# Alternative Investments: The Consultant Effect

Shubham Roy*

July 2026

**Abstract**

This paper studies the role of investment consultants in institutional investors' private equity manager selection and performance. I show that consultant networks causally affect manager selection: an investor's probability of investing with a given GP rises from 1 in 13 to 1 in 9 when that GP is in the consultant's network. In explaining heterogeneity in investor performance, consultant fixed effects account for 77% of the variation and increase the model's $R^2$ from 0.051 to 0.131. Finally, I document systematic differences in performance between investors with internal teams and those that engage consultants: investors with internal teams invest in funds with IRRs that are, on average, 70 to 80 bps higher than those of investors that engage consultants.

*PhD Candidate, The Ohio State University

# 1 Introduction

Over the last few decades, alternative assets have become a significant component of institutional investors' portfolios.[1] Investors typically gain exposure to these assets by allocating capital to external asset managers. Considering the high degree of information asymmetry in alternative assets (Ivashina & Lerner, 2018), identifying and evaluating managers is a time-consuming process that requires specialized expertise and has high costs of information acquisition (Andonov, 2024). Rationed access to top-performing managers further complicates this process (Kaplan & Schoar, 2005; Lerner, Schoar, & Wongsunwai, 2007; Sensoy, Wang, & Weisbach, 2014). These frictions make information and skill potentially central determinants of portfolio performance.

Acquiring pertinent information is central to allocation decisions. In opaque markets, relationships play an important role in lowering the cost of gathering information for two mutually nonexclusive reasons. First, they facilitate information sharing, thereby mitigating asymmetric information problems, reducing moral hazard, and lowering search costs (Lakonishok, Shleifer, & Vishny, 1992; Cohen, Frazzini, & Malloy, 2008, 2010; Rossi, Blake, Timmermann, Tonks, & Wermers, 2018). Second, they reduce an investor's anxiety about risk and uncertainty (Gennaioli, Shleifer, & Vishny, 2015). Turning to investor skill, there is a significant persistent dispersion in expected net-of-fee future returns between top- and bottom-performing managers. But this dispersion is not observable ex ante (Korteweg & Sorensen, 2017). Consequently, selecting asset managers requires substantial judgment. Investors must evaluate a manager's strategy, skill, experience, and alignment with the existing portfolio (Gârleanu & Pedersen, 2018). Thus, investor skill becomes an important factor for portfolio performance.

Building the relationships necessary to gather information and developing the skills required to evaluate managers may take considerable time, involve substantial costs, and, in

[1] Begenau, Liang, and Siriwardane (2025) report that alternatives accounted for 39% of institutions' risky investments in 2021.

some cases, may not be feasible within an investor's institutional framework (Dyck, Manoel, & Morse, 2022). To mitigate these constraints, investors often engage investment consultants.[2] Consultants act as intermediaries, adding value by providing scale economies in information gathering (Goyal & Wahal, 2008) and specialized expertise in evaluating asset managers (Allen, 2001).

These considerations are especially salient in private equity, an asset class in which information frictions, access constraints, and the need for specialized evaluation are particularly pronounced.[3] Against this backdrop, I study the role of consultants in investors' private equity allocations. Specifically, I examine two related questions. First, do consultants have an influence on an investor's choice of private equity general partner? Second, does this influence affect portfolio performance?

Evidence from public equity and debt manager selection shows that consultant recommendations (Jenkinson, Jones, & Martinez, 2016) and consultant connections (Goyal, Wahal, & Yavuz, 2024) meaningfully shape institutional fund flows. This effect is likely to be amplified in private equity, where informational asymmetries are greater. Turning to performance, the literature documents significant dispersion in performance among investors that allocate capital to private equity managers (Cavagnaro, Sensoy, Wang, & Weisbach, 2019). Some investors consistently outperform, investing in funds that yield higher IRRs than the average investor, while others consistently underperform. Cavagnaro et al. (2019) attribute part of this heterogeneity to investor skill. To the extent that consultants influence manager selection, part of this skill may be attributed to choosing the "right" consultant.

Consistent with this idea, I find that the probability of an investor investing with a given GP increases from 7.5 p.p. to 11.0 p.p. if the GP is in the network of the investor's consultant.[4] This estimate controls for prior investor-GP relationships, ensuring that the

[2] Goyal and Wahal (2008) estimate that 82% of U.S. public pension plan sponsors and 50% of corporate sponsors engage investment consultants.

[3] Private equity is a major asset class within alternatives, accounting for approximately 30% of total alternative assets under management, second only to real estate at approximately 35% (Andonov, 2024).

[4] A consultant's network in year $t$ is defined as the set of all GPs that received investments from the consultant's clients during the previous three years ($t-1$ to $t-3$). Details in Section 3.

results are not driven by existing partnerships. Additionally, the influence of consultants remains significant after accounting for observable GP characteristics such as size and past performance, indicating that consultant networks provide additional explanatory power. The effect is strongest for smaller GPs, suggesting that consultants play a key role in certifying lesser-known firms, helping them attract capital despite their lower visibility.

Consultant networks tend to be highly persistent, which raises the concern of spurious correlations. To address this, I use a first-differencing approach, focusing on cases where a specific investor's consultant network changes. The results confirm that an investor is significantly more (less) likely to invest with a GP after that GP is added to (removed from) the investor's consultant network. While there is an immediate short-term benefit for a GP when entering a consultant's network, long-term network presence also plays a crucial role in attracting capital.

Another concern is that consultant network formation may be endogenous, potentially influenced by unobservable investor or consultant preferences. To address this, I limit the sample to years in which an investor engaged a new consultant, ensuring that any observed effects are not driven by endogenously formed consultant networks. The results remain robust under this restriction.

A final concern is that consultant selection may be endogenous. Investors may choose consultants specifically to gain access to particular GPs. If consultant selection is driven by investor preferences, the estimated coefficient may overstate the causal effect by conflating consultant influence with investors' underlying preferences. To address this concern, I implement an instrumental-variable strategy motivated by the finding that pension funds are more likely to hire geographically proximate consultants (Andonov, Bonetti, & Stefanescu, 2026).

Building on this insight, I construct a Bartik-style instrument that weights consultants by their proximity to each investor. The logic is that consultants' geographic proximity generates plausibly exogenous variation in investors' exposure to consultant networks. Intu-

itively, investors are more exposed to the networks of nearby consultants for reasons that are not directly related to their preferences for specific managers. One might argue, however, that consulting is a travel-intensive business, so distance might not constrain a consultant's ability to work with investors located far away. To address this possibility, I also construct an alternative instrument based on state-level licensing. This specification assigns equal weight, $1/N$, to each consultant licensed in the investor's state, where $N$ is the number of such consultants, reflecting the idea that investors are equally exposed to the networks of all consultants authorized to operate in that state.

Across all instrumental-variable specifications, the estimates remain positive and statistically significant, although smaller than the corresponding OLS estimates. This pattern suggests that part of the baseline association reflects endogenous consultant selection, but also that consultant networks have an independent effect on manager choice. Taken together, these findings support a causal interpretation in which consultant networks influence investors' private equity manager selection.

Turning to the second question of whether consultants affect portfolio performance, I ask to what extent the documented heterogeneity in investors' PE/VC portfolio performance, which Cavagnaro et al. (2019) attribute to investor skill, can be explained by investors' choice of consultant. I find that, under a set of simplifying assumptions, consultant fixed effects explain 77% of the variation in investor performance and increase the explanatory power of the model by $2.6x$, with $R^2$ rising from 0.051 to 0.131.[5] These results suggest that consultant identity accounts for a non-trivial share of the heterogeneity in investor skill and that some consultants are associated with clients whose portfolios outperform those of clients advised by other consultants.

Given this heterogeneity among consultants, I next examine which observable consultant characteristics are associated with stronger estimated consultant effects. I find that larger consultants, measured by office count, employee count, and assets under advisement, tend to

[5] Assumptions are detailed in Section 4.2.

be associated with better client performance. This pattern is consistent with the idea that consultants generate value through scale economies in information gathering: consultants with more employees and broader office networks may possess stronger information networks, which in turn improve the information available to clients and the performance of their clients' private equity portfolios.

Not all investors approach private equity investing in the same way. While many engage external consultants, others build internal private equity teams.[6] This distinction raises a question: are there systematic differences in outcomes between investors that build internal capability and those that engage an intermediary? I find that investors with internal private equity teams earn excess IRRs that are, on average, 70 to 80 basis points higher than those of investors that engage consultants. This performance gap is concentrated among pension funds and foundations.

This finding should be interpreted with caution. The analysis does not account for the institutional and financial costs of building an internal team. An important avenue for future research would be to examine the institutional and financial constraints that shape an investor's decision to engage a consultant vis-à-vis building an internal team.

This paper contributes to three strands of the literature. First, it contributes to the literature on institutional consultants. Existing studies examine the role of consultants in shaping manager selection in both public markets (Jenkinson et al., 2016; Jones & Martinez, 2017; Cookson, Jenkinson, Jones, & Martinez, 2022) and private markets (Martinez & Qian, 2025; Andonov et al., 2026). This paper complements that work in the context of private equity and is, to my knowledge, the first to identify the causal effect of consultants on manager selection. Existing studies also examine whether consultants help investors select higher-performing funds (Martinez & Qian, 2025; Andonov et al., 2026). In contrast, this paper shifts the focus from fund-level outcomes to investor-level portfolio performance. It is the first to examine heterogeneity in investor performance at the portfolio level and to study

[6] Whyte (2019) estimates that approximately two-thirds of institutional investors engage a consultant.

the role of consultants in explaining that heterogeneity. It also provides the first evidence of systematic differences in performance between investors that engage consultants and those that do not. More broadly, this paper is the first to study the effect of consultants on overall investor performance.

Second, this paper contributes to the literature on delegation and networks (Cohen et al., 2008; Goyal et al., 2024; Goyal, Wahal, & Yavuz, 2026) by showing that consultant networks are an important channel through which consultants affect investors' GP selection, with meaningful consequences for real outcomes. Finally, this paper contributes to the literature on investor skill in private equity (Lerner et al., 2007; Sensoy et al., 2014; Cavagnaro et al., 2019) by showing that a non-trivial share of the dispersion in investor performance can be attributed to the investor's choice of consultant.

The remainder of the paper is organized as follows. Section 2 describes the data and sample. Section 3 presents evidence on the impact of consultants on manager selection. Section 4 examines the impact of consultants on investor performance. Section 5 concludes.

## 2 Data and Sample Description

I combine data from multiple sources to construct a sample of investors, private equity and venture capital (PE/VC) funds, general partners (GPs), and consultants. My primary data source is *Preqin*, which provides information on investors, funds, GPs, and consultants as of the end of Q4 CY2024. For investors, I supplement the Preqin data with the Public Plans Database (PPD) maintained by the Center for Retirement Research (CRR) at Boston College and the National Association of College and University Business Officers (NACUBO) Historic Endowment Study. For consultants, I supplement the Preqin data with SEC Form ADV disclosures. Finally, I use news feeds to identify additional investor-consultant relationships.[7]

For investors, I observe investor type (pension funds, endowments, and foundations),

[7]This study focuses on advisory relationships in which a consultant provides recommendations on asset allocation or manager selection to the investment committee, while the committee retains full discretion over the final investment decisions.

location (city and state), assets under management (AUM), asset allocation, and the funds in which each investor is invested. Because *Preqin* provides only a cross-sectional snapshot, I supplement it with the Public Plans Database (PPD) and the NACUBO Historic Endowment Study to construct time-series measures of AUM. In addition, I use the PPD to obtain time-series data on investor-consultant relationships for pension funds, i.e., the identity of the consultant(s) for a given investor-year. The investor sample is limited to U.S.-based institutions, with $AUM_i > \$125Mn$, who have made $>= 5$ allocations to PE/VC funds.[8]

For PE/VC funds, I observe GP name, fund sequence ID and number, vintage year, asset class, investment strategy, fund size, geographic focus, internal rate of return (IRR), and multiple. The sample includes funds managed by GPs based both in the United States and abroad. When fund size is unavailable, I impute it using the mean size of funds previously raised by GP $g$ up to the fund's preceding vintage year.

For GPs, I observe founding year and location, and I construct time-varying GP characteristics from the fund-level data. Specifically, I measure the number of funds raised by GP $g$ at time $t$ as the count of funds raised up to vintage year $t-1$, and total capital raised as the sum of fund sizes across all funds raised up to vintage year $t-1$. I measure past performance as the value-weighted mean IRR or multiple across all funds raised up to vintage year $t-8$. I use an eight-year lag to mitigate look-ahead bias and to ensure that only realized performance known at time $t$ is included, since early fund valuations are largely subjective until returns are realized (Lerner et al., 2007).

For consultants, I observe firm location (city, state, and country), a snapshot of current and former clients, and the role of the consultant in each engagement (general, PE, VC, hedge fund, real estate, or infrastructure). I supplement this data with additional consultant characteristics from Form ADV, specifically the number of clients, assets under advisement (AUA), team size, and all office locations.[9]

[8] Among U.S.-based investors, institutions with $AUM_i > \$125Mn$ cumulatively account for $\sim 67\%$ of all investors and $> 99\%$ of total AUM.

[9] Consultants with clients in the United States are required to file Form ADV annually with the U.S. Securities and Exchange Commission.

To extend the investor-consultant relationship data beyond public pension plans, I manually parse *Preqin* news feeds (see Figure 1a). These news items provide information on when an investor issued a request for proposal (RFP) for a consultant, when a consultant was hired, the length of the consulting term, and when a new consultant was appointed. I use this information to infer the timing and duration of investor-consultant relationships. When no subsequent news appears after a consultant was hired, I assume a five-year consulting term, which is the modal term in the sample (see Figure 1b).

Some large endowments and foundations do not appear in the *Preqin* news feeds, likely because they rely on internal investment teams rather than external consultants. For economically significant institutions not already included in the sample, I search *Factiva* news items dating back to 2000 to determine whether they ever engaged an external consultant.[10] If I find no evidence of consultant engagement or of an issuance of a request for proposal (RFP), I classify these investors as never having engaged a consultant.

## 2.1 Sample Description

My sample consists of $1,527$ investors investing in $10,503$ funds, managed by $2,755$ GPs and advised by 167 consultants, over the period 1985–2024. Of these investors, 468 never engaged a consultant during the sample period, while the remaining $1,059$ engaged a consultant in some capacity at least once.[11] Within the latter group, 321 engaged a consultant at least once for PE/VC advisory.

*Preqin* only provides a snapshot of investor–consultant relationships over the full sample period. To construct time-series data on investor–consultant relationships, I rely on the Public Plans Database (PPD) and news feeds, which cover a smaller sample of investors. From the PPD, I identify a sample of 147 investors investing in $5,414$ funds, managed by $1,513$ GPs and advised by 57 consultants, over the period 2001–2024. I then augment this

[10] For the purposes of identifying investor-consultant relationships, I consider investors with $AUM > \$7.5Bn$ to be economically significant. Collectively, these institutions account for more than 50% of total assets under management within their respective investor types.

[11] This is consistent with the estimate in Whyte (2019).

sample with news data, which adds 195 investors investing in 2,552 funds, managed by 866 GPs and advised by 27 additional consultants, over the period 2006–2024.

Table 1 presents summary statistics for the investor sample. The *Full Sample* column refers to all investors available in *Preqin*. The *Consultant Subsample* column refers to the subset of investors for whom consultant relationships have been identified. The total $AUM$ of investors in the *Consultant Subsample* is \$5.9 Tn, covering 53% of all $AUM$ for which data is available in *Preqin*. This coverage is substantially higher than in prior studies because it includes private pension funds, endowments, and foundations, which were not captured in the prior literature.[12] The *Consultant Subsample* is skewed towards larger investors (mean AUM: \$17.4 Bn versus \$7.3 Bn in the Full Sample), but it captures a substantial share of total institutional capital and therefore covers an economically important segment of the market.

Figure 2 shows the coverage of PE/VC funds in my sample. I include only General Partners (GPs) that have raised capital from at least one of the 412 investors in my smaller sample, in which I have time-series data on the investor-consultant relationship. The blue section represents all funds for which data is available in *Preqin*, while the red section highlights the funds included in my sample. As shown in the figure, my sample captures over 80% of the total capital raised. Since most of the missing coverage comes from smaller, less economically significant funds, the sample can be considered representative.

The assets under advisement of the investment consulting industry have grown substantially over the last quarter century Figure 3b.[13] Similar trends are observed in the number of consultant offices and employees Figure 4, indicating the increasing importance of consultants to institutional investors. At the same time, the industry is also highly concentrated: the top decile of consultants consistently accounts for approximately 90% of total assets under advisement. This concentration is stable through time, consistent with evidence in the literature (Jenkinson et al., 2016; Jones & Martinez, 2017; Andonov et al., 2026).

[12] Andonov et al. (2026) has coverage of 22%, while Begenau et al. (2025) has coverage of 29%.
[13] Annualized growth rate of $\sim 11.4\%$.

A consultant turnover event is defined as the termination of engagement with one consultant followed by the initiation of engagement with another. Figure 5 shows the count of turnover events over the sample period, with a total of 354 events. The temporal pattern of turnover events is similar to that documented in Andonov et al. (2026), while the overall number of events is higher in my sample. This provides evidence that there are many instances in which an investor terminates a relationship with one consultant and begins working with another.

## 2.2 Clustering in Fund Selection

At the retail investor level, Foerster, Linnainmaa, Melzer, and Previtero (2017) show that delegated investment advice often leads to more standardized portfolio choices. Similarly, Andonov et al. (2026) find that institutional consultants recommend homogeneous strategies across clients. Consistent with this evidence, investors advised by the same consultant may be more likely to invest in the same funds. This, in turn, can generate clustering among otherwise unrelated investors, such that investors sharing a common consultant invest with the same pool of GPs.

To test this, I construct two measures, the *Overlap Ratio* and the *Co-Investment Ratio*, which capture the extent to which investors cluster at an economy-wide level. If the *Overlap Ratio* and *Co-Investment Ratio* for the true sample are higher than what we would expect by chance, then it suggests that some clustering in fund selection can be attributed to investors sharing a common consultant.

*Overlap Ratio* for a fund is defined as the largest fraction of its investors who share a common consultant. *Co-Investment Ratio* for an investor is defined as the fraction of funds in which the investor co-invests with other clients of its consultant. Both are calculated at an aggregate level. Formally, let $i$ represent an investor investing in fund $f$ of vintage year $t$, and let $c(i,t)$ denote the consultant associated with investor $i$ in vintage year $t$. The *Overlap*

*Ratio* is defined as:

$$
\begin{aligned}
\textit{Overlap Ratio}_{c,f} &= \frac{\text{Number of investors } i \text{ in } f \text{ for whom } c(i,t) = c}{\text{Total number of investors in } f}, \\
\textit{Overlap Ratio}_{f} &= \max_{c}\big(\text{Overlap Ratio}_{c,f}\big), \\
\textit{Overlap Ratio} &= \frac{1}{F}\sum_{f=1}^{F} \text{Overlap Ratio}_{f}
\end{aligned} \tag{1}
$$

The *Co-Investment Ratio* is defined as:

$$
\begin{aligned}
\textit{Co-Investment}_{i,f} &= \begin{cases} 1, & \text{if clients of } c(i,t) \text{ except } i \text{ have invested in } f \\ 0, & \text{otherwise} \end{cases} \\
\textit{Co-Investment Ratio}_{i} &= \frac{\sum_f \textit{Co-Investment}_{i,f}}{\text{Total number of investments by } i}, \\
\textit{Co-Investment Ratio} &= \frac{1}{I}\sum_{i=1}^{I} \text{Co-Investment Ratio}_{i}
\end{aligned} \tag{2}
$$

The values of *Overlap Ratio* and *Co-Investment Ratio* are calculated for the true sample. These values are then compared with those obtained from 10,000 bootstrapped samples. In the bootstrapping procedure, investors retain their consultants but are randomly assigned to funds, controlling for vintage, size group, strategy, and regional focus.

The results are presented in Figure 6. Both measures of investor clustering, the *Overlap Ratio* and the *Co-Investment Ratio*, are higher in the true sample compared to the bootstrapped samples. This difference is statistically significant, as confirmed by a t-test in Table 2.

The economic magnitude of the difference in the Overlap Ratio is relatively small (0.32 for the true sample versus 0.28 for the bootstrapped sample). In contrast, the difference in the Co-Investment Ratio is more pronounced. In a random sample, an investor is expected to co-invest with other clients of its consultant about 1 in 3 times, whereas in the true sample, this occurs about 2 in 5 times, highlighting an economically meaningful effect. These findings

suggest there is clustering in fund selection, and that some of it can be attributed to investors sharing a common consultant.

# 3 Consultants and Manager Selection

Having established the presence of clustering among investors, the next step is to quantify the extent to which consultants influence an investor's choice of a private equity GP. In this section, I answer the question: By how much does an investor's probability of investing with a given GP increase when that GP is part of the investor's consultant's network?

The first step is to define the opportunity set for an investor. Following the approach of Goyal et al. (2026), I define it as the set of GPs raising funds that share key characteristics with a fund in which the investor has actually invested.[14] For instance, if an investor in the sample invested in a 2006 vintage fund with a size of $50–$400 million, focused on Buyout deals in North America, then all GPs raising funds in 2006 within the same size group, strategy, and regional focus are included in the plan sponsor's opportunity set.[15] Using this definition, I construct my dependent variable $P(Invest)_{i,g,t}$, a binary indicator that equals 1 if investor $i$ invests with GP $g$ in time $t$, and 0 otherwise.

Ideally, the opportunity set would include all funds an investor evaluated prior to committing capital. However, empirically, I only observe those funds in which the investor ultimately invested. As a result, an implicit assumption in defining the opportunity set is that the investor considered only those funds sharing the same characteristics as the fund

[14] Because of data limitations, I am unable to account for two restrictions considered in Goyal et al. (2026): (a) heterogeneity in LPs' access to elite GPs and (b) personal connections between LPs and GPs.

[15] Description of fund characteristics that define the investor's opportunity set:

- **Fund Size Group:** Funds are classified into one of four groups: $0 - 50 Mn, $50 - 400 Mn, $400 - 2500 Mn, and $2500+ Mn. For reference, the mean fund size is $54 Mn, with one standard deviation above the mean at $372 million and two standard deviations above the mean at $2.56 billion.
- **Fund Strategy:** Preqin classifies funds into 15 distinct strategies. In this paper, these strategies are aggregated into five broader categories: PE: Buyout, PE: Fund of Funds, PE: Others (comprised of PE: Growth, PE: Co-Investment, PE: Secondaries, and PE: Others), Venture Capital (comprised of VC: Early Stage, VC: Late Stage, and Venture (General)), and Other (comprised of Hedge Funds, Real Estate, Infrastructure, Private Debt, Natural Resources, and Multi).

to which it committed capital.[16] Without this assumption, the opportunity set would span the entire universe of funds raised in a given vintage, which would be unfeasibly large. This assumption does not cause significant issues because prior to committing capital, investors typically issue Requests for Proposals (RFPs) that clearly define their preferences. Thus, using ex-post realizations to construct the ex-ante opportunity set is reasonable.

Another limitation in defining the opportunity set is that I would like to control for investment ticket size when defining the opportunity set.[17] However, since data on ticket size is not available, I use fund size group as a proxy. The second step is to define the consultant's network of GPs. I define a consultant's network in year $t$ as the set of all GPs that received investments from the consultant's clients during the previous three years ($t-1$ to $t-3$).[18] This measure captures the consultant's exposure to GPs through the investment decisions of its clients and may, in turn, shape the consultant's future recommendations and clients' subsequent allocations.

Investors may invest with a GP based on prior relationships rather than consultant recommendations. To control for this, I define:

$$PastRelation_{i,g,t} = \begin{cases} 1, & \text{if } i \text{ has invested at least once with } g \text{ in the last 15 years} \\ 0, & \text{otherwise} \end{cases}$$

If an investor reinvests with a GP, the decision is attributed entirely to the investor rather than the consultant. The underlying assumption is that if the consultant's role is to reduce information asymmetry, its influence should be most relevant for the investor's *initial*

[16] The fund characteristics used to define the opportunity set are vintage, size group, strategy, and geographic focus.

[17] The ticket size of an investor is defined as the amount of capital the investor commits to a specific fund. For example, if a GP is raising a $100 million fund and an investor commits $10 million, the investor's ticket size is $10 million.

[18] For data on consultant recommendations, Jenkinson et al. (2016) and Jones and Martinez (2017) rely on survey data from Greenwich Associates, which is limited to public equity asset managers. For consultant-manager linkages, Goyal et al. (2024) use proprietary data from Relationship Science, while Martinez and Qian (2025) and Goyal et al. (2026) use private equity mandate information from Fundmap (part of With Intelligence, S&P Global). Because these consultant-manager linkages are not directly observed in my data, I instead construct a consultant's network from my sample.

investment decision. Once an investor has engaged with a GP, they gain direct experience, making the consultant's role less critical in subsequent reinvestments.

A potential issue arises if the consultant initially influenced the investor's decision to invest with the GP. In that case, the consultant may also have some influence over the reinvestment decision. Controlling for $PastRelation_{i,g,t}$ could, therefore, lead to an *underestimation* of the consultant's impact, biasing the coefficient downward. Since this bias works against my finding, it is an acceptable limitation.

Defining the consultant network this way has certain limitations. First, $ConsultNetwork_{i,g,t}$ may capture historical client preferences rather than direct consultant influence. Second, the consultant's network could be shaped by market conditions. Third, $ConsultNetwork_{i,g,t}$ may be understated following periods of low investment activity, such as the aftermath of the global financial crisis, or overstated after periods of excessive fundraising, like the late 1990s tech boom. Finally, the definition excludes new GPs or inactive GPs that raise capital infrequently. Despite these limitations, in the absence of data on direct consultant relationships, $ConsultNetwork_{c(i),g,t}$ provides a useful approximation of a consultant's potential influence on investment decisions.

## 3.1 Exploring the Consultant's Network

In this section, I explore the coverage of, heterogeneity among, and evolution of consultant networks as defined above. I also address potential concerns arising from the high concentration in the investment consulting industry and the persistence built into the definition of consultant networks.

One concern, arising because of the high concentration in the industry (Figure 3), is that an individual consultant may include a large share of GPs in their network. In such cases, any investment decision made by clients could be attributed to a GP being part of a consultant's network, even if the network itself played no meaningful role. To assess the scope of this issue, I define a measure of network coverage. A consultant's coverage in a given year is the

share of total capital raised (or number of funds raised) by GPs in that consultant's network, relative to the total raised by all GPs that appear in at least one consultant's network that year. GPs not in any consultant's network in a given year are excluded, in order to avoid understating the consultants' coverage.

Figure 7 illustrates the variation in consultant network coverage using a boxplot of coverage by consultant-year. The distribution is highly skewed. The median consultant covers $\sim 5\%$ of total capital raised ($\sim 2\%$ of total funds raised), while the outliers exceed $\sim 30\%$ of capital ($\sim 4\%$ of funds). Even the largest consultants, however, do not cover more than about $\sim 40\%$ of total capital or $\sim 7\%$ of total funds. This suggests that no single consultant network dominates the industry.

Next, I examine the characteristics of GPs that are associated with broader coverage across consultant networks. Coverage is measured as the proportion of consultant networks in which a GP appears in a given year. The median GP is present in 4.6% of networks. Figure 8 presents a scatter plot relating GP characteristics to network coverage. GPs that are larger, older, and raise larger funds tend to be included in more consultant networks. In contrast, past performance does not appear to be systematically related to network coverage.

Finally, I examine how consultant networks evolve over time. I track the number of GPs, total capital raised, and number of funds raised within each consultant's network, expressed as a proportion of their respective values at $t = 0$. I then compute the average across consultants. Figure 9a shows that the average consultant network grows over time, consistent with increasing concentration in the investment consulting industry.

Another aspect of network evolution is whether consultant networks are stable or experience frequent turnover. To assess this, I examine the Network Survival Rate, defined as the proportion of GPs in a consultant's network at $t = 0$ that remain in the network at time $t$. Figure 9b shows that survival rates decline over time, even as networks grow in size, indicating ongoing turnover. The network also has a persistent component. $\sim 25\%$ of GPs present at $t = 0$ remain in the network at $t = 10$.

## 3.2 Impact on Manager Selection

Now that the dependent and independent variables have been defined, the next step is to examine how much an investor's probability of investing with a GP increases when that GP is within the investor's consultant's network. To do so, I estimate the following regression specification:

$$P(Invest)_{i,g,t} = \beta_1 \cdot ConsultNetwork_{c(i,t),g,t} + \beta_2 \cdot PastRelation_{i,g,t} + \beta_3 \cdot InvestorControls_{i,t} + \beta_4 \cdot GPSizeControls_{g,t} + \beta_5 \cdot GPPerfControls_{g,t} + \lambda_t + \lambda_c + \epsilon_{i,g,t}; \quad (3)$$

where:

- $i$: Investor, $g$: General Partner, $t$: Vintage year, $c$: Consultant, $\lambda$: Fixed Effects
- $P(Invest)_{i,g,t}$, $ConsultNetwork_{c(i,t),g,t}$, and $PastRelation_{i,g,t}$ are as previously defined
- $InvestorControls_{i,t}$ include investor size decile, and type
- $GPSizeControls_{g,t}$ include GP age, number of funds raised, and $ln(CapitalRaised)_{g,t}$
- $GPPerfControls_{g,t}$ include the observable weighted average IRR and multiple of prior GP funds

The coefficient on $ConsultNetwork_{c(i,t),g,t}$ captures the extent to which the likelihood of investment increases when a GP is within an investor's consultant network.

The results are presented in Table 3. The coefficient for $ConsultNetwork_{c(i,t),g,t}$ is positive and significant across all model specifications. The strongest effect in terms of coefficient and explanatory power is captured by $PastRelation_{i,g,t}$. This is unsurprising given that 50% of all investments in the sample involve GPs with whom the investor has previously invested. The sharp decline in the number of observations from column (5) to (6) is due to missing data on GP performance. In conclusion, the findings suggest that the probability of

investor $i$ investing with GP $g$ increases from 7.5 p.p. to 11.0 p.p. if $g$ is in the network of $i$'s consultant $c$.

The coefficient for $ConsultNetwork_{c(i,t),g,t}$ becomes slightly stronger when controlling for GP size (proxy for GP's credibility), suggesting that consultant networks provide explanatory power beyond GP reputation. Prior research shows that investors are more likely to allocate capital to larger, well-known GPs (Lerner et al., 2007; Sensoy et al., 2014). The increase in the coefficient suggests that smaller, lesser-known GPs benefit more from being in consultant networks. This could be because being in a consultant's network could help compensate for a lack of established reputation. Omitting GP size controls could have previously masked part of the effect.

## 3.3 Robustness Checks

Given how $ConsultNetwork_{c(i,t),g,t}$ is defined, a GP's presence in the network is highly persistent. This persistence may lead to spurious correlations and incorrect inferences. To address this issue, I define difference variables that capture changes in consultant networks.

$NetworkAdditions_{c(i,t),g,t}$ is defined as a binary indicator that equals 1 if in year $t$ GP $g$ was added to the network of consultant $c(i,t)$, and 0 otherwise; $NetworkDeletions_{c(i,t),g,t}$ is defined as a binary indicator that equals 1 if in year $t$ GP $g$ was newly deleted from the network of consultant $c(i,t)$, and 0 otherwise. These variables help isolate the impact of changes in consultant networks and address the problem of persistent network connections as defined.

The coefficient on $NetworkAdditions_{c(i,t),g,t}$ captures the effect of newly formed network connections on the probability of a GP $g$ raising capital from investor $i$. Larger GPs, such as BlackRock or KKR, raise capital annually and are consistently present in $ConsultNetwork_{c(i,t),g,t}$. As a result, differencing primarily captures the effects on smaller or less well-known GPs that raise capital less frequently. Similarly, $NetworkDeletions_{c(i,t),g,t}$ captures the impact of losing a network connection on the probability of a GP $g$ raising

capital from investor $i$. To quantify these effects, I estimate the following regression specification:

$$\begin{aligned} P(Invest)_{i,g,t} = \beta_1 \cdot ConsultNetwork_{c(i,t),g,t} + \beta_2 \cdot PastRelation_{i,g,t} \\ + \beta_3 \cdot NetworkAdditions_{c(i,t),g,t} + \beta_4 \cdot NetworkDeletions_{c(i,t),g,t} \\ + \gamma_1 \cdot X_{i,t} + \gamma_2 \cdot Y_{g,t} + \lambda_t + \lambda_c + \epsilon_{i,g,t}; \end{aligned} \tag{4}$$

where:

- $i$: Investor, $g$: General Partner, $t$: Vintage year, $c$: Consultant, $\lambda$: Fixed Effects
- $P(Invest)_{i,g,t}$, $ConsultNetwork_{c(i,t),g,t}$, $PastRelation_{i,g,t}$, $NetworkAdditions_{c(i,t),g,t}$, and $NetworkDeletions_{c(i,t),g,t}$ are previously defined
- $X_{i,t}$ is a vector of investor controls that include investor size and type
- $Y_{g,t}$ is a vector of GP controls that include GP age, number of funds raised, $ln(Capital\ Raised)_{g,t}$, lagged observable weighted average IRR and multiple of prior GP funds

The results are presented in Table 4. The coefficient on $NetworkAdditions(Deletions)_{c(i,t),g,t}$ is positive (negative), indicating that a GP is significantly more (less) likely to raise capital from investor $i$ after being added to (removed from) its consultant's network. The coefficient on $NetworkAdditions_{c(i,t),g,t}$ captures only the immediate effect of a GP's addition to the network. Since its magnitude is lower than that of $ConsultNetwork_{c(i,t),g,t}$, this suggests that while short-term certification matters, long-term network presence is also crucial for raising capital. Given these results, we can conclude that the initial result is not driven by persistence in the independent variable.

Another limitation of $ConsultNetwork_{c(i,t),g,t}$ is that the presence of a general partner (GP) in the network is endogenous. It may be influenced by unobservable investor or consultant preferences. Ideally, an exogenous change in an investor's network would provide a clean identification strategy. However, in the absence of such a shock, I take a second-best

approach. I run the regression specified in Equation (3) on a subsample that includes only years in which investor $i$ hired a new consultant (consultant turnover events as defined).

The results in Column (5) of Table 4 show a positive and statistically significant coefficient. The reduction in statistical power is expected due to the smaller sample size, as there are only 206 consultant turnover events in the dataset. These findings suggest that the initial results are not solely driven by endogenous network formation.

### 3.3.1 Endogeneity in Consultant Selection

The estimation in Equation (3) poses an identification challenge. Investors may select consultants specifically to gain access to specific GPs. If consultant selection is driven by an investor's preferences, the estimated coefficient may overstate the causal effect by conflating consultant recommendations with investors' preferences.

To address this concern, I use an instrumental variable based on an insight from Andonov et al. (2026). They find that pension funds have a preference for hiring consultants that are geographically closer. Leveraging this insight, I build a Bartik-style instrument that assigns weights to consultants based on their proximity to the investor. Specifically, I define the instrument as:

$$z_{c(i,t),g,t} = \sum_{j=1}^{C} (w_{j,i,g,t} * ConsultNetwork_{j,g,t}); \tag{5}$$

where,

- $i$: Investor, $g$: General Partner, $t$: Vintage year, $j$: Consultant
- $w_{j,i,g,t}$ is the weight assigned to the network of consultant $j$ based on the inverse of the distance between $i$ and $j$
- $ConsultNetwork_{j,g,t}$ is the network of consultant $j$ as defined above

Estimating Equation (3) by instrumenting $ConsultNetwork_{c(i,t),g,t}$ with $z_{c(i,t),g,t}$ exploits

cross-sectional variation driven entirely by the distances between the investor and consultants, as captured by the weights $w_{j,i,g,t}$. For instance, an investor on the East Coast is more exposed to consultant networks in Boston or New York than to those in San Francisco. If this differential geographic exposure is orthogonal to latent investment preferences, the instrument isolates plausibly exogenous variation in consultant-network exposure and identifies its effect on manager selection.

Because consultants may operate from multiple offices, I measure distance using the office closest to investor $i$. These distances are calculated annually, so changes in consultant locations arising from branch openings or mergers are incorporated into the weights assigned to each consultant's GP network. I construct two versions of the instrument $z$: one based on raw distance and another based on the natural log of distance. The log specification reflects the idea that distance may matter less at longer ranges. For example, for an investor in Pittsburgh, PA, the difference between consultants located in New York, Boston, or Chicago may be limited in practice, since each location is effectively one flight away. Using raw distance would therefore place disproportionately lower weight on the GP networks of Boston- or Chicago-based consultants relative to those of New York-based consultants.

A related concern is that consulting is a travel-intensive business, so distance may not substantially constrain a consultant's ability to work with investors located far away. To address this concern, I exploit the legal requirement that consultants must be licensed in a given state to provide financial advisory services to clients from that state. I therefore construct an alternative version of the instrument $z$ that assigns equal weights of $1/N$ to each consultant licensed in the investor's state, where $N$ is the number of licensed consultants. The underlying intuition is that an investor has equal exposure to the GP networks of all consultants licensed to operate in that state.

The results are reported in Table 5. Column (1) presents estimates from the OLS specification in Equation (3). Columns (2)–(7) report the first- and second-stage results from instrumental variable specifications using instruments based on distance, log distance, and

state licensing, respectively. The first-stage estimates in Columns (2), (4), and (6) have F-statistics consistently above 100, indicating that the instruments satisfy the relevance criterion. Based on the instrument construction described above, the exclusion restriction is also arguably satisfied. The second-stage estimates in Columns (3), (5), and (7) show that the coefficient of $ConsultNetwork_{c(i,t),g,t}$ is positive and statistically significant across all specifications.

The IV coefficients are smaller than the corresponding OLS estimate, suggesting that the OLS coefficient partly captures investors' underlying preferences. Importantly, however, the IV estimates remain positive and statistically significant, indicating that consultant networks have an effect on manager selection after accounting for those preferences. In addition, the coefficient on $ConsultNetwork_{c(i,t),g,t}$ declines as the instrument is broadened from distance to log distance and then to state licensing. This pattern is consistent with the construction of the instruments, since each successive specification expands an investor's exposure to consultant networks. As the exposure set widens, the relative influence of any individual consultant's network is likely to diminish, which can mechanically lower the estimated coefficient. Even in the broadest specification based on state licensing, the coefficient remains positive and significant at the 5% level. Taken together, these findings suggest that consultant networks have a causal impact on investors' choice of PE/VC manager.

# 4 Consultants and Performance

Having established the influence of consultants on manager selection, the next natural question is whether that influence extends to portfolio performance. More specifically, to what extent can the documented heterogeneity in investors' PE/VC portfolio performance, which Cavagnaro et al. (2019) attribute to investor skill, be explained by investors' choice of consultant? I begin by describing the measure of investor-level private equity portfolio performance used to answer this question.

## 4.1 Measuring Portfolio Performance

In the context of private equity, measuring aggregate portfolio performance is challenging because returns are not observed at regular frequencies, reported fund valuations may be stale (Agarwal, Barber, Cheng, Hameed, & Yasuda, 2023) or biased (Brown, Gredil, & Kaplan, 2019), and payoff distributions are highly skewed. To overcome these challenges, I use the parametric estimates of investor skill (Cavagnaro et al., 2019) as a measure of investor performance.

Cavagnaro et al. (2019) extend the KS model of (Korteweg & Sorensen, 2017) to incorporate investor allocations. The KS model decomposes the variance of fund returns into three components: a GP-specific effect, a GP-time effect, and a fund-specific effect. Building on this framework, Cavagnaro et al. (2019) isolate the portion of a fund's returns attributable to GP skill and fund-specific factors. They then estimate a hierarchical regression of adjusted fund returns on investor characteristics and decompose the variation in returns into an investor-specific effect and an idiosyncratic component. Mathematically, under a simplifying assumption that all private equity funds have 10-year lives, for an investor $i$ investing in fund $f$ managed by a GP $g$:

$$\text{Fund Performance}: \quad y_{f,g} = y_f = 10 \cdot \ln(1 + IRR_f) \tag{6}$$

$$\text{KS Model}: \quad y_{f,g} = X_{f,g} \cdot \beta + \sum_{\tau=t_{f,g}}^{t_{f,g}+9} \Big( \underbrace{\gamma_i}_{\text{GP-effect}} + \underbrace{\eta_{i,\tau}}_{\text{GP-time effect}} \Big) + \underbrace{\epsilon_{f,g}}_{\text{Fund-specific effect}} \tag{7}$$

$$\text{Cavagnaro et al. (2019) Ext.}: \quad \hat{y}_{f,g} = y_{f,g} - X_{f,g} \cdot \beta - \sum_{\tau=t_{f,g}}^{t_{f,g}+9} \eta_{i,\tau} \tag{8}$$

$$\hat{y}_{i,f,g} = X_i \cdot \beta_i + 10 \cdot \underbrace{\lambda_i}_{\text{Investor-specific effect}} + \underbrace{\pi_{i,f,g}}_{\text{Idiosyncratic Component}} \tag{9}$$

where,

- $i$: Investor, $f$: Fund, $g$: General Partner
- $X_{f,g}$: Observable fund and GP characteristics
- $X_i$: Observable investor characteristics

In this model, the estimate $\lambda_i$ has an intuitive economic interpretation. It represents the excess return that an investor earns across all its PE/VC investments that is attributable to the investor but not explained by observable investor characteristics. If an investor's $\lambda_i$ is estimated to be 0.01, the model predicts that the investor's PE/VC investments have an IRR that is 1% higher than that of a typical investor. Cavagnaro et al. (2019) interpret this term as investor skill, but it can also be interpreted as a proxy of an investor's portfolio-level performance.

I estimate $\lambda_i$ using Bayesian Markov Chain Monte Carlo (MCMC) techniques and use it as a measure of aggregate investor performance. The results are presented in Figure 10. The estimated dispersion in $\lambda_i$ and the implied excess IRR are very similar to those reported by Cavagnaro et al. (2019). This similarity suggests that my estimates are reliable and can be used as a proxy for investor performance.

Table 6 presents summary statistics for estimated excess IRR and investor characteristics. *With Consultant* refers to investors who have engaged a consultant at least once during the sample period, while *Without Consultant* refers to investors who have never engaged a consultant.[19] Consistent with the literature (Lerner et al., 2007; Sensoy et al., 2014; Cavagnaro et al., 2019), endowments have higher equal-weighted mean excess IRR than pension funds and foundations. Within endowments, mean excess IRR is nearly identical for investors with and without consultants. In contrast, among pension funds and foundations, investors that have never engaged a consultant exhibit higher mean excess IRR than their counterparts that have engaged a consultant. Across all investor types, investors with consultants tend

[19]Consultant relationships are identified from the *Preqin* snapshot of consultants' current and former clients. Investors not listed as either current or former clients are classified as never having engaged a consultant.

to have higher investment counts and slightly longer experience of investing in PE.

The magnitude of excess IRR may raise concerns about economic significance, but a simple back-of-the-envelope calculation shows that the implied effect is not trivial. The mean(median) excess IRR of an investor is 0.2%(0.7%). For an allocation size of $\$200Mn(\$88Mn)$ and an investment count of 44.7(17), this corresponds to an implied value of $\$18Mn(\$10Mn)$ for the mean(median) investor. Assuming a private equity portfolio weight of 10% (Begenau et al., 2025), this amounts to 2%(10%) of the investor's total private equity portfolio value. This suggests that even modest differences in excess IRR can translate into economically meaningful differences for investors.

## 4.2 Investor Performance and Consultant Fixed Effects

With a measure of investor performance in hand, the next question is how much of the heterogeneity in performance can be explained by investors' choice of consultant. Before turning to the empirical analysis, it is necessary to impose a simplifying assumption to address a key data limitation. Specifically, investor performance is observed only as a point estimate, even though an investor may engage multiple consultants over time. To address this limitation, each investor is assigned a main consultant, defined as the consultant engaged for the greatest number of years over the sample period. Under this assumption, any excess IRR associated with the consultants an investor has engaged over its lifetime is fully attributed to the main consultant. Because identifying the main consultant requires time-series data on investor–consultant relationships, the sample is reduced to 314 investors.[20]

To assess the extent to which investor performance can be explained by investors' choice of consultant, the analysis employs a simple parametric framework, analysis of covariance (ANCOVA). Specifically, the following model is estimated with and without consultant fixed

[20] Table 1 reports 342 investors in the *Consultant Subsample*. The sample here includes only 314 investors because 28 investors in that subsample are never observed to engage a consultant in the time-series data.

effects:

$$\lambda_i = \beta_1 \cdot ln(AUM_i) + \beta_2 \cdot ln(InvestmentCount_i) + \beta_3 \cdot YrsExp_i + \delta_{Type(i)} + \Lambda_{c(i)} + \epsilon_i; \tag{10}$$

where,

- $i$: Investor, $c(i)$: Main consultant engaged by investor $i$, $Type(i)$: Investor Type, $\delta$: Fixed Effects
- $\lambda_i$ is the measure of investor skill as previously defined
- $ln(AUM_i)$ is the natural log of the investor's assets under management in USD Bn
- $ln(InvestmentCount_i)$ is the natural log of the number of PE/VC investments an investor has made to date
- $YrsExp_i$ is the number of years for which the investor has been investing in PE/VC

To assess how much variation in fund-level performance is attributable to consultants, I examine the proportion of the total Type III partial sum of squares explained by the consultant fixed effects. To evaluate whether consultant fixed effects add explanatory power, I compare the $R^2$ from models estimated with and without fixed effects.

The results are reported in Table 7. The values in the table represent the fraction of the model sum of squares attributable to each covariate. Consultant fixed effects account for 77% of the variation explained by the model and increase its explanatory power by a factor of 2.6, with $R^2$ rising from 0.051 to 0.131. This suggests that investors' choice of consultant explains a non-trivial share of the heterogeneity in investor performance and that some consultants are associated with clients whose portfolios outperform those of clients of other consultants. At the same time, the fact that $R^2$ remains 0.131 after including consultant fixed effects indicates that meaningful heterogeneity in investor performance is still driven by investor-specific unobservable factors.

Since some consultants are associated with clients that perform better than others, a question arises: what distinguishes these consultants from the rest? To explore this, the estimated consultant fixed effects from Equation (10) are regressed on observable consultant characteristics. Because these fixed effects do not vary over time, consultant characteristics are measured using their mean values over the full sample period. The following regression is estimated:

$$\Lambda_c = \beta_1 \cdot ln(AUA_c) + \beta_2 \cdot ln(EmpCount_c) + \beta_3 \cdot ln(OfficeCount_c) + \epsilon_c; \tag{11}$$

where,

- $c$: Consultant
- $\Lambda_c$ is the fixed-effect coefficient for consultant $c$ as estimated in Equation (10)
- $ln(AUA_c)$ is the natural log of the mean assets under advisement over the full sample period for consultant $c$
- $ln(EmpCount_c)$ is the natural log of the mean number of consultant employees over the full sample period for consultant $c$
- $ln(OfficeCount_c)$ is the natural log of the mean number of consultant offices over the full sample period for consultant $c$.

The results are reported in Table 8b. Columns (1)–(3) show that, when considered individually, consultant $AUA$, employee count, and office count are positively associated with the estimated consultant fixed effect. However, these characteristics are also strongly correlated with one another, as shown in Table 8a, so their explanatory power overlaps in the multivariate setting. Among them, office count has the strongest univariate association with consultant fixed effects.

This evidence is consistent with the idea that consultants create value through scale economies in information gathering (Goyal & Wahal, 2008). Consultants with more employ-

ees and a broader office footprint are likely to possess stronger information networks, which may improve the information available to clients and ultimately their portfolio performance. Overall, the results suggest that observable scale-related consultant characteristics account for part of the cross-consultant variation in client performance.

## 4.3 Performance: Internal Teams vs. Consultants

Table 6 reveals an interesting pattern: investors, particularly pension funds and foundations, that have never engaged a consultant exhibit higher average excess IRR than those that have engaged a consultant. One can reasonably assume that investors that have never engaged a consultant rely on an internal private equity team. To examine whether there is a systematic difference in performance between investors with internal private equity teams and those that engage an investment consultant, I estimate the following regression specification:

$$\lambda_i = \beta_1 \cdot UsedConsult_i + \beta_2 \cdot UsedConsult_i \times UsedPE/VCConsult_i + \gamma_1 \cdot ln(AUM_i) + \gamma_2 \cdot ln(InvestmentCount_i) + \gamma_3 \cdot YrsExp_i + \delta_{Type(i)} + \epsilon_i; \quad (12)$$

where:

- $i$: Investor, $\delta_{Type(i)}$: Investor Type Fixed Effects
- $\lambda_i$ is the measure of investor skill as previously defined
- $UsedConsult_i$ is an indicator variable that equals 1 if investor $i$ has ever used a consultant in any capacity, 0 otherwise
- $UsedPE/VCConsult_i$ is an indicator variable that equals 1 if investor $i$ has ever used a consultant for advisory on PE/VC investments, 0 otherwise
- $ln(AUM_i)$ is the natural log of the investor's assets under management in USD Bn

- $ln(InvestmentCount_i)$ is the natural log of the number of PE/VC investments an investor has made to date
- $YrsExp_i$ is the number of years for which the investor has been investing in PE/VC

The results are presented in Table 9. The coefficient on $UsedConsult_i$ is negative and statistically significant across all specifications, suggesting that investors who rely on external consultants systematically underperform those with internal investment teams. The coefficient on the interaction term is statistically insignificant, indicating that engaging a consultant for PE/VC advisory does not improve performance, consistent with the evidence on fund-level returns in Andonov et al. (2026). Economically, the estimates imply that investors with internal teams invest in funds with IRRs that are, on average, 70 to 80 b.p.s. higher than those of investors who engage an external consultant.

Looking at the other coefficients, investor-type fixed effects add substantial explanatory power, consistent with the fact that the performance differential is concentrated primarily among pension funds and foundations. Investor size and investment count also enter positively and significantly when included separately. However, these effects disappear once both variables are included jointly, suggesting that they capture related dimensions of investor scale and sophistication rather than distinct channels of performance.

This evidence suggests that investors with internal private equity teams make systematically better investments than those that use a consultant as an intermediary. That said, this finding should be interpreted with caution. The analysis does not account for the institutional and financial costs of building an internal private equity team, including the time required to develop relationships and investment expertise, or the cost of attracting and retaining specialized talent.

# 5 Conclusion

Alternative investments have become an important component of institutional portfolios. But these markets are also unusually difficult to navigate: market signals are limited, access is relationship-driven, due diligence is costly, and performance is difficult to evaluate ex ante. In this environment, investment consultants have become an increasingly important intermediary, helping institutions bridge the informational and organizational frictions inherent in alternatives.

The central message of this paper is that consultants add value not only by providing cover for investment decisions, but also by supplying information and expertise that shape real outcomes. Their importance reflects a broader feature of alternative assets: as institutions seek exposure to markets that are specialized and opaque, intermediaries with knowledge and networks become essential to the allocation process. A natural direction for future research is to examine the institutional and financial constraints that shape an investor's decision to engage a consultant rather than build an internal private equity team, thereby shedding further light on the economic value of consultants as information intermediaries.

# References


Agarwal, V., Barber, B., Cheng, S., Hameed, A., & Yasuda, A. (2023). Private company valuations by mutual funds. *Review of Finance*, *27*(2), 693–738.

Allen, F. (2001). Do financial institutions matter? *The Journal of Finance*, *56*(4), 1165–1175.

Andonov, A. (2024). Delegated investment management in alternative assets. *The Review of Corporate Finance Studies*, *13*(1), 264–301.

Andonov, A., Bonetti, M., & Stefanescu, I. (2026). Choosing pension fund investment consultants. *Available at SSRN*.

Begenau, J., Liang, P., & Siriwardane, E. (2025). The rise of alternatives. *Available at SSRN 4940886*.

Brown, G. W., Gredil, O. R., & Kaplan, S. N. (2019). Do private equity funds manipulate reported returns? *Journal of Financial Economics*, *132*(2), 267–297.

Cavagnaro, D. R., Sensoy, B. A., Wang, Y., & Weisbach, M. S. (2019). Measuring institutional investors' skill at making private equity investments. *The Journal of Finance*, *74*(6), 3089–3134.

Cohen, L., Frazzini, A., & Malloy, C. (2008). The small world of investing: Board connections and mutual fund returns. *Journal of Political Economy*, *116*(5), 951–979.

Cohen, L., Frazzini, A., & Malloy, C. (2010). Sell-side school ties. *The Journal of Finance*, *65*(4), 1409–1437.

Cookson, G., Jenkinson, T., Jones, H., & Martinez, J. V. (2022). Virtual reality? investment consultants' claims about their own performance. *Management Science*, *68*(11), 8301–8318.

Dyck, A., Manoel, P., & Morse, A. (2022). Outraged by compensation: Implications for public pension performance. *The Review of Financial Studies*, *35*(6), 2928–2980.

Foerster, S., Linnainmaa, J. T., Melzer, B. T., & Previtero, A. (2017). Retail financial advice: does one size fit all? *The Journal of Finance*, *72*(4), 1441–1482.

Gârleanu, N., & Pedersen, L. H. (2018). Efficiently inefficient markets for assets and asset management. *The Journal of Finance*, *73*(4), 1663–1712.

Gennaioli, N., Shleifer, A., & Vishny, R. (2015). Money doctors. *The Journal of Finance*, *70*(1), 91–114.

Goyal, A., & Wahal, S. (2008). The selection and termination of investment management firms by plan sponsors. *The Journal of Finance*, *63*(4), 1805–1847.

Goyal, A., Wahal, S., & Yavuz, M. D. (2024). Choosing investment managers. *Journal of Financial and Quantitative Analysis*, *59*(8), 3531–3563.

Goyal, A., Wahal, S., & Yavuz, M. D. (2026). Picking partners: Manager selection in

private markets. *Journal of Financial Economics*, *178*, 104250.

Ivashina, V., & Lerner, J. (2018). Looking for alternatives: Pension investments around the world, 2008 to 2017. *Unpublished working paper. Harvard University*.

Jenkinson, T., Jones, H., & Martinez, J. V. (2016). Picking winners? investment consultants' recommendations of fund managers. *The Journal of Finance*, *71*(5), 2333–2370.

Jones, H., & Martinez, J. V. (2017). Institutional investor expectations, manager performance, and fund flows. *Journal of Financial and Quantitative Analysis*, *52*(6), 2755–2777.

Kaplan, S. N., & Schoar, A. (2005). Private equity performance: Returns, persistence, and capital flows. *The journal of finance*, *60*(4), 1791–1823.

Korteweg, A., & Sorensen, M. (2017). Skill and luck in private equity performance. *Journal of Financial Economics*, *124*(3), 535–562.

Lakonishok, J., Shleifer, A., & Vishny, R. (1992). The structure and performance of the money management industry. *Brookings Papers on Economic Activity: Microeconomics*.

Lerner, J., Schoar, A., & Wongsunwai, W. (2007). Smart institutions, foolish choices: The limited partner performance puzzle. *The Journal of Finance*, *62*(2), 731–764.

Martinez, J. V., & Qian, Y. (2025). Selectivity, favoritism, and performance: The role of investment consultants in private equity. *Available at SSRN 4322963*.

Rossi, A. G., Blake, D., Timmermann, A., Tonks, I., & Wermers, R. (2018). Network centrality and delegated investment performance. *Journal of Financial Economics*, *128*(1), 183–206.

Sensoy, B. A., Wang, Y., & Weisbach, M. S. (2014). Limited partner performance and the maturing of the private equity industry. *Journal of Financial Economics*, *112*(3), 320–343.

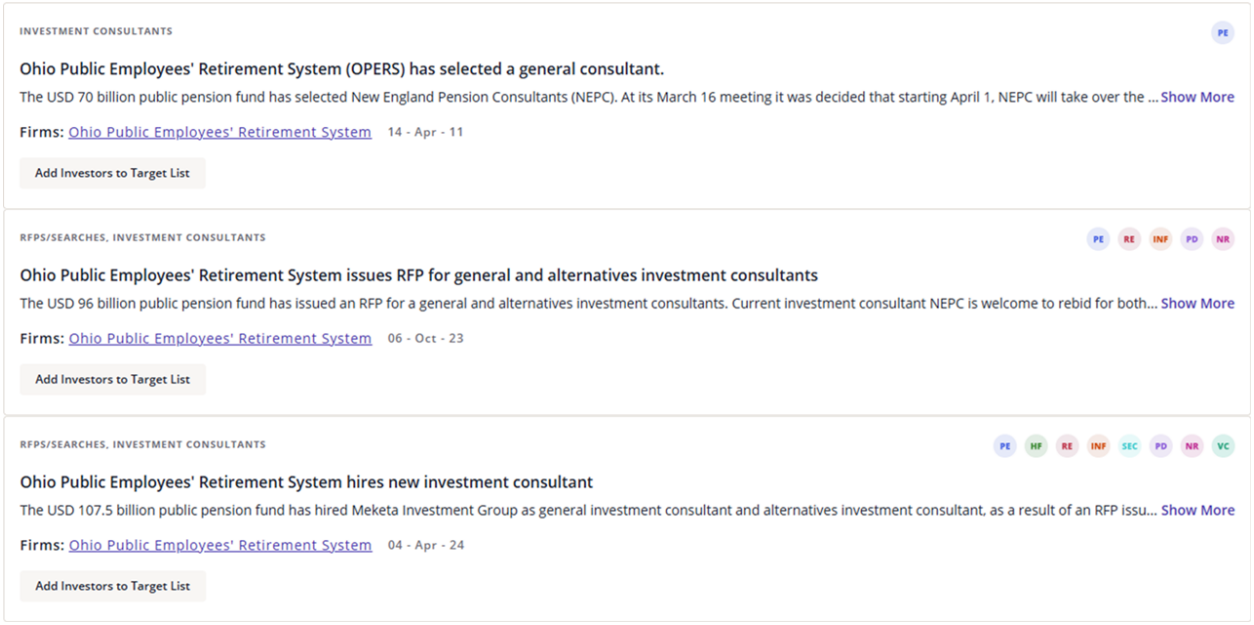
Whyte, A. (2019). Allocators need them, asset managers resent them,

and everyone is afraid of them. *Institutional Investor*. Retrieved from https://www.institutionalinvestor.com/article/2bsw9kgsnxczgzyyz8w74/corner-office/allocators-need-them-asset-managers-resent-them-and-everyone-is-afraid-of-them

# Figures

## Figure 1: Example of Linking Investors and Consultants

**(a)** Relevant news events for Ohio Public Employees Retirement System (OPERS)




**(b)** News event on consultant term

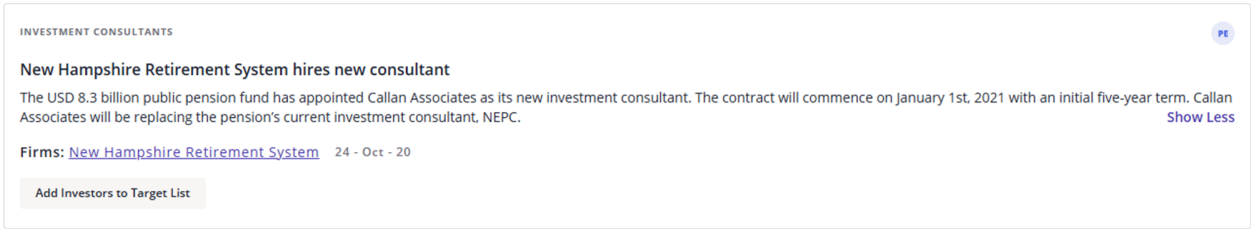
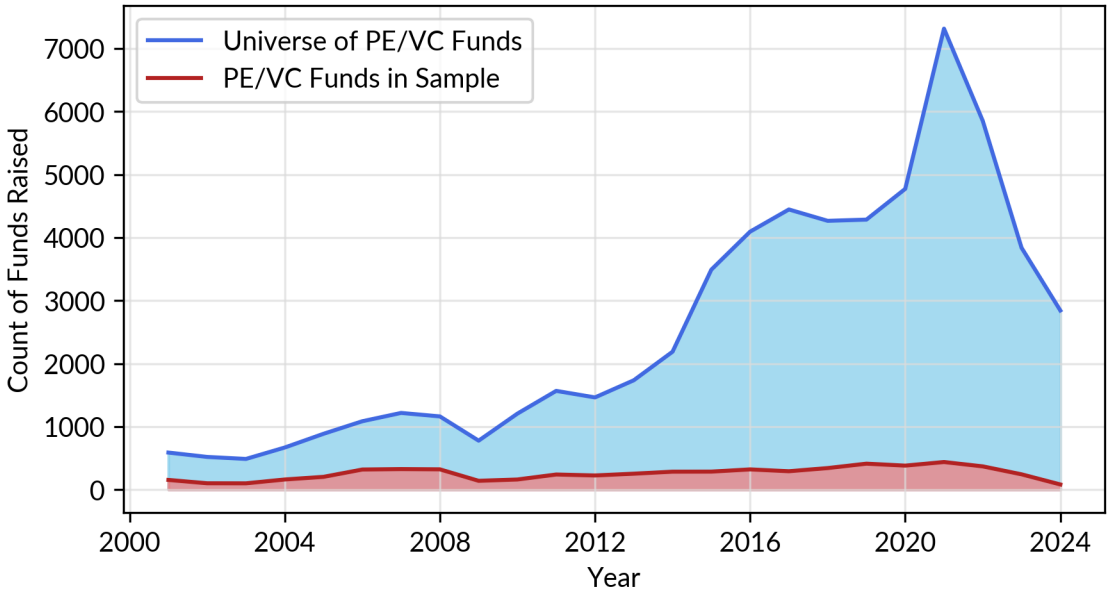


**Figure 2: Sample Coverage of Private Equity/Venture Capital Funds**

**(a)** Count of Funds Raised




**(b)** Capital Raised (USD Bn)

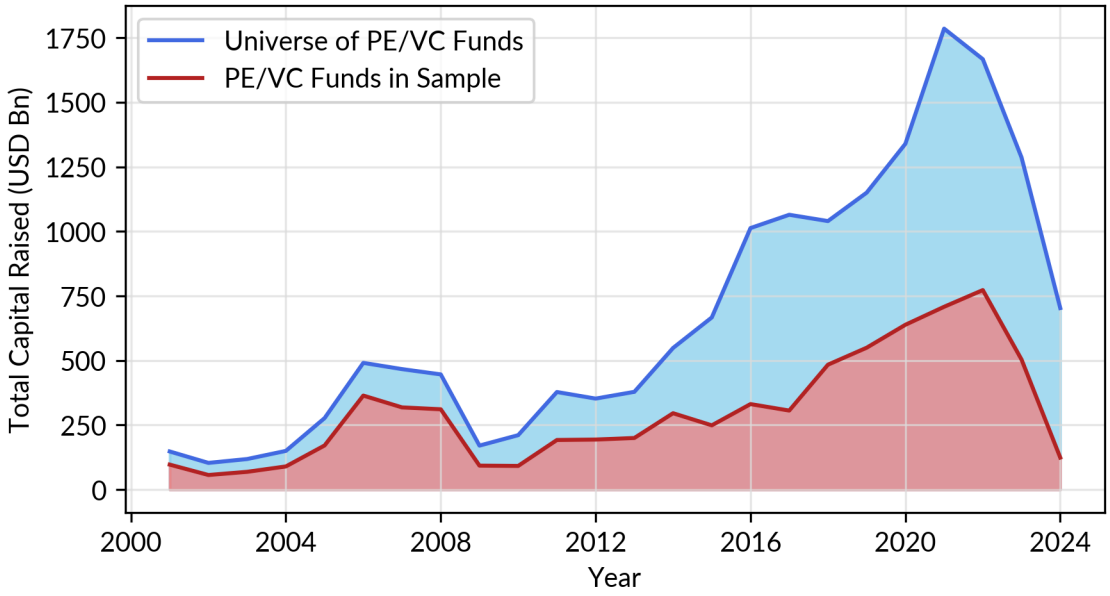
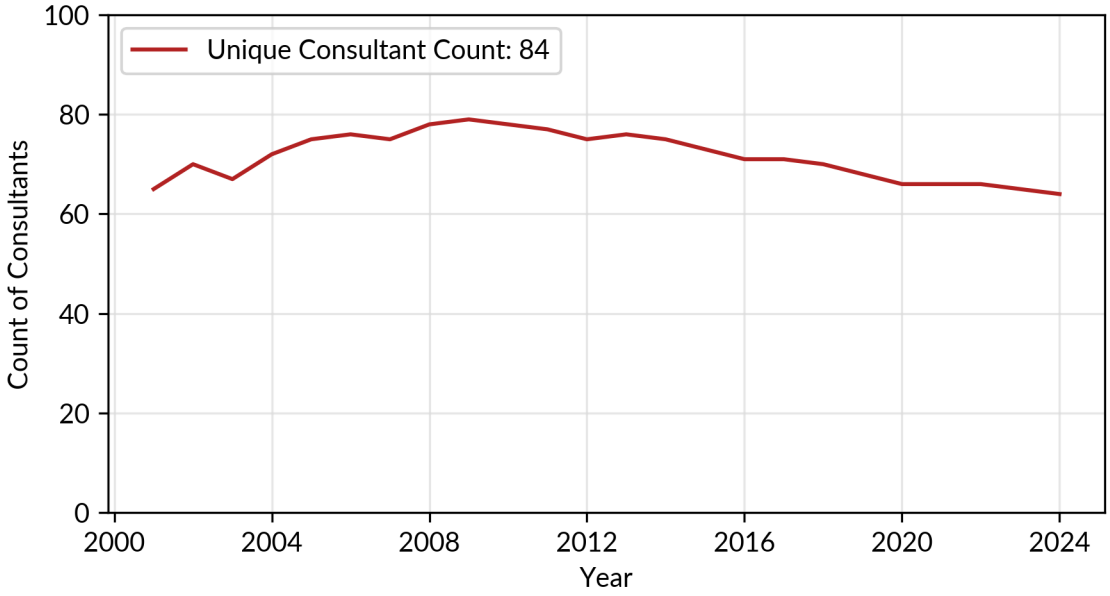


**Figure 3: Characteristics of Institutional Consultant Industry**

**(a)** Count of Consultants




**(b)** Total Assets under Advisement (AUA) (USD Bn)

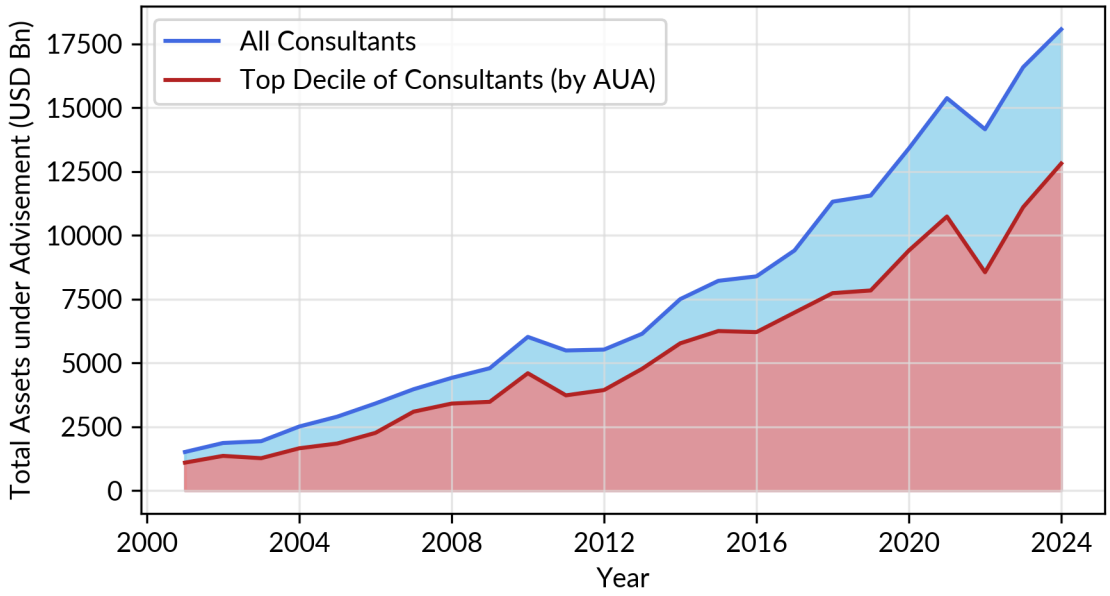
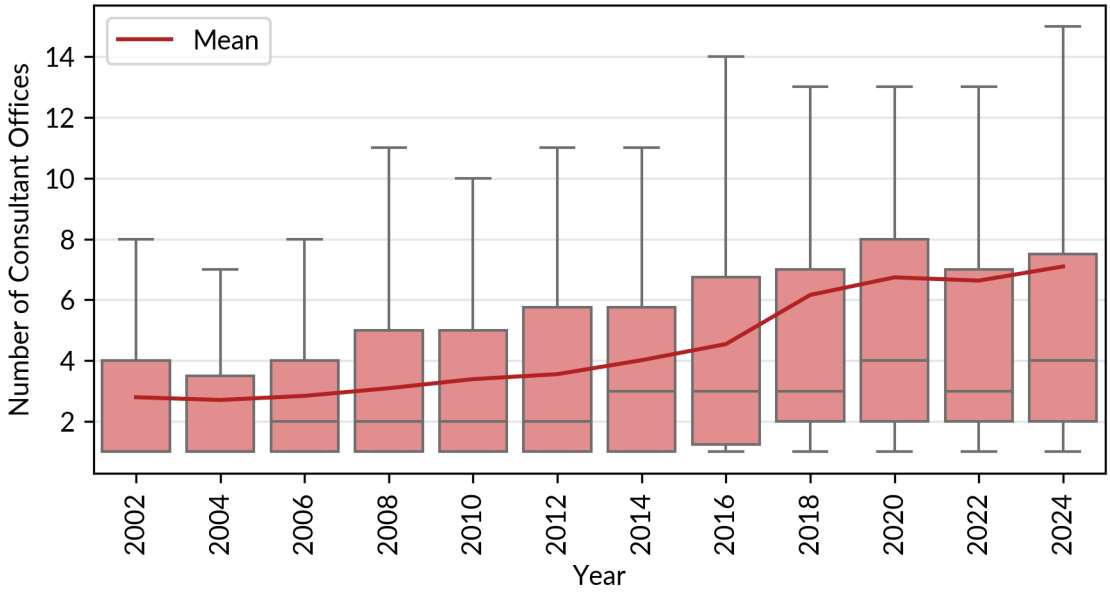


**Figure 4: Characteristics of Institutional Consultants**

**(a)** Number of Consultant Offices




**(b)** Number of Consultant Employees

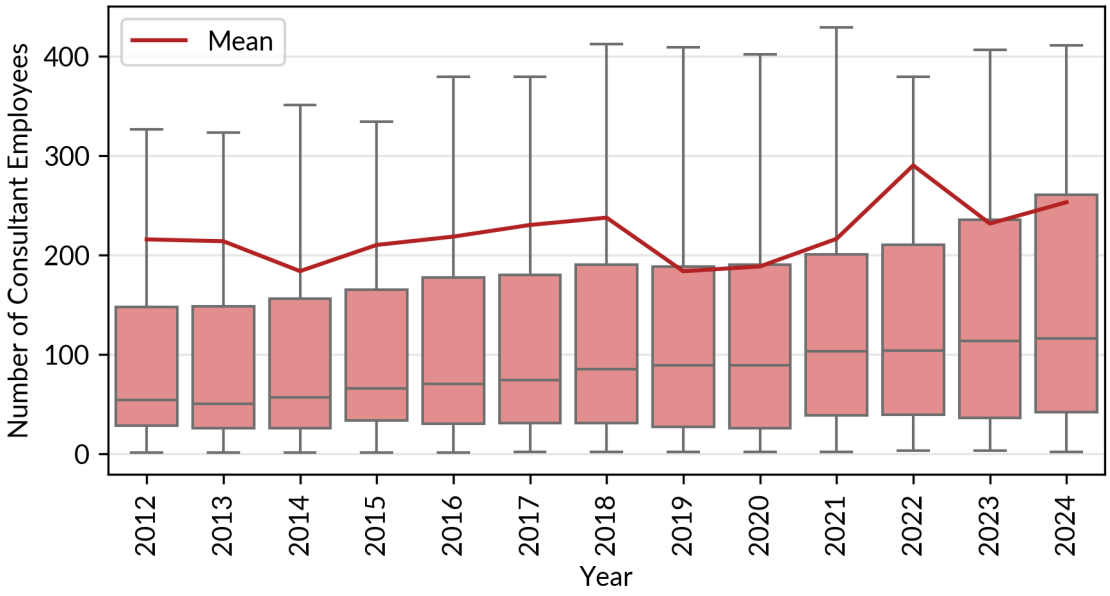


**Figure 5: Consultant Turnover Events**

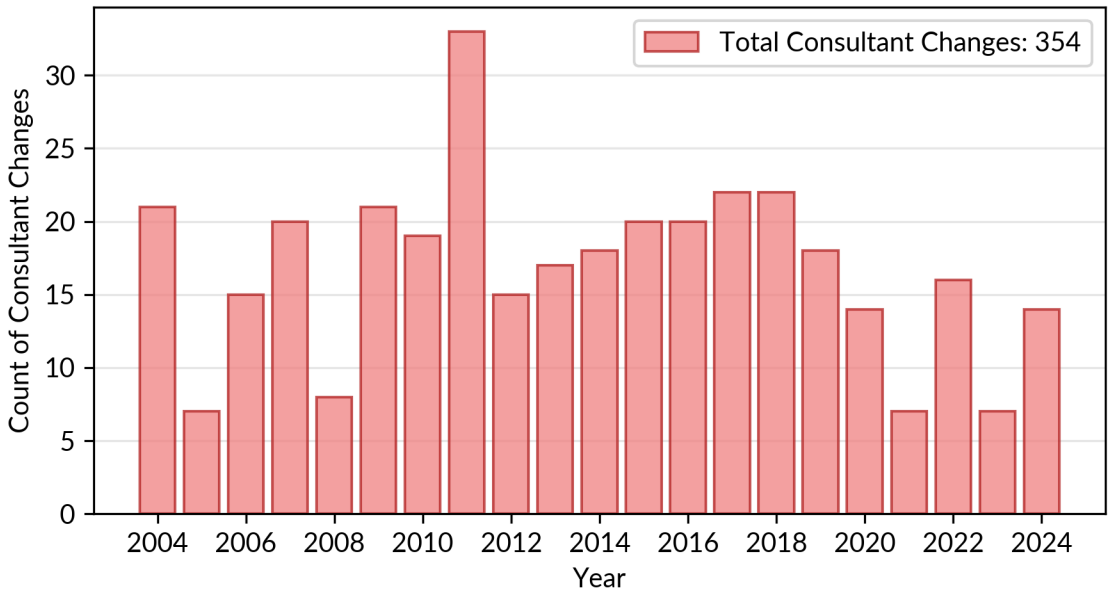
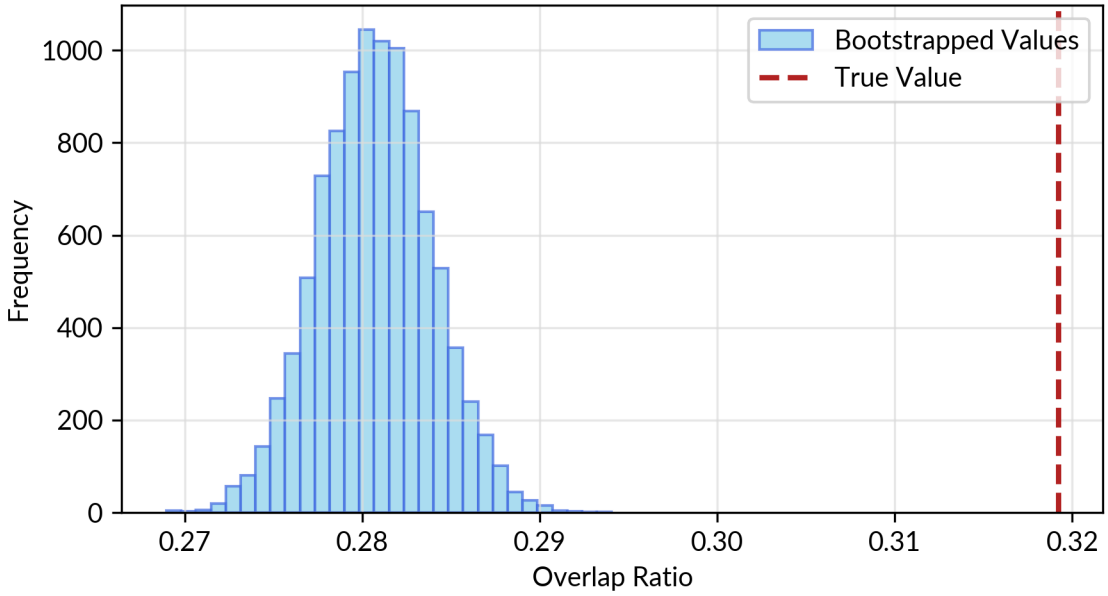


**Figure 6: Clustering in Investors' Choice of General Partner (GP)**

**(a)** Overlap Ratio




**(b)** Co-Investment Ratio

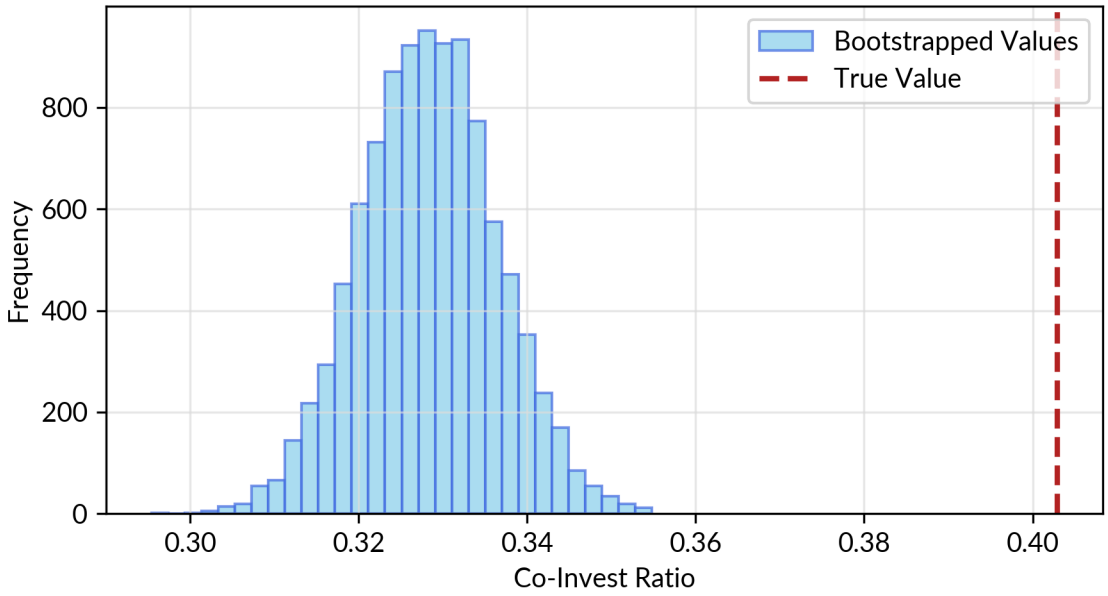
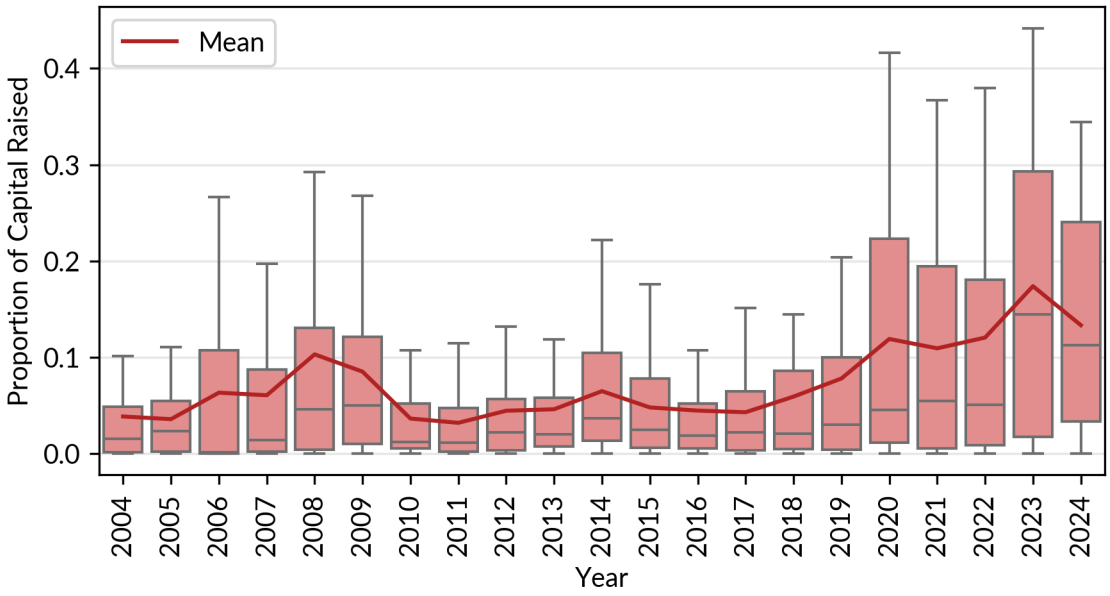


**Figure 7: Coverage of Consultant Networks**

**(a)** Proportion of Capital Raised




**(b)** Proportion of Funds Raised

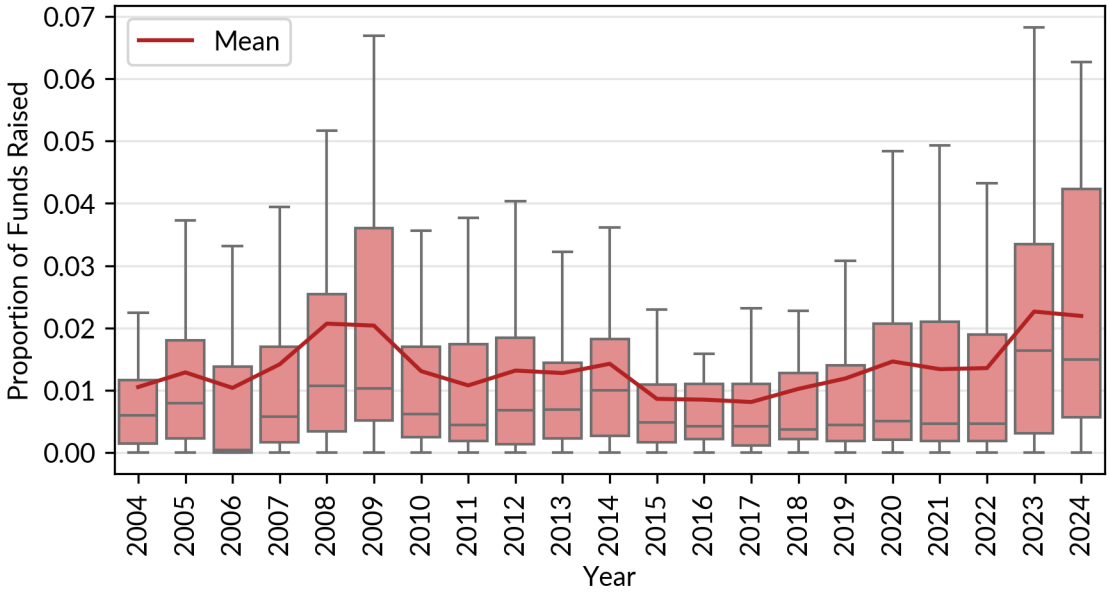


**Figure 8: GP Characteristics and Coverage in Consultant Networks**

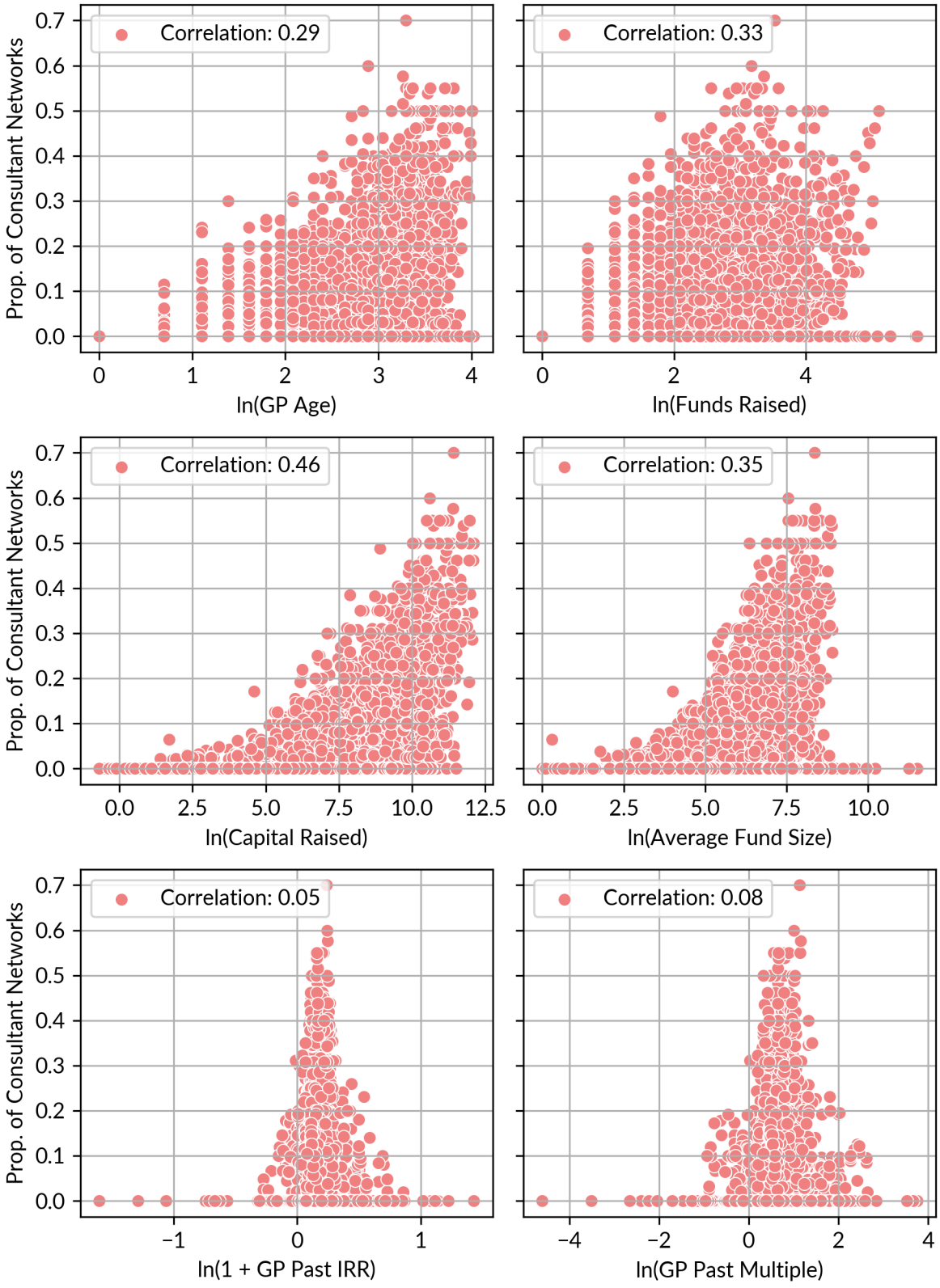
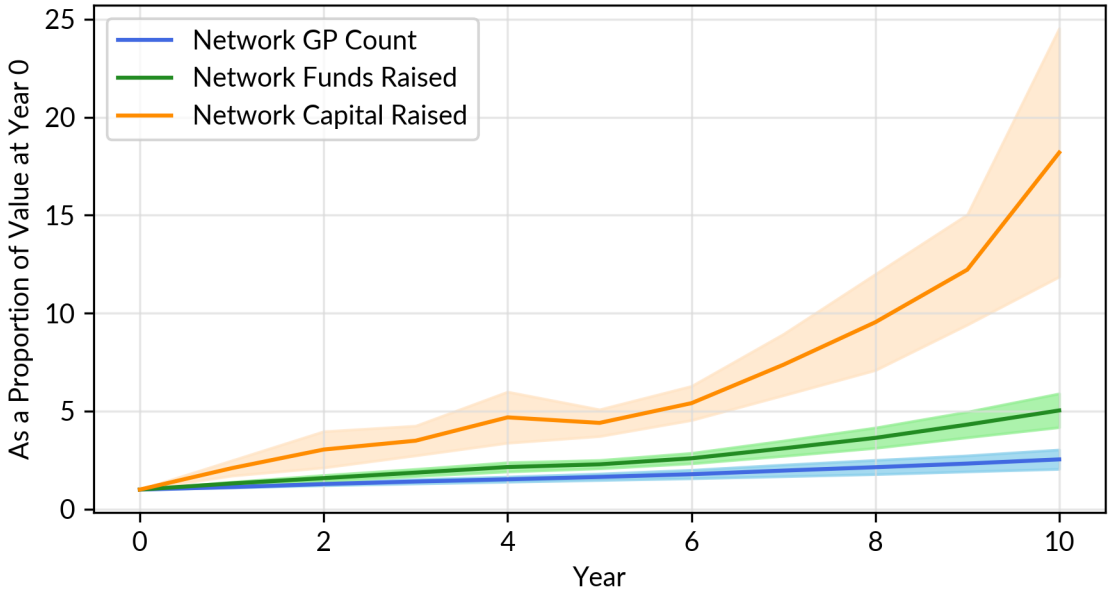


**Figure 9: Evolution of Consultant Networks**

**(a)** Evolution of Network Characteristics




**(b)** Survival of GPs in Network

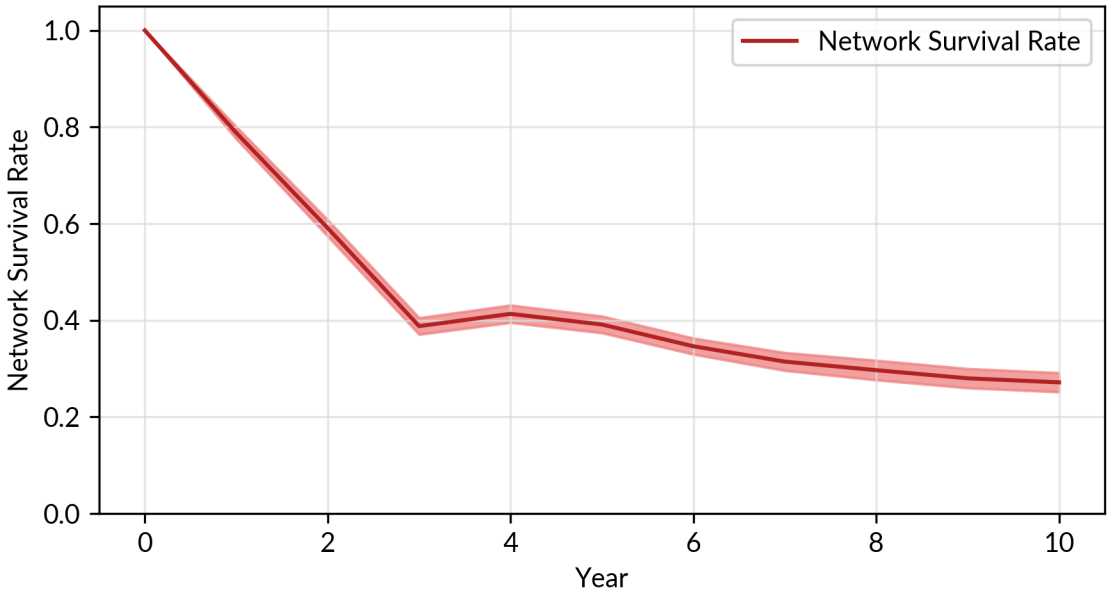
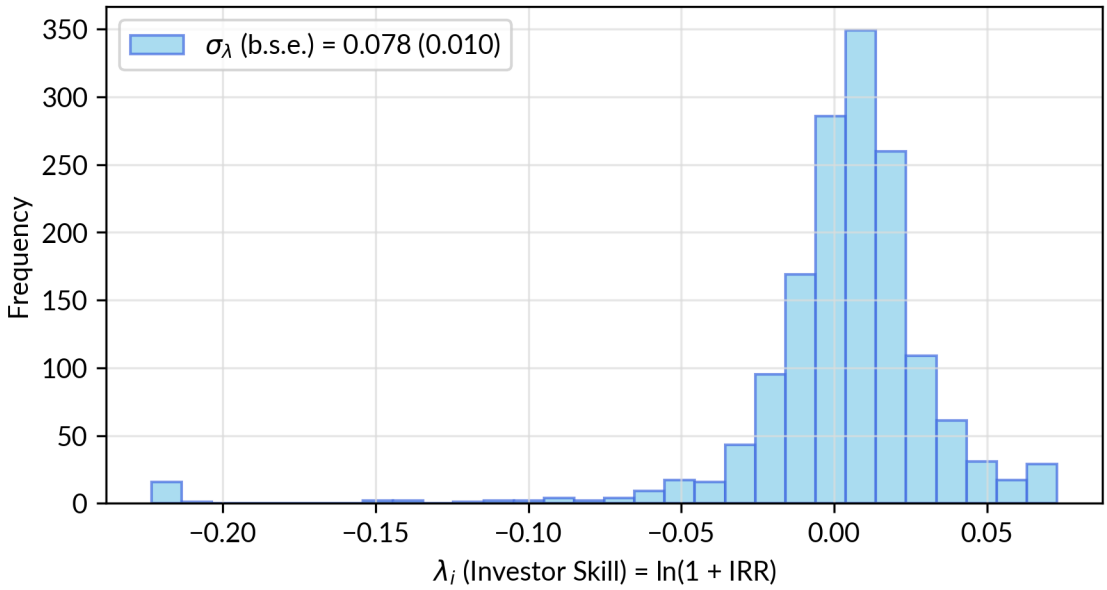
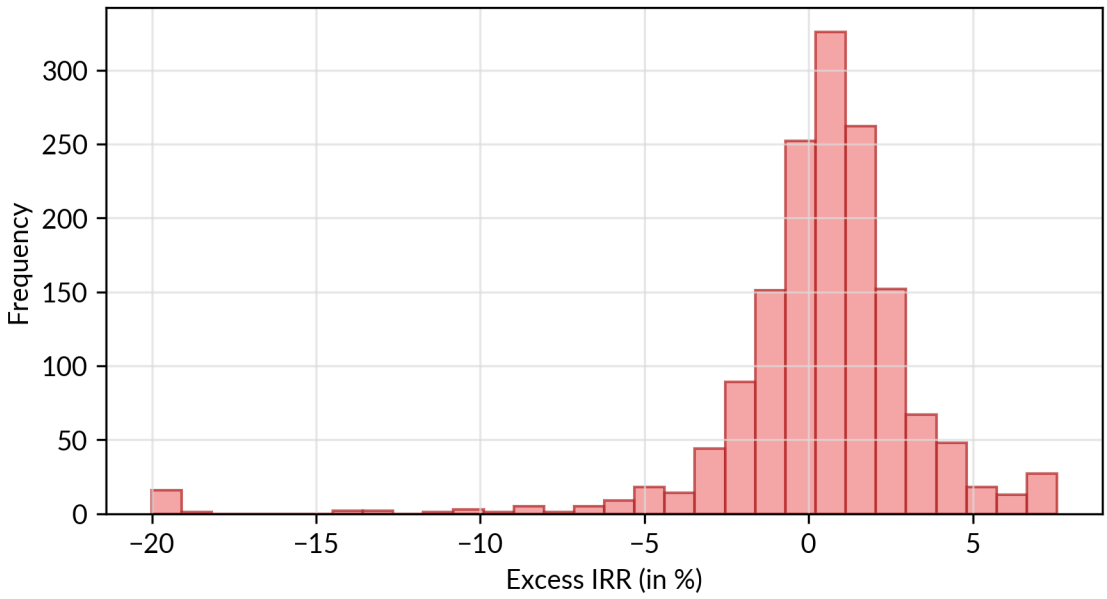


**Figure 10: Estimation of Investor Skill**

**(a)** Estimates of Investor Skill




**(b)** Excess IRR Contribution of Estimated Skill



# Tables

**Table 1: Investor Summary Statistics**

This table presents the summary characteristics of investors in the sample. $AUM_i$ is the investor's assets under management in USD Bn at the end of Q4 CY2024; *All Investors* column refers to all investors in *Preqin* with $AUM_i > \$125Mn$, who have made >= 5 allocations to PE/VC funds; *Matched Sample* column refers to the subset of investors for whom the identity of the consultant is observed by investor-year.

| Statistic | Full Sample | Consultant Subsample | *Coverage* |
|---|---|---|---|
| Total $AUM_i$ (USD Bn) | 11220.4 | 5946.3 | 53.0% |
| Pension Fund | 9403.3 | 5375.4 | 57.2% |
| Foundation | 978.1 | 64.9 | 6.6% |
| Endowment Plan | 839.0 | 506.1 | 60.3% |
| Investor Count | 1527 | 342 | 22.4% |
| Pension Fund | 769 | 242 | 31.5% |
| Foundation | 472 | 38 | 8.1% |
| Endowment Plan | 286 | 62 | 21.7% |
| Mean (Median) $AUM_i$ (USD Bn) | 7.3 (1.1) | 17.4 (2.8) | |
| Pension Fund | 12.2 (2.1) | 22.2 (3.7) | |
| Foundation | 2.1 (0.5) | 1.7 (0.6) | |
| Endowment Plan | 2.9 (0.7) | 8.2 (1.5) | |

## Table 2: Investor Summary Statistics

This table presents the *Overlap Ratio* and the *Co-Investment Ratio* for the *True Sample* and compares it with values for 10,000 bootstrapped samples. Samples are bootstrapped such that investors retain their consultants but are randomly assigned to funds, controlling for fund vintage, size, region, strategy, and number of investors in a given fund. Given investor $i$, fund $f$, and consultant $c(i,t)$, The *Overlap Ratio* is defined as:

$$\begin{aligned}
\textit{Overlap Ratio}_{c,f} &= \frac{\text{Number of investors } i \text{ in } f \text{ for whom } c(i,t) = c}{\text{Total number of investors in } f}, \\
\textit{Overlap Ratio}_f &= \max_c \big(\text{Overlap Ratio}_{c,f}\big), \\
\textit{Overlap Ratio} &= \frac{1}{F}\sum_{f=1}^{F} \text{Overlap Ratio}_f
\end{aligned}$$

The *Co-Investment Ratio* is defined as:

$$\begin{aligned}
\textit{Co-Investment}_{i,f} &= \begin{cases} 1, & \text{if clients of } c(i,t) \text{ except } i \text{ have invested in } f \\ 0, & \text{otherwise} \end{cases} \\
\textit{Co-Investment Ratio}_i &= \frac{\sum_f \textit{Co-Investment}_{i,f}}{\text{Total number of investments by } i}, \\
\textit{Co-Investment Ratio} &= \frac{1}{I}\sum_{i=1}^{I} \text{Co-Investment Ratio}_i
\end{aligned}$$

| Statistic | True Value | Boot. Sample | Diff. | t-stat |
|---|---|---|---|---|
| Overlap Ratio | | | | |
| Mean | 0.32 | 0.28 | 0.04 | $(12.09)^{***}$ |
| Standard Error | | (0.0) | | |
| Co-Investment Ratio | | | | |
| Mean | 0.4 | 0.33 | 0.07 | $(9.23)^{***}$ |
| Standard Error | | (0.01) | | |

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

## Table 3: Consultant Network and Manager Selection

This table estimates the following regression:

$$P(Invest)_{i,g,t} = \beta_1 \cdot ConsultNetwork_{c(i,t),g,t} + \beta_2 \cdot PastRelation_{i,g,t} + \beta_3 \cdot InvestorControls_{i,t} + \beta_4 \cdot GPSizeControls_{g,t} + \beta_5 \cdot GPPerfControls_{g,t} + \lambda_t + \lambda_c + \epsilon_{i,g,t}$$

The dependent variable $P(Invest)_{i,g,t}$ is a binary indicator that equals 1 if investor $i$ invests with GP $g$ in time $t$, 0 otherwise; $PastRelation_{i,g,t}$ is a binary indicator that equals 1 if in year $t$ investor $i$ has invested at least once with GP $g$ in the last 15 years, 0 otherwise; $ConsultNetwork_{c(i,t),g,t}$ is a binary indicator that equals 1 if in year $t$ GP $g$ belongs to the network of consultant $c(i,t)$, and 0 otherwise; $InvestorControls_{i,t}$ include $ln(AUM)$ and investor type; $GPSizeControls_{g,t}$ include GP age, number of funds raised, and $ln(CapitalRaised)$; $GPPerfControls_{g,t}$ include the weighted average IRR and multiple of prior GP funds; $\lambda$ is fixed effects. Standard Errors are clustered at the consultant and vintage levels.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| $PastRelation_{i,g,t}$ | 0.404*** | 0.389*** | 0.387*** | 0.387*** | 0.383*** | 0.359*** |
| | (16.25) | (16.03) | (16.12) | (16.15) | (17.35) | (17.04) |
| $ConsultNetwork_{c(i,t),g,t}$ | | 0.031*** | 0.031*** | 0.032*** | 0.030*** | 0.035*** |
| | | (7.15) | (7.11) | (6.98) | (6.48) | (6.44) |
| Observations | 372671 | 372671 | 371956 | 371956 | 333365 | 178060 |
| $R^2$ | 0.2050 | 0.2068 | 0.2072 | 0.2077 | 0.2255 | 0.2416 |
| Adjusted $R^2$ | 0.2049 | 0.2068 | 0.2071 | 0.2075 | 0.2253 | 0.2410 |
| Mean $P(Invest)_{i,g,t}$ | 0.0528 | 0.0528 | 0.0528 | 0.0528 | 0.0554 | 0.0747 |
| Vintage Fixed Effects | Y | Y | Y | Y | Y | Y |
| Investor Controls | | | Y | Y | Y | Y |
| Consultant Fixed Effects | | | | Y | Y | Y |
| GP Size Controls | | | | | Y | Y |
| GP Performance Controls | | | | | | Y |

$t$ statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

## Table 4: Network Changes and Manager Selection

This table estimates the following regression:

$$\begin{aligned} P(Invest)_{i,g,t} = \beta_1 \cdot ConsultNetwork_{c(i,t),g,t} + \beta_2 \cdot PastRelation_{i,g,t} \\ + \beta_3 \cdot NetworkAdditions_{c(i,t),g,t} + \beta_4 \cdot NetworkDeletions_{c(i,t),g,t} \\ + \gamma_1 \cdot X_{i,t} + \gamma_2 \cdot Y_{g,t} + \lambda_t + \lambda_c + \epsilon_{i,g,t} \end{aligned}$$

The dependent variable $P(Invest)_{i,g,t}$ is a binary indicator that equals 1 if investor $i$ invests with GP $g$ in time $t$, 0 otherwise; $PastRelation_{i,g,t}$ is a binary indicator that equals 1 if in year $t$ investor $i$ has invested at least once with GP $g$ in the last 15 years, 0 otherwise; $ConsultNetwork_{c(i,t),g,t}$ is a binary indicator that equals 1 if in year $t$ GP $g$ belongs to the network of consultant $c(i,t)$, and 0 otherwise; $NetworkAdditions_{c(i,t),g,t}$ is a binary indicator that equals 1 if in year $t$ GP $g$ was added to the network of consultant $c(i,t)$, and 0 otherwise; $NetworkDeletions_{c(i,t),g,t}$ is a binary indicator that equals 1 if in year $t$ GP $g$ was newly deleted from the network of consultant $c(i,t)$, and 0 otherwise; Column (5) reports results for the subsample in which for an investor $i$, consultant in time $t$ is different from time $t-1$; $X_{i,t}$ is a vector of investor controls; $Y_{g,t}$ is a vector of GP controls; $\lambda$ is fixed effects. Standard Errors are clustered at the consultant and vintage levels.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| $PastRelation_{i,g,t}$ | 0.359*** | 0.369*** | 0.371*** | 0.370*** | 0.391*** |
| | (17.04) | (17.22) | (17.14) | (17.15) | (73.12) |
| $ConsultNetwork_{c(i,t),g,t}$ | 0.035*** | | | | 0.009** |
| | (6.44) | | | | (2.11) |
| $NetworkAdditions_{c(i,t),g,t}$ | | 0.022*** | | 0.020** | |
| | | (2.85) | | (2.69) | |
| $NetworkDeletions_{c(i,t),g,t}$ | | | -0.041*** | -0.040*** | |
| | | | (-5.13) | (-5.12) | |
| Observations | 178060 | 178060 | 178060 | 178060 | 25874 |
| $R^2$ | 0.2416 | 0.2395 | 0.2399 | 0.2401 | 0.1921 |
| Adjusted $R^2$ | 0.2410 | 0.2390 | 0.2394 | 0.2396 | 0.1893 |
| Mean $P(Invest)_{i,g,t}$ | 0.0747 | 0.0747 | 0.0747 | 0.0747 | 0.0571 |

$t$ statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

## Table 5: Robustness Check on Investor and Consultant Sizes

This table estimates the following regression:

$$P(Invest)_{i,g,t} = \beta_1 \cdot ConsultNetwork_{c(i,t),g,t} + \beta_2 \cdot PastRelation_{i,g,t} + \gamma_1 \cdot X_{i,t} + \gamma_2 \cdot Y_{g,t} + \lambda_t + \lambda_c + \epsilon_{i,g,t}$$

The dependent variable $P(Invest)_{i,g,t}$ is a binary indicator that equals 1 if investor $i$ invests with GP $g$ in time $t$, 0 otherwise; $PastRelation_{i,g,t}$ is a binary indicator that equals 1 if in year $t$ investor $i$ has invested at least once with GP $g$ in the last 15 years, 0 otherwise; $ConsultNetwork_{c(i,t),g,t}$ is a binary indicator that equals 1 if in year $t$ GP $g$ belongs to the network of consultant $c(i,t)$, and 0 otherwise; $X_{i,t}$ is a vector of investor controls; $Y_{g,t}$ is a vector of GP controls; $\lambda$ is fixed effects. Column (1) presents the results of the OLS regression. Columns (2)-(7) present results in which $ConsultNetwork_{c(i,t),g,t}$ is instrumented by $z_{c(i,t),g,t}$ as defined in Section 3.3.1. Standard Errors are clustered at the consultant and vintage levels.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| $ConsultNetwork_{c(i,t),g,t}$ | 0.035*** | | 0.022*** | | 0.017*** | | 0.012** |
| | (6.44) | | (3.28) | | (3.01) | | (2.31) |
| $z_{c(i,t),g,t}$ | | 1.539*** | | 3.458*** | | 2.826*** | |
| | | (10.53) | | (13.02) | | (12.78) | |
| Observations | 178060 | 178060 | 178060 | 178060 | 178060 | 178060 | 178060 |
| $R^2$ | 0.2416 | 0.3628 | 0.2413 | 0.4467 | 0.2409 | 0.4326 | 0.2406 |
| Adjusted $R^2$ | 0.2410 | 0.3623 | 0.2407 | 0.4463 | 0.2404 | 0.4322 | 0.2400 |
| Instrument | | Dist. | Dist. | ln(Dist.) | ln(Dist.) | License | License |
| Stage | | First | Second | First | Second | First | Second |
| F-stat | | 110.74 | | 169.54 | | 163.23 | |

$t$ statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

**Table 6: Excess IRR and Investor Characteristics**

This table presents the mean(median) of the characteristics of investors in the sample. *With Consultant* refers to investors who have engaged a consultant at least once in the sample. *Without Consultant* refers to investors who have never engaged a consultant. The columns report summary statistics by investor type. *Excess IRR* refers to the excess return that an investor earns across all its PE/VC investments as defined in Section 4.1. $AUM_i$ is the investor's assets under management in USD Bn at the end of Q4 CY2024; $InvestmentCount_i$ is the number of PE/VC investments an investor has made to date; $YrsExp_i$ is the number of years for which the investor has been investing in PE/VC.

| Statistic | All Investors | Pension Fund | Endowment | Foundation |
|---|---|---|---|---|
| No. of Investors | 1527 | 769 | 286 | 472 |
| With Consultant | 1059 | 541 | 218 | 300 |
| Without Consultant | 468 | 228 | 68 | 172 |
| Excess IRR (in %) | 0.2 (0.7) | 0.1 (0.7) | 0.5 (0.5) | 0.3 (0.6) |
| With Consultant | 0.1 (0.7) | -0.2 (0.7) | 0.6 (0.5) | 0.2 (0.7) |
| Without Consultant | 0.6 (0.6) | 0.7 (0.8) | 0.5 (0.4) | 0.6 (0.5) |
| $AUM_i$ | 7.3 (1.1) | 12.2 (2.1) | 2.9 (0.7) | 2.1 (0.5) |
| With Consultant | 7.3 (1.1) | 12.5 (2.4) | 2.7 (0.7) | 1.3 (0.4) |
| Without Consultant | 7.4 (1.1) | 11.5 (1.7) | 3.6 (1.2) | 3.4 (0.6) |
| $InvestmentCount_i$ | 44.6 (17.0) | 62.9 (21.0) | 24.7 (15.5) | 27.0 (16.0) |
| With Consultant | 48.8 (18.0) | 71.1 (24.0) | 24.7 (15.5) | 26.1 (17.0) |
| Without Consultant | 35.2 (15.0) | 43.4 (16.5) | 24.5 (15.5) | 28.5 (14.0) |
| $YrsExp_i$ | 21.6 (20.0) | 22.9 (22.0) | 18.7 (18.0) | 21.1 (20.0) |
| With Consultant | 22.0 (21.0) | 23.8 (23.0) | 18.4 (18.0) | 21.4 (20.5) |
| Without Consultant | 20.5 (19.0) | 20.8 (19.0) | 19.9 (19.5) | 20.5 (20.0) |

**Table 7: Investor Skill and Consultant Fixed Effect**

This table reports the partial sum of squares for each of the covariates the following regression:

$$\lambda_i = \beta_1 \cdot ln(AUM_i) + \beta_2 \cdot ln(InvestmentCount_i) + \beta_3 \cdot YrsExp_i + \delta_{Type(i)} + \lambda_{c(i)} + \epsilon_i$$

The dependent variable $\lambda_i$ is the measure of investor skill as defined in Section 4.1; $ln(AUM_i)$ is the natural log of an investor's assets under management in USD Bn; $ln(InvestmentCount_i)$ is the natural log of the number of PE/VC investments an investor has made till date; $YrsExp_i$ is the number of years for which the investor has been investing in PE/VC; $\delta_{Type(i)}$ is investor-type fixed effects; $\lambda_{c(i)}$ is investor-main consultant fixed effect. Main consultant is defined as the consultant $c(i)$ with whom investor $i$ has had the longest relationship in the sample period. The partial sum of squares for each effect is divided by the aggregate partial sum of squares across all effects in the model, normalizing the sum of each column to 1.

| Variable | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Investor Type Fixed Effects | 0.73 | 0.57 | 0.38 | 0.27 | 0.04 |
| $ln(AUM_i)$ | | 0.32 | 0.04 | 0.04 | 0.04 |
| $ln(InvestmentCount_i)$ | | | 0.43 | 0.47 | 0.13 |
| $YrsExp_i$ | | | | 0.1 | 0.02 |
| Main Consultant Fixed Effects | | | | | 0.77 |
| Intercept | 0.27 | 0.11 | 0.15 | 0.12 | 0 |
| $R^2$ | 0.012 | 0.023 | 0.045 | 0.051 | 0.131 |
| Observations | 314 | 314 | 314 | 314 | 314 |

## Table 8: Consultant Fixed Effect and Characteristics

This table estimates the following regression:

$$\Lambda_c = \beta_1 \cdot ln(AUA_c) + \beta_2 \cdot ln(EmpCount_c) + \beta_3 \cdot ln(OfficeCount_c) + \epsilon_c$$

The dependent variable $\Lambda_c$ is the coefficient consultant fixed effect for consultant $c$ as estimated in Equation (10); $ln(AUA_c)$ is the natural log of the mean assets under advisement over the full sample period for consultant $c$ in USD Bn; $ln(EmpCount_c)$ is the natural log of the mean number of consultant employees over the full sample period for consultant $c$; $ln(OfficeCount_c)$ is the natural log of the mean number of consultant offices over the full sample period for consultant $c$. (a) presents the correlation between all the dependent and independent variables. (b) presents the regression results.

**(a)** Correlation

| | $\Lambda_c$ | $ln(AUA_c)$ | $ln(EmpCount_c)$ | $ln(OfficeCount_c)$ |
|---|---|---|---|---|
| $\Lambda_c$ | 1.000 | | | |
| $ln(AUA_c)$ | 0.355** | 1.000 | | |
| $ln(EmpCount_c)$ | 0.567*** | 0.669*** | 1.000 | |
| $ln(OfficeCount_c)$ | 0.628*** | 0.464*** | 0.703*** | 1.000 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**(b)** Consultant Fixed Effect Coefficient and Characteristics

| | (1) | (2) | (3) |
|---|---|---|---|
| $ln(AUA_c)$ | 0.003*** | -0.000 | -0.000 |
| | (2.74) | (-0.04) | (-0.12) |
| $ln(EmpCount_c)$ | | 0.004*** | 0.002 |
| | | (3.41) | (1.07) |
| $ln(OfficeCount_c)$ | | | 0.007*** |
| | | | (3.44) |
| Observations | 54 | 54 | 53 |
| $R^2$ | 0.1263 | 0.2883 | 0.4358 |
| Adjusted $R^2$ | 0.1095 | 0.2604 | 0.4012 |

$t$ statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

## Table 9: Investor Skill and Use of Consultant

This table estimates the following regression:

$$\lambda_i = \beta_1 \cdot UsedConsult_i + \beta_2 \cdot UsedConsult_i \times UsedPE/VCConsult_i + \gamma_1 \cdot ln(AUM_i) + \gamma_2 \cdot ln(InvestmentCount_i) + \gamma_3 \cdot YrsExp_i + \delta_{Type(i)} + \epsilon_i$$

The dependent variable $\lambda_i$ is the measure of investor skill as defined in Section 4.1; $UsedConsult_i$ is a binary indicator that equals 1 if investor $i$ has ever used a consultant in any capacity, 0 otherwise; $UsedPE/VCConsult_i$ is an indicator variable that equals 1 if investor $i$ has ever used a consultant for advisory on PE/VC investments, 0 otherwise; $ln(AUM_i)$ is the natural log of an investor's assets under management in USD Bn; $ln(InvestmentCount_i)$ is the natural log of the number of PE/VC investments an investor has made till date; $YrsExp_i$ is the number of years for which the investor has been investing in PE/VC; $\delta_{Type(i)}$ is investor-type fixed effects.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| $UsedConsult_i$ | -0.007* | -0.008** | -0.008** | -0.007* | -0.008** | -0.008** |
| | (-1.92) | (-2.08) | (-2.12) | (-1.91) | (-2.16) | (-2.00) |
| $... \times UsedPE/VCConsult_i$ | | 0.004 | 0.004 | 0.001 | 0.001 | 0.000 |
| | | (0.81) | (0.86) | (0.19) | (0.23) | (0.04) |
| $ln(AUM_i)$ | | | | 0.003*** | | 0.002 |
| | | | | (2.80) | | (1.51) |
| $ln(InvestmentCount_i)$ | | | | | 0.004*** | 0.003 |
| | | | | | (2.74) | (1.40) |
| Observations | 1527 | 1527 | 1527 | 1527 | 1527 | 1527 |
| $R^2$ | 0.0024 | 0.0028 | 0.0045 | 0.0096 | 0.0094 | 0.0109 |
| Adjusted $R^2$ | 0.0018 | 0.0015 | 0.0019 | 0.0064 | 0.0062 | 0.0070 |
| Mean Excess IRR (%) | 0.24 | 0.24 | 0.24 | 0.24 | 0.24 | 0.24 |
| Investor Type Fixed Effects | N | N | Y | Y | Y | Y |

$t$ statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$