

E. Robustness Tests

We carry out several robustness tests to address concerns about our results. The first concern is that our consultant data is based on news, and we might not collect all the consultants employed by pension funds. However, our public pension funds' consultants mostly come from PPD, and this provides us a complete consultant data, at least for public pension funds. In addition, we re-run all the regressions with vintage years starting in 2006. The main assumption is that the more recent consultant information should be more reliable and complete. The results remain robust.

The second concern is that we build network centralities based on a 5-year window. But networks may be less or more persistent. Therefore, we build network centralities with a 3-year, 4-year, 6-year, and 7-year transaction window to alleviate this concern. The results remain robust (See Appendix for details).

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 concern is whether each centrality measurement captures the other two centrality components. For example, although the degree centrality has a clear meaning of frequency, it still correlates with betweenness and eigenvector centralities. We solve this issue 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 analyzes 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, especially risky investment behaviors (the back end). We analyze network formations through three channels: asset growth components, benchmark standards, and CEO and board of trustee turnover rates. The back end is investigated by whether pension funds increase their risky investment behaviors.

IV.I. Front End: Network Formation

A. Asset Growth Rates

The first stage of the 2SLS model (Table V) shows that at the investment level, a faster asset growth rate over the past four years (lower lagged five-year asset values) causes increases in degree and eigenvector centrality but a decrease in betweenness centrality. The higher degree and eigenvector centralities in turn harm pension fund returns, while betweenness centralities help increase pension fund returns. In this section, we decompose asset growth components. Because these asset growth components are fund sources for investments based on which we build networks, we run the regressions with network centralities as dependent variables and lagged six-year asset growth components as independent variables to investigate how networks form.

The annual asset growth into its components:

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

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. Regressions are weighted by investment numbers at the pension fund level. Results without these variables are largely similar. We find that contribution is the main source for the increase in degree and eigenvector centralities.

When pension funds contribute more, they form more bad networks. One standard deviation increase in pension contribution leads to 0.003 and 0.077 increases in degree and eigenvector centralities, which in turn reduces 0.773 % and 2.149% returns using coefficients in Table V with the control of commitment amounts. Those are a total of 292 basis point decrease in returns. However, contributions are not significant in betweenness centralities. A higher contribution does not mean pension funds can enter the right networks, and this further confirms good networks are not easy to build.

Expected returns have a positive effect on bad networks but a negative effect on good networks. When pension funds are eager for a higher return, they end up in bad networks. One standard deviation increase in expected returns causes 0.001 and 0.030 increases in degree and eigenvector centralities and 0.0002 decreases in betweenness centralities, which in turn lead to a 279-basis point reduction in returns. Situations could be even worse if pension funds have a bad tracking record in the past 1-year returns. One standard deviation decrease in 1-year returns can lead to 0.001 increases in degree centralities, which causes 18-basis point reductions in returns. 5-year return changes have homogenous effects on all kinds of networks. The overall effect is only 49-basis point changes in returns with one standard deviation change. One thing to note is that although a better past 5-year performance led to stronger connections, it also blocks pension funds from accessing other participants, thus reducing network access (betweenness centralities).

B. Benchmark Standards

Pension fund benchmarks can influence pension fund investment behaviors. A stricter benchmark standard may make pension funds chase higher returns and enter bad networks. To test this assumption, we do a rough benchmark rating based on how strict the benchmark is. A stricter benchmark generally means a higher benchmark return over the same sample period. Based on the PPD data, we merge our investment data with the pension fund benchmark standard. The benchmark ratings are mainly based on three indices: the NFI/ODCE index[19], the private index, and the public index. Pension fund benchmarks are classified into 6 categories: 0-Positive allocation, but not index identified; 1-less than NPI/ODCE only (with or without CPI); 2- equal to NPI/ODCE only (within +/- 100 bps); 3- greater than NPI/ODCE only; 4- Combined public/private index; 5- Public index only; 6- Unspecified/Custom/Blended/Other.

TABLE VIII ABOUT HERE

We delete category 6 as they are unspecified and further classify categories 1-2 as median benchmarks and 3-5 as strong benchmarks. We leave category 0 as the base category. We lag six years for the benchmark rating as the benchmarks as independent variables and use network centrality as the dependent variable with the control of LP and vintage year fixed effects. As networks are formed over the past five years, the lagged six-year benchmark ratings are non-overlapping with the network centralities. For our 2,312 matched investments, we have 904 investments using the median strict standard, 479 investments using the strong benchmarks, and the remaining 929 investments using the base standards. Table VII reports the results. Pension funds with median benchmark ratings show a strong preference for bad networks with 0.004 higher degree centralities and 0.113 higher eigenvector centralities. This adds up to a 424-basis point lower returns based on the average returns. Pension funds with strong benchmarks are even worse. They have 0.006 higher degree centralities and 0.221 higher eigenvector centralities. This means 779 basis points decrease in returns compared to pension funds with the base case (positive allocations, but not index identified).

[19] The NFI/ODCE index is the NCREIF fund index- Open End Diversified Core Equity.

C. 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 analysis directly looks at how relational networks transit to transactional networks.

We hand-collected 1,338 CEO names and 14,492 board of trustee names of 111 public pension funds from 2001 and 2015. CEO turnover measures whether there is a CEO turnover before we form the networks. The board of trustee turnover rate is calculated as members left of the year divided by the average member numbers between the beginning. We run the network centralities on the lagged 6-year two turnover rates as the network centralities are built based on the past 5 years' transactions. CEO turnovers happen every 4.5 years, while the board of trustee turnover happens about 3-5 years with each member having different terms.

TABLE IX ABOUT HERE

Table IX shows the results. We found that higher board of trustee turnover rates lead to weaker networks. One standard deviation increase in the board of trustee turnover rates causes a 254-basis point decrease in pension fund returns (0.422% from degree, 1.276% from betweenness, and 0.841% from eigenvector). CEO turnover also has a bad influence on performance but mainly through degree centralities. New CEOs are more likely to start new investments, which causes a 163-basis point decrease in returns. CEO and trustee board member turnovers both negatively influence networks, which in turn harms performance. However, the mechanism behind is unknown, and we leave it for future study.

IV.II. Back end: Risky Investments

We further test what causes the negative or positive relationships between networks and performance by investigating how networks influence pension funds' risk-taking behaviors. We assume that pension funds may be misled by their networks to invest in risky assets. Because those assets are risky, the return may experience considerable variation, potentially harming pension funds' performance.

Different strategies in PERE possess heterogeneous risks in nature. We classify strategies into three types by strategies' risk levels. The lowest risk level strategies include real estate debt funds and real estate core/core+ funds. Real estate core/core+ funds use relatively low risks and mainly invest in core assets. Real estate debt funds are loans secured by real estate, including B-note, CMBS, preferred equity, etc. The middle-risk level strategy is the value-added fund, and the highest-risk level funds are real estate opportunistic and real estate distressed funds. Value-added funds have lower leverage values and invest in lower-risk real estate than opportunistic funds. Real estate distressed funds invest in distressed properties. We label the lowest-risk level strategies, middle-risk strategies, and the highest risk level strategies as 1, 2, and 3, and use this variable as the dependent variable[20].

TABLE X ABOUT HERE

Table X presents the results. When incorporating all three participants, we find that connecting to more or more influential participants enhances risk-taking behaviors. Combined with the unweighted poor performance of fund strategies in high-risk categories, weaker networks mislead pension funds into the wrong investments. Consultant centralities could help to reduce the risk-taking in degree and eigenvector centralities. Having more access to the whole network structure (higher betweenness centrality) does not have a significant influence on risky investments.

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

V. Conclusions

In this paper, we investigate how pension fund networks in PERE influence their performance and explore the mechanisms behind network formation. We build pension fund networks through direct and indirect connections through consultants between pension funds and fund managers, and separately investigate pension funds', fund managers', and consultants' networks. We find that networking plays an important and distinctive role in pension funds' performance. It is essential for pension funds to form good networking. Private equity, by its nature, is not transparent. Therefore, it needs pension funds' skills to access more networks, which helps distinguish good investment projects. Simply networking with more or more influential participants does harm pension funds' performance. We further investigate the mechanisms of how networks influence performance from both the front and back ends. At the front end, we explore how networks form. At the back end, we examine how networks influence risk-taking. We find a dangerous trap in pension funds' PERE investments: pension funds that target high expected returns, generate lower short-term returns, implement more aggressive performance benchmarking standards, require higher employee pension fund contributions, and experience higher CEO and board turnover rates form weaker networks that impair their performance. Pension funds with weak networks stick to the pre-existing GPs' follow-on networks and are not good at selecting their one-off investments. The weak networks incentivize them to take more risks in investments that perform poorly. In contrast, pension funds with more access to networks switch among GPs and select good-performing funds. We also confirmed the role of consultants in assisting pension funds to access good investments.

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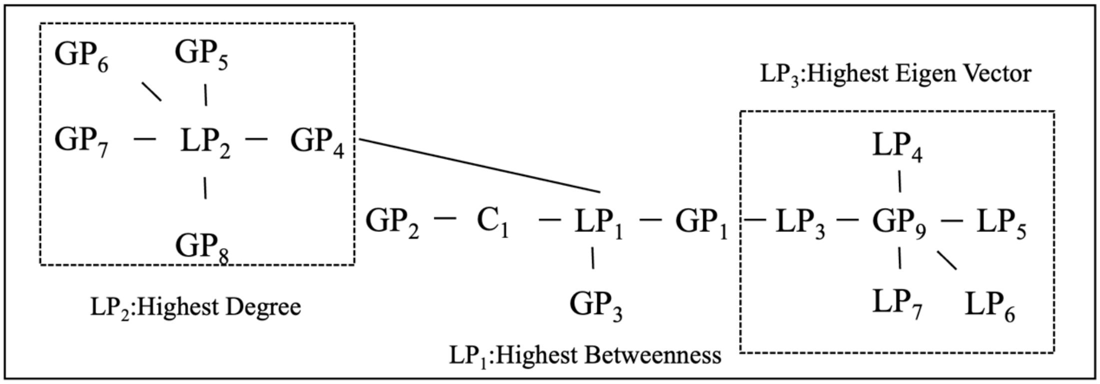


Figure 1. A typical network structure.

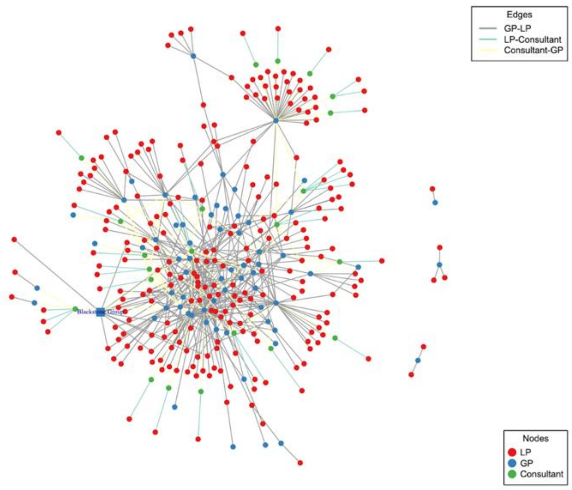


Figure 2. Network graph example: 2001 networks among pension funds, GPs, and consultants.

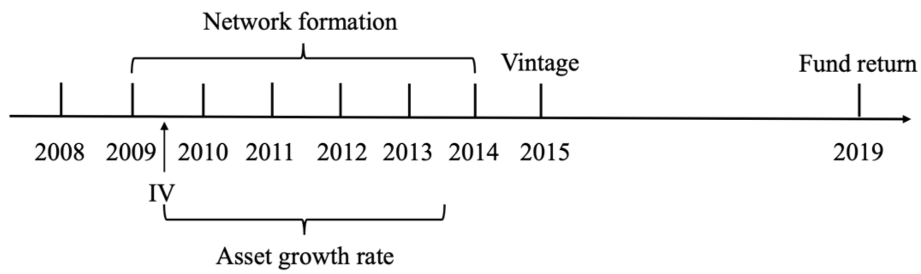


Figure 3. An empirical strategy example.

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. 1^{st} 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 (1^{st})	0.058 (1^{st})	0.154 (1^{st})	US	-	1,100,000
NEPC	47	425	1986	0.144 (1^{st})	0.073 (1^{st})	0.056 (1^{st})	US	11,500	1,100,000
Pension Consulting Alliance	10	416	1988	0.191 (1^{st})	0.040 (1^{st})	0.595 (1^{st})	US	-	1,374,000
Callan Associates	39	560	1973	0.235 (1^{st})	0.063 (1^{st})	0.354 (1^{st})	US	75,000	2,300,000
Aon Hewitt Investment Consulting	62	675	1974	0.209 (1^{st})	0.094 (1^{st})	0.333 (1^{st})	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	1519	0.019	0.029	0.000	0.006	0.180
Eigenvector		0.039	0.143	0.000	0.005	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	-0.802***	-0.826**	2.868**	3.331**	-0.045**	-0.052**
	(0.304)	(0.347)	(1.196)	(1.378)	(0.022)	(0.022)
GP Centrality	-0.242	-0.353	0.068	-0.139	-0.126	-0.166
	(0.346)	(0.353)	(0.278)	(0.334)	(0.132)	(0.140)
Consultant Centrality	-0.009	-0.021	-0.004	-0.000	0.017**	0.019**
	(0.029)	(0.032)	(0.061)	(0.071)	(0.008)	(0.009)
log(Pension fund commitment)		-0.000		-0.002		-0.000
		(0.004)		(0.004)		(0.004)
Pension fund firm type(Public pension fund=1)	-0.019	0.060*	-0.011	0.066*	-0.014	0.039
	(0.027)	(0.036)	(0.028)	(0.037)	(0.027)	(0.036)
Pension fund investment sequence	0.000	0.000	0.000	0.000	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	-0.061**	-0.055*	-0.059**	-0.054*
	(0.031)	(0.031)	(0.030)	(0.030)	(0.029)	(0.029)
log(Fund size)	0.001	0.002	0.001	0.002	0.001	0.002
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Constant	0.157**	0.106	0.135**	0.080	0.152**	0.103
	(0.068)	(0.088)	(0.066)	(0.083)	(0.066)	(0.085)
Observations	3,248	2,126	3,248	2,126	3,248	2,126
Adjusted R-squared	0.605	0.612	0.606	0.613	0.605	0.612
Pension fund firm FE	YES	YES	YES	YES	YES	YES
GP firm 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	-3.115***	-2.713***	84.211***	60.565**	-0.340***	-0.279***
	(0.893)	(0.913)	(32.108)	(25.304)	(0.104)	(0.096)
GP Centrality	-0.817**	-0.831**	-1.281**	-1.303**	-0.122	-0.172
	(0.373)	(0.378)	(0.649)	(0.607)	(0.131)	(0.128)
Consultant Centrality	0.125***	0.109***	0.329***	0.280***	0.121***	0.101***
	(0.036)	(0.039)	(0.124)	(0.106)	(0.034)	(0.032)
log(Pension fund commitment)		0.003		-0.004		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	0.261***	0.243***	0.257***	0.226***	0.272***	0.258***
	(0.068)	(0.056)	(0.067)	(0.050)	(0.069)	(0.059)
L.Assumed (expected) return	-1.737**	-1.609**	-1.000	-1.057	-0.693	-0.845
	(0.714)	(0.798)	(0.874)	(0.895)	(0.805)	(0.861)
L.1-year investment return	0.008	0.001	-0.137*	-0.133*	0.004	-0.002
	(0.024)	(0.026)	(0.080)	(0.073)	(0.027)	(0.028)
L.5-year investment return	-0.147	-0.121	-0.052	-0.046	-0.157*	-0.149*
	(0.092)	(0.093)	(0.141)	(0.125)	(0.090)	(0.089)
GP fund sequence	0.003**	0.004**	0.003**	0.004**	0.004***	0.004***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
GP listed=1	-0.030	-0.031	-0.046*	-0.039	-0.045*	-0.045*
	(0.024)	(0.024)	(0.027)	(0.025)	(0.025)	(0.024)
log(Fund size)	0.026***	0.026***	0.030***	0.030***	0.025***	0.025***
	(0.008)	(0.007)	(0.009)	(0.008)	(0.008)	(0.007)
Constant	-0.221***	-0.252***	-0.257***	-0.231**	-0.414***	-0.403***
	(0.080)	(0.085)	(0.096)	(0.094)	(0.111)	(0.115)
Observations	1,619	1,450	1,619	1,450	1,619	1,450
Adjusted R-squared	0.693	0.697	0.327	0.485	0.636	0.660
Pension fund firm FE	YES	YES	YES	YES	YES	YES
GP firm 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):	-0.056***	-0.057***	0.002**	0.003**	-0.514***	-0.548***
Pension fund asset value lag 5 years	(0.009)	(0.011)	(0.001)	(0.001)	(0.132)	(0.156)
Hausman p-value	0.010	0.049	0.001	0.005	0.003	0.021
Under identification test						
Kleibergen-Paap rk F statistic	81.966***	89.584***	14.345***	17.841***	73.988***	79.050***

Weak identification test						
Cragg-Donald Wald F statistic	228.702	319.097	17.743	22.059	184.078	179.046
Kleibergen-Paap rk Wald F statistic	127.139	131.713	12.033	14.816	109.301	111.393

Table VI 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	0.008**	0.008**	0.007**			
	(0.003)	(0.003)	(0.003)			
Betweenness-Eigen				0.004*	0.004*	0.004
				(0.002)	(0.002)	(0.002)
log(Fund size)			0.011			0.011
			(0.008)			(0.008)
Constant	0.009	0.005	-0.054	0.012	0.008	-0.054
	(0.028)	(0.034)	(0.054)	(0.028)	(0.034)	(0.054)
Observations	1,534	1,534	1,526	1,534	1,534	1,526
Adjusted R-squared	0.417	0.419	0.426	0.414	0.417	0.424
Vintage FE	YES	YES	YES	YES	YES	YES
Strategy FE	YES	YES	YES	YES	YES	YES

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: Benchmarks

In this table, centrality is formed by transactions between GPs and pension funds over a trailing 5-year window. Pension fund benchmark ratings are classified into three categories, 0-Positive allocation but not index identified, moderate, and strong. 0-Positive allocation but not index identified is the base variable. All ratings are lagged by six years to be non-overlapping with centralities. 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. Moderate Benchmark Rating	0.004***	-0.598*	0.113***
	(0.001)	(0.319)	(0.014)
L6. Strong Benchmark Rating	0.006***	-0.079	0.221***
	(0.001)	(0.149)	(0.020)
Constant	0.004***	0.797**	-0.015
	(0.001)	(0.350)	(0.018)
Observations	2,286	2,286	2,286
R-squared	0.847	0.698	0.627
Pension Fund firm FE	YES	YES	YES
Fund vintage FE	YES	YES	YES

Table IX 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	0.006***	0.238*	0.020
	(0.001)	(0.136)	(0.019)
L6. Board of Trustee turnover rate	0.010***	-1.356***	0.194***
	(0.002)	(0.287)	(0.036)
Constant	0.021***	0.416***	-0.042**
	(0.001)	(0.121)	(0.019)
Observations	1,017	1,017	1,017
R-squared	0.847	0.785	0.624
Pension Fund firm FE	YES	YES	YES
Fund vintage FE	YES	YES	YES

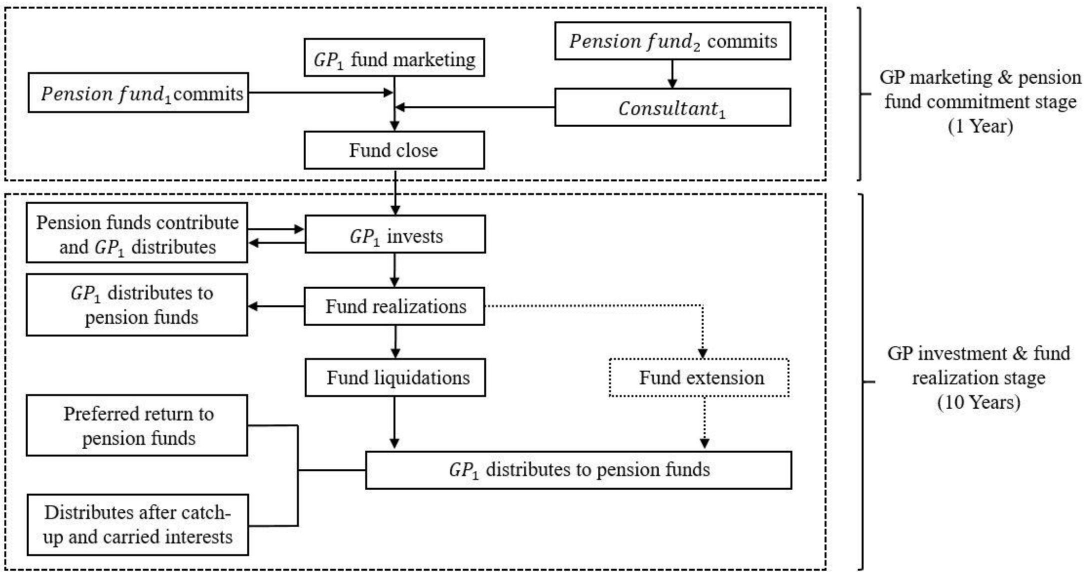
Table X Risk Investment Behavior

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	-1.377***	-1.364***	0.719	2.257*	-0.065***	-0.067***
		(0.391)	(0.450)	(0.849)	(1.361)	(0.024)	(0.025)
	GP centrality	0.175	0.286	-0.525	-0.452	-0.022	-0.009
		(0.482)	(0.546)	(0.416)	(0.457)	(0.137)	(0.141)
	Consultant centrality	0.013	0.016	0.022	0.062	0.020*	0.018
		(0.030)	(0.034)	(0.059)	(0.065)	(0.010)	(0.012)
	Observations	2,656	1,758	2,656	1,758	2,656	1,758
	Adjusted R-squared	0.650	0.658	0.648	0.656	0.647	0.656
OLS-Basic Model	Pension fund centrality	-0.953***	-0.984***	0.361	0.644	-0.023	-0.029**
		(0.277)	(0.329)	(0.291)	(0.425)	(0.014)	(0.015)
	Observations	5,576	2,988	5,576	2,988	5,576	2,988
	Adjusted R-squared	0.619	0.648	0.618	0.646	0.618	0.646
2SLS-Full Model	Pension fund centrality	-2.501***	-2.082**	68.546*	44.743	-0.261***	-0.202**
		(0.837)	(0.904)	(37.249)	(30.750)	(0.086)	(0.084)
	GP centrality	0.605	0.484	-0.484	-0.411	0.339**	0.263*
		(0.449)	(0.456)	(0.487)	(0.482)	(0.158)	(0.156)
	Consultant centrality	0.094**	0.085*	0.199**	0.196**	0.086***	0.066**
		(0.040)	(0.045)	(0.090)	(0.083)	(0.030)	(0.029)
	Observations	1,353	1,214	1,456	1,302	1,353	1,214
	Adjusted R-squared	0.724	0.722	0.551	0.625	0.700	0.710
2SLS-Basic Model	Pension fund centrality	-2.230***	-1.867***	46.331**	29.324	-0.154***	-0.120***
		(0.661)	(0.692)	(23.465)	(20.107)	(0.048)	(0.046)
	Observations	2,044	1,807	2,226	1,961	2,044	1,817
	Adjusted R-squared	0.729	0.728	0.497	0.603	0.712	0.721

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	-1.048***	-1.059***	3.399**	3.724**	-0.053**	-0.055**
		(0.338)	(0.392)	(1.373)	(1.555)	(0.022)	(0.022)
	GP centrality	-0.111	-0.164	-0.144	-0.643	-0.081	-0.088
		(0.349)	(0.387)	(0.429)	(0.603)	(0.135)	(0.143)
	Consultant centrality	-0.001	-0.015	0.028	0.032	0.017**	0.015*
		(0.028)	(0.032)	(0.058)	(0.065)	(0.008)	(0.009)
	Observations	3,056	1,998	3,056	1,998	3,056	1,998
	Adjusted R-squared	0.612	0.626	0.614	0.630	0.610	0.625
OLS-Basic Model	Pension fund centrality	-0.719***	-0.746**	0.652	0.908	-0.020	-0.025*
		(0.261)	(0.307)	(0.416)	(0.652)	(0.014)	(0.015)
	Observations	5,596	2,979	5,596	2,979	5,596	2,979
	Adjusted R-squared	0.618	0.652	0.618	0.651	0.617	0.651
2SLS-Full Model	Pension fund centrality	-2.713***	-2.228***	44.157***	33.108**	-0.271***	-0.210***
		(0.726)	(0.739)	(16.972)	(15.053)	(0.075)	(0.070)
	GP centrality	-0.419	-0.482	-0.926	-1.063*	-0.031	-0.092
		(0.368)	(0.381)	(0.645)	(0.635)	(0.146)	(0.145)
	Consultant centrality	0.075**	0.061*	0.177**	0.164**	0.090***	0.070***
		(0.031)	(0.033)	(0.081)	(0.076)	(0.024)	(0.023)
	Observations	1,716	1,525	1,854	1,641	1,716	1,525
	Adjusted R-squared	0.681	0.686	0.352	0.475	0.650	0.668
2SLS-Basic Model	Pension fund centrality	-2.146***	-1.782***	29.147**	19.258	-0.174***	-0.135***
		(0.635)	(0.652)	(13.354)	(12.107)	(0.055)	(0.051)
	Observations	2,056	1,813	2,245	1,974	2,056	1,823
	Adjusted R-squared	0.726	0.728	0.578	0.637	0.702	0.716

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	-0.453	-0.454	2.633**	2.678**	-0.063***	-0.072***
		(0.288)	(0.319)	(1.158)	(1.333)	(0.021)	(0.022)
	GP centrality	-0.021	-0.184	0.115	-0.055	-0.202	-0.228
		(0.343)	(0.351)	(0.271)	(0.326)	(0.166)	(0.171)
	Consultant centrality	-0.005	-0.029	0.042	0.032	0.022**	0.025***
		(0.028)	(0.031)	(0.064)	(0.075)	(0.009)	(0.009)
	Observations	3,333	2,183	3,333	2,183	3,333	2,183
	Adjusted R-squared	0.618	0.624	0.622	0.627	0.622	0.629
OLS-Basic Model	Pension fund centrality	-0.416	-0.481*	0.996	1.324	-0.025*	-0.030**
		(0.257)	(0.282)	(0.656)	(0.895)	(0.014)	(0.015)
	Observations	5,489	2,918	5,489	2,918	5,489	2,918
	Adjusted R-squared	0.625	0.658	0.625	0.659	0.625	0.659
2SLS-Full Model	Pension fund centrality	-4.287***	-3.637***	39.245	41.443*	-0.387***	-0.311***
		(1.284)	(1.282)	(25.650)	(25.073)	(0.128)	(0.116)
	GP centrality	-0.852**	-0.851**	-2.268***	-2.373***	-0.017	-0.086
		(0.365)	(0.365)	(0.779)	(0.838)	(0.156)	(0.152)
	Consultant centrality	0.162***	0.136***	0.284**	0.318**	0.130***	0.106***
		(0.046)	(0.048)	(0.142)	(0.148)	(0.041)	(0.038)
	Observations	1,677	1,494	1,493	1,342	1,677	1,494
	Adjusted R-squared	0.694	0.699	0.615	0.582	0.651	0.676
2SLS-Basic Model	Pension fund centrality	-3.584***	-2.911***	44.677**	34.570**	-0.287***	-0.217**
		(1.129)	(1.109)	(17.691)	(15.639)	(0.108)	(0.091)
	Observations	2,066	1,821	2,066	1,821	2,066	1,831
	Adjusted R-squared	0.704	0.712	0.459	0.544	0.655	0.686

D. Empirical results with networks formed by transactions over a trailing 7-year window

Appendix Table A4: Results of Networks Formed by Transactions over A Trailing 7-year Window

In this table, centrality is formed by transactions between GPs and pension funds over a trailing 7-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	-0.438	-0.351	3.096***	2.636**	-0.055***	-0.062***
		(0.270)	(0.299)	(1.149)	(1.169)	(0.020)	(0.020)
	GP centrality	-0.599	-0.657*	-0.819	-1.163**	-0.322*	-0.317*
		(0.382)	(0.379)	(0.573)	(0.574)	(0.172)	(0.175)
	Consultant centrality	0.000	-0.023	0.026	0.021	0.019**	0.023***
		(0.027)	(0.029)	(0.067)	(0.079)	(0.008)	(0.009)
	Observations	3,365	2,202	3,365	2,202	3,365	2,202
	Adjusted R-squared	0.623	0.628	0.625	0.633	0.627	0.633
OLS-Basic Model	Pension fund centrality	-0.430*	-0.358	1.367**	1.357*	-0.031**	-0.028**
		(0.249)	(0.261)	(0.605)	(0.761)	(0.014)	(0.014)
	Observations	5,414	2,878	5,414	2,878	5,414	2,878
	Adjusted R-squared	0.633	0.665	0.633	0.665	0.633	0.665
2SLS-Full Model	Pension fund centrality	-7.087***	-5.751**	57.830**	51.444*	-0.437***	-0.326**
		(2.452)	(2.318)	(26.239)	(28.035)	(0.152)	(0.128)
	GP centrality	-0.897**	-0.889**	-0.713	-0.600	-0.089	-0.156
		(0.396)	(0.405)	(0.560)	(0.555)	(0.160)	(0.159)
	Consultant centrality	0.181***	0.148***	0.370*	0.403*	0.146***	0.113***
		(0.059)	(0.056)	(0.200)	(0.234)	(0.048)	(0.041)
	Observations	2,090	1,838	2,090	1,838	2,090	1,838
	Adjusted R-squared	0.645	0.668	0.217	0.268	0.641	0.682
2SLS-Basic Model	Pension fund centrality	-7.550***	-6.049**	59.111**	54.566*	-0.431**	-0.324**
		(2.797)	(2.584)	(27.642)	(30.856)	(0.188)	(0.151)
	Observations	2,066	1,821	2,066	1,821	2,066	1,831
	Adjusted R-squared	0.615	0.648	0.195	0.212	0.559	0.625

E. *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	-0.656**	-0.663**	1.483**	1.874**	-0.046**	-0.053***
		(0.272)	(0.302)	(0.577)	(0.737)	(0.019)	(0.020)
	GP centrality	-0.253	-0.361	0.095	-0.039	-0.187	-0.150
		(0.321)	(0.339)	(0.241)	(0.285)	(0.120)	(0.128)
	Consultant centrality	0.025	0.008	0.057	0.046	0.022***	0.024***
		(0.023)	(0.025)	(0.047)	(0.056)	(0.008)	(0.009)
	Observations	6,021	3,055	6,021	3,055	6,021	3,055
	Adjusted R-squared	0.619	0.652	0.619	0.652	0.621	0.653
OLS-Basic Model	Pension fund centrality	-0.578**	-0.620**	1.469**	1.847**	-0.015	-0.020
		(0.264)	(0.293)	(0.576)	(0.737)	(0.015)	(0.015)
	Observations	6,021	3,055	6,021	3,055	6,021	3,055
	Adjusted R-squared	0.619	0.651	0.619	0.652	0.618	0.650
2SLS-Full Model	Pension fund centrality	-2.606***	-2.152***	38.669***	31.124**	-0.272***	-0.206***
		(0.768)	(0.774)	(13.616)	(13.256)	(0.084)	(0.075)
	GP centrality	-0.734*	-0.781*	-0.776	-0.867	-0.118	-0.172
		(0.390)	(0.405)	(0.574)	(0.582)	(0.135)	(0.136)
	Consultant centrality	0.093***	0.078**	0.173**	0.161**	0.146***	0.113***
		(0.032)	(0.033)	(0.079)	(0.080)	(0.048)	(0.041)
	Observations	2,089	1,837	2,089	1,837	2,089	1,837
	Adjusted R-squared	0.724	0.728	0.528	0.581	0.696	0.714
2SLS-Basic Model	Pension fund centrality	-2.621***	-2.160***	39.472***	32.158**	-0.239***	-0.179**
		(0.783)	(0.790)	(14.003)	(13.604)	(0.082)	(0.070)
	Observations	2,089	1,837	2,089	1,837	2,089	1,847
	Adjusted R-squared	0.717	0.721	0.517	0.568	0.670	0.696

F. 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	-0.785**	-0.879**	3.533***	3.667***	-0.048**	-0.048**
		(0.325)	(0.359)	(0.958)	(1.119)	(0.023)	(0.023)
	GP centrality	0.101	0.052	0.152	0.087	-0.059	-0.102
		(0.112)	(0.135)	(0.116)	(0.145)	(0.054)	(0.068)
	Consultant centrality	0.005	0.005	0.047	0.062	0.014	0.014
		(0.028)	(0.032)	(0.061)	(0.073)	(0.009)	(0.009)
	Observations	3,218	2,085	3,218	2,085	3,218	2,085
	Adjusted R-squared	0.614	0.627	0.618	0.630	0.613	0.626
OLS-Basic Model	Pension fund centrality	-0.452*	-0.445	1.279**	1.765**	-0.016	-0.017
		(0.259)	(0.308)	(0.552)	(0.753)	(0.017)	(0.017)
	Observations	5,216	2,780	5,216	2,780	5,216	2,780
	Adjusted R-squared	0.625	0.661	0.625	0.663	0.624	0.661
2SLS-Full Model	Pension fund centrality	-2.951***	-3.368***	80.788**	77.853***	-0.318***	-0.346***
		(0.988)	(0.991)	(33.785)	(29.223)	(0.111)	(0.105)
	GP centrality	-0.491***	-0.419***	-1.269**	-1.259**	-0.012	-0.066
		(0.160)	(0.160)	(0.505)	(0.503)	(0.084)	(0.091)
	Consultant centrality	0.155***	0.163***	0.442***	0.411***	0.114***	0.128***
		(0.039)	(0.041)	(0.136)	(0.123)	(0.037)	(0.036)
	Observations	1,584	1,413	1,584	1,413	1,584	1,413
	Adjusted R-squared	0.708	0.724	0.423	0.451	0.669	0.677
2SLS-Basic Model	Pension fund centrality	-1.840**	-2.226**	29.617*	35.199**	-0.168**	-0.175**
		(0.865)	(0.879)	(15.118)	(15.650)	(0.082)	(0.072)
	Observations	2,027	1,773	2,027	1,773	2,027	1,773
	Adjusted R-squared	0.698	0.710	0.698	0.710	0.680	0.691

G. *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	-1.934	-1.664	8.700**	11.088***	-0.145	-0.137
		(1.332)	(1.468)	(3.438)	(4.093)	(0.096)	(0.097)
	GP centrality	-0.482	-0.453	0.547	0.650	-0.875***	-0.752***
		(0.518)	(0.605)	(0.487)	(0.564)	(0.252)	(0.271)
	Consultant centrality	0.029	0.032	0.167	0.236	0.062*	0.051
		(0.113)	(0.126)	(0.251)	(0.297)	(0.033)	(0.035)
	Observations	2,735	1,788	2,735	1,788	2,735	1,788
	Adjusted R-squared	0.604	0.627	0.606	0.631	0.608	0.631
OLS-Basic Model	Pension fund centrality	-2.158**	-1.375	6.097***	7.936***	-0.038	-0.045
		(1.078)	(1.268)	(1.818)	(2.256)	(0.072)	(0.075)
	Observations	4,654	2,448	4,654	2,448	4,654	2,448
	Adjusted R-squared	0.619	0.651	0.621	0.655	0.619	0.651
2SLS-Full Model	Pension fund centrality	-10.323***	-9.892***	233.999**	182.834**	-1.158**	-1.059**
		(3.652)	(3.542)	(94.149)	(72.120)	(0.484)	(0.435)
	GP centrality	-3.561***	-3.431***	-2.767	-1.874	-1.165***	-1.186***
		(0.640)	(0.631)	(1.778)	(1.651)	(0.342)	(0.332)
	Consultant centrality	0.451***	0.416***	1.127***	1.091***	0.357**	0.335**
		(0.134)	(0.138)	(0.412)	(0.376)	(0.146)	(0.134)
	Observations	1,335	1,199	1,335	1,199	1,335	1,199
	Adjusted R-squared	0.703	0.722	0.527	0.606	0.654	0.683
2SLS-Basic Model	Pension fund centrality	-9.908***	-8.777***	141.123**	116.620**	-0.992**	-0.760**
		(3.397)	(3.212)	(55.323)	(47.436)	(0.453)	(0.334)
	Observations	1,663	1,466	1,663	1,466	1,663	1,466
	Adjusted R-squared	0.722	0.740	0.579	0.622	0.671	0.711

H. 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	-0.357	-0.321	1.246**	1.746**	-0.013	-0.019
		(0.248)	(0.287)	(0.579)	(0.758)	(0.020)	(0.020)
	GP centrality	-0.249	-0.131	0.673	0.558	0.032**	0.011
		(0.170)	(0.189)	(0.442)	(0.573)	(0.015)	(0.016)
	Consultant centrality	-0.067	0.032	-0.165	-0.401	0.020	0.024
		(0.199)	(0.213)	(0.580)	(0.804)	(0.018)	(0.020)
	Observations	5,192	2,781	5,192	2,781	5,246	2,781
	Adjusted R-squared	0.620	0.653	0.621	0.656	0.620	0.653
OLS-Basic Model	Pension fund centrality	-0.462*	-0.325	1.499***	1.840***	-0.002	-0.013
		(0.239)	(0.273)	(0.532)	(0.690)	(0.018)	(0.019)
	Observations	5,549	2,951	5,549	2,951	5,549	2,951
	Adjusted R-squared	0.621	0.653	0.622	0.655	0.620	0.653
2SLS-Full Model	Pension fund centrality	-9.532**	-11.821	16.628***	15.045**	-0.520**	-0.364**
		(4.687)	(8.080)	(5.450)	(6.181)	(0.207)	(0.144)
	GP centrality	-0.200	-0.204	0.306	0.786	0.124***	0.120***
		(0.375)	(0.568)	(0.699)	(0.699)	(0.033)	(0.027)
	Consultant centrality	2.119**	2.847	-1.262	-1.463	0.264**	0.183**
		(1.053)	(1.916)	(0.892)	(0.961)	(0.111)	(0.078)
	Observations	1,961	1,728	1,961	1,728	1,961	1,728
	Adjusted R-squared	0.452	0.257	0.679	0.682	0.554	0.646
2SLS-Basic Model	Pension fund centrality	-10.869*	-17.386	16.375***	14.789**	-0.435**	-0.282**
		(6.300)	(17.591)	(5.554)	(6.327)	(0.187)	(0.126)
	Observations	2,063	1,818	2,063	1,818	2,063	1,818
	Adjusted R-squared	0.355	-0.332	0.683	0.686	0.579	0.664

I. *Basic model results with networks formed by transactions over a trailing 5-year window*

Appendix Table A9: Basic Results with Networks Formed by Transactions over A Trailing 5-year Window
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-Basic Model	Pension fund centrality	-1.954**	-1.688*	3.151***	4.895***	-0.014	-0.073
		(0.851)	(1.005)	(1.185)	(1.713)	(0.083)	(0.090)
	Observations	3,867	2,052	3,867	2,052	3,865	2,051
	Adjusted R-squared	0.655	0.668	0.655	0.669	0.654	0.667
2SLS-Basic Model	Pension fund centrality	-4.591***	-4.087**	160.163**	137.861**	-0.481**	-0.406**
		(1.752)	(1.779)	(74.271)	(69.673)	(0.190)	(0.179)
	Observations	1,517	1,357	1,517	1,357	1,517	1,357
	Adjusted R-squared	0.714	0.722	0.570	0.615	0.709	0.720