Choosing Pension Fund Investment Consultants*

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Abstract

We examine the role of investment consultants in shaping the investment policies of public pension funds. Using comprehensive data on general and specialized consulting relationships, we exploit hiring events to show that pension funds realign their asset allocations toward the consultant's client base and commit more capital to private funds within the consultant's network. These effects reflect standardization rather than informational value, as neither allocation convergence nor network ties improve performance or access to superior investments. As industry concentration increases, a small number of consultants shape a large share of pension assets, reinforcing portfolio similarity and common exposures across institutional investors.

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1 Introduction

Investment consultants are among the most influential yet opaque intermediaries in the asset management industry (Inderst and Ottaviani, 2012; Gennaioli, Shleifer, and Vishny, 2015; Spatt, 2020). They play a pivotal role in shaping the portfolios of institutional investors, especially public pension funds, which often face constraints on expertise and access. As of June 2024, consultants advised $19.5 trillion in pension assets (Pensions & Investments Data Center). Despite this scale, existing studies primarily examine the supply side of the consulting market, focusing on consultants' recommendations, searches, and product-level outcomes (Goyal and Wahal, 2008; Jenkinson, Jones, and Martinez, 2016). We know much less about the demand for consulting services by pension funds and how these advisory relationships shape portfolio decisions at the pension fund level over time.

We address this gap by examining how public pension funds hire consultants, take-up advice, and consequently adjust asset allocations, manager selection, and performance. We treat consultants not merely as service providers, but as institutional players whose influence reflects both their beliefs about returns and allocations and their position within investment networks. This perspective clarifies the mechanism through which consultants shape pension behavior. If consultants add value through superior recommendations, their clients should experience performance improvements. In contrast, if consultants primarily induce standardization in asset allocation and manager selection, their role is less about informational skill or tailored advice and more about propagating common decision frameworks and coordinating flows across investors. Understanding which channel dominates has implications for how pension funds delegate investments and for the dynamics of capital flows across the asset management industry.

We examine these demand-side effects using novel and comprehensive data on consultant relationships for U.S. public pension funds. Our analysis focuses on portfolio changes when a fund hires a new consultant, and addresses four questions: First, do pension funds realign their asset allocations toward allocation profiles common among the consultant's existing clients? Second, do they disproportionately select private market funds connected to the consultant's network? Third, does consultant hiring expand access to asset managers that are otherwise difficult to reach? And, ultimately, do these changes improve investment performance?

Our analysis exploits turnover and hiring events in a difference-in-difference framework, and documents both allocation convergence and network investing. After hiring a new consultant, pension funds adjust their asset allocations toward the average portfolios of the consultant's existing clients and are more likely to invest in private funds connected to the consultant's network. These reallocations and investments do not improve performance or expand access to superior opportunities, consistent with advice that standardizes behavior rather than adds informational value. As the consulting industry has become more concentrated, this micro-level convergence around consultant hiring aggregates into a broad clustering of portfolio structures and common exposures across the $6.7 trillion U.S. public pension industry.[1]

Our sample of U.S. public pension funds represents over 90% of all state and local defined benefit pension assets. We hand-collect data on all investment consultants employed by public pension funds over the 2001–2020 period, from annual reports, newswires, and other disclosures. This dataset enables us to accurately identify consultant hiring events and categorize consultant types: (a) general consultants, who provide recommendations on asset allocation policy, return expectations, managerial selection, and performance benchmarking, and (b) specialized consultants, who focus on alternative asset classes, such as real assets, private equity, and hedge funds, with a primary role in managerial selection.

[1] The U.S. Financial Accounts, October 2025 publication.

We begin by focusing on general consultants, who serve as primary advisors to nearly all funds in our sample. Hiring a new general consultant leads to substantial and systematic shifts in asset allocation: pension funds realign target weights toward the average allocations of the consultant's existing clients. This convergence starts already in the first year after turnover. For example, a 10 percentage point higher allocation to alternatives among the new consultant's other clients is associated with a 2.64 percentage point increase in the hiring pension fund's target allocation to alternatives within two years of the hire.

While convergence could reflect pension funds selecting consultants whose risk-return expectations support their desired allocations, we provide evidence that influence runs primarily from consultants to clients. We implement an instrumental variable strategy that exploits geographic proximity between pension funds and consultants. The instrument for consultant recommendations is a distance-weighted average of the target allocations of each consultant's other clients, where weights are based on the inverse distance between pension fund and consultants' headquarters. Since the historical headquarters of consultants were established before our sample period and pension fund headquarters are fixed by sponsoring institutions, this geographic variation is plausibly exogenous to contemporaneous allocation choices. Our analysis is supported by our consultant selection result that pension funds are more likely to hire consultants with existing relationships in the same state. The IV estimates support the interpretation that consultants actively shape pension fund asset allocations rather than merely reflecting preexisting preferences. Our findings complement Begenau, Liang, and Siriwardane (2025), who show that consultants' return expectations shape institutional beliefs, by providing evidence on how the consulting relations translate into portfolio decisions. We identify the timing and magnitude of these adjustments, providing direct evidence that consulting relationships serve as a mechanism through which asset allocation norms propagate across institutional investors.

Although general consultant turnover is often triggered by pension fund underperformance, we find no evidence that subsequent reallocations improve performance. Using a stacked difference-in-differences design to compare funds that replace their consultant to never-treated funds, we show that pension funds implementing larger post-hiring allocation changes do not obtain higher returns attributable to asset allocation in the next three years. Overall, general consultants appear to propagate standardized portfolio structures across clients, with influence reflecting coordination rather than value-added customization.

While general consultants primarily influence strategic asset allocation choices, the hiring of specialized consultants in alternative assets is driven by pension funds' need to close gaps between actual and target allocations. We show that a shortfall of actual relative to target exposure to alternatives is the main predictor of first-time hiring of a specialized consultant, consistent with pension funds seeking to scale existing alternative investments. Leveraging this setting, our paper provides the first comprehensive evidence on how U.S. public pension funds' alternative asset investments are shaped by consultants' recommendations, with a focus on private fund selection, access, and performance. Prior evidence shows that consultant recommendations in public markets deliver little value (Jenkinson, Jones, and Martinez, 2016), consistent with the view that capacity constraints and diseconomies of scale limit persistent outperformance (e.g., Berk and Green, 2004; Gârleanu and Pedersen, 2018). Alternative assets, however, are characterized by limited transparency, wide performance dispersion, and restricted access to top-tier managers—conditions under which specialized advisory services may plausibly play a more substantive role.

Pension funds that hire specialized consultants typically already invest in alternative assets but seek advice to scale exposures toward stated targets. One plausible interpretation is that pension funds view limited access to high-quality or capacity-constrained managers as a key obstacle to achieving these targets. To evaluate the nature of the services specialized consultants provide, we examine three potential channels: (a) access to restricted funds, (b) selection and expansion of fund relationships, and (c) performance outcomes. We begin by testing whether specialized consultants expand the set of fund investments by channeling pension funds toward managers already within their network. To conduct this analysis, we use data from Preqin, which covers over 20,000 private fund commitments by U.S. public pension funds. The Preqin dataset provides precise investment timing (i.e. the vintage year), allowing us to match fund commitments to the consultant employed by the pension fund at the time of investment. Each year, we construct a comprehensive opportunity set of all private funds available to a pension fund and classify them based on their connection to the consultant. Across multiple network definitions, we find that a private fund is two to four times more likely to receive a commitment if it is connected to the consultant. These results hold after controlling for private fund fixed effects, which isolate the impact of the consultant connection on investment probability.

A natural question is whether this pattern reflects valuable gatekeeping or simply the reuse of familiar managers. If specialized consultants provide true access advantages, we would expect their clients to invest more frequently in capacity-constrained funds, such as oversubscribed vehicles, later-stage GPs, or co-investment platforms. To test this, we examine whether consultant-advised pension funds are more likely to commit to funds with three characteristics commonly associated with limited access: (a) later-stage funds with an established GP track record; (b) funds with a final size exceeding their target; and (c) co-investment or separately managed account structures (Lerner, Schoar, and Wongsunwai, 2007; Sensoy, Wang, and Weisbach, 2014; Fang, Ivashina, and Lerner, 2015). Our results do not support the access hypothesis: we find no evidence that specialized consultants significantly improve access to these high-demand opportunities, with only marginal effects observed in later-stage real assets funds.

Finally, we test whether consultants add value through superior selection. Private markets are notoriously difficult to evaluate, with limited disclosure and wide performance dispersion across funds. If consultants are effective selectors, their clients should earn superior returns. Using three standard performance metrics—public market equivalent, internal rate of return, and multiple of invested capital—we find no meaningful performance differences between pension funds advised by specialized consultants and those selecting funds without such advisors.

Taken together, these results indicate that fund recommendations are driven less by tailored diligence and more by existing relationships and network effects. In practice, specialized consultants function less as individualized gatekeepers and more as centralized conduits through which capital flows are repeatedly directed toward a given set of managers. These findings closely mirror our earlier results on general consultants: in both asset allocation and manager selection, consultant influence operates through standardization rather than through differentiated, performance-enhancing advice.

While the average consultant does not generate measurable value through recommendations on asset allocation or private fund selection, consultants with certain observable characteristics may be more effective advisers. Using consultant-level information from SEC ADV filings, we document that pension funds are more likely to hire large consultants with client bases of similar size and with an in-state presence. We examine whether these characteristics are associated with differential post-hiring performance. The evidence suggests limited heterogeneity in outcomes. Broad advisory scope is associated with somewhat stronger performance when hiring general consultants, whereas lower levels of discretionary assets under management are modestly associated with better outcomes for specialized consultants, consistent with concerns about potential conflicts of interest. However, these effects are not consistent across specifications or performance measures. Overall, heterogeneity analyses across consultant characteristics indicate that observable differences among consultants do not materially alter the limited impact of consultant hiring on pension fund performance.

The convergence in allocations and manager choices is amplified by the growing concentration of the consulting industry. By 2020, the top three consultants advised half of all public pension assets. Using cosine similarity, we show that funds sharing a consultant hold markedly more similar portfolios than those advised by different consultants. As concentration rises, a larger share of assets lies within these high-similarity clusters, increasing aggregate portfolio resemblance. This consolidation reduces cross-fund diversification and concentrates advisory influence, suggesting that a few consultants now coordinate portfolio structures across much of the public pension sector.[2]

Related literature. This paper contributes to several streams of literature. First, our paper connects to the literature on institutional consultants, which has focused predominantly only on their role in recommending managers in public and private markets (Jenkinson, Jones, and Martinez, 2016; Jones and Martinez, 2017; Cookson, Jenkinson, Jones, and Martinez, 2022; Martinez and Qian, 2024).[3] While these studies document the influence consultants exert through the managerial selection channel, we provide a comprehensive overview of all employed consultants and examine their influence on the *overall portfolio structure* of the investor. We show that general consultants affect allocations and specialized consultants are hired to advise on scaling-up investments in private markets. One contribution of our approach is that we observe the role of consultants in directing flows across asset classes and can study the dynamics around the turnover of consultants.

[2] Related research documents how portfolio overlap and network connectedness generate correlated exposures across intermediaries and investors (e.g., Rossi, Blake, Timmermann, Tonks, and Wermers, 2018a; Jotikasthira, Lundblad, and Ramadorai, 2012; Greenwood, Landier, and Thesmar, 2015).

[3] Extensive research has also examined the role and conflicts of interest among financial advisors hired by individual investors (e.g., Foerster, Linnainmaa, Melzer, and Previtero, 2017; Da, Larrain, Sialm, and Tessada, 2018; Gurun, Stoffman, and Yonker, 2018; Egan, Matvos, and Seru, 2019; Chalmers and Reuter, 2020; Schoar and Sun, 2024).

Second, we contribute to research on institutional asset allocation and belief transmission. Pension funds and other institutions have steadily increased exposure to risky assets, and especially alternatives (e.g., Pennacchi and Rastad, 2011; Ivashina and Lerner, 2018; Andonov and Rauh, 2022; Korteweg, Panageas, and Systla, 2024). Consultants play a central role in shaping those shifts, and their expectations help explain variation in portfolio targets (Begenau, Liang, and Siriwardane, 2025; Couts, Gonçalves, and Loudis, 2024). Augustin, Binfarè, and Fermand (2023) study the role of specialized consultants in benchmarking performance, which can influence the expected alpha by an asset class. We complement this work by providing evidence on how these beliefs are implemented. Exploiting consultant hiring and turnover, we show that pension funds realign asset allocations toward consultants' portfolio norms and translate beliefs into realized portfolio choices through reallocation and repeated investment decisions.

Third, our paper relates to the literature on delegation, networks, and portfolio convergence. Consultants, like other financial intermediaries, influence capital flows through their network ties (Cohen, Frazzini, and Malloy, 2008; Goyal, Wahal, and Yavuz, 2024). Similar to Foerster, Linnainmaa, Melzer, and Previtero (2017), who document standardized advice in retail settings, we show that institutional consultants recommend homogeneous strategies across clients. This is consistent with delegation models in which monitoring frictions and competition lead advisers to adopt standardized, benchmark-oriented strategies across portfolios (Binsbergen, Brandt, and Koijen, 2008; Gârleanu and Pedersen, 2018). Our findings align with this view: a small number of consultants, through repeated advisory relationships, serve as coordination mechanisms, embedding common portfolio models and fund relationships across clients. Finally, by documenting convergence in allocation and manager choice across large public pension systems, our research has implications for systemic risk arising from portfolio similarity (Jotikasthira et al., 2012; Ellul et al., 2022).

2 Consulting Relationships and Institutional Constraints

U.S. public pension funds are not subject to federal regulation and are instead governed by different state laws. They are governed by boards of trustees who hold fiduciary responsibility over asset allocation and manager selection. While trustees are legally accountable for these decisions, they often lack investment expertise and face constraints in attracting professional staff due to compensation limits (Andonov, Hochberg, and Rauh, 2018; Dyck, Manoel, and Morse, 2022; Lu, Mullally, and Ray, 2023). As fiduciaries, they are expected to exercise prudence in the absence of expertise—a standard that often justifies the use of external consultants (Fisch, 2008; Munnell and Sass, 2006). Though public pension funds are not governed by the Employee Retirement Income Security Act (ERISA), many operate under parallel prudent-person fiduciary standards, and the use of consultants serves both as a governance safeguard and a political buffer. Consultants typically serve in an advisory capacity and are not fiduciaries by default.[4] Many pension funds also formalize consultant oversight through periodic Requests for Proposals (RFPs), ensuring engagements are competitively rebid and procedurally defensible. In this context, consultants serve not only as financial experts, but also as delegated risk-bearers, shielding trustees from reputational or legal fallout when underperformance occurs (Lakonishok, Shleifer, and Vishny, 1992; Goyal and Wahal, 2008).

Pension fund investment consultants typically fall into two categories: general and specialized consultants. The main responsibility of general consultants is to provide asset allocation advice, but they also advise pension funds on formulating return expectations, selecting asset managers, benchmarking performance, and implementing risk control policies. In contrast, specialized consultants

[4]International practices differ in how pension systems structure advisory relationships. In the U.K., pension funds are legally required to obtain written investment advice under the 2005 Occupational Pension Schemes (Investment) Regulations (Jenkinson, Jones, and Martinez, 2016). In the Netherlands, while there is no formal legal requirement, regulatory guidance strongly encourages trustees to seek professional advice. Both countries make extensive use of fiduciary management—delegated models in which providers both advise and implement investment strategies, whereas U.S. consultants typically operate in a non-discretionary, advisory role.

focus only on selecting and evaluating managers in alternative asset classes such as private equity, real assets, and hedge funds.

Consultants are often perceived as gatekeepers to the asset management industry. Their long-standing relationships and information advantages may allow pension funds to access restricted funds or top-tier managers, especially in alternatives (Lerner, Schoar, and Wongsunwai, 2007; Sensoy, Wang, and Weisbach, 2014; Goyal, Wahal, and Yavuz, 2022). Consultants' network can influence the investment decisions of their clients as institutional capital flows often follow relational or network-based patterns (Cohen, Frazzini, and Malloy, 2008; Hochberg, Ljungqvist, and Lu, 2010; Rossi, Blake, Timmermann, Tonks, and Wermers, 2018a). While these studies examine networks between investors and asset managers, our analysis explores a related dynamic on the advisory side and implications for asset allocations and access in private markets.

3 Data on Pension Funds Consulting Relationships

3.1 Pension Funds Sample

Our analysis focuses on the investment consultants and asset management decisions of U.S. public defined benefit pension funds from 2001 to 2020. Pension funds are defined at the retirement system level.[5] The sample includes 173 unique pension funds, representing 3,138 annual observations, and Online Appendix Table IA.1 shows the sample over time. As of 2020, these funds collectively managed $4.2 trillion in assets, accounting for over 90% of all U.S. public DB pension assets.[6]

We construct the sample using two sources. First, we rely on the Public Plans Database (PPD),

[5] For example, the Washington State Investment Board is responsible for the asset management of the Washington PERS 1/2/3, LEOFF 1/2, School Employees 2/3, and Teachers 1/2/3 pension plans. For this reason, we aggregate the investment and performance data of these pension plans at the retirement system and treat it as one unique entity.

[6] The U.S. Financial Accounts report $4.6 trillion in state and local pension assets in June 2020.

published by the Center for Retirement Research at Boston College, for information on 138 large state and local pension funds (2,624 annual observations). Second, we expand coverage by manually collecting data for 35 additional county and municipal pension funds (514 observations) that are not included in the PPD. Panel A of Table 1 reports summary statistics. The average pension fund holds $19 billion in assets. We follow Andonov and Rauh (2022) and calculate the *net return* as the ratio between net investment income and beginning-of-year assets. The average net return is 6.5% over the sample. These returns incorporate investment expenses, changes in the value of assets, realized capital gains, interest and dividends, and securities lending income.

We also manually review and adjust PPD-reported asset allocations to correct for common issues, such as missing or misclassified entries, mismatches between target and actual categories, and misreported leverage.[7] On average, pension funds have a target allocations of 51% to public equity, 26% to fixed income, 9% to real assets, 6% to private equity, and 5% to hedge funds. The residual is allocated to cash and other alternative asset classes. Panel A of Figure 1 shows that, over the sample period, target allocations to public equity and fixed income declined from roughly 90% to 70%, while allocations to alternatives rose from 10% to 30%.

3.2 Investment Consultants Sample

We manually identify investment consultants engaged by U.S. public pension funds using their annual reports, websites, and Pensions & Investments news coverage. We classify consultants into two distinct groups: general consultants, who provide broad investment strategy advice, and specialized consultants, who focus on a specific alternative asset class.[8] The list of specialized consultants includes only cases where the specialized consultant is a separate firm from the general

[7] See Online Appendix Section IA.1 for full documentation of PPD data adjustments.

[8] Our sample construction excludes consultants providing only non-investment services (e.g., actuarial, audit, proxy voting) or short-term engagements lasting less than one year.

consultant or its subsidiaries. Our definition of specialized consultants encompasses the narrower "search consultant" definition, which focuses only on mandate-specific engagements (e.g., Jenkinson, Jones, and Martinez, 2016; Martinez and Qian, 2024).

Panel B of Figure 1 shows that nearly all pension funds employ a general consultant, while use of specialized consultants has grown substantially alongside rising allocations to alternatives. For instance, the average number of specialized private equity consultants per pension fund rose from 0.20 in 2001 to 0.57 in 2020. The increase is mainly due to pension funds hiring specialized consultants for the first time and, to a smaller extent, to the increase in the number of consultants employed by pension funds that already had one.[9] Outside of alternatives, few pension funds hire specialized consultants, with only rare use of their services in public equity or credit mandates.

Table 2 reports statistics at the investment consultant level. Across the sample, pension funds employed 129 distinct consultants, but industry concentration has increased markedly over the sample period. Figure 2 shows that the share of the top 10 general consultants based on assets under advisement increased from 68% to 88%, while the number of unique general consultants declined from 32 to 19. Figure 3 provides a complementary perspective by visualizing how this consolidation reshaped the structure of advisory relationships over time. The consultant–pension fund network becomes increasingly centralized, with a small number of consultants emerging as dominant hubs advising a large share of pension assets by the end of the sample. Specialized consulting is also consolidating, with declining numbers of distinct consultants by asset class following the expansion of the 2000s and early 2010s (see Online Appendix Figure IA.1).

To further understand the dynamics of this industry, we collect information on consultant

[9]For instance, the Teacher Retirement System of Texas had one specialized consultant for domestic private equity investments and another specialized consultant for international private equity investments from 2005 to 2010.

characteristics from the SEC ADV form over the 2010–2020 period.[10] Panel B of Table 2 shows that the average consultant advises 862 clients and pension funds are important for their business. For 30% of the consultants, pension funds account for more than 50% of their clients. Most consultants combine advisory services with asset management services, and 58% of their assets come from discretionary mandates. The ADV form also allows us to identify that 19% of the consultants report at least one legal or regulatory infraction over the period.

We examine which pension fund characteristics are associated with the use of investment consultants. Online Appendix Table IA.2 shows that larger funds and those with greater target allocations to alternative assets hire more investment consultants. Pension funds with internal investment teams are somewhat less likely to employ specialized consultants, consistent with in-house capacity substituting for external advice. Governance structure also plays a role. Pension funds with a higher share of politically appointed board members are more likely to use consultants, consistent with the notion that politically exposed trustees may seek to diffuse responsibility and mitigate reputational risk through delegation (Goyal and Wahal, 2008; Andonov, Hochberg, and Rauh, 2018). In contrast, we find no significant association between consultant use and the share of elected board members, despite prior evidence that elected participants often lack investment expertise (Andonov, Hochberg, and Rauh, 2018; Dyck, Manoel, and Morse, 2022).

4 Hiring Investment Consultants

To assess the impact of consultants on pension funds' asset allocation and performance, we apply a difference-in-differences (DID) framework centered on consultant turnover. This approach isolates

[10]The structure of the AVD form has changed several times during this period (in 2011, 2012, 2014, and 2018). To construct our variables, we match the questions across different forms and use the most granular variable measurement available throughout the sample period.

changes attributable to new advisory relationships while controlling for time-varying factors affecting all funds. Before evaluating the implications of consultant turnover for pension fund investment policies, this section examines the hiring events of both general and specialized consultants. We also incorporate consultant characteristics relevant to hiring decisions, enabling us to link selection drivers to subsequent outcomes.

4.1 Turnover of Consultants

We identify consultant turnover based on the first and last year of the consultant's employment. Figure 4 and Online Appendix Table IA.3 show the distribution of hiring events by type, including first-time hires, new consultant engagements, and replacements, over the sample period. For general consultants, we document 187 hiring events, of which 181 follow the termination of a previous general consultant. These events are relatively evenly distributed over time. Two features make general consultant hiring events a suitable basis for our DID analysis. First, pension funds terminate around 6% of their general consultant relationships annually. This turnover rate ensures a sufficient number of events in the sample while avoiding overlap across event windows, as general consultants typically serve for extended periods. Second, there is substantial heterogeneity across funds, as 51 of the 173 pension funds never replaced their general consultant during the sample period.

The turnover of specialized consultants exhibits more variety. We record 150 first-time hires—62 in private equity, 47 in real assets, and 41 in hedge funds—plus 117 replacements and 47 cases of additional hires alongside existing advisers.[11] Unlike general consultants, pension funds may employ multiple specialized consultants per asset class. For the DID analysis, we focus on first-time hiring events, which reflect substantive policy shifts and allow us to evaluate the effects of specialized

[11]In 12 cases, specialized investment consultants were replaced only after a period of two or more years.

consultant employment on access to asset managers and performance within the asset class.

Table 3 examines the factors influencing pension funds' decisions to hire new consultants. Columns (1) and (2) show that general consultant turnover is strongly linked to sustained underperformance. We measure performance over the prior three years, which is consistent with typical contract length, and adjust for market-wide fluctuations by including year–reporting-month fixed effects. In line with the Pennacchi and Rastad (2011) results on peer-effects in tracking error volatility, this approach accounts for differences in fiscal year-ends across funds and ensures that coefficients capture peer-adjusted returns. To sharpen the focus on peer-adjusted performance, we also create relative performance rankings by sorting pension funds within a year-reporting-month based on their geometric return over the previous three years.[12] A decrease in the 3-year performance ranking from the 75$^{\text{th}}$ to the 25$^{\text{th}}$ percentile increases the probability of hiring a new general consultant by 3.2 percentage points ($= -0.5 \times -0.064$). Larger funds change consultants more often, but target allocations and actual–target gaps are not significant predictors.[13]

Columns (3) and (4) examine pension funds' decisions to hire specialized consultants on a pension-fund-asset-class-year basis. The dependent variable indicates whether pension fund i hired a specialized consultant in asset class j (real assets, private equity, or hedge funds) for the first time in year t. The sample is restricted to pension funds that do not already have a specialized consultant in the respective asset class, making them eligible for a first-time hire. As a result, each pension fund can appear in the sample up to three times per year, corresponding to the three alternative asset classes under consideration.

[12] We standardize the percentile ranking by the total number of pension funds in each year-reporting-month group, ensuring that the variable is bounded between zero and one. Nine pension funds (145 annual observations) with fiscal year-ends in March, August, or September are excluded due to insufficient observations during these months to create rankings. The remaining pension funds in the sample have fiscal year ends in June or December.

[13] Results are robust to alternative return measures (Online Appendix Table IA.4) and remain qualitatively unchanged when including the GASB Funded Ratio, which captures asset-liability considerations (Table IA.5); in the latter, a 10 percentage point drop in the funded ratio raises hiring probability by 0.8 percentage points.

We find that specialized consultant hiring is driven primarily by asset allocation rather than performance.[14] If pension funds were hiring specialized consultants in alternative assets due to limited experience, we would expect a negative relation between actual allocation and the probability of a first-time hire. Instead, we document that pension funds with a higher actual allocation to asset class j in $t-1$ are more likely to hire a specialized consultant in t. Large gaps between target and actual allocations are the main driver of such hires, indicating that pension funds seek advisory services to scale up their exposure to alternative investments. Based on Column (3), a 10 percentage point gap between target and actual allocations increases the probability of hiring a specialized consultant by 1.8 percentage points. These results suggest that pension funds often establish alternative allocations independently of specialized consultants but turn to them as allocation targets increase. Specialized consultants seem to be used to accelerate the pension fund allocations toward their strategic targets.

4.2 Selection of Consultants

In this section, we focus on the characteristics of the consultants that pension funds choose to hire. To evaluate how pension funds select investment consultants, we first define the opportunity set as the pool of all consultants employed by at least one pension fund during the sample period.[15] This opportunity set evolves over time, reflecting mergers, closures of existing consultants, and entry of new consultancy firms.

In addition to the SEC ADV filings, we also use the pension fund–consultant relationship data to construct three consultant characteristics.[16] First, we classify consultants by scope of services:

[14] We use the overall returns as consistent granular performance data by asset class is unavailable (Ennis, 2021).

[15] Goyal, Wahal, and Yavuz (2024) use a similar approach in their analysis of asset manager selection.

[16] Our analysis is limited to hiring events over the 2010–2020 period, as the SEC ADV data does not cover the earlier period.

GC Broad denotes general consultants that also provide specialized advice in alternatives, while *GC Narrow* covers general-only advisers; *SC Broad* denotes specialized consultants that also serve as general consultants, and *SC Narrow* covers specialized-only advisers. Second, we measure client-size homogeneity (*%PF Clients Same Size*), defined as the share of a consultant's pension fund clients in the same asset-size quartile as the hiring pension fund, capturing experience with similarly sized clients. Third, we compute geographic concentration (*%PF Clients Same State*), the share of a consultant's pension fund clients located in the same state as the hiring pension fund, capturing possible preferences for advisers with local regulatory familiarity or network ties.

In Table 4, we estimate a logit model where the dependent variable equals one for the consultant ultimately hired in a given event. Specifications include pension fund fixed effects, which are equivalent to hiring-event fixed effects. Columns (1) and (2) focus on selecting general consultants from an opportunity set that contains 48 eligible firms.[17] Funds tend to select larger, multi-service consultants: lacking a specialized role in alternatives reduces the hiring probability by 2.1 percentage points. Funds also prefer consultants serving similarly sized clients and those with a local presence. A 100% same-size client base increases the hiring probability by 1.3, while a 100% same-state client base raises it by 2.4 percentage points.

Columns (3) and (4) examine first-time hires of specialized consultants from an opportunity set of 31 unique real assets consultants, 38 private equity consultants, and 14 hedge fund consultants. Funds prefer larger consultants, but avoid those with high shares of discretionary AUM, or that also serve as general consultants. Consultants with legal or regulatory charges are 3.5 percentage points less likely to be hired, a large effect relative to the baseline. As with general consultants, same-size and same-state client experience significantly increases hiring likelihood.

[17] The maximum is 48 rather than 52 (Table 2) because four firms either exited before 2010 or could not be matched to SEC ADV data.

These selection patterns indicate that pension funds place weight on consultant scale, specialization, and familiarity with peers—by size and location—when making hiring decisions. This geographic clustering, combined with variation in consultant allocation styles, allows us later to use pension fund–consultant distance as a source of identifying variation for a given consultant's portfolio weights, in line with Begenau, Liang, and Siriwardane (2025).

5 General Consultants: Post-Hiring Allocations and Performance

In the previous section, we documented that relative underperformance is the main driver of general consultant hiring decisions. The main responsibility of general consultants is to provide advice on the strategic asset allocation and, through changes in the asset allocation, the new consultants can potentially help pension funds improve their performance. We proceed by examining the direction of overall allocation adjustments, followed by a decomposition of performance changes.

5.1 General Consultants: Post-Hiring Changes in Asset Allocation

We hypothesize that pension funds make significant adjustments to their asset allocation policies following the hiring of a new general consultant. If investment consultants base recommendations primarily on their own subjective beliefs about expected returns across assets (Begenau, Liang, and Siriwardane, 2025; Couts, Gonçalves, and Loudis, 2024), we also expect convergence in asset allocations among pension funds advised by the same consultant. Specifically, our convergence hypothesis predicts that pension funds adjust target allocations after hiring a new general consultant toward the average allocations of the consultant's existing clients. This prediction is consistent with evidence from the retail investment advisory market, where financial advisors influence client portfolios while offering limited customization (Foerster, Linnainmaa, Melzer, and Previtero, 2017).

Online Appendix Figure IA.3 shows that indeed pension funds make significantly larger absolute changes to their target allocations in equity and alternatives in the two years following the hiring of a new general consultant. Thus, consultant turnover is associated with above-average adjustments in target allocation weights, but the direction of changes is shaped by each fund's historical allocations. To test the convergence hypothesis, we examine whether pension funds adjust their target allocations toward the average allocations of other clients of their newly hired consultant, moving away from the allocations associated with their previous consultant. For pension funds that hire a new general consultant, we estimate the following specification:

$$\Delta \text{Risky}_{i,t+1}^{\text{Post}-\text{Pre}} = \alpha + \beta_1 \, \Delta \text{AvgRisky}_{-i,t-1}^{\text{NewGCpre}-\text{OldGCpre}} + \gamma X_{i,t+1} + T_{t+1} + C_j + \epsilon_{i,t+1}, \tag{1}$$

where year t is the hiring year. The dependent variable, $\Delta \text{Risky}_{i,t+1}^{\text{Post}-\text{Pre}}$, measures the change in fund i's target allocation to risky assets (equity and alternatives) from the year before the turnover ($t-1$) to the year after ($t+1$). The key independent variable, $\Delta \text{AvgRisky}_{-i,t-1}^{\text{NewGCpre}-\text{OldGCpre}}$, is the difference in target allocations to risky assets between the new and old consultant's other clients in $t-1$, excluding pension fund i. $X_{i,t+1}$ is a set of fund-level controls, including pension fund size, internal mandates, and governance. We include year fixed effects (T_{t+1}) to absorb macroeconomic and industry trends, and consultant fixed effects (C_j) to account for consultant-specific factors.

Table 5 Panel A shows that pension funds adjust their target allocations toward the average allocations of other clients advised by the newly hired consultant. Columns (1) and (2) indicate that consultant turnover leads to changes in the level of risk-taking within the following year. These effects extend beyond aggregate risky asset exposure, with more pronounced adjustments in the *composition* of risky assets and changes in equity and alternative allocations. For example, the results in Column (6) imply that a 10 percentage point higher target allocation to alternatives among the new consultant's other clients in year $t-1$ corresponds to a 2.64 percentage point increase in the pension fund's own target allocation to alternatives. This effect is economically significant, given that the average two-year change in allocation to alternatives is 3.59 percentage points. Overall, pension funds advised by the same consultant appear to receive and follow relatively homogeneous asset allocation recommendations.

The observed convergence in asset allocation among pension funds sharing the same consultant is consistent with two interpretations. One is that investment consultants actively shape allocation decisions rather than merely endorsing portfolios their clients wish to pursue. If consultants simply ratified client proposals, pension funds would have little reason to switch consultants, and we would not observe the systematic convergence in portfolio composition documented above. This suggests that consultants influence allocations through their recommendations. An alternative interpretation is that pension funds strategically match with consultants whose risk-return expectations align with their desired allocations. Importantly, under this view, pension funds must still align with consultants who support their preferred allocation choices, even if consultants do not directly initiate the changes. The observed convergence implies that pension funds cannot freely implement their desired allocations without securing the endorsement of a consultant whose investment beliefs are consistent with theirs.

We use an instrumental variable (IV) approach to provide more evidence on the first interpretation that investment consultants actively drive asset allocation adjustments in the portfolios of their pension clients. Our instrument for $\Delta \text{AvgRisky}^{\text{NewGCpre}-\text{OldGCpre}}_{-i,t-1}$ exploits the geographical distance between pension funds and consultants. Specifically, for pension fund i in year t we compute a distance-weighted allocation ($\text{DistRisky}_{i,t}$):

$$\text{DistRisky}_{i,t} = \sum_{j=1}^{J} w_{i,j}\,\text{Risky}_{j,t}, \tag{2}$$

where $\text{Risky}_{j,t}$ is the average target allocation to risky assets among all clients of consultant j in year t, excluding fund i. The weights $w_{i,j}$ are based on the inverse distance between pension fund i headquarters and consultant j original historical headquarters: $w_{i,j} = \frac{1}{d_{i,j}^{0.5}} / \sum_{j=1}^{N} \frac{1}{d_{i,j}^{0.5}}$, where $d_{i,j}$ is the log of 2 plus the distance in miles and $\sum_{j=1}^{N} \frac{1}{d_{i,j}^{0.5}}$ is the total inverse distance of pension fund i to all J active consultants in year t.[18]

The variation in the $\text{DistRisky}_{i,t}$ instrument arises entirely from the distance-based weights. This instrument is valid if these weights are exogenous to pension funds' allocation policies (Goldsmith-Pinkham, Sorkin, and Swift, 2020). To strengthen this assumption, we measure distances using consultants' original headquarters when they were established, mostly in the 1980s. Hence, our distance measures are not affected by decisions to relocate later, and we do not consider regional consultancy offices. Internet Appendix Table IA.6 confirms that all major consultants were founded before our sample period, and before pension funds increased their allocation to risky assets. The consultancy firms are dispersed across U.S. financial centers, generating substantial cross-sectional variation.[19] Important for our identification, pension funds have been established a long time ago, do not change their headquarters, and are located in state or county capitals tied to their

[18] Inverse distance is normally used to weight the influence of geographically connected outcomes (Lesage and Pace, 2010). The log transformation uses 2 plus the distance in miles so that pension funds and consultants located in the same city have a non-zero distance. The parameter 0.5 serves as a power-law decay factor that sets $w_{i,j} \to 0$ as $d_{i,j} \to \infty$, but ensures a gradual reduction in weights as distance increases. This transformation ensures positive weights for pairs located in the same city, assigns higher weights to consultants located closer to pension fund i, and attenuates the differences in relative influence of long distances.

[19] In most cases, consultant headquarters locations reflect the residence of founding partners and rarely change. If consultants relocate, we continue to use the original location. For example, although Wilshire Associates was acquired by CC Capital Partners and Motive Partners, we use its historical headquarters in Santa Monica.

sponsoring employers. These features make it unlikely that consultant or pension fund headquarter locations were chosen based on future pension fund allocation preferences, supporting the exogeneity assumption.

The instrument is motivated by the tendency of pension funds to hire consultants advising other clients in the same state, which suggests that geographical proximity is an important factor. Online Appendix Table IA.7 reports the first stage results. Across all specifications, we observe that the distance-weighted allocations are positively related to the difference in target allocations to risky assets between the new and old consultant's other clients. The large first-stage Kleibergen–Paap rk Wald F-statistics confirm the relevance of the instrument.

Table 5 Panel B reports the results of the second stage. The instrumented allocations of the newly hired consultant significantly predict changes in pension funds' target allocations to risky assets and alternatives. The magnitudes are similar to the OLS estimates, suggesting limited selection in consultant–fund matching. For example, Column (1) implies that a 1 percentage point higher risky-asset allocation among the new consultant's other clients leads to a 0.14 percentage point increase in fund i's allocation. Overall, the IV results indicate that the observed convergence primarily reflects a causal effect of consultants on pension fund allocations. Some estimated coefficients in the IV specifications are slightly larger in magnitude than those in the OLS specifications. Furthermore, the IV specifications confirm Panel A finding that most of the convergence effects originates from alternatives allocation, as not significant effect is present in equity allocation. Based on the large Kleibergen–Paap rk Wald F statistic, we interpret the IV results as indicator of the important role that geographical proximity plays in shaping the influence of consultants' clients' asset allocations on a pension fund's allocation. This effect is not captured in the OLS specifications.

Pension funds retain their general consultant for several years, which ensures that the analysis avoids overlap across event windows. However, to address the concern that the results in Table 5 are based on a relatively small set of turnover events, we show in Internet Appendix Table IA.8 that the results remain qualitatively unchanged when we apply the Cameron, Gelbach, and Miller (2008) wild bootstrap procedure to estimate the standard errors.

Our findings complement the study of Begenau, Liang, and Siriwardane (2025), who show that investment consultant fixed effects explain a large share of cross-sectional variation in allocations to alternative assets and that consultant beliefs about expected returns predict client allocations. We expand further by showing that the convergence is triggered by consultant turnover and begins immediately after a new consultant is hired. Our contribution is to pin down both the timing and magnitude of these adjustments, demonstrating that consultants exert a swift and systematic influence on pension fund allocations.

5.2 General Consultants: Post-Hiring Changes in Performance

Our findings indicate that poor past performance is a key factor driving pension funds to replace their general consultants. To assess whether such replacements lead to performance improvements, we treat each turnover as a treatment event and exploit the staggered timing of these events across funds. We estimate a stacked difference-in-differences (DID) model, which forms separate event-time cohorts and compares treated funds to a matched set of never-treated funds. This design addresses the comparison problems in two-way fixed effects settings and accounts for treatment heterogeneity across time and funds (Cengiz, Dube, Lindner, and Zipperer, 2019; Callaway and Sant'Anna, 2021; Baker, Larcker, and Wang, 2022). By focusing on within-cohort before–after differences, the approach mitigates endogeneity concerns and isolates performance changes attributable to consultant replacement events. The never-treated funds serve as a credible control group because they are subject to the same macroeconomic and market shocks, follow similar reporting practices, and differ from treated funds primarily in the absence of consultant turnover.

Our analysis focuses on hiring a new general consultant, treating each turnover as a discrete event. The event window spans seven years: three years before and three years after the hiring year. The three-year window matches the typical frequency of strategic asset allocation review by pension funds and the length of the standard consulting contract.[20] The treated group consists of 95 pension funds that replaced their general consultant during 2001–2020. The control group comprises 51 never-treated funds that retained the same consultant throughout the period, providing a consistent benchmark for market-wide shocks and reporting practices. We estimate the following stacked difference-in-differences (DID) model:

$$Y_{i,t} = \beta\,(\text{Treated} \times \text{Post}) + \gamma X_{i,t} + \eta_{i,c} + \nu_{t,c} + \tau_t + \epsilon_{i,t}, \tag{3}$$

where $Treated \times Post$ captures the average post-turnover effect in the treatment year and the subsequent three years. The specifications control for unobserved heterogeneity via pension fund $\times$ stacked-cohort fixed effects ($\eta_{i,c}$), year $\times$ cohort fixed effects ($\nu_{t,c}$), and year $\times$ reporting-month fixed effects (τ_t). Here, a cohort is defined as all funds experiencing turnover in the same year, matched to the never-treated controls.[21]

Our analysis evaluates multiple performance metrics. Column (1) of Table 6 reports the impact of consultant turnover on within-cohort performance rank, calculated by ordering funds in each sub-experiment cohort based on annual returns. Treated funds improve by roughly 8 percentile points, or nearly a full decile, after hiring a new general consultant. Column (2) examines raw

[20] Pension funds review their target allocations typically every three to five years by conducting a formal asset-liability study. This study models long-term asset returns, volatilities, correlations, and liability growth.

[21] For example, the 2014 cohort includes six treated funds and all 51 never-treated controls.

returns and finds a post-treatment increase of 30 basis points. Although this gain is not statistically significant, it is economically meaningful and sufficient to shift relative rankings, particularly for funds clustered near the distribution mean.

While these findings point to a potential value-add from new consultants, they do not reveal how these gains are achieved. Aggregate return measures combine the influence of inherited allocations and incumbent managers with the effects of changes initiated under the new consultant's advisory. To disentangle these channels, we next examine whether the substantial target allocation adjustments documented after turnover account for the observed performance changes.

Therefore, we next isolate the portion of performance attributable purely to changes in asset allocation by constructing benchmark returns from the CEM dataset.[22] A key advantage of the CEM dataset is that it collects granular data on the allocations and benchmarks by asset class of U.S. pension funds while remaining anonymous. This anonymity reduces strategic benchmark selection. So, the benchmark returns in CEM reflect geographical allocation and risk exposure, and funds do not consistently outperform their benchmarks. This contrasts with the PPD benchmarks, which are public, non-anonymous, and more prone to manipulation and strategic reporting (Ennis, 2021; Augustin, Binfarè, and Fermand, 2023).

To isolate the performance attributable exclusively to changes in asset allocation, we begin by aligning each pension fund's policy allocations with the average benchmark returns by asset class. In the CEM dataset, we restrict our selection to the benchmarks used by U.S. pension funds. For

[22]CEM Benchmarking Inc. collects anonymous data from pension funds on their asset allocation, costs, and performance. These data have been used by French (2008) to study the cost of active investing, by Andonov, Bauer, and Cremers (2017) to examine the link between liability discounting rules and risk-taking, and by Dyck and Pomorski (2016) and Andonov (2024) to analyze performance in alternative assets.

fund i in year t, the total benchmark return is:

$$\text{BmkRet}_{i,t} = \sum_{n=1}^{7} \text{PolicyAllocation}_{i,t}^{n} \times \text{CEMBmkRet}_{t}^{n}, \tag{4}$$

where n indexes the asset classes in Table 1. Since benchmark returns are uniform across funds, cross-sectional differences in $BmkRet_{i,t}$ reflect allocation choices rather than performance differences due to managerial selection or active versus passive asset management. By including interacted pension-fund-cohort fixed effects and year-cohort fixed effects, which absorb general market performance, we isolate allocation-driven performance within a pension fund.

We find that, although consultant turnover is accompanied by substantial changes in asset allocation policy, these shifts translate into only modest and highly concentrated gains in allocation-driven performance. As shown in Column (4) of Table 6, benchmark returns improve by roughly 50 basis points only for the small subset of funds that maintain their overall risky-asset share but significantly rebalance within it—most often by shifting between equities and alternatives. However, this group represents a minority of turnover events. By contrast, the much larger set of funds that either increase or decrease their risky-asset share, without targeted compositional changes, sees no measurable improvement. Column (5) further confirms that the observed gains stem from these within-risky reallocations, and that funds keeping both the risky share and its composition unchanged achieve similar magnitudes, suggesting that mean-reversion, rather than consultant-driven restructuring, may explain the improvement.

Overall, hiring a new general consultant is typically followed by sizable adjustments to asset allocations, with portfolios tending to resemble those of the consultant's other clients. However, these allocation changes are associated with only modest performance improvements, suggesting that convergence in asset mix does not necessarily lead to materially better outcomes.

6 Specialized Consultants: Post-Hiring Access and Performance

In Section 4, we show that pension funds turn to specialized advisory services as they expand their allocations to alternative assets. Here, we test whether these relationships translate into more and better performing private market investments. Our setting captures the full set of ongoing pension fund - specialized consultant relationships linked to *all* private fund commitments. This broader coverage allows us to observe whether ongoing advisory ties influence repeated investment decisions, not just mandate related searches.

Few U.S. public pension funds have the in-house resources to invest directly in private markets (Dyck, Manoel, and Morse, 2022; Lerner, Mao, Schoar, and Zhang, 2022). Instead, they commit capital to external funds raised by general partners. Given the limited disclosure, performance opacity, and access constraints in alternatives (Lerner, Schoar, and Wongsunwai, 2007; Sensoy, Wang, and Weisbach, 2014), specialized consultants' expertise and networks could be particularly valuable.[23] We examine whether specialized consultants help pension funds (i) scale up private market commitments, (ii) access highly sought-after general partners, and (iii) improve investment performance. The vintage year of each fund provides a precise investment date, allowing us to attribute each commitment to the specialized consultant advising the pension fund at that time.

6.1 Pension Funds Investments in Private Funds

For this analysis, we match pension funds with their capital commitments to private funds as reported by Preqin. Online Appendix Table IA.9 presents summary statistics of our matched

[23] Binfarè, Brown, Harris, and Lundblad (2023) show, in the context of university endowments, that professional networks help overcome barriers to accessing certain funds.

sample of 164 pension funds and their private fund investments.[24] Overall, we examine 22,744 pension investments in 6,504 private funds, managed by 1,943 general partners. Among these, 49% investments are in buyout, 11% in venture capital, 22% in real estate, 4% in natural resources, 4% in infrastructure, and 10% in private debt funds. Since the investment universe includes private equity and real assets funds, we separately analyze the role of specialized private equity (PE) and real assets (RA) consultants. In our sample, 67% of investments are made by pension funds employing a specialized PE consultant, and 62% by pension funds with a specialized RA consultant.

6.2 Specialized Consultants: Selection of Private Funds

In this section, we examine whether specialized consultants are important intermediaries that influence the selection of private funds. Our analysis reveals that pension funds using the same consultants not only implement similar target asset allocations but are also more likely to invest in the same private funds. The increasing concentration of consultants and their influence on private fund selection may expose pension funds to correlated risks. A notable example is the collapse of Abraaj Investment Management Ltd. as many pension funds that invested in the Abraaj funds had the same specialized PE consultant, Hamilton Lane.[25]

To examine the role of consultants in selecting private funds, we generate an opportunity set that includes all potential private funds available to a pension fund in a given vintage year, following the approach of Goyal, Wahal, and Yavuz (2022). We then assess whether the likelihood of selecting a specific private fund increases if the fund is part of the consultant's network. We restrict the

[24] In our previous analyses we included 173 pension funds. However, 9 pension funds do not have allocations to alternative assets (e.g., Georgia Teachers' Retirement System, Oklahoma Public Employees' Retirement System, etc).

[25] Pensions & Investments April 29, 2019: "Abraaj Investment Management Ltd. is in liquidation and its founders have been indicted, while institutional investors in its funds and their consultant, Hamilton Lane Inc., are left to deal with the fallout. [...] What remains to be determined is whether the debacle will lead to investors taking a harder look at the due diligence conducted by their advisers in general and Hamilton Lane in particular. All institutional investors in Abraaj funds reviewed by Pensions & Investments had Hamilton Lane as the private equity consultant."

opportunity set to PE and RA fund categories, based on the assumption that pension funds primarily search for investments within a specified asset class. The PE category includes investments in buyout, venture capital, and private debt fund types, while the RA category includes investments in real estate, natural resources, and infrastructure fund types.

Consultant networks can be defined at multiple levels of granularity. At the broadest level, a consultant network includes all investments made by the pension funds a consultant advises. Alternatively, the scope can be narrowed by distinguishing between general and specialized consultants. Finally, these networks can be extended to the general partner (GP) level, where connections are defined based on any prior relationships between GPs and the consultant. To provide an example, pension fund PF_1 chooses to invest in private fund PE_1 out of all PE funds available during the same year (the opportunity set). PE_1 belongs to the specialized consultant's network if another pension fund PF_2, advised by the same consultant, has also invested in PE_1 (SC network). Controlling for pension fund characteristics, vintage year, and private fund characteristics, we then ask whether pension funds using the same consultant are more likely to invest in the same private funds.

Table 7 presents the results for PE funds, and Table 8 for RA funds. The dependent variable is one if the pension fund invests in the private fund, and zero otherwise. The variable of interest, *Same Consultant* is an indicator equal to one if the private fund is in the pension fund consultant's network. Importantly, the same private fund will appear in different pension fund rosters, and sometimes it will be connected with the consultant and sometimes not.[26] Columns (1) and (2) include fund connections with all consultants in the network, Columns (3) and (4) include only general consultant connections, while Columns (5) and (6) include only specialized consultant connections. We control for private fund and pension fund size as well as for other characteristics.

[26]If a pension fund invests in multiple private funds in a given vintage year, these private funds will be excluded from the opportunity set of private funds of each other.

The specifications include either pension fund fixed effects or private fund fixed effects. Pension fund fixed effects allow us to control for time-invariant pension fund characteristics and preferences. These specifications address the possibility that pension funds have stable preferences to select certain private funds regardless of the consultant networks by exploiting variation in the *Same Consultant* variable within a pension fund. The private fund fixed effects allow us to test if the very same private fund is more likely to be selected as an investment based on its connection to the consultant. Given the opacity of private funds characteristics, the later test allows us to directly isolate the impact of the consultant connection on the probability of investment.

Across all specifications, we find that pension funds using the same consultant are more likely to invest in the same private funds. Based on Column (6) of Table 7, a pension fund has a 2.1 percentage points higher probability of investing in a PE fund if another pension fund using the same specialized PE consultant also invests in the private fund. Table 8 shows that using the same RA consultants increases the probability of investing in the same RA fund by 3.2 percentage points. These coefficients suggested that a private fund is two to four times more likely to be selected by the pension fund if it has a prior connection with the consultant.

The connections of general consultants are almost as important as those of specialized consultants, as many pension funds do not have specialized consultants in alternative assets and rely on the recommendations of general consultants when making the selection. In addition, even among pension funds that employ specialized consultants, general consultants attend pension fund board meetings and could influence the selection of private funds.

The selection of private funds is also influenced by the private fund characteristics and pension fund governance. For instance, larger private funds raise more capital and are more likely to be selected by more pension funds. One concern is that, given the high concentration of consultants, the results on the consultants' network stem from the private fund size. Under this alternative hypothesis, consultants can make similar recommendations across pension funds only if the private funds they are recommending are large. To address this concern, in Online Appendix Table IA.10 we split private funds into small and large funds. Our results show the opposite of the alternative hypothesis, as we find stronger results for small private funds. The role of consultants' network is significant for both small and large private funds, but pension funds using the same consultant are even more likely to invest in the same small private funds.

In Online Appendix Table IA.11, we provide alternative specifications that expand the definition of consultants' networks. In Panel A, we expand the connections of the consultant to include all the funds raised by the GPs the consultants have a connection with (i.e., GP network). The results are similar, but slightly smaller in magnitude, as the connections to the same private funds are weaker at the GP level. In Panels B and C, we require that a consultant-private-fund connection shows up at least twice across all the pension funds in the sample.

Rather than simply reflecting correlation in investment choices, these patterns highlight the role of ongoing advisory relationships as a channel for investment. Because our data link every private fund commitment to all ongoing pension fund–consultant relationships, we capture a wider and more persistent influence of consultants. By constructing opportunity sets that include all investable funds in a given vintage year, in the spirit of Goyal, Wahal, and Yavuz (2022), we more directly estimate the incremental likelihood of selecting a consultant-connected fund relative to its peers. Moreover, our framework extends naturally beyond private equity to real assets and also allows us to assess the role of general consultants in shaping private fund choices, providing a more complete view of how concentrated advisory networks propagate capital flows across multiple asset classes, vintage years, and institutional portfolios.

6.3 Specialized Consultants: Accessing and Scaling Up of Private Investments

Our earlier analysis of first-time hires shows that pension funds bringing on specialized consultants typically already have experience investing in alternative assets. However, before the hiring year, their actual allocations fall well short of stated targets. This pattern suggests that the primary constraint is not initiating exposure, but scaling allocations to meet portfolio targets. Specialized consultants can help overcome this constraint through two channels. First, by broadening the range of viable investments, they can increase both the number of commitments and the speed at which clients reach their target allocations. Second, by leveraging their industry networks, they may improve access to sought-after general partners and capacity-constrained private funds. In this section, we examine the incremental added value of having a specialized consultant relative to having only a general consultant.

We test the first channel by examining whether pension funds make more private fund investments after hiring a specialized consultant for the first time. Using pension-fund–vintage-year data, we measure the change in the number of annual commitments within a stacked DID framework:

$$Y_{i,c,t} = \beta_1 \, \mathrm{Treat}_{i,c,t} \times \mathrm{EarlyPost}_{i,c,t} + \beta_2 \, \mathrm{Treat}_{i,c,t} \times \mathrm{LatePost}_{i,c,t} + \gamma X_{i,c,t} + \eta_{i,c} + \nu_{c,t} + \epsilon_{i,c,t}, \quad (5)$$

where i is a pension fund, c is the cohort associated with the hiring of a specialized consultant for the first time, and t is a vintage year. The interaction term $Treat \times EarlyPost$ captures the effect in the treatment year and the first post-treatment year, while $Treat \times LatePost$ captures the effect in the second and third post-treatment years. We expect the main effect to be concentrated in the later stage, as some investments in private funds in the early stage may have been initiated even before the hiring event. $X_{i,c,t}$ are control variables at the pension fund level, such as size and target allocation to different risky asset classes. $\eta_{i,c}$ are interacted pension fund and stacked cohort fixed effects, and $\nu_{t,c}$ are interacted cohort and vintage-year fixed effects.

Compared to the literature, we take a broader perspective, following public pension funds at the system level across both private equity and real assets, and tracking all subsequent investments and allocation changes after the first hiring of a specialized consultant. This portfolio-wide lens allows us to capture scaling-up dynamics, convergence in manager choices, and longer-horizon performance patterns that are outside the scope of mandate-level analyses.

In Panel A of Table 9, we examine the effect of first-time PE consultant hires on the number of private equity investments, using a stacked DID with 42 treated and 92 never-treated control pension funds. In Panel B, we perform a parallel analysis for RA consultants on 36 treated and 91 control funds. The pension funds in our sample make 2.48 PE and 1.01 RA investments per year on average, which is below the typical 8 private investments per year, because our design excludes the always-treated (larger) pension funds.

We find that specialized consultants accelerate the scaling-up of PE allocations, roughly doubling the number of investments per year. Based on Column (1), pension funds hiring a PE consultant for the first time increase the number of PE investments almost immediately: 1.68 more investments in the hiring year and the year after, and 2.95 more in years two and three. For RA consultants, point estimates are also positive, but the effects are smaller and not statistically significant.

While the balanced panel better reflects the full range of investment decisions available to pension funds, a potential concern is that it mechanically assigns zero private-market investments to funds that do not invest in alternatives and therefore have no need for a specialized consultant. In Column (2) of Table 9, we address this by using an unbalanced panel that includes a pension fund in the sample only if it makes at least one private-fund investment in a given year. The results remain robust to this alternative definition of the dependent variable.

The second channel posits that specialized consultants help overcome barriers to investing with asset managers that are otherwise difficult to access. Networks in the asset management industry can create value for clients (e.g., Cohen, Frazzini, and Malloy, 2008; Hochberg, Ljungqvist, and Lu, 2010; Rossi et al., 2018b). Pension funds may therefore engage consultants to secure entry into highly sought-after private funds. Rationed access to top-performing managers is particularly relevant in private markets, where funds often face capacity constraints within their strategy and may value the confidentiality of their investment decisions (Lerner, Schoar, and Wongsunwai, 2007; Abuzov, Gornall, and Strebulaev, 2024). If specialized consultants mitigate these constraints, we would expect their clients to invest more frequently in such high-demand private funds.

To test the rationed access hypothesis, we use a similar stacked DID setup but on an expanded pension-fund-private-fund level dataset:

$$
\begin{aligned}
Y_{i,c,t,j} = {} & \beta_1 \,\mathrm{Treat}_{i,c,t,j} \times \mathrm{EarlyPost}_{i,c,t,j} + \beta_2 \,\mathrm{Treat}_{i,c,t,j} \times \mathrm{LatePost}_{i,c,t,j} \\
& + \gamma X_{i,c,t,j} + \eta_{i,c,j} + \nu_{c,t,j} + \epsilon_{i,c,t,j},
\end{aligned}
\tag{6}
$$

where j is a private fund. In this setting, we can include more saturated fixed effects to examine whether pension funds with specialized consultants have better access to private funds of the same type and raised in the same vintage year. $\eta_{i,c,j}$ are interacted pension fund, stacked cohort, and fund type fixed effects, and $\nu_{t,c}$ are interacted cohort, vintage year, and fund type fixed effects. Fund types are buyout, private debt, and venture capital in Panel A, and real estate, infrastructure, and natural resources in Panel B.

We measure potential access constraints along three dimensions. (i) First-time funds—the first fund raised by a general partner—are less likely to restrict entry given their need to build a track record (Sensoy, Wang, and Weisbach, 2014; Goyal, Wahal, and Yavuz, 2022). (ii) Oversubscribed funds, identified by a higher final-to-target size ratio, are more likely to reject commitments. (iii) Co-investment vehicles and separately managed accounts allow LPs to access deals alongside GPs and lower costs (Fang, Ivashina, and Lerner, 2015; Lerner, Mao, Schoar, and Zhang, 2022). If specialized consultants improve access, their clients should allocate less to first-time and under-subscribed funds and more to co-investments and separate accounts.

Columns (3) to (8) of Table 9 report the estimates for the three access measures. Hiring a PE consultant does not reduce allocations to first-time PE funds. By contrast, RA consultants improve access to later-stage funds: treated pensions are 8.5 percentage points less likely to invest in first-time funds in years 0–1 and 12.5 less likely in years 2–3 post-treatment. We find no evidence of better access based on fund size ratio for either consultant type, and results for co-investments and separate accounts are mixed. Given the low baseline incidence of co-investments, these estimates are concentrated among a few private funds. Overall, specialized consultants deliver only marginal improvements in access to high-demand private funds.

6.4 Specialized Consultants: Post-Hiring Performance of Private Funds

Although specialized consultants provide only modest improvements in access to sought-after private funds, they may still create value by directing clients toward better-performing funds (Lerner, Schoar, and Wongsunwai, 2007; Brown, Gredil, and Kantak, 2023). Since specialized consultants affect the selection of private funds and capital flows, it is important to assess whether this advice improves outcomes. Using the stacked DID in equation (6), we test whether hiring a specialized consultant for the first-time leads to commitments in better-performing private funds, Performance is measured by public market equivalent (PME), internal rate of return (IRR), and multiple of invested capital (MOIC), with PME calculated using the S&P 500 as the benchmark (Kaplan and Schoar, 2005). We restrict the performance analysis to vintages before 2017 to ensure at least a five-year track record.

Panel A of Table 10 shows little evidence that PE consultants improve performance: PME and IRR coefficients on $Treat \times EarlyPost$ and $LatePost \times Treated$ are insignificant, and the only significant MOIC effect, observed in the first year, does not persist. Panel B finds similarly null effects for RA consultants across all three metrics. Thus, specialized consultant involvement does not robustly translate into superior private fund performance. A possible explanation is stricter valuation standards among consultant-advised funds, while non-advised funds may report inflated valuations for younger vintages (Phalippou and Gottschalg, 2009). To address this, we re-estimate on the 2001–2010 vintage subsample (Online Appendix Table IA.12), where most funds are liquidated or fully distributed. Results remain null for both PE and RA consultants.

We also test whether specialized consultants reduce the probability of investing in bottom-decile funds, defined either in the aggregate or within fund-type-vintage-year strata (Online Appendix Tables IA.13–IA.14). Results show no consistent left-tail protection; only PE consultants modestly reduce exposure to low-PME funds, and even this is not robust across metrics. Finally, we examine whether specialized consultants improve selection among first-time private funds, where informational asymmetries are highest. For PE (the only asset class with sufficient observations), results in Online Appendix Table IA.15 indicate no improvement; if anything, treated funds exhibit lower PME.

Overall, we conclude that specialized PE and RA consultants do not guide pension funds toward higher-performing private funds, challenging the view that they possess superior selection ability in these markets.

7 Consultant Characteristics and Performance Heterogeneity

Section 4 showed that, on average, new general consultants have only a limited impact on asset allocation–driven performance. A natural question is whether this average masks meaningful variation, that is, whether certain types of consultants consistently deliver better results. Earlier, we documented several attributes that influence the likelihood of a consultant being hired: mandate breadth, the scale of discretionary assets under management (AUM), and the size of their pension fund client base. In this section, we test whether these same attributes are associated with differential post-hiring performance.

We build on the baseline specification in Column (3) of Table 6, replacing the single $Treated \times Post$ interaction in equation (3) with subgroup interactions. First, we split by mandate breadth: $Treated \times Post \times Broad$ for consultants serving as both general and specialized advisors, versus $Treated \times Post \times Narrow$ for consultants serving exclusively as general advisors. This classification proxies for informational scope: broad-mandate consultants may have more exposure to opportunities and risks across asset classes, potentially translating into higher-quality allocation advice. Second, we split by discretionary AUM (above vs. below the sample median) and by client base size (above vs. below the sample median) to test whether scale or market reach correlate with performance.

Figure 5 presents the results. Panel A shows that broad-mandate general consultants are associated with larger improvements in allocation-driven performance. By contrast, differences by discretionary AUM or client base size are statistically and economically insignificant. The results imply that, beyond the broad-mandate effect, the limited average impact documented in Section 4 is not masking large pockets of outperformance. In short, observable characteristics explain little of the variation in post-hiring performance.

We next turn to specialized consultants, focusing on their role in private market investments.

While Section 4 established the average effects of hiring a specialized consultant on access and performance, we now ask whether these effects vary systematically with consultant characteristics. As with general consultants, we examine mandate breadth, discretionary AUM, and client base size.

Figure 6 reports the results for the subsample of PE consultants, where the number of fund commitments is larger, and consultant characteristics are most varied.[27] We add separate post-hiring indicators for $Post \times Broad$ and $Post \times Narrow$ consultants, and repeat the exercise for high vs. low discretionary AUM and client base size. Across all splits, the results reveal no statistically meaningful differences: consultant characteristics do not appear to influence access to high-demand funds or the performance of selected funds.

In summary, specialized consultants reliably help pension funds increase the *number* of private fund commitments, thereby facilitating faster progress toward allocation targets. However, there is little evidence that any subset of specialized consultants consistently delivers superior access or fund-selection performance. The skills and networks of specialized consultants appear broadly homogeneous, at least along the observable dimensions we study.

8 Cross-Sectional Portfolio Similarity and Industry Concentration

Our results show that investment consultants induce convergence in both asset allocations and private fund selection among their pension clients. Following consultant hiring, pension funds realign their portfolios toward allocation profiles common among the consultant's existing clients, and funds advised by the same consultant are more likely to invest in the same PE and RA funds. At the same time, Figures 2 and 3 show that the consulting industry has become increasingly concentrated, with a small number of consultants advising a growing share of total pension assets.

[27] We present PE results for tractability; results for RA are qualitatively similar.

This combination matters because portfolio similarity reduces cross-fund diversification and can amplify common exposure to asset-class, manager-level, or liquidity shocks. Importantly, a higher likelihood of selecting investments from the same consultant network does not mechanically imply portfolio similarity. Similarity arises only through the cumulative aggregation of consultant-linked investment choices across pension funds, particularly as assets become concentrated within a limited number of advisors. As a result, consolidation among consultants can increase system-wide exposure correlation even if portfolio behavior within each consultant's client base remains stable over time.

Accordingly, in this section we quantify the cross-sectional similarity of pension fund portfolios and discuss its relation to consultant concentration. Our analysis focuses on alternative assets, where fund-type and manager-level data allow us to directly measure overlap in investment choices and link similarity to consultant networks. We measure the similarity of pension fund investments in alternative assets using cosine similarity between their private fund holdings and then, separately, between pension funds' asset allocations. Cosine similarity captures the degree of overlap in investment portfolios at the private fund level and has been widely used in studies of portfolio holdings overlap and systemic exposure (e.g., Sias, Turtle, and Zykaj, 2016; Girardi, Hanley, Nikolova, Pelizzon, and Sherman, 2021).

To illustrate the construction, for each pension fund i in year t, we construct a vector of commitment weights in PE funds, defined as the ratio between the dollar amount committed to each PE fund and the pension fund's total commitments to PE in that year. If a pension fund does not commit to a given private equity fund in year t, its commitment weight for that fund is set to zero. We then calculate the cosine similarity between the portfolios of pension funds i and j in year t as:

$$Similarity_{ij,t} = \frac{\mathbf{w}_{i,t} \cdot \mathbf{w}_{j,t}}{\|\mathbf{w}_{i,t}\| \cdot \|\mathbf{w}_{j,t}\|}, \tag{7}$$

where $\mathbf{w}_{i,t}$ and $\mathbf{w}_{j,t}$ are the vectors of commitment weights of pension funds i and j, respectively. Because all commitment weights are non-negative, cosine similarity is bounded between zero and one, with higher values indicating greater portfolio overlap.

Panels A and B of Figure 7 report average cosine similarity at the PE and RA fund levels, separately for pension funds sharing the same consultant and for those advised by different consultants or no consultant. Pension funds advised by the same general or specialized consultant exhibit substantially higher portfolio similarity throughout the sample period. In PE, similarity remains stable over time despite a large expansion in the investable universe of funds and general partners. Absent coordinated investment choices, this expansion would mechanically reduce overlap. Instead, the persistence of similarity indicates that investment consultants continue to channel their clients' commitments toward a common set of investment opportunities. By contrast, similarity in RA portfolios declines over time, consistent with increasing diversification as the opportunity set expands. Computing similarity at the general partner level yields qualitatively similar results.

We also compute cosine similarity at the alternative asset-class level using vectors of target allocations to private equity, real assets, hedge funds, and other alternatives. Panel C of Figure 7 shows that similarity in alternative asset mixes increases over time and is consistently higher among pension funds sharing the same general consultant, consistent with Begenau et al. (2025), while Panel D shows that asset-weighted similarity rises sharply, indicating increasing aggregation of pension assets into similar alternative allocation structures.

Overall, pension funds advised by the same consultant exhibit persistently higher portfolio similarity than funds advised by different consultants. While within-consultant similarity is relatively stable over time, consolidation in the consulting industry implies that an increasing share of total pension assets is concentrated within a small number of highly homogeneous consultant clusters, as shown in Figure 3.

Our analysis relates to a growing literature studying portfolio similarity and its implications for financial stability. Prior work shows that overlapping portfolios amplify shocks through correlated liquidation and fire-sale externalities (Greenwood et al., 2015; Ellul et al., 2022). At the micro level, delegated investment advice often induces standardized portfolio choices across heterogeneous investors (Foerster et al., 2017). Our results suggest that increasing concentration among investment consultants may transform consultant-level standardization in delegated advice into system-wide exposure correlation.

9 Conclusion

This paper examines how investment consultants shape the portfolio decisions of institutional investors using novel comprehensive data on relationships between U.S. public pension funds and their consultants. General consultants assist pension funds with asset allocation decisions, while specialized consultants are hired to advise on scaling-up investments in private markets.

We provide the first systematic evidence on the prevalence, turnover, and determinants of these relations, and examine their dynamic effects on portfolio decisions. Exploiting consultant hiring and turnover in difference-in-differences designs, we show that pension funds realign their asset allocations toward those of the consultant's client base and increase commitments to private equity funds within the consultant's network. These allocation convergence and network investing reflect coordination in delegated investment rather than informational advantages, as neither allocation shifts nor network ties improve performance or provide access to high-demand private funds.

Industry consolidation amplifies these dynamics. By 2020, a few large consultants advised half of all pension assets, contributing to pronounced clustering in portfolio choices across funds.

Overall, our findings highlight the role of advisory intermediation in coordinating institutional investment decisions and shaping capital flows. Advancing this research requires more granular, higher-frequency data to capture how consultants influence pension fund behavior and adjustment to market shocks in real time.

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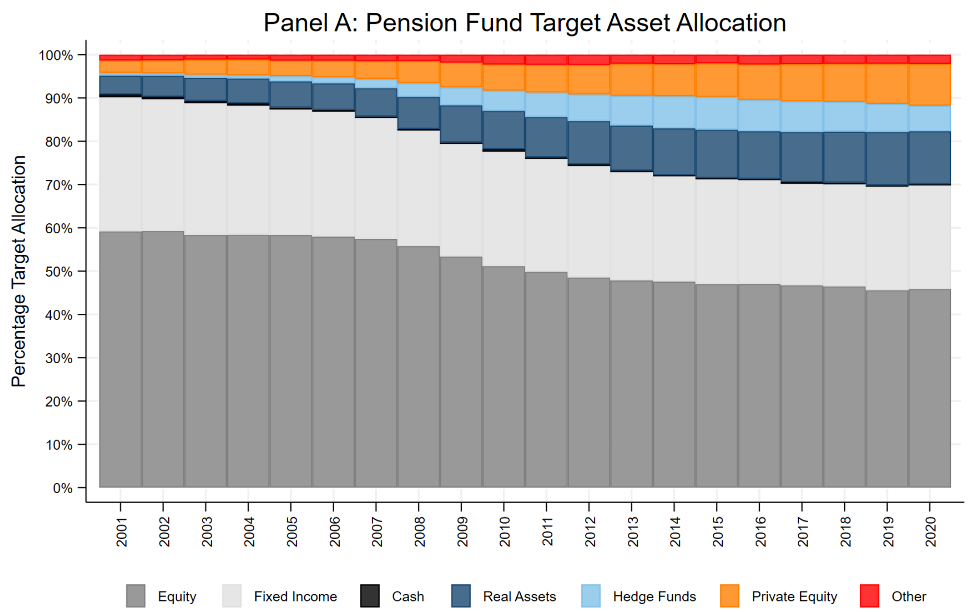
Figure 1: Pension Fund Target Asset Allocation and Investment Consultants

Panel A presents the average target asset allocation of pension funds. Panel B shows the average number of consultants per pension fund, differentiated by type: general consultants, other investment consultants, and specialized consultants in real assets, private equity, or hedge funds. Pension funds can have only one general consultant, but they can hire multiple specialized consultants in each asset class.



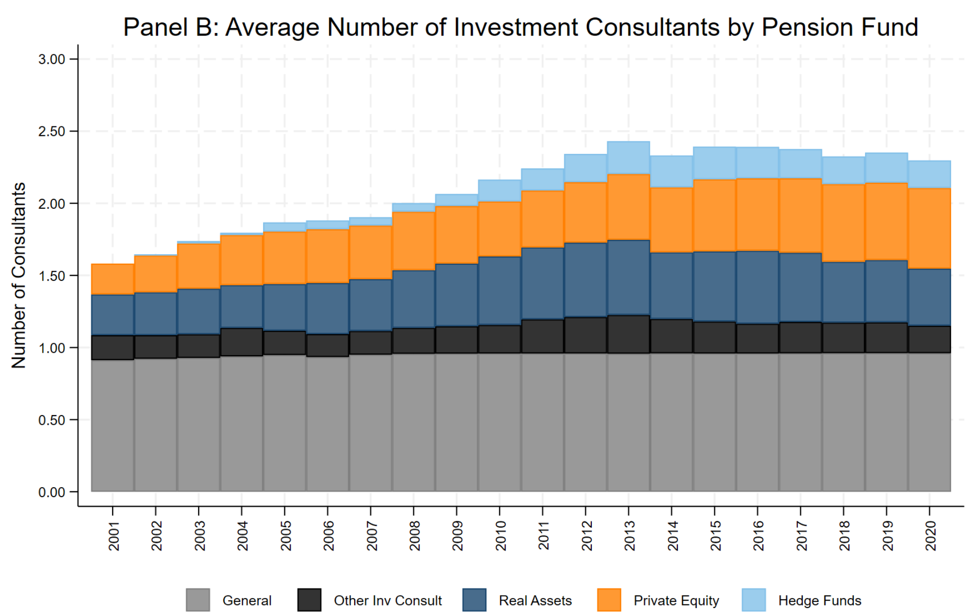


Figure 2: Concentration of General and Specialized Consultants

This figure shows the concentration of general and specialized consultants during the 2001–2020 period. Panels A and C rank consultants based on the number of pension funds they advise, presenting the percentage of pension funds advised by the 10 largest consultants, all other consultants, and those without consultants. Panels B and D rank consultants based on the aggregate assets under management (AUM) of their pension fund clients, reporting pension fund assets under advisory (in trillions of USD) by the 10 largest consultants and all other consultants. The secondary axis in all panels shows the number of unique general or specialized consultants by year. In Panels A and B, each pension fund employs one general consultant. In Panels C and D, if a pension fund has more than one specialized consultant in alternative assets, we split the mandate and assets under advisory by the number of specialized consultants.

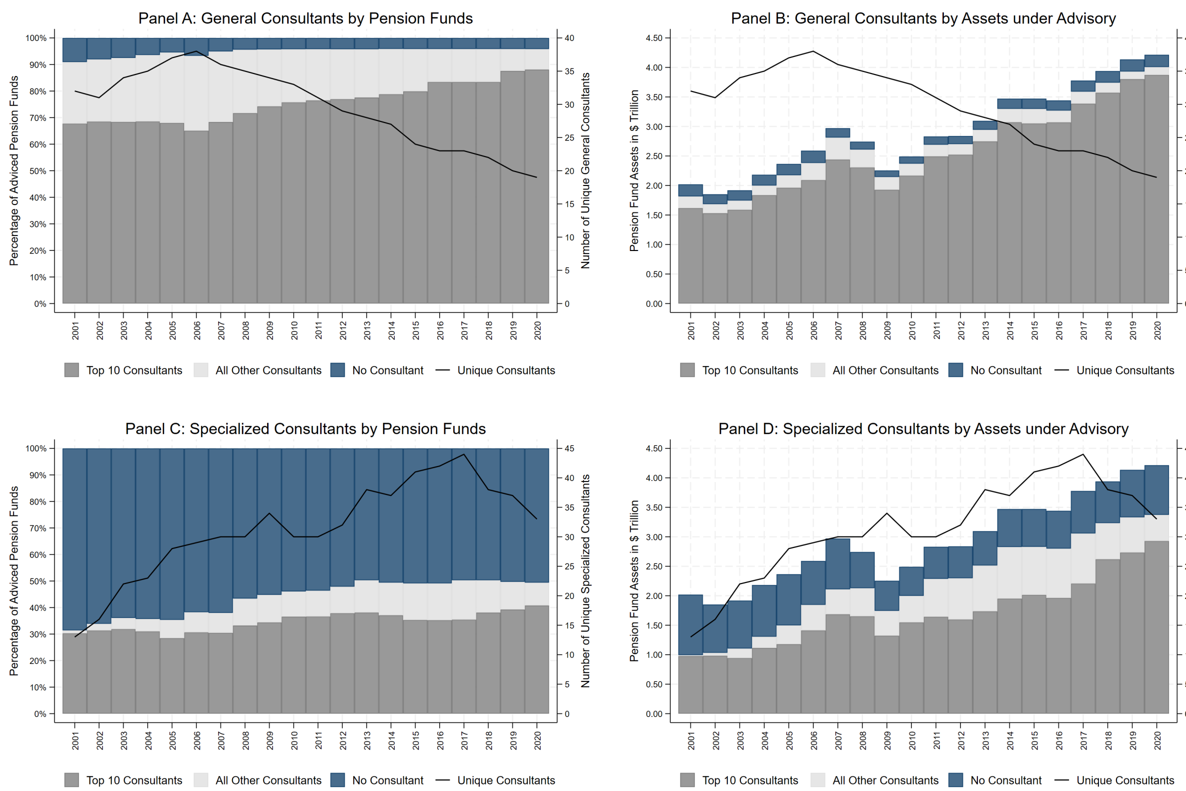
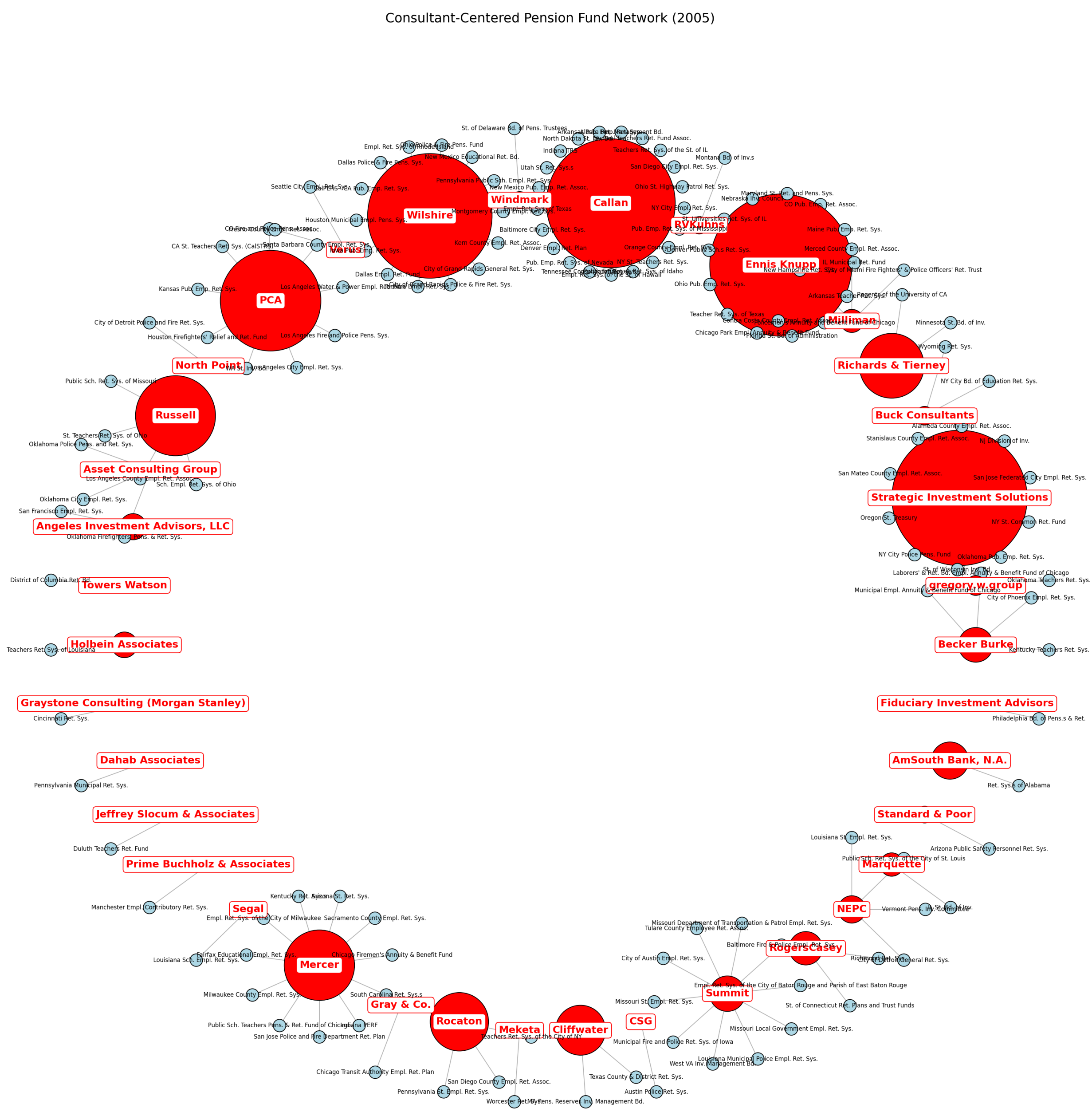


Figure 3: General Consultant Networks Over Time

This figure illustrates the network of U.S. public pension funds and their general investment consultants. The red nodes represent the consultants and links indicate advisory relationships with public pension funds. Node size is defined by the total assets under avice of each consultant in a year. Namely, the sum of the assets under management of all pension plans advised by a given consultant.

Panel A: General Consultant Networks in 2005



Panel B: General Consultant Networks in 2020

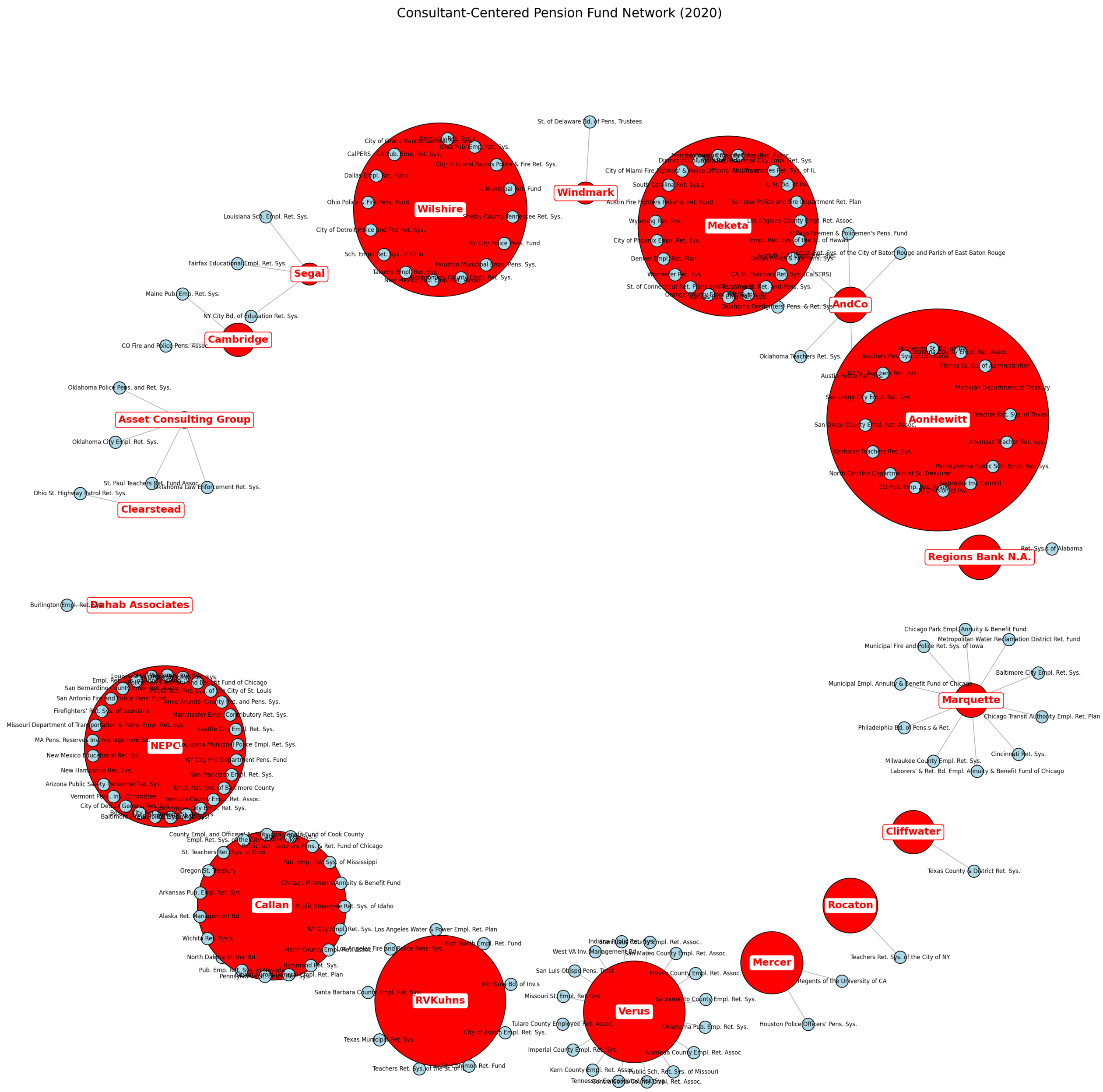


Figure 4: Hiring of Consultants over Time

This figure shows the distribution of hiring events of general and specialized consultants over time. *Replace* refers to hiring a new consultant within one year of the termination of the incumbent consultant. *First* refers to a pension fund hiring a consultant for the first time. *Additional* refers to a pension fund hiring additional consultants. The distribution of firing events is shown in the Online Appendix Figure IA.2.

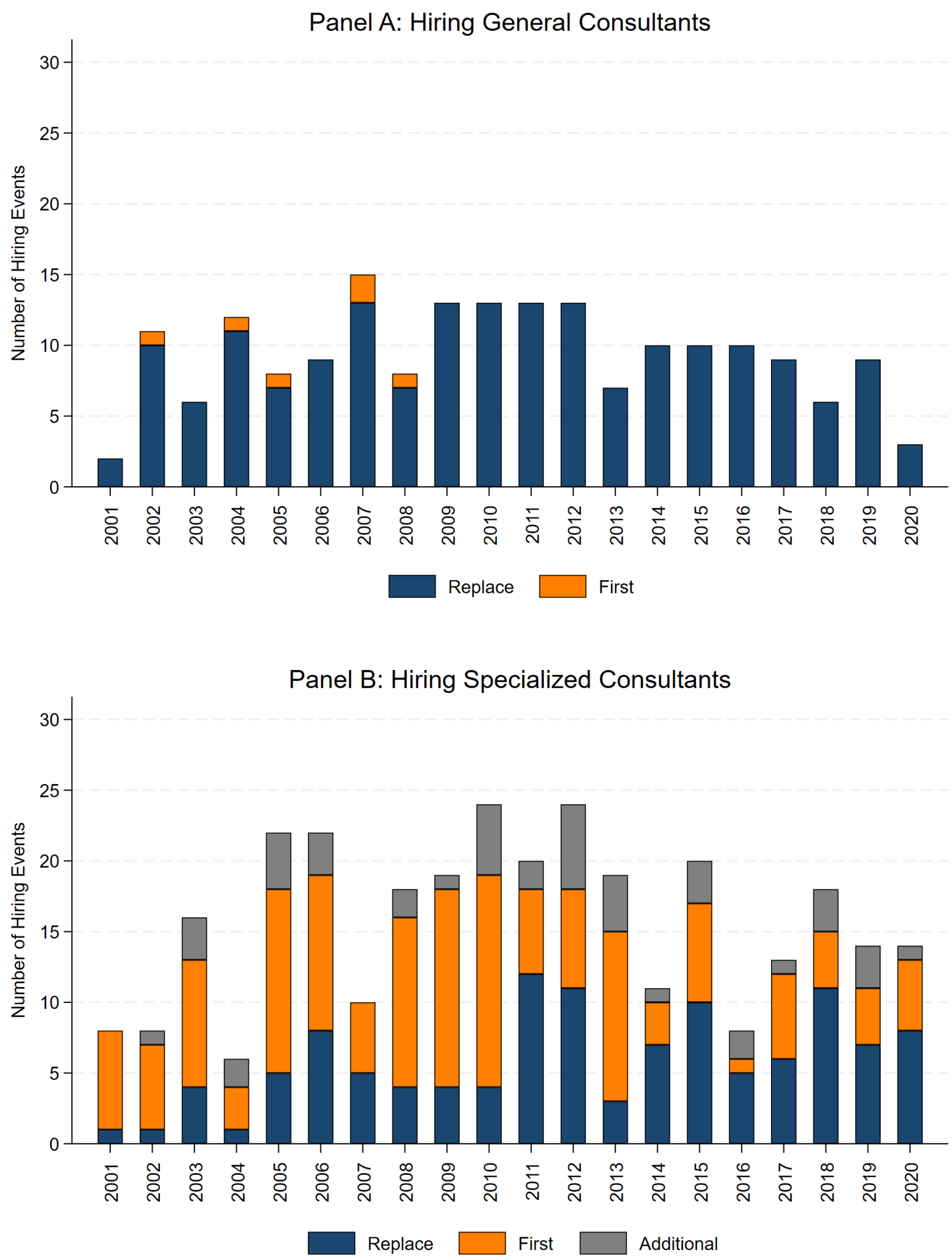
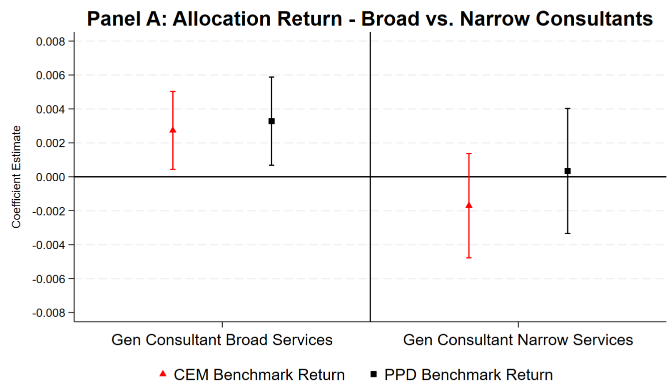
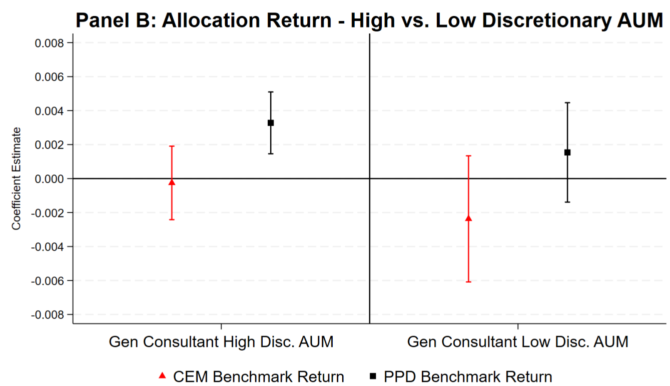


Figure 5: Allocation-Driven Performance by Consultant Characteristics

This figure plots estimated coefficients from stacked difference-in-differences (DID) regressions of allocation-driven performance, estimated separately for consultant subgroups. The specification follows column (3) of Table 6. Subgroups are defined along three dimensions: (i) type of services—Broad (serving as both general and specialized consultants) vs. Narrow (serving only as general consultants); (ii) discretionary assets under management (AUM), split at the sample median; and (iii) number of clients, also split at the median. Allocation-driven performance is calculated by multiplying each pension fund's target asset-class weights by either CEM average benchmark returns or PPD average asset-class returns. Vertical lines represent 95% confidence intervals.





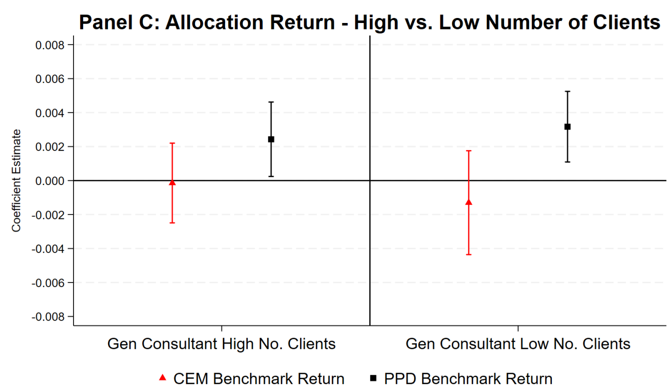


Figure 6: Heterogeneity Among Specialized PE Consultants

This figure presents the performance regression coefficients from stacked difference-in-differences (DID) models. The heterogeneity among private equity (PE) consultants is examined along three dimensions: (1) Type of services—consultants are categorized as Broad (serving as both specialized PE consultants and general consultants) or Narrow (serving exclusively as specialized PE consultants); (2) Discretionary assets under management (AUM), based on median; and (3) Number of clients, based on median. Panels A, C, and E focus on access to private markets, using first-time funds, final private fund size to target fund size, and co-investment funds or SA mandates. The panels present coefficients from stacked DID models in Columns (4), (6), and (8) of Table 9. Panels B, D, and F focus on performance, using PME and multiple measures, and present coefficients from stacked DID models consistent with Columns (2), (4), and (6) of Table 10.

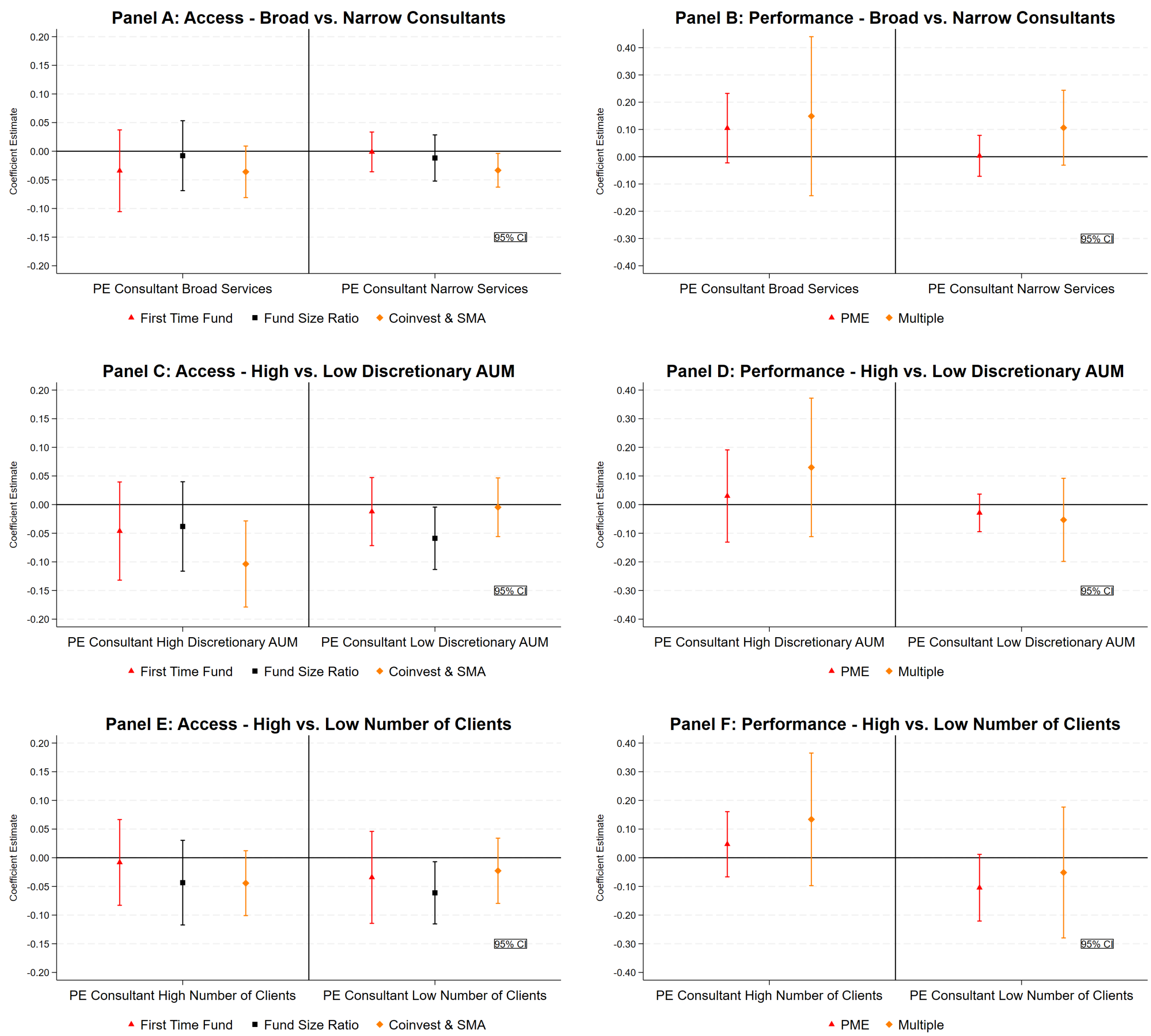


Figure 7: Portfolio Similarity within and across Alternative Asset Classes

Panels A and B report average cosine similarity of pension funds' alternative asset portfolios at the private fund level for private equity and real assets. Similarity is computed using pension fund pairs' private fund commitment vectors and is shown separately for funds sharing the same general or specialized investment consultant and for funds advised by different or no consultants. Panels C and D report cosine similarity in pension funds' target allocations across alternative asset classes (private equity, real assets, hedge funds, and other alternatives). Panel C shows the average similarity across all pension fund pairs separately for funds sharing the same general investment consultant and for funds advised by different or no consultants. Panel D reports the asset-weighted average similarity, where weights are given by the product of pension fund market shares. Higher values indicate greater similarity in alternative asset exposures.

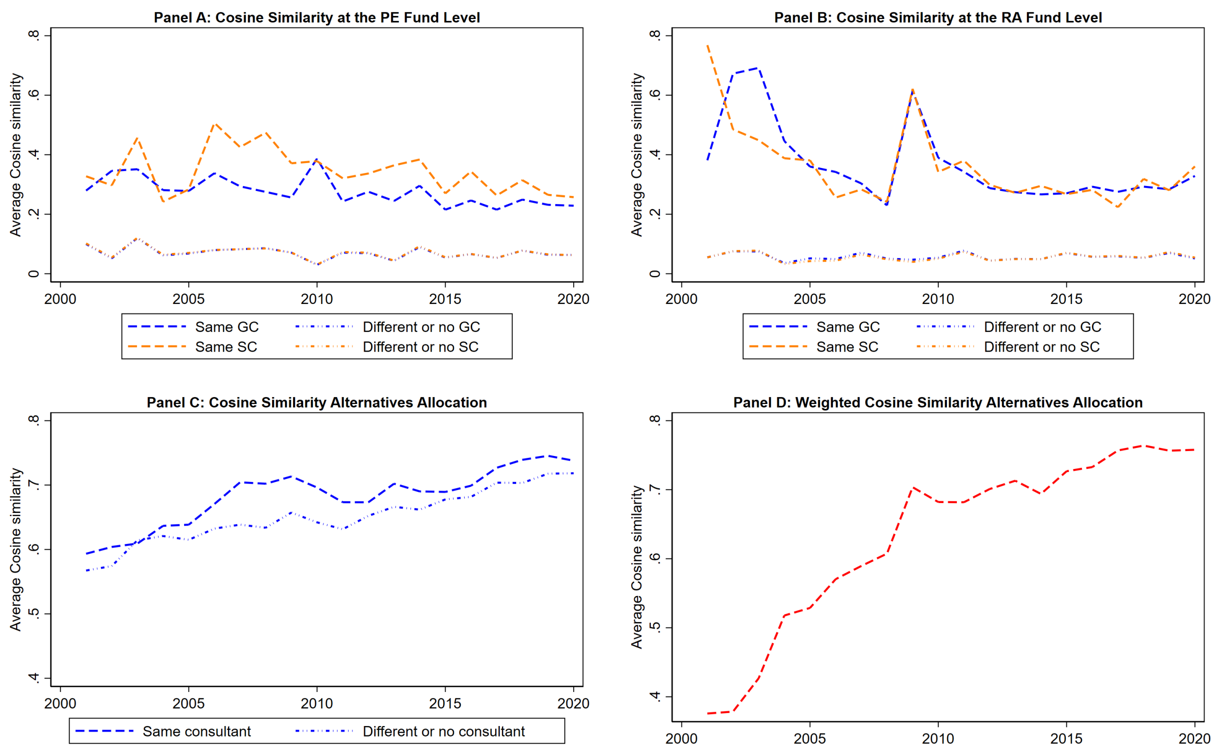


Table 1: Summary Statistics: Pension Fund Level

This table presents summary statistics on our sample of 173 public pension funds and their relations with investment consultants over the 2001–2020 period. Panel A shows statistics on pension fund characteristics. *Assets* is the total pension fund assets under management in $bln. *Return* is the pension fund's annual return calculated as net investment income divided by the total assets at the beginning of the year. *3Y Return* is the geometric average pension fund returns over the previous 3 years. *%Equity*, *%Fixed Income %Real Assets*, *%Private Equity*, *%Hedge Funds*, *%Other Alternatives*, and *%Cash* measure the target asset allocation. Panel B presents information on the number of pension fund-consultant relations. *#Consultants* reports the statistics for the total number of consultants by the pension fund. We also report the statistics for the number of general, real assets, private equity, hedge funds, and other investment consultants by pension fund.

	Obs	Mean	Median	StDev
Panel A: Pension Funds				
Assets ($ bil)	3,138	18.674	6.181	34.190
Return	3,138	0.064	0.081	0.103
3Y Return	2,660	0.065	0.076	0.053
%Equity	2,852	0.514	0.520	0.105
%Fixed Income	2,852	0.262	0.260	0.072
%Real Assets	2,852	0.091	0.095	0.061
%Private Equity	2,852	0.062	0.055	0.055
%Hedge Funds	2,852	0.048	0.000	0.067
%Other Alternatives	2,852	0.019	0.000	0.055
%Cash	2,852	0.004	0.000	0.023
Panel B: Investment Consultants				
#Consultants	3,138	1.939	1.000	1.465
#General Consultants	3,138	0.950	1.000	0.218
#Real Assets Consultants	3,138	0.370	0.000	0.587
#Private Equity Consultants	3,138	0.366	0.000	0.590
#Hedge Fund Consultants	3,138	0.123	0.000	0.342
#Other Consultants	3,138	0.129	0.000	0.494

Table 2: Summary Statistics: Investment Consultant Level

This table summarizes the data at the investment consultant level. Panel A reports the number of unique consultants by type and the number of pension fund-consultant-year observations with a consultant. Panel B reports statistics on investment consultant observations merged with the SEC ADV Form over the 2010–2020 period. We report the mean of the following characteristics. *#Clients* is the total number of clients served by the consultant. *%Discretionary AUM* measures the percentage of assets managed by the consultant under discretionary mandates. A low value of the *%Discretionary AUM* variable corresponds to a consulting firm that offers little or no asset management services. *Legal Issue* is an indicator for consultants reporting legal issues in the ADV annual form. *PF Clients 11-25%*, *PF Clients 26-50%*, *PF Clients 51-75%*, *PF Clients >75%* are indicators for consultants whose pension fund clients account for 0-10%, 11-25%, 26-50%, 51-75% or >75% of the total amount of assets under advisory.

	All	General	Real Assets	Private Equity	Hedge Funds	Other Consult.
Panel A: Pension-Fund-Consultant Relations						
#Unique Consultants	129	52	35	40	16	35
Observations	6,085	2,981	1,162	1,150	386	406
Panel B: Consultants Characteristics (Mean Values)						
Observations	3,767	1,755	736	779	328	169
#Clients	862	1,454	146	147	129	2,546
%Discretionary AUM	0.580	0.696	0.584	0.423	0.287	0.661
Legal Issues	0.192	0.290	0.132	0.055	0.043	0.367
PF Clients 0-10%	0.165	0.107	0.118	0.330	0.149	0.243
PF Clients 11-25%	0.223	0.172	0.306	0.142	0.537	0.160
PF Clients 26-50%	0.308	0.386	0.201	0.259	0.216	0.373
PF Clients 51-75%	0.215	0.271	0.152	0.204	0.098	0.195
PF Clients >75%	0.083	0.064	0.217	0.044	0.000	0.030

Table 3: Hiring General and Specialized Investment Consultants

In Columns (1) and (2), observations are at the pension-fund-year level. The dependent variable equals one if a pension fund hires a new general consultant. In Columns (3) and (4), observations are at the pension-fund-alternative-asset-class-year level and we focus on specialized consultants hired for the first time in each alternative asset class. In all columns, we present the results of logit specifications and report the marginal effects at the means of the independent variables. *3Y Rank* measures the percentile ranking of pension funds based on the geometric average performance over the past 3 years, i.e., *3Y Return*. We also control for the lagged target allocation as well as the difference between the lagged target and actual allocation in each risky asset class. In Columns (3) and (4), *%Target* and *%Actual* measure the lagged target and actual allocation in each alternative asset class. *PE Consultant* and *HF Consultant* are indicators for specialized consultants in private equity and hedge funds (the omitted category is real assets). All specifications include controls for pension fund assets under management, internal asset management divisions, governance, and year-reporting-month fixed effects. We double cluster standard errors by pension fund and year, and report standard errors in brackets. $p < .10$; **$p < .05$; ***$p < .01$.

	General		**Specialized**	
	(1)	(2)	(3)	(4)
Mean Dependent Variable	0.059	0.059	0.022	0.022
3Y Return	-1.066***		-0.129	
	[0.336]		[0.084]	
3Y Rank		-0.064***		-0.011**
		[0.021]		[0.005]
$\%\text{Actual}_{t-1}$			0.039*	0.035*
			[0.021]	[0.021]
$\%\text{Target}_{t-1} - \%\text{Actual}_{t-1}$			0.180***	0.167***
			[0.053]	[0.054]
HF consultant			-0.008*	-0.008**
			[0.004]	[0.004]
PE consultant			0.006	0.005
			[0.005]	[0.004]
Fund Size	0.009**	0.010**	0.011***	0.011***
	[0.004]	[0.004]	[0.001]	[0.001]
Internal Mandate	-0.086*	-0.083	-0.037*	-0.036*
	[0.052]	[0.053]	[0.020]	[0.020]
State-political	-0.002	-0.005	0.024***	0.023***
	[0.032]	[0.031]	[0.008]	[0.008]
Participant-elected	0.022	0.021	0.007	0.007
	[0.034]	[0.034]	[0.008]	[0.008]
Investment Board	0.003	0.003	-0.009***	-0.009***
	[0.016]	[0.014]	[0.003]	[0.003]
Other Board Members	Yes	Yes	Yes	Yes
Lagged Target Allocation (all risky)	Yes	Yes		
Lagged Gap Allocation (all risky)	Yes	Yes		
Year × Reporting Month FE	Yes	Yes	Yes	Yes
Observations	2,306	2,306	4,259	4,259

Table 4: Selection of General and Specialized Consultants

In this table, observations are at the pension-fund-consultant-year level over the 2010–2020 period. Columns (1) and (2) present the results of logit specifications where the dependent variable equals one for the hired general consultant. In Columns (3) and (4), the dependent variable equals one for the hired specialized consultant. We report the marginal effects at the means of the independent variables. *GC Narrow* is an indicator for general consultants that only serve as a general consultant and do not have a specialized position. *SC Narrow* is an indicator for consultants that have only a specialized mandate. *%PF Clients Same Size* is the percentage of pension funds served by the consultant that belong to the same size quartile as the pension fund making the hiring decision. *%PF Clients Same State* measures for each consultant the percentage of pension clients located in the same state as the pension fund making the hiring decision. *%Discretionary AUM*, *LogClients*, *Legal Issue*, and *PF Clients* are consultant characteristics from the SEC ADV Form. *HF* and *PE Consultant* are indicators for the type of consultant hired (the omitted category is RA consultants). The specifications include pension fund and year-reporting-month fixed effects. We double cluster standard errors by pension fund and year, and report standard errors in brackets. *$p < .10$; **$p < .05$; ***$p < .01$.

	General		**Specialized**	
	(1)	(2)	(3)	(4)
Mean Dependent Variable	0.024	0.024	0.041	0.041
Log Clients	0.002***	0.002***	0.004***	0.004***
	[0.000]	[0.001]	[0.001]	[0.001]
Discretionary AUM	0.003	0.002	-0.042***	-0.022**
	[0.003]	[0.003]	[0.008]	[0.009]
GC Narrow	-0.022***	-0.021***		
	[0.002]	[0.004]		
SC Narrow			0.013	0.014*
			[0.013]	[0.009]
%PF Clients Same Size	0.014***	0.013***	0.029***	0.021**
	[0.004]	[0.004]	[0.009]	[0.009]
%PF Clients Same State	0.024***	0.024***	0.027	0.032**
	[0.007]	[0.008]	[0.019]	[0.015]
Legal Issues		0.000		-0.035***
		[0.005]		[0.012]
PF Clients 11-25%		0.004		0.027***
		[0.006]		[0.008]
PF Clients 26-50%		0.003		0.018
		[0.007]		[0.012]
PF Clients 51-75%		0.010		0.024**
		[0.006]		[0.012]
PF Clients >75%		0.007		0.017
		[0.006]		[0.020]
HF Consultant			0.023***	0.028***
			[0.003]	[0.007]
PE Consultant			-0.011***	-0.005
			[0.003]	[0.005]
Pension Fund FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4,061	4,061	1,569	1,569

Table 5: Post-Hiring General Consultants: Convergence of Allocations

In the table, we analyze the turnover of general consultants. Panel A shows the results of OLS specifications. Panel B shows the results of IV specifications with first-stage estimates described in the Online Appendix Table IA.7. In Columns (1) to (2), for each pension fund i that hires a new general consultant in year t, we measure the target allocation to risky assets made with the old general consultant in year $t-1$ ($\text{Risky}_{i,t-1}^{\text{Pre}}$) and with the new general consultant in year $t+1$ ($\text{Risky}_{i,t+1}^{\text{Post}}$). The dependent variable, $\Delta\text{Risky}_{i,t+1}^{\text{Post}-\text{Pre}}$, is the difference between these two variables. As a measure of each consultant's stance toward risk-taking, we also measure the average target allocation to risky assets of both the new and old consultant's other clients (excluding pension fund i) during the period before the turnover event ($\text{AvgRisky}_{-i,t-1}^{\text{OldGCpre}}$ and $\text{AvgRisky}_{-i,t-1}^{\text{NewGCpre}}$). The main independent variable of interest, $\Delta\text{AvgRisky}_{-i,t-1}^{\text{NewGCpre}-\text{OldGCpre}}$, is the difference between the average risky allocation of the new and old consultant's other clients (excluding pension fund i) during the period before the turnover event. Equation (1) outlines the regression model in detail. In Columns (3) and (4), we replicate the analysis for the target allocation to equity. In Columns (5) and (6), we replicate the analysis for the target allocation to alternative asset classes. All specifications include a pension fund size and governance-related variables, year fixed effects, and consultant fixed effects. We double cluster standard errors by pension fund and year, and report standard errors in brackets. *$p < .10$; **$p < .05$; ***$p < .01$.

	$\Delta\text{Risky}_{i,t+1}^{\text{Post}-\text{Pre}}$		$\Delta\text{Equity}_{i,t+1}^{\text{Post}-\text{Pre}}$		$\Delta\text{Alt}_{i,t+1}^{\text{Post}-\text{Pre}}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Mean Dependent Variable	0.010	0.010	-0.026	-0.026	0.036	0.036
Panel A: OLS Models						
$\Delta\text{AvgRisky}_{-i,t-1}^{\text{NewGCpre}-\text{OldGCpre}}$	0.090**	0.094**				
	[0.033]	[0.036]				
$\Delta\text{AvgEquity}_{-i,t-1}^{\text{NewGCpre}-\text{OldGCpre}}$			0.162**	0.066		
			[0.069]	[0.076]		
$\Delta\text{AvgAlt}_{-i,t-1}^{\text{NewGCpre}-\text{OldGCpre}}$					0.333***	0.264***
					[0.070]	[0.068]
Controls in $t+1$	Yes	Yes	Yes	Yes	Yes	Yes
Year FE in $t+1$	Yes	Yes	Yes	Yes	Yes	Yes
Consultant FE in $t+1$		Yes		Yes		Yes
Observations	117	115	117	115	117	115
Adjusted R-squared	0.110	0.157	0.169	0.206	0.285	0.281
Panel B: IV Models						
$\Delta\text{AvgRisky}_{-i,t-1}^{\widehat{\text{NewGC}}\text{pre}-\text{OldGCpre}}$	0.138*	0.180*				
	[0.067]	[0.086]				
$\Delta\text{AvgEquity}_{-i,t-1}^{\widehat{\text{NewGC}}\text{pre}-\text{OldGCpre}}$			-0.085	-0.148		
			[0.158]	[0.184]		
$\Delta\text{AvgAlt}_{-i,t-1}^{\widehat{\text{NewGCpre}}-\text{OldGCpre}}$					0.307**	0.321**
					[0.114]	[0.127]
Controls in $t+1$	Yes	Yes	Yes	Yes	Yes	Yes
Year FE in $t+1$	Yes	Yes	Yes	Yes	Yes	Yes
Consultant FE in $t+1$		Yes		Yes		Yes
Observations	117	115	117	115	117	115
K-P F-Stat	13.301	13.165	25.197	13.705	23.753	36.349

Table 6: Post-Hiring General Consultants: Future Performance

This table reports stacked difference-in-differences (DID) estimates of pension funds' performance, at the pension-fund-year level, calculated in various ways. In Column (1), the dependent variable is the percentile rank of a fund's total return within the same experiment cohort. In Column (2), the dependent variable is the total return of a pension fund. Columns (3)–(5) use benchmark returns based on CEM average asset-class returns and the fund's target allocations (same as Eq. 4):

$$BmkRet_{i,t} = \sum_{n=1}^{7} PolicyAllocation_{i,t}^{n} * CEMBmkRet_{t}^{n}, \tag{8}$$

where n indexes the asset class. The treatment is the hiring of a general investment consultant; the event window spans three years before and after the hiring year. Each treated fund is matched to never-treated funds that either never changed or never employed a general consultant. The coefficient on $Treated \times Post$ captures the average treatment effect over years 0–3. Post-treatment interaction terms indicate whether the fund increased, decreased, or maintained its share of risky assets, equities, or alternatives relative to the pre-treatment year. All specifications include pension-fund × stacked-cohort, year × stacked-cohort, and year × reporting-month fixed effects. Standard errors, clustered by pension-fund × stacked-cohort, are in brackets. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Pension Fund Performance Measure	Rank (1)	Ret (2)	Bmk Ret (3)	Bmk Ret (4)	Bmk Ret (5)
Mean Dependent Variable	0.527	0.071	0.079	0.079	0.079
Treated × Post	0.077***	0.003	0.002		
	[0.028]	[0.002]	[0.001]		
Treated × Post × Increase Risky				-0.001	-0.001
				[0.002]	[0.002]
Treated × Post × Decrease Risky				0.001	0.001
				[0.002]	[0.002]
Treated × Post × Same Risky				0.005*	
				[0.002]	
Treated × Post × Same Risky Same Comp					0.004
					[0.003]
Treated × Post × Same Risky Diff Comp					0.005**
					[0.002]
Pension Fund Size and Target Allocation	Yes	Yes	Yes	Yes	Yes
Pension Fund × Cohort FE	Yes	Yes	Yes	Yes	Yes
Year × Cohort FE	Yes	Yes	Yes	Yes	Yes
Year × Reporting Month FE	Yes	Yes	Yes	Yes	Yes
#Treated PFs	89	93	93	93	93
#Never-Treated PFs	49	50	50	50	50
Observations	4,454	4,487	4,487	4,487	4,487
Adjusted R-squared	0.074	0.965	0.976	0.976	0.976

Table 7: Private Equity Funds and Consultant Networks

The table reports the OLS coefficient estimates from a linear probability specification where the dependent variable is an indicator variable that takes the value of one if the PE fund is added to the pension fund roster during the year, and zero otherwise. The dataset includes pension-fund-investment level observations from 2001 to 2020 and it is expanded to include all potential private funds the pension fund can choose from in any given year. *SameConsultant* is equal to 1 if the fund is in the same consultant network. In columns (1) to (2) the consultant network includes all the private equity funds that any consultant of the pension plan included in the investment roster in any of the public funds in our sample. In columns (3) to (4) the consultant network includes all the private equity funds that any general consultant of the pension plan included in the investment roster in any of the public pension funds in our sample. In columns (5) to (6) the consultant network includes all the private equity funds that any private equity consultant of the pension plan included in the investment roster in any of the public pension funds in our sample. We also control for private fund size, pension fund assets under management, internal asset management divisions, board composition, and target allocation to equity, real assets, private equity, hedge funds, and other risky assets. The specifications include target asset allocations, and pension fund or private equity fund fixed effects. We double cluster standard errors by pension fund and vintage year, and report standard errors in brackets. *$p < .10$; **$p < .05$; ***$p < .01$.

	All Consultants		**General Consultant**		**PE Consultants**	
	(1)	(2)	(3)	(4)	(5)	(6)
	0.0046	0.0046	0.0046	0.0047	0.0058	0.0058
Same consultant	0.008***	0.008***	0.015***	0.015***	0.021***	0.021***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
PE Fund Size	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pension Fund Size	-0.000***	0.000	-0.000*	-0.000	-0.000	-0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.004)
Internal Mandate	0.001		-0.003*		-0.002	
	(0.001)		(0.001)		(0.004)	
Investment Board	-0.000*		-0.002**		-0.001*	
	(0.000)		(0.001)		(0.001)	
State-political	-0.002**		-0.002**		0.001	
	(0.001)		(0.001)		(0.002)	
Participant-elected	-0.001		-0.001		0.002	
	(0.001)		(0.001)		(0.002)	
Public-elected	-0.001*		-0.000		0.002	
	(0.001)		(0.001)		(0.002)	
Target Asset Allocation	Yes	Yes	Yes	Yes	Yes	Yes
Other Board Members	Yes	Yes	Yes	Yes	Yes	Yes
Vintage-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
PE-Fund FE	Yes		Yes		Yes	
Pension-Fund FE		Yes		Yes		Yes
Observations	3,303,201	3,311,153	3,241,357	3,249,265	1,784,937	1,786,943
R-squared	0.006	0.006	0.012	0.013	0.018	0.018

Table 8: Real Assets Funds and Consultant Networks

The table reports the OLS coefficient estimates from a linear probability specification where the dependent variable is an indicator variable that takes the value of one if the RA fund is added to the pension fund roster during the year, and zero otherwise. The dataset includes pension-fund-investment level observations from 2001 to 2020 and it is expanded to include all potential private funds the pension fund can choose from in any given year. *SameConsultant* is equal to 1 if the fund is in the same consultant network. In columns (1) to (2) the consultant network includes all the RA funds that any consultant of the pension plan included in the investment roster in any of the public funds in our sample. In columns (3) to (4) the consultant network includes all the RA funds that any general consultant of the pension plan included in the investment roster in any of the public pension funds in our sample. In columns (5) to (6) the consultant network includes all RA funds that any RA consultant of the pension plan included in the investment roster in any of the public pension funds in our sample. We also control for private fund size, pension fund assets under management, internal asset management divisions, board composition, and target allocation to equity, real assets, private equity, hedge funds, and other risky assets. The specifications include target asset allocations, and pension fund or private equity fund fixed effects. We double cluster standard errors by pension fund and vintage year, and report standard errors in brackets. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

	All Consultants		**General Consultant**		**RA Consultants**	
	(1)	(2)	(3)	(4)	(5)	(6)
	0.0087	0.0087	0.0088	0.0088	0.0118	0.0118
Same consultant	0.015***	0.016***	0.030***	0.031***	0.030***	0.032***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
PE Fund Size	0.004***	0.004***	0.003***	0.003***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Pension Fund Size	-0.001***	0.001	-0.001*	0.001	-0.000	0.001
	(0.000)	(0.001)	(0.000)	(0.002)	(0.001)	(0.004)
Internal Mandate	0.002		-0.006**		0.013**	
	(0.002)		(0.003)		(0.006)	
Investment Board	-0.000		-0.003**		0.001	
	(0.001)		(0.001)		(0.001)	
State-political	-0.003*		-0.005***		0.001	
	(0.001)		(0.002)		(0.003)	
Participant-elected	-0.001		-0.004**		0.004	
	(0.001)		(0.002)		(0.003)	
Public-appointed	-0.003*		-0.002		0.005	
	(0.002)		(0.003)		(0.003)	
Target Asset Allocation	Yes	Yes	Yes	Yes	Yes	Yes
Other Board Members	Yes	Yes	Yes	Yes	Yes	Yes
Vintage-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
PE-Fund FE	Yes		Yes		Yes	
Pension-Fund FE		Yes		Yes		Yes
Observations	754,973	756,406	734,174	735,594	362,965	363,915
R-squared	0.011	0.012	0.025	0.026	0.022	0.023

Table 9: Post-Hiring Specialized Consultants: Access to Private Funds

We estimated stacked DID specifications. The treatment is hiring a specialized consultant for the first time and the event window spans seven years, covering 3 years before and after the hiring. We stack each treated pension fund with a sample of never-treated pension funds that never had a specialized consultant. Panel A focuses on PE consultants and examines investments in buyout, private debt, and venture capital funds. Panel B focuses on RA consultants and examines investments in real estate, infrastructure, and natural resources funds. $Treated \times EarlyPost$ captures the treatment effect in years 0 and 1, whereas $Treated \times LatePost$ captures the effect in years 2 and 3. In Columns (1) and (2), observations are at the pension-fund-year level. The dependent variable is the total number of private fund investments made by a pension fund in a given year. In Column (1), if a pension fund did not make any investments in private funds in a given year, the dependent variable equals zero. Column (2) excludes the observations with zero investments. In Columns (3) to (8), observations are at the pension-fund-investment level. The dependent variables are three measures of access in private markets: an indicator for investing in first-time funds; the ratio of final private fund size to target fund size (winsorized at the 1.00% level); and an indicator for investing in co-investment funds or separate account mandates. The specifications include either interacted pension-fund-stacked-cohort and vintage-year-stacked-cohort or interacted pension-fund-stacked-cohort-fund-type and vintage-year-stacked-cohort-fund-type fixed effects. We cluster standard errors by pension-fund-stacked-cohort or by pension-fund-stacked-cohort-fund-type. *$p < .10$; **$p < .05$; ***$p < .01$.

	#Investments Private Funds		**Overall First Time Fund**		**Fund Size Ratio**		**Coinvest & SMA**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Panel A: PE Specialized Consultant					
Mean Dependent Variable	2.475	4.541	0.068	0.068	1.107	1.107	0.042	0.042
Treated × Early Post	1.684***	1.177*	-0.017	-0.016	-0.006	-0.021	-0.026*	-0.028**
	[0.591]	[0.626]	[0.018]	[0.019]	[0.018]	[0.020]	[0.013]	[0.014]
Treated × Late Post	2.950***	2.351***	-0.013	-0.015	0.016	-0.007	-0.027*	-0.033**
	[0.698]	[0.728]	[0.019]	[0.019]	[0.018]	[0.017]	[0.014]	[0.015]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PF × Cohort FE	Yes	Yes	Yes		Yes		Yes	
Vintage × Cohort FE	Yes	Yes	Yes		Yes		Yes	
PF × Cohort × Fund-Type FE				Yes		Yes		Yes
Vintage × Cohort × Fund-Type FE				Yes		Yes		Yes
#Treated PFs	41	41	42	42	42	42	42	42
#Never-Treated PFs	90	74	74	74	74	73	74	74
Observations	6,288	3,529	16,177	15,884	14,160	13,879	16,896	16,610
Adjusted R-squared	0.763	0.711	0.054	0.083	0.072	0.119	0.055	0.060
			Panel B: RA Specialized Consultant					
Mean Dependent Variable	1.013	2.562	0.117	0.117	1.106	1.106	0.023	0.023
Treated × Early Post	0.689	0.548	-0.044	-0.085**	-0.022	-0.045	0.039	0.063*
	[0.681]	[0.755]	[0.046]	[0.040]	[0.036]	[0.040]	[0.030]	[0.037]
Treated × Late Post	1.013	0.583	-0.119***	-0.125***	0.015	0.015	0.044*	0.063**
	[0.799]	[0.887]	[0.044]	[0.041]	[0.038]	[0.041]	[0.025]	[0.027]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
PF × Cohort FE	Yes	Yes	Yes		Yes		Yes	
Vintage × Cohort FE	Yes	Yes	Yes		Yes		Yes	
PF × Cohort × Fund-Type FE				Yes		Yes		Yes
Vintage × Cohort × Fund-Type FE				Yes		Yes		Yes
#Treated PFs	34	34	34	34	34	34	34	34
#Never-Treated PFs	89	62	63	62	60	60	64	62
Observations	5,247	2,230	6,192	6,015	5,315	5,134	6,370	6,185
Adjusted R-squared	0.589	0.470	0.073	0.165	0.145	0.222	0.059	0.042

Table 10: Post-Hiring Specialized Consultants: Performance of Private Funds

We estimated stacked DID specifications and the observations are at the pension fund-investment level over the 2001–2016 period. The treatment is hiring a specialized consultant for the first time and the event window spans seven years, covering 3 years before and after the hiring. We stack each treated pension fund with a sample of never-treated pension funds that never had a specialized consultant. Panel A focuses on PE consultants and examines investments in buyout, private debt, and venture capital funds. Panel B focuses on RA consultants and examines investments in real estate, infrastructure, and natural resources funds. $Treated \times EarlyPost$ captures the treatment effect in years 0 and 1, whereas $Treated \times LatePost$ captures the effect in years 2 and 3. The dependent variables are three performance measures: the public market equivalent with the S&P500 index as a benchmark; the net internal rate of return (IRR); and the multiple of the total value to paid-in capital. We include either interacted pension-fund-stacked-cohort and vintage-year-stacked-cohort or interacted pension-fund-stacked-cohort-fund-type and vintage-year-stacked-cohort-fund-type fixed effects. We cluster standard errors by pension-fund-stacked-cohort or by pension-fund-stacked-cohort-fund-type and report standard errors in brackets. *$p < .10$; **$p < .05$; ***$p < .01$.

	PME		**IRR**		**Multiple**	
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: PE Specialized Consultant					
Mean Dependent Variable	1.092	1.092	14.208	14.208	1.938	1.938
Treated × Early Post	0.060	0.051	0.586	0.382	0.144**	0.111*
	[0.038]	[0.036]	[0.975]	[0.901]	[0.069]	[0.061]
Treated × Late Post	0.013	0.015	0.006	-0.085	0.083	0.125
	[0.036]	[0.041]	[1.000]	[0.888]	[0.089]	[0.094]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
PF × Cohort FE	Yes		Yes		Yes	
Vintage × Cohort FE	Yes		Yes		Yes	
PF × Cohort × Fund-Type FE		Yes		Yes		Yes
Vintage × Cohort × Fund-Type FE		Yes		Yes		Yes
#Treated PFs	42	42	42	42	42	42
#Never-Treated PFs	68	66	70	70	70	69
Observations	12,352	12,059	13,819	13,524	14,347	14,053
Adjusted R-squared	0.076	0.159	0.149	0.215	0.110	0.307
	Panel B: RA Specialized Consultant					
Mean Dependent Variable	0.806	0.806	6.535	6.535	1.298	1.298
Treated × Early Post	0.043	0.019	-0.235	-0.127	0.051	0.005
	[0.056]	[0.054]	[2.120]	[1.976]	[0.067]	[0.067]
Treated × Late Post	0.063	0.041	3.642	3.567	0.117	0.058
	[0.063]	[0.063]	[2.960]	[2.616]	[0.079]	[0.075]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
PF × Cohort FE	Yes		Yes		Yes	
Vintage × Cohort FE	Yes		Yes		Yes	
PF × Cohort × Fund-Type FE		Yes		Yes		Yes
Vintage × Cohort × Fund-Type FE		Yes		Yes		Yes
#Treated PFs	34	34	34	34	33	33
#Never-Treated PFs	54	52	58	55	57	55
Observations	3,734	3,511	4,533	4,288	4,668	4,463
Adjusted R-squared	0.172	0.251	0.061	0.057	0.086	0.110

Internet Appendix

Choosing Pension Fund Investment Consultants

IA.1 Pension Fund and Investment Consultants Data

The unit of observation in our analysis is a pension fund and one pension fund (retirement system) can manage the assets of multiple pension plans. We collect information on the pension fund's total assets under management, actual and target asset allocations, and performance from their Comprehensive Annual Financial Reports (CAFRs). Online Appendix Table IA.1 shows that our total sample covers 173 unique pension funds over the 2001–2020 period, corresponding to 3,138 pension-fund-year observations, and we construct this sample of pension funds from two sources. First, the majority of observations (138 pension funds with 2,624 annual observations) comes from the Public Plans Database (PPD), published by the Center for Retirement Research at Boston College. Second, we extend the sample coverage by collecting data on 35 unique pension funds (514 annual observations). This additional sample covers primarily local county and city pension funds that are not part of the PPD dataset.

We also manually verify and adjust the PPD data on asset allocations:

- We make adjustments for misclassified asset classes in 23 pension plans over multiple years. For example, in the PPD data, the Alabama Employees' Retirement System's policy allocation to "fixed" includes fixed income, real estate, and alternative miscellaneous. Over the entire sample period, we separate the policy allocation into these three asset classes, consistent with the Alabama ERS CAFR report.

- We also fill in missing allocation data for 14 pension plans by integrating PPD data with information from the plans' CAFR reports. For instance, the City of Phoenix Employees' Retirement System has missing target and actual allocation data in PPD from 2001 to 2014. We fill this gap by manually collecting information from the plan's CAFR reports.

- We correct mismatches between target and actual asset allocation categories for 6 pension plans by cross-checking with CAFR reports. For example, in PPD, the 2003 policy allocation to equity for the Minnesota Teacher Retirement Association is 0.62708, whereas in the CAFR report, it is 0.6.

- We make adjustments for 3 pension plans where leverage is not categorized as a negative allocation to cash in PPD. For example, the San Diego County Employees Retirement Association shows a zero target allocation to cash in 2012 in PPD. However, based on the weights of other asset classes, it should be -0.36.

In our analysis, we classify pension fund investment consultants into general or specialized consultants. General investment consultants make recommendations on the asset allocation policy, formulating return expectations, selection of asset managers, benchmarking of performance, asset-liability management, risk control policies, reporting, and education services. Specialized investment consultants are typically hired in alternative asset classes, such as real assets, private equity, and hedge funds, and have a narrow set of responsibilities, focusing primarily on the selection of asset managers and performance evaluation.

In the paper, we show that the industry of pension fund investment consultants is highly concentrated. Figure 2 shows that the concentration of consultants has continuously increased over our sample period based on the number of relations as well as based on the amount of assets under advisory. In this appendix, we show a similar degree of concentration in the provision of specialized consultant services. Figure IA.1 shows that the top 10 specialized consultants account for the vast majority of pension-fund-consultant relationships in real assets, private equity, and hedge funds. The other non-10 specialized consultants account for less than 5% of the relations and in the earlier years of our sample there are even more than 10 unique specialized consultants in all alternative assets classes. Thus, the degree of concentration among specialized consultants is even higher than for general consultants. Still, there is a substantial share of pension funds that operate without having a specialized consultant.

IA.2 Consulting Relationships

Our analysis focuses on the initiation and termination of contracts between pension funds and investment consultants. We identify hiring events based on the first year of employment of new general consultants and distinguish four different types of hiring events: first-time hiring, immediate replacement hiring, additional hiring, and later replacement hiring. Table IA.3 shows the distribution of these events over time. We observe 6 first-time hiring events of general consultants and 150 first-time hiring events of specialized consultants (41 in hedge funds, 62 in private equity, and 47 in real assets). We also observe 181 immediate replacements of general consultants and 117 replacement events of specialized consultants (10 in hedge funds, 65 in private equity, and 42 in real assets). Pension funds are not limited to having only one specialized consultant per asset class and could hire additional new specialized consultants. These additional hiring events of specialized consultants often follow specific mandates within a certain asset class, such as domestic private equity and international private equity. These additional hiring events are relatively rare (5 in hedge funds, 23 in private equity, and 19 in real assets). Finally, we observe 12 events in which investment consultants are replaced only after a longer period of two or more years.

Online Appendix Table IA.3 shows also the distribution of termination events which we identify based on the last year of employment of old consultants. Most terminations are followed by a replacement and hiring of a new consultant. For instance, 186 out of 188 terminations of general consultants and 121 out of 221 terminations of specialized consultants are followed by the immediate hiring of a new consultant. However, for specialized consultants, we still observe 77 terminations without a replacement.

IA.3 Allocation changes following general consultant turnover

Pension funds may implement changes to allocations following new consultant recommendations, but the direction of change will likely be fund-specific, varying with the pension fund's characteristics and past allocation decisions. Therefore, we start by looking at absolute changes to risky share allocations, which include both public equity and alternative investments, followed by absolute changes to allocations to individual asset classes. To control for any time-specific events that may have tilted allocations of all pension funds into one particular direction, we subtract the average absolute changes in allocations of all other pension funds during the same year. Figure IA.3 show that pension funds make significantly larger changes to their target allocation in both equity and alternative asset classes in the two years following the employment of new consultants. This finding indicates that general investment consultants turnover is positively correlated with larger-than-average changes (in absolute value) in target allocation.

IA.4 IV Details: Post-Hiring Convergence in Asset Allocation

To construct our instrumental variable, we rely on the distance between pension funds and consultants headquarters. Table IA.6 list the location of the twenty most-employed general consultants over the sample period.

In the first stage of the IV setup, the dependent variable is $\Delta \text{AvgRisky}_{-i,t-1}^{\text{NewGCpre}-\text{OldGCpre}}$, which is the difference between the average risky allocation of the new and old consultant's other clients (excluding pension fund i) during the period before the turnover event. Given that consultant turnover might not be exogenous to future investment decisions, we instrument $\Delta \text{AvgRisky}_{-i,t-1}^{\text{NewGCpre}-\text{OldGCpre}}$ with the average risky allocation of the clients of all consultants active in year t weighted by the geographical distance between a pension fund headquarter and the consultant headquarter. The selection of this instrument is motivated by the results in Table 4, which indicate that consultant turnover is affected by geographical proximity. Therefore, the first stage looks as follows:

$$\Delta \text{AvgRisky}^{\text{NewGCpre}-\text{OldGCpre}}_{-i,t-1} = \alpha + \beta_1 \text{DistRisky}_{i,t} + \gamma X_{i,t-1} + T_{t-1} + \epsilon_{i,t-1}, \tag{9}$$

where $X_{i,t+1}$ is a set of pension-fund control variables. We then also include year fixed effects (T_{t+1}) and consultant fixed effects (C_j).

We report the first-stage results in Table IA.7. Across asset classes, we observe positive and significant coefficients associated with pension fund allocations weighted by the geographical distance between pension funds' headquarters and consultants' headquarters. In addition, the Kleibergen–Paap rk Wald F-statistic is large and highly significant across all specifications. These results provide confidence in the ability of our instrument to predict the average difference in allocations between the pre- and post-turnover periods for pension funds that replaced their general consultants. Hence, geographical proximity appears to play a role in shaping the influence of consultants' clients' asset allocations on a pension fund's own allocation.

Finally, we acknowledge that the standard errors Table 5 are based on a relatively small number of consultant hiring events. To address this sample size issue, we apply the wild bootstrap procedure proposed by Cameron, Gelbach, and Miller (2008) and test the null hypothesis that the estimated coefficient of the key variable of interest is equal to zero. Bootstrapped standard errors are reported in Table IA.8, and they are very close to the one reported in Table 5. Therefore, we can reject the null hypothesis that these coefficients are zero. Because the bootstrap procedure requires and explicit specification of the fixed effects structure, for simplicity, we implemented it only for specifications with a single set of fixed effects.

IA.5 Pension Fund Investments in Alternative Assets

We use the Preqin dataset to obtain information on the commitments by pension funds to private funds in alternative asset classes. Online Appendix Table IA.9 shows summary statistics of our sample of 164 pension funds that report investments in private funds in the Preqin dataset over the 2001–2020 period. Overall, we analyze 22,744 pension fund investments in 6,504 private funds, managed by 1,943 unique general partners. Panel A presents summary statistics of pension fund characteristics. Preqin covers investments in various types of private funds, and we analyze the role of both specialized private equity and real assets investment consultants. We document that 67% of the investments in private funds are made by pension funds that employed a specialized private equity consultant, and 62% of the investments are made by pension funds that had a specialized real assets consultant. The percentage of investments made with the advice of specialized consultants is higher than the percentage of pension funds employing a specialized consultant as large pension funds are more likely to hire a specialized consultant (see Table IA.2) and have more investments in private funds.

Panel B of Online Appendix Table IA.9 reports summary statistics of private funds. We use four fund characteristics as proxies to test the rationed access hypothesis: (a) an indicator equal to one if the fund is the first fund ever raised by the general partner; (b) an indicator variable equal to one if a private fund is the first fund raised by the general partner within the specific series of funds raised by this general partner; (c) the ratio of the final private fund size relative to the target fund size; (d) an indicator equal to one if a private fund is a co-investment fund or a separate account mandate. Preqin covers investments in several types of private funds: 49% of the pension fund investments are in buyout funds, 11% in venture capital funds, 22% in real estate funds, 4% in infrastructure funds, 4% in natural resources funds, and 10% in private debt funds.

Online Appendix Table IA.9 Panel C presents summary statistics on the performance measures. We use three performance measures on private funds: public market equivalent, internal rate of return, and multiple of invested capital (total value to paid-in capital). The public market equivalent measure is estimated using the S&P 500 equity index as a benchmark.

Figure IA.1: Concentration of Specialized Consultants in Alternative Assets

We replicate the analysis from Figure 2 for specialized consultants instead of general consultants. If a pension fund has more than one specialized consultant in an alternative asset class, we split the mandate and assets under advisory by the number of specialized consultants. In the left panels, we rank the specialized consultants based on the number of pension funds that they advise. In the right panels, we rank the specialized consultants based on the aggregate amount of assets under management of their pension fund clients. The second axis in all panels presents the number of unique general consultants by year.

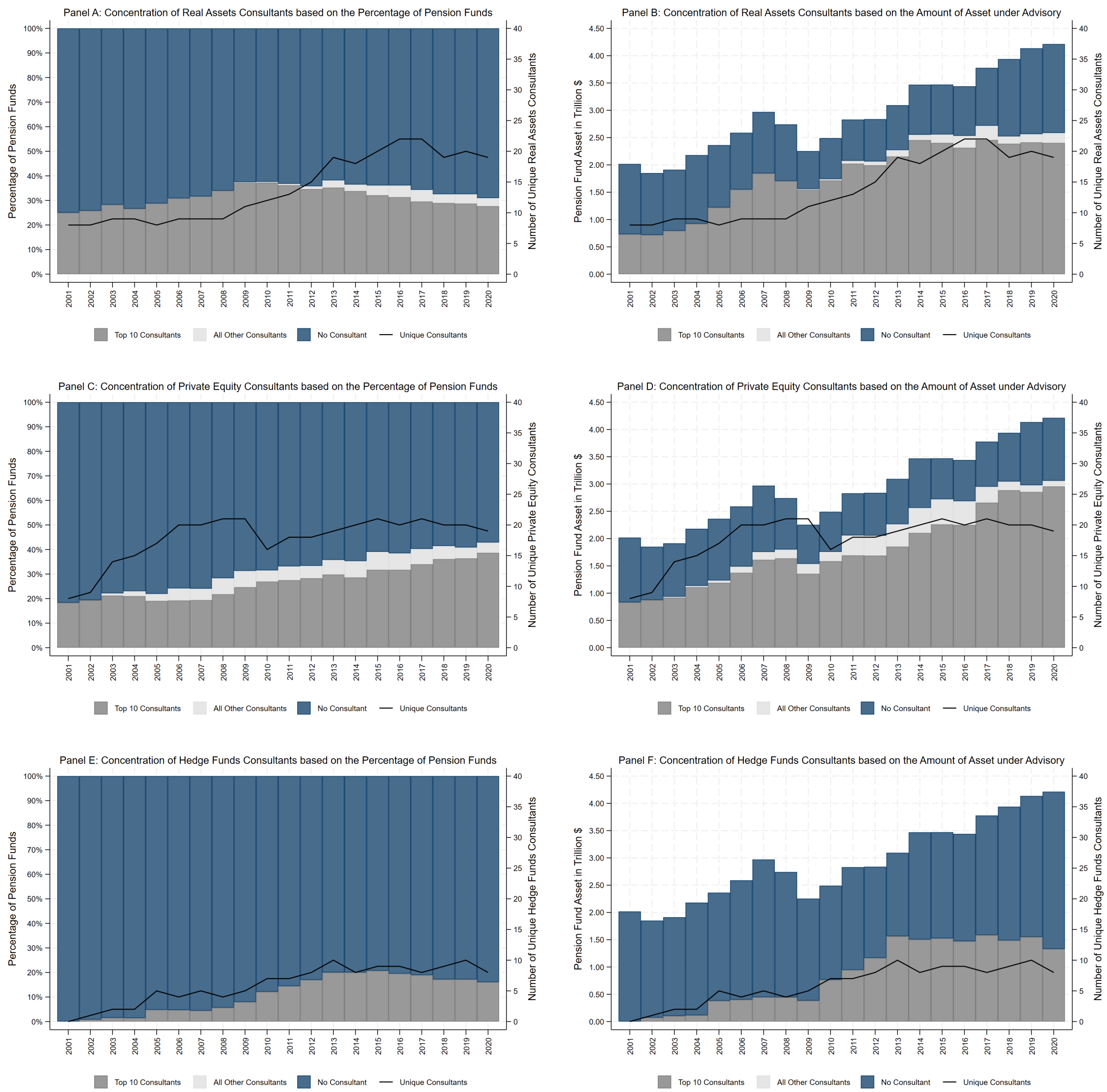


Figure IA.2: Firing of Consultants over Time

This figure extends Figure 4. Panel C and Panel D show the distribution of firing events of general and specialized consultants over time. *Replace* refers to a termination, which was followed by the appointment of a new consultant the following year. Hence, these events mirror the hiring events exhibited in Figure 4. In order to show the round trips of consultants, we plot the lagged value of the firing with replacement. *No Replace* refers to a pension fund replacing its general and specialized without a reappointment of a new consultant in the following years included in the sample period.

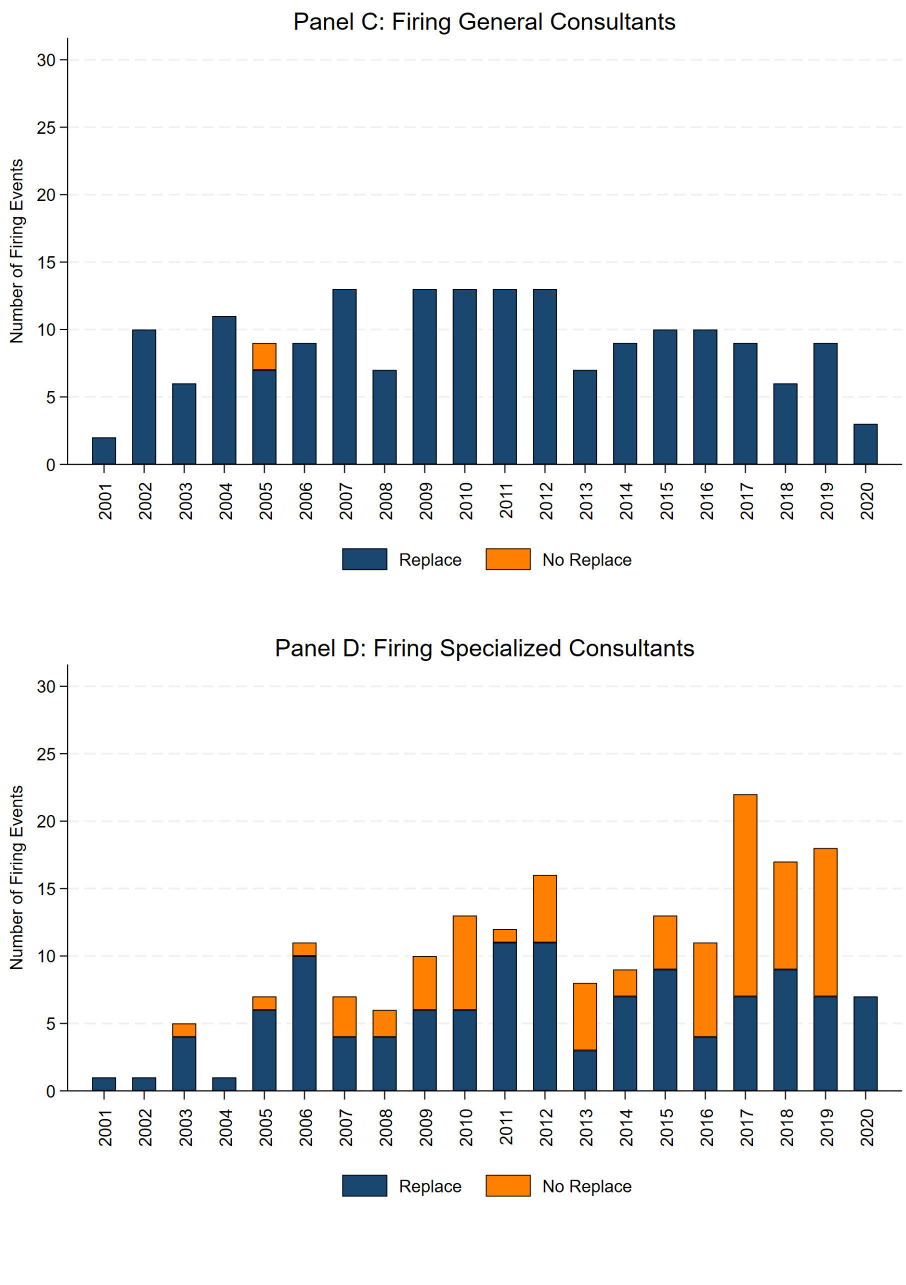


Figure IA.3: Average Deviation in Absolute Changes in the Target Asset Allocation

This figure shows the average deviation in absolute changes in the target allocations to different asset classes of pension funds in the three years before and following the replacement of a general investment consultant. Year *t=0* corresponds to the first year when the new general consultant is employed. The deviation is computed for each pension fund i by taking the difference between the absolute value of the change in allocation to an asset class of i (allocation in t minus allocation in *t-1*) and the absolute value of the average change in allocation to the same asset class of all other pension funds in the sample. We report the average deviation in allocation across all pension funds replacing general investment consultants in the three years before and following the hiring event.

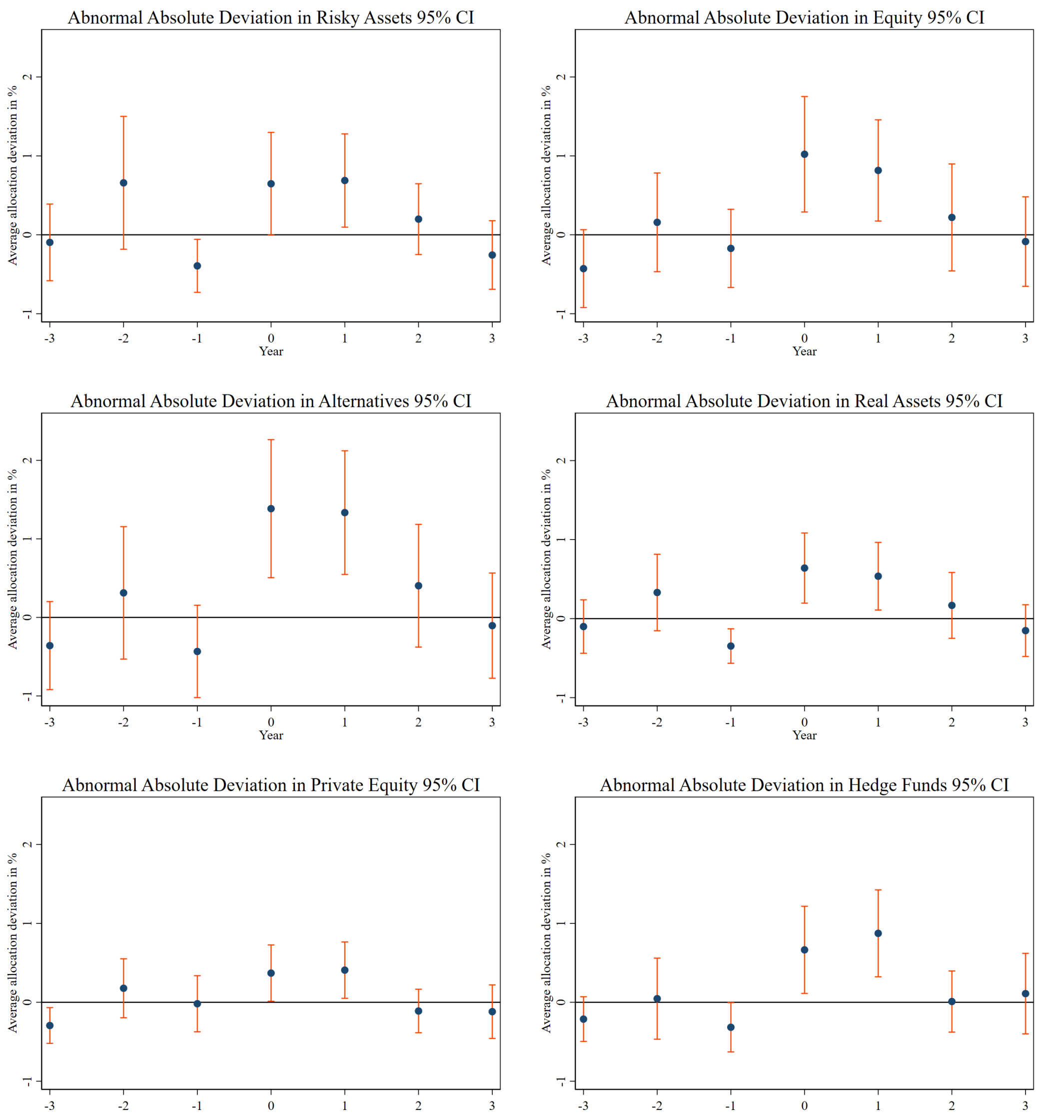


Table IA.1: Pension Fund Observations with Consultants Data

This table presents the number of observations of pension funds with investment consultants data over the 2001–2020 period. We collect data on 173 unique pension funds which corresponds to 3,138 annual observations. The PPD dataset provides information on the asset allocation and performance of 138 unique pension funds (2,624 annual observations). In addition, we collect asset allocation and performance data for 35 unique pension funds (514 annual observations). This additional sample covers local city or county pension funds that are not part of the PPD.

Year	PPD Sample	Local Sample	Total Sample
2001	114	7	121
2002	117	7	124
2003	122	11	133
2004	127	13	140
2005	130	17	147
2006	131	18	149
2007	133	25	158
2008	134	25	159
2009	136	27	163
2010	136	29	165
2011	136	30	166
2012	135	30	165
2013	135	30	165
2014	135	35	170
2015	134	35	169
2016	134	35	169
2017	134	35	169
2018	134	35	169
2019	134	35	169
2020	133	35	168
Total	2,624	514	3,138

Table IA.2: Which Pension Funds Have More Consultants

This table examines which factors determine the number of hired consultants and the probability of hiring a general or a specialized consultant. The observations are at the pension fund-year level. In Column (1), the dependent variable is the total number of investment consultants hired by a pension fund. In Column (2), the dependent variable is the total number of specialized consultants, which excludes general and other investment consultants. Columns (3) to (6) present the results of logit specifications where the dependent variable equals one if a pension fund has a general consultant or specialized consultant in real assets, private equity, and hedge funds. We report the marginal effects at the means of the independent variables. *Fund Size* is the natural logarithm of total pension fund assets under management. *Internal Mandate* shows the 13F internally managed equity holdings as a percentage of assets under management. *%Equity*, *%Real Assets*, *%Private Equity*, *%Hedge Funds*, and *%Other Alternatives* measure the target asset allocation. *State Political* captures the percentage of appointed or ex officio board members who are state officials. *Participant-elected* captures the percentage of board members elected by plan participants. We also control for percentage representation by the other types of trustees: state-elected, participant-exofficio, public-exofficio, and public-elected. *Investment Board* is an indicator for pension funds with a separate investment board. The specifications include year-reporting-month fixed effects. We double cluster standard errors by pension fund and year, and report standard errors in brackets. *$p < .10$; **$p < .05$; ***$p < .01$.

	OLS Specifications		**Logistic Probability Specifications**			
	#Total Consult. (1)	# Special. Consult. (2)	General (3)	Real Assets (4)	Private Equity (5)	Hedge Funds (6)
Fund Size	0.524***	0.460***	0.001	0.218***	0.208***	0.052***
	[0.067]	[0.059]	[0.005]	[0.030]	[0.030]	[0.013]
Internal Mandate	0.045	-0.533	-0.048	-0.697**	-0.352	-0.205
	[0.851]	[0.705]	[0.045]	[0.277]	[0.234]	[0.168]
State-political	1.130**	0.925**	0.093*	0.222	0.293	0.095
	[0.467]	[0.427]	[0.048]	[0.170]	[0.208]	[0.078]
Participant-elected	0.227	0.274	0.032	0.067	0.195	-0.009
	[0.355]	[0.268]	[0.032]	[0.139]	[0.164]	[0.064]
Investment Board	-0.086	-0.283	-0.013	-0.035	-0.113	-0.028
	[0.339]	[0.221]	[0.038]	[0.087]	[0.076]	[0.037]
%Equity	-0.502	-0.493	0.087			
	[0.969]	[0.750]	[0.104]			
%Real Assets	4.545***	3.664***	0.211	3.038***		
	[1.278]	[0.904]	[0.204]	[0.547]		
%Private Equity	4.404*	3.039**	0.030		2.569***	
	[2.117]	[1.145]	[0.099]		[0.687]	
%Hedge Funds	0.273	0.852	0.030			0.687***
	[1.183]	[0.905]	[0.099]			[0.195]
%Other Alternatives	1.274	0.609	0.107	-0.869	0.638	-0.010
	[1.186]	[1.036]	[0.157]	[0.821]	[0.703]	[0.280]
Other Board Members	Yes	Yes	Yes	Yes	Yes	Yes
Year × Reporting Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,815	2,815	2,687	2,765	2,769	2,212
Adjusted R-squared	0.484	0.484				

Table IA.3: Number of consultants hired and fired by type

The table shows the number of consultants hired and fired by type, from 2001 to 2020. *Hire First* refers to the first time hiring of a general or specialized consultant by a pension fund. *Hire Addition* refers to the hiring of an additional specialized consultant in one asset class for which at least one consultant was already employed in the previous year(s). *Hire Replace* refers to the hiring of a consultant after the firing of one consultant in the same asset class, or replacement of the general consultant. An event is categorized as *Hire Replace* if the replacement occurs in the year after the incumbent consultant was dismissed. *Hire Long Replacement* refers to the hiring as replacement of a consultant in the same asset class or replacement of a general consultant where the position of the incumbent consultant remains vacant for more than two years before the actual replacement occurs. *Firing with replacement* refers to a consultant being discontinued in a given year and then replaced in the next year(s). *Firing with no replacement* refers to a discontinuation of a consultant without hiring of a new one for that specific asset class.

	Hire					**Fire**			
	First	Addition	Replace	Long Replace	Total	Replace	Long Replace	No Replace	Total
General	6		181		187	186		2	188
Hedge Funds	41	5	10	1	57	10	1	17	28
Private Equity	62	23	65	3	153	68	3	19	90
Real Assets	47	19	42	8	116	43	6	41	90
Total	156	47	298	12	513	307	10	79	396

Table IA.4: Hiring General and Specialized Investment Consultants

Robustness test of Table 3: In this table, we use a performance measure computed over a 5-year period instead of a 3-year period.

In Columns (1) and (2), observations are at the pension-fund-year level. The dependent variable equals one if a pension fund hires a new general consultant. In Columns (3) and (4), observations are at the pension-fund-alternative-asset-class-year level and we focus on specialized consultants hired for the first time in each alternative asset class. In all columns, we present the results of logit specifications and report the marginal effects at the means of the independent variables. *5Y Rank* measures the percentile ranking of pension funds based on the geometric average performance over the past 5 years, i.e., *5Y Return*. We also control for the lagged target allocation as well as the difference between the lagged target and actual allocation in each risky asset class. In Columns (3) and (4), *%Target* and *%Actual* measure the lagged target and actual allocation in each alternative asset class. *PE Consultant* and *HF Consultant* are indicators for specialized consultants in private equity and hedge funds (the omitted category is real assets). All specifications include controls for pension fund assets under management, internal asset management divisions, governance, and year-reporting-month fixed effects. We double cluster standard errors by pension fund and year and report standard errors in brackets. $p < .10$; $^{**}p < .05$; $^{***}p < .01$.

	General		**Specialized**	
	(1)	(2)	(3)	(4)
5Y Return	-1.503***		-0.154	
	[0.294]		[0.156]	
5Y Rank		-0.068***		-0.011
		[0.017]		[0.007]
$\%\text{Actual}_{t-1}$			0.042*	0.038*
			[0.023]	[0.023]
$\%\text{Target}_{t-1}$ - $\%\text{Actual}_{t-1}$			0.186***	0.176***
			[0.057]	[0.059]
HF consultant			-0.006	-0.006
			[0.004]	[0.004]
PE consultant			0.008**	0.008**
			[0.004]	[0.004]
Fund Size	0.010**	0.010**	0.010***	0.010***
	[0.005]	[0.004]	[0.001]	[0.001]
Internal Mandate	-0.087	-0.082	-0.022	-0.022
	[0.062]	[0.063]	[0.024]	[0.023]
State-political	0.029	0.025	0.026***	0.025***
	[0.031]	[0.030]	[0.009]	[0.009]
Participant-elected	0.045	0.042	0.004	0.004
	[0.032]	[0.031]	[0.008]	[0.008]
Investment Board	0.002	0.002	-0.010***	-0.010***
	[0.014]	[0.014]	[0.003]	[0.003]
Other Board Members	Yes	Yes	Yes	Yes
Lagged Target Allocation (all risky)	Yes	Yes		
Lagged Gap Allocation (all risky)	Yes	Yes		
Year × Reporting Month FE	Yes	Yes	Yes	Yes
Observations	2,058	2,058	3,721	3,721

Table IA.5: Hiring General and Specialized Investment Consultants with Funded Ratio

Robustness test of Table 3: In this table, we add one additional control variable: *GASB Funded Ratio* that measures the funding status of a pension fund under traditional GASB 25 standards. The (GASB 25) funded ratio equals the actuarial assets divided by the actuarial liability. The number of observations is reduced due to missing funded ratio data for local pension funds.

In Columns (1) and (2), observations are at the pension-fund-year level. The dependent variable equals one if a pension fund hires a new general consultant. In Columns (3) and (4), observations are at the pension-fund-alternative-asset-class-year level and we focus on specialized consultants hired for the first time in each alternative asset class. In all columns, we present the results of logit specifications and report the marginal effects at the means of the independent variables. All specifications are similar to Table 3, with the exception that the *GASB Funded Ratio* is also included . We double cluster standard errors by pension fund and year and report standard errors in brackets. $p < .10$; $^{**}p < .05$; $^{***}p < .01$.

	General		**Specialized**	
	(1)	(2)	(3)	(4)
3Y Return	-1.106***		-0.143	
	[0.397]		[0.112]	
3Y Rank		-0.070***		-0.013**
		[0.026]		[0.006]
%Actual$_{t-1}$			0.042*	0.037*
			[0.022]	[0.021]
%Target$_{t-1}$ - %Actual$_{t-1}$			0.153**	0.139**
			[0.063]	[0.064]
HF consultant			-0.012***	-0.012***
			[0.004]	[0.004]
PE consultant			0.007	0.007
			[0.005]	[0.005]
Fund Size	0.011**	0.011**	0.013***	0.013***
	[0.005]	[0.005]	[0.002]	[0.002]
GASB Funded Ratio	-0.089***	-0.083**	-0.013	-0.012
	[0.033]	[0.033]	[0.008]	[0.008]
Internal Mandate	-0.088	-0.084	-0.043*	-0.043*
	[0.056]	[0.057]	[0.024]	[0.023]
State-political	0.006	0.003	0.031***	0.030***
	[0.032]	[0.031]	[0.009]	[0.009]
Participant-elected	0.025	0.024	0.008	0.008
	[0.038]	[0.037]	[0.009]	[0.009]
Investment Board	0.001	0.001	-0.011***	-0.011***
	[0.015]	[0.014]	[0.003]	[0.003]
Other Board Members	Yes	Yes	Yes	Yes
Lagged Target Allocation (all risky)	Yes	Yes		
Lagged Gap Allocation (all risky)	Yes	Yes		
Year × Reporting Month FE	Yes	Yes	Yes	Yes
Observations	1,872	1,872	3,302	3,302

Table IA.6: Headquarters location of most-employed general consultants

Consultant Report	Freq.	HQ City	HQ State	Year Established
NEPC	380	Boston	MA	1986
Callan	370	San Francisco	CA	1973
Wilshire	279	Santa Monica	CA	1972
AonHewitt	184	Chicago	IL	1940
Strategic Investment Solutions	170	San Francisco	CA	1994
Summit	157	St. Louis	MO	1995
PCA	150	Portland	OR	1988
RVKuhns	133	Portland	OR	1985
Mercer	132	New York City	NY	1959
Verus	120	Seattle	WA	1986
Meketa	113	Westwood	MA	1978
Marquette	109	Chicago	IL	1986
Ennis Knupp	106	Chicago	IL	1981
Asset Consulting Group	65	St. Louis	MO	1989
Milliman	43	Seattle	WA	1947
Dahab Associates	33	Bay Shore	NY	1986
Rocaton	32	Norwalk	CT	2002
Russell	32	Seattle	WA	1936
Becker Burke	27	Chicago	IL	1985
Segal	27	New York City	NY	1939

Table IA.7: Post-Hiring General Consultants: Convergence of Allocations - IV setup

First stage of Table 5 Panel B:

In the table, observations are at the pension-fund-year level and we analyze the turnover of general consultants. In Columns (1) to (2), for each pension fund i that hires a new general consultant in year t, we measure the target allocation to risky assets made with the old general consultant in year $t-1$ ($\text{Risky}^{\text{Pre}}_{i,t-1}$) and with the new general consultant in year $t+1$ ($\text{Risky}^{\text{Post}}_{i,t+1}$). In the first stage of the IV setup, the dependent variable is $\Delta\text{AvgRisky}^{\text{NewGCpre}-\text{OldGCpre}}_{-i,t-1}$, which is the difference between the average risky allocation of the new and old consultant's other clients (excluding pension fund i) during the period before the turnover event. Given that consultant turnover might not be exogenous to future investment decisions, we instrument $\Delta\text{AvgRisky}^{\text{NewGCpre}-\text{OldGCpre}}_{-i,t-1}$ with the average risky allocation of the clients of all consultants active in year $t-1$ weighted by the geographical distance between a pension fund headquarter and the consultant headquarter, as we discuss in Section 5.1. The selection of this instrument is motivated by the results in Table 4, which indicate that consultant turnover is affected by geographical proximity. The first stage regression is described is Equation 9. In columns (3) to (6), we replicate the analysis for e replicate the analysis for the target allocation to equity and alternatives. We double-cluster standard errors by pension fund and year, and report standard errors in brackets. *$p < .10$; **$p < .05$; ***$p < .01$.

	$\Delta\text{AvgRisky}^{\text{NewGCpre}-\text{OldGCpre}}_{-i,t-1}$		$\Delta\text{AvgEquity}^{\text{NewGCpre}-\text{OldGCpre}}_{-i,t-1}$		$\Delta\text{AvgAlt}^{\text{NewGCpre}-\text{OldGCpre}}_{-i,t-1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{DistRisky}_{i,t}$	6.913***	6.650***				
	[1.895]	[1.833]				
$\text{DistEquity}_{i,t}$			7.952***	6.353***		
			[1.584]	[1.716]		
$\text{DistAlt}_{i,t}$					11.872***	11.854***
					[2.436]	[1.966]
Controls_{t+1}	Yes	Yes	Yes	Yes	Yes	Yes
Year FE_{t+1}	Yes	Yes	Yes	Yes	Yes	Yes
Cons FE_{t+1}		Yes		Yes		Yes
Observations	117	115	117	115	117	115
K-P F-Stat	13.301	13.165	25.197	13.705	23.753	36.349

Table IA.8: Post-Hiring General Consultants: Convergence of Allocations with boostrap standard errors

Robustness test of Table 5: We replicate the specifications in columns (1), (3), and (5) of both Panel A and B of Table 5 using a wild bootstrap to test that the coefficient of the key variable of interest is different from 0. Panel A below replicates Columns (1), (3), and (5) in Panel A of Table 5, whereas Panel B replicates Columns (1), (3), and (5) in Panel B of Table 5. All specifications include pension fund size, governance-related variables, and year fixed effects. We double cluster standard errors by pension fund and year, and report standard errors in brackets. $^*p < .10$; $^{**}p < .05$; $^{***}p < .01$.

	$\Delta\text{Risky}_{i,t+1}^{\text{Post}-\text{Pre}}$ (1)	$\Delta\text{Equity}_{i,t+1}^{\text{Post}-\text{Pre}}$ (2)	$\Delta\text{Alt}_{i,t+1}^{\text{Post}-\text{Pre}}$ (3)
Mean Dependent Variable	0.010	-0.026	0.036
Panel A: OLS Models			
$\Delta\text{AvgRisky}_{-i,t-1}^{\text{NewGCpre}-\text{OldGCpre}}$	0.090**		
	[0.033]		
$\Delta\text{AvgEquity}_{-i,t-1}^{\text{NewGCpre}-\text{OldGCpre}}$		0.162**	
		[0.069]	
$\Delta\text{AvgAlt}_{-i,t-1}^{\text{NewGCpre}-\text{OldGCpre}}$			0.333***
			[0.070]
Controls in $t+1$	Yes	Yes	Yes
Year FE in $t+1$	Yes	Yes	Yes
Observations	117	117	117
Adjusted R-squared	0.110	0.169	0.285
Panel B: IV Models			
$\Delta\text{AvgRisky}_{-i,t-1}^{\text{NewGCpre}-\text{OldGCpre}}$	0.138*		
	[0.067]		
$\Delta\text{AvgEquity}_{-i,t-1}^{\text{NewGCpre}-\text{OldGCpre}}$		-0.085	
		[0.159]	
$\Delta\text{AvgAlt}_{-i,t-1}^{\text{NewGCpre}-\text{OldGCpre}}$			0.307**
			[0.114]
Controls in $t+1$	Yes	Yes	Yes
Year FE in $t+1$	Yes	Yes	Yes
IV-setup	Yes	Yes	Yes
Observations	117	117	117
K-P F-Stat	13.301	25.197	23.753

Table IA.9: Summary Statistics: Pension Funds Investments in Private Funds

In this table, observations are at the pension-fund-investment level. We match the investment consultants' data for 164 pension funds to 22,744 investments in private funds during the 2001–2020 period. Panel A presents summary statistics of pension fund characteristics. *PE Consultant* and *RA Consultant* are indicators for pension funds that have a specialized consultant in private equity and real assets. *Assets* is the total pension fund assets under management in $bln. Panel B presents summary statistics of the characteristics of private funds. *Overall First Time Fund* is an indicator equal to one if a private fund is the first fund raised by the general partner based on all funds raised by this general partner. *Series First Time Fund* is an indicator equal to one if a private fund is the first fund raised by the general partner within the specific series of funds raised by this general partner. We also present the final size, target size, and ratio of final to target size for the private funds. We winsorize the size ratio at the 1.00% level. *Coinvestments and Separate Accounts* is an indicator equal to one if a private fund is a co-investment fund or a separate account mandate. We classify private funds into six types: buyout, venture capital, real estate, infrastructure, natural resources, and private debt. Panel C presents summary statistics of the performance of private funds raised during 2001-2016 vintages. We present statistics on the public market equivalent (PME) performance measure based on the S&P500 index as a benchmark, internal rate of return (IRR), and multiple of the total value to paid in capital (TVPI).

	PFs	Observations	Mean	Median	StDev
Panel A: Pension Fund Characteristics (2001–2020 Vintage Years)					
PE Consultant	164	22,744	0.666		0.472
RA Consultant	164	22,744	0.619		0.486
Assets ($ bil)	164	22,744	49.592	26.079	60.593
Internal Mandate	164	22,744	0.081	0.000	0.139
State-political	164	22,744	0.298	0.222	0.284
Participant-elected	164	22,744	0.266	0.250	0.259
Investment Board	164	22,744	0.171		0.377
Panel B: Pension Fund Investments in Private Funds (2001–2020 Vintages)					
Overall First Time Fund	164	21,605	0.082		0.274
Series First Time Fund	164	21,604	0.137		0.344
PE Fund Final Size ($ bil)	164	22,160	2.909	1.200	4.144
PE Fund Target Size ($ bil)	164	18,889	2.843	1.250	3.864
Ratio PE Fund Final Size / Target Size	164	18,675	1.131	1.111	0.251
Coinvestments and Separate Accounts	164	22,744	0.050	0.000	0.219
Buyout	164	22,744	0.494		0.500
Venture Capital	164	22,744	0.107		0.309
Real Estate	164	22,744	0.217		0.412
Infrastructure	164	22,744	0.043		0.204
Natural Resources	164	22,744	0.040		0.196
Private Debt	164	22,744	0.098		0.298
Panel C: Pension Fund Performance of Private Funds (2001–2016 Vintages)					
Public Market Equivalent (PME)	160	12,836	1.041	1.011	0.481
Internal Rate of Return (IRR)	163	14,922	12.515	11.860	15.732
Multiple (TVPI)	163	15,296	1.731	1.600	0.964

Table IA.10: Consultant Networks by Private Fund Size

Robustness test of Tables 7 and 8: We replicate all specifications for private funds above and below the median size. We expand the connections of the consultant (the network) to include all private equity and real assets funds raised by the general partners the consultants have a connection with. The specifications include target asset allocations, and pension fund or private fund fixed effects. We double cluster standard errors by pension fund and vintage year and report standard errors in brackets. $p < .10$; $^{**}p < .05$; $^{***}p < .01$.

	All Consultants		General Consultants		PE Consultants	
	Small	Large	Small	Large	Small	Large
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Private Equity Funds - Consultant Network						
Mean Dep. Variable	0.005	0.005	0.005	0.005	0.006	0.006
Same consultant	0.010***	0.005***	0.018***	0.012***	0.025***	0.018***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Observations	1,617,860	1,685,341	1,591,647	1,649,710	842,087	942,850
R-squared	0.005	0.015	0.013	0.020	0.019	0.026
Panel B: Real Assets Funds - Consultant Network						
Mean Dep. Variable	0.009	0.009	0.009	0.009	0.011	0.011
Same consultant	0.020***	0.012***	0.034***	0.027***	0.036***	0.025***
	(0.001)	(0.001)	(0.003)	(0.002)	(0.003)	(0.003)
Observations	365,955	389,018	356,255	377,919	179,618	183,347
R-squared	0.011	0.025	0.027	0.037	0.025	0.037
Panel C: Private Equity Funds - General Partner - Consultant Network						
Mean Dep. Variable	0.009	0.009	0.009	0.009	0.011	0.011
Same consultant	0.020***	0.012***	0.034***	0.027***	0.036***	0.025***
	(0.001)	(0.001)	(0.003)	(0.002)	(0.003)	(0.003)
Observations	1,617,860	1,685,341	1,591,647	1,649,710	842,087	942,850
R-squared	0.004	0.015	0.010	0.019	0.016	0.025
Panel D: Real Assets Funds - General Partner - Consultant Network						
Mean Dep. Variable	0.009	0.009	0.009	0.009	0.0119	0.0119
Same consultant	0.018***	0.011***	0.030***	0.023***	0.033***	0.022***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)
Observations	365,955	389,018	356,255	377,919	179,618	183,347
R-squared	0.010	0.024	0.022	0.033	0.022	0.034
Target Asset Allocation	Yes	Yes	Yes	Yes	Yes	Yes
Plan and Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes
Vintage-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Private-Fund FE	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.11: PE and RA General Partners and Consultant Networks

Robustness test of Tables 7 and 8: The specifications use alternative definitions of the dependent variables. We expand the connections of the consultant (the network) to include all private equity and real assets funds raised by the general partners the consultants have a connection with.

The table reports the OLS coefficient estimates from a linear probability specification where the dependent variable is an indicator variable that takes the value of one if the PE or the RA fund is added to the pension fund roster during the year, and zero otherwise. As before, the dataset is expanded to include all potential private funds the pension fund can choose from in any given year. *SameConsultant* is equal to 1 if the fund is in the same consultant network. The dataset includes pension fund investment level observations and covers the period from 2001 to 2020. In Panel A, *SameConsultant* is equal to 1 if the fund is in the same consultant-general-partner (GP) network, where the consultant-GP network includes all the PE/RA funds of a GP whose funds are included in any public pension fund roster during that vintage year. In Panel B, private funds belong to the consultant GP network only if they are chosen by 2 or more pension funds advised by the consultant. In Panel C, private funds belong to the consultant network only if they are chosen by 2 or more pension funds advised by the consultant. Column (1) and (4) concentrate on all consultants, column (2) and (5) concentrate on general consultants, column (3) and (6) concentrate on specialized consultants. We double cluster standard errors by pension fund and vintage year and report standard errors in brackets. $p < .10$; $^{**}p < .05$; $^{***}p < .01$.

	Private Equity Funds			Real Assets Funds		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: GP network						
Mean Dep. Variable	0.005	0.005	0.006	0.009	0.009	0.011
Same consultant	0.007***	0.013***	0.019***	0.014***	0.026***	0.027***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
Observations	3,303,201	3,241,357	1,784,937	754,973	734,174	362,965
R-squared	0.006	0.011	0.016	0.010	0.021	0.020
Panel B: Restricted GP network						
Mean Dep. Variable	0.008	0.011	0.012	0.016	0.021	0.024
Same consultant	0.017***	0.039***	0.056***	0.038***	0.084***	0.065***
	(0.002)	(0.003)	(0.007)	(0.003)	(0.008)	(0.007)
Observations	1,585,620	976,612	544,206	332,083	205,259	108,475
R-squared	0.014	0.035	0.051	0.031	0.078	0.054
Panel C: Restricted Private Fund network						
Mean Dep. Variable	0.016	0.021	0.024	0.008	0.011	0.013
Same consultant	0.038***	0.084***	0.065***	0.017***	0.039***	0.056***
	(0.003)	(0.008)	(0.007)	(0.002)	(0.003)	(0.007)
Observations	332,083	205,259	108,475	1,585,620	976,612	544,206
R-squared	0.031	0.078	0.054	0.014	0.035	0.051
Target Asset Allocation	Yes	Yes	Yes	Yes	Yes	Yes
Plan and Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes
Vintage-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Private-Fund FE	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.12: Specialized Consultants and Performance (2000-2010 Period)

Robustness test of Table 10: We limit attention to the subsample of private funds raised in vintages 2001–2010 so they have existed for more than 12 years and most of them are liquidated or distributed. Thus, returns on these private funds are not driven by accounting valuations of assets.

In this table, observations are at the pension fund-investment level over the 2001–2010 period. In columns (1) to (3) performance is measured using the public market equivalent based on the S&P500 index as a benchmark. In columns (4) to (6) performance is measured using the net internal rate of return (IRR), and in columns (7) to (9) performance is measured using the multiple of the total value to paid-in capital (TVPI). We control for pension fund assets under management and target allocation to equity, real assets, private equity, hedge funds, and other risky assets. We include either interacted pension-fund-stacked-cohort and vintage-year-stacked-cohort or interacted pension-fund-stacked-cohort-fund-type and vintage-year-stacked-cohort-fund-type fixed effects. We cluster standard errors by pension-fund-stacked-cohort or by pension-fund-stacked-cohort-fund-type and report standard errors in brackets. $p < .10$; **$p < .05$; ***$p < .01$.

	PME		**IRR**		**Multiple**	
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: PE Specialized Consultant					
Mean Dependent Variable	1.034	1.034	11.155	11.155	1.794	1.794
Treated × Early Post	0.049	0.038	1.072	0.707	0.098	0.064
	[0.052]	[0.047]	[1.197]	[1.172]	[0.066]	[0.077]
Treated × Late Post	-0.025	-0.062	-0.795	-1.192	0.020	-0.041
	[0.045]	[0.045]	[1.589]	[1.394]	[0.095]	[0.086]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
PF × Cohort FE	Yes		Yes		Yes	
Vintage × Cohort FE	Yes		Yes		Yes	
PF × Cohort × Fund-Type FE		Yes		Yes		Yes
Vintage × Cohort × Fund-Type FE		Yes		Yes		Yes
#Treated PFs	30	30	30	30	30	30
#Never-Treated PFs	47	46	53	51	53	51
Observations	6,444	6,237	7,314	7,109	7,630	7,412
Adjusted R-squared	0.034	0.081	0.113	0.139	0.092	0.188
	Panel B: RA Specialized Consultant					
Mean Dependent Variable	0.729	0.729	4.265	4.265	1.235	1.235
Treated × Early Post	-0.032	-0.048	-3.099	-2.140	-0.044	-0.076
	[0.061]	[0.061]	[2.147]	[2.266]	[0.065]	[0.070]
Treated × Late Post	-0.065	-0.083	-3.726	-2.477	-0.034	-0.089
	[0.085]	[0.087]	[3.022]	[3.076]	[0.089]	[0.091]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
PF × Cohort FE	Yes		Yes		Yes	
Vintage × Cohort FE	Yes		Yes		Yes	
PF × Cohort × Fund-Type FE		Yes		Yes		Yes
Vintage × Cohort × Fund-Type FE		Yes		Yes		Yes
#Treated PFs	27	27	27	27	27	27
#Never-Treated PFs	33	32	36	34	37	35
Observations	1,610	1,481	2,121	1,990	2,232	2,119
Adjusted R-squared	0.082	0.140	0.071	0.068	0.041	0.054

Table IA.13: Specialized Consultants and Probability of Investing in Underperforming Left-Tail PE Funds

Robustness test of Table 10 Panel A: We examine the probability that a pension fund invests in a private equity fund that delivers performance in the bottom 10 percentile of all pension fund investments.

We estimated stacked DID specifications and the observations are at the pension fund-investment level over the 2001–2016 period. The treatment is hiring a specialized consultant for the first time and the event window spans seven years, covering 3 years before and after the hiring. In Panel A, we classify private funds in the low left-tail 10th percentile based on the aggregate performance distribution. In Panel B, we classify private funds in the low left-tail 10th percentile based on the performance distribution within each fund-type-vintage-year subset of observations. In columns (1) to (3) performance is measured using the public market equivalent based on the S&P500 index as a benchmark. In columns (4) to (6) performance is measured using the net internal rate of return (IRR), and in columns (7) to (9) performance is measured using the multiple of the total value to paid-in capital (TVPI). We control for pension fund assets under management and target allocation to equity, real assets, private equity, hedge funds, and other risky assets. We include either interacted pension-fund-stacked-cohort and vintage-year-stacked-cohort or interacted pension-fund-stacked-cohort-fund-type and vintage-year-stacked-cohort-fund-type fixed effects. We cluster standard errors by pension-fund-stacked-cohort or by pension-fund-stacked-cohort-fund-type and report standard errors in brackets. $^{*}p < .10$; $^{**}p < .05$; $^{***}p < .01$.

	PME		**IRR**		**Multiple**	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Low 10th Percentile Based on Aggregate Distribution						
Treated × Early Post	-0.017	-0.004	-0.011	-0.008	-0.003	0.010
	[0.016]	[0.018]	[0.016]	[0.015]	[0.018]	[0.016]
Treated × Late Post	-0.031*	-0.018	-0.005	-0.008	-0.013	-0.009
	[0.018]	[0.018]	[0.015]	[0.015]	[0.014]	[0.015]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
PF × Cohort FE	Yes		Yes		Yes	
Vintage × Cohort FE	Yes		Yes		Yes	
PF × Cohort × Fund-Type FE		Yes		Yes		Yes
Vintage × Cohort × Fund-Type FE		Yes		Yes		Yes
#Treated PFs	42	42	42	42	42	42
#Never-Treated PFs	68	66	70	70	70	69
Observations	12,352	12,059	13,819	13,524	14,347	14,053
Adjusted R-squared	0.024	0.054	0.051	0.091	0.055	0.087
Panel B: Low 10th Percentile Based on within Fund-Type-Vintage-Year Distribution						
Treated × Early Post	0.000	-0.005	-0.011	-0.007	0.011	0.023
	[0.022]	[0.021]	[0.019]	[0.021]	[0.020]	[0.021]
Treated × Late Post	-0.033*	-0.032*	-0.020	-0.023	-0.004	-0.002
	[0.019]	[0.019]	[0.021]	[0.022]	[0.020]	[0.019]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
PF × Cohort FE	Yes		Yes		Yes	
Vintage × Cohort FE	Yes		Yes		Yes	
PF × Cohort × Fund-Type FE		Yes		Yes		Yes
Vintage × Cohort × Fund-Type FE		Yes		Yes		Yes
#Treated PFs	42	42	42	42	42	42
#Never-Treated PFs	68	66	70	70	70	69
Observations	12,352	12,059	13,819	13,524	14,347	14,053
Adjusted R-squared	0.009	0.019	0.033	0.044	0.045	0.063

Table IA.14: Specialized Consultants and Probability of Investing in Underperforming Left-Tail RA Funds

Robustness test of Table 10 Panel B: We examine the probability that a pension fund invests in a real assets fund that delivers performance in the bottom 10 percentile of all pension fund investments.

We estimated stacked DID specifications and the observations are at the pension fund-investment level over the 2001–2016 period. The treatment is hiring a specialized consultant for the first time and the event window spans seven years, covering 3 years before and after the hiring. In Panel A, we classify private funds in the low left-tail 10^{th} percentile based on the aggregate performance distribution. In Panel B, we classify private funds in the low left-tail 10^{th} percentile based on the performance distribution within each fund-type-vintage-year subset of observations. In columns (1) to (3) performance is measured using the public market equivalent based on the S&P500 index as a benchmark. In columns (4) to (6) performance is measured using the net internal rate of return (IRR), and in columns (7) to (9) performance is measured using the multiple of the total value to paid-in capital (TVPI). We control for pension fund assets under management and target allocation to equity, real assets, private equity, hedge funds, and other risky assets. We include either interacted pension-fund-stacked-cohort and vintage-year-stacked-cohort or interacted pension-fund-stacked-cohort-fund-type and vintage-year-stacked-cohort-fund-type fixed effects. We cluster standard errors by pension-fund-stacked-cohort or by pension-fund-stacked-cohort-fund-type and report standard errors in brackets. *$p < .10$; **$p < .05$; ***$p < .01$.

	PME		**IRR**		**Multiple**	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Low 10^{th} Percentile Based on Aggregate Distribution						
Treated x Early Post	-0.013	-0.014	0.074	0.093*	0.048	0.063
	[0.068]	[0.068]	[0.052]	[0.052]	[0.049]	[0.055]
Treated x Late Post	0.000	0.008	0.011	0.022	0.006	0.037
	[0.081]	[0.081]	[0.060]	[0.058]	[0.056]	[0.062]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
PF × Cohort FE	Yes		Yes		Yes	
Vintage × Cohort FE	Yes		Yes		Yes	
PF × Cohort × Fund-Type FE		Yes		Yes		Yes
Vintage × Cohort × Fund-Type FE		Yes		Yes		Yes
#Treated PFs	34	34	34	34	33	33
#Never-Treated PFs	54	52	58	55	57	55
Observations	3,734	3,511	4,533	4,288	4,668	4,463
Adjusted R-squared	0.150	0.202	0.124	0.126	0.104	0.101
Panel B: Low 10^{th} Percentile Based on within Fund-Type-Vintage-Year Distribution						
Treated x Early Post	0.062	0.046	0.066	0.033	0.061*	0.050
	[0.039]	[0.046]	[0.042]	[0.038]	[0.037]	[0.040]
Treated x Late Post	-0.010	-0.047	-0.012	-0.042	-0.010	-0.003
	[0.033]	[0.040]	[0.040]	[0.041]	[0.050]	[0.049]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
PF × Cohort FE	Yes		Yes		Yes	
Vintage × Cohort FE	Yes		Yes		Yes	
PF × Cohort × Fund-Type FE		Yes		Yes		Yes
Vintage × Cohort × Fund-Type FE		Yes		Yes		Yes
#Treated PFs	34	34	34	34	33	33
#Never-Treated PFs	54	52	58	55	57	55
Observations	3,734	3,511	4,533	4,288	4,668	4,463
Adjusted R-squared	0.059	0.146	0.024	0.045	0.032	0.041

Table IA.15: Specialized Consultants and Performance in First Time PE Funds

Robustness test of Table 10 Panel A: We examine the performance in private equity funds conditioned on the investment being made in an overall first-time private fund.

We estimated stacked DID specifications and the observations are at the pension fund-investment level over the 2001–2016 period. The treatment is hiring a specialized consultant for the first time and the event window spans seven years, covering 3 years before and after the hiring. In Panel A, we isolate the treated and control sample to private equity funds that are *Overall First Time Fund*, the first fund raised by the general partner based on all funds raised by this general partner. This panel focuses on private equity consultant turnover. In Panel B, we replicate the analysis for real asset funds and focusing on real asset consultants turnover. In columns (1) to (3) performance is measured using the public market equivalent based on the S&P500 index as a benchmark. In columns (4) to (6) performance is measured using the net internal rate of return (IRR), and in columns (7) to (9) performance is measured using the multiple of the total value to paid-in capital (TVPI). We control for pension fund assets under management and target allocation to equity, real assets, private equity, hedge funds, and other risky assets. We include either interacted pension-fund-stacked-cohort and vintage-year-stacked-cohort or interacted pension-fund-stacked-cohort-fund-type and vintage-year-stacked-cohort-fund-type fixed effects. We cluster standard errors by pension-fund-stacked-cohort or by pension-fund-stacked-cohort-fund-type and report standard errors in brackets. *$p < .10$; **$p < .05$; ***$p < .01$.

	PME		**IRR**		**Multiple**	
	(1)	(2)	(3)	(4)	(5)	(6)
	PE Specialized Consultant					
Treated × Early Post	-0.146	0.175	-3.816	-7.939	0.185	0.242
	[0.173]	[0.205]	[5.199]	[6.097]	[0.295]	[0.241]
Treated × Late Post	-0.471**	-0.919***	-9.507	-4.411	-0.366	0.045
	[0.189]	[0.180]	[6.986]	[7.242]	[0.301]	[0.215]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
PF × Cohort FE	Yes		Yes		Yes	
Vintage × Cohort FE	Yes		Yes		Yes	
PF × Cohort × Fund-Type FE		Yes		Yes		Yes
Vintage × Cohort × Fund-Type FE		Yes		Yes		Yes
#Treated PFs	16	11	19	15	19	15
#Never-Treated PFs	19	14	26	17	28	22
Observations	436	215	637	344	711	400
Adjusted R-squared	0.123	0.182	0.179	-0.150	0.025	0.010