How do Barbarians Get to the Gates? Private Equity Careers, Styles, and Returns*

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August 27, 2025

Job Market Paper

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Abstract

I study how individual investment professionals acquire investment skills using a novel dataset tracking the careers and investments of private equity (PE) investment professionals who have invested 97% of capital for U.S. PE firms over the past three decades. I find that about 40% of PE partners' role in explaining the financial returns of their investments comes from which PE firm they worked at as a junior associate. Who a professional worked with the most during their associate years accounts for two-thirds of the associate experience effect. Comparisons of investment returns led by former associates from the same PE firm or the same mentor indicate the results are driven by capital structure and portfolio company management approaches partners learned how to implement early in their careers. Instrumental variable estimates at the PE firm level indicate PE partners tradeoff the costs of providing these learning experiences with the benefits of more deal-making. Overall, my results show investment professionals' success at investing in financial markets significantly depends on where their investment careers begin.

*I especially thank Andy Naranjo, Jay Ritter, and Ilya Strebulaev for numerous discussions and incredibly generous support. For helpful comments and discussions, I thank Murillo Campello, Harry Cooperman, Ege Ercan, Michael Ewens, Minmo Gahng, Guilherme Junqueira, Tao Li, Justin Murfin, Gavin Pearson, Roham Rezaei, Michael Ryngaert, Yuehua Tang, Andrew Teodorescu, Baolian Wang, Oliver Xie, many private equity professionals, and seminar participants at the University of Florida, WEFI student seminar series, and the WEFI conferences. Part of this work was completed while I was a visiting Ph.D. student at Stanford University Graduate School of Business.

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Private equity (PE) fund managers have become increasingly important investors in financial markets over the past few decades. PE fund assets under management exceed $4 trillion (Bain 2025), and recent regulatory efforts seek to further open PE investments to 401(k) plan participants in the United States (Suzanne and Claire 2025). In its simplest form, a buyout transaction aims to acquire a business, own the business for several years, and sell it profitably. While an extensive literature examines whether, how, and for whom these deals create economic value, this paper takes a new approach to studying investment outcomes in PE, instead focusing on how individual buyout managers develop the investment skills that can explain differences in their investment success.

Recent studies, for instance, suggest PE fund managers have been able to affect investment outcomes by changing the portfolio companies in which they invest, adjusting total factor productivity (Davis et al. 2014), managerial practices (Bloom et al. 2015), access to capital markets (Bernstein et al. 2018), product offerings (Fracassi et al. 2022), chief executive officers (Gompers et al. 2023), and capital structures (Bhardwaj et al. 2025). However, little research has focused on identifying the source of these investment skills. Since the skills fund managers possess matters for which assets they invest in, the real effects for their portfolio companies, and the financial returns they generate for clients, understanding their accumulation is central to understanding investment behavior and outcomes. Where, when, and how do fund managers acquire investment skills? What comprises these skills? And how does such skill accumulation matter for their investment success?

The novel contribution of this paper is to show that individual PE fund managers' differing investment approaches and return outcomes are substantially driven by an important but previously unexplored source of investment skills: the firms they worked at, the mentors they worked for, and resulting differences in the investment approaches they were exposed to early in their investing careers. I assemble a new and detailed dataset tracking the careers and investments of the near universe of PE investment professionals over the past three decades. Using these data, I quantify the contribution of different experiences to return outcomes, identify the economic mechanisms behind their contributions, and provide evidence on the central tradeoffs in organizing PE firms to split investment tasks among senior and junior investment professionals. Taken together, my results indicate investment skills are developed early in careers and that investors' success at investing in financial markets depends largely on where their careers began.

I start by introducing a new dataset of PE investment professionals drawing from the histor-

ical webpages of nearly every institutional U.S. buyout firm each year the firm has an active website from 1997 to 2025. I assemble these data using a system of Large Language Models (LLMs) prompted to collect the biographical information about each professional listed on archived websites alongside my hand collections that help validate the quality of extracted information.[1] The resulting 31,500 investment professionals in my sample combine to have raised and deployed 97% of all capital for U.S. buyout funds covered in commercial datasets over my sample period. The data are remarkably detailed, including all information as of the year it was posted on a firm's website. For example, I can observe that Leonard Green & Partners (LGP), a Los Angeles-based PE firm, employed 17 investment professionals in September 2006, five of whom were junior investment associates at LGP. Of these five junior associates, two later became partners at LGP (Alyse Wagner and Usama Cortas), while another two graduated from University of California, Berkeley, and worked in the investment banking division of Credit Suisse before joining LGP. Many of these data are often missing from other datasets; for example, Usama Cortas does not maintain a LinkedIn profile, Alyse Wagner's LinkedIn does not list her associate experience, and more generally, 50% of entry-level PE associate experiences available from historical website data in any year are not available in standard LinkedIn data.

I use these data to estimate the relative contribution of different early career experiences to buyout investment returns. An important feature of buyout investing is that each deal has a lead partner who is primarily responsible for the investment, allowing me to assign deals to partners of different backgrounds and track them as they move across different PE firms. I match the career and team information from the archival website data with commercial datasets to obtain PE partners' investment histories. I further include data from a large fund of funds to estimate the gross-of-fee Net Present Value (NPV) of deals, following Braun et al. (2025). The resulting dataset enables variance decompositions of NPV using five main fixed effects: the PE firm where a partner began their investing career as an associate; their pre-PE employer (about 80% come from an investment banking or consulting firm); where they went to school (about 70% come from a Top-30 U.S. school); the PE firm the partner represents in the deal; and the year the deal closed.

These variance decompositions build on the Abowd et al. (1999) ("AKM") style decompo-

[1] Jackson and Strebulaev (2025) subsequently use similar approaches to extract historical information about U.S. venture capitalists.

sitions estimated by Ewens and Rhodes-Kropf (2015) in venture capital (VC) by replacing individual partner fixed effects with early career experience fixed effects (associate experience, pre-PE experience, and education). This substitution helps quantify the determinants of persistent differences in outcomes across PE partners. My approach separates the contribution of PE associate experiences from that of other fixed effects based on connected professionals who do not perfectly sort to PE firms as partners. If partners of specific backgrounds tend to outperform or underperform those with other backgrounds after accounting for the other fixed effects, variation in return outcomes is allocated to that experience.

I find that early career experiences explain most of individual PE partners' contribution to deal returns. About 60% of the variation in the NPV of a deal explained by *who* is leading the deal is driven by *where* they worked and studied before they began leading buyout deals. Among these experiences, where the partner worked as a PE associate is the most important, capturing about 40% of variation explained by partner fixed effects in baseline specifications. The variation attributed to where the partner worked as a PE associate is about 1.5-times larger than the variation attributed to which PE firm the partner represents in the investment. For example, whether a partner worked as a PE associate at Blackstone versus at KKR is more important for variation in deal returns than where they went to school, whether they were a banker at Goldman Sachs versus a consultant at McKinsey, or whether they are a partner at Bain Capital or at Carlyle.

Theory emphasizes that an important role for associate experiences in explaining the NPV of buyout deals could be driven by two main economic channels. Associate experiences may help junior professionals acquire particular investment skills from the particular deals they were exposed to or worked on (e.g., Gibbons and Waldman (2006)). Alternatively, associate experience effects can arise because more skilled future partners sort to particular firms early in their careers (e.g., Jovanovic (1979)). While distinguishing the importance of assortative matching and learning is inherently challenging – most crucially, newcomers to the industry are not randomly assigned to work as associates at particular PE firms – the remaining tests in my paper help to do so.[2]

[2]Anecdotal evidence, however, suggests a substantial component of the matching process is random, conditional on professionals' education and pre-PE employer. PE associates are often interviewed and hired during the first few months of joining an investment bank, between 16 and 25 months before they start as a PE associate where selection on skills or talent is challenging (e.g., Levine (2018) and Cumming (2023)). Jamie Dimon, the CEO of JP Morgan, referred to this process as "unethical" (Dimon 2024) and several PE firms have adjusted their hiring timeline starting for the 2027 associate class (Fuchs 2025).

As a first step, I show that associate experiences explain not just NPV outcomes, but also the investment approaches, or "styles," of partners. Investment styles are persistent patterns in which types of portfolio companies PE partners tend to invest in and how their portfolio companies tend to change once the partners acquire them. Most buyout targets are privately held with little available financial data, making more standard classifications (e.g., value versus growth) difficult. Accordingly, I estimate style classifications for each deal based on the full suite of portfolio company and deal characteristics I can observe; namely, portfolio company locations, industries, and changes during the holding period related to capital structure composition, debt characteristics, top management turnover, and subsequent acquisitiveness. Each captures an investment approach that a professional may learn about how to implement or be exposed to during their associate years. Analogous to the performance tests, I then estimate variance decompositions that attribute variation in adherence to a particular investment style to early experiences, controlling for other observable factors.

I find that about 50 to 70% of partners' persistent investment approaches related to deal structures, industry selection, geography selection, and subsequent capital structure decisions is attributed to experiences the partner had before they began investing. Educational and pre-PE backgrounds have slightly reduced roles in explaining investment approaches compared to explaining NPV. PE associate experience remains the most important early career experience, also capturing about 30 to 40% of variation explained by partner fixed effects in baseline specifications. Further investigating this relationship, I find that the characteristics of deals partners were exposed to through their associate firm predict characteristics of deals they later lead themselves, estimated based on the cosine similarities of deals. Such similarities persist throughout their careers. About 93% of the cosine similarity between a partners' first deal and the deals they were exposed to as associates is retained on their fifth deal and 75% is retained on their tenth deal.

As a more direct test distinguishing the role of assortative matching and learning in explaining associate experience effects, I also compare how investment approaches relate to deal returns among partners who were associates of the same firm. The results favor a learning or imprinting channel. Estimating these cross-sectional regressions shows that, among two partners who are both former associates of the same PE firm, the one who does deals closer to what they observed while they were an associate tends to outperform the other. A one standard deviation increase in similar-

ity correlates with a 10% increase in gross deal return multiples relative to the mean. The resulting distribution of deal returns is less risky if similarity scores are higher, displaying few large losses and more material gains. The results also run counter to a positive assortative matching channel. If more skilled future partners sort to particular firms early in their careers, there should be a positive bias in estimated coefficients when the cross-sectional regressions are estimated without associate firm fixed effects, arising because more skilled partners would tend to perform better regardless of this experience. However, this bias does not appear in the data, failing to support this assortative matching channel.

These findings combine to suggest the existence of what I refer to as "style-specific" investment skills – skills that are useful when the partner follows an investment approach they were exposed to early in their careers but not if they follow a different investment approach. An important way such style-specific skills are transmitted comes from the partner that associates primarily work with, not just the associate firm itself. The archival website data are able to recover deal involvements for a subset of associates, and therefore partner-associate deal team relationships (estimated based on measures of who professionals worked with the most as associates). Standard commercial datasets do not list deal involvements for associates. Estimating an extended AKM-style variance decompositions shows associates' mentors are roughly two-times more important than the associate firm itself for explaining subsequent styles and returns.

I also document a positive relationship between similarity and returns after further including fixed effects for mentors, which holds fixed average differences in more stringent assortative matching between associates and mentors. However, the relationship exhibits a marginally positive bias when estimated with-associate firm rather than within-mentor. This suggests the more relevant dimension of assortative matching occurs within PE firms between junior professionals and their mentors, but is overall not strong enough to account for the majority of associate experience effects among professionals that led deals as partners.

The data further reveal heterogeneity in the attribution of deal outcomes to associate experiences. First, associate firms have similar explanatory power for investment NPV among partners of larger or smaller PE firms (by assets under management), or for a partner's first few deals versus their later deals. This suggests associate experiences are not fully eroded away by later experiences. Second, there is more variation in associate firm effects among smaller PE firms than among larger

PE firms. This indicates learning experiences are significantly less variable among larger PE firms, which tend to be more similar in terms of the quality of their deal flow or the investment success of their partners. Third, associate experiences are more important for deal NPV among partners of more prestigious backgrounds, particularly those from top schools or investment banks, compared to those from others. This indicates professionals who make it into the industry with an uncommon background tend to depend less on the associate firm experience.

Providing these learning experiences is, however, costly for firm partners, requiring their time and other resources. What is the benefit for partners? The last step of my empirical approach presents a striking finding on associate experience effects that helps address this question: associates have an economically meaningful impact on their PE firms' investing activity. While it is generally challenging to isolate the effect of any one group of employees on firm outcomes, key features of associate employment at PE firms allow me to do so by directly relating the turnover of associates to the number of buyout deals a PE firm completes. Associates work at PE firms in programs of quasi-fixed periods of two or three years in up-or-out contracts, after which they are directly promoted, temporarily leave the firm to pursue an MBA before promotion, or separate from the firm. This turnover is predictable and replaces more experienced associates with marginally less experienced associates (or none at all) as the later cohort moves up or out.

These standard employment structures motivate a simple instrument for associate turnover: the fraction of a firm's associates *predicted* to be at the end of their scheduled associate programs. A negative relationship between instrumented associate turnover and deal-making implies that associates, particularly separating associates that are marginally more experienced than those that remain, are important inputs to PE investment activity. A positive relationship instead implies departing associates are, on balance, a constraint on partners' time. The instrument is strong (F-stat $\approx$ 200) and an extensive set of cross-sectional tests provide confidence in the exclusion restriction. I estimate that a one standard deviation increase in instrumented associate turnover causes a 20% decline in the number of deals a PE firm completes relative to the mean. Equivalently, PE firms complete about one fewer deal for every two associates predicted to turnover (a decline in investment of about $200 million). The partners of a PE firm forgo some investments (or fail to find investable companies) if they lack sufficiently experienced associates, suggesting an important role of associate experience for PE firms.

Related Literature and Contribution. The results in this paper contribute to the literature studying how investment fund managers can accumulate investment knowledge and skills. This literature, focused mostly on mutual fund managers, generally suggests that superior investment performance is related to specialized knowledge and information acquired from multiple channels including past investing experiences, education, and prior work experiences (e.g., Chevalier and Ellison (1999), Coval and Moskowitz (2001), Kacperczyk et al. (2005), Cohen et al. (2008), Kacperczyk et al. (2014), Kempf et al. (2017), Cici et al. (2018), and Bai et al. (2024)). The distinction of my paper is to instead highlight the importance of specialized knowledge and information acquired from early career investment experiences in explaining cross-sectional variation in returns for PE investment managers.

My findings further contribute to an important literature on human capital acquisition. A consequential strand shows early career work experiences matter for productivity, wages, and labor market outcomes (e.g., Acemoglu and Pischke (1998), von Wachter and Bender (2006), and Arellano-Bover and Saltiel (2024)). My contribution is to introduce new results on the relevance and returns of human capital accumulation from early work experiences for professional investors. These findings are relevant for the literature documenting the importance of path dependence and initial conditions for wages and careers in the finance industry (e.g., Oyer (2008) and Ellul et al. (2021)). The novel aspect of my paper is to show that initial experiences as a junior finance professional are an important contributor to such path dependence through their relationship with later investment styles and returns.

In the private equity literature, Ewens and Rhodes-Kropf (2015) is most closely related to my work. They show variation in venture investment exits is attributable more so to the individual partner that served on the board of the portfolio company than to VC firm at which they are a partner. The distinctions of my paper are to decompose the partner fixed effects and to further study investment styles in a different setting using different data. Among buyout partners, recent work by Braun et al. (2017) and Braun et al. (2025) finds persistence in deal returns, especially in the NPV of deals, consistent with evidence of investment skill. Relative to these papers, my contribution is to provide evidence identifying the source of PE partner fixed effects and skills based on their early career experiences.

The findings in my paper also contribute to a strand of the private equity literature studying

the determinants of PE investment returns and activity (e.g., Kaplan and Schoar (2005), Phalippou and Gottschalg (2009), Axelson et al. (2013), Harris et al. (2014), Haddad et al. (2017), Korteweg and Sorensen (2017), and Brown et al. (2024)). The distinguishing aspect of my paper is to offer a new explanation for cross-sectional variation in PE returns based on where partners may learn varying investment approaches. Another strand of the PE literature has documented several ways that buyout investors expect to select and add value to their portfolio companies (e.g., Acharya et al. (2013), Davis et al. (2014), Bernstein and Sheen (2016), Gompers et al. (2016), Eaton et al. (2020), Gompers et al. (2023), Ewens et al. (2024), Bhardwaj et al. (2025), and Davis et al. (2025)). My contribution is to show that many PE investment styles captured in this literature, ranging from changing the CEO of a portfolio company to pursuing add-on acquisitions or engaging in a dividend recapitalization, are driven in part by associate experiences of partners leading the deal. More generally, my findings add to the literature documenting styles and sources thereof among other types of economically important professionals such as CEOs and CFOs (e.g., Bertrand and Schoar (2003), Malmendier et al. (2011), and Schoar and Zuo (2017)).

Lastly, my findings contribute to the literature examining the role of asset management firms. The relative importance of VC partners over VC firms for explaining returns helps Ewens and Rhodes-Kropf (2015) conclude the boundaries of a VC firm are driven by fundraising purposes. Berk et al. (2017) and Braun et al. (2025) find the internal capital markets of investment firms add value for outside investors. My results highlight that transferring knowledge intergenerationally is also an important role for buyout firms.

1 Buyout Investment Professionals: Data Sources and Uses

As background, institutional PE investing involves three main economic layers: PE firms, the funds sponsored by these firms, and the investments held in funds sponsored by the firms. The funds are typically closed-end, limited life, limited partnerships, lasting eight or more years. Funds raise and manage capital on behalf of large institutional investors (e.g., pension funds, endowments, and sovereign wealth funds) and high net worth individuals. In turn, the sponsoring PE firm is predominantly compensated with management fees and carried interest.

This study focuses on the investment professionals employed by the firm that are respon-

sible for investing and managing capital raised by the funds. Doing so requires identifying the relevant investment professionals and collecting data on their deals and career experiences. Several aspects of these data are novel to this study, each of which I discuss in turn.

1.1 Buyout Investment Professionals

The main sample includes all investment professionals employed by the near universe of institutional U.S. buyout firms from 1997 to 2025. I consider institutional U.S. buyout firms to be all firms that are (1) headquartered in the United States; (2) have raised at least $10 million for a closed or liquidated buyout fund in 1995 or later according to PitchBook or Preqin; (3) primarily sponsor buyout funds (i.e., excluding firms that mostly sponsor fund of funds or hedge funds); and (4) are not captive arms of a parent firm. 1,179 firms meet these criteria.

Data Collection: I attempt to collect investment professionals for each of these firms using archived webpages hosted on the internet archive and accessed via the Wayback machine. 1997 is the first year that archived website data are available for a firm in my sample. The archived website data on PE professionals, which are novel to this study, provide historical snapshots of a firm's investment professionals over time, displaying the team of professionals who work for a given PE firm each year as of that year. Figure 1 displays an example of archived webpages for Hellman & Friedman (a large PE firm) in 2003.

An important advantage of these historical website data is that they allow me to track early career experiences which are often missing from other datasets. For example, Figure 2 shows no more than 40% of investment partners' entry-level PE associate experiences I collect are available on LinkedIn. These early experiences are often missing from LinkedIn due to the tendency for professionals to only list their most recent title within a firm or to omit early experience altogether.

I collect the website data by prompting a Large Language Model (LLM) to iterate through each firm's archived website, locate the team and personal pages of each professional displayed on the website, and then return the biographical information about each person contained in the underlying HTML. Section IA.1 further discusses the dataset construction. To help limit the role of hallucinations, I further hand-collect the archived websites for a sample of the 100 largest non-listed firms and about 100 randomly selected firms. Importantly, the results in this paper are robust

to using only the websites I hand-collect, indicating the two methods are of similar quality. In subsequent work, Jackson and Strebulaev (2025) also use LLMs and hand-collections to parse the historical webpages of U.S. venture capital firms.

The final sample includes historical webpage data for 969 of the 1,179 U.S. buyout firms (83% of firms). The 17% of firms that are not retained in the final sample do not have accessible URLs, do not list professionals on their website, or are firms where I was otherwise unable to collect professionals from the historical websites. The firms in the resulting final sample are economically representative of the U.S. buyout industry, combining to have raised $3.6 trillion of capital for buyout funds according to Pitchbook. Over my sample period, this represents about 97% of all buyout capital raised by U.S. buyout firms in Pitchbook and about 92% of buyout funds sponsored by U.S. buyout firms in PitchBook (3,256 of 3,551). The average firm has 15 years of collected historical webpage data, covering 95% of the years it was active from 1997 to 2025.

The 969 firms in this sample combine to have listed about 55,000 professionals on their websites. Within each year a professional is observed, I use reported titles to flag whether the person is an investment professional – individuals working on PE deal teams and responsible for investing the capital raised by the funds sponsored by their firm.[3] The main sample of people includes 31,590 investment professionals. Using the title stems, I further assign investment professional to one of three layers in each year they are observed reflecting the hierarchy observed in practice: a junior-level (associates), a middle-level (vice presidents and principals), and a top-level (partners). Doing so allows investment professionals' career progressions to be reasonably comparable across firms and over time.

Alongside other statistics about firms' investing and fundraising activity, Panel A of Table 1 shows that the average firm employs about 15 investment professionals in a given year, split evenly across junior-, middle-, and top-level investment professionals. Firm-year cells with only top-level professionals typically appear at the beginning or end of a firm's life.[4]

Summary Statistics: Panel B of Table 1 describes the characteristics of investment professionals collected from historical websites. These biographical data are retrieved from historical

[3]Non-investment professionals are primarily firm operations professionals (involved in internal functions such as compliance and human resources), portfolio operations professionals (often operating partners and advisors), and retired investment professionals (such as emeritus partners).

[4]Assets under Management (AUM) is estimated by aggregating fund-quarter level data from Preqin in each firm-year cell following Gahng and Jackson (2023).

websites, Revelio, PitchBook biographies, and LinkedIn scrapes. I obtain these additional data by merging each professional collected from websites to a profile in the other datasets – attempting a sequence of matches based on names and affiliations and then manually reviewing unmatched professionals. Where information is available from multiple datasets, I prioritize data obtained from historical websites. The union of these datasets increases the number of observations for each variable by 10 to 30% compared to commercial datasets alone. Section IA.1.2 discusses the calculation of each characteristic in detail.

17% of professionals are female. 61% of professionals have a degree from a Top-30 U.S. school. University of Pennsylvania is the most common undergraduate school (5.5% of investment professionals). The most common MBA is from Harvard Business School (24% of those with MBAs). Most joined the PE industry after working in investment banking (65%) or management consulting (20%). Few PE professionals have VC (2%), hedge fund (1.5%), law firm (2.5%), or government (3%) backgrounds. The most common prior employer is Goldman Sachs (7%). Table IA1 and Table IA2 list the top schools and previous employers. Trends in these data are presented in Section IA.1.2.

70% of junior-level professionals work in PE for five years or less. Less than 10% of junior-level professionals are subsequently observed as a top-level professional at a firm in my sample. Figure 3 reports promotion and separation rates over PE careers, reflecting an "up-or-out" structure.

1.2 Buyouts Deals and Outcomes

The main sample of deals includes all stand-alone or platform buyout investments in U.S. companies made by a professional representing any of the 969 sample firms. This dataset comes from PitchBook, including approximately 4,600 lead professionals that represented 865 U.S. buyout firms in 12,000 buyouts of 10,000 companies completed in May 2025 or earlier. The firms that do not have deals in this sample sponsored add-ons but have never sponsored a platform buyout of a U.S. company tracked by PitchBook (30% of excluded firms) or do not have data on any lead partners (70%).

For a subset of buyout investments in the sample, I additionally obtain the gross perfor-

mance of the investment and the dollar amount a General Partner (GP) invested in a company via StepStone, a private markets investor, consultant, and sponsor. For U.S. buyout funds, StepStone data are similar to Burgiss data, one of the most reliable performance datasets used in PE research (Ercan et al. 2024). These data are useful for this study because they are de-anonymized, allowing for matches between partners, deals, and companies across datasets. Gross performance is measured as a Total Value Multiple (TVM), equaling the dollar amount of capital returned to the GP from its investment divided by the amount of capital the GP invested. After standardizing StepStone deal returns and investment amounts to account for duplicated entries (arising primarily when the GP acquires a portfolio company using multiple funds or through multiple tranches within the same fund), I attempt to merge each PitchBook deal with a StepStone deal – attempting a sequence of matches based on portfolio company names, GPs, and a window of no more than three years around the entry years. I exclude a handful of deals where the GP invested less than $1 million and censor deal returns where the TVM was negative (due to relative changes in currency valuations).

Panel A of Table 2 reports that TVM data are available for about 60% of exited deals and the average deal has a gross TVM of 2.7x. Exited deals with TVM data account for invested capital of about $1.2 trillion. 10% of exited deals have a gross return exceeding 5-times the amount invested. Around 20% returned no more than the amount invested (TVM $\leq$ 1x). Value add is calculated as the dollar amount invested multiplied by the TVM exceeding one and averages about $230 million. The Net Present Value (NPV) of a deal is estimated by discounting the exit value (TVM $\times$ entry value inflation adjusted to 2024) over its holding period and subtracting the entry value. This method parallels Braun et al. (2025). A key distinction, however, is that I cannot observe interim cash flows, which understates estimated NPV relative to actual NPV for a given discount rate. Assuming a 15% discount rate, NPV averages $20 million, similar to NPVs reported in Braun et al. (2025). Setting the discount rate to about 20% produces an average NPV near zero.

Subsequent panels of Table 2 further describe the investments. These characteristics are useful for measuring any investing styles towards which partners tend. The most common type of buyout is a secondary buyout (25% of deals). 11% of targets are in Texas and 20% focus broadly on commercial services. Within the first five years following the investment, 30% of portfolio companies issue new debt, 8% undergo dividend recapitalizations, and 53% make at least one add-

on acquisition. Inclusive of transaction debt, 45% of deals have debt with an observed revolving feature. Within the first three years following the investment, 23% of portfolio companies replace the CEO and 35% replace at least one C-suite level professional. 41% of exits are to a fund sponsored by another PE firm.

2 Decomposing Investment Styles and Returns

This section quantifies how important early career experiences are for investment approaches and returns. I do so by estimating the variation in buyout returns and styles attributable to various fixed effects for each of these different experiences. Partner i, representing PE firm j, makes investments in year t with characteristics and outcomes (y) according to the following equation:

$$y_{d,i(j,t)} = \lambda_j + \delta_i + \omega_t + \epsilon_{d,i(j,t)}. \tag{1}$$

This specification follows from the Abowd et al. (1999) ("AKM") style variance decompositions estimated by Ewens and Rhodes-Kropf (2015). Relative to prior literature, I innovate on Equation (1) in two main ways. First, rather than focus on deal returns alone, I also study investment styles. $y_{d,i(j,t)}$, therefore, is intended to also represent key features of buyout investing—such as the types of companies partners invest in and the changes they tend to make to portfolio companies' capital structure, operations, or acquisitiveness.

Second, I substitute the partner fixed effect with separate fixed effects representing early career experiences partners accumulate before they start making any investments. Specifically, I include fixed effects for the firm where partner i worked as a PE associate when they first entered the PE industry ($i(a)$), the non-PE firm where the partner worked before entering the PE industry ($i(f)$), and school the partner attended ($i(s)$). If a partner has more than one pre-PE firm experience, the firm is selected sequentially by prioritizing any investment banking experience, consulting experience, VC experience, hedge fund experience, other financial firm experience, law firm experience, government experience, and then any other unclassified firm. Schools are selected sequentially by prioritizing MBA schools, other Master's schools, and then undergraduate schools.

The main estimating regression becomes:

$$y_{d,i(j,t)} = \lambda_j + \delta_{a(i)} + \delta_{f(i)} + \delta_{s(i)} + \omega_t + \varepsilon_{d,i(j,t)}. \tag{2}$$

To study the role of these early experiences in buyout investing, I attribute R^2 obtained from estimating Equation (2) to each of the five estimated fixed effects $\chi_b \in \{\hat{\lambda}_j, \hat{\delta}_{a(i)}, \hat{\delta}_{f(i)}, \hat{\delta}_{s(i)}, \hat{\omega}_t\}$. The associate experience fixed effects, $\delta_{a(i)}$, are the main coefficients of interest.

Conceptual Framework Discussion. The conceptual framework underlying my empirical specification assumes partner i has investment skills H_{it} as of year t, where H_{it} equals the sum of the investment talent they accumulated before entering the PE industry (η_i) and the investing skills they acquire while working in the industry (h_{it}). Once entering the industry, new investment skills are acquired as a byproduct of working at PE firm $j \in \{1, \ldots, J\}$. The law of motion for investment skill accumulation sums prior experience with the investment skills acquired in a given year: $h_{i,t+1} = h_{it} + \sum_j e^j_{it}\mu^j_{it}$, where e^j represents an indicator for working at firm j and μ^j denotes the value of investment skills acquired from working at firm j. The expected financial return of a PE investment $y_{d,i(j,t)}$ led by partner i in year t combines their accumulated investing skills and the financial market conditions of year t, with an additional effect for the firm j they represent on the investment:

$$\begin{aligned} E[y_{d,i(j,t)}] &= \lambda_{i(k,t)} + \omega_t + E[H_{it}] \\ &= \lambda_{i(j,t)} + \omega_t + \underbrace{\eta_i + \sum_{t}^{t-1} \sum_{j} e^j_{it} E[\mu^j]}_{\text{Investment Skills}}. \end{aligned} \tag{3}$$

Investment Skill Accumulation Interpretation: Equation (2) may not be able to directly map to this conceptual framework if η_i plays an important role in explaining outcomes, as this term is not directly observed, thereby introducing potential bias into my estimates. Economically, the extent of this potential bias depends on assortative matching between new associate entrants to the PE industry and PE firms. In the most extreme form, associate experiences have homogeneous effects ($\mu^j = \mu^k \quad \forall i, k$), but new entrants have significant unobserved heterogeneity in their investment

skills or propensity to acquire investment skills ($\text{Cov}(\eta_i, \varepsilon_{d,i(j,t)}) \neq 0$). The additional fixed effects and tests decomposing variation in investment styles help to limit the scope of this potential bias in two ways. First, they show which investment skills partners have acquired or been exposed to. Second, they ensure that the omitted η_i term must also not be accounted after absorbing variation explained by where the professional went to school or worked before entering the PE industry.

I also assess the validity of the investment skill accumulation interpretation in Section 3 by comparing investment approaches and deal returns among partners who were former associates of the same firm. The results run counter to a positive assortative matching channel. If more skilled future partners sort to particular firms early in their careers, there should be a positive bias in estimated coefficients when regressions of deal returns are estimated without associate firm fixed effects, arising because more skilled partners would tend to perform better regardless of this experience. However, this bias does not appear in the data, failing to support this assortative matching channel.

Later Experiences: Equation (2) estimates the contribution of $\sum_t^{t-1} \sum_j e_{it}^j E[\mu^j]$ through associate experience effects ($\hat{\delta}_{a(i)}$), omitting any investment skills acquired if some professionals work at firms as principals without leading any deals. I account for the effect of this omission in two main ways. First, in Section 2.4, I find that estimating Equation (2) comes close to replicating the variation explained by estimating Equation (1), the latter of which does not suffer from this omission because such experiences are absorbed by person fixed effects. This suggests unmodeled later experiences are either absorbed by early experiences or do not add much incremental explanatory power. Second, in Section 2.5, I estimate variance decompositions separately for earlier deals and for later deals in a partner's career, where the role of later experiences is likely to play a larger role. I find a decline in attribution, but results that are similar overall, suggesting the role of unmodeled later experiences (or depreciation) does not impose considerable bias on the main decompositions.

2.1 Decomposition Specifications

Regression Samples: Equation (2) restricts the set of observations on which the fixed effect coefficients can be estimated in two ways. First, it requires that I focus on deals led by partners with PE associate experience, which excludes about 50% of the deals. The middle column of Table 2

shows that this restriction tends to exclude deals with lower NPV, pre-2000 deals, smaller deals, and deals without documented capital structure changes. Deals are otherwise compositionally similar to deals in the full sample. Both samples have an average TVM of 2.7, indicating the NPV difference is driven by investment amounts and holding period lengths.

To assess the effect of this restriction, Table IA3 reports results that retain these omitted deals by treating partners without PE associate experience as having worked as associates at the same pseudo-PE associate firm. Associate experience attribution declines some and pre-PE firm experience attribution increases in its place, but results are otherwise similar to the main variance decomposition. This suggests the omission of these deals in the main sample does not impose considerable bias on the estimates, but it is important to caveat that the results focus on partners who have accumulated such associate experiences.

Second, Equation (2) also requires that PE associates do not perfectly sort into PE firms upon promotion, in the spirit of the AKM mover design. As shown by AKM, separating worker and firm fixed effects is possible for the largest connected set of workers across firms. Similarly, I restrict regression samples to deals completed by professionals representing a partner firm in the largest connected set of partner firms based on associate experience. Two PE firms are connected if they hire former associates from the same firm and any string of PE firms is connected if they are connected to a PE firm that is connected to another PE firm. If partners of specific backgrounds tend to outperform or underperform those with other backgrounds after accounting for the other fixed effects, variation in return outcomes is allocated to that experience. I hand collect associate firm experience where it is not available elsewhere. The right-most column of Table 2 reports that the connectedness restriction excludes only about 7% of remaining deals, indicating the sample of deals is fairly connected overall. The connectedness sample includes about $1.2 trillion of invested equity capital for buyout deals.

Table IA4 summarizes observation counts in the resulting sample of deals. The average partner leads three deals in the connectedness sample. The average PE firm in the connectedness sample employs partners from three different associate firms. The average associate firm produces four partners leading deals. Table IA5 lists the top PE firms lead partners worked at as associates, the most common of which is Bain Capital. About half of the partners in the sample worked as PE associates at a firm that is different than where they work as an investment partner.

Decomposition Method: I attribute R^2 to each fixed effect based on its Shapley value (Shapley 1953). In this setting, the Shapley value of fixed effect χ_b, denoted φ_b, equals its average marginal contribution to R^2 across all combinations of fixed effect groupings, equivalent to the average increase in R^2 when fixed effect χ_b is added to a model already containing a subset T of all possible sets of fixed effects, K.[5] The Shapley values sum to the R^2 of the regression ($\sum_b \varphi_b = R^2$), implying the fraction of R^2 attributed to a given fixed effect equals φ_b/R^2 and the overall variation in y explained by χ_b equals φ_b. The Shapley value decomposition is equivalent to the approach followed by Ewens and Rhodes-Kropf (2015) ($\frac{\text{Cov}(\chi_b, y)}{\text{Var}(\hat{y})}$) if there are only two regressors or if any two regressors are perfectly correlated, but has the benefit of not requiring covariance terms to be equally split among regressors.

Because I decompose R^2, rather than adjusted R^2, the explanatory power of a fixed effect increases with the number of levels it has. Fixed effects with comparatively more levels (PE firms and associate firms) could therefore have an overstated attribution. I assess the effect of this concern in Table IA6 by reporting the Shapley value decompositions after bootstrap sampling 100 levels of each fixed effect variable. Doing so ensures the results cannot be driven by the number of levels since every fixed effect has approximately the same number of levels by construction. The average attribution assigned to PE firms and associate firms declines relative to the main results, while the attribution given to fixed effects with fewer levels (deal years, schools, and pre-PE firms) increases some. However, results are overall similar to the main variance decomposition, suggesting this concern does not impose considerable bias on the estimates.

Additive Separability: Equation (2) models associate firm experience ($\delta_{a(i)}$) and PE firm effects (λ_j) as additively separable, which assumes away any potential match effects. I compare the R^2 of regressions with an additive specification to the R^2 obtained from a fully saturated match-effects model (including separate fixed effects for associate firm × PE firm pairs) as a simple test for whether match effects are likely to account for most variation in deal returns and styles. An important role for match effects ought to explain significantly more variation than the baseline

[5] Formally, the Shapley value attributing R^2 (total surplus) among fixed effects (coalitions) equals:

$$\varphi_b = \sum_{T \subseteq K \setminus \{\chi_b\}} \frac{|T|!(|K| - |T| - 1)!}{|K|!} \left(R^2(T \cup \{\chi_b\}) - R^2(T) \right),$$

which weights the marginal increase in R^2 from adding χ_b to each possible subset T by the proportion of possible orderings in which χ_b would be added at that stage.

specification with separated fixed effects (e.g., Card et al. (2013)). This is not the case in my setting. Including the interacted fixed effects has a small effect on R^2, suggesting limited incremental explanatory power for match effects beyond the additive specification. For example, the R^2 of NPV regressions increases from 32.8% to 34.7% and the R^2 of style regressions increases from 28.9% to 30.5% (varying some by how style is measured).

2.2 Early Career Experience Attribution

Table 3 presents results documenting the fraction of total variation in subsequent deal returns attributed to each set of fixed effects in Equation (2) based on their Shapley value. Panel A uses deal-level gross return data from StepStone. Panel B uses exits from PitchBook. Regression samples are restricted to the connectedness sample of deals and are further required to exclude singletons across the fixed effects.

Panel A of Table 3 displays the R^2 decomposition of different measures of gross investment returns. Focusing on the estimated NPV of the deal (Row 1), estimating Equation (2) results in an R^2 of about 33%. 39% of the 33% is attributed to the associate firm. 10% to the pre-PE firm, 13% to the school, 15% to the deal year, and 22% to the PE firm the partner represented in the deal. These results indicate that about 56% of explained variation in whether a partner invests in a company through a secondary buyout or not is attributed to early experiences they had before they started making buyout investments. The NPV regression sample includes fewer observations because NPV calculations additionally require known exit dates.

The fixed effect specification in Equation (2) explains about 35% of variation in the value add of a deal, which applies no discounting to cash flows. A sizeable fraction (30%) of this explained variation is attributable to the firm at which the lead professional worked as a PE associate. 10% goes to the pre-PE firm and the remaining 10% is split between the school and deal year. Compared to gross returns presented in dollars, return multiples (TVM) have a lower R^2 of about 15% but an otherwise similar percentage decomposition. Distributional properties of TVM (whether the multiple falls within a given threshold), and how the partner exited the investment (e.g., through an LBO or not) have similar decompositions to NPV and value add.

Investment Styles. Table 4 presents results relating early career experiences to subsequent investment styles and approaches. Panel A displays the R^2 decomposition of different ways that partners can invest in portfolio companies. Focusing on the indicator for whether the partner acquired the company through a secondary buyout (Row 3), estimating Equation (2) results in an R^2 of about 22%. 33% of the 22% is attributed to the associate firm. 10% to the pre-PE firm, 10% to the school, 7% to the deal year, and 40% to the PE firm the partner represented in the deal. These results indicate that about 50% of explained variation in whether a partner invests in a company through a secondary buyout or not is attributed to early experiences they had before they started making buyout investments.

Panel B presents other aspects of styles, focused primarily on characteristics of the companies that partners invest in. Similarly, about half of explained variation in the location and industry of companies that partners invest in is attributed to early career experiences. Of the early career experiences, the associate firm the partner worked at is most important, accounting for about 1/3 of the R^2 in each regression.

Panel C focuses on the capital structure of portfolio companies. Subsequent capital structure changes, such as whether the portfolio company issues new debt, refinances its debt, has a dividend recapitalization, or has a leveraged recapitalization, are also similarly explained by early experiences. R^2's are around 20% and about 1/3 of each R^2 estimate similarly is attributed to which PE firm the partner worked at as an associate. Time-series variation (deal years) has more explanatory power than elsewhere for debt issuances. Characteristics of the debt (inclusive of transaction debt) are also correlated with early experiences. In round numbers, 30% of explained variation in whether the target company issues debt with a revolving feature is attributed to associate firms. 40% goes to the PE firm, 10% to the pre-PE firm, 10% to the school, and the remaining 10% goes to the deal year.

Panel D shows that whether the target company changes its management (Chief Executive Officer, Chief Financial Officer, or other C-suite executive, respectively CEO, CFO, and CXO) or makes subsequent add-on acquisitions are also features of buyout investing that are explained by early experiences. Decompositions are qualitatively similar to other measures of investing styles.

Decomposition Diagnostics and Supplements. Throughout Table 3 and Table 4, the re-

ported p-values obtained from the F-tests tend to reject the null that associate firm coefficients jointly equal zero across both performance and style outcomes, with almost every specification achieving statistical significance at the 1% level.

Figure IA1 indicates that the economic magnitude of differences in associate firm fixed effect coefficients is sizeable. For example, associate programs at the 75th percentile (of estimated associate firm fixed effect coefficients) produce partners leading deals predicted to generate $892 million more in value-add compared to associate programs at the 25th percentile. This amount is inflation adjusted to 2024. This difference corresponds to about 1.2 standard deviations in value-add and about 3-times the average value-add of a deal in the regression sample. The NPV difference is exceptionally large due to skewness in the data. Such increases in estimated associate firm coefficients imply 10 to 50 percentage point increases in style differences measured via location, industry, entry methods, and financial or operational changes, each of which is economically meaningful.

Table IA7 reports bootstrapped 95 percent confidence intervals for several of the decomposition point estimates. 95 percent confidence intervals are constructed from the standard error estimated by partner-level re-sampling with 100 bootstrap replications. Associate firms explain between 25 and 50% of NPV R^2 calculations. Schools account for 6 to 30%. Pre-PE firms typically account for about 10 to 20%. Deal years 10 to 25% and PE firms 25 to 55%.

Additional Specifications. Table IA8 re-estimates the Shapley value decomposition after additionally including fixed effects for the year the professional first entered the buyout industry. This is motivated by related work in other settings documenting persistence in outcomes due to cohort effects (e.g., Oyer (2008), Malmendier and Nagel (2011), and Schoar and Zuo (2017)). The cohort fixed effects explain little of the variation in deal outcomes, hovering around an attribution of 2 to 10%. Table IA9 focuses on deals where the lead professional is representing a firm other than their associate firm. This is a "switchers" approach, analogous to Bertrand and Schoar (2003). The fraction of R^2 attributed to associate programs is robust to using this set of deals, nearing 20 to 40% across all outcomes. Table IA10 replaces firm fixed effects with fund fixed effects from StepStone where available. Doing so focuses on more narrow variation, comparing investments led by different professionals after partialling out fund-specific factors. The fraction of R^2 attributed to

fund fixed effects is higher than the fraction attributed to firm fixed effects. The fraction attributed to early career firms is also robust to this tighter specification, hovering between 30 and 50% of explained variation for most outcomes.

2.2.1 Investment Style Groupings

As another way of measuring investment styles, I assign deals into style groups by training an autoencoder to compress 30 deal characteristics into five latent dimensions. The encoder portion of the model then produces five continuous style components for each deal. The resulting five dimensions explain about 60% of variation in deal characteristics. The choice of five styles is somewhat arbitrary, but is meant to balance interpretability of the styles with the overall variation explained after performing the dimension reduction. I use this approach to estimate styles, rather than other factor or principal analysis approaches, to better account for potential non-linearities in how the variables may interact. Principal component analysis, for instance, requires about 12 principal components to similarly explain about 60% of variation in considered deal characteristics.

Table IA11 presents correlations between estimated style factors and deal characteristics for deals in the connectedness sample. There is inherent subjectivity in how I label the resulting styles, and the results do not depend on how I choose to do so. But for illustrative purposes, deals in the connectedness sample sort into groups of investments that have a: conservative/traditional focus (tending not to add new debt or change the management); technology/growth focus (favoring software companies); operational/turnaround focus (favoring add-ons, CXO turnover, and debt refinancing); services/flexible credit focus (favoring commercial services companies, uni-tranche debt, and debt with delayed draws); and a financial engineering focus (favoring new debt more generally). Figure IA2 reports style trends over time, showing that the growth/technology focus and services/flexible credit focus have become more pronounced. Similar but noisier trends appear by cohort.

Table IA12 reports the highest and lowest average loading on each style by PE firm, which is generally consistent with the assigned labels. Technology focused PE firms such as Thoma Bravo, Vista Equity Partners, Francisco Partners, and Symphony Technology Group load positively on style 2 (technology/growth). In contrast, manufacturing-focused PE firms such as Fulhalm & Co. or Altus Capital Partners load negatively on style 2. Clayton, Dubilier, & Rice often relies on

operating partners and loads positively on style 3 (operations/turnaround). Larger firms with more "generalist" investment approaches, such as Blackstone, KKR, or Carlyle, tend to load negatively on style 4, but otherwise do not rank in the extremes of other styles. The firms that load positively on style 4 (e.g., Greenbriar, Knox Lane, Warren Equity Partners) often concentrate on investments in the "lower-middle market," characterized by services companies with flexible capital structures in my sample.

Table IA13 shows the fraction of R^2 for whether a partner leads a deal following any of the five estimated styles attributed to early career experiences is between 30 and 50%. Associate firms are the most important, capturing about 30% of R^2. PE firms are important for these measures of styles as well, but less important compared to professionals leading the deal by a factor of two to three. These decompositions are similar to other style results that do not rely on these groupings.

2.3 Associate Experiences: Mentors versus Firms

Table 5 re-estimates the Shapley decomposition after including an additional fixed effect for the more senior professional that each partner worked with while they were an associate ($\delta_{m(i)}$). I refer to these professionals as "mentors." The estimating regression becomes:

$$y_{d,i(j,t)} = \lambda_j + \delta_{m(i)} + \delta_{a(i)} + \delta_{f(i)} + \delta_{s(i)} + \omega_t + \varepsilon_{d,i(j,t)}. \tag{4}$$

This specification helps distinguish whether associate experiences are important for explaining variation in returns and styles because of the people the associates worked for or the associate firm itself. A role for mentors is motivated by literature that emphasizes the importance of intergenerational knowledge transfers in partnerships (e.g., Morrison and Wilhelm (2004)). A relatively larger role for associate firms in explaining associate experience effects is motivated by peer effects from work colleagues other than direct bosses (e.g., Lerner and Malmendier (2013)), or less portable features of the firm such as investment committee voting or evaluation processes (e.g., Gompers et al. (2016) and Malenko et al. (2024)).

I use the historical website data to extract mentor-mentee relationships that are otherwise not available in standard datasets. I first construct a list of all companies that each professional worked on (but did not lead an investment in) within their first five years of entering the industry

by parsing person-company relationships from archived websites. I attempt to focus on new investments by requiring that the PE firm employing the professional made the investment in each portfolio company on or after the year they first hired the professional. I then find all other professionals at the same firm who worked on these companies using the union of deal and board relationships in PitchBook, VentureSource, and archived website data. The mentor for each professional, $m(i)$, is said to be the middle or top-level professional who overlapped with the junior professional on these early company involvements the most. Ties are broken based on how active the mentor is, measured by the total number of companies they ever were affiliated with. Based on the combination of commercial and archival website data, the average junior professional has 2.8 portfolio company affiliations over their first five years and overlaps with their mentor on 2.1. Mentors, meanwhile, have 1.5 mentees on average. Section IA.1.3 further discusses this process.

Figure IA3 displays an example. Panel A shows that Alyse Wagner was involved with HITS inc. (a special events management company focused primarily on horse shows) while listed as an associate at Leonard Green & Partners (LGP) in 2006. A professional from LGP first had a board seat in HITS in 2005 based on the union of archival and commercial datasets. Panel B extends the example for Alyse Wagner, showing the profile of Todd Purdy, who overlapped with her on the LGP investment in HITS inc. Completing the example, the website data display six companies that Alyse Wagner was involved with for LGP over her first five years in PE after joining LGP in 2003 (Brightview Holdings, HITS inc., Motorsport Aftermarket, Varsity Brands, Del Taco, and IQVIA). None of these affiliations are available in the union of commercial data as she did not lead the deal or take a board seat recorded by commercial data vendors on any. She overlaps with Todd Purdy on four of these investments. Three overlap with John Danhakl; three with Jonathan Seiffer; two with John Baumer; and seven other LGP professionals overlap with her on one investment each. Todd Purdy is then estimated to be her "mentor."

This approach to estimating mentor relationships entails three caveats. First, it requires that I observe associate experience and early company involvements in the archived website data. These data are available for about 3/5 of lead professionals that completed 2/3 of deals in the connected sample. Second, this method of estimating company affiliations can include companies the professional worked with while they were vice presidents (or other middle-level professionals) because firms do not always list involvements for associates or because professionals' affiliations

with companies reflect them joining the deal team after the investment was already made. Third, I cannot view staffings on potential investments that a firm did not successfully complete. Hence, it is important to caveat that this measure of mentorship captures which more senior professionals PE investment professionals worked with early in their careers (before leading any investments themselves), not always a staffing on a new potential investment the firm was able to complete.

Turning to results, Table 5 shows mentor fixed effects are up to two-times more important than associate firms for explaining return outcomes and various measures of investment styles. Mentors capture about 40% of explained variation in styles and returns, while the attribution given to associate firms is reduced from 30% to 20%. Mentor fixed effects further account for a larger share of explained variation than firm fixed effects, suggesting that who partners worked with on their initial staffing relationships are important for the investment styles and returns of PE professionals. This finding indicates that an important channel for why associate experiences are important comes from the senior professionals that associates work with, not just the associate firm itself.

2.4 Comparison with Lead Professional Fixed Effects

Figure 4 benchmarks the investment style and return decomposition against Shapley value R^2 decompositions obtained from a regression of deal outcomes and styles on lead professional and partner firm fixed effects (Equation (1)). Regressions samples vary slightly across specifications. Partner fixed effects require that the professional led more than one deal. Mentor fixed effects require that the mentor was recovered.

Figure 4 shows that estimating Equation (2) obtains an R^2 close to that resulting from estimating Equation (1). Further, the R^2 comes closer if additionally including mentor fixed effects (estimating Equation (4)). In some cases, the variation in regression samples means the R^2 with mentor fixed effects exceeds the R^2 with partner fixed effects. The R^2 of NPV regressions equals 33% when estimated using early career experience fixed effects (Equation (2)), 41.7% when additionally including a mentor fixed effect Equation (4)), and 42% when the partner fixed effects are not replaced by the early career fixed effects. The below Table summarizes back-of-the-envelope calculations estimating the contribution of these experiences to partners' overall contribution to

deal NPV.

	NPV($MM; 15%)	
Partner R^2 (φ_{Partner})	31.80%	31.80%
FE Spec.	Equation (2)	Equation (4)
φ_b	% Decomposition ($\varphi_b/\varphi_{\text{Partner}}$)	
Associate Firm	40.4%	31.7%
Pre-PE Firm	9.8%	10.7%
School	13.5%	9.0%
Mentor		45.6%
Total % Explained	63.8%	97.0%

Partner fixed effects account for about 31% of total variation in NPV (75% of explained variation). Meanwhile, in the first specification, associate firms, schools, and pre-PE firms account for 19% of total variation in NPV (60% of explained variation). As a back of the envelope calculation, this indicates that about two-thirds of the variation explained by partner fixed effects comes from early career experiences (=19% / 30%). In the second specification with mentor fixed effects, the variation attributed to associate firms, education backgrounds, and pre-PE firms declines some, but the inclusion of mentor fixed effects brings up the overall explained variation to about 42%. As a back of the envelope calculation, this indicates that almost all (97%) of the variation explained by partner fixed effects can be accounted for by variation in early career experiences. Figure IA4 shows similar decompositions for the auto-encoded styles of Section 2.2.1.

The explanatory power of partner fixed effects when estimating Equation (1) is similar to that documented by Ewens and Rhodes-Kropf (2015) in VC, despite different sample periods, investment firms, types of investments, mappings of partners to deals, outcomes, and decomposition approaches. The explanatory power given to partners, rather than firms, that I document is however higher if returns are measured using NPV rather than gross return multiples. One new contribution of my paper is to show that the partner fixed effects can be further decomposed into early experience fixed effects.

2.5 Sub-Sample Analysis

This section estimates the R^2 decomposition of investment NPV and approaches among different subsets of partners and deals. Doing so provides additional insights into how heterogeneous associate experiences matter for different PE professionals and investments. Table 6 reports results. Panel A shows that the R^2 attributed to associate firms is higher for partners who worked at smaller associate firms (11% of explained variation equal to 25% of R^2) compared to the attribution for partners who worked at the largest associate firms (15% of R^2).[6] For this sample split, the largest firms have top-quartile AUM among in-sample firms as of the year the partner previously joined as an associate; partners from remaining firms with AUM data are said to be from the smaller firms. For partners who worked as associates at smaller firms compared to partners who worked as associates at larger firms, the PE firm at which they are a partner receives a relatively higher share (42% versus 21%) and time-series variation is less important for variation in deal NPV (10% versus 30%).

R^2 attributions also vary by the backgrounds of PE professionals. Associate firm fixed effects have larger attributions among professionals with a degree from Harvard, Stanford, or Wharton (the three most common degrees for PE professionals) or one of the 27 other Top-30 U.S. schools, equal to about 40%. The attribution is only about 20% of R^2 among professionals without a degree from one of these schools. The decompositions are also relatively higher at around 40% for partners from more prestigious investment banks (Goldman Sachs, JPMorgan, Morgan Stanley, Merrill Lynch, or Credit Suisse) compared to those without this background (around 30%). Attributions are 15% for partners with a prestigious consulting background (McKinsey, Bain, or BCG). The variance attributed to the PE firm the professional works at as a partner are similar across these sub-groups, estimated to be between 25 and 30%.

Variance decompositions are similar for earlier deals (the first two deals a partner leads) and later deals (any subsequent deals). There is some decline in attribution to associate firms, but the main finding is that a similar fraction of explained variance in returns and styles is attributed to the associate program for both early and later deals, similarly hovering between 20 and 40%. Similarly,

[6]The largest associate firms include many firms that are now publicly listed (e.g., Blackstone and KKR). As noted in the introduction, the full sample differences in coefficient estimates for associate experiences at many of the large firms (e.g., Blackstone versus KKR) are still larger than differences in coefficients between, for instance, Goldman Sachs and McKinsey or partner experiences at Carlyle versus Bain Capital (two other large PE firms).

among partners of large PE firms or small PE firms (calculated based on AUM quartiles as of the deal year), the associate firm attribution equals about 30%. However, the firm the professional works at as a partner has much more explanatory power within smaller PE firms (40%) compared to within larger PE firms (15%). Figure IA5 displays these decompositions visually.

Panel B of Table 6 repeats the decomposition for investment styles. To conserve space, I present only the decomposition of autoencoded style 2 (the loading on growth / technology buy-outs) but similar results are present for the other investment style variables. Panel B presents markedly less variation when estimated within different subgroups compared to Panel A. For instance, the R^2 attributed to associate firms is 20% for partners who were associates of large PE firms and 27% for partners who worked as associates at smaller PE firms.

The results in this section indicate that there is more variation in associate firm effects among deals led by partners who worked as associates at smaller PE firms than larger PE firms, where firms tend to be more similar in terms of the quality of their deal flow. Associate experiences explain NPV throughout a PE professional's career and are more important for deal NPV among partners of more prestigious backgrounds compared to those from others. The role of associate experiences in explaining subsequent investment approaches is similar for partners with different backgrounds.

3 Associate Program Effects: Cross-Sectional Evidence

Results presented in Section 2 show a significant portion of variation in investment professionals' deal returns and investment styles is attributed to their early career experiences. Partners' associate experiences, in particular, have substantial explanatory power. Further, the senior professionals that associates work with, not just the PE firm itself, are an important component of associate experiences. This section examines the economic forces that contribute to the associate experience effects.

Discussion of the underlying conceptual framework in Section 2 highlights two main economic channels. Associate experiences may help junior professionals acquire particular investment skills from the deals they were exposed to or worked on (e.g., Gibbons and Waldman (2006)).[7]

[7]In the model, workers acquire human capital (investing skills in my context) specific to the tasks they work

The high explanatory power of associate experiences for subsequent investment styles offers some preliminary support for this channel insofar as associate experiences help partners learn how to implement a particular investment approach. Alternatively, associate experience effects can arise because more skilled future partners sort to particular firms early in their careers (e.g., Jovanovic (1979)).

As a direct test distinguishing the role of assortative matching and learning in explaining associate experience effects, I compare investment approaches and deal returns among partners who were former associates of the same firm. The key econometric assumption is that this comparison holds fixed average differences in assortative matching that could arise from comparisons between partners with different associate experiences.

I estimate how similar any two deals are based on their cosine similarity. Deals are characterized by vectors including indicators for 75 measures of styles (15 deal type (e.g., management buyouts versus take-privates) ; 20 target company industry; 20 target company location; 5 capital structure changes; 11 debt characteristics; 4 management changes). The cosine similarity measure of interest is between a focal deal (d_i) and the set of deals partner i leading the focal deal observed while they were an associate (A_i). Main specifications have A_i include all platform buyout deals completed by the firm the partner worked at as an associate over the first five years the partner worked in the PE industry. For example, if the professional first led a deal for GTCR in 2011 and was an associate at Blackstone starting in 2003, I calculate the cosine similarity between each deal the professional led in 2011 and later to all platform U.S. buyouts completed by Blackstone from 2003 to 2007 (spanning five years). Indicators in the comparison vector equal 1 if they are observed once across any deal in the comparison set A_i and 0 otherwise. This method allows me to later include fixed effects for style groupings estimated in Section 2.2.1. I choose a five-year window because the exact length of associate tenure is not available for all partners and this length captures how many years typically minimally elapse before a professional begins leading deals. Results are, however, robust to other more precise estimates of the length of a partners' prior as-

on, which goes unutilized if the worker is assigned to different tasks. In PE, the tasks assigned to associates are homogenous across firms, centered around performing due diligence on potential investments and monitoring pre-existing investments. These tasks typically involve building financial models, helping to draft investment memos, coordinating external consultants, and attending board meetings alongside more senior members of their deal teams (e.g., United States Private Equity Council (2024)). Heterogeneous effects of associate experiences instead come from idiosyncratic features of associate firms, partners, and deals the junior professionals are exposed to.

sociate tenure. Regression samples use the full sample of deals with lead professionals but are marginally stronger using the connectedness sample.

Figure 5 summarizes trends in cosine similarity over professionals' investing careers. Panel A shows that cosine similarities with associate firms' deals trend downwards, starting near 0.35 for the partner's first deal and equaling about 0.25 on the partner's tenth deal. This trend, although declining, shows about 93% of the cosine similarity between a partners' first deal and the deals they were exposed to as associates is retained on their fifth deal. 75% is retained on their tenth deal. There is a strong path dependency investment approaches over partners' careers, starting with the deals they were initially exposed to. The relationship is similar if restricting the sample to only partners that led, for example, five or more deals in total, indicating this pattern is not driven by short or incomplete careers.

Panel B plots cosine similarities between the first deal a partner leads and each subsequent deal. The second deal and first deal have a cosine similarity of about 0.37. The tenth deal (and later) and the first deal have a cosine similarity of about 0.30. This trend shows initial similarity predicts subsequent similarity and that partners tend to do similar deals over their careers. Further, similarity with associate firm deals captures a sizeable portion of within-partner deal similarity.

3.1 Deal Returns and Cosine Similarities

Table 7 presents regressions of gross deal TVM on the cosine similarity between a focal deal and the deals the partner was exposed to during their associate years. In addition to controls for deal characteristics (e.g., deal size) and fixed effects for the deal year or the PE firm at which a professional is a partner, Panel A also includes fixed effects for the PE firm the partner leading the deal worked at as an associate. This comparison aims to hold fixed average differences in assortative matching that could arise from comparisons between partners with different associate experiences. The results indicate that a one standard deviation increase in cosine similarity is associated with a 0.30 increase in gross TVM (0.17 standard deviation $\times$ 1.75 estimated coefficient). This association is economically sizeable, equal to about a 10% increase relative to the mean. The remaining columns in Panel A show that similarities tend not to result in deals with large losses that deliver a return between 0 to 1x. Instead, deals with high similarity are more likely to result in TVM

between 2 to 4x. These results imply similarity helps partners avoid poor return outcomes.

Figure 6 plots binscatter relationships between TVM and similarity when similarity is calculated using only subsets of the style vector inputs. Deals that are similar to associate firm deals based on industry, target company location, or deal entry style do not correlate with higher TVM (after including fixed effects for the PE firm the partner worked at as an associate). The upwards sloping relationship between TVM and similarity instead comes mostly from similarities based on capital structure changes, debt characteristics, and subsequent management changes at the portfolio company. These results indicate shared asset selection components of style are less important for returns compared to shared active management components of style.

Panel B of Table 7 focuses on tighter variation to estimate the relationship between similarity and deal returns. The specifications in this panel additionally include fixed effects for the more senior professional the partner worked with the most while they were an associate. Section 2.3 discusses how I estimate this relationship based on overlap of portfolio companies listed on historical webpages for associates and more senior professionals. This specification additionally holds fixed average differences in assortative matching between associates and partners within the PE firm they worked at as an associate, further accounting for potential selection concerns. The results presented in Panel B are similar to those presented in Panel A. There is a positive correlation between similarity and returns, due mostly to a decrease in deals with large losses (0 to 1x) paired with an increase in deals with material gains (2 to 4x).

Table IA14 reports a similar finding after including fixed effects for the main style of the deal or for the partner leading the deal. These specifications hold fixed differences in average returns using tighter variation, further accounting for potential selection concerns. Table IA15 indicates that a one standard deviation increase in cosine similarity is correlated with an NPV increase of $30 to 40 million.

Positive Assortative Matching. The regression specifications estimated in Table 7 also allow further investigation of the scope of potential assortative matching on two dimensions. The first is between junior professionals and PE firms. In particular, if more skilled future partners sort to particular firms early in their careers as associates, there should be a positive bias in estimated coefficients when the cross-sectional regressions are estimated without associate firm fixed effects,

arising because more skilled partners would tend to perform better regardless of this experience. Panel A and B of Figure 7 investigate, showing that regressions of TVM on cosine similarities result in a slope of about 1.3 without fixed effects for which firm a partner worked at as a PE associate and a slope of about 1.85 once these fixed effects are included. (Note that all regression samples in Figure 7 match that used in Panel C, which varies slightly compared to that used in Table 7 to allow for subsequent comparisons, but the resulting conclusions are otherwise the same.) A positive bias without fixed effects for which firm a partner worked at as a PE associate does not appear in the data, failing to support positive assortative matching.

A second possible source of positive assortative matching occurs within PE firms, between junior associates and their mentors. The nature of the bias is the same: if more skilled future partners sort to particular mentors early in their careers as associates, there should be a positive bias in estimated coefficients when the cross-sectional regressions are estimated without mentor firm fixed effects, arising because more skilled partners would tend to perform better regardless of which mentor they sort to. Panel C of Figure 7 investigates, showing a slope of about 1.6 once mentor fixed effects are included. The relationship between returns and similarities, therefore, exhibits a marginally positive bias when estimated with-associate firm rather than within-mentor. This suggests the more relevant dimension of assortative matching occurs within PE firms between junior professionals and their mentors, but is overall not strong enough to account for the majority of associate experience effects among professionals that led deals as partners.

The results in this section combine to suggest the existence of what I refer to as "style-specific" investment skills – an investment skill that is useful when the partner follows an investment approach they were exposed to early in their careers but not if they follow a different investment approach. This is similar to task-specific human capital in the model of Gibbons and Waldman (2006).

4 Associate Program Effects and Tradeoffs for Partners

Results presented in Section 3 show learning or imprinting during associate years are important for PE professionals that go on to be partners. Providing these learning experiences is, however, costly for firm partners and principals, requiring their time and other resources to employ and

coordinate the associates. Why hire associates? What is the benefit for incumbent partners? This section presents evidence estimating the effect of associates on PE firm investing activity that helps address these questions.

While it is generally challenging to isolate the effect of any one group of employees on firm outcomes, key features of associate employment at PE firms allow me to do so by directly relating the turnover of associates to the number of buyout deals a PE firm completes. Associates work at PE firms in programs of quasi-fixed periods of two or three years in up-or-out contracts. At the end of the scheduled associate program, four main outcomes are possible for the associate: (1) direct promotions, (2) temporary separations from the firm to pursue an MBA before a promotion, (3) staying on for a few years as a senior associate prior to promotion, or (4) separations from the firm.

Berkshire Partners, a Boston based PE firm, provides an example of outcomes (2) and (4), where MBAs typically precede promotion and non-promoted associates sharply separate. Berkshire Partners lists eight associates on its website in October 2006, each of whom remained at Berkshire Partners as an associate for three calendar years. Jonathan Altman is listed as an associate from 2005 to 2007; Andrew Ferrer from 2005 to 2007; Alan Ghelberg from 2005 to 2007; Paul Maasdorp from 2006 to 2008; Nii Amaah Ofosu-Amaah from 2006 to 2008; Daniel Osnoss from 2005 to 2007; Ajay Prakash from 2006 to 2008; Evan Richardson from 2006 to 2008. Alan Ghelberg and Nii Amaah Ofosu-Amaah both separated to pursue an MBA (at Harvard Business School) before returning to Berkshire Partners at a more senior position. The remaining associates separated and did not return. Returning to Figure 3 also shows this pattern is more general, with associate promotions and separations occurring primarily around the third calendar year.

These standard employment structures motivate a simple instrument for associate turnover: the fraction of a firm's associates *predicted* to be at the end of their scheduled associate programs. I test whether incumbent PE partners benefit from increased investment activity that comes with developing their associates by estimating the relationship between instrumented associate turnover and the number of deals a PE firm does. Partners and other senior professionals typically source and complete transactions. Associates are responsible for due diligence, financial modeling, and other pre-investing work that may otherwise go uncompleted if the firm lacks sufficiently experienced associates, potentially leading partners to forgo some investments (or fail to find investable companies). A negative relationship between instrumented associate turnover and deal-making im-

plies that associates, particularly separating associates that are marginally more experienced than those that remain, are important inputs to PE investment activity. A positive or null relationship instead implies departing associates are, on balance, a constraint on partners' time.

I predict the fraction of associates at the end of their scheduled associate programs with the fraction of a firm's associates in their third calendar year or later with their firm. First- and second-stage equations take the form:

$$\%\ \text{Turnover}_{jt} = \beta_1 \times \text{Predicted Turnover}\ \%_{jt} + \lambda_j + \gamma_{j(s,t)} + \gamma_{j(\ell,t)} + \epsilon_{jt} \tag{5}$$

$$y_{jt} = \beta_{IV} \times (\%\ \widehat{\text{Turnover}})_{jt} + \lambda_j + \gamma_{j(s,t)} + \gamma_{j(\ell,t)} + \varepsilon_{jt}, \tag{6}$$

where j indexes the PE firm and t indexes the year. Equation (5) is the first-stage. Equation (6) is the second-stage. Program expirations are staggered across firms and time, so these regressions benefit from firm fixed effects, denoted λ_j. Regressions further benefit from year fixed effects, which I interact with the main locations (s) and industries (ℓ) in which a firm invests (denoted by γ). These fixed effects partial out any firm-invariant, geography-time-invariant, or industry-time-invariant factors that may also influence deal activity or turnover. I weight regressions by the number of associates employed by firm j in year t. Counts of professionals are based on archived website data. Standard errors are clustered at the firm level. The associate turnover effect on investment is identified from within-firm variation in years when a higher fraction of associates is predicted to reach the end of their fixed-term programs.

Relevance Condition. Table 8 presents the results of estimating the first-stage regression. Column (1) indicates that a one standard deviation increase in the fraction of associates that are in their third year or higher (26%) is associated with a 7% increase in the fraction of associates that turnover (= 26% ×0.212 estimated regression coefficient). Panel A of Figure 8 presents this relationship visually, showing an upwards-sloping linear relationship between the two variables. Column (2) shows a slightly stronger relationship that does not vary across market conditions. Associate turnover also is not positively correlated with the hiring or investing activity of the firm when the associates affected by the instrument were hired. The first-stage F-statistic obtained in subsequent 2SLS regressions of nearly 200 indicates a strong instrument.

Exclusion Restriction. For the instrument to be valid, associate tenure must also be related to a firms' investing activity only through associate turnover. I conduct several tests to support this assumption.

Comparison on Observables: First, Table 9 compares firm-years that have a higher fraction of associates in their third calendar year or later to firm-years that do not based on observable characteristics. Samples are split based on medians within each calendar year. Panel A, B, and C respectively show the instrument does not meaningfully correlate with trends in firm investing activity, firm characteristics, or investment team characteristics. The instrument does not favor, for instance, firms with differential dry powder, fund performance, or investment team compositions. These results indicate associates of observably similar firms are exposed to the instrument.

Reverse Causality Placebo Tests: Second, I assess the potential for reverse causality to drive the results. Reverse causality means associates do not affect investment, rather differences in investments determine how long associates are predicted to remain at their firm. Under this interpretation, PE associates may seek to leave firms differentially based on their firm's deal-making prospects. If so, the IV results should be driven by firms with differential deal-making prospects. To examine this possibility, I split the sample to isolate GPs that have different deal-making prospects and estimate the 2SLS specification separately in each sub-sample of firms. Several rows displayed in Panel B of Table 10 present these tests. I consider various proxies for a firms' investment prospects, each of which are intended to isolate whether results are driven by firms that overall are doing fewer deals or otherwise lack the capital to make more investments. Rows 2 and 3 show similar results if firm-year cells are split based on whether the GPs hired new associates (and therefore had success in recruiting new talent, which is less likely if the firm was distressed). Rows 4 through 7 show similar results if splitting based on other measures of hiring. Row 8 shows results attain in firm-year cells where the partners do not separate from the investment team, which is reassuring given evidence (and alternative reverse interpretation) that firms tend to lose skilled employees leading up to distress (e.g., Baghai et al. (2021)). Row 9 shows results are present if the GP has raised a new fund in the prior three calendar years (over the associate's predicted tenure). Rows 10 and 11 show similar results based on whether deal volume was high or low when the associates most directly affected by the instrument were initially hired. Inconsistent with reverse causality, these results indicate the IV results are not driven by firms with different deal-making

prospects.

Omitted Variables Placebo Tests: Third, I assess whether other potentially omitted variables may drive my results. Panel B of Table 10 presents the first set of tests. Rows 12 through 15 show the IV does not concentrate in years with relatively higher or lower equity returns or credit spreads. This is reassuring given these factors matter for aggregate buyout activity (e.g., Axelson et al. (2013) and Haddad et al. (2017)). Row 16 presents similar results after excluding junior-level professionals with analyst or senior associate positions (which may otherwise result in endogenous deviations from a standard associate program). Table IA16 shows results are robust to the inclusion of extensive controls for potentially omitted variables and several other specifications. These results indicate the IV results are not driven by any of the considered potentially omitted variables.

2SLS Estimate. Panel A of Table 10 presents the results of estimating the 2SLS regression presented in Equation (6). The estimated coefficient has a value of -2.2, indicating that a one standard deviation increase in instrumented associate turnover results in a decline of about 0.6 buyouts per year ($\approx$ 2.2 regression coefficient $\times$ 0.27 standard deviation). This estimated effect is economically meaningful, equaling about 22% of the average number of deals completed each year per standard deviation of associate turnover. Panel B of Figure 8 presents this relationship visually, showing a downwards-sloping relationship between deal quantities and instrumented associate turnover. Figure IA6 displays the results using the alternative *binsreg* command introduced by Cattaneo et al. (2024), which adjusts the residualization and the number of bins.

These results provide evidence that the partners of a PE firm forgo some investments (or fail to find investable companies) if they lack sufficiently experienced associates, suggesting an important role of associate experience for PE firms. Because associate turnover replaces more experienced associates with less experienced associates, a complementary interpretation of this result is that it further provides evidence that associate experiences help junior investment professionals acquire human capital independent of assortative matching.

4.1 Additional Benefits for Partners

Partners may also benefit from managing associates if hiring and staffing them on deals helps to identify future partners with investment skills. Figure IA7 presents simple descriptive statistics that inform the role of this screening channel for understanding the potential benefits of associates to partners. The plot is limited to professionals that entered the industry between 1995 and 2012, the window at which website coverage is complete and professionals have sufficient time to become a partner. The sample includes about 14,000 investment professionals. Approximately 6,600 are partners, 5,900 are associates, and about 1,500 were observed as both investment associates and partners. For a given cohort of associates, about 10 to 15% become a partner at the firm they worked at as an associate. For a given cohort of eventual partners, about 10% were previously associates at the same PE firm. For a given cohort of associates that became partners, nearly 60% were previously associates at the same firm. These findings show that few associates become partners and firms typically source their partners from elsewhere; however, among the associates that became partners, they tend to have become a partner at the same firm, rather than a different firm. These results are consistent with PE firms benefiting from associate programs by using them to selectively identify, develop, and promote internal talent.

5 Conclusion

The central conclusion of this paper is that PE return outcomes can often be attributed to the deal structure, industry selection, and subsequent investment management decisions that PE partners learned as junior PE associates when they first entered the PE industry.

Using a newly-created dataset of PE investment professionals and their careers combined with several other datasets, I estimate that a sizeable fraction of the explained cross-sectional variation in deal returns and deal characteristics is attributable to where PE partners first worked as PE associates. Decomposing the variation in deal returns, for example, shows that about 33% of the R^2 in deal-level performance regressions can be explained by which firm the lead partner worked at as a PE associate. Similar results attain for investment "styles": PE associate programs explain 20 to 40% of the explained variation in various deal characteristics, ranging from which industries the partner invests in to whether the portfolio company changes its CEO. The more senior profes-

sional the partner worked with the most, their "mentor," accounts for a majority of the associate experience effect.

Cross-sectional regressions comparing the investment decisions and returns of partners from the same PE firm or with the same mentor help to disentangle whether associate experience effects arise because of learning opportunities or assortative matching. Regressions show a partner's deals deliver higher returns if they are relatively more like deals they observed as an associate, even among two partners who worked at the same firm as an associate or had the same mentor. Similarities in investment styles related to capital structure or management changes are the most important for deal returns.

The experience of junior PE professionals also directly relates to their PE firm's investing activity. I document that a marginal decrease in associate experience causes about a 20% decline in a firm's investing activity, indicating that the partners of a PE firm forgo some investments (or fail to find investable companies) if they lack sufficiently experienced associates to carry out pre-investment work. These results indicate PE partners tradeoff the costs of providing these learning experiences with the benefits of more deal-making.

Overall, my results provide new evidence that individual fund managers' differing investment approaches and return outcomes are driven by differences in the investment approaches they were exposed to early in their investing careers. The results imply investment careers are at least partially path-dependent; investors' success at investing in financial markets depends largely on where their careers begin.

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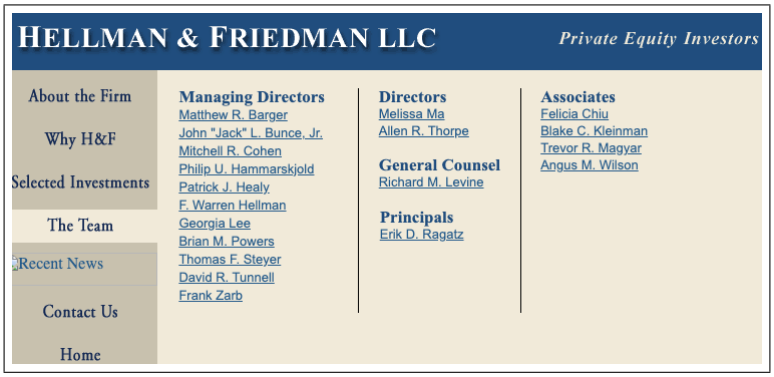
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Figure 1: Example Archived Webpages

Panel A: Hellman & Friedman 2003 Team Page



Panel B: Hellman & Friedman 2003 Personal Page Example

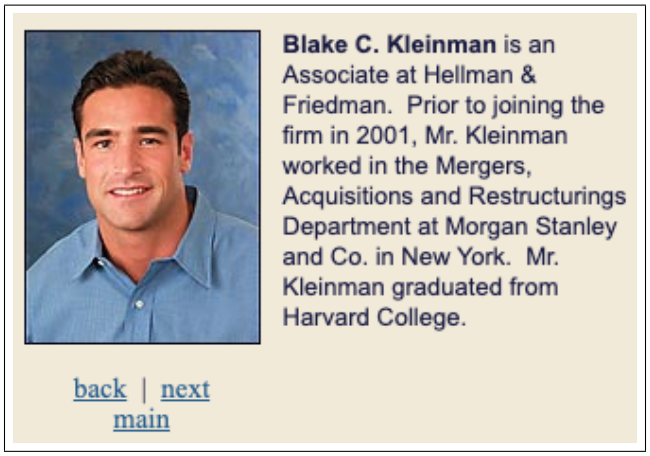


Figure 1: Displays example webpages archived from the Wayback Machine used to construct the dataset of PE investment professionals. Panel A shows the 2003 team page for Hellman & Friedman (linked here). Panel B displays the 2003 personal page for the associate Blake C. Kleinman (linked here).

Figure 2: PE Associate Experience Trends Among Buyout Professionals

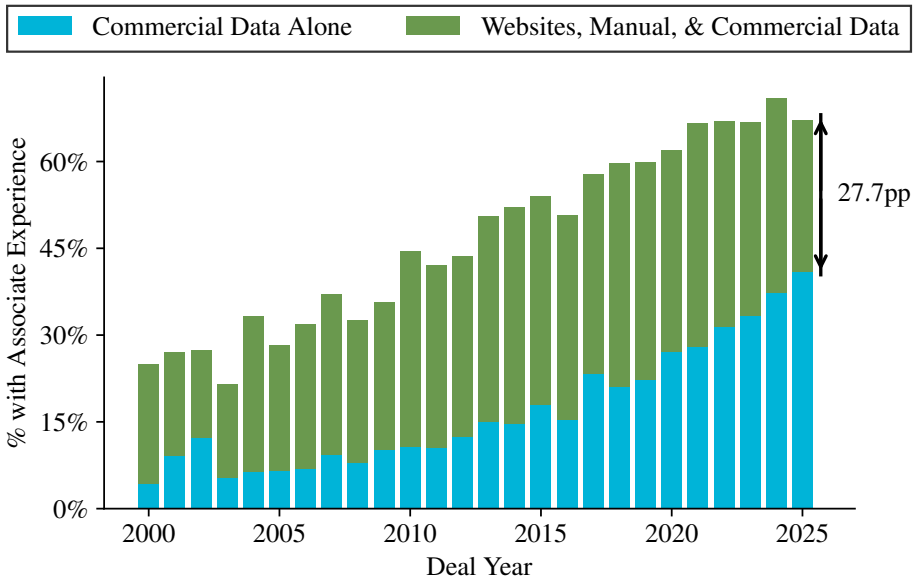


Figure 2: Plots the fraction of lead professionals of stand-alone leveraged buyouts of U.S. companies that had previously worked as an associate at a PE firm. In 2015, for example, about 50% of all lead professionals had previously worked as an associate at a PE firm. Deal data are from PitchBook. The sample includes about 12,000 deals led by about 4,500 professionals. PE associate program experience (if any) is hand-collected if not observed, usually using archived websites. The annotation highlights the incremental coverage for 2025 in percentage points relative to commercial data alone.

Figure 3: PE Career Paths

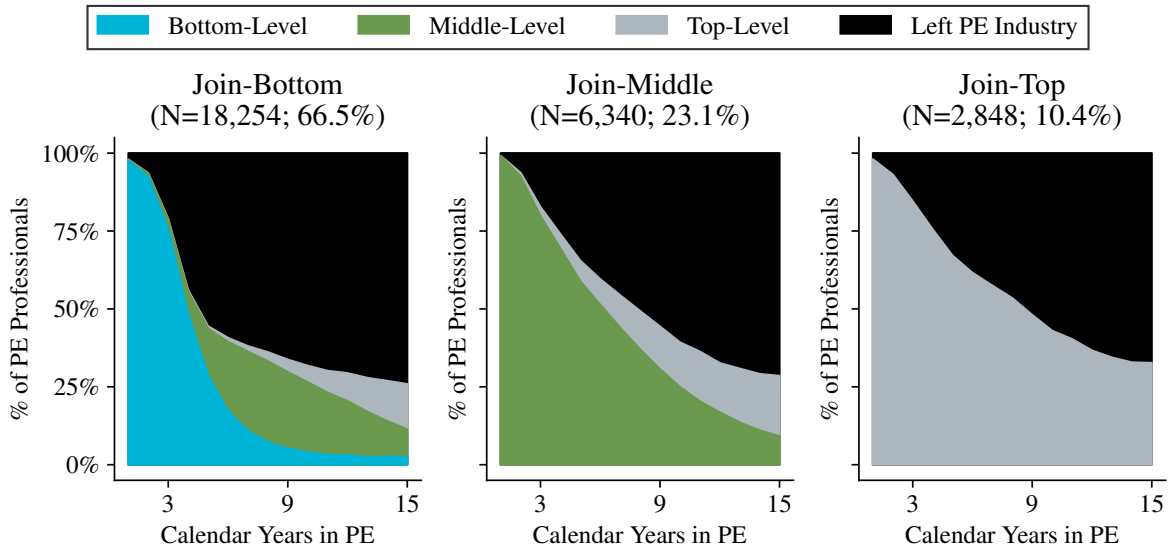


Figure 3: Plots the fraction of private equity professionals that separated from their firm or were promoted to a subsequent hierarchal level conditioned on (1) how many years have elapsed since the year they first joined their firm and (2) their seniority upon joining the firm. Only employment at in-sample firms is considered. Professionals that temporarily leave the PE industry (for example, leave to get an MBA and then come back as a vice president) are treated as having left the industry for years they are not employed by an in-sample firm. Years since joining equals the count of unique calendar years elapsed since professional *i* joined firm *j*. For example, an associate that joined in August 2018 would be in their third *calendar* year as of January 2020. Panels are unbalanced; individuals joining in, for example, 2020, have at most six years of data (2020 to 2025, inclusive). Each plot is smoothed by a lowess function with a smoothing weight of 0.05. "N" displays the total number of investment professionals included in each subsample. Percentages refer to the percent of professionals summarized in the subplot out of all professionals in the Figure.

Figure 4: Investment Style and Return Decomposition

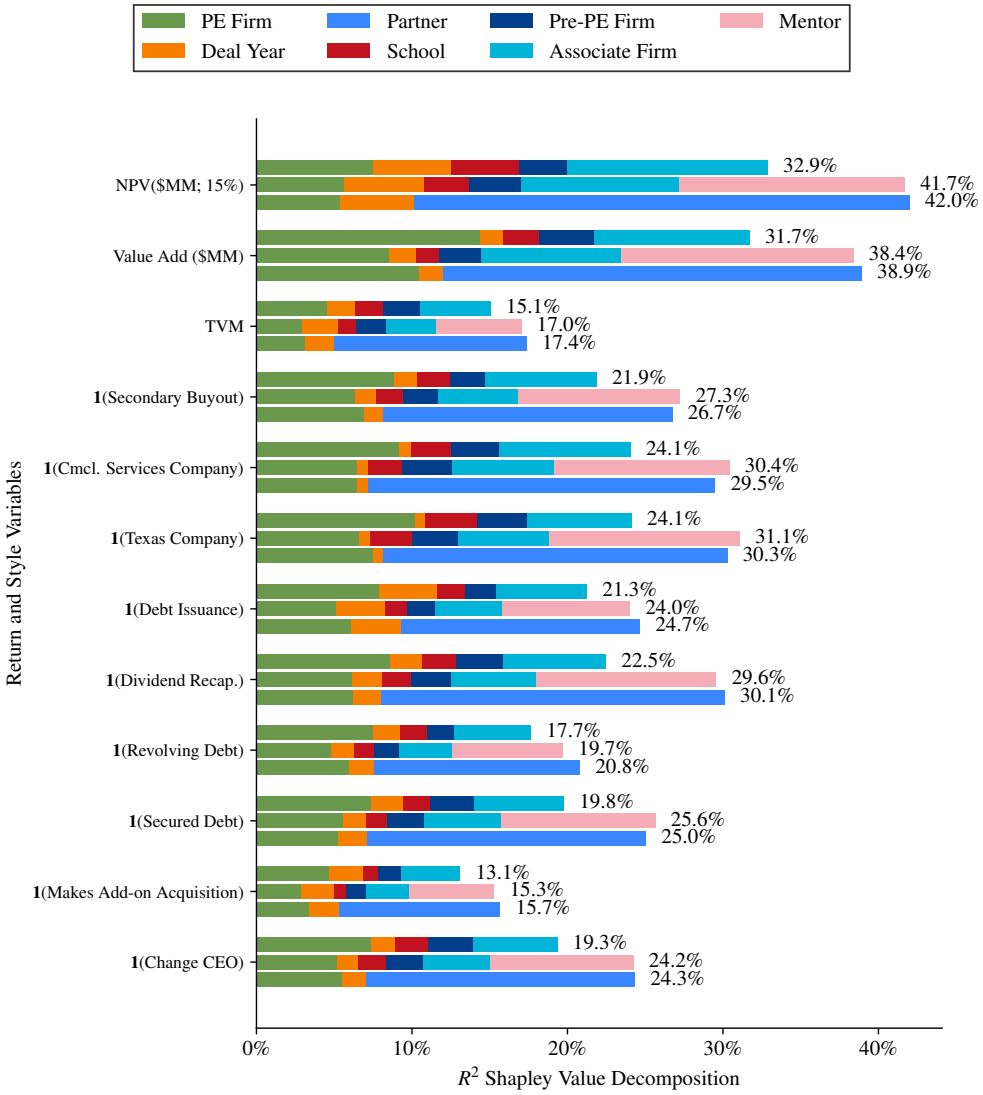


Figure 4: Plots Shapley value decompositions of several fixed effects in explaining variation in investment styles and returns. Decompositions are calculated separately after estimating two different regressions for each outcome variable. The first bar for each variable estimates Equation (2), which includes fixed effects for the PE firm, deal year, and early career experiences (the partner's associate firm, school, and pre-PE firm). The second bar estimates Equation (4) which additionally includes a fixed effect for who a professional worked with the most on completed deals in their first five years after joining the PE industry as an associate. This specification requires that the mentor is known. The third bar for each variable estimates Equation (1), which includes a partner fixed effect rather than the three early career experience fixed effects. Values at the top of each bar report the full model R^2. Bands on each bar report the estimated contribution to the full model R^2 resulting from each set of fixed effects based on a Shapley value decomposition. Regressions estimated with partner fixed effects additionally require that the professional led at least two investments. Deals are from PitchBook and deal returns are from StepStone. Total Value Multiples (TVM; the gross cash flows to the GP divided by their gross investment amount), NPV, and value-add regressions additionally restrict the sample to only exited deals.

Figure 5: Cosine Similarity Over Careers

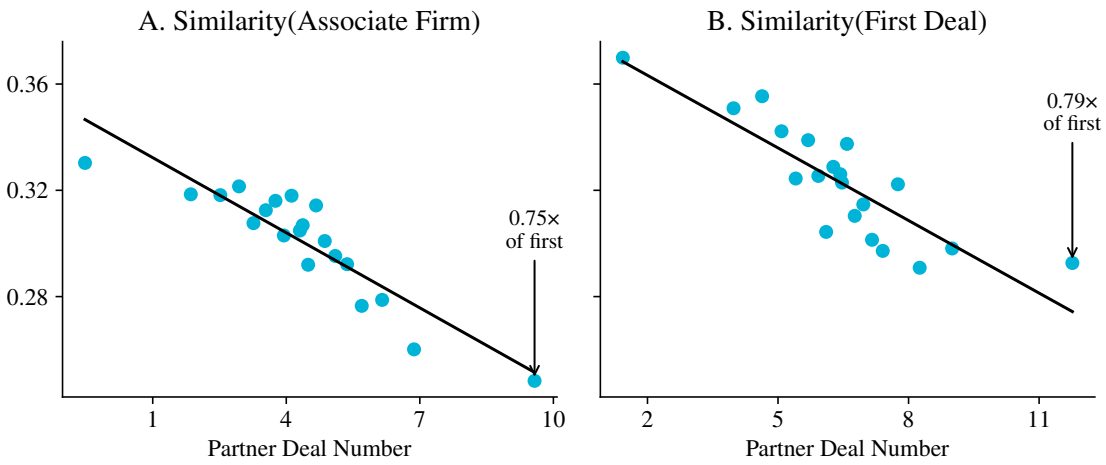


Figure 5: Panel A shows binned scatter plots estimated from regressions of buyout deal returns on the similarity between the deal and buyout deals done by the firm the partner worked at as a PE associate over the first five years of the partner's PE career (starting when they were an associate at the firm). Panel B plots similarities between a partner's first deal and the partner's subsequent deals. Similarities are cosine similarities. Deals are characterized by vectors including indicators for 75 measures of styles (15 entry; 20 target company industry; 20 target company location; 5 capital structure changes; 11 debt characteristics; 4 management changes). Binned scatter plot regressions include fixed effects for the PE firm the partner worked at as an associate, the PE firm the partner represented in the deal, and the year of the deal.

Figure 6: Deal Returns and Dimensions of Similarities with Associate Firms' Deals

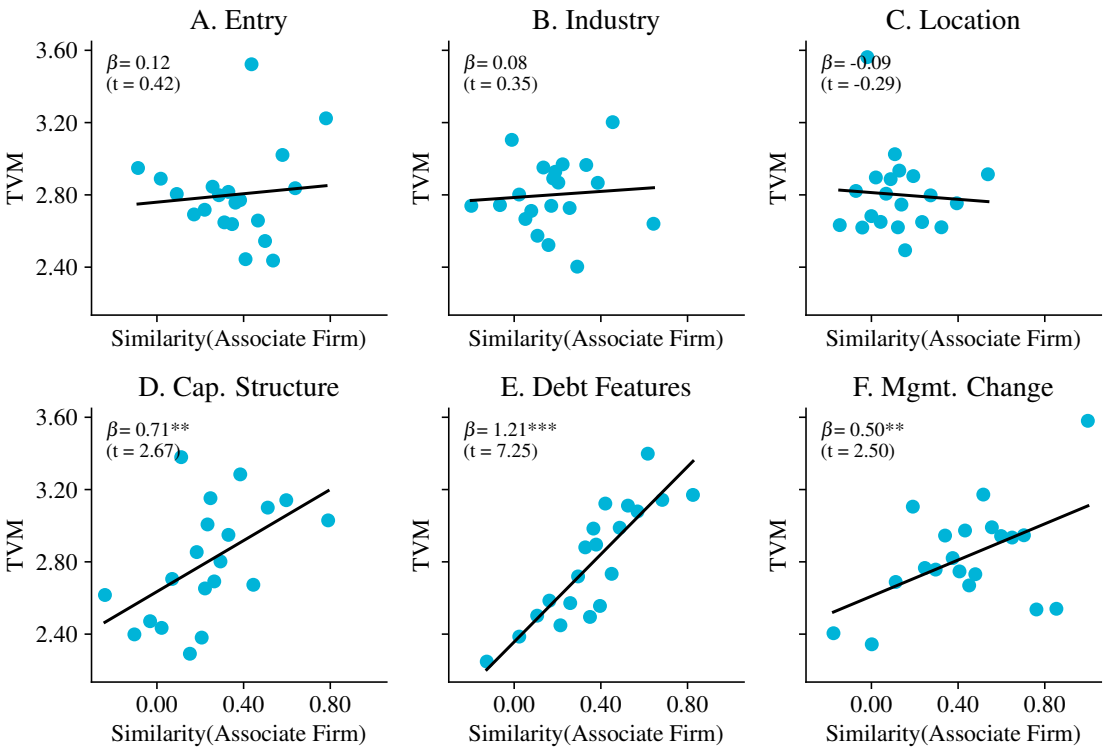


Figure 6: Plots binscatters estimated from regressions of the return of a deal on the similarity between the deal and buyout deals done by the firm the partner worked at as a PE associate over the first five years of the partner's PE career (starting when they were an associate at the firm) on the cumulative count of a partner's deals. Deals are characterized by vectors of different characteristics according to the panel (15 entry; 20 target company industry; 20 target company location; 5 capital structure changes; 11 debt characteristics; 4 management changes). Binscatter regressions include fixed effects for the PE firm the partner worked at as an associate, the PE firm the partner represented in the deal, and the year of the deal. All regressions include controls for the dollar amount invested, the partner's deal number, whether the firm the partner worked at as a PE associate also invested, and the number of years elapsed since the professional started working in PE. Slopes and *t*-stats are calculated using the binscatter results.

Figure 7: Deal Returns and Similarities with Associate Firms' Deals

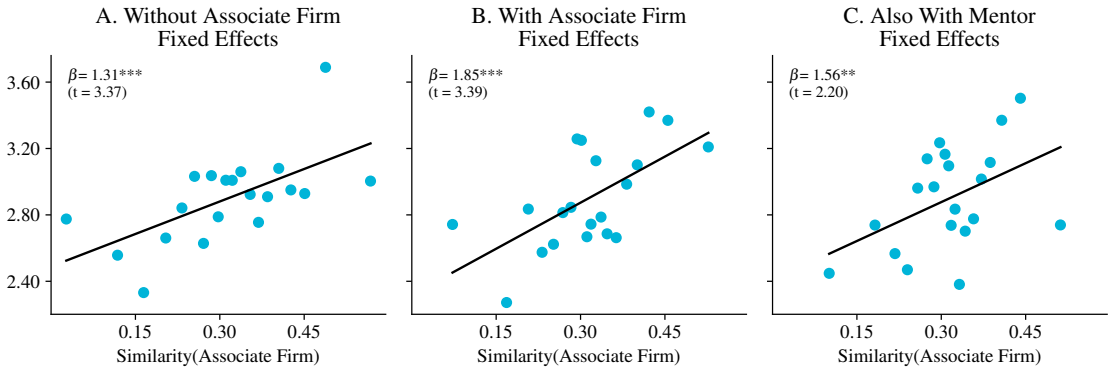


Figure 7: Displays binscatters estimated from regressions of the return of a deal on the similarity between the deal and buyout deals done by the firm the partner worked at as a PE associate over the first five years of the partner's PE career (starting when they were an associate at the firm) on the cumulative count of a partner's deals. Deals are characterized by vectors including indicators for 75 measures of styles (15 entry; 20 target company industry; 20 target company location; 5 capital structure changes; 11 debt characteristics; 4 management changes). Panel A includes fixed effects for the PE firm the partner represented in the deal, and the year of the deal. Panel B includes the same fixed effects and an incremental set of fixed effects for the PE firm the partner worked at as an associate. Panel C also includes fixed effects for a partner's estimated mentor during their associate years. All regression samples are restricted to match those in Panel C. Slopes and t-stats are calculated using the binscatter results, which differ slightly from coefficients presented in Table 7. All regressions include controls for the dollar amount invested, the partner's deal number, whether the firm the partner worked at as a PE associate also invested, and the number of years elapsed since the professional started working in PE.

Figure 8: Instrumented Associate Turnover and Buyout Deals

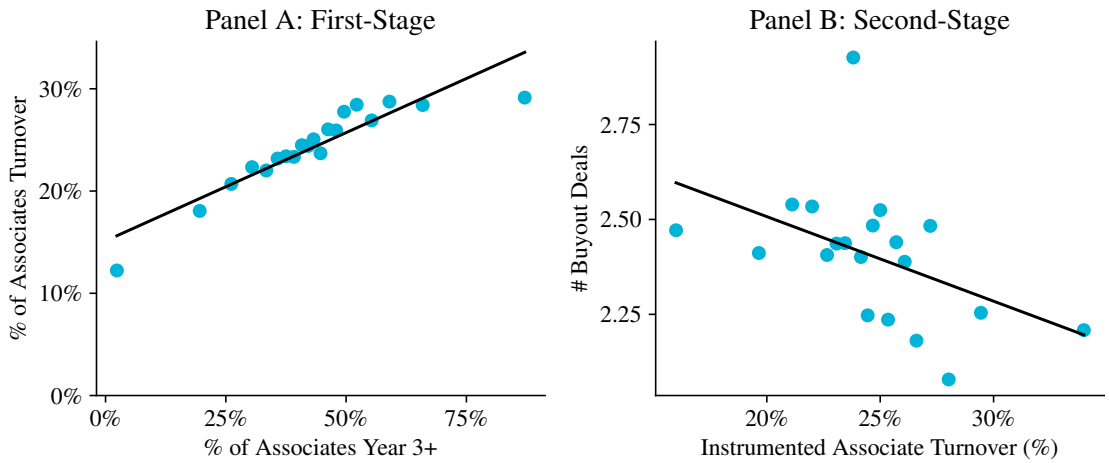


Figure 8: Displays binscatter regressions of the count of PE firms' buyout investments on the instrumented fraction of its associates that turnover each year. The unit of observation is the firm-year (jt). Associates turnover in year t if they are separated from firm j by year $t+1$ or are promoted to the Vice-President seniority or higher within firm j by the next year they are observed (often following a temporary separation to pursue an MBA). Associate turnover is instrumented with the fraction of firm j's associates that have been observed with the firm for three or more *calendar* years as of year t, representing the increasing likelihood that their associate program has ended. Tenure is calculated using calendar years. For example, an associate that joined in August 2018 would be in their third *calendar* year as of January 2020. Regressions are weighted by the number of associates employed by firm j in year t. Panel A displays the first stage of the IV regression (Equation (5)). Panel B displays the second stage of the IV regression (Equation (6)).

Table 1: Summary Statistics

Panel A. Firm-Year Level Statistics

	Nobs.	Avg.	25p	75p
Year	12,193	2014.5	2009	2020
AUM ($B)	8,520	2.1	0.1	1.2
# Funds < 15 Yrs.	10,050	2.8	1	3
# Funds < 5 Yrs.	10,050	1.3	0	2
# Platform Buyout Deals	12,193	1.2	0	2
# Top-Level	12,193	5.5	2	6
# Middle-Level	12,193	5	0	4
# Junior-Level	12,193	4.8	0	5

Panel B. Investment Professional Statistics

	All	Junior	Middle	Top
# Professionals	31,590	18,352	13,255	8,827
# w/ Gender	31,252	18,167	13,142	8,773
# w/ Age	17,542	10,994	7,531	4,809
# w/ Education	28,087	16,730	11,906	7,929
# w/ Work Experience	25,948	15,039	11,338	7,485
1(Female)	17.3%	19.3%	16.3%	7.9%
1(Ivy Degree)	31.5%	27.7%	35.6%	42.3%
1(Ivy/Ivy+ Degree)	43.2%	38.9%	48.9%	56.6%
1(Ivy/Ivy+/Top-30 Degree)	60.9%	59.5%	64.4%	70.4%
1(Observed w/ MBA)	30.4%	18.7%	41.7%	52.3%
1(Investment Banking Exp.)	65.8%	74.4%	64.6%	58.4%
1(Consulting Exp.)	20.6%	16.9%	24.3%	22.4%
1(Other Finance Exp.)	16.1%	11.8%	18.1%	20.1%
1(Hedge Fund Exp.)	1.5%	0.8%	2.0%	2.1%
1(Venture Capital Exp.)	1.8%	1.2%	2.0%	2.6%
1(Government Exp.)	3.3%	2.0%	3.5%	4.8%
1(Law Firm Exp.)	2.5%	0.8%	2.7%	5.1%
1(Observed Junior-Level)	58.1%	100.0%	39.7%	18.3%
1(Observed Middle-Level)	42.0%	28.7%	100.0%	36.9%
1(Observed Top-Level)	27.9%	8.8%	24.6%	100.0%
1(Observed 1-5 Years)	55.5%	68.0%	32.2%	19.8%
1(Observed 6-10 Years)	22.5%	18.2%	35.4%	24.4%
1(Observed 10+ Years)	25.8%	16.2%	38.2%	61.6%
1(Observed at 1 Firm)	85.2%	83.1%	76.8%	78.0%
1(Observed at 2 Firms)	12.3%	13.6%	18.5%	17.3%
1(Observed at 3+ Firms)	2.6%	3.3%	4.7%	4.7%

Table 1: Panel A tabulates the distribution of firm size and investing activity across firm-year cells. Panel B tabulates characteristics of firm investment professionals sorted by whether they were *ever* observed at each seniority. Column counts do not sum to the "All" column if professionals are observed at more than one seniority. Panel B counts report the number of professionals for whom data are available. The sample covers 1997 to 2025. Education includes undergraduate, masters, and post-masters degrees. Work experience is calculated before the professional entered the PE industry.

Table 2: Deal Statistics

	All	Has Associate Experience	Connected
# Lead Partner × Deals	12,908	6,404	5,973
# Deals	12,388	6,273	5,854
# Exited Deals	9,917	4,591	4,286
# Exited Deals w/ Performance	5,850	2,792	2,680
Panel A: Gross Deal Returns (StepStone)			
Investment ($MM)	193	198	201
TVM	2.7	2.8	2.7
1(TVM of 0x)	3.8%	3.5%	3.6%
1(TVM of 0-1x)	20.3%	16.9%	16.9%
1(TVM of 1-2x)	26.9%	26.4%	26.3%
1(TVM of 2-3x)	18.8%	20.9%	20.9%
1(TVM of 3-4x)	11.8%	13.9%	13.9%
1(TVM of 4-5x)	7.1%	7.5%	7.5%
1(TVM > 5x)	11.4%	11.0%	10.9%
Value Add ($MM)	226.3	273.1	276.1
NPV ($MM; 15%)	21.6	42.4	43.5
Panel B: Company & Deal Composition (PitchBook)			
1(Pre-2000)	3.7%	1.5%	1.5%
1(2001 to 2010)	23.5%	14.7%	14.8%
1(2011 to 2020)	46.0%	48.3%	48.4%
1(2021 or later)	26.8%	35.5%	35.4%
1(Lead Investor)	30.4%	27.8%	28.2%
1(2+ Investors)	42.3%	40.5%	40.1%
1(Secondary Buyout)	25.7%	29.3%	30.1%
1(Management Buyout)	17.0%	16.6%	16.3%
1(Texas Company)	11.4%	12.1%	12.2%
1(California Company)	10.7%	10.6%	10.8%
1(Cmcl. Services Company)	20.5%	21.3%	21.0%
1(Cmcl. Products Company)	16.3%	14.5%	14.0%
Panel C: Subsequent Financing Events (PitchBook)			
1(Debt Issuance)	30.3%	35.9%	37.0%
1(Dividend Recap.)	8.3%	8.7%	9.0%
1(Leveraged Recap.)	3.6%	3.9%	4.0%
Panel D: Debt Characteristics (PitchBook - LCD)			
1(Revolving Debt)	43.7%	50.6%	52.1%
1(Senior Debt)	33.5%	36.6%	37.4%
1(Floating Rate Debt)	32.8%	37.0%	38.1%
Panel E: Subsequent Acquisitions and Turnover (PitchBook)			
1(Makes Add-on Acquisition)	52.6%	57.5%	58.4%
1(Change CEO)	22.9%	24.2%	24.7%
1(Change CFO)	20.4%	23.3%	23.7%
1(Change CXO)	35.5%	38.6%	39.4%
Panel F: Exits (PitchBook)			
1(LBO Exit)	41.3%	43.2%	43.5%
1(M&A Exit)	30.7%	28.5%	28.7%
1(IPO Exit)	5.5%	5.0%	5.2%

Table 2: Summarizes the composition of deals in the sample. Additional columns require that the lead partner has entry-level PE associate experience or the partner-deal pair is in the largest connected graph of deals by partner firms and associate firms. Panel A requires performance data from StepStone and that the investment was exited or made prior to 2020. NPV is understated if the deal generates interim cash flows. Company financing and subsequent add-on acquisitions are measured over the first five years following the investment. Debt characteristics refer to any debt issued by the company within the first five years of the buyout (inclusive of transaction debt).

Table 3: Investment Return Decomposition

			% of R^2 Attributable to Fixed Effects							
	Y-Var.	R^2	Associate Firm	p-val.	Pre-PE Firm	School	Deal Year	PE Firm	Y-Mean	Nobs.
	Panel A: NPV, Value Add, and Gross Returns									
(1)	NPV($MM; 15%)	32.9%	39.1%	<.01	9.5%	13.1%	15.4%	22.8%	53.19	1,508
(2)	Value Add ($MM)	31.7%	31.6%	<.01	11.1%	7.1%	4.8%	45.4%	284.98	2,072
(3)	Investment ($MM)	41.1%	26.5%	<.01	7.9%	6.9%	6.0%	52.6%	203.97	2,072
(4)	TVM	15.1%	30.1%	<.01	15.7%	12.3%	11.9%	30.0%	2.8	2,072
(5)	**1**(TVM of 0x)	33.3%	33.5%	<.01	14.8%	9.3%	6.7%	35.7%	0.03	2,072
(6)	**1**(TVM of 0-1x)	22.9%	33.9%	<.01	18.2%	10.7%	4.7%	32.5%	0.16	2,072
(7)	**1**(TVM of 1-2x)	27.6%	28.7%	<.01	12.5%	8.2%	21.0%	29.7%	0.26	2,072
(8)	**1**(TVM of 2-3x)	21.8%	36.1%	<.01	17.9%	8.6%	5.2%	32.1%	0.21	2,072
(9)	**1**(TVM of 3-4x)	22.8%	33.4%	<.01	17.3%	13.3%	6.5%	29.5%	0.14	2,072
(10)	**1**(TVM of 4-5x)	20.9%	34.4%	<.10	19.1%	9.4%	9.4%	27.7%	0.08	2,072
(11)	**1**(TVM > 5x)	28.4%	33.2%	<.01	14.7%	10.0%	10.6%	31.6%	0.11	2,072
	Panel B: Exit Styles									
(12)	**1**(LBO Exit)	19.1%	26.2%	<.01	12.0%	8.6%	20.8%	32.5%	0.43	3,048
(13)	**1**(M&A Exit)	22.1%	25.4%	<.01	12.7%	7.2%	26.0%	28.7%	0.29	2,925
(14)	**1**(IPO Exit)	30.9%	25.0%	<.01	13.0%	9.6%	20.9%	31.5%	0.05	2,892

Table 3: Tabulates the fraction of explained variation in buyout investment returns attributable to a set of fixed effects based on Shapley value decompositions. TVM stands for (gross) Total Value Multiple, which equals the ratio of the dollar returns generated from the deal to the dollar amount the GP invested. Regression samples only include exited deals or investments made before 2021. NPV calculations further require exit dates. The p-value column reports the p-value obtained from F-tests for the joint significance of associate firm fixed effects on each characteristics. Rows report decompositions for separate regressions estimated for the outcome variable in the "Y-Var." column. The unit of observation is the person × deal level. Standard errors are clustered at the deal level.

Table 4: Investing Style Decomposition

			% of R^2 Attributable to Fixed Effects							
	Y-Var.	R^2	Associate Firm	p-val.	Pre-PE Firm	School	Deal Year	PE Firm	Y-Mean	Nobs.
	Panel A: Investment Methods									
(1)	**1**(Lead Investor)	26.0%	18.5%	<.01	9.4%	5.5%	46.3%	20.4%	0.28	4,748
(2)	**1**(2+ Investors)	16.8%	30.9%	<.01	13.6%	10.6%	3.7%	41.2%	0.4	4,748
(3)	**1**(Secondary Buyout)	21.9%	32.8%	<.01	10.4%	9.7%	6.5%	40.6%	0.31	4,748
(4)	**1**(Management Buyout)	25.9%	30.0%	<.01	12.2%	9.2%	5.5%	43.1%	0.16	4,748
(5)	**1**(Take-Private)	26.4%	26.2%	> .10	15.2%	11.0%	5.9%	41.8%	0.05	4,748
	Panel B: Company Industry & Location									
(6)	**1**(Texas Company)	24.1%	28.0%	<.01	13.2%	14.0%	2.5%	42.3%	0.12	4,748
(7)	**1**(California Company)	22.2%	32.8%	<.01	16.3%	10.8%	4.1%	35.9%	0.11	4,748
(8)	**1**(New York Company)	21.5%	32.0%	<.01	13.6%	11.8%	2.8%	39.9%	0.06	4,748
(9)	**1**(Massachusetts Company)	19.6%	35.2%	<.01	13.7%	14.9%	2.6%	33.5%	0.05	4,748
(10)	**1**(Cmcl. Services Company)	24.1%	35.1%	<.01	12.8%	10.7%	3.3%	38.2%	0.22	4,748
(11)	**1**(Cmcl. Products Company)	31.8%	31.4%	<.01	13.7%	9.5%	1.7%	43.7%	0.14	4,748
(12)	**1**(Software Company)	40.4%	32.3%	<.01	10.2%	9.0%	1.9%	46.7%	0.13	4,748
(13)	**1**(Health Services Company)	36.5%	29.7%	<.01	15.0%	6.6%	2.4%	46.4%	0.09	4,748
	Panel C: Company Capital Structure & Debt Characteristics									
(14)	**1**(Debt Issuance)	21.3%	27.3%	<.01	9.5%	8.5%	17.5%	37.2%	0.39	4,748
(15)	**1**(Debt Refinancing)	25.6%	27.7%	<.01	11.2%	9.9%	8.9%	42.3%	0.18	4,748
(16)	**1**(Dividend Recap.)	22.5%	29.4%	<.01	13.4%	9.9%	9.1%	38.3%	0.09	4,748
(17)	**1**(Leveraged Recap.)	18.9%	28.5%	> .10	16.3%	13.9%	4.4%	36.9%	0.04	4,748
(18)	**1**(Revolving Debt)	17.7%	27.9%	<.01	10.1%	9.5%	10.1%	42.3%	0.53	4,748
(19)	**1**(Floating Rate Debt)	25.2%	28.5%	<.01	8.3%	9.6%	11.0%	42.5%	0.39	4,748
(20)	**1**(Senior Debt)	17.8%	29.5%	<.01	11.3%	9.3%	7.5%	42.3%	0.38	4,748
(21)	**1**(Secured Debt)	19.8%	29.2%	<.01	14.3%	8.8%	10.3%	37.4%	0.19	4,748
(22)	**1**(Cov-lite Debt)	32.8%	28.7%	<.01	10.1%	9.1%	6.5%	45.7%	0.13	4,748
(23)	**1**(Unsecured Debt)	27.7%	27.6%	> .10	14.3%	11.3%	6.8%	39.9%	0.04	4,748
	Panel D: Acquisitions & Management Changes									
(24)	**1**(Makes Add-on Acquisition)	13.1%	28.7%	<.01	11.5%	7.2%	16.8%	35.8%	0.6	4,748
(25)	**1**(Change CEO)	19.3%	28.0%	<.01	14.7%	11.0%	8.2%	38.0%	0.25	4,390
(26)	**1**(Change CFO)	18.4%	27.9%	<.01	13.8%	10.6%	12.7%	35.0%	0.24	4,390
(27)	**1**(Change CXO)	16.6%	25.9%	<.01	13.6%	9.6%	15.7%	35.3%	0.4	4,390

Table 4: Tabulates the fraction of explained variation in buyout investment styles attributable to a set of fixed effects based on Shapley value decompositions. The p-value column reports the p-value obtained from F-tests for the joint significance of associate firm fixed effects on each characteristic. Rows report decompositions for separate regressions estimated for the outcome variable in the "Y-Var." column. The unit of observation is the person × deal level. CEO/CFO/CXO turnover is measured over the three years following the LBO. CXO includes any C-suite position. Other changes are measured over the first five years. Standard errors are clustered at the deal level.

Table 5: Style and Return Decomposition by Mentors

			% of R^2 Attributable to Fixed Effects							
	Y-Var.	R^2	Associate Firm	Mentor	Pre-PE Firm	School	Deal Year	PE Firm	Y-Mean	Nobs.
	Panel A: Gross Returns and Value Add									
(1)	NPV($MM; 15%)	41.7%	24.2%	34.8%	8.1%	6.9%	12.4%	13.6%	62.51	1,068
(2)	Value Add ($MM)	38.4%	23.3%	38.9%	7.2%	3.7%	4.5%	22.3%	307.42	1,494
(3)	Investment ($MM)	47.1%	20.3%	34.4%	6.2%	7.6%	6.8%	24.6%	208.91	1,494
(4)	TVM	17.0%	18.6%	32.3%	11.6%	6.7%	13.3%	17.5%	2.85	1,494
(5)	**1**(TVM of 0x)	32.2%	16.3%	36.6%	11.6%	8.1%	7.8%	19.5%	0.03	1,494
(6)	**1**(TVM of 0-1x)	28.2%	20.1%	36.6%	13.8%	6.8%	4.4%	18.2%	0.15	1,494
(7)	**1**(TVM of 1-2x)	33.9%	19.7%	30.0%	10.0%	6.4%	16.0%	17.9%	0.26	1,494
(8)	**1**(TVM of 2-3x)	27.1%	22.8%	34.9%	12.1%	5.5%	4.8%	19.9%	0.21	1,494
(9)	**1**(TVM of 3-4x)	26.9%	21.4%	36.6%	12.7%	7.7%	6.5%	15.0%	0.15	1,494
(10)	**1**(TVM of 4-5x)	27.8%	18.8%	38.7%	12.8%	6.4%	8.4%	14.8%	0.08	1,494
(11)	**1**(TVM > 5x)	34.0%	21.0%	31.8%	12.3%	6.6%	10.1%	18.1%	0.12	1,494
	Panel B: Exit Styles									
(12)	**1**(LBO Exit)	20.5%	18.9%	31.4%	9.1%	6.3%	16.6%	17.6%	0.44	2,128
(13)	**1**(M&A Exit)	25.7%	17.1%	31.0%	10.1%	5.4%	20.2%	16.2%	0.29	2,048
(14)	**1**(IPO Exit)	41.0%	15.7%	41.1%	8.1%	7.9%	10.8%	16.4%	0.04	2,021
	Panel C: Investment Methods									
(15)	**1**(Lead Investor)	29.5%	12.5%	25.7%	7.3%	4.2%	35.8%	14.4%	0.3	3,294
(16)	**1**(2+ Investors)	21.0%	19.6%	39.1%	10.0%	6.3%	3.5%	21.5%	0.39	3,294
(17)	**1**(Secondary Buyout)	27.3%	18.9%	38.1%	8.2%	6.6%	4.9%	23.2%	0.32	3,294
(18)	**1**(Management Buyout)	31.8%	20.0%	36.2%	8.6%	6.6%	4.3%	24.2%	0.17	3,294
(19)	**1**(Take-Private)	36.6%	16.5%	40.6%	8.9%	8.1%	3.2%	22.7%	0.05	3,294
	Panel D: Company Industry & Location									
(20)	**1**(Texas Company)	31.1%	18.7%	39.5%	9.6%	8.6%	2.3%	21.3%	0.12	3,294
(21)	**1**(California Company)	27.5%	19.2%	39.6%	9.8%	7.5%	3.6%	20.4%	0.1	3,294
(22)	**1**(New York Company)	28.7%	18.6%	41.5%	10.1%	6.7%	2.6%	20.5%	0.06	3,294
(23)	**1**(Massachusetts Company)	29.2%	19.0%	40.5%	9.8%	10.5%	2.5%	17.7%	0.05	3,294
(24)	**1**(Cmcl. Services Company)	30.4%	21.6%	37.0%	10.6%	7.3%	2.3%	21.3%	0.22	3,294
(25)	**1**(Cmcl. Products Company)	39.2%	20.3%	37.9%	10.5%	6.7%	2.4%	22.2%	0.13	3,294
(26)	**1**(Software Company)	51.6%	20.7%	38.5%	7.4%	6.0%	1.6%	25.8%	0.15	3,294
(27)	**1**(Health Services Company)	48.6%	19.2%	39.7%	12.4%	4.5%	1.5%	22.6%	0.09	3,294
	Panel E: Company Capital Structure & Debt Characteristics									
(28)	**1**(Debt Issuance)	24.0%	17.9%	34.2%	7.5%	5.9%	13.0%	21.5%	0.41	3,294
(29)	**1**(Debt Refinancing)	32.1%	16.4%	38.9%	8.0%	7.0%	6.3%	23.4%	0.19	3,294
(30)	**1**(Dividend Recap.)	29.6%	18.4%	39.1%	8.9%	6.1%	6.7%	20.7%	0.1	3,294
(31)	**1**(Leveraged Recap.)	25.0%	17.1%	39.5%	11.7%	8.1%	4.2%	19.3%	0.04	3,294
(32)	**1**(Revolving Debt)	19.7%	17.3%	36.2%	7.9%	6.6%	7.6%	24.5%	0.56	3,294
(33)	**1**(Floating Rate Debt)	28.5%	18.0%	36.3%	6.7%	6.9%	7.7%	24.4%	0.41	3,294
(34)	**1**(Senior Debt)	21.5%	18.7%	37.6%	9.5%	5.9%	5.2%	23.1%	0.4	3,294
(35)	**1**(Secured Debt)	25.6%	19.1%	38.7%	9.4%	5.1%	6.0%	21.7%	0.2	3,294
(36)	**1**(Cov-lite Debt)	41.7%	17.6%	39.5%	6.9%	6.4%	4.9%	24.6%	0.15	3,294
(37)	**1**(Unsecured Debt)	40.1%	15.6%	45.2%	9.3%	6.9%	3.5%	19.5%	0.04	3,294
	Panel F: Acquisitions & Management Changes									
(38)	**1**(Makes Add-on Acquisition)	15.3%	17.9%	35.7%	8.6%	4.8%	14.1%	18.9%	0.62	3,294
(39)	**1**(Change CEO)	24.2%	17.9%	38.0%	9.8%	7.4%	5.5%	21.4%	0.26	3,056
(40)	**1**(Change CFO)	24.7%	18.0%	37.2%	10.3%	7.0%	9.0%	18.5%	0.26	3,056
(41)	**1**(Change CXO)	20.3%	16.6%	35.2%	8.8%	7.3%	11.6%	20.5%	0.42	3,056

Table 5: Tabulates the fraction of explained variation in buyout investment styles and returns attributable to a set of fixed effects based on Shapley value decompositions. Rows report decompositions for separate regressions estimated for the outcome variable in the "Y-Var." column. The estimating regression is Equation (4). The unit of observation is the person × deal level. Panel A and B only include exited deals or investments made before 2021. CEO/CFO/CXO turnover is measured over the three years following the LBO. Other changes are measured over the first five years. Standard errors are clustered at the deal level.

Table 6: Investment Net Present Value and Style Decomposition Heterogeneity

			% of R^2 Attributable to Fixed Effects						
	Sub-Sample	R^2	Associate Firm	Pre-PE Firm	School	Deal Year	PE Firm	Y-Mean	Nobs.
	Panel A: NPV($ MM; 15%)								
(1)	**1**(Associate @ Large PE Firm)	41.3%	14.9%	12.8%	18.6%	31.9%	21.7%	69.1	252
(2)	**1**(Associate @ Small PE Firm)	45.1%	25.4%	13.0%	9.1%	10.5%	42.1%	55.45	730
(3)	**1**(McKinsey/Bain/BCG)	42.8%	15.5%	15.0%	21.7%	21.7%	26.0%	88.87	220
(4)	**1**(Non McKinsey/Bain/BCG)	39.4%	42.6%	10.8%	9.8%	13.7%	23.1%	46.95	1,251
(5)	**1**(Top-Bank)	45.3%	41.1%	1.6%	9.6%	21.5%	26.2%	77.29	513
(6)	**1**(No Top-Bank)	38.3%	31.7%	15.5%	17.0%	12.0%	23.8%	42.28	926
(7)	**1**(Ivy/Ivy-Plus/Top-30 Degree)	31.7%	41.7%	9.3%	4.4%	17.5%	27.2%	63.8	1,192
(8)	**1**(No Ivy/Ivy-Plus/Top-30 Degree)	61.8%	22.5%	17.7%	23.9%	16.4%	19.5%	11.77	266
(9)	**1**(Harvard/Stanford/Wharton Degree)	36.5%	38.6%	9.0%	3.5%	22.8%	26.0%	70.84	867
(10)	**1**(No Harvard/Stanford/Wharton Degree)	56.5%	24.7%	14.6%	24.0%	9.8%	26.9%	34.05	590
(11)	**1**(Partner @ Large PE Firm)	42.7%	30.9%	10.8%	14.5%	28.9%	14.9%	84.12	486
(12)	**1**(Partner @ Small PE Firm)	37.2%	28.9%	11.8%	11.2%	9.2%	39.0%	42.66	962
(13)	**1**(First 2 Deals)	44.3%	36.0%	11.4%	13.9%	13.6%	25.1%	39.78	806
(14)	**1**(Deals 3+)	45.0%	30.7%	13.6%	13.8%	19.3%	22.6%	66.89	592
	Panel B: [S2] Growth / Tech Investment Style								
(15)	**1**(Associate @ Large PE Firm)	48.3%	20.3%	19.1%	12.2%	6.7%	41.7%	0.84	740
(16)	**1**(Associate @ Small PE Firm)	50.2%	27.1%	11.7%	9.1%	7.7%	44.4%	0.48	2,446
(17)	**1**(McKinsey/Bain/BCG)	51.5%	26.1%	7.6%	14.1%	15.2%	36.9%	0.55	575
(18)	**1**(Non McKinsey/Bain/BCG)	46.3%	29.9%	11.2%	8.0%	7.0%	43.9%	0.52	3,772
(19)	**1**(Top-Bank)	47.6%	31.3%	0.9%	8.7%	7.7%	51.5%	0.64	1,551
(20)	**1**(No Top-Bank)	50.2%	32.8%	13.3%	8.5%	7.5%	37.9%	0.45	2,735
(21)	**1**(Ivy/Ivy-Plus/Top-30 Degree)	43.6%	31.3%	11.3%	2.5%	8.7%	46.1%	0.57	3,298
(22)	**1**(No Ivy/Ivy-Plus/Top-30 Degree)	59.3%	28.9%	12.6%	19.2%	5.4%	33.9%	0.34	1,018
(23)	**1**(Harvard/Stanford/Wharton Degree)	43.8%	31.7%	12.6%	2.0%	9.5%	44.2%	0.62	2,211
(24)	**1**(No Harvard/Stanford/Wharton Degree)	55.5%	31.0%	12.5%	12.1%	6.1%	38.2%	0.4	2,099
(25)	**1**(Partner @ Large PE Firm)	41.8%	33.8%	15.0%	10.6%	8.9%	31.7%	1.14	1,220
(26)	**1**(Partner @ Small PE Firm)	46.0%	27.5%	13.2%	8.6%	9.3%	41.5%	0.28	3,033
(27)	**1**(First 2 Deals)	52.9%	31.2%	10.8%	8.6%	7.2%	42.2%	0.43	2,219
(28)	**1**(Deals 3+)	50.1%	31.2%	13.8%	8.5%	6.4%	40.1%	0.65	1,998

Table 6: Tabulates the fraction of explained variation in investment NPV and style attributable to a set of fixed effects based on Shapley value decompositions. NPV calculations require exit dates. Rows report decompositions for separate regressions estimated for the described sample. Decompositions are calculated separately and within subsets of deals and professionals characterized by the label. Large PE firms have top-quartile AUM in a given year based on aggregations of fund-quarter level Preqin data. Top-30 schools are based on 2024 U.S. news rankings. Top-banks include Goldman Sachs, JPMorgan, Morgan Stanley, Merrill Lynch, and Credit Suisse. The unit of observation is the person × deal level. Standard errors are clustered at the deal level. Section 2.2.1 discusses the style classification presented in this table, covering the loading of a deal on the "Growth/Technology" investment style.

Table 7: Deal Returns and Similarity to Associate Firm's Previous Deals

Panel A: Includes Associate Firm Fixed Effects

	(1) TVM	(2) **1**(TVM of 0-1x)	(3) **1**(TVM of 1-2x)	(4) **1**(TVM of 2-4x)	(5) **1**(TVM > 4x)
Similarity(Associate Firm)	1.753***	-0.284***	-0.118	0.292***	0.110
	(3.40)	(-3.71)	(-1.50)	(3.25)	(1.35)
Y-Mean	2.830	0.176	0.275	0.360	0.189
Y-Std. Dev.	3.047	0.381	0.447	0.480	0.392
Controls	x	x	x	x	x
PE Firm FE	x	x	x	x	x
Deal Year FE	x	x	x	x	x
PE Associate Firm FE	x	x	x	x	x
Adj. R^2	-0.000	0.014	0.122	0.013	0.041
N	2,144	2,144	2,144	2,144	2,144

Panel B: Includes Fixed Effects for who the Partner Worked with the Most as a PE Associate

	(1) TVM	(2) **1**(TVM of 0-1x)	(3) **1**(TVM of 1-2x)	(4) **1**(TVM of 2-4x)	(5) **1**(TVM > 4x)
Similarity(Associate Firm)	1.493**	-0.279**	-0.185	0.353***	0.111
	(2.14)	(-2.25)	(-1.52)	(2.78)	(0.97)
Y-Mean	2.898	0.167	0.276	0.357	0.201
Y-Std. Dev.	2.933	0.373	0.447	0.479	0.401
Controls	x	x	x	x	x
PE Firm FE	x	x	x	x	x
Deal Year FE	x	x	x	x	x
PE Associate Firm FE	x	x	x	x	x
PE Associate Firm Partner FE	x	x	x	x	x
Adj. R^2	-0.013	-0.075	0.057	-0.096	-0.022
N	1,555	1,555	1,555	1,555	1,555

Table 7: Tabulates coefficients estimated from regressions of buyout deal returns on the similarity between the deal the partner led and buyout deals done by the firm the partner worked at as a PE associate over the first five years of the partner's PE career (starting when they were an associate at the firm). Regression samples only include exited deals. Similarities are cosine similarities. Deals are characterized by vectors including indicators for 75 measures of styles (15 entry; 20 target company industry; 20 target company location; 5 capital structure changes; 11 debt characteristics; 4 management changes). Panel B includes an additional fixed effect for the partner the professional worked with the most during their first five years in PE, estimated using historical website data. All regressions include controls for the dollar amount invested, the partner's deal number, whether the firm the partner worked at as a PE associate also invested, and the number of years elapsed since the professional started working in PE. Standard errors are clustered at the PE associate firm level. *t*-stats are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table 8: Associates' Effects on Firms: Instrument First Stage

	Associate Turnover (%)	
	(1)	(2)
% of Associates Year 3+	0.212***	0.293***
	(16.41)	(5.41)
% of Associates Year 3+ × S&P Return (%)		0.010
		(0.09)
% of Associates Year 3+ × US HY Spread (bps)		-0.014
		(-1.56)
# Buyout Deals (t-3)		-0.004
		(-1.34)
# First-Year Associates (t-3)		-0.001
		(-0.59)
Y-Mean	0.214	0.240
Y-Std. Dev.	0.267	0.253
Firm FE	x	x
Industry × Year FE	x	x
State × Year FE	x	x
Adj. R^2	0.105	0.100
N	7,961	5,042

Table 8: Tabulates coefficients estimated from the first stage of a 2SLS regression (First stage: Equation (5); Second stage: Equation (6)). The unit of observation is the firm-year (*jt*). Associates turnover in year *t* if they are separated from firm *j* by year $t+1$ or are promoted to the Vice-President seniority or higher within firm *j* by the next year they are observed (often following a temporary separation to pursue an MBA). Tenure is calculated using calendar years. For example, an associate that joined in August 2018 would be in their third *calendar* year as of January 2020. Regressions are weighted by the number of associates employed by firm *j* in year *t*. The regression sample in Column (2) omits firms-years where lagged data are not available. State × Year FE and Industry × Year FE are fixed effects for the modal state or industry of a PE firm's platform buyout investments interacted with the observation year calculated over a rolling 10 year window (e.g., Commercial services × 2015). Standard errors are clustered at the firm level. *t*-stats are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table 9: Associate Tenure and Firm Characteristics

	% of Associates Year 3+		
	Below-Median	Above-Median	Above - Below
Panel A. Investment Trends			
# Buyout Deals (t-3)	1.28	1.32	0.04
# Buyout Deals (t-2)	1.35	1.41	0.07
# Buyout Deals (t-1)	1.51	1.44	-0.07
# Buyout Deals (t+1)	1.57	1.42	-0.15
# Buyout Deals (t+2)	1.61	1.37	-0.25
# Buyout Deals (t+3)	1.55	1.46	-0.1
Panel B. Firm & Fund Characteristics			
AUM ($B)	1.83	1.79	-0.04
NAV ($B)	1.15	1.14	-0.01
Dry Powder ($B)	0.68	0.65	-0.04
# Funds < 15 Yrs.	3.02	3.16	0.13
# Funds < 5 Yrs.	1.45	1.39	-0.06
PME	1.35	1.33	-0.02
IRR	0.1	0.11	0.01
TVPI	1.47	1.47	-0.01
DPI	0.71	0.76	0.05
Panel C. Investment Team Characteristics			
# Investment Professionals	16.84	15.9	-0.94
# Top-Level	5.65	5.83	0.17
# Middle-Level	4.9	4.35	-0.55
# Junior-Level	6.29	5.72	-0.57
1(Ivy Degree)	0.39	0.39	0
1(Ivy/Ivy+ Degree)	0.54	0.51	-0.02
1(Ivy/Ivy+/Top-30 Degree)	0.7	0.68	-0.02
1(IB. Exp.)	0.63	0.62	-0.01
1(Consulting Exp.)	0.22	0.21	-0.02

Table 9: Tabulates average firm characteristics and investment trends between firms that have a high fraction of associates in their third calendar year with the firm and those that do not. The unit of observation is the firm-year level. A firm is said to have a high fraction of associates in their third calendar year or later if this fraction is above the median for a given a given calendar year. Fund performance metrics are from Preqin and are the average of all underlying funds active in a firm-year cell. "Above – Below" reports the difference between the average high and low columns; *p*-values are accordingly calculated based on the distribution of averages for the high and low groups respectively. */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table 10: Associates' Effects on Firms: Instrument Second Stage

	Sample Description	Coefficient for Associate $\widehat{\text{Turnover}}$ (%)	t-stat.	Y-Mean	F-stat.	N
	Panel A: Main 2SLS Estimate					
(1)	Baseline	-2.192***	(-3.07)	2.595	187.477	7,077
	Panel B: Robustness: Buyout Activity in Different Sub-Samples					
(2)	≤ 1 Asso. Hire	-1.131***	(-2.64)	1.406	96.413	3,997
(3)	> 1 Asso. Hire	-2.820*	(-1.69)	3.139	56.155	2,331
(4)	≤ 1 Asso. Hire (t-3)	-1.407**	(-2.01)	1.824	62.708	2,474
(5)	> 1 Asso. Hire (t-3)	-2.992**	(-2.32)	2.905	76.160	3,981
(6)	≤ 1 Hire (t-3)	-1.479**	(-2.49)	1.695	69.125	2,305
(7)	> 1 Hire (t-3)	-3.088***	(-2.63)	2.875	87.280	4,124
(8)	No Partner Turnover	-1.811**	(-2.45)	2.296	172.430	5,541
(9)	≤ 3 Yrs. Since Last Fund	-3.184***	(-2.84)	2.901	98.159	4,844
(10)	≤ 1 Deal (t-3)	-1.102***	(-2.83)	1.534	148.582	4,405
(11)	> 1 Deal (t-3)	-3.854*	(-1.69)	3.547	35.040	2,098
(12)	Exclude S&P Ret. Q1	-3.378***	(-4.05)	2.618	151.202	5,399
(13)	Exclude S&P Ret. Q4	-1.738**	(-2.13)	2.591	157.189	5,822
(14)	Exclude U.S. HY-Spread Q1	-2.120**	(-2.40)	2.442	152.463	5,567
(15)	Exclude U.S. HY-Spread Q4	-1.574**	(-2.39)	2.718	174.638	5,847
(16)	Exclude Sr. Asso./Analysts	-2.154***	(-2.90)	2.647	148.673	6,173

Includes: Firm FE, State × Year FE, and Industry × Year FE.

Table 10: Tabulates 2SLS regressions of the count of PE firm's buyout investments on the instrumented fraction of its associates that turnover each year. Equation (6) is the estimating equation. The unit of observation is the firm-year (jt). Associates turnover in year t if they are separated from firm j by year $t+1$ or are promoted to the Vice-President seniority or higher within firm j by the next year they are observed (often following a temporary separation to pursue an MBA). Associate turnover is instrumented with the fraction of firm j's associates that have been observed with the firm for three or more *calendar* years as of year t, representing the increasing likelihood that their associate program has ended. Tenure is calculated using calendar years. For example, an associate that joined in August 2018 would be in their third *calendar* year as of January 2020. Regressions are weighted by the number of associates employed by firm j in year t. Specifications include fixed effects for the firm, State × Year, and Industry × Year. Interacted fixed effects equal the modal state or industry of a PE firm's buyout investments, calculated over a rolling 10 year window, interacted with the observation year (e.g., Commercial Services × 2015). Panel B presents regressions estimated within different sub-samples described by the Description column. F-stat. reports the Kleibergen-Paap F-stat from the regression. Standard errors are clustered at the firm level. t-stats are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Internet Appendix for: How do Barbarians Get to the Gates? Private Equity Careers, Styles, and Returns

August 27, 2025

IA.1 PE Firm Investment Professional Database Construction

This section details the steps taken to compile a database of private equity firm investment professionals. I collect the data primarily by prompting a Large Language Model (LLM) to iterate through each firm's archived website hosted on the wayback machine, locate the team and personal pages of each professional displayed on the website, and then return the biographical information about each person contained in the underlying HTML.

IA.1.1 PE Firm Website Collections

The main sample contains 1,179 institutional U.S. buyout firms. These are all firms that are (1) headquartered in the United States; (2) have raised at least $10 million for a closed or liquidated buyout fund in 1995 or later according to PitchBook or Preqin; (3) primarily sponsor buyout funds (i.e., excluding firms that mostly sponsor fund of funds or hedge funds); and (4) are not captive arms of a parent firm. Table IA.B1 summarizes the application of these filters alongside large "non-U.S. buyout" firms the respective filter incrementally excludes.

Table IA.B1: Sample Construction

Step	# Firms	# Funds	$ Capital	Large Excluded Firms
All Investor firms in PitchBook	335,031	10,724	$7.41 Tr.	
(+) Filter to: US firms	97,131	6,002	$4.48 Tr.	CVC, EQT, Apax, Permira, Cinven
(+) Filter to: PE/Buyout firms	5,217	3,862	$3.84 Tr.	HarbourVest, Adams Street
(+) Filter to: One+ PE fund	1,266	3,862	$3.84 Tr.	Starwood, EnCap, TCV
(+) Filter to: Independent firms	1,179	3,551	$3.63 Tr.	Goldman Sachs Asset Management

Table IA.B1: Tabulates the sample of firms after incrementally applying filters. Funds and capital are calculated from closed or liquidated buyout funds that raised $10 million or more with a vintage year of 1995 or later in PitchBook.

I attempt to retrieve historical website data for each firm from 1996 to 2025 from the Internet Archive. The Internet Archive is a nonprofit digital library that retains and provides free access to, among other digital media, historical websites starting in 1996. These data are available for firms in the sample starting in 1997. I also scrape the live website for each firm active in 2025 if it exists. Website addresses are from iterations of PitchBook data dating to 2017 and manual lookups to account for website changes and otherwise defunct firms.

Each year, I extract website data from two main pages: team pages and personal pages. Team pages list professionals working at the firm. Personal pages may include additional information about the person not available on the team page. Figure 1 displays an example of archived webpages for Hellman & Friedman (a large PE firm) in 2003. Given a website address on the internet archive (or a live website address), I prompt an LLM to search over the directory of pages on the website, identify the team page, extract information from the team page, and repeat the process for personal pages. The prompts specify common features of team pages to identify (e.g., based on key words often contained in the URL or characteristics of the underlying HTML) and rules for progressing through the directory of pages on the website each year. After retrieving team and personal pages, the LLM is then prompted to extract names and biographical information (e.g., education and prior work experience). This process uses the google/gemini2.5-flash-preview model. Table IA.B2 and Table IA.B3 summarize the successful collections.

Table IA.B2: Website Data Coverage

	Total	Collected	% Coverage
# Firms	1,179	969	82.2%
PitchBook Coverage:			
# Buyout Funds	3,551	3,256	91.7%
$ Capital Raised	$3.63 Tr.	$3.52 Tr.	97.0%
Preqin Coverage:			
# Buyout Funds	2,898	2,762	95.3%
$ Capital Raised	$3.13 Tr.	$2.94 Tr.	94.1%

Table IA.B2: Tabulates fundraising coverage for collected firms. PitchBook data are through May 2025, Preqin through November 2023.

Addressing Potential Hallucinations: A concern with automated collections via LLMs is the potential for hallucinations. I take three steps to address this. First, I set the temperature to zero on the LLM and specify in the prompts to only extract data precisely from the underlying webpage HTML in the prompts. Second, as a further check, I require that the exact text parsed about the professional (name, title, biographical data, and so on) appears verbatim on the underlying HTML. Only about 1.5% of subsequent person-firm-year cells are affected by this requirement, indicating the LLM tends to parse data as it appears.

Third, and most comprehensively, I also hand collect a sample of the firms' historical web-

Table IA.B3: Data Point Counts by Firm

	Nobs.	Avg.	25p	50p	75p
# Unique Years	969	13.39	8	13	19
# Unique Names	969	79.67	18	38	84
# Unique People	969	67.31	16	32	68
# Unique Titles	969	35.75	11	21	42
# Unique Bios.	969	144.63	30	65	157
# Unique Bios. $\geq$ 250 Chars.	969	131.83	28	62	145
# Unique Bios. $\geq$ 500 Chars.	969	93.43	21	48	109

Table IA.B3: Tabulates the distribution of data points collected from websites across firms.

site data by manually specifying (a) the URLs for team and personal pages each year the firm is active from 2000 to 2022 and (b) the precise tags in the underlying HTML where information about the professional is available. These data are not affected by hallucinations. The hand-collected sample includes the 100 largest non-listed U.S. buyout firms (based on cumulative capital raised) and 96 randomly selected firms. Importantly, earlier versions of this paper used only these hand-collected data and found similar results. The main sample uses the union of these data, prioritizing data from the LLM process where they overlap.

IA.1.2 Variable Construction and Statistics

Merging Across Datasets: I collect biographical data on each professional from historical websites. I further supplement these archived data with a suite of commercial datasets from Revelio, PitchBook biographies, VentureSource, and LinkedIn scrapes (via scrapin.io). I attempt to merge each professional collected from websites to a profile in the other datasets – attempting a sequence of matches based on names and affiliations and then manually reviewing unmatched professionals. The merge sequence iterates over potential matches of exact names within the same firm; cleaned names within the same firm; and then "standout" names within the same firm (e.g., if the website and LinkedIn data for firm A both contain only one person with the name "Blake"). I cross-match and standardize across each commercial dataset. 87% of investment professionals are successfully mapped to at least one of these datasets.

Table IA.B4 summarizes observation counts by source. Characteristics are generally the

same across datasets where they overlap. Subsequent sections discuss their construction. Where information is available from multiple datasets, I prioritize data obtained from historical websites in the final dataset. Including website data in addition to commercial data generally increases coverage for a given variable by 10 to 30%.

Table IA.B4: Data Point Counts by Source

	# of Observations					
	Max Possible	Combined Count	From Cmcl.	From Websites	Overlapping Count	% The Same
1(Investment Team)	181,645	172,485	139,718	163,101	125,601	86.42%
1(Junior-Level)	181,645	172,485	181,306	181,306	181,306	87.11%
1(Middle-Level)	181,645	172,485	181,306	181,306	181,306	81.39%
1(Top-Level)	181,645	172,485	181,306	181,306	181,306	77.32%
Start Year	37,902	37,340	37,246	21,301	21,207	95.93%
Gender	31,590	31,252	31,169	19,970	19,887	98.64%
Undergrad School	31,590	28,019	23,382	23,858	19,221	92.98%
Undergrad Year	31,590	17,298	16,930	1,646	1,028	90.37%
Undergrad Degree Type	31,590	28,019	23,382	23,858	19,221	100.00%
Master's School	31,590	12,997	10,745	9,769	7,517	93.30%
Master's Year	31,590	8,056	7,897	654	415	91.33%
Master's Degree Type	31,590	12,562	10,310	9,769	7,301	93.34%
1(Accounting Exp.)	31,590	25,948	17,681	21,688	13,421	96.07%
1(Big-3 Consulting Exp.)	31,590	25,948	17,681	21,688	13,421	98.47%
1(Other Consulting Exp.)	31,590	25,948	17,681	21,688	13,421	96.69%
1(Govt. Exp.)	31,590	25,948	17,681	21,688	13,421	97.91%
1(Hedge Fund Exp.)	31,590	25,948	17,681	21,688	13,421	97.65%
1(IB. Exp.)	31,590	25,948	17,681	21,688	13,421	92.55%
1(Law Exp.)	31,590	25,948	17,681	21,688	13,421	99.02%
1(VC Exp.)	31,590	25,948	17,681	21,688	13,421	99.10%

Table IA.B4: Tabulates the number of observations for several variables by source. The right-most column reports the fraction of cells commercial data and website data are the same conditional on both being available.

Investment Teams: I identify whether each professional is on the investment team or not every year they are observed based on their title reported on the website. Those on the investment team have a title containing one of 16 phrases typically assigned to investment professionals that does not contain any of 309 phrases that typically correspond to a non-investment role. Positive flags include "associate" and "Partner." Negative flags include "Operat", "Emeritus", "Compliance", and "Counsel." Titles such as "General Partner" are on the investment team. Titles such as "Operating Partner" are not on the investment team. If the listed title is uninformative or missing, I further parse the title from the biography extracted from the website. There are about 180,000 annual observations of 31,590 investment professionals. Investment team classifications are more likely to differ in Table IA.B4 due primarily to present day bias in commercial datasets. Investment team and seniority classifications do not use commercial data. Table IA.B5 reports common titles

among investment professionals and non-investment professionals.

Table IA.B5: Common Titles

Rank	Investment Team	Non-Investment Team
1	Associate (6.8%)	Operating Partner (1.4%)
2	Vice President (3.6%)	Executive Assistant (1.1%)
3	Principal (2.6%)	Senior Advisor (0.8%)
4	Managing Director (2.4%)	Controller (0.4%)
5	Senior Associate (2.3%)	Chief Financial Officer (0.4%)
6	Partner (1.6%)	Administrative Assistant (0.3%)
7	Analyst (1.3%)	Advisory Board Member (0.3%)
8	Director (0.9%)	Operating Advisor (0.3%)
9	Managing Partner (0.5%)	Office Manager (0.2%)
10	Senior Vice President (0.3%)	Advisor (0.2%)

Table IA.B5: Tabulates common titles for professionals on the investment team and those that are not. Numbers in the parentheses report the fraction of firm-year cells in the group with that precise title.

Seniority: Using the title stems, I further assign investment professional to one of three layers in each year they are observed reflecting the hierarchy observed in practice: a junior-level, a middle-level, and a top-level. Doing so allows investment professionals' career progressions to be reasonably comparable across firms and over time. The top-level always includes managing partners, general partners, and active founders. If none of these positions are listed on the website, partners are included in the top-level. This allows for firms to distinguish between more senior general partners and more junior investment partners. If none of these previous positions are listed on the website, managing directors are included in the top-level. If still none of these previous positions are listed on the website, principals are included in the top-level. The junior-level always includes analysts and associates. The middle-level includes vice presidents, assistant directors, and any other positions not included in the junior- or top-levels based on the previously discussed hierarchy. I do not allow for demotions within firms, which occur artificially if a firm changes the titling it uses to refer to professionals of a different seniority over time.

VC firms often similarly have three layers (Jackson and Strebulaev 2025). Law firms historically have had two-layer structures with a partner layer and an associate layer (e.g., Garicano and Hubbard (2016)). More recently, law firm hierarchies also resemble PE/VC three-level stratifications with equity partners (top-level), non-equity partners (middle-level), and associates (junior-level). Corporations, more generally, are larger and have more layers, averaging about ten (Ewens

and Giroud 2025).

Table IA.B6 summarizes the most common positions by each seniority. Figure IA.B1 reports counts of investment professionals based on which seniority layers they were observed at. Figure IA.B2 summarizes time trends in the seniority at which investment professionals entered the PE industry.

Table IA.B6: Common Titles by Seniority

Rank	Junior-Level	Middle-Level	Top-Level
1	Associate (21.6%)	Vice President (11.0%)	Managing Director (5.7%)
2	Senior Associate (7.3%)	Principal (7.5%)	Partner (3.9%)
3	Analyst (4.0%)	Director (2.5%)	Managing Partner (1.4%)
4	Investment Professional (0.7%)	Managing Director (1.3%)	Principal (0.6%)
5	Senior Analyst (0.4%)	Senior Vice President (1.0%)	Senior Managing Director (0.5%)
6	Associates (0.3%)	Partner (0.9%)	General Partner (0.4%)
7	Investment Team (0.3%)	Associate Director (0.2%)	Senior Partner (0.2%)
8	Investing (0.1%)	Executive Vice President (0.2%)	Founding Partner (0.2%)
9	Associate Analyst (0.1%)	Senior Director (0.1%)	Director (0.2%)
10	Investment Associate (0.1%)	Investment Professional (0.1%)	Cofounder (0.1%)

Table IA.B6: Tabulates common titles for professionals assigned to each seniority. Numbers in the parentheses report the fraction of firm-year cells in the group with that precise title (e.g., "Blake Kleinman, Associate" does not count for "Associate").

Figure IA.B1: Investment Professional Counts by Seniority

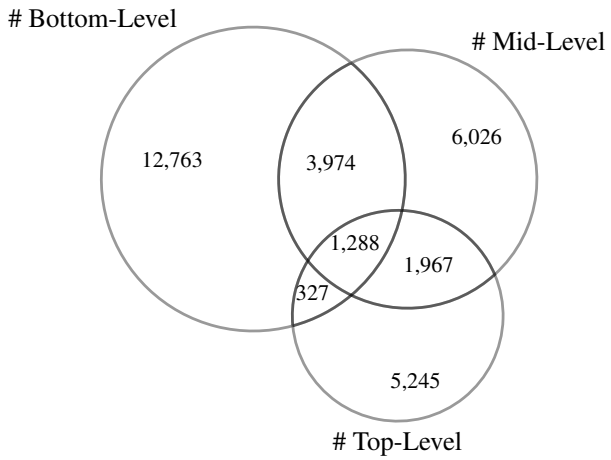


Figure IA.B1: Tabulates the count of investment professionals that appear in each seniority layer.

Employment Spells: End years with the firm, if any, equal the latest year the person is observed at the firm. For each person i working at firm j, this is the maximum value contained in the set of: {last year observed on the website, last year affiliated with the firm on LinkedIn, last

Figure IA.B2: Seniority Trends by Entry Cohort

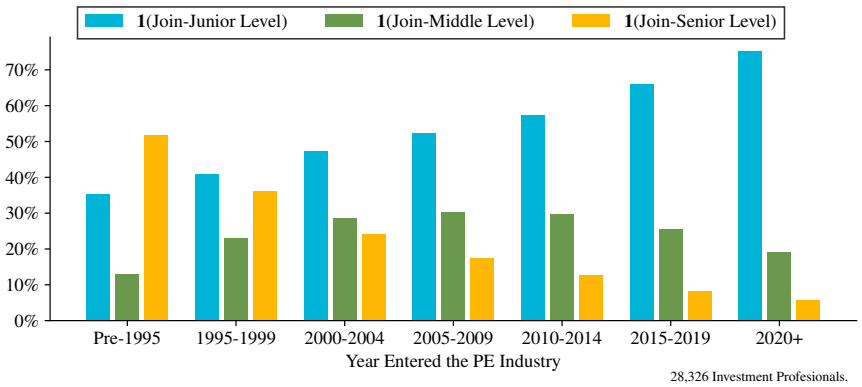


Figure IA.B2: Tabulates the fraction of investment professionals joining the industry at a given seniority.

year affiliated with the firm on PitchBook, last year affiliated with the firm on VentureSource}. In effect, person i is said to separate from firm j in year t if there is evidence that they are not working at firm j in year $t+1$. Otherwise, they are considered to still be with firm j.

Conversely, a professional is said to start at firm j in the earliest year the person is observed at the firm or said to be working at firm j based on their biography. For each person i working at firm j, this is the minimum value contained in the set of: {first year observed on the website, first year affiliated with the firm on LinkedIn, first year affiliated with the firm on PitchBook, joining year mentioned in the biography}. Only years observed on or after the founding year of firm j and before the professional separates from firm j (if at all) are retained in the set.

Professionals may have gaps in employment spells within firm j given (a) a legitimate break in employment with the firm, often to pursue an MBA or work at a portfolio company or (b) if the historical webpages for a firm were not comprehensively archived in a given year. Person i is said to have a legitimate gap in their employment spell with firm j in year t if they are missing from the website but 90% or more of the other investment team members are not. For other gaps in employment spells within firm j that are instead due to lapses in archival data, I backfill seniority data so long as year t is within a person's employment spell within the firm. For firm-year level analysis and statistics, I further exclude firm-year cells where the year over year percentage changes in the number of top-level professionals exceeds 75% and does not subsequently. This accounts for cases where firms have years where collection success was low or the types of individuals reported on the website differs dramatically. For example, suppose I collect 75, 74, 22, 20, 23, 80 top-level

professionals for firm j over six consecutive years. Only the observations from years with 75, 74, and 80 professionals are retained in the final sample. Results are, however, robust to not applying this restriction. Figure IA.B3 summarizes trends in the number of years investment professionals have worked in the PE industry. Gaps in employment are not counted.

Figure IA.B3: Years Working in PE Over Time

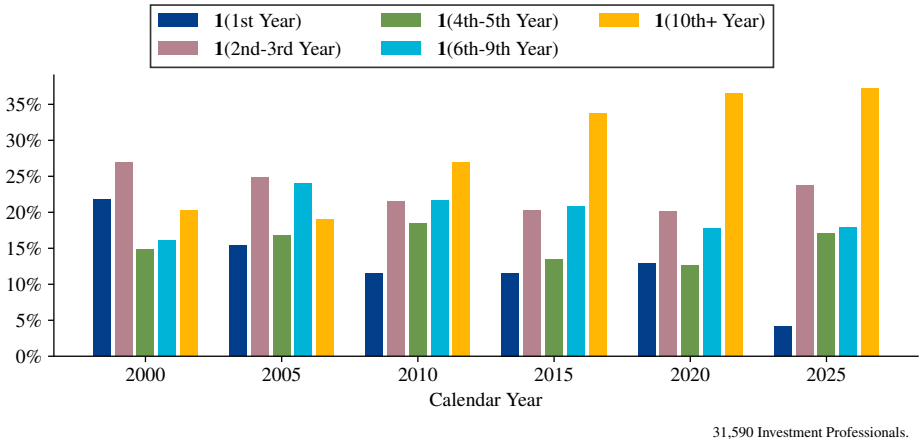


Figure IA.B3: Tabulates trends in the number of years investment professionals have worked in the PE industry for snapshots of six years. Gaps in employment are not counted.

Gender: Gender is estimated based on the gender reported in LinkedIn or in biographies. Gender estimates from biographies on websites assume a person to be of a female gender if their biographical data in any year includes pronouns associated with the female gender ("Mrs.", "Ms.", "Miss", "her", or "she") but not the male gender ("Mr.", "Mister", "he", or "him"). For remaining cases where the gender could not be determined based on biographical data, I also use the `gender_guesser.detector` package in Python to subsequently infer the person's gender based on their first name. Figure IA.B4 summarizes time trends in gender. Ewens (2024) reports similar numbers in recent years.

Education: Education is parsed from website biographies by prompting LLMs and further extracted from educational data available on LinkedIn and other commercial datasets. I manually standardize each raw school name in my sample. For example, "Stanford Business School" and "Stanford GSB" are both treated as "Stanford." Also based on a manual reading of raw extracted degree names, I group degrees from each school into three main categories: undergraduate, master's, and post-master's. MBA degrees are in the master's degree group and are often reported

Figure IA.B4: Gender Trends by Entry Cohort

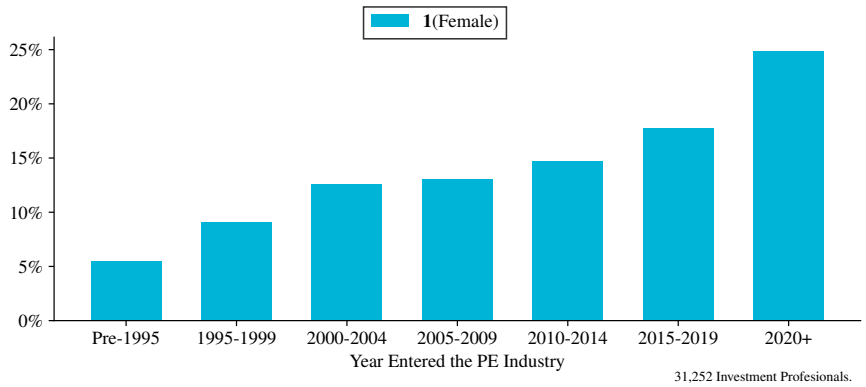


Figure IA.B4: Tabulates the fraction of investment professionals joining the industry that are female.

separately given their higher frequency. Samples exclude degrees or affiliations falling outside of these groups (e.g., certificates) or that are otherwise not reported.

Throughout, I categorize schools into four main types. Ivy League schools include: Brown; Columbia; Cornell; Dartmouth; Harvard; Princeton; University of Pennsylvania; and Yale. Ivy-plus schools are other top-private schools. This includes: Stanford; MIT; CalTech; Duke; Johns Hopkins; Northwestern; and University of Chicago. The Top-30 schools are the 15 other schools listed in the 2024 U.S. News Top-30 schools: Carnegie Mellon University; Emory University; Georgetown University; New York University; Rice University; University of California, Berkeley; University of California, Los Angeles; University of California, San Diego; University of Michigan; University of North Carolina, Chapel Hill; University of Notre Dame; University of Southern California; University of Virginia; Vanderbilt University; and Washington University in St. Louis. Table IA.B7 reports common undergraduate and MBA schools outside of these 30 schools for investment professionals. Figure IA.B5 summarizes trends in education.

Work Experience: Work experience is parsed from website biographies by prompting LLMs and further extracted from data available on LinkedIn, VentureSource, and PitchBook. I only consider pre-PE work experience, which includes all full-time positions a professional had before they first were employed by a PE firm. This sample excludes affiliations from internships or those that lasted for a year or less. Based on prior employers, I group experience into: consulting, investment banking, hedge fund, VC firm, law firm, government, more general finance, or other unclassified experiences. To form such groupings, I manually classify every firm that employed 50 or more pro-

Table IA.B7: Common Schools Outside of the U.S. News Top-30

Rank	Undergrad (N = 14,988)	MBA (N = 1,357)
1	UT-Austin (3.6%)	UT-Austin McCombs (6.7%)
2	Indiana (2.8%)	INSEAD (6.6%)
3	Boston College (2.8%)	Indiana Kelley (3.4%)
4	UIUC (2.1%)	Fordham (2.7%)
5	BYU (2.0%)	SMU (2.4%)
6	SMU (1.6%)	LBS (2.4%)
7	Washington & Lee (1.5%)	IIT-Ahmedabad (2.0%)
8	Williams (1.3%)	Babson (1.8%)
9	UW-Madison (1.3%)	BYU (1.8%)
10	Wake Forest (1.2%)	Boston University (1.7%)

Table IA.B7: Tabulates common schools outside the Top-30 for investment professionals. Numbers in the parentheses report the fraction of firm-year cells in the group with that precise title.

Figure IA.B5: Education Trends by Entry Cohort

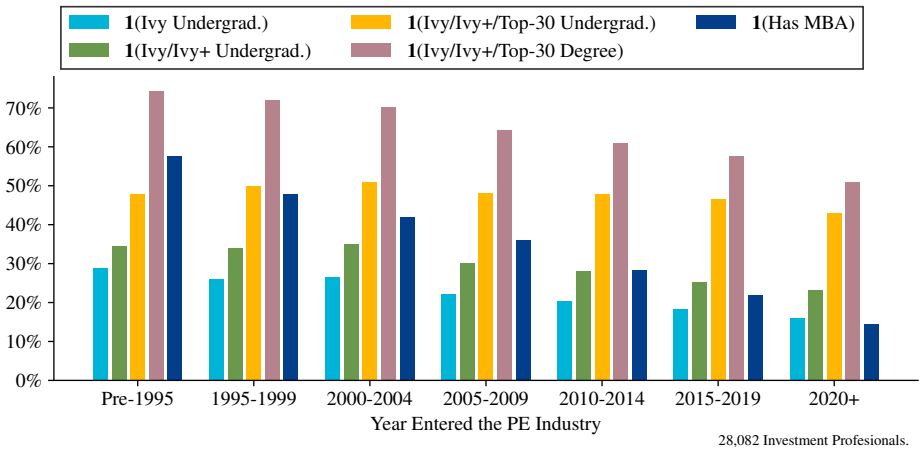


Figure IA.B5: Tabulates trends in education among investment professionals upon entering the PE industry.

fessionals in my sample (and a few thousand other randomly selected firms) as one of the above firm types. I then extrapolate classifications assigned in this subsample to other firms with the same NAICs code not in the manually reviewed sample. Figure IA.B6 summarizes time trends in pre-PE work experience. Figure IA.B7 summarizes time trends in post-PE work experience, which is calculated using LinkedIn profiles.

Figure IA.B6: Work Experience Trends by Entry Cohort

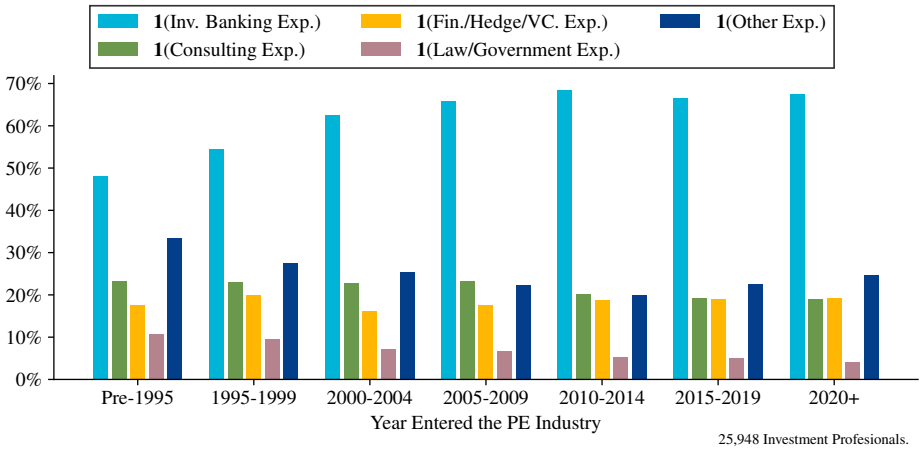


Figure IA.B6: Tabulates trends in pre-PE work experience among investment professionals.

Figure IA.B7: Post-PE Work Experience Trends by Entry Cohort

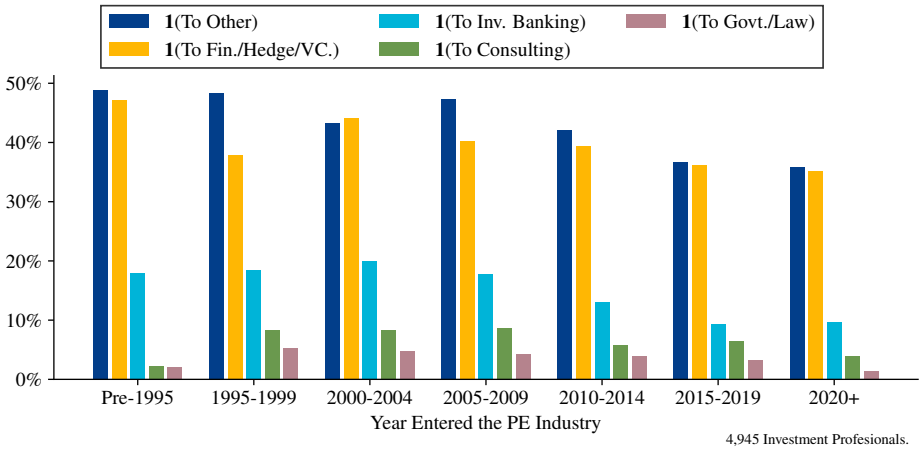


Figure IA.B7: Tabulates trends in post-PE work experience among investment professionals. Numbers can exceed one for professionals with multiple post-PE work experiences.

IA.1.3 Additional Variables for Lead Partners

This subsection discusses the additional variables calculated or extracted for lead partners of buy-out deals in the main samples.

Associate Experience for Lead Investors on Deals: An additional work experience of interest is the firm a professional worked at as an associate when first entering the PE industry. These are not Pre-PE work experiences summarized previously. These data are often omitted from standard LinkedIn data, as Figure 2 documents. I attempt to retrieve these data for all approximately

4,500 lead professionals of stand-alone/platform buyouts representing an in-sample PE firm in the deal. The data are sequentially drawn from (a) historical websites based on direct observations as previously discussed, (b) Linkedin firms (where the position mentions "associate") and the firm is a PE firm, and then (c) manual hand collections. Manual hand collections involve reading historical websites, google searches, and manual readings of website and PitchBook biographies.

Estimating Mentors From Additional Company Involvements: In tests that require estimates of early career mentors, companies that professional i worked on are drawn from PitchBook, VentureSource, and historical websites. Affiliations based on archival website data are parsed from website biographies by prompting LLMs. Professional i is said to have worked on an investment in portfolio company c if they (i) sat on the board of company c (according to PitchBook, VentureSource, or historical websites), (ii) led an investment in company c (according to PitchBook or historical websites), or (iii) were actively involved in an investment in company c (according to historical websites). This set of relationships is larger than the data used in the main body of the paper (deal leads from PitchBook) because its purpose is to calculate early career deal involvements, rather than deals that partners were primarily responsible for. Specifically, this approach allows me to recover affiliations between professionals and companies beyond what is available in commercial datasets alone, which is important for tracking which partners professionals were exposed to early in their careers.

I further require that professional i entered the PE industry weakly after the firm employing them (denoted j) first invested in company c. For each PE firm $\times$ portfolio company pair jc, this year is the minimum year contained in the set of: {first investment in c in PitchBook, first investment in c in VentureSource, first board seat in c taken by an employed professional in PitchBook, first board seat in c taken by an employed professional in VentureSource , first time mentioned as an investment on firm j's archived website}. Figure IA.B8 summarizes the resulting fraction of professionals with at least one portfolio company involvement by source.

Using these affiliations, the mentor for each professional, denoted $m(i)$, is said to be the middle or top-level professional who overlapped with the junior professional on early company involvements the most. Early company involvements include all companies professional i worked on (but did not lead an investment in) within their first five years of entering the industry. Ties are broken based on how active the mentor is, measured by the total number of companies they ever

were affiliated with. Table IA.B8 summarizes resulting mentor relationships for lead partners.

Figure IA.B8: Company Involvement Coverage by Source

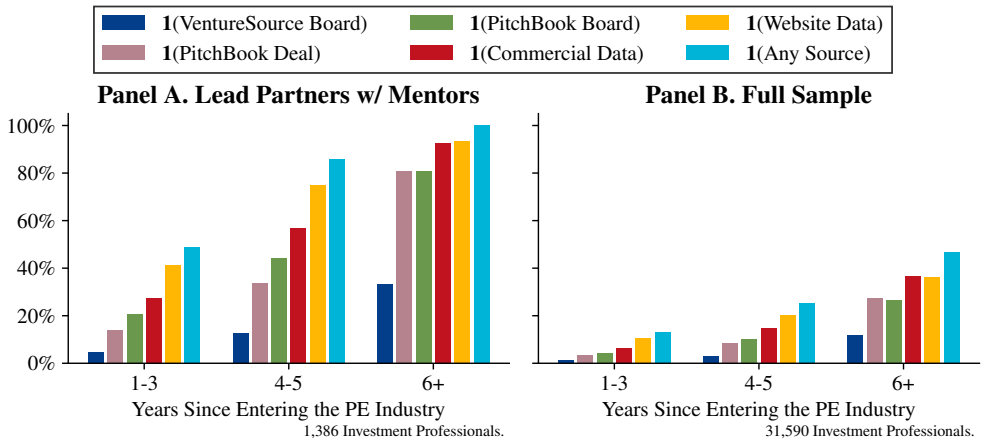


Figure IA.B8: Tabulates the fraction of professionals with at least one company involvement by source conditioned on how many years elapsed since they joined the PE industry as of their involvement with the company. Panel A only summarizes lead partners. Panel B conditions on years that could have elapsed but does not condition on having achieved a particular tenure; for instance the 6+ block reports fractions for all investment professionals that joined in 2019 or earlier and could have been in the industry for 6+ years.

Table IA.B8: Data Point Counts by Former Associates

	Nobs.	Avg.	25p	50p	75p
# Company Involvements	1,386	2.83	1	2	4
# Company Involvements (Web.)	1,386	2.33	1	2	3
# Company Involvements (Cmcl.)	1,386	1.53	0	1	2
# Potential Mentors	1,386	5.24	2	4	7
# Potential Mentors (Web.)	1,386	4.7	2	3	7
# Potential Mentors (Cmcl.)	1,386	2.67	0	2	4
# Companies with Main Mentor	1,386	2.1	1	2	3

Table IA.B8: Tabulates the distribution of data points collected from websites across former associates that lead deals in the connected sample. Only early company involvements are included.

Internet Appendix References

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Garicano, L., & Hubbard, T. N. (2016). The Returns to Knowledge Hierarchies. *Journal of Law, Economics, and Organization*, *32*(4), 653–684.

Jackson, B., & Strebulaev, I. A. (2025). Human Capital in Venture Capital: Evidence from 100,000 Venture Capitalists. *Working Paper*.

IA.2 Additional Figures and Tables

Figure IA1: Implied Economic Magnitudes of Associate Firm Fixed Effect Coefficients

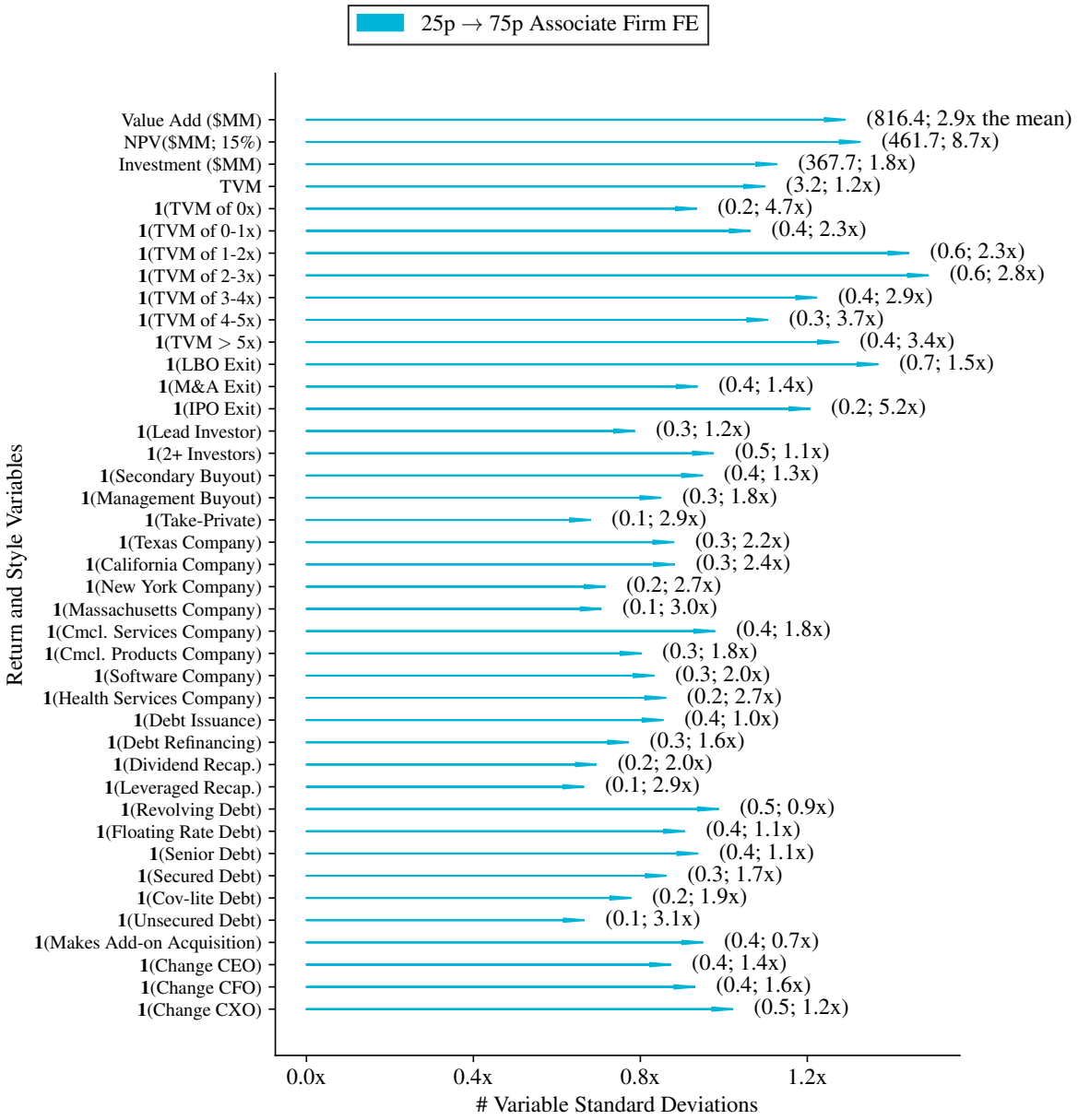


Figure IA1: Plots the predicted differences in economic magnitudes of measures of investment styles and returns given changes in the percentile ranking of the associate firm fixed effect coefficient. The x-axis reports the number of standard deviations the outcome variable is predicted to increase by if the associate firm fixed effect coefficient is at the 75th percentile of associate firm fixed effects for that outcome variable rather than the 25th percentile. Numbers in parentheses report the level change in outcome variable alongside and compares it to the mean. For example, (0.5, 2x) indicates 75th percentile associate firm fixed effect coefficient is 50 percentage points higher than the 25th percentile fixed effect coefficient and that this 50 percentage points is 2-times the sample mean for the variable.

Figure IA2: Deal Style Loadings Over Time

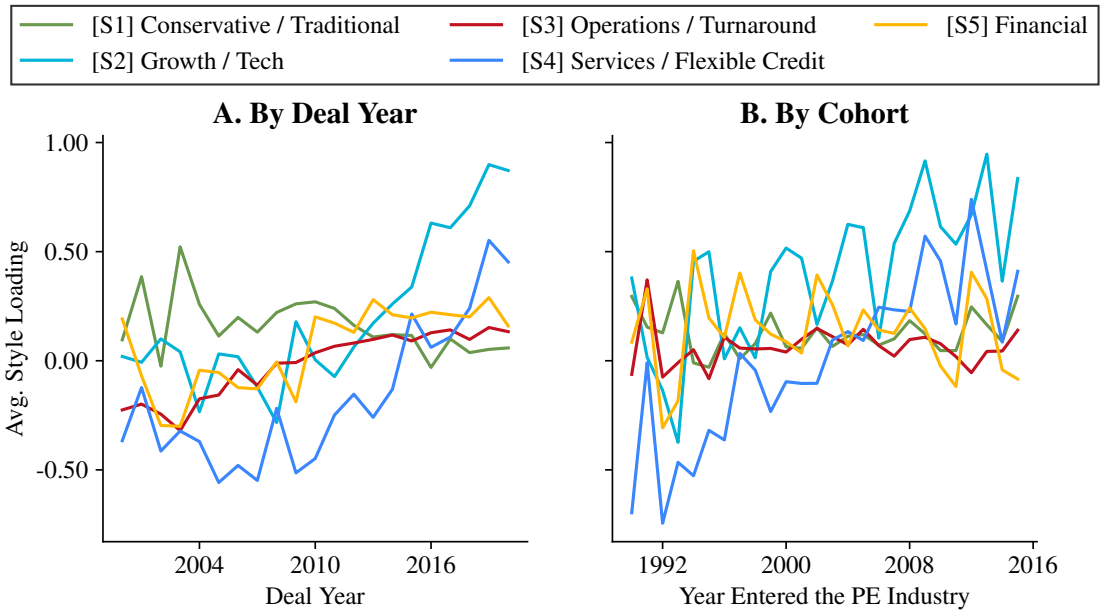
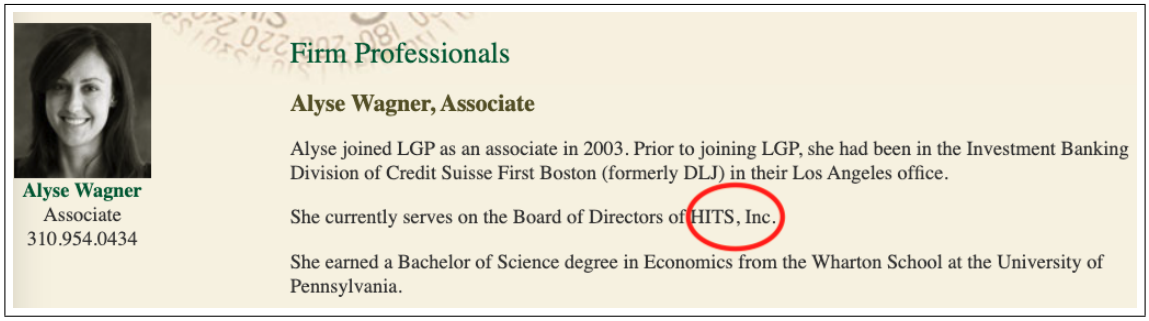


Figure IA2: Plots the average style loading of buyout deals over time. Styles are defined in Section 2.2.1 and attributes of each style are presented in Table IA11. The sample includes about 4,000 deals led by professionals in the connectedness sample from 2000 through 2020 (allowing a five year holding period). Panel A shows the average loading for each style by deal year. Panel B shows the average loading by the year the professional leading the deal first entered the PE industry. Panel B is further restricted to investor cohorts from 1990 to 2015.

Figure IA3: Estimating Mentors: Example Archived Webpages with Portfolio Company Involvements

Panel A: Associate Personal Page 2006



Panel B: Vice President Personal Page 2006

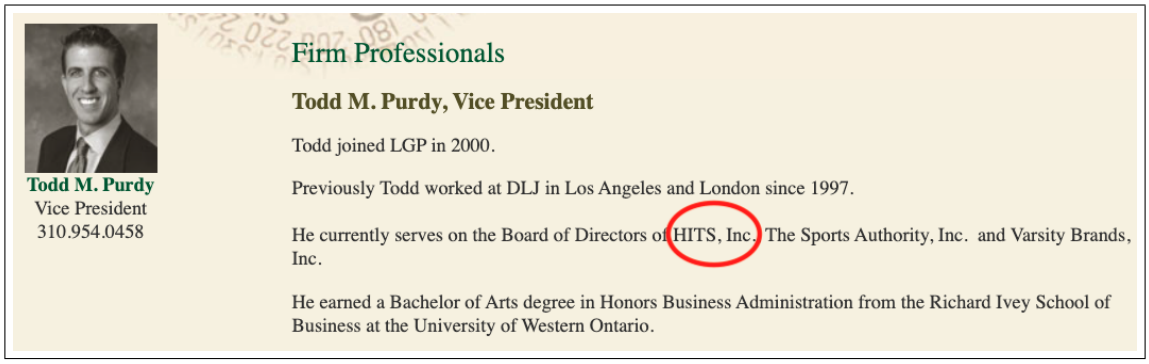


Figure IA3: Displays example webpages archived from the Wayback Machine used to estimate professionals who junior professionals worked with early in their careers. The example focuses on the firm Leonard Green & Partners. Panel A shows the 2006 personal page for Alyse Wagner (linked here). Panel B displays the 2006 personal page for Todd M. Purdy, a vice president (linked here). Red circles denote companies the two overlap on.

Figure IA4: Alternate Condensed Investment Style and Return Decomposition

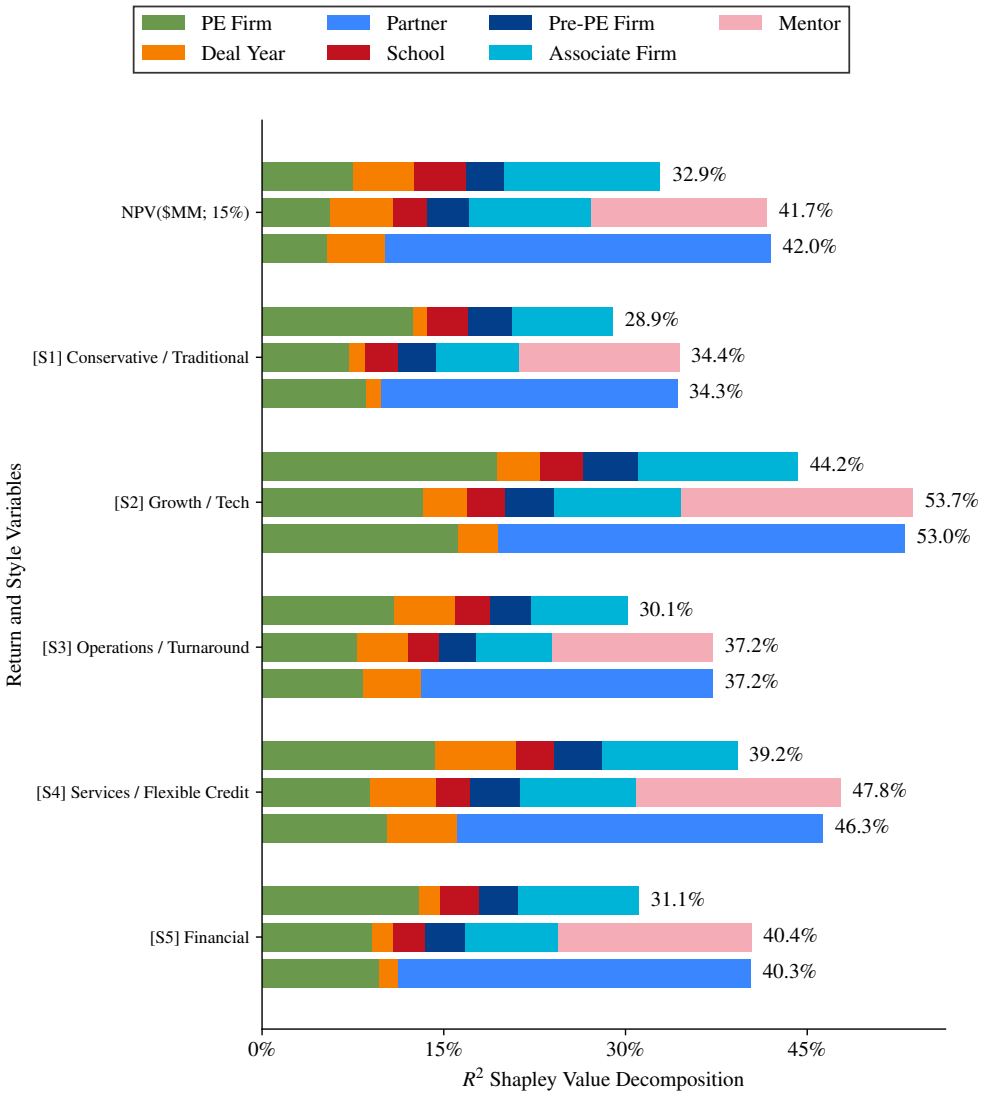


Figure IA4: Plots Shapley value decompositions of several fixed effects in explaining variation in investment styles and returns. Decompositions are calculated separately after estimating two different regressions for each outcome variable. The first bar for each variable estimates Equation (2), which includes fixed effects for the PE firm, deal year, and early career experiences (the partner's associate firm, school, and pre-PE firm). The second bar estimates Equation (4) which additionally includes a fixed effect for who a professional worked with the most on completed deals in their first five years after joining the PE industry as an associate. This specification requires that the mentor is known. The third bar for each variable estimates Equation (1), which includes a partner fixed effect rather than the three early career experience fixed effects. Values at the top of each bar report the full model R^2. Bands on each bar report the estimated contribution to the full model R^2 resulting from each set of fixed effects based on a Shapley value decomposition. Regressions estimated with partner fixed effects additionally require that the professional led at least two investments. Deals are from PitchBook and deal returns are from StepStone. NPV regressions restrict the sample to only deals with known entry and exit dates. Section 2.2.1 discusses styles.

Figure IA5: Investment Return Decomposition Heterogeneity

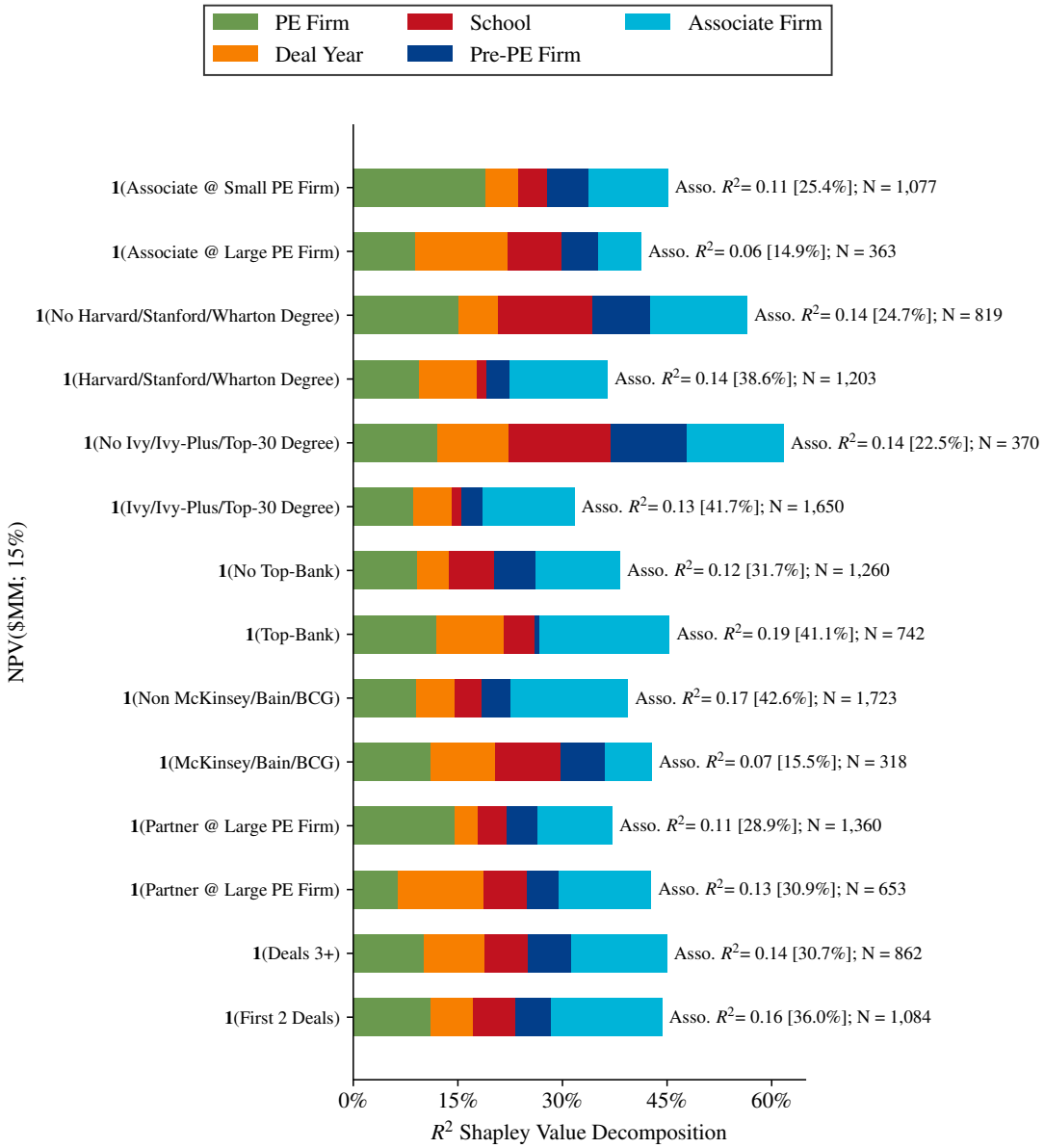


Figure IA5: Plots Shapley value decompositions of several fixed effects in explaining variation in the NPV of buyout investments. Decompositions are calculated separately and within subsets of deals and professionals characterized by the label. Large PE firms have top-quartile AUM in a given year based on aggregations of fund-quarter level Preqin data. Top-30 schools are based on 2024 U.S. news rankings. Top-banks include Goldman Sachs, JPMorgan, Morgan Stanley, Merrill Lynch, and Credit Suisse. Values at the top of each bar report the model R^2 arising from associate firm fixed effects and the percentage of full model R^2 this equals. Bands on each bar report the estimated contribution to the full model R^2 resulting from each set of fixed effects based on a Shapley value decomposition. Deals are from PitchBook and deal returns are from StepStone. NPV calculations additionally restrict the sample to only deals with known exit and entry dates.

Figure IA6: Alternative Display: Instrumented Associate Turnover and Buyout Deals

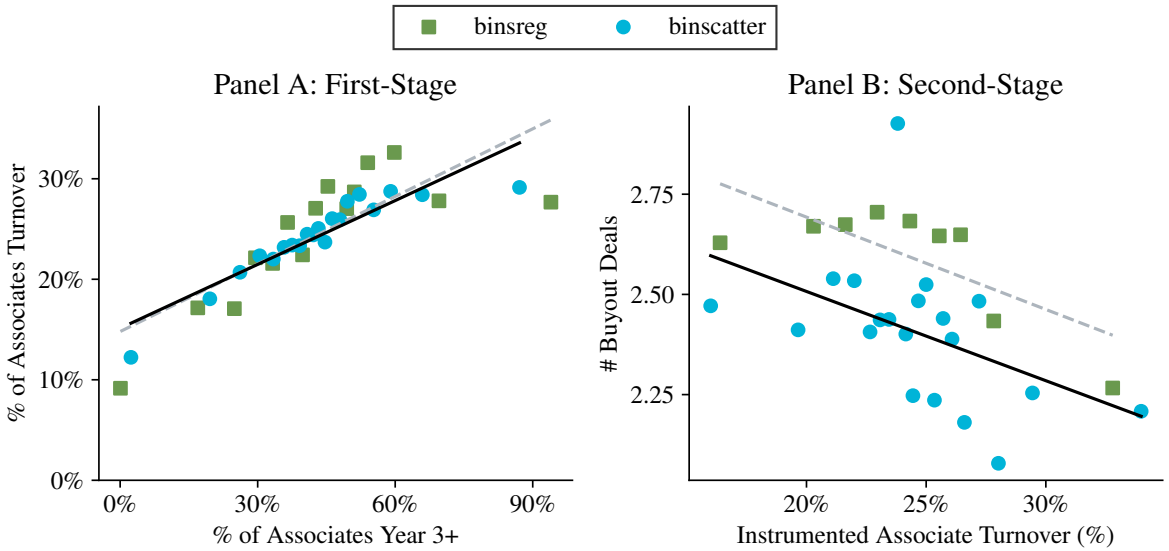


Figure IA6: Displays *binscatter* and *binsreg* regressions of the count of PE firm's buyout investments on the instrumented fraction of its associates that turnover each year. *binsreg* regressions are reported following the procedure in Cattaneo et al. (2024), which performs the correct residualization and chooses the number of bins to balance variance and (squared) bias when estimating conditional means. *binscatter* uses 20 bins for both subplots. *binsreg* results in 16 bins for the first-stage plot and 9 bins for the second-stage plot. The unit of observation is the firm-year (jt). Associates turnover in year t if they are separated from firm j by year $t+1$ or are promoted to the Vice-President seniority or higher within firm j by the next year they are observed (often following a temporary separation to pursue an MBA). Associate turnover is instrumented with the fraction of firm j's associates that have been observed with the firm for three or more *calendar* years as of year t, representing the increasing likelihood that their associate program has ended. Tenure is calculated using calendar years. For example, an associate that joined in August 2018 would be in their third *calendar* year as of January 2020. Regressions are weighted by the number of associates employed by firm j in year t. Panel A displays the first stage of the IV regression (Equation (5)). Panel B displays the second stage of the IV regression (Equation (6)).

Figure IA7: Promotions to Partner Over Time

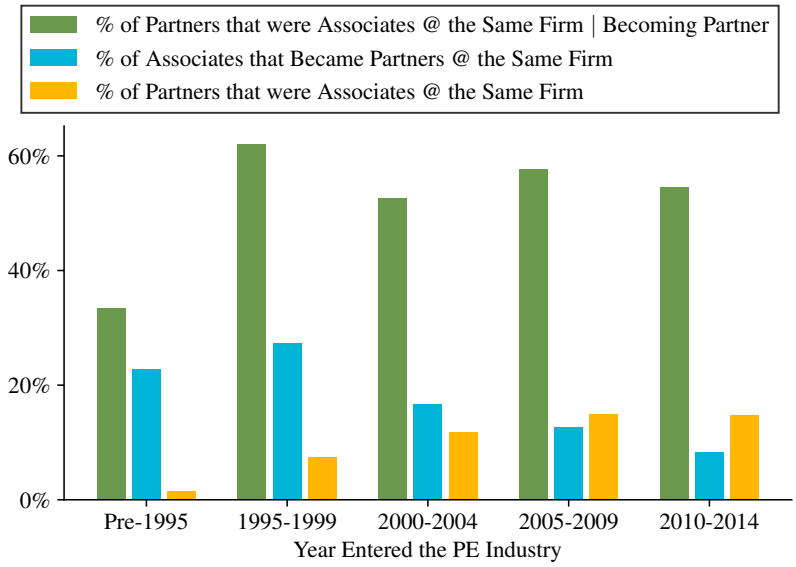


Figure IA7: Plots the average fraction of professionals that became a partner at the same firm they worked as an associate conditioned on several samples. Fractions are calculated within each cohort (the year the professional first entered the PE industry). The sample includes about 14,000 investment professionals. Approximately 6,600 are partners, 5,900 are associates, and about 1,500 were observed as both investment associates and partners.

Table IA1: Top Schools Among PE Professionals

Panel A. Top-20 Undergraduate Schools

Rank	All (N = 28,019)	Junior (N = 16,708)	Middle (N = 11,873)	Top (N = 7,905)
1	UPenn (5.5%)	UPenn (6.1%)	UPenn (5.4%)	UPenn (5.8%)
2	Harvard (3.6%)	Harvard (3.4%)	Harvard (3.8%)	Harvard (4.7%)
3	UVA (2.7%)	UVA (3.2%)	Princeton (2.4%)	Princeton (3.1%)
4	UMichigan (2.4%)	UMichigan (2.7%)	UMichigan (2.4%)	Dartmouth (2.5%)
5	Princeton (2.3%)	Notre Dame (2.7%)	UVA (2.4%)	Stanford (2.3%)
6	Notre Dame (2.2%)	Georgetown (2.3%)	Duke (2.2%)	UVA (2.3%)
7	Dartmouth (2.2%)	Dartmouth (2.3%)	Notre Dame (2.1%)	UMichigan (2.2%)
8	Georgetown (2.1%)	Princeton (2.1%)	Dartmouth (2.1%)	Yale (2.2%)
9	Yale (2.0%)	Duke (2.1%)	Georgetown (2.0%)	Duke (2.1%)
10	Duke (2.0%)	Cornell (2.1%)	Yale (1.9%)	Cornell (2.1%)
11	Cornell (2.0%)	UT-Austin (2.1%)	Stanford (1.9%)	Georgetown (2.1%)
12	UT-Austin (1.9%)	Yale (2.0%)	UT-Austin (1.8%)	Notre Dame (1.9%)
13	Stanford (1.9%)	Indiana (2.0%)	Cornell (1.7%)	UT-Austin (1.7%)
14	NYU (1.5%)	NYU (1.9%)	Boston College (1.6%)	Brown (1.4%)
15	Indiana (1.5%)	Stanford (1.8%)	NYU (1.5%)	Vanderbilt (1.3%)
16	Boston College (1.5%)	Boston College (1.7%)	Indiana (1.4%)	Boston College (1.3%)
17	UC-Berkeley (1.5%)	UC-Berkeley (1.7%)	UNC-Chapel Hill (1.3%)	UNC-Chapel Hill (1.2%)
18	UNC-Chapel Hill (1.4%)	UNC-Chapel Hill (1.7%)	Northwestern (1.3%)	UIUC (1.2%)
19	Northwestern (1.3%)	Northwestern (1.7%)	UC-Berkeley (1.3%)	Williams (1.1%)
20	Vanderbilt (1.3%)	Vanderbilt (1.5%)	Vanderbilt (1.3%)	UC-Berkeley (1.1%)

Panel B. Top-20 MBA Schools

Rank	All (N = 8,536)	Junior (N = 3,133)	Middle (N = 4,970)	Top (N = 4,147)
1	HBS (23.9%)	HBS (23.2%)	HBS (24.6%)	HBS (25.8%)
2	UPenn-Wharton (14.1%)	UPenn-Wharton (17.3%)	UPenn-Wharton (16.0%)	UPenn-Wharton (11.9%)
3	Stanford GSB (8.5%)	Stanford GSB (10.1%)	Stanford GSB (9.3%)	Stanford GSB (7.9%)
4	UChicago Booth (7.2%)	Northwestern Kellogg (9.0%)	Northwestern Kellogg (8.1%)	UChicago Booth (7.6%)
5	Northwestern Kellogg (7.2%)	UChicago Booth (8.0%)	UChicago Booth (7.3%)	Columbia (7.6%)
6	Columbia (6.9%)	Columbia (6.5%)	Columbia (6.8%)	Northwestern Kellogg (7.4%)
7	NYU Stern (2.3%)	Dartmouth Tuck (2.1%)	NYU Stern (2.0%)	NYU Stern (2.7%)
8	Dartmouth Tuck (2.2%)	UMichigan Ross (1.2%)	Dartmouth Tuck (1.9%)	Dartmouth Tuck (2.4%)
9	UCLA Anderson (1.5%)	UCLA Anderson (1.1%)	UVA Darden (1.3%)	UCLA Anderson (1.7%)
10	UVA Darden (1.4%)	MIT Sloan (1.1%)	UCLA Anderson (1.2%)	UVA Darden (1.5%)
11	MIT Sloan (1.1%)	INSEAD (1.0%)	UMichigan Ross (1.1%)	UT-Austin McCombs (1.1%)
12	UT-Austin McCombs (1.1%)	NYU Stern (1.0%)	MIT Sloan (1.1%)	Duke Fuqua (1.0%)
13	UMichigan Ross (1.1%)	UVA Darden (1.0%)	INSEAD (1.0%)	UMichigan Ross (1.0%)
14	INSEAD (1.0%)	UT-Austin McCombs (0.9%)	UT-Austin McCombs (0.9%)	UNC-Keenan Flagler (0.9%)
15	Duke Fuqua (1.0%)	Duke Fuqua (0.9%)	Duke Fuqua (0.9%)	MIT Sloan (0.8%)
16	Cornell Johnson (0.8%)	UC-Berkeley (0.9%)	Cornell Johnson (0.6%)	Cornell Johnson (0.7%)
17	UNC-Keenan Flagler (0.7%)	Indiana Kelley (0.8%)	Georgetown (0.6%)	INSEAD (0.7%)
18	Yale SOM (0.6%)	Yale SOM (0.6%)	Yale SOM (0.5%)	Fordham (0.6%)
19	UC-Berkeley (0.6%)	UNC-Keenan Flagler (0.5%)	UNC-Keenan Flagler (0.5%)	Emory Goizueta (0.5%)
20	USC Marshall (0.6%)	Cornell Johnson (0.5%)	Indiana Kelley (0.5%)	Yale SOM (0.5%)

Table IA1: Tabulates top schools among PE firm investment professionals sorted by whether they were *ever* observed at each seniority. Column counts do not sum to the "All" column if professionals are observed at more than one seniority. "N" reports the number of professionals described in the column from which percentages are calculated. Panel A reports undergraduate education. Panel B reports MBA education.

Table IA2: Top Prior Employers of PE Professionals

Rank	All (N = 26,519)	Junior (N = 15,384)	Middle (N = 11,560)	Top (N = 7,610)
1	Goldman Sachs (6.9%)	Morgan Stanley (6.6%)	Goldman Sachs (7.5%)	Morgan Stanley (7.7%)
2	Morgan Stanley (6.7%)	Goldman Sachs (6.5%)	Morgan Stanley (7.3%)	Goldman Sachs (7.4%)
3	J.P. Morgan (5.0%)	J.P. Morgan (5.8%)	Credit Suisse (5.5%)	Credit Suisse (5.5%)
4	Merrill Lynch (4.9%)	Merrill Lynch (5.0%)	Merrill Lynch (5.4%)	Merrill Lynch (5.2%)
5	Credit Suisse (4.9%)	Credit Suisse (4.9%)	J.P. Morgan (5.2%)	Bain & Co. (4.3%)
6	Citi (3.8%)	Citi (4.1%)	McKinsey (4.5%)	McKinsey (4.2%)
7	McKinsey (3.5%)	Barclays (3.2%)	Bain & Co. (3.9%)	J.P. Morgan (3.8%)
8	Bain & Co. (3.4%)	Bain & Co. (3.1%)	Citi (3.8%)	Lehman Brothers (3.8%)
9	UBS (2.7%)	UBS (2.8%)	UBS (2.9%)	Citi (3.5%)
10	Barclays (2.5%)	McKinsey (2.7%)	Deutsche Bank (2.7%)	UBS (2.8%)
11	Deutsche Bank (2.4%)	Deutsche Bank (2.6%)	PwC (2.5%)	BofA (2.7%)
12	BofA (2.1%)	Lazard (2.5%)	Barclays (2.4%)	DLJ (2.3%)
13	Lazard (2.0%)	Jefferies (2.3%)	Lehman Brothers (2.2%)	JPMorgan Chase (2.2%)
14	Lehman Brothers (2.0%)	BofA (2.1%)	BCG (2.1%)	PwC (2.1%)
15	PwC (2.0%)	Houlihan Lokey (2.1%)	Deloitte (2.1%)	Deutsche Bank (2.1%)
16	BCG (1.9%)	Piper Sandler (1.7%)	EY (2.1%)	Bear Sterns (1.9%)
17	Deloitte (1.8%)	BCG (1.7%)	Lazard (2.0%)	Deloitte (1.7%)
18	EY (1.8%)	EY (1.6%)	BofA (1.9%)	EY (1.6%)
19	Jefferies (1.7%)	Harris Williams (1.6%)	KPMG (1.7%)	BCG (1.6%)
20	Houlihan Lokey (1.5%)	William Blair (1.6%)	Jefferies (1.6%)	Arthur Andersen (1.6%)

Table IA2: Tabulates top prior employers among PE firm investment professionals sorted by whether they were *ever* observed at each seniority. Column counts do not sum to the "All" column if professionals are observed at more than one seniority. "N" reports the number of professionals described in the column from which percentages are calculated. For example, 10% indicates that 10% of all professionals worked at the firm. Individuals can have worked at more than one firm. The Table only includes employer firms before the professional began working in PE. Firm names are as reported based on a cross-merge between LinkedIn, PitchBook, and website data.

Table IA3: Robustness: Inclusion of Professionals Without PE Associate Experience

			% of R^2 Attributable to Fixed Effects						
	Y-Var.	R^2	Associate Firm	Pre-PE Firm	School	Deal Year	PE Firm	Y-Mean	Nobs.
	Panel A: Gross Returns and Value Add								
(1)	NPV($MM; 15%)	28.0%	28.5%	15.2%	11.5%	25.5%	19.2%	29.36	3,047
(2)	Value Add ($MM)	28.1%	22.2%	12.8%	7.7%	4.0%	53.3%	249.81	3,949
(3)	Investment ($MM)	39.4%	15.7%	10.8%	6.7%	9.9%	57.0%	183.23	3,949
(4)	TVM	16.7%	13.8%	35.7%	14.8%	12.4%	23.3%	2.9	3,949
(5)	**1**(TVM of 0x)	25.3%	25.3%	22.6%	13.8%	6.8%	31.5%	0.04	3,949
(6)	**1**(TVM of 0-1x)	21.0%	22.0%	22.0%	13.7%	5.6%	36.7%	0.17	3,949
(7)	**1**(TVM of 1-2x)	22.5%	22.8%	16.5%	9.5%	22.8%	28.4%	0.25	3,949
(8)	**1**(TVM of 2-3x)	19.2%	26.6%	20.7%	11.4%	3.7%	37.5%	0.2	3,949
(9)	**1**(TVM of 3-4x)	18.7%	28.7%	21.0%	13.2%	6.0%	31.0%	0.14	3,949
(10)	**1**(TVM of 4-5x)	18.5%	23.4%	23.3%	14.5%	8.9%	29.9%	0.08	3,949
(11)	**1**(TVM > 5x)	23.0%	21.9%	17.9%	12.5%	13.2%	34.6%	0.12	3,949
	Panel B: Exit Styles								
(12)	**1**(LBO Exit)	16.4%	16.7%	18.6%	10.1%	18.7%	35.9%	0.42	6,702
(13)	**1**(M&A Exit)	18.5%	16.7%	17.8%	10.3%	22.1%	33.0%	0.3	6,521
(14)	**1**(IPO Exit)	28.8%	13.2%	15.6%	10.2%	17.3%	43.8%	0.05	6,463
	Panel C: Investment Methods								
(15)	**1**(Lead Investor)	21.7%	13.4%	14.4%	7.3%	40.6%	24.3%	0.29	9,351
(16)	**1**(2+ Investors)	16.4%	18.8%	18.9%	9.1%	3.1%	50.2%	0.42	9,351
(17)	**1**(Secondary Buyout)	19.9%	24.9%	15.4%	9.1%	8.5%	42.1%	0.27	9,351
(18)	**1**(Management Buyout)	24.4%	19.2%	16.5%	8.7%	3.9%	51.7%	0.17	9,351
(19)	**1**(Take-Private)	22.9%	18.9%	18.1%	10.9%	5.2%	46.9%	0.04	9,351
	Panel D: Company Industry & Location								
(20)	**1**(Texas Company)	22.0%	19.9%	18.8%	13.6%	1.9%	45.8%	0.12	9,351
(21)	**1**(California Company)	19.6%	20.9%	21.2%	11.5%	2.7%	43.7%	0.11	9,351
(22)	**1**(New York Company)	19.3%	22.7%	23.6%	11.8%	1.8%	40.1%	0.06	9,351
(23)	**1**(Massachusetts Company)	18.3%	25.6%	21.1%	11.7%	2.4%	39.1%	0.04	9,351
(24)	**1**(Cmcl. Services Company)	20.8%	23.6%	20.2%	11.3%	2.8%	42.1%	0.21	9,351
(25)	**1**(Cmcl. Products Company)	28.5%	19.6%	18.8%	9.8%	1.2%	50.6%	0.16	9,351
(26)	**1**(Software Company)	40.5%	21.2%	12.8%	9.2%	2.1%	54.7%	0.11	9,351
(27)	**1**(Health Services Company)	31.7%	21.6%	19.4%	8.6%	2.1%	48.3%	0.08	9,351
	Panel E: Company Capital Structure & Debt Characteristics								
(28)	**1**(Debt Issuance)	21.2%	20.4%	15.2%	7.7%	16.3%	40.4%	0.33	9,351
(29)	**1**(Debt Refinancing)	24.2%	19.1%	15.8%	10.0%	6.1%	49.0%	0.16	9,351
(30)	**1**(Dividend Recap.)	20.1%	19.5%	21.1%	9.5%	8.0%	42.0%	0.09	9,351
(31)	**1**(Leveraged Recap.)	15.7%	21.9%	20.7%	15.1%	4.2%	38.1%	0.04	9,351
(32)	**1**(Revolving Debt)	19.5%	18.6%	15.1%	9.0%	8.7%	48.6%	0.47	9,351
(33)	**1**(Floating Rate Debt)	24.5%	19.2%	13.5%	9.3%	7.7%	50.3%	0.34	9,351
(34)	**1**(Senior Debt)	17.5%	20.0%	16.7%	10.4%	7.6%	45.4%	0.35	9,351
(35)	**1**(Secured Debt)	17.9%	20.2%	19.8%	10.3%	11.0%	38.8%	0.18	9,351
(36)	**1**(Cov-lite Debt)	31.8%	20.5%	12.5%	8.7%	6.1%	52.2%	0.11	9,351
(37)	**1**(Unsecured Debt)	24.8%	17.0%	17.6%	10.1%	7.0%	48.3%	0.04	9,351
	Panel F: Acquisitions & Management Changes								
(38)	**1**(Makes Add-on Acquisition)	13.7%	19.3%	16.7%	8.3%	15.0%	40.8%	0.55	9,351
(39)	**1**(Change CEO)	18.0%	19.5%	20.6%	10.2%	9.9%	39.9%	0.23	8,287
(40)	**1**(Change CFO)	17.4%	21.0%	19.3%	10.3%	13.6%	35.8%	0.22	8,287
(41)	**1**(Change CXO)	16.4%	18.0%	19.4%	8.9%	17.5%	36.1%	0.37	8,287

Table IA3: Tabulates the fraction of explained variation in buyout investment styles and returns attributable to a set of fixed effects based on Shapley value decompositions. Professionals without associate experience are included by assuming they all worked at the same pseudo-PE firm as an associate. Doing so mechanically reduces the explanatory power of associate firm fixed effects. Rows report decompositions for separate regressions estimated for the outcome variable in the "Y-Var." column. The estimating regression is Equation (2). The unit of observation is the person × deal level. Panel A and B only include exited deals or investments made before 2021. CEO/CFO/CXO turnover is measured over the three years following the LBO. Other changes are measured over the first five years. Standard errors are clustered at the deal level.

Table IA4: Connectededness Sample Observation Counts

	Nobs.	Avg.	25p	75p
A. Per Partner				
# of Deals Per Partner	2,069	2.89	1	4
# of PE Firms Per Partner	2,069	1.06	1	1
B. Per Associate Firm				
# of Deals Per Associate Firm	499	11.95	2	13
# of Partners Per Associate Firm	499	4.15	1	5
# of PE Firms Per Associate Firm	499	2.84	1	3
# of Pre-PE Firms Per Associate Firm	499	2.70	1	4
# of Schools Per Associate Firm	499	2.62	1	3.5
C. Per PE Firm				
# of Deals Per PE Firm	490	12.19	3	15
# of Partners Per PE Firm	490	4.48	2	5
# of Associate Firms Per PE Firm	490	2.89	1	3
# of Pre-PE Firms Per PE Firm	490	3.11	1	4
# of Schools Per PE Firm	490	2.92	1	4
D. Per Pre-PE Firm				
# of Deals Per Pre-PE Firm	247	20.23	1	9
# of Partners Per Pre-PE Firm	247	6.89	1	3
# of PE Firms Per Pre-PE Firm	247	6.18	1	3
# of Associate Firms Per Pre-PE Firm	247	5.45	1	3
# of Schools Per Pre-PE Firm	247	3.41	1	3
E. Per School				
# of Deals Per School	173	31.99	2	12
# of Partners Per School	173	10.77	1	5
# of PE Firms Per School	173	8.27	1	5
# of Associate Firms Per School	173	7.55	1	4
# of Pre-PE Firms Per School	173	4.87	1	4

Table IA4: Tabulates distributions of observations per different fixed effect variables in the connectedness sample. For example, Panel C shows that the average PE firm had 4.48 partners that led deals and employed partners from 2.89 different associate firms over the sample.

Table IA5: Top Associate Firms in the Connectededness Sample

Rank	All (N = 2,069)	To Same-Firm (N = 954)	To Different-Firm (N = 1,180)
1	Bain (53; 2.6%)	KKR (34; 3.6%)	Bain (40; 3.4%)
2	Summit Partners (41; 2.0%)	TA Associates (22; 2.3%)	Summit Partners (29; 2.5%)
3	KKR (40; 1.9%)	Carlyle (20; 2.1%)	GTCR (28; 2.4%)
4	Carlyle (37; 1.8%)	Berkshire Partners (17; 1.8%)	Sun Capital Partners (20; 1.7%)
5	GTCR (37; 1.8%)	Warburg Pincus (16; 1.7%)	Carlyle (18; 1.5%)
6	TA Associates (34; 1.6%)	Bain (16; 1.7%)	Blackstone (18; 1.5%)
7	Blackstone (32; 1.5%)	AEA Investors (15; 1.6%)	TPG (13; 1.1%)
8	Sun Capital Partners (28; 1.4%)	Blackstone (14; 1.5%)	H&F (13; 1.1%)
9	Berkshire Partners (27; 1.3%)	The Riverside Company (14; 1.5%)	American Capital (13; 1.1%)
10	Warburg Pincus (26; 1.3%)	THL (13; 1.4%)	TA Associates (12; 1.0%)
11	THL (25; 1.2%)	Apollo (13; 1.4%)	Warburg Pincus (12; 1.0%)
12	The Riverside Company (25; 1.2%)	Abry Partners (13; 1.4%)	THL (12; 1.0%)
13	AEA Investors (24; 1.2%)	Summit Partners (12; 1.3%)	The Riverside Company (12; 1.0%)
14	TPG (21; 1.0%)	Francisco Partners (12; 1.3%)	Apax Partners (11; 0.9%)
15	Apollo (20; 1.0%)	Charlesbank (11; 1.2%)	Berkshire Partners (11; 0.9%)
16	H&F (19; 0.9%)	New Mountain Capital (10; 1.0%)	H.I.G. Capital (11; 0.9%)
17	Abry Partners (17; 0.8%)	Insight Partners (10; 1.0%)	AEA Investors (9; 0.8%)
18	Francisco Partners (17; 0.8%)	Stone Point Capital (10; 1.0%)	CD&R (9; 0.8%)
19	Advent (16; 0.8%)	Sun Capital Partners (10; 1.0%)	Golden Gate Capital (9; 0.8%)
20	H.I.G. Capital (16; 0.8%)	GTCR (9; 0.9%)	Advent (9; 0.8%)

Table IA5: Tabulates top firms that PE partners in the connectedness sample worked at as PE associates. In order, columns restrict the sample to professionals that led a deal representing at any in-sample firm; representing the same firm they worked at as an associate; and representing a firm other than the firm they worked at as an associate. Column counts do not sum to the "All" column if professionals led deals for the same firm they worked at as an associate and for another in-sample firm. "N" reports the number of professionals described in the column from which percentages are calculated. For example, (20, 10%) indicates that 20 lead partners in the column worked as a PE associate at the firm, and that these 20 professionals account for 10% of the sample in the column. Firm names are sometimes abbreviated for space.

Table IA6: Robustness: Bootstrap Decomposition with Pre-Determined Levels

			Average % of R^2 Attributed Across Bootstrapped Samples				
	Y-Var.	R^2	Associate Firm	Pre-PE Firm	School	Deal Year	PE Firm
	Panel A: Gross Returns and Value Add						
(1)	NPV($MM; 15%)	32.9%	33.5%	19.6%	20.6%	21.7%	26.2%
(2)	Value Add ($MM)	31.7%	24.4%	16.2%	12.0%	9.7%	28.4%
(3)	Investment ($MM)	41.1%	30.3%	15.9%	16.1%	13.4%	40.4%
(4)	TVM	15.1%	20.3%	18.1%	14.8%	18.6%	21.6%
(5)	**1**(TVM of 0x)	33.3%	24.5%	21.4%	16.2%	17.2%	28.0%
(6)	**1**(TVM of 0-1x)	22.9%	26.0%	23.1%	17.0%	15.5%	27.6%
(7)	**1**(TVM of 1-2x)	27.6%	23.9%	19.3%	14.0%	23.6%	26.5%
(8)	**1**(TVM of 2-3x)	21.8%	24.8%	22.1%	14.1%	15.4%	25.6%
(9)	**1**(TVM of 3-4x)	22.8%	19.8%	18.4%	15.3%	14.8%	20.4%
(10)	**1**(TVM of 4-5x)	20.9%	22.9%	22.3%	14.7%	24.2%	22.9%
(11)	**1**(TVM > 5x)	28.4%	27.9%	21.7%	17.5%	21.8%	28.4%
	Panel B: Exit Styles						
(12)	**1**(LBO Exit)	19.1%	18.2%	15.9%	13.6%	26.8%	20.6%
(13)	**1**(M&A Exit)	22.1%	24.6%	21.4%	17.5%	47.7%	27.1%
(14)	**1**(IPO Exit)	30.9%	12.7%	11.8%	12.5%	26.2%	15.0%
	Panel C: Investment Methods						
(15)	**1**(Lead Investor)	26.0%	16.9%	14.9%	11.8%	55.2%	18.3%
(16)	**1**(2+ Investors)	16.8%	16.4%	13.6%	12.1%	24.6%	18.9%
(17)	**1**(Secondary Buyout)	21.9%	27.8%	22.6%	19.8%	37.9%	30.3%
(18)	**1**(Management Buyout)	25.9%	19.0%	16.3%	12.8%	28.8%	20.8%
(19)	**1**(Take-Private)	26.4%	37.0%	33.1%	34.1%	66.3%	40.5%
	Panel D: Company Industry & Location						
(20)	**1**(Texas Company)	24.1%	17.7%	13.8%	12.4%	22.9%	20.4%
(21)	**1**(California Company)	22.2%	19.5%	17.6%	14.9%	34.3%	22.2%
(22)	**1**(New York Company)	21.5%	19.9%	16.5%	15.3%	31.2%	21.7%
(23)	**1**(Massachusetts Company)	19.6%	17.0%	15.4%	13.6%	31.4%	20.6%
(24)	**1**(Cmcl. Services Company)	24.1%	19.4%	15.9%	14.7%	26.7%	21.8%
(25)	**1**(Cmcl. Products Company)	31.8%	23.9%	19.3%	17.0%	26.2%	27.1%
(26)	**1**(Software Company)	40.4%	21.1%	15.7%	12.1%	14.5%	23.1%
(27)	**1**(Health Services Company)	36.5%	28.7%	23.9%	17.7%	23.4%	33.2%
	Panel E: Company Capital Structure & Debt Characteristics						
(28)	**1**(Debt Issuance)	21.3%	20.6%	15.4%	15.1%	34.4%	23.7%
(29)	**1**(Debt Refinancing)	25.6%	19.2%	16.3%	13.8%	32.1%	22.2%
(30)	**1**(Dividend Recap.)	22.5%	16.1%	14.1%	11.1%	32.6%	17.8%
(31)	**1**(Leveraged Recap.)	18.9%	17.5%	15.4%	13.4%	36.8%	18.4%
(32)	**1**(Revolving Debt)	17.7%	21.5%	16.5%	14.0%	26.8%	24.1%
(33)	**1**(Floating Rate Debt)	25.2%	25.4%	18.5%	15.7%	30.7%	28.2%
(34)	**1**(Senior Debt)	17.8%	19.0%	16.8%	13.6%	26.4%	21.5%
(35)	**1**(Secured Debt)	19.8%	14.9%	12.7%	10.9%	24.6%	16.8%
(36)	**1**(Cov-lite Debt)	32.8%	28.3%	20.6%	20.0%	32.1%	32.4%
(37)	**1**(Unsecured Debt)	27.7%	21.6%	18.3%	11.8%	37.0%	23.8%
	Panel F: Acquisitions & Management Changes						
(38)	**1**(Makes Add-on Acquisition)	13.1%	21.5%	17.0%	14.5%	33.0%	22.4%
(39)	**1**(Change CEO)	19.3%	16.4%	13.5%	11.3%	21.9%	17.9%
(40)	**1**(Change CFO)	18.4%	19.4%	17.4%	13.9%	28.7%	21.3%
(41)	**1**(Change CXO)	16.6%	18.2%	14.3%	13.1%	29.1%	19.7%

Table IA6: Tabulates the fraction of explained variation in buyout investment styles and returns attributable to a set of fixed effects based on Shapley value decompositions. Fractions in the Table equal averages across bootstrap samples containing 100 levels of each fixed effect variable. Rows report decompositions for separate regressions estimated for the outcome variable in the "Y-Var." column. R^2 is from the full sample. The unit of observation is the person × deal level. Panel A and B only include exited deals or investments made before 2021. CEO/CFO/CXO turnover is measured over the three years following the LBO. Other changes are measured over the first five years. Standard errors are clustered at the deal level.

Table IA7: Robustness: Bootstrap Decomposition with Empirical Confidence Intervals

			Average % of R^2 Attributed Across Bootstrapped Samples				
	Y-Var.	R^2	Associate Firm	Pre-PE Firm	School	Deal Year	PE Firm
(1)	NPV($MM; 15%)	32.9%	37.2% [25.1%, 53.1%]	14.5% [9.0%, 20.1%]	16.0% [6.4%, 29.7%]	18.4% [11.6%, 26.4%]	35.4% [24.6%, 54.5%]
(2)	TVM	15.1%	29.1% [22.3%, 37.4%]	15.8% [10.1%, 20.5%]	13.1% [6.8%, 23.6%]	14.7% [9.8%, 21.9%]	31.4% [23.1%, 43.2%]
(3)	[S1] Conservative / Traditional	28.9%	28.7% [24.5%, 32.6%]	12.8% [10.1%, 15.5%]	10.8% [8.6%, 13.4%]	4.8% [2.9%, 7.3%]	38.7% [33.6%, 44.3%]
(4)	[S2] Growth / Tech	44.2%	30.1% [26.5%, 34.6%]	12.2% [9.7%, 15.4%]	9.1% [7.2%, 10.9%]	7.0% [5.0%, 8.9%]	38.2% [33.2%, 43.4%]
(5)	[S3] Operations / Turnaround	30.1%	28.3% [24.4%, 31.8%]	12.0% [9.7%, 14.9%]	10.1% [8.4%, 12.8%]	13.6% [9.9%, 17.9%]	36.2% [32.1%, 40.6%]
(6)	[S4] Services / Flexible Credit	39.2%	28.6% [25.2%, 32.1%]	11.6% [9.0%, 14.2%]	9.4% [7.7%, 11.1%]	13.0% [9.8%, 17.9%]	35.2% [30.5%, 40.3%]
(7)	[S5] Financial	31.1%	31.6% [28.0%, 36.4%]	12.2% [9.6%, 15.2%]	10.0% [8.1%, 12.5%]	6.2% [3.8%, 8.8%]	38.5% [33.5%, 43.3%]

Table IA7: Tabulates the fraction of explained variation in buyout investment styles and returns attributable to a set of fixed effects based on Shapley value decompositions. Fractions in the Table equal averages obtained by partner-level re-sampling across 100 bootstrap replications, each of which includes deals led by 50% of the partners in the full sample. Bracketed numbers report the [2.5th, 97.5th] percentiles of the attribution across the 100 bootstrap samples. Rows report decompositions for separate regressions estimated for the outcome variable in the "Y-Var." column. R^2 is from the full sample. Percentage attributions use the R^2 calculated using the corresponding bootstrap sample. The unit of observation is the person × deal level. Deals are from PitchBook and deal returns are from StepStone. NPV regressions restrict the sample to only deals with known entry and exit dates. Section 2.2.1 discusses styles.

Table IA8: Robustness: Associate Program Effects with Additional Cohort Fixed Effects

			% of R^2 Attributable to Fixed Effects							
	Y-Var.	R^2	Associate Firm	Cohort	Pre-PE Firm	School	Deal Year	PE Firm	Y-Mean	Nobs.
	Panel A: Gross Returns and Value Add									
(1)	NPV($MM; 15%)	35.1%	35.8%	7.4%	10.0%	11.6%	13.8%	21.3%	53.81	1,485
(2)	Value Add ($MM)	33.2%	30.3%	7.7%	10.9%	6.4%	4.5%	40.1%	286.52	2,047
(3)	Investment ($MM)	42.3%	25.4%	5.1%	7.8%	6.6%	6.0%	49.0%	205.25	2,047
(4)	TVM	16.0%	28.1%	7.9%	15.3%	10.9%	11.2%	26.5%	2.8	2,047
(5)	**1**(TVM of 0x)	35.1%	31.4%	5.2%	13.9%	9.1%	6.6%	33.8%	0.03	2,047
(6)	**1**(TVM of 0-1x)	23.7%	32.3%	5.0%	17.8%	10.0%	4.4%	30.6%	0.16	2,047
(7)	**1**(TVM of 1-2x)	28.9%	27.1%	5.4%	11.8%	7.8%	19.8%	28.1%	0.26	2,047
(8)	**1**(TVM of 2-3x)	23.1%	34.0%	5.9%	15.5%	8.6%	5.3%	30.7%	0.21	2,047
(9)	**1**(TVM of 3-4x)	24.7%	31.4%	6.8%	16.2%	12.0%	5.9%	27.7%	0.15	2,047
(10)	**1**(TVM of 4-5x)	21.9%	32.9%	4.5%	18.3%	8.9%	8.6%	26.8%	0.08	2,047
(11)	**1**(TVM > 5x)	30.0%	32.1%	4.3%	14.0%	9.6%	10.0%	29.9%	0.11	2,047
	Panel B: Exit Styles									
(12)	**1**(LBO Exit)	19.9%	24.9%	4.0%	11.4%	8.2%	19.7%	31.7%	0.43	3,014
(13)	**1**(M&A Exit)	22.7%	24.6%	3.5%	12.1%	6.8%	25.3%	27.7%	0.29	2,892
(14)	**1**(IPO Exit)	32.7%	23.6%	6.6%	12.5%	8.8%	19.1%	29.4%	0.05	2,859
	Panel C: Investment Methods									
(15)	**1**(Lead Investor)	26.6%	17.4%	6.5%	8.7%	5.2%	42.6%	19.6%	0.28	4,701
(16)	**1**(2+ Investors)	17.3%	29.7%	3.3%	13.6%	10.1%	3.3%	39.9%	0.4	4,701
(17)	**1**(Secondary Buyout)	22.5%	31.4%	4.0%	9.9%	9.2%	5.9%	39.6%	0.31	4,701
(18)	**1**(Management Buyout)	26.6%	29.0%	3.2%	12.0%	9.3%	4.6%	41.9%	0.16	4,701
(19)	**1**(Take-Private)	27.6%	25.2%	5.8%	13.9%	10.1%	5.2%	39.8%	0.05	4,701
	Panel D: Company Industry & Location									
(20)	**1**(Texas Company)	24.8%	27.3%	3.1%	12.8%	13.4%	2.4%	41.0%	0.13	4,701
(21)	**1**(California Company)	23.1%	31.8%	4.0%	15.4%	10.4%	3.5%	35.0%	0.11	4,701
(22)	**1**(New York Company)	22.1%	31.6%	3.2%	13.1%	11.0%	2.5%	38.6%	0.06	4,701
(23)	**1**(Massachusetts Company)	20.1%	33.4%	3.8%	13.6%	14.1%	2.5%	32.6%	0.05	4,701
(24)	**1**(Cmcl. Services Company)	24.9%	33.6%	2.7%	12.6%	10.6%	2.9%	37.4%	0.22	4,701
(25)	**1**(Cmcl. Products Company)	32.5%	30.7%	2.1%	13.5%	9.3%	1.8%	42.6%	0.14	4,701
(26)	**1**(Software Company)	41.2%	31.6%	2.4%	9.9%	9.0%	1.7%	45.4%	0.13	4,701
(27)	**1**(Health Services Company)	38.4%	29.4%	3.9%	14.4%	6.5%	2.2%	43.6%	0.09	4,701
	Panel E: Company Capital Structure & Debt Characteristics									
(28)	**1**(Debt Issuance)	21.6%	26.7%	2.8%	9.3%	8.6%	16.4%	36.1%	0.39	4,701
(29)	**1**(Debt Refinancing)	26.4%	26.3%	5.4%	10.5%	9.6%	7.8%	40.3%	0.18	4,701
(30)	**1**(Dividend Recap.)	23.4%	28.1%	5.4%	12.4%	9.6%	8.0%	36.5%	0.09	4,701
(31)	**1**(Leveraged Recap.)	19.9%	27.2%	4.4%	15.9%	13.6%	4.1%	34.8%	0.04	4,701
(32)	**1**(Revolving Debt)	17.9%	27.0%	3.2%	10.0%	9.3%	9.6%	40.9%	0.53	4,701
(33)	**1**(Floating Rate Debt)	25.6%	27.4%	4.2%	8.1%	9.6%	9.9%	40.7%	0.39	4,701
(34)	**1**(Senior Debt)	18.2%	28.8%	3.1%	11.1%	9.1%	7.0%	40.9%	0.38	4,701
(35)	**1**(Secured Debt)	20.3%	28.7%	3.0%	13.9%	8.7%	9.8%	35.9%	0.19	4,701
(36)	**1**(Cov-lite Debt)	34.1%	27.7%	4.8%	9.2%	9.0%	5.8%	43.5%	0.13	4,701
(37)	**1**(Unsecured Debt)	28.9%	26.5%	7.3%	13.3%	10.3%	5.8%	36.8%	0.04	4,701
	Panel F: Acquisitions & Management Changes									
(38)	**1**(Makes Add-on Acquisition)	13.3%	27.8%	3.9%	11.1%	7.0%	15.4%	34.8%	0.6	4,701
(39)	**1**(Change CEO)	19.9%	27.1%	3.5%	13.9%	10.7%	7.6%	37.2%	0.25	4,350
(40)	**1**(Change CFO)	18.8%	27.2%	2.6%	13.7%	10.4%	12.0%	34.1%	0.24	4,350
(41)	**1**(Change CXO)	17.0%	25.2%	3.2%	13.0%	9.3%	14.9%	34.4%	0.4	4,350

Table IA8: Tabulates the fraction of explained variation in buyout investment styles and returns attributable to a set of fixed effects based on Shapley value decompositions. The estimating regression augments the main specification, Equation (2), by including fixed effects for the year a partner first began working in the U.S. buyout industry ("Cohort"). Rows report decompositions for separate regressions estimated for the outcome variable in the "Y-Var." column. The unit of observation is the person × deal level. Panel A and B only include exited deals or investments made before 2021. CEO/CFO/CXO turnover is measured over the three years following the LBO. Other changes are measured over the first five years. Standard errors are clustered at the deal level.

Table IA9: Robustness: Decomposition with Only Switchers

			% of R^2 Attributable to Fixed Effects						
	Y-Var.	R^2	Associate Firm	Pre-PE Firm	School	Deal Year	PE Firm	Y-Mean	Nobs.
	Panel A: Gross Returns and Value Add								
(1)	NPV($MM; 15%)	42.9%	54.4%	8.3%	3.4%	12.2%	21.7%	52.27	781
(2)	Value Add ($MM)	39.0%	45.0%	8.8%	4.6%	3.8%	37.8%	216.85	1,120
(3)	Investment ($MM)	47.4%	26.8%	11.9%	7.2%	11.4%	42.7%	156.92	1,120
(4)	TVM	18.1%	32.1%	13.8%	12.9%	12.7%	28.5%	2.86	1,120
(5)	**1**(TVM of 0x)	38.3%	37.4%	10.6%	6.6%	8.1%	37.3%	0.03	1,120
(6)	**1**(TVM of 0-1x)	28.2%	34.2%	15.4%	7.4%	6.5%	36.5%	0.17	1,120
(7)	**1**(TVM of 1-2x)	34.2%	32.0%	11.4%	6.2%	16.4%	34.0%	0.26	1,120
(8)	**1**(TVM of 2-3x)	27.5%	36.6%	12.3%	5.3%	7.5%	38.2%	0.2	1,120
(9)	**1**(TVM of 3-4x)	26.3%	39.8%	14.0%	7.1%	6.3%	32.8%	0.14	1,120
(10)	**1**(TVM of 4-5x)	25.2%	35.0%	13.2%	6.0%	13.5%	32.3%	0.07	1,120
(11)	**1**(TVM > 5x)	32.9%	35.6%	13.8%	9.0%	11.3%	30.3%	0.13	1,120
	Panel B: Exit Styles								
(12)	**1**(LBO Exit)	21.9%	27.7%	12.1%	7.3%	18.0%	34.8%	0.44	1,719
(13)	**1**(M&A Exit)	25.3%	26.7%	13.4%	5.6%	22.5%	31.8%	0.29	1,647
(14)	**1**(IPO Exit)	40.0%	31.1%	11.8%	5.5%	17.3%	34.3%	0.03	1,626
	Panel C: Investment Methods								
(15)	**1**(Lead Investor)	29.1%	21.5%	11.1%	5.6%	37.5%	24.4%	0.27	2,754
(16)	**1**(2+ Investors)	20.6%	32.5%	12.6%	8.9%	3.9%	42.0%	0.39	2,754
(17)	**1**(Secondary Buyout)	27.2%	33.6%	10.7%	7.9%	4.8%	43.0%	0.28	2,754
(18)	**1**(Management Buyout)	30.3%	30.9%	11.1%	6.4%	5.4%	46.2%	0.17	2,754
(19)	**1**(Take-Private)	34.9%	31.0%	14.4%	7.5%	3.3%	43.9%	0.04	2,754
	Panel D: Company Industry & Location								
(20)	**1**(Texas Company)	31.8%	28.5%	13.0%	10.3%	3.0%	45.2%	0.12	2,754
(21)	**1**(California Company)	28.5%	33.4%	16.2%	7.3%	2.3%	40.8%	0.1	2,754
(22)	**1**(New York Company)	27.9%	34.7%	15.1%	8.6%	4.2%	37.4%	0.05	2,754
(23)	**1**(Massachusetts Company)	24.8%	36.2%	14.0%	11.2%	2.9%	35.7%	0.05	2,754
(24)	**1**(Cmcl. Services Company)	30.4%	34.8%	13.4%	9.3%	3.2%	39.2%	0.23	2,754
(25)	**1**(Cmcl. Products Company)	37.3%	29.7%	13.4%	9.3%	2.8%	44.8%	0.14	2,754
(26)	**1**(Software Company)	48.7%	34.3%	12.5%	6.8%	1.8%	44.7%	0.13	2,754
(27)	**1**(Health Services Company)	44.0%	31.2%	14.1%	5.2%	2.4%	47.1%	0.09	2,754
	Panel E: Company Capital Structure & Debt Characteristics								
(28)	**1**(Debt Issuance)	25.4%	30.2%	9.7%	7.6%	13.2%	39.3%	0.35	2,754
(29)	**1**(Debt Refinancing)	30.9%	31.8%	13.1%	7.0%	5.7%	42.4%	0.15	2,754
(30)	**1**(Dividend Recap.)	27.8%	33.7%	11.6%	8.4%	6.8%	39.5%	0.08	2,754
(31)	**1**(Leveraged Recap.)	26.3%	31.0%	13.0%	11.0%	5.0%	40.0%	0.04	2,754
(32)	**1**(Revolving Debt)	22.9%	29.5%	9.7%	8.6%	9.7%	42.4%	0.5	2,754
(33)	**1**(Floating Rate Debt)	30.3%	31.5%	9.5%	8.5%	8.8%	41.6%	0.34	2,754
(34)	**1**(Senior Debt)	22.4%	31.0%	12.7%	7.5%	6.0%	42.8%	0.35	2,754
(35)	**1**(Secured Debt)	26.0%	30.0%	14.6%	7.5%	9.3%	38.6%	0.19	2,754
(36)	**1**(Cov-lite Debt)	40.4%	31.4%	10.6%	7.6%	4.6%	45.8%	0.1	2,754
(37)	**1**(Unsecured Debt)	32.2%	30.6%	13.2%	6.1%	4.7%	45.4%	0.03	2,754
	Panel F: Acquisitions & Management Changes								
(38)	**1**(Makes Add-on Acquisition)	16.0%	29.6%	11.2%	7.0%	13.7%	38.5%	0.59	2,754
(39)	**1**(Change CEO)	26.1%	29.7%	11.9%	8.3%	8.8%	41.2%	0.25	2,523
(40)	**1**(Change CFO)	24.6%	31.0%	13.5%	7.2%	11.3%	37.0%	0.24	2,523
(41)	**1**(Change CXO)	22.0%	27.7%	12.0%	7.4%	14.6%	38.4%	0.39	2,523

Table IA9: Tabulates the fraction of explained variation in buyout investment styles and returns attributable to a set of fixed effects based on Shapley value decompositions. Samples only include deals led by professionals representing a PE firm that is not the firm they worked at as a PE associate. Rows report decompositions for separate regressions estimated for the outcome variable in the "Y-Var." column. The estimating regression is Equation (2). The unit of observation is the person × deal level. Panel A and B only include exited deals or investments made before 2021. CEO/CFO/CXO turnover is measured over the three years following the LBO. Other changes are measured over the first five years. Standard errors are clustered at the deal level.

Table IA10: Robustness: Decomposition with Fund Fixed Effects

			% of R^2 Attributable to Fixed Effects						
	Y-Var.	R^2	Associate Firm	Pre-PE Firm	School	Deal Year	PE Fund	Y-Mean	Nobs.
	Panel A: Gross Returns and Value Add								
(1)	NPV($MM; 15%)	51.2%	23.4%	5.9%	8.9%	9.8%	52.1%	56.4	1,257
(2)	Value Add ($MM)	49.1%	18.8%	7.0%	6.1%	2.6%	65.5%	286.75	1,840
(3)	Investment ($MM)	57.2%	17.1%	5.2%	5.5%	3.4%	68.7%	206.31	1,840
(4)	TVM	24.7%	18.2%	9.1%	7.5%	5.9%	59.4%	2.78	1,840
(5)	**1**(TVM of 0x)	46.2%	23.2%	10.8%	8.2%	4.4%	53.3%	0.03	1,840
(6)	**1**(TVM of 0-1x)	36.3%	20.0%	12.4%	7.2%	3.7%	56.7%	0.16	1,840
(7)	**1**(TVM of 1-2x)	38.1%	20.2%	9.4%	6.6%	9.8%	54.0%	0.27	1,840
(8)	**1**(TVM of 2-3x)	35.8%	21.5%	10.9%	5.3%	3.5%	58.8%	0.21	1,840
(9)	**1**(TVM of 3-4x)	35.4%	21.3%	13.3%	10.1%	3.7%	51.6%	0.15	1,840
(10)	**1**(TVM of 4-5x)	35.9%	20.2%	11.1%	5.1%	5.0%	58.6%	0.08	1,840
(11)	**1**(TVM > 5x)	40.2%	20.7%	10.0%	6.8%	6.0%	56.5%	0.11	1,840
	Panel B: Exit Styles								
(12)	**1**(LBO Exit)	26.9%	22.3%	10.2%	6.5%	9.1%	51.9%	0.45	1,701
(13)	**1**(M&A Exit)	35.0%	21.0%	11.1%	6.7%	10.2%	51.0%	0.28	1,668
(14)	**1**(IPO Exit)	54.7%	16.9%	9.1%	7.0%	6.6%	60.4%	0.05	1,655
	Panel C: Investment Methods								
(15)	**1**(Lead Investor)	31.1%	16.8%	8.3%	4.7%	19.5%	50.8%	0.36	2,236
(16)	**1**(2+ Investors)	27.9%	21.1%	10.2%	5.1%	2.9%	60.7%	0.41	2,236
(17)	**1**(Secondary Buyout)	31.8%	24.6%	10.3%	6.4%	3.5%	55.2%	0.37	2,236
(18)	**1**(Management Buyout)	41.2%	25.9%	9.3%	4.9%	3.1%	56.8%	0.18	2,236
(19)	**1**(Take-Private)	47.8%	19.4%	11.5%	7.1%	5.3%	56.8%	0.05	2,236
	Panel D: Company Industry & Location								
(20)	**1**(Texas Company)	36.6%	21.1%	11.3%	7.9%	2.3%	57.4%	0.12	2,236
(21)	**1**(California Company)	40.8%	21.2%	11.8%	8.6%	1.9%	56.5%	0.1	2,236
(22)	**1**(New York Company)	40.2%	22.3%	9.6%	6.8%	3.4%	58.0%	0.06	2,236
(23)	**1**(Massachusetts Company)	39.3%	20.1%	11.8%	6.5%	3.0%	58.7%	0.05	2,236
(24)	**1**(Cmcl. Services Company)	40.0%	26.0%	10.7%	8.2%	2.8%	52.4%	0.2	2,236
(25)	**1**(Cmcl. Products Company)	45.2%	26.7%	10.5%	7.7%	2.2%	52.9%	0.13	2,236
(26)	**1**(Software Company)	54.0%	26.6%	10.3%	6.6%	2.2%	54.4%	0.17	2,236
(27)	**1**(Health Services Company)	50.4%	27.7%	14.2%	5.6%	3.4%	49.2%	0.09	2,236
	Panel E: Company Capital Structure & Debt Characteristics								
(28)	**1**(Debt Issuance)	26.8%	21.6%	9.1%	6.1%	6.1%	57.0%	0.5	2,236
(29)	**1**(Debt Refinancing)	36.4%	21.8%	9.2%	7.0%	3.3%	58.7%	0.26	2,236
(30)	**1**(Dividend Recap.)	37.6%	20.2%	11.7%	6.4%	5.4%	56.2%	0.14	2,236
(31)	**1**(Leveraged Recap.)	40.2%	18.7%	9.6%	11.0%	2.8%	57.9%	0.05	2,236
(32)	**1**(Revolving Debt)	20.3%	22.3%	8.0%	6.2%	4.9%	58.6%	0.63	2,236
(33)	**1**(Floating Rate Debt)	28.1%	24.2%	8.0%	6.6%	3.2%	58.0%	0.52	2,236
(34)	**1**(Senior Debt)	25.7%	23.0%	9.1%	5.5%	3.0%	59.4%	0.46	2,236
(35)	**1**(Secured Debt)	32.4%	20.6%	10.3%	4.8%	4.2%	60.0%	0.24	2,236
(36)	**1**(Cov-lite Debt)	45.6%	23.1%	9.1%	6.9%	3.8%	57.1%	0.21	2,236
(37)	**1**(Unsecured Debt)	47.0%	18.3%	10.5%	7.6%	3.7%	59.9%	0.06	2,236
	Panel F: Acquisitions & Management Changes								
(38)	**1**(Makes Add-on Acquisition)	15.1%	26.9%	9.6%	6.1%	5.8%	51.6%	0.69	2,236
(39)	**1**(Change CEO)	30.5%	23.9%	10.2%	10.0%	3.9%	52.1%	0.27	2,088
(40)	**1**(Change CFO)	31.8%	21.4%	10.0%	8.0%	3.8%	56.9%	0.27	2,088
(41)	**1**(Change CXO)	25.1%	20.5%	10.1%	8.2%	5.4%	55.9%	0.44	2,088

Table IA10: Tabulates the fraction of explained variation in buyout investment styles and returns attributable to a set of fixed effects based on Shapley value decompositions. Rows report decompositions for separate regressions estimated for the outcome variable in the "Y-Var." column. The estimating regression is Equation (2) but with a fund fixed effect in place of a PE firm fixed effect. The unit of observation is the person × deal level. Panel A and B only include exited deals or investments made before 2021. CEO/CFO/CXO turnover is measured over the three years following the LBO. Other changes are measured over the first five years. Standard errors are clustered at the deal level.

Table IA11: Correlations Between Style Factors and Deal Characteristics

	Style Number: 1	2	3	4	5
Label (Main Focus)	Conservative / Traditional	Growth / Tech	Operations / Turnaround	Services / Flexible Credit	Financial
Key Elements	Stable Management; No New Debt; No Add-ons	Software Companies	CXO Changes; Add-ons; Refinancing	Commercial Services; Unitranche; Delay Draw	New Debt
# Deals	1,277	1,240	498	1,516	966
1(Take-Private)				-0.25	
1(Secondary Buyout)					0.31
1(California Company)	-0.35				
1(Texas Company)	0.56				
1(New York Company)	-0.18				
1(Florida Company)				0.17	-0.63
1(Cmcl. Services Company)				0.48	0.22
1(Cmcl. Products Company)		-0.3			
1(Software Company)	-0.17	0.84		-0.23	-0.17
1(Health Services Company)					
1(Dividend Recap.)			0.16	-0.19	0.24
1(Leveraged Recap.)					
1(Debt Issuance)	-0.21	0.17	0.3		0.4
1(Debt Refinancing)			0.27	-0.26	0.28
1(Mezzanine Debt Issue)	-0.58				
1(Floating Rate Debt)	-0.21		0.32		0.46
1(Senior Debt)	-0.17		0.23		0.4
1(Cov-lite Debt)			0.33	-0.41	0.3
1(Delay Draw)	-0.26	0.37		0.45	0.31
1(Mezzanine Debt)	-0.32				
1(Secured Debt)			0.2		0.24
1(Revolving Debt)	-0.23	0.21	0.28		0.47
1(Unitranche Debt)	-0.29	0.4		0.57	0.25
1(Unsecured Debt)				-0.37	
1(2nd Lien Debt)			0.26	-0.28	0.34
1(Bonds)				-0.42	
1(Makes Add-on Acquisition)	-0.18	0.19	0.2	0.16	0.3
1(Change CEO)			0.69		
1(Change CFO)		0.17	0.66		
1(Change CXO)		0.18	0.88		

Table IA11: Tabulates the correlation between deal characteristics and styles. Deal styles are formed by first training an autoencoder to compress 30 deal characteristics into five latent dimensions and reconstruct the original input. The encoder portion of the model then produces five continuous style components for each deal. The resulting five dimensions explain about 60% of variation in deal characteristics. Considered deal characteristics are indicators for common industries (4), states (4), entry methods (2), capital structure changes (5), debt characteristics (11), and management changes (4). Styles are formed using all platform buyout U.S. deals completed by firms in my sample in PitchBook. The table reports results for the connectedness sample. Correlations with an absolute value below 0.15 are omitted. Style labels are manually assigned. Deal counts are the number of deals where a focal style loading was the highest.

Table IA12: Highest and Lowest Average Style Loadings by Firm

	[S1] Conservative/ Traditional	[S2] Growth/ Tech	[S3] Operations/ Turnaround	[S4] Services/ Flexible Credit	[S5] Financial
			Panel A: Top-20		
1	Amberjack (1.36)	Xenon (3.65)	Siris (0.46)	Knox Lane (2.65)	Knox Lane (1.00)
2	Cotton Creek (1.32)	Strattam (3.33)	Rhone Group (0.44)	Warren (1.77)	CI Capital (0.87)
3	Rock Hill (1.20)	Vista (3.28)	SK (0.40)	Palm Beach Cap. (1.36)	Kohlberg & Co. (0.85)
4	Riverstone (1.10)	K1 (3.17)	H&F (0.40)	Greenbriar (1.34)	Odyssey (0.85)
5	Genesis Park (1.08)	Insight (3.11)	Searchlight (0.40)	Shoreline (1.33)	Olympus (0.82)
6	TGF (1.07)	Accel-KKR (2.98)	Crestview (0.36)	Arcline (1.16)	Warren (0.81)
7	Brazos (1.04)	Thoma Bravo (2.96)	CD&R (0.34)	LightBay (1.14)	Rhone Group (0.80)
8	Pelican Energy (0.98)	Rubicon Tech. (2.82)	Blue Wolf (0.33)	Periscope (1.14)	Genstar (0.72)
9	CIC (0.95)	STG (2.56)	May River (0.32)	Sole Source (1.11)	Gridiron (0.70)
10	First Reserve (0.87)	Serent (2.23)	NMC (0.30)	Eagle Merchant (1.09)	Greenbriar (0.69)
11	SK (0.76)	Sumeru (2.22)	Avista (0.29)	Incline (1.09)	NMC (0.66)
12	Argonaut (0.74)	Francisco Partners (2.21)	Advent (0.26)	Platte River (1.08)	American Securities (0.65)
13	MidStates (0.71)	L Capital (2.15)	Bregal (0.26)	Cornell Cap. (1.06)	Pritzker Priv. (0.65)
14	ORG (0.70)	Marlin (2.14)	Gridiron (0.25)	CenterOak (1.02)	LightBay (0.64)
15	Blue Sage (0.66)	ParkerGale (2.09)	Stone Point (0.25)	GenNx360 (1.01)	Harvest (0.64)
16	Trinity Hunt (0.66)	Bow River (1.89)	TriArtisan (0.25)	KLH (0.98)	Fenway (0.64)
17	B12 (0.66)	HGGC (1.76)	Cornell Cap. (0.25)	Southfield (0.97)	TJC (0.60)
18	Linx (0.65)	Tritum (1.75)	Excellere (0.24)	Sterling (0.96)	Littlejohn (0.59)
19	HM (0.65)	InTandem (1.65)	JLL (0.24)	TruArc (0.93)	Leonard Green (0.59)
20	MiddleGround (0.64)	TPE Boulder (1.59)	Nexus (0.22)	Bertram (0.93)	Quadrangle (0.56)
			Panel B: Junior-20		
-20	Insight (-0.21)	MCM (-0.89)	Maven (-0.38)	Providence (-0.69)	Pine Tree (-0.73)
-19	Stone-Goff (-0.22)	Hamilton Robinson (-0.89)	Century (-0.38)	Weston Presidio (-0.70)	Kingswood (-0.74)
-18	TruArc (-0.23)	Bradford Equities (-0.89)	Liberty (-0.38)	Thoma Bravo (-0.70)	Alta Comm. (-0.75)
-17	Gemspring (-0.23)	Cyprium (-0.89)	TGF (-0.39)	MDP (-0.71)	Parallel (-0.76)
-16	STG (-0.24)	Auxo (-0.89)	Argonaut (-0.39)	Searchlight (-0.71)	Operand (-0.78)
-15	Rubicon Tech. (-0.24)	Monomoy (-0.91)	Keystone (-0.40)	KKR (-0.71)	Rubicon Tech. (-0.79)
-14	Knox Lane (-0.24)	Advantage (-0.91)	Pouschine Cook (-0.40)	Spectrum (-0.72)	Maven (-0.81)
-13	Swander Pace (-0.24)	Vance Street (-0.92)	Boathouse (-0.41)	TPG (-0.76)	Varsiy Health. (-0.81)
-12	Prism (-0.25)	Industrial Opp. (-0.97)	Churchill (-0.41)	CCMP (-0.77)	Cornerstone Equity (-0.81)
-11	Sumeru (-0.27)	MPE (-0.98)	Gen Cap (-0.42)	Golden Gate (-0.81)	Trilogy Search (-0.82)
-10	Behrman (-0.31)	Wingate (-0.98)	Encore (-0.42)	Bain (-0.86)	Strattam (-0.85)
-9	Tengram (-0.32)	B12 (-0.99)	Bradford Equities (-0.43)	American Securities (-0.91)	Next Coast (-0.87)
-8	Thoma Bravo (-0.32)	Metapoint (-1.03)	ACI (-0.45)	Apollo (-0.92)	Search Fund Ptnrs. (-0.92)
-7	Greenbriar (-0.34)	Champlain (-1.05)	Invision (-0.46)	H&F (-0.97)	Trivest (-0.94)
-6	Wedbush (-0.38)	Prism (-1.05)	Cornerstone Equity (-0.46)	Riverstone (-1.01)	RLH (-0.97)
-5	L Capital (-0.39)	Shorehill (-1.06)	LightBay (-0.48)	Siris (-1.01)	Pacific Lake (-0.98)
-4	SBJ (-0.40)	CW Industrial (-1.09)	Greybull (-0.50)	Blum (-1.02)	BelHealth (-1.09)
-3	Celerity (-0.41)	LFM (-1.14)	Metapoint (-0.51)	Xenon (-1.25)	Xenon (-1.24)
-2	CenterOak (-0.45)	Altus (-1.16)	Xenon (-0.52)	CD&R (-1.38)	HealthEdge (-1.35)
-1	Shoreline (-0.47)	Fulham (-1.19)	Lubar (-0.52)	Silver Lake (-1.40)	Palm Beach Cap. (-1.48)

Table IA12: Tabulates the firms with the highest and lowest average loading on each style. The sample is restricted to in-sample firms that have completed at least 10 platform or stand-alone buyouts of U.S. companies. Styles are defined in Table IA11. Numbers in parentheses report the average loading on each style. Firm names are typically abbreviated for space.

Table IA13: Robustness: Decomposition with Auto-encoded Styles

			% of R^2 Attributable to Fixed Effects										
	Y-Var.	R^2	Partner	Associate Firm	Pre-PE Firm	School	Deal Year	PE Firm	Fund	Cohort	Mentor	Y-Mean	Nobs.
	Panel A: Partner vs. Firm (following Ewens and Rhodes-Kropf (2015))												
(1)	[S1] Conservative / Traditional	34.3%	71.4%				3.4%	25.2%				0.1	3,954
(2)	[S2] Growth / Tech	53.0%	63.3%				6.2%	30.6%				0.49	3,954
(3)	[S3] Operations / Turnaround	37.2%	64.8%				12.7%	22.6%				0.05	3,954
(4)	[S4] Services / Flexible Credit	46.3%	65.2%				12.5%	22.3%				0.25	3,954
(5)	[S5] Financial	40.3%	72.2%				3.9%	24.0%				0.15	3,954
	Panel B: Baseline												
(6)	[S1] Conservative / Traditional	28.9%		28.7%	12.4%	11.9%	3.9%	43.2%				0.1	4,390
(7)	[S2] Growth / Tech	44.2%		29.8%	10.2%	8.0%	8.0%	43.9%				0.52	4,390
(8)	[S3] Operations / Turnaround	30.1%		26.4%	11.0%	9.7%	16.8%	36.1%				0.04	4,390
(9)	[S4] Services / Flexible Credit	39.2%		28.4%	10.0%	8.1%	17.0%	36.4%				0.25	4,390
(10)	[S5] Financial	31.1%		32.0%	10.4%	10.2%	5.7%	41.7%				0.15	4,390
	Panel C: Fund Fixed Effects												
(11)	[S1] Conservative / Traditional	46.2%		24.1%	10.6%	9.0%	2.4%		53.8%			0.03	2,088
(12)	[S2] Growth / Tech	57.9%		25.6%	9.0%	6.7%	6.7%		52.1%			0.69	2,088
(13)	[S3] Operations / Turnaround	44.1%		22.4%	9.0%	7.9%	3.8%		56.9%			0.13	2,088
(14)	[S4] Services / Flexible Credit	59.8%		23.4%	9.1%	7.7%	9.0%		50.8%			0.1	2,088
(15)	[S5] Financial	46.6%		24.3%	9.1%	8.0%	2.6%		56.0%			0.29	2,088
	Panel D: Add Cohort Fixed Effects												
(16)	[S1] Conservative / Traditional	30.0%		28.0%	12.1%	11.5%	3.7%	41.4%		3.4%		0.1	4,350
(17)	[S2] Growth / Tech	44.8%		29.2%	9.9%	8.1%	7.2%	42.7%		2.9%		0.53	4,350
(18)	[S3] Operations / Turnaround	31.0%		25.8%	10.5%	9.4%	15.7%	35.2%		3.5%		0.04	4,350
(19)	[S4] Services / Flexible Credit	40.3%		27.2%	9.6%	7.8%	14.4%	35.6%		5.4%		0.25	4,350
(20)	[S5] Financial	32.5%		30.5%	10.3%	10.0%	5.2%	39.2%		4.7%		0.14	4,350
	Panel E: Add Mentor Fixed Effects												
(21)	[S1] Conservative / Traditional	34.4%		19.7%	9.3%	7.7%	3.9%	21.0%			38.4%	0.08	3,056
(22)	[S2] Growth / Tech	53.7%		19.6%	7.4%	5.9%	6.8%	24.8%			35.6%	0.6	3,056
(23)	[S3] Operations / Turnaround	37.2%		16.9%	8.2%	7.1%	11.2%	21.1%			35.5%	0.07	3,056
(24)	[S4] Services / Flexible Credit	47.8%		20.0%	8.6%	6.0%	11.3%	18.7%			35.4%	0.23	3,056
(25)	[S5] Financial	40.4%		19.0%	8.1%	6.7%	4.2%	22.5%			39.5%	0.18	3,056

Table IA13: Tabulates the fraction of explained variation in buyout investment styles and returns attributable to a set of fixed effects based on Shapley value decompositions. Rows report decompositions for separate regressions estimated for the outcome variable in the "Y-Var." column. The unit of observation is the person × deal level. Panels vary the fixed effects included in the estimating regressions. Styles are defined in Table IA11. Mentors are discussed in Section 2.3. Standard errors are clustered at the deal level.

Table IA14: Robustness: Deal Returns and Similarity to Associate Firm's Previous Deals

Panel A: Includes PE Partner Fixed Effects

	(1) TVM	(2) **1**(TVM of 0-1x)	(3) **1**(TVM of 1-2x)	(4) **1**(TVM of 2-4x)	(5) **1**(TVM > 4x)
Similarity(Associate Firm)	1.797***	-0.373***	-0.105	0.380***	0.098
	(2.81)	(-3.62)	(-0.94)	(3.33)	(0.96)
Y-Mean	2.895	0.174	0.265	0.366	0.195
Y-Std. Dev.	3.171	0.379	0.441	0.482	0.397
Controls	x	x	x	x	x
Person FE	x	x	x	x	x
PE Firm FE	x	x	x	x	x
Deal Year FE	x	x	x	x	x
Adj. R^2	-0.114	-0.099	-0.004	-0.147	-0.068
N	1,812	1,812	1,812	1,812	1,812

Panel B: Includes Deal Style Fixed Effects

	(1) TVM	(2) **1**(TVM of 0-1x)	(3) **1**(TVM of 1-2x)	(4) **1**(TVM of 2-4x)	(5) **1**(TVM > 4x)
Similarity(Associate Firm)	1.526***	-0.237***	-0.095	0.255***	0.077
	(3.03)	(-2.99)	(-1.12)	(2.64)	(0.93)
Y-Mean	2.830	0.176	0.275	0.360	0.189
Y-Std. Dev.	3.047	0.381	0.447	0.480	0.392
Controls	x	x	x	x	x
PE Firm FE	x	x	x	x	x
Deal Year FE	x	x	x	x	x
PE Associate Firm FE	x	x	x	x	x
Style (Autoencoded) FE	x	x	x	x	x
Adj. R^2	0.004	0.022	0.121	0.014	0.045
N	2,144	2,144	2,144	2,144	2,144

Table IA14: Tabulates coefficients estimated from regressions of buyout deal returns on the similarity between the deal the partner led and buyout deals done by the firm the partner worked at as a PE associate over the first five years of the partner's PE career (starting when they were an associate at the firm). Regression samples only include exited deals. Similarities are cosine similarities. Deals are characterized by vectors including indicators for 75 measures of styles (15 entry; 20 target company industry; 20 target company location; 5 capital structure changes; 11 debt characteristics; 4 management changes). Panel A includes a fixed effect for the professional leading the deal. Panel B includes a fixed effect for autoencoded styles of the deals, calculated as the style on which a deal has the highest loading. Table IA11 presents features of the five different styles. All regressions include controls for the dollar amount invested, the partner's deal number, whether the firm the partner worked at as a PE associate also invested, and the number of years elapsed since the professional started working in PE. Standard errors are clustered at the PE associate firm level. *t*-stats are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table IA15: Robustness: Deal NPV and Similarity to Associate Firm's Previous Deals

	NPV ($MM; 15%)			NPV ($MM; 20%)		
	(1)	(2)	(3)	(4)	(5)	(6)
Similarity(Associate Firm)	177.615**	200.439*	190.859*	166.783**	186.089*	188.698**
	(2.33)	(1.70)	(1.92)	(2.51)	(1.73)	(2.04)
Y-Mean	62.824	68.208	67.844	13.806	18.137	16.904
Y-Std. Dev.	369.905	381.661	385.679	341.854	351.285	356.104
Controls	x	x	x	x	x	x
PE Firm FE	x	x	x	x	x	x
Deal Year FE	x	x	x	x	x	x
PE Associate Firm FE	x	x		x	x	
PE Associate Firm Partner FE		x			x	
Person FE			x			x
Adj. R^2	-0.025	-0.041	-0.075	-0.028	-0.045	-0.084
N	1,510	1,074	1,241	1,510	1,074	1,241

Table IA15: Tabulates coefficients estimated from regressions of buyout deal NPV on the similarity between the deal the partner led and buyout deals done by the firm the partner worked at as a PE associate over the first five years of the partner's PE career (starting when they were an associate at the firm). Discount rates for NPV are reported in the column headers. Regression samples only include exited deals. Similarities are cosine similarities. Deals are characterized by vectors including indicators for 75 measures of styles (15 entry; 20 target company industry; 20 target company location; 5 capital structure changes; 11 debt characteristics; 4 management changes). All regressions include controls for the dollar amount invested (taken in logs in these specifications), the partner's deal number, whether the firm the partner worked at as a PE associate also invested, and the number of years elapsed since the professional started working in PE. Standard errors are clustered at the PE associate firm level. *t*-stats are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.

Table IA16: Robustness: Associates' Effects on Deal Counts

	Description	Coefficient for Associate $\widehat{\text{Turnover}}$ (%)	t-stat.	Y-Mean	F-stat.	N
(1)	Baseline	-2.192***	(-3.07)	2.595	187.477	7,077
(2)	(+) Non US Deals	-3.628***	(-3.07)	3.707	187.477	7,077
(3)	(+) Non US and Add on Deals	-36.217***	(-2.64)	17.981	187.477	7,077
(4)	Unweighted	-0.934***	(-3.55)	1.470	269.356	7,961
(5)	Year Cluster	-2.192***	(-3.04)	2.595	129.510	7,077
(6)	Firm Year Double Cluster	-2.192***	(-2.89)	2.595	132.523	7,077
(7)	(+) AUM Bin FE	-2.453***	(-3.10)	2.735	147.459	6,004
(8)	(+) AUM Bin and PME Bin FEs	-3.328***	(-2.86)	3.122	82.062	3,197
(9)	(+) AUM Bin PME Bin Num Funds FEs	-2.729**	(-2.44)	2.984	94.309	3,189
(10)	Drop 2020+	-2.243**	(-2.52)	2.638	115.000	5,221
(11)	Drop 2008/2009	-2.118***	(-3.14)	2.666	182.672	6,544
(12)	(+) Controls for Senior Turnover	-2.545***	(-2.59)	2.709	129.820	5,693
(13)	(+) Controls for Deals (t-3)	-2.161***	(-3.04)	2.595	189.029	7,077
(14)	(+) Controls for Associate Hiring (t-3)	-2.128**	(-2.07)	2.761	101.163	4,795
(15)	(+) Controls for Associate Composition	-2.285***	(-3.09)	2.613	189.684	6,665
(16)	Promotions Only	-4.321***	(-2.97)	2.595	117.576	7,077
(17)	Separations Only	-4.410***	(-2.99)	2.595	60.703	7,077
(18)	Exclude Public PE Firms	-2.051***	(-2.98)	2.420	186.618	7,049

Includes: Firm FE, State × Year FE, and Industry × Year FE unless otherwise specified.

Table IA16: Tabulates 2SLS regressions of the count of PE firm's buyout investments on the instrumented fraction of its associates that turnover each year. Equation (6) is the estimating equation. The unit of observation is the firm-year (jt). The caption describes the baseline specification, which is adjusted according to the description column. Associates turnover in year t if they are separated from firm j by year $t+1$ or are promoted to the Vice-President seniority or higher within firm j by the next year they are observed (often following a temporary separation to pursue an MBA). Associate turnover is instrumented with the fraction of firm j's associates that have been observed with the firm for three or more *calendar* years as of year t, representing the increasing likelihood that their associate program has ended. Tenure is calculated using calendar years. For example, an associate that joined in August 2018 would be in their third *calendar* year as of January 2020. Regressions are weighted by the number of associates employed by firm j in year t. Specifications include fixed effects for the firm, State × Year, and Industry × Year. Interacted fixed effects equal the modal state or industry of a PE firm's buyout investments, calculated over a rolling 10 year window, interacted with the observation year (e.g., Commercial Services × 2015). F-stat. reports the Kleibergen-Paap F-stat from the regression. Standard errors are clustered at the firm level. t-stats are in parentheses and */**/*** respectively denote significance at the 10, 5, and 1 % levels.