Portfolio Management in Private Equity*

Gregory W. Brown
Kenan-Flagler, UNC
gregwbrown@unc.edu

Celine (Yue) Fei
Kenan-Flagler, UNC
Celine_Fei@kenan-flagler.unc.edu

David T. Robinson
Duke and NBER
davidr@duke.edu

First Draft: October 30, 2021
This Version: October 28, 2022

Abstract

General Partners (GPs) in private equity face a trade-off between focusing their skills and effort on fewer investments to earn higher returns, or investing more broadly to reduce risk through diversification. Using a novel, deal-level dataset of 5,925 global investments from 1999 to 2016, we show that these portfolio considerations are important for understanding fund-level private equity returns. The largest investments in PE funds typically have the lowest returns on average, but are also the least risky. Returns and risk are both increasing in industry or geographic concentration. And while GP skill only accounts for 4%-6% of the total return variation of a typical investment, it accounts for more than 40% of the return variation at the fund level. These findings show that GPs use portfolio construction, and not just deal selection, to seek risk-adjusted fund-level returns.

*The authors thank the Institute for Private Capital and Burgiss for support of this project including access to the primary data set utilized in the analysis, and Wendy Hu for providing research support. We also thank William Cong, Peter Cornelius, Olivier Darmouni, Paolo Fulghieri, Will Gornall (discussant), Oleg Gredil, Lu Han, Ulrich Hege, Gerard Hoberg, Philip Howard, Niklas Huether, Arthur Korteweg, Peng (Peter) Liu, Tong Liu, Erik Loualiche, Nadya Malenko, Filippo Mezzanotti, Andrea Rossi, Albert Sheen, Morten Sorensen (discussant), Christophe Spaenjers (discussant), Andreas Stathopoulous, Eva Steiner, Ting Xu, Michael Weisbach, Ayako Yasuda as well as participants of Tulane, UNC brownbag, and the 2021 IPC Spring Research Symposium, 2022 USC Finance, Organizations and Markets Conference, 2022 WashU St. Louis Annual Conference on Corporate Finance, 2022 UNC Annual Private Equity Research Consortium, 2022 Conference on Financial Economics and Accounting, 2022 Society of Quantitative Analysts conference for useful comments and suggestions.

1 Introduction

The private equity industry has grown over the last forty years from a relatively niche investment segment to a $6 trillion asset class. It is now a major component of the portfolios of many insurance companies, pension funds, university endowments and sovereign wealth funds. Accordingly, many industry and academic observers have approached private equity performance measurement through the lens of the *investor's* portfolio management decision; asking, for example, how a retirement system might optimally add private equity commitments to a portfolio including public equities, fixed income, and other asset classes (see Korteweg and Westerfield (2022) for a review and also Gredil et al. (2020), Giommetti and Sorensen (2021), Gourier et al. (2022)). This approach implicitly informs relative performance measures in private equity and is the subject of much practical debate in industry circles on private equity investing (Kaplan and Schoar (2005), Robinson and Sensoy (2013), Harris et al. (2020)).

There is yet another, perhaps more important, portfolio management decision in private equity, one that is intrinsic to the delegated nature of the investment process itself. Specifically, general partners (GPs), who are responsible for investing the capital committed by limited partners (LPs), deploy their fund's capital sequentially, building a portfolio of individual investments. Indeed, the very term *portfolio company*, commonly used to refer to the targets of private equity investment, reflects the fact that the GP is forming a portfolio of investments when they raise a fund and deploy the capital. Nevertheless, most discussions of GP investment behavior couch their investment decision in terms of "deal selection", treating the merits of an individual investment in isolation, rather in terms of "portfolio formation".

How is a fund's committed capital allocated across investments, and what are the implications of this for the risk and return associated with a specific manager or fund? Do GPs trade off specialization and diversification? Under what conditions are specialist GPs better than generalist GPs? The goal of this paper is to take a step toward answering these questions. Using a novel dataset of holdings-level returns and portfolio composition, we explore the portfolio of individual investment decisions made by a GP during the life of a private equity fund and connect the characteristics of these investments to deal-level and fund-level performance.

The tradeoffs that GPs face when forming portfolios are natural in light of the standard contract between LPs and GPs in private equity. Because most PE funds make only a small number of investments (usually no more than a dozen per fund), the carried interest that they earn on exited investments compensates them both for their effort in selecting and improving companies, as well as for bearing idiosyncratic risk. Indeed, Ewens et al. (2013) argue that requiring GPs to bear idiosyncratic risk is part of the solution to the agency conflict between LPs and GPs. They face a natural tradeoff between exploiting specialized skills, which likely requires a smaller, more focused portfolio, or minimizing the idiosyncratic risk they face through one of several mechanisms: they can diversify idiosyncratic risk by making a larger number of smaller investments; they can diversify across industries and/or regions to benefit from lower correlations between portfolio companies; and they can choose to invest in less risky companies or structure their investments so they are less risky.

To study these tradeoffs we use a novel dataset of 5,925 portfolio company holdings for 467 distinct buyout funds with vintage years from 1999-2016 operated by 315 distinct private equity firms. Our investment and return data are updated through 2020.[1] The data are broad in terms of industry and geography. For example, 52% of the portfolio companies in our data are located in North America, 34% are in Western Europe, and portfolio companies operate in all 11 GICS sectors (consumer discretionary, health care, information technology, etc.)

Our most basic results relate to sector- and geographic-specialization within a fund. Here we find that more focused funds generate higher returns. These results are consistent with GPs benefiting from expertise in specific geographies or industries. Yet, specialized funds are, by definition, less diversified and so are likely bearing more region-specific or industry-specific risks. In fact, we find that more specialized funds have higher overall risk. Thus, a risk-return tradeoff exists at the fund level with regard to the degree of specialization in investment focus.

To dig deeper, we next ask how GPs allocate the money inside the fund to build a

[1]While we the data we use are technically the holdings in funds reported to GPs, they are fully representative of the deals done by the funds, so we use the terms "holding" and "deal" interchangeably. We do not consider fund vintages after 2016 since most newer funds will still be in their investment period.

portfolio of different investments. We focus on two dimensions: deal size and deal timing.[2] Ranking holdings from largest to smallest as a percentage of fund size, we find that the largest investments have, on average, the lowest returns. This stands in sharp contrast to evidence from mutual funds and hedge funds, which invest in public companies, whose highest returns come from outsized positions in their "best ideas" (Antón et al. (2021)). In fact, returns within a typical PE fund increase monotonically as the investment size rank increases through the 5th largest investment made by a PE fund. To see whether our finding is due to the diseconomies of scale and quick flips, we control for fund size and deal duration.[3] The results continue to hold after controlling for fund size and deal duration.

Why do PE buyout funds make outsized bets on low-returning investments? One reason could be the return-risk trade-off discussed above: GPs do not want to "bet the ranch" on any one investment. Indeed, when we calculate a ratio of average deal returns to average risk by size rank of the investments, we find it is essentially constant. In other words, larger investments are associated with lower risk, so that on average the risk-return profile of investments are the same regardless of investment size. This is consistent with a portfolio strategy where GPs identify good investments of various sizes but are mindful of the risks.[4] This risk management concern is consistent with the findings of Braun et al. (2020) who find that large deals (relative to fund size) are significantly more likely to be offered for co-investment. In sum, in private equity, managers take their biggest bets on their "safest ideas" instead of "best ideas."

In a similar vein, we sort deals based on their investment year within the fund to study deal timing. The "risk-management" view would suggest that managers start with safer (lower-return) deals and then explore riskier (higher-return) deals as they are increasingly confident that they have locked in returns sufficient to meet the hurdle rates required to earn carried interest. Alternatively, the "exploration" view would predict that managers first bet on riskier (higher-return) deals and then invest in safer (lower-return) deals later on to hedge

[2] Unlike (Lopez-de Silanes et al. (2015)), we focus on investments held at the fund level rather than aggregate across funds to the firm level.

[3] Lopez-de Silanes et al. (2015) show that quick flips are associated with the highest returns. In our sample, we do find that quick flips tend to be smaller within funds.

[4] Our data do not allow us to examine whether managers apply lower leverage to larger deals to mitigate risk. This is an interesting avenue to pursue with data availability.

risks. Empirically, we find that funds start with higher-return deals. That is the earlier deals in the fund are of higher-return and higher risks. The deals made in the later years are of lower return and lower risks. Interestingly, when we examine the "Private Equity Sharpe Ratio" (information ratio) |the ratio of standard deviation to the mean of the investment's PME|we find that it is essentially constant across deals.

Do general partners and their investors benefit from the portfolio management decisions they make? Is portfolio management skill a source of persistent differences across GPs? To investigate this issue, we extend the model of Korteweg and Sorensen (2017) to incorporate deal-level data. Our method provides a way to separate GP portfolio management skills, i.e., the GP intrinsic value at the fund level that contain asset selection skills common to all deals in the same fund, and deal-selection skills conditional on fund-level skills.

Following Cavagnaro et al. (2019), we develop two extensions of the Korteweg-Sorensen framework, one with and one without deal-level idiosyncratic risks. This helps us distinguish between portfolio management skills and deal selection skills.[5] Similar to Cavagnaro et al. (2019), we we use a combination of a fund-deal (first stage) and a GP-deal (second stage) hierarchical linear model to represent the GP-fund-deal model, so as to quantify variations across GPs in fund-specific effects and deal-specific effects. Using Bayesian methods, we decompose the total variance of returns into different random effects. In the first stage, we decompose deal return variation into fund-specific, fund-year-specific, fund-deal-specific random effects, conditional on covariates. In the second stage, we estimate adjusted deal returns on GP-specific, GP-year-specific, and GP-deal-specific random effects and covariates. The two extensions differ in the adjusted deal return entering the second stage. In the first extension, we adjust the deal return by subtracting the fund-specific and fund-year-specific effects from the actual deal return, leaving the deal-specific effect (deal selection skills) entering the second stage. In the second extension, we subtract the fund-year-specific and fund-deal-specific effects from the actual deal return, leaving the fund-specific effect (portfolio management skills) entering the second stage. The difference in the estimated GP-specific effect between the two extensions reflects the GP's fund management skills.

[5] Cavagnaro et al. (2019) extend the KS model to the LP-fund-GP setting to study the skills of LPs, which is a different question than the one in this paper. The techniques are similar in CSWW and our paper.

We find that around 90% of performance variation can be attributed to idiosyncratic risk at the deal level, suggesting that GPs bear substantial deal-level risk. This is in alignment with the argument by Korteweg and Sorensen (2017) that, to a large extent, luck drives the return variation for any particular deal. However, our results at the fund-level show that GP skill accounts for more than 40% of return variation. This is consistent with GPs benefiting from diversification (risk reduction) in a fund structure that increases the signal-to-noise ratio for LPs evaluating their skill when deciding on re-upping for subsequent funds.

In spite of the centrality of the issue we study in this paper, almost no work to date has studied the GP's investment decision through the lens of portfolio construction. The closest are Lopez-de Silanes et al. (2015), which documents the decreasing returns to scale of buyout funds, and Spaenjers and Steiner (2021), which shows that specialized investors in hotels outperform generalist funds. In venture capital, Gompers et al. (2009) and Hochberg et al. (2015) investigate the specialization of funds. Almost all existing work in private equity research either focuses on the performance of individual investments made by GPs or else focuses on the net-of-fee returns earned by investors in private equity funds.

The remainder of the paper proceeds as follows: section 2 provides a conceptual framework that motivates the portfolio management approach of our analysis. section 3 presents our data and discusses the main variables used in the analysis. section 4 examines how within-fund relative deal size is related to deal performance. section 5 examines the relation between overall portfolio concentration and specialization and fund-level performance. In section 6 we present the estimates of hierarchical linear models where we learn more GP skills. section 7 concludes.

2 Conceptual Framework

Extant research examining private equity largely takes as granted the model where GPs periodically raise capital in a fund structure and then invest it by acquiring controlling stakes in a portfolio of companies over (typically) a five-year period. After acquiring a company, GPs employ any number of techniques to build value and then exit the investments and return capital to LPs. It is widely believed by market participants that GPs have different skill levels and LPs try to evaluate that skill when deciding whether or not to invest in a GP's next fund (so-called "re-ups"). However, it is not immediately clear why this organizational structure dominates the industry. For example, why don't GP's raise money on a deal-by-deal basis. Or why do GPs have a fixed fund life that requires them to return capital? Why do we often see GPs specializing in industries or geographies? Why does the typical fund invest in 10-20 portfolio companies, and not more or less? In this section, we propose an economic framework from the perspective of a profit-maximizing GP that can help us better understand the answers to some of these questions. Our goal is to propose testable hypotheses derived from the trade-offs facing GPs that we can take to the data. We start by outlining at a high level a framework that makes predictions of PE portfolio management based on a set of assumptions. We then discuss the literature related to our assumptions in more detail.

We propose the following situation: There exists organizations (or individuals) with the ability to generate high risk-adjusted investment returns by buying controlling stakes in companies. For convenience, we think of these as firms that seek to operate on an ongoing basis and are typically a collection of "deal partners" who identify investment opportunities, close transactions, add value to the purchased companies, and ultimately exit the deals through another transaction (e.g., initial public offering (IPO), sale to strategic buyer or secondary PE deal). We assume that deal partners have increasing returns to scale for individual deals as well as value-relevant expertise in some specific dimensions, such as industry or geography (see Braun et al. (2019)). This then suggests that deal partners have an incentive to take on a small (perhaps just one) investment at a time in their area of expertise (i.e., industry and region). We also assume that deal partners vary in their ability to add value to companies and that there is a large random component to both the availability and the performance of any given deal. Specifically, deal partners may target deals of a certain size, but the actual opportunities could be substantially larger or smaller than the target. Likewise, the returns for any particular deal are highly uncertain even for a deal partner with high skill. Consequently, a GP's skill level is not easily observed with precision by others. Instead, others infer a noisy signal of skill through costly "due diligence" including observing the performance of previous (and existing) investments.

We also assume that while some of the funding for the investment opportunities comes from the firm (e.g., deal partners), most of the capital can be obtained from outside investors. Given the right structure, this allows the firm to increase returns by leveraging the expertise of deal partners. However, utilizing outside capital requires some form of investment vehicle such as a partnership where, for example, the firm serves as the GP and outside investors are LPs. The GP and LPs must then decide on the terms of the investment relationship and each faces trade-offs.

LPs are reluctant to provide a blank check because they are uncertain of the GP's skill level. In addition, LPs require a mechanism for realizing investment returns from the partnership such as the return of proceeds from individual investments. This arrangement reduces the risk of agency costs from asset substitution and shirking. For example, if GPs seek to do additional future investments they must go back to the market of LPs and demonstrate a performance track record that (partially) reveals their superior skill. The due diligence involved with evaluating GPs is costly and has a fixed component for each GP/fund. As a result, LPs face trade-offs between the cost of identifying skilled GPs and the benefits of earning high risk-adjusted returns which results in LPs making investments in a relatively small number of funds (GPs).

Given this market arrangement, a given GP firm then faces a fundamental trade-off when making investment decisions in such a fund structure: The GP will expect to earn high returns from making a small number of investments, however they run the risk of being labelled as low-skilled if the small number of investments experience bad luck. Being perceived as low-skilled would limit the GP's ability to raise future outside capital and thus reduce the franchise value of the firm. Making more investments increases the signal-to-noise ratio for outside investors by reducing the idiosyncratic risk of the fund's portfolio, but doing more deals also lowers the expected return of the fund. The same trade-off applies to specialization by industry or geography if there are industry-specific or region-specific risks that can be diversified away. Finally, GPs will consider the size of deals given the implications of doing very large risky deals, and in particular GPs may choose to only do large deals with below-average risk, or alternatively, GPs may finance large deals more conservatively (i.e., with lower than typical leverage) to mitigate deal-specific risk.

This framework results in a series of testable hypotheses: H1: GPs with more concentrated portfolios will have higher returns and higher risk, ceteris paribus H2: GPs will manage risk so that larger investments will have lower risk, even at the cost of lower returns. H3: GPs with more specialized portfolios (e.g., by industry and region) will have higher returns and higher risk, ceteris paribus H4: GP skill will be easier to observe (have a higher signal-to-noise ratio) at the fund level than at the deal level. While this framework is both simple and intuitive, it is worth relating our assumptions to previous findings in detail.

2.1 Specialization, Human Capital and Resource Exchanges

Specialization is related to superior risk-adjusted investment opportunities (e.g., Kacperczyk et al. (2005, 2016)). Furthermore, evidence suggests that generating excess returns requires scarce expertise and thus exhibits decreasing returns to scale. The portfolio management problem facing private fund GPs can then be considered in an organizational economics framework (much as any company makes resource allocation decisions) as well as a portfolio management context.

Many companies acquired by buyout funds are similar to publicly-traded companies (and many PE deals take public companies private), but, of course, the governance systems utilized by PE owners and public company fund investors are typically very different. For example, buyout funds usually have controlling stakes and monitor the performance of the portfolio companies as insiders on an ongoing basis. Likewise, buyout funds typically assume control of the board of directors. With this control, GPs provide detailed input into strategy, operations, and management recruitment. Again, the deep knowledge and time commitment likely needed for optimal advisory efforts limits the number of portfolio companies a particular PE manager can effectively manage. In other words, spreading human capital too thinly by investing in too many companies could dilute the value added by the GP.

Private equity GPs commonly undertake substantial governance and operational interventions in portfolio companies. A frequently stated objective of PE ownership is to improve operational performance and productivity (e.g., Kaplan (1989), Davis et al. (2014), Bloom et al. (2015)). Evidence suggests that specialized human capital is a distinctive feature in this process. Moreover, prior evidence suggests that agency conflicts between the GPs and founders can result in concentration and specialization providing a more efficient way of utilizing human capital (see, Marquez et al. (2015), Kanniainen and Keuschnigg (2003, 2004), and Lopez-de Silanes et al. (2015)).

On the other hand, active involvement of PE managers can also facilitate resource exchanges. For example, being advisors and board members can allow for punishing expropriation behavior (Lerner (1995) and Hellmann and Puri (2002)). As in the model of Fulghieri and Sevilir (2009), technology relatedness between the portfolio companies of the same VC increases the benefits of human knowledge. Gompers et al. (2009) show that generalist firms tend to underperform relative to specialist firms, especially when the individual venture capitalists are not industry specialists. Lindsey (2008) finds that alliances are more frequent among companies sharing a common venture capitalist. Bayar et al. (2020) find that specialist VCs are more likely to join in a VC syndicate to finance an entrepreneurial firm while generalist VCs are more likely to invest in the firm alone. González-Uribe (2020) provides empirical evidence on the existence and benefits of resource exchanges within a given VC portfolio. Specifically, more specialized funds can provide more opportunities for innovation and operational resource exchanges between portfolio companies that generate higher returns. This predicts a positive relationship between industry concentration and fund returns.

2.2 Information Asymmetry

Both public and private equity fund investments can suffer from asymmetric information between the portfolio company and the fund manager prior to an investment.[6] However, given that due diligence is typically more costly and time-consuming for private investments and fixed costs of transactions are considerable, private investors are likely more limited in the number of deals they can thoroughly investigate. Consequently, concentration and specialization in information collection can generate greater economic benefits for PE investors because deals often rely on more costly operational interventions that require a deeper under-

[6]See, for example, Van Nieuwerburgh and Veldkamp (2009, 2010) for discussion of public equity funds and Bernstein et al. (2017), and Gompers et al. (2020) for discussions of venture capital. More recent evidence in venture capital and private equity includes Cao (2020), Howell (2020).

standing of a company. For example, GPs with deep industry or geographic expertise may be able to better identify the opportunities for a portfolio company than a generalist. By bridging information asymmetries (e.g., in their role of screeners and monitors; see Sørensen (2007), and Kaplan and Strömberg (2001, 2003)), a portfolio approach may generate higher returns than single deal approach in PE.

Information benefits related to deal flow and due diligence can also arise from network effects (Sorenson and Stuart (2001, 2008), Hochberg et al. (2007)). Gaining access to networks of other investors can offer advantages in collecting information about a potential portfolio company, its product market, and related deal terms. Localized and specialized information exchanges may provide more useful information than information gained through loose contacts. For example, prior research that examines the venture capital industry suggests information-sharing and learning benefits from specialization (Bygrave (1987, 1988), Sahlman (1990), Norton and Tenenbaum (1993)).

2.3 Franchise Value of GP and Risk Management

At a very basic level, fund managers seek to allocate their efforts across investment decisions they make so as to maximize their utility. Fundamentally, this means that fund managers will make deliberate decisions on the number and type of investments in the portfolios under their management. In the case of a PE fund, the end result is a finite set of portfolio companies with observable characteristics that can be viewed as the outcome of the GPs optimization problem discussed above. However, GPs clearly seek to maximize the total value of the firm as a going concern which will depend on the performance of current fund(s) but also revenue associated with operating future funds (Chung et al. (2012), Barber and Yasuda (2017), Chakraborty and Ewens (2018), Brown et al. (2019)). Consequently, it is likely that the GP will consider both the *return and the risk* of portfolio company investments. For example, a GP will not want to take undo risk with a fund that could jeopardize the ability to raise future funds. This suggests that GPs will consider the portfolio properties of their funds as well as the prospects of individual investments. Thus, GPs likely face a trade-off between the value-creation achieved through focusing their scarce and specialized skills and the idiosyncratic risk of an overly concentrated portfolio.

The GPs problem is further complicated by the lumpiness and illiquidity of the controlling-stake investments they typically make. So, while GPs have some ability to control investment size (e.g., through offering co-investment or doing club deals),[7] the flexibility is limited compared to investments a mutual fund or hedge fund makes in the equity of a publicly-traded company. Instead, private funds typically have the ability to determine the financial structure of a deal (e.g., degree of leverage) which in turn is a determinant of the riskiness of the deal. For example, private fund managers may seek to limit the risk of larger deals by using less leverage.

Performance is often measured relative to peer funds. This exposes GPs to certain risks related to portfolio concentration and specialization. If a GP is highly specialized in terms of industry or geography there will likely be a large component of performance related to that industry or geography. If the fund performance is compared to peers outside that industry or performance then the fund could face difficulties in fundraising. Being a generalist mitigates this risk. A similar case can be made for the concentration of investments in a fund. A smaller number of larger investments means that the fund performance will have a larger idiosyncratic component. The idiosyncratic risk means the GP is more heavily exposed to fundraising risk that is likely undesirable for the GP. Consequently, GPs will likely seek to balance the benefits of concentration and specialization with the GP's business risks of being undiversified.[8]

3 Data

3.1 Data Source

In this study, we rely on a new dataset of private equity buyout holdings (i.e., investment "deals") and return information from Burgiss, a global provider of data management services

[7] Club deals with multiple PE sponsors provides some flexibility. This has become less common since the US Securities and Exchange Commission brought antitrust lawsuits against 11 large GPs alleging collusion. Another route is co-investments, but co-investments may or may not provide the same set of investment opportunities as existing evidence on whether there is adverse selection in co-investments is mixed (Fang et al. (2015); Braun et al. (2020).

[8] GPs have taken other approaches to diversify this risk by having dedicated fund products across multiple industries and geographies.

for the limited partner community. Additional information on the Burgiss holding-level dataset is provided in Brown et al. (2020). Sourced directly from LPs, Burgiss provides a set of detailed, verified and cross-checked portfolio company information for a large sample of institutional-quality private equity funds. In this analysis, we specifically examine buyout funds because portfolio characteristics of buyout funds are especially under-researched. While this paper is among the first to use the holdings-level dataset from Burgiss, fund-level data from Burgiss have been used extensively in recent academic work.[9].

Because including funds with incomplete holdings information may have a significant effect on the precision of our concentration measures, we require nearly complete holdings history for a fund to be included in our sample. As a result, we focus on funds with vintages from 1999 to 2016 where vintage year is defined as the year of the first portfolio company investment. We only include vintage years through 2016, because more recent funds are still in their investment period. We impose some further restrictions for a fund to be included in the sample to prevent extreme or unusual situations from affecting our variables of interest. Specifically, we require that i) all the holdings in the fund have deal size information (no missing values), ii) the fund made at least three, but less than 50 deals, deals and iii) $0.25 < \frac{\Sigma DealSize_i}{FundSize} < 2$, i.e., at least 25% of the amount of the fund size are covered by the sum of deal sizes and the fraction does not surpass 200% where fund size is defined as the total value of commitments to the fund. In total, we use data for 468 buyout funds investing in 5,925 portfolio companies.

We also emphasize that we define *Deal Size* as the investment value provided by the fund. The actual value of individual buyout deals (e.g., total enterprise value) would typically be larger because of debt and potentially other equity investors. Because we are looking at deals through the lens of the GPs portfolio management decisions, this is the most appropriate measure of size, and we refer to the capital committed by the fund as *Deal Size* just to simplify the exposition.

[9]See, for example, Brown et al. (2019, 2021); Harris et al. Harris et al. (2014, 2018, 2020)

3.2 Performance Measures

PE performance can be measured in a variety of ways. Two popular metrics that can be applied to both holdings and funds are the investment multiple and the public-market equivalent (PME). Our preferred measure of performance is the Kaplan and Schoar (2005) PME which compares a deal in a private holding or fund to an equivalently timed investment in a public market benchmark index. The Kaplan and Schoar (2005) PME effectively calculates the ratio of private asset investment multiple to the public market multiple, so for example, a PME of 1.15, indicates that, at the end of the evaluation period, an investor ended up with 15% more than if they had invested in the public market index. Korteweg and Nagel (2016) and Sorensen and Jagannathan (2015) provide theoretical descriptions and justifications for PME. We use gross PMEs that represent the experience of GPs in individual deals (i.e., that exclude fund-level fees and carried interest) because of data availability. A general concern with the PME measure is whether the benchmark accurately represents the risk faced by investors. The strength of this method is its economic grounding of the opportunity cost of capital use and its transparency in evaluation.

As discussed in length in Harris et al. (2014), the calculation of PME may depend on the choice of the public market benchmark index. In general, the findings in Harris et al. (2014) suggest that the average PMEs is fairly robust to a range of different public market benchmarks.[10] Following Braun et al. (2017), we choose the benchmark index based on the region of the holding. We use Russell 3000 for holdings in North America, the Asia and Pacific MSCI performance index for Asian and Pacific holdings, the Europe MSCI performance index for European holdings, and the MSCI World performance index for other holdings. All indices are in USD as we utilize data in Burgiss that has all been converted to USD.[11]

We also look at the ratio of total fund value to paid-in capital (TVPI), which is defined as the ratio of the sum of current fund net asset value and total distributions to total amount invested. The TVPI compares the sum of all distributions and the value of unrealized investments to the sum of all contributed cash. It is an absolute measure of performance

[10]SP 500, Nasdaq, Russell 3000, Russell 2000, and Fama-French 8th, 6th, 4th, and 2nd size deciles.

[11]At this time, the Burgiss holding database only provides the investment entry and exit year (instead of exact date), and we assume July as the entry month and June as the exit month when comparing with public market benchmarks.

and does not take into account the return of the public markets over the investment period. This provides a measure that is unadjusted for public market risks which may be more appropriate when considering the total riskiness of the portfolio. For the realized deals, the total amount of funding into the deal and the actual realized return out of the deal (including escrow) are used to calculate the TVPI. For unrealized deals, the most recent net asset valuation (NAV) is used to calculate performance. This study uses the valuation information updated through the third quarter of 2020.

3.3 Summary Statistics

Table 1 reports the summary statistics and correlations for the primary variables utilized in our analysis. Panel A reports the summary statistics of deal-level characteristics. Our deal sample has a mean (median) PME of 1.63 (1.27) and an interquartile range is 0.62 to 2.17. Panel B reports the summary statistics of fund-level variables, and Panels C and D report the pairwise correlations between the deal-level and fund-level variables, respectively. Definitions of other variables are discussed below in related sections and also can be found in Appendix Table A1.

[INSERT Table 1 AROUND HERE]

4 Deal Sizing and Deal Timing

In this section, we study how private equity funds allocate assets to different investments inside their portfolios.

The first dimension we investigate is the deal sizing. A typical buyout transaction results in a controlling equity position by the GP and often a near 100% ownership stake. Thus, in most cases GPs cannot precisely determine the size of their investments as it is determined by the total equity value of the deal. However, GPs can do club deals or offer co-investment to reduce their ownership stake and in turn reduce total risk exposure to a given deal. GPs can also typically adjust the level of debt (i.e., financial leverage) of a deal which would in turn determine the level of risk. As described in Section 2, GPs may want to invest more in deals that the believe are likely to outperform in the same way investors in public equity load up on their "best ideas." On the other hand, the risk-return trade-off and portfolio rebalancing concerns will likely limit how much GPs are willing to risk on a given deal. Therefore, it is an empirical question as to whether larger deals will tend to outperform or underperform smaller deals for a particular fund and whether these deals are more or less risky than smaller deals.

In addition, we study a second dimension – the deal timing. As discussed above, the "exploration" view suggests that managers start with safer (lower-return) deals and then explore riskier (higher-return) deals. Alternatively, the "risk management" view predicts that managers first beg on riskier (higher-return) deals and then invest in safer (lower-return) deals later on to hedge risks. We test the relation between deal timing sequence within the fund and deal return.

4.1 Measures

We use the deal size rank measure to capture the within-fund size rank of deals. More specifically, our relative deal size measure is *Deal-Size Rank*, which is the rank of deal size within a given fund as measured by the dollar value of the investment. For example, a *Deal-Size Rank* of one means that the deal is the largest investment made by a fund, a Deal-Size Rank of two represents the second largest deal in the fund, and so on. We group ranks of ten or more into a single rank category (the maximum of deals in a fund is 49; there are 72 deals with ranks of 31 or higher, 246 deals with ranks of 21 to 30, and 1299 deals with ranks of 11 to 20). Figure 1 shows the distribution of deal sizes (dollar value) for different ranks. The largest deal is often exceptionally large – more than $1/7^{\text{th}}$ of total fund value. This concentration falls off quickly so that the fifth largest deal is about $1/12^{\text{th}}$ of total fund value.

[INSERT Figure 1 AROUND HERE]

We emphasize that the rank measure is a relative measure that takes the variation in fund size into account. Bigger funds tend to have larger deal sizes, and bigger funds may (or may not) have better investment opportunities that lead to higher returns. We control for absolute fund size in our regression analysis.

Our measure of the within-fund timing sequence of deals is based on the deal's investment year. Due to data limitations, we only have information on deal entry timing by year. More specifically, our deal timing measure is *Deal Sequence*, which is the year of a funds life when a given deal is done. For example, a *Deal Sequence* of one means that the deal is made in the first year when the fund starts to invest, a *Deal Sequence* of two represents the deals made in the second year, and so on. We group sequences of five or more into a single category (there are 350 deals with a sequence six, 130 deals with a sequence seven, and 46 deals with a sequence of eight or higher).

[INSERT Figure 2 AROUND HERE]

Figure 2 plots the distribution of deal sizes as a percent of fund size for different sequences. The deal average deal sizes across different sequences are similar, however there appears to be a slight downward trend in the dispersion of size by sequence.

4.2 Illustrative Results

We start by examining performance results by emphDeal-size Rank by plotting summary staistics by *Deal-Size Rank*) in Table 2. Plot (a) shows average deal PMEs as the solid blue line and indicates that a fund's largest deal has the lowest return on average with a mean PME of 1.26. As the *Deal-Size Rank* increases, the mean return increases monotonically for the first five *Deal-Size Rank* groups and then becomes relatively stable around 1.7. Table 2 shows that the results are similar across different percentiles except for the very bottom of the distribution where PMEs are zero regardless of rank and for the maximum PME which exhibits no pattern. This suggests that the relation between *Deal-Size Rank* and PMEs is not driven by outliers but instead a fairly stable feature across funds.[12]

[12]We also examine other characteristics by *Deal-Size Rank* group. Detailed results are provided in Internet Appendix Table B1. We have sufficiently large dispersion in deal size (and the relative ratio to fund size) across different rank groups which is important for the validity of our analysis. We also observe that relatively larger deals (lower ranks) have longer duration suggesting that these deals are less likely to be quick flips. We do not observe any trends in fund age at deal entry, deal entry year, or deal exit year by *Deal-Size Rank*.

[INSERT Figure 3 AROUND HERE]

[INSERT Table 2 AROUND HERE]

The finding that larger deals have lower returns is in contrast to the findings for mutual funds and hedge funds (Antón et al. (2021)). As noted above, an important factor could be risk management. Because larger deals in PE funds are typically a much larger percentage of fund value than the largest position in a mutual fund, larger PE deals pose a greater risk to overall fund performance. Thus, GPs may only undertake larger deals if they are less risky. We consider the standard deviation of PMEs across funds as a proxy for the average risk of each *Deal-Size Rank* group. Table 2 tabulates these values and Plot (a) of Figure 3 plots them as the dashed red line. The results indicate that variation in PMEs is lower for relatively large deals. The largest deal group has a standard deviation of PMEs of 1.24, and values trend up to about 1.6 for the fifth largest deal in a fund and then show no obvious trend for higher ranks.

These results are consistent with the lower average performance for relatively large investments being a choice by GPs. Specifically, larger deals also have lower risk, which is consistent with the notion that GPs do not want to "bet the ranch" on large deals, but this comes with the sacrifice of lower average returns. It is also consistent with a risk return trade-off in private equity which we examine in more detail later.

A logical next question is if this behavior is related to agency issues facing the LP-GP relationship. Excessive risk-aversion by GPs could lead to sub-optimal risk-return decisions from the LPs' perspectives. One crude way to see if GPs are overly risk-averse in relatively large deals is to calculate the ratio of mean PME to the standard deviation of PMEs for each *Deal-Size Rank* group – akin to a Sharpe Ratio (information ratio) for each group. Results are shown in the last column of Table 2 and plotted in Plot (b) of Figure 3 and indicate that the ratio of return to risk is essentially constant across *Deal-Size Rank* groups. This finding is consistent with GPs evening out risk-adjusted returns across relative deal sizes. We interpret this as evidence consistent with the hypothesis that there are not significant agency costs associated with GP risk-aversion as it pertains to deal sizing.

[INSERT Figure 4 AROUND HERE]

[INSERT Table 3 AROUND HERE]

The second dimension we study is how deal investment sequence relates to deal return (PME) and riskiness. We sort deals by their investment sequence within the fund (i.e., by *Deal Sequence*) from the early deals (sequence one) to late deals (sequence five and greater). Plot (a) in Figure 4 shows average deal PMEs as the solid blue line and Panel A of Table 3 reports summary statistics of deal PMEs for each *Deal Sequence*. The results indicate that on average deal returns in the first few years of a fund's life have higher returns with a mean PME of 1.68. Mean (and median) PMEs decrease for deals done later in the investment period (i.e., for *Deal Sequence* 4 and 5). The dashed red line in Plot (a) of Figure 4 shows the riskiness of the deals made in different years of the fund life (as measured by the standard deviation of PMEs) and that risk follows the same tendency to decline as funds age. Plot (b) of Figure 4 shows that the ratio of mean to standard deviation of PMEs is quite stable around 1.00 for all *Deal Sequence* groups.

Taken together, the results in this section show that GPs appear to systematically balance the risk and return of their portfolio by managing the relative size and timing of investments.

4.3 Regression Results

In this section we further investigate the relation between performance, *Deal-size rank*, and *Deal Sequence* in the presence of other deal characteristics in a regression framework. In particular, we examine the importance of other variables that measure the absolute deal size, if the investment is fully exited, the size of the fund, and the duration of the deal, fixed effects for the deal industry, and geographic region,[13] and GP fixed effects.

[13] We do not control for deal entry and exit fixed effects because they are co-linear with deal sequence and deal duration. Deal sequence is calculated based on the deal investment year. Deal duration is the number of years spanning the investment and exit years.

[INSERT Table 4 AROUND HERE]

Table 4 reports the results. As was the case in the univariate analysis, the regression results indicate that larger deals tend to have lower returns. Columns (1) to (3) of Table 4 report results without GP fixed effects. In column (1), we regress deal PME on *Deal-Size Rank* and *Deal Sequence*. A one-notch increase in size rank is associated with an average increase in PME of 0.05, which is similar to what we inferred from averages shown in Table 2. A one year increase in deal sequence is associated with an average decrease in PME of 0.05. Column (2) includes the absolute deal size to capture ant effect of larger deals having potentially lower returns. The effect of absolute deal size is negative and marginally significant, but the coefficients on *Deal-Size Rank* and *Deal Sequence* are largely unchanged.

Column (3) shows the results with the full set of control variables and location and industry fixed effects. We find that the positive and statistically significant relationship between PME and *Deal-Size Rank* persists after controlling for for other variables, however, the magnitude of the relation is somewhat smaller. For example, in specification (3), a one-notch increase in rank is associated with a 0.03 increase in PME. The the negative and statistically significant relation between *Deal Sequence* and PME also persists in the presence of other control variables and the magnitude does not change. The coefficient on the dummy variable indicating fully exited deals is positive and significant, consistent with anecdotal evidence that better deals realize exits more quickly (and counter to the hypothesis that value creation is still occurring or interim valuations are conservative). Similarly, longer duration deals have lower PMEs. Controlling for deal exit dummy and deal duration also mitigates the concerns that our results on deal sequence merely reflects the mechanical fact that earlier deals are more likely to exit up to a given time period or earlier deals may have shorter duration.

Columns (4) – (6) report the specifications with GP fixed effects. We observe the same relationship that relative larger deals within the fund have lower returns (a positive relation between *Deal-Size Rank* and deal PME). We also observe the same negative relation between deal sequence and deal PME, implying that later deals have lower returns. All coefficients on

Deal-Size Rank remain positive and significant at the 99% confidence level. All coefficients on *Deal Sequence* remain negative and significant at the 99% confidence level. This implies that the incentive to balance between different deals within the fund is not GP-specific. The magnitude of the coefficients on *Deal-Size Rank* and *Deal Sequence* are even slightly larger after controlling for GP fixed effects, suggesting that the portfolio management pattern is stronger after accounting for any differences in GP styles. In the Internet Appendix, we also report results including *Deal-Size Rank* (Table B3) and *Deal Sequence* (Table B4) separately.

Take together, our findings suggest that PE managers actively manage risk-return trade-offs in deals by carefully allocating equity investments in portfolio companies of the different underlying risks. While the data do not allow us to accurately determine whether this is done through deal selection, capital structure, or a combination, our findings are consistent with the portfolio management view. Speaking to relative deal size position, our finding stands in contrast to the "best ideas" findings in mutual funds and hedge funds where relatively large positions have higher returns on average. Instead, we find that managers balance between deals with different sizes to control for the overall riskiness of the portfolio. In terms of timing, we find evidence that managers take on more risks and invest in higher return deals in the beginning and then put in deals with lower risks and returns in the later life of the fund.

4.4 Robustness of Regression Results

One concern is that some funds have not fully invested all the capital committed by limited partners by the end of the sample period. This might affect our results if there is a trend in deal size over the investment period of recent funds. For example, if funds invest larger and higher returning deals later in the investment period, then our sample could be missing these realizations, and thus overestimate the negative relationship between deal size and return.

In addition, evidence indicates that NAVs suffer from smoothing and systematic misvaluation (Barber and Yasuda (2017), Brown et al. (2019)). However, due to data availability, we have little choice but to use reported NAVs at our ending date for unrealized deals. Of course, cash flows are not subject to the same biases and so we have more confidence in results based only (or primarily) on realized deals. Given the high proportion of unrealized deals for more recent vintages, the accuracy of the valuation information is important for proper return measurement.

To address these concerns, we examine the subsample of deals held by funds that have a $FractionInvestedratio \geq 80\%$. We also allow for a time gap of at least four years to have investments to be realized (our sample ends in 2016 while the data is collected in the third quarter of 2020). Results are robust to this sample restriction (and presented in Internet Appendix Table B2.

We also do robustness checks using the full rank number and sequence number of the deals (i.e., we do not group deals with rank higher than ten together, similarly, we do not group deals with a sequence later than five together). Results are reported in Table B5 in the Internet Appendix. Our main findings that relative larger deals within the fund and relative later deals made by the fund being lower return are essentially unchanged.

5 Concentration, Specialization and Fund Performance

In this section, we investigate how other portfolio management considerations contribute to performance at the fund level. First, we examine the relation between portfolio investment size concentration and fund returns. For example, do funds that focus on fewer investments outperform? Second, we examine how industry and geographic specialization affect the fund performance.

5.1 Measures

We develop fund-level portfolio concentration and specialization measures based on Gini and Herfindahl-Hirschman-style indices.

5.1.1 Gini Index

Our *Gini Index* is borrowed from the wealth inequality literature (e.g., Atkinson et al. (1970)) and measures the ideal size distribution within a fund. The larger the *Gini Index*, the higher the more highly concentration a fund's investments. By construction, the index is always between [0,1]. As reported in Panel B of Table 1, the median buyout fund has a *Gini Index* of 0.25. The *Gini Index* ranges from 0.05 to 0.69 for the sample under study. The wide range of values indicates significant cross-sectional variations in terms of the degree of portfolio concentration.

5.1.2 Industry Concentration Index

Our fund-level Herfindahl-Hirschman-style industry concentration index is calculated as the sum of the squared within-fund portfolio weights for each of the 11 GICS sectors (and an "other" category where the GICS sector is not identified).[14] Specifically, we define,

$$HHIsector_f = \Sigma_{i=1}^{12} w_{s,f}^2 \tag{1}$$

where f is the fund identifier, and s represents the sector so that $w_{s,f}$ is the share of deal size in sector s held by fund f, i.e., $w_{s,f} = \frac{\Sigma_{i \in s} dealsize_i}{max\{FundSize_f, \Sigma_{i \in F} DealSize_i\}}$. The larger the index, the higher the industry concentration.

Panel B of Table 1 tabulates summary statistics for the industry concentration index. The mean (median) HHI sector concentration index is 0.26 (0.22) with an interquartile range of 0.16 to 0.30. These values demonstrate that there also exists a considerable cross-sectional variation in industry concentration.

5.1.3 Geographic Concentration Index

In a similar fashion to the industry concentration index, our measure of fund-level geographic concentration is calculated as

$$HHIregion_f = \Sigma_{i=1}^{11} w_{r,f}^2 \tag{2}$$

where f is the fund identifier, r represents the geographic region and $w_{r,f}$ is the share of deal size in region r held by fund f, i.e., $w_{r,f} = \frac{\Sigma_{i \in r} dealsize_i}{max\{FundSize_f, \Sigma_{i \in F} DealSize_i\}}$. Deals in the Burgiss holding database span in 11 geographic regions. Appendix Table A2 shows the detailed composition of the regions for our sample. Summary statistics for the region concentration index are in Panel B of Table 1. The funds in our sample have a mean (median) of 0.65

[14] Appendix Table A2 presents the detailed composition of sectors for our sample of deals in this study.

(0.66) for the HHI region index with an interquartile range of 0.51 to 0.81. This implies that the cross-sectional variation in fund-level geographic concentration is also sufficiently large in our sample.

5.1.4 Fund-Level Performance

Fund level returns are calculated as the weighted-average of deal-level returns (where the weights are the deal sizes) for all deals in the fund. This is essentially a gross PME and not the same fund-level return calculated from LP cash flows as in Harris et al. (2014) and Brown et al. (2019) because it does not account for fees and other fund-level characteristics such as fund-level leverage. To avoid results being driven by a few extremely high deal-level returns, we Winsorize the TVPIs at the 99th percentile before calculating fund-level PMEs. Panel B of Table 1 shows the mean (median) buyout fund has a value-weighted PME of 1.54 (1.46). The fund-level value-weighted PME interquartile range is 1.20 to 1.82.

5.2 Regression Results

In this section, we investigate how concentration and specialization are related to return and risks at the fund level. To get a rough feel for the industry and geographic specialization at the fund-level versus the overall sample concentration, Figure 5 plots the industry (panel (a)) and region (panel(b)) concentrations by year for the full sample of deals and by vintage year for funds.

[INSERT Figure 5 AROUND HERE]

The results indicate that the degree of specialization at the fund level is fairly high. In other words, funds typically focus on a subset of industries and regions (compared to the universe of all deals) when making their investment decisions.

[INSERT Table 5 AROUND HERE]

To better understand how concentration and specialization relate to fund risk and return we estimate two sets of fund-level regressions. As a proxy for fund returns we use the fund-level (gross) PME as the dependent variable. As a proxy for fund-level risk we use the standard deviation of deal-level PMEs within a fund. Table 5 reports results from regressions with fund-level deal concentration, specialization and other control variables as the independent variables. Columns (1) to (4) present the results for fund-level returns. Column (1) shows a negative relation between the *Gini Index* and *value-weighted PME* indicating a lower return for more concentrated funds. However, the coefficient is not statistically different from zero which suggests that benefits to economies of scale from more concentrated bets are offset by the previously documented tendency for larger positions to have lower returns.

Column (2) in Table 5 presents results on the relation between fund-level industry specialization and return. We find a positive and statistically significant relation between *HHI sector* and *PME*, indicating higher returns for funds with more industry specialization. Column (3) presents the results on the fund-level relationship between performance and geographic concentration of the portfolio companies held by the fund. Similar to the results on industry specialization, funds with a higher geographic concentration level have a higher return *ceteris paribus*.

In column (4), we include all the three measures: the *Gini Index*, the *HHI sector* and the *HHI region*. We continue to find the positive and significant relationship between industry/geographic concentration and fund returns in the specification with the full set of control variables. A one standard deviation increase in the *HHI sector* (*HHI region*) index is associated with a 0.48 (0.46) increase in *PME*. Both results are significant at the 95% level.

It is important to consider the risk-return trade-off related to concentration on the fund level. Columns (5) to (8) show results with the dependent variable as the standard deviation of PMEs of deals within the fund (i.e., fund deal riskiness). Column (1) shows that a higher level of portfolio concentration is related to a higher standard deviation of PMEs. The implication is that even if large deals are less risky (as shown in the previous section), the overall effect on the fund-level risk of a concentrated portfolio is positive. A one standard deviation increase in the *Gini Index* contributes to a 0.097 increase in the *standard deviation of PME* of deals in the fund. The result is statistically different from zero at the 95% confidence level.

Columns (6) – (8) show the results on risk and *HHI sector* and *HHI region*. Results are generally consistent across different specifications. In our preferred specification which includes all variables and vintage fixed effects (column (8)), a one standard deviation increase in the *HHI sector* (*HHI region*) index is associated with a 0.062 (0.124) increase in the standard deviation of deal PMEs. The coefficient for the *HHI sector* variable is significant at the 90% confidence level, and the coefficient for *HHI region* variable is significant at the 95% level.

Overall, our results suggest that concentration in a few deals generates higher fund-level risk without a commensurate increase in return. However specialization by industry and geography is associated with both higher returns and higher risk.

The PME performance measure adjusts for public market returns, and thus, implicitly systematic market risk of the portfolio deals. As a result, using the standard deviation of the deal PMEs to measure the riskiness of the fund portfolio may underestimate the risk. As a robustness check, we conduct similar analysis as to Table 5, but use TVPI as the performance measure.

[INSERT Table 6 AROUND HERE]

Table 6 reports the regression results where the dependent variables are calculated using TVPI performance measures. Columns (1) to (4) report the effects of concentration and specialization on fund TVPI. We observe mostly similar patterns to results with PMEs as the dependent variable – coefficients on independent variables of interests always have the same sign but significance levels differ somewhat. Specifically, the results for concentration (Gini Index) are stronger and the results for regional specialization (HHI Region) are weaker. Columns (5) to (8) report the results on the riskiness of the portfolio as measured by the standard deviation of the deal TVPIs in the fund. The coefficient on the Gini index is somewhat smaller and not significant. However, the coefficients for the industry and specialization HHI indices are larger as compared to the results using the standard deviation of deal PMEs and both remain statistically different from zero. Overall, our findings are always in the same direction and of simlar magnitude when using TVPI but significance levels change. These results could derive from TVPI being a noisier measure of deal-partner skill than PME.

5.2.1 Robustness: Alternative Measures of Fund Size

We also conduct robustness checks by examining how alternative methods of measuring fund size affect the results. In the regressions in Table 5, we measure fund size as the *maximum* of total capital commitment and the sum of deal sizes. As an alternative measure, we use the total capital commitment. The alternative measures of fund size also affect the calculation of the HHI indices and we adjust correspondingly. Results are similar (and reported in Internet Appendix Table B6 for PME and B7 for TVPI).

6 Parametric Estimation of the Hierarchical Linear Model

The OLS regression analyses in the previous sections show that GPs balance risk and return among deals of different sizes within a fund and also that fund concentration and specialization are related to the fund performance. These patterns suggest that portfolio management at the fund level is important. The regression analyses have the advantage of being easy to interpret. However, we do not learn the magnitude of fund-level portfolio effects from such analyses. In this section, we quantify the portfolio effect by separating the (fund-level) portfolio management dimension and the deal-selection dimension of GP skills.

To study these questions, we adopt hierarchical linear models to our GP-Fund-Deal level dataset. As shown in Figure 6, the private equity industry features a clear hierarchical structure, with the GP firms being at the top of the tree, funds as a middle layer, and deals being the bottom nodes. Hierarchical linear models are widely used, for example, in education research to capture the hierarchical structure of school-class-student, and were first introduced to study PE return in Korteweg and Sorensen (2017) (KS model henceforth) and later extended by Cavagnaro et al. (2019) (CSWW henceforth) to the LP-Fund-GP setting to study the skill of LPs.

[INSERT Figure 6 AROUND HERE]

6.1 The Model

The original model developed in Korteweg and Sorensen (2017) is a two-layer GP-Fund hierarchical linear model where one can learn about the relative importance of GP intrinsic value (skill) to the fund-level idiosyncratic risks (luck) in explaining fund return. The KS model also contains a GP-time-specific effect that tells us how much covariance in the returns of funds with overlapping fund years is due to common exposure to market conditions and investment strategy. More discussions about the fund-level model and estimation results using our sample are provided in the Internet Appendix.

We extend the KS model to a three-layer GP-Fund-Deal hierarchical regression model. Using the GP-Fund-Deal model, we can quantify the variation across GPs in their intrinsic value in terms of portfolio management. In the model, idiosyncratic risks are captured by deal-specific random effects. Because we are interested in comparing the GP-specific effects with and without idiosyncratic risks, we need to estimate the GP-Fund layer using the estimation of deal-specific random effects from the Fund-Deal layer. Therefore, we estimate the model in two stages. That is to say, in order to distinguish between GP skills in deal selection and portfolio management, we need to estimate GP skills in two different models, as presented below.

First Stage (Fund-Deal Level) In the first stage, we estimate a hierarchical linear model at the fund-deal level using the deal return as the left-hand side variable.

$$DealReturn_{iuj} = X'\beta + \Sigma_{\tau=t_{iuj}}^{t_{iuj}+DealLife_{iuj}}(FundRE_u + FundYearRE_{u\tau}) + \epsilon_{uj} \tag{3}$$

where i represents the GP firms, u represents funds, j represents deals, X are the observed covariates (in the estimation, we control for deal entry and exit year fixed effects), t_{iuj} denotes the deal's first year (entry year), $DealLife_{iuj}$ denotes the deal life which is the number of years from the deal entry to the deal exit, $FundRE_u$ is the fund-specific random effect, $FundYearRE_{u\tau}$ is the fund-time random effect, and ϵ_{uj} is the fund-level deal-specific random effect. Deal return is measured using TVPI.

Second Stage (GP-fund level) In the second stage, we estimate a hierarchical linear model at the GP-fund level using the *adjusted* deal return as the left-hand side variable.

$$\widehat{DealReturn}_{iuj} = \Sigma_{\tau=t_{iuj}}^{t_{iuj}+DealLife_{iuj}}(GPRE_i + GPYearRE_{i\tau}) + \nu_{ij} \tag{4}$$

where i represents the GP firms, u represents funds, j stands for deals, t_{iuj} denotes the deal's first year (entry year), $DealLife_{iuj}$ denotes the deal life which is the number of years from the deal entry to the deal exit, $GPRE_i$ is the GP-specific random effect, $GPYearRE_{i\tau}$ is the GP-time random effect, and ν_{ij} is the GP-level deal-specific random effects. Deal return is measured using TVPI.

We examine two models that differ in how the *adjusted* deal return is calculated. The estimated GP-specific effect ($GPRE_i$) from Model 1 tells how skillful GPs are at achieving high-return deals. The estimated GP-specific effect ($GPRE_i$) from Model 2 tells how skillful GPs are at managing funds.

In Model 1, the adjusted return for each deal is after subtracting estimated fund-specific effect and fund-year-specific effect from the *actual* deal returns (Equation 5). The variation left in the *adjusted* deal returns reflects GP's skills to achieve high return deals (the deal-specific effect ϵ_{uj}).

$$\widehat{DealReturn}_{iuj} = DealReturn_{iuj} - X'\hat{\beta} - \Sigma_{\tau=t_{iuj}}^{t_{iuj}+DealLife_{iuj}}(\widehat{FundRE}_u + \widehat{FundYearRE}_{u\tau}) \tag{5}$$

Where $\widehat{FundRE}_{iu\tau}$ is the estimated fund random effect, $\widehat{FundYearRE}_{u\tau})$ is the estimated fund-year random effect.

In Model 2, when computing the *adjusted* return for each deal, we subtract the estimated fund-year-specific effect and the fund-level deal-specific effect from the *actual* deal return (Equation 5′). The variation left in the adjusted deal returns reflects the GP's value-added in fund management (the fund-specific effect $FundRE_u$).

$$\widehat{DealReturn}_{iuj} = DealReturn_{iuj} - X'\hat{\beta} - \Sigma_{\tau=t_{iuj}}^{t_{iuj}+DealLife_{iuj}}\widehat{FundYearRE}_{u\tau} - \widehat{\epsilon}_{uj} \tag{5′}$$

Where $\widehat{FundYearRE}_{iu\tau}$ is the estimated fund-time random effect, and $\widehat{\epsilon}_{uj}$ is the estimated fund-level deal-specific random effect.

The assumptions on the parameter distribution are the same in the GP-Fund level model (KS model) and discussed in the Internet Appendix. The variance decomposition in the first and second stages is similar. Using the second stage as an example, the total variance in $DealReturn_{iu}$ is the sum of the variances of the above discussed three random effects,

$$\sigma^2(DealReturn) = N^2\sigma^2(GPRE) + N\sigma^2(GPYearRE) + \sigma^2(\epsilon) \tag{6}$$

and we further define the percentage of skill (i.e., signal-to-noise ratio), overlap effect, and noise as

$$\text{Signal to Noise (Skill)\%} = \frac{N^2\sigma^2(GPRE)}{\sigma^2(DealReturn)}, \tag{7a}$$

$$\text{Overlap Effect\%} = \frac{N\sigma^2(GPYearRE)}{\sigma^2(DealReturn)}, \tag{7b}$$

$$\text{Noise\%} = \frac{\sigma^2(\epsilon)}{\sigma^2(DealReturn)}. \tag{7c}$$

6.2 Bayesian Estimator

Following KS and CSWW, we estimate our model using a Bayesian estimator, techniques of Markov Chain Monte Carlo (MCMC), and Gibbs sampling.[15] While the model could also be estimated by classical maximum likelihood estimation (MLE), Bayesian estimation is better for estimating parameters with non-negativity constraints (e.g., variance), small sample inferences (the mean number of funds managed by GPs is 1.74, and the mean number of deals in a fund is 11.78 in our sample), and allowing for non-normal distributions, which suit the skewed return pattern in PE.

Each MCMC cycle g in the algorithm consists of two steps. Following the approach outlined in sections A1 to A5 of the appendix in Korteweg and Sorensen (2017), the first step is to obtain a random draw of each parameter in the KS model. We employ the priors and initial values described in section A7 of the Korteweg and Sorensen (2017) appendix.

[15]For more details on the estimation procedure and why the Bayesian estimator fits the PE setting, see Korteweg and Sorensen (2017) and Korteweg (2011).

The priors are sufficiently diffuse for the results to be determined by the data instead of by the prior assumptions. In KS model, the random effects ϵ_{uj} are redefined so that their mean is the fund effect $FundRE_u$. We instead leave them as mean zero to ease interpretation of the second step of our estimation.

At the end of the first stage, we adjust the total return of each fund according to equation Equation 5 or Equation 5′ in order to account for the fund-time random effects (or plus deal-specific random effects). Then, based on the current cycle's adjusted returns, we obtain a draw of each parameter in Equation Equation 4 and their variances. As in the first stage, the priors in the second step are also diffuse so that the data, rather than prior assumptions, drive the outcomes.

6.3 Results

[INSERT Table 11 AROUND HERE]

Table 11 shows the results estimated from the first stage of the model (Equation 3), which decomposes the variance into fund-specific random effect, fund-year-specific random effect, and deal-specific random effect (conditional on the fund). The estimates are close to those in the GP-deal model, as reported in Internet Appendix Table B9. The first-stage analysis provides several findings. First, we find that noise accounts for 80% to 90% (depending on specifications) of the deal-level total return variation. This implies that idiosyncratic risk at the deal level accounts for a large part of return variation. Second, overlapping effects account for 16.14% without controlling for deal year fixed effects and account for 4.62% after controlling for deal entry and exit year fixed effects. The difference between the overlapping effects, which are random effects, and the deal year fixed effects is that the former captures the time effects only common to all deals in the same fund and the latter captures the time effects common to all deals. Therefore, our findings suggest that 71.38% ($\frac{16.14-4.62}{16.14}$) of the overlapping effects at the deal level come from factors affecting all deals such as common market risk exposure, and the rest 28.62% come from fund-level common strategies that impose a time-variant effect to deal return. Finally, fund-specific effects account for 4.52% of the deal returns after controlling for deal entry and exit year fixed effects.

[INSERT Table 12 AROUND HERE]

Table 12 reports the results of second-stage estimates. Columns (1) to (4) report the results of Model 1 where we subtract fund-specific fund-year-specific effects when adjusting the deal return entering the second-stage estimation (Equation 5). The results tell us how GP skill affects deal returns if we take into account both fund-specific effects (i.e., how good GPs are at portfolio management) and deal-specific effects (i.e., how good GPs are at selecting deals conditional on funds). We find that GP-skill only accounts for 6.43% of the total variance of returns. Noise accounts for more than 87.06% of the return variation. This implies that GP-specific effects do not play an important role in achieving high-return deals. Put differently, the variance in how much one GP can systematically differ from another GP in the deal idiosyncratic component (luck) is small.

Columns (5) to (8) report the results of Model 2 where we subtract both fund-year-specific and deal-specific effects when adjusting the deal returns entering the second-stage estimation (Equation 5′). This case measures how GP skills in the fund-specific component (i.e., GP's portfolio management skills) affect returns. We find that skill accounts for a much larger part of the return variation, 45.69%, in this case. This implies that GPs differ to a large degree in their portfolio management skills. The noise component only accounts for 8.53% of the return variation. The difference in the results from Model 1 and Model 2 sheds light on which dimension lies GP skills. Our findings suggest that GPs mainly differ in their portfolio management skills. Specific deal-picking skills are limited given the high riskiness of the PE industry.

To clarify, we mean deal-picking in a broad sense that includes both ex-ante selection and ex-post monitoring. Also, skills that can lead to an overall high return for all deals in the fund are included in the fund-specific component (and thus in portfolio management). However, our findings suggest that GPs do not differ much in finding particular high-return deals. This is consistent with our findings in the regression analysis that GPs do not chase extreme alpha in the scarification of bringing additional riskiness to the whole fund.

There is also a difference in the overlapping effect between Models 1 and 2. In Model 1, GP-year random effects are around half of the GP random effects while the GP-year random effects are close to GP random effects in Model 2. Examples of the overlapping effect at the GP level are the GP common strategies (e.g., management-team-year specific effect) and risk exposures to the market conditions that are common for funds managed by the same GP. The contrast in the results in the GP-year effects between Models 1 and 2 implies that GP styles are around twice as important as GP-year strategies for return with idiosyncratic risks, but as important as GP-year strategies for return deducting idiosyncratic risks.

6.4 Discussions

The value generated by portfolio management is not simply the mechanical reduction in return dispersion when we aggregate more granular return observations (i.e., deal-level) to a higher level (i.e., fund-level). Without careful portfolio management, as long as holdings are not wrapped into funds in a monotonic way from low return to high return, there would be a greater reduction in return dispersion at the fund level than at the deal level.[16] Internet Appendix Figure A1 shows that the return dispersion is lower at the fund level than at the deal level. However, this can be due to two distinct effects: the value added by portfolio management and the reduction in return dispersion at a more aggregate level. Using a three-layer GP-Fund-Deal hierarchical regression model, we provide estimates of the portfolio effect in this section.

One way of thinking about a portfolio is the group of all the deals managed by the GP in a given time period (Lopez-de Silanes et al. (2015)). For a couple of reasons, we define a portfolio by considering a fund as a distinct subset of all deals managed by the GP. First, we have the advantage that our data provides clear structure of the GP-Fund-Deal. Second, there are economic reasons (e.g., those discussed above) for how funds select portfolio companies (e.g., some funds invest in specific industries or regions) and thus analyses using funds as a middle-layer is potentially more economically insightful.

Taken together, using the three-layer GP-fund-deal model, we provide novel evidence on the magnitude of the relative importance of portfolio management in private equity.

[16] Braun et al. (2020), using simulations of portfolio sizes, show that portfolios of ten buyout deals on average outperform fund returns, net of fees and costs.

Consistent with the literature, we find that noise (luck in the expression in Korteweg and Sorensen (2017)) explains a large part of return variation. However, conditional on deal-specific "luck", GPs show a large variation in their skills in portfolio management.

7 Conclusion

In this paper we use novel, investment-level data to explore the tradeoff that general partners in private equity face between specialization and diversification. Studying the investment decisions of private equity general partners through the lens of portfolio formation allows us to learn more about how the fund-level risk and return measures are influenced by the interdependencies between individual fund-level investment decisions.

In keeping with the idea that an important source of value creation in private equity is focused, context-specific knowledge about a sector or a market, we find that focused funds earn higher returns than funds that pursue a diversified investment strategy. This focus, however, comes at the cost of higher volatility. On balance, the ratio of market-adjusted performance to overall volatility is similar across strategies, suggesting that there is an equilibrium tradeoff at the fund-level between focus and diversification.

Digging more deeply into the sequence and size of individual investments, we find that general partners do not place the biggest bets on their "best"|i.e., highest return|ideas; instead, they place the biggest bets on the safest ideas. Within a fund, ranking individual investments in increasing order of size would rank them in decreasing order of riskiness. At the same time, we find evidence of *exploration* early in the life of the fund, as smaller and riskier investments tend to occur earlier, while larger, safer investments occur later. Even though idiosyncratic risk accounts for a large part of the total variance of deal returns, GP skill accounts for more than 40% of the return variation at the fund level.

These findings suggest a fruitful avenue for theoretical work in exploring the tradeoffs that general partners face between exploiting specialized knowledge and benefitting from diversification. This raises interesting questions in organizational economics about the optimal formation of investment teams inside private equity funds. It also raises questions about how the use of leverage in an individual buyout transaction is influenced not just by market conditions but by risk-mitigation concerns vis-a-vis the other deals in the fund's portfolio. We leave these questions for future work.

References

Antón, M., Cohen, R. B., and Polk, C. (2021). Best ideas. *Available at SSRN 1364827*.

Atkinson, A. B. et al. (1970). On the measurement of inequality. *Journal of Economic Theory*, 2(3):244–263.

Barber, B. M. and Yasuda, A. (2017). Interim fund performance and fundraising in private equity. *Journal of Financial Economics*, 124(1):172–194.

Bayar, O., Chemmanur, T. J., and Tian, X. (2020). Peer monitoring, syndication, and the dynamics of venture capital interactions: Theory and evidence. *Journal of Financial and Quantitative Analysis*, 55(6):1875–1914.

Bernstein, S., Korteweg, A., and Laws, K. (2017). Attracting early-stage investors: Evidence from a randomized field experiment. *The Journal of Finance*, 72(2):509–538.

Bloom, N., Sadun, R., and Van Reenen, J. (2015). Do private equity owned firms have better management practices? *American Economic Review*, 105(5):442–46.

Braun, R., Dorau, N., Jenkinson, T., and Urban, D. (2019). Whom to follow: Individual manager performance and persistence in private equity investments. In *Proceedings of Paris December 2019 Finance Meeting EUROFIDAI-ESSEC*.

Braun, R., Jenkinson, T., and Schemmerl, C. (2020). Adverse selection and the performance of private equity co-investments. *Journal of Financial Economics*, 136(1):44–62.

Braun, R., Jenkinson, T., and Stoff, I. (2017). How persistent is private equity performance? evidence from deal-level data. *Journal of Financial Economics*, 123(2):273–291.

Brown, G., Harris, R., Hu, W., Jenkinson, T., Kaplan, S. N., and Robinson, D. T. (2021). Can investors time their exposure to private equity? *Journal of Financial Economics*, 139(2):561–577.

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

Brown, G. W., Harris, R. S., Hu, W., Jenkinson, T., Kaplan, S. N., and Robinson, D. T. (2020). Private equity portfolio companies: A first look at burgiss holdings data. *Available at SSRN 3532444*.

Bygrave, W. D. (1987). Syndicated investments by venture capital firms: A networking perspective. *Journal of Business Venturing*, 2(2):139–154.

Bygrave, W. D. (1988). The structure of the investment networks of venture capital firms. *Journal of Business Venturing*, 3(2):137–157.

Cao, R. (2020). Information frictions in new venture finance: Evidence from product hunt rankings. *Available at SSRN 3774227*.

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

Chakraborty, I. and Ewens, M. (2018). Managing performance signals through delay: Evidence from venture capital. *Management Science*, 64(6):2875–2900.

Chung, J.-W., Sensoy, B. A., Stern, L., and Weisbach, M. S. (2012). Pay for performance from future fund flows: the case of private equity. *The Review of Financial Studies*, 25(11):3259–3304.

Davis, S. J., Haltiwanger, J., Handley, K., Jarmin, R., Lerner, J., and Miranda, J. (2014). Private equity, jobs, and productivity. *American Economic Review*, 104(12):3956–90.

Ewens, M., Jones, C. M., and Rhodes-Kropf, M. (2013). The price of diversifiable risk in venture capital and private equity. *The Review of Financial Studies*, 26(8):1854–1889.

Fang, L., Ivashina, V., and Lerner, J. (2015). The disintermediation of financial markets: Direct investing in private equity. *Journal of Financial Economics*, 116(1):160–178.

Fulghieri, P. and Sevilir, M. (2009). Size and focus of a venture capitalist's portfolio. *The Review of Financial Studies*, 22(11):4643–4680.

Giommetti, N. and Sorensen, M. (2021). Optimal allocation to private equity. *Available at SSRN 3761243*.

Gompers, P., Kovner, A., and Lerner, J. (2009). Specialization and success: Evidence from venture capital. *Journal of Economics & Management Strategy*, 18(3):817–844.

Gompers, P. A., Gornall, W., Kaplan, S. N., and Strebulaev, I. A. (2020). How do venture capitalists make decisions? *Journal of Financial Economics*, 135(1):169–190.

González-Uribe, J. (2020). Exchanges of innovation resources inside venture capital portfolios. *Journal of Financial Economics*, 135(1):144–168.

Gourier, E., Phalippou, L., and Westerfield, M. M. (2022). Capital commitment.

Gredil, O., Liu, Y., and Sensoy, B. A. (2020). Diversifying private equity. *Available at SSRN 3535677*.

Harris, R. S., Jenkinson, T., and Kaplan, S. N. (2014). Private equity performance: What do we know? *The Journal of Finance*, 69(5):1851–1882.

Harris, R. S., Jenkinson, T., Kaplan, S. N., and Stucke, R. (2018). Financial intermediation in private equity: How well do funds of funds perform? *Journal of Financial Economics*, 129(2):287–305.

Harris, R. S., Jenkinson, T., Kaplan, S. N., and Stucke, R. (2020). Has persistence persisted in private equity? evidence from buyout and venture capital funds. Technical report, National Bureau of Economic Research.

Hellmann, T. and Puri, M. (2002). Venture capital and the professionalization of start-up firms: Empirical evidence. *The Journal of Finance*, 57(1):169–197.

Hochberg, Y. V., Ljungqvist, A., and Lu, Y. (2007). Whom you know matters: Venture capital networks and investment performance. *The Journal of Finance*, 62(1):251–301.

Hochberg, Y. V., Mazzeo, M. J., and McDevitt, R. C. (2015). Specialization and competition in the venture capital industry. *Review of Industrial Organization*, 46(4):323–347.

Howell, S. T. (2020). Reducing information frictions in venture capital: The role of new venture competitions. *Journal of Financial Economics*, 136(3):676–694.

Kacperczyk, M., Sialm, C., and Zheng, L. (2005). On the industry concentration of actively managed equity mutual funds. *The Journal of Finance*, 60(4):1983–2011.

Kacperczyk, M., Van Nieuwerburgh, S., and Veldkamp, L. (2016). A rational theory of mutual funds' attention allocation. *Econometrica*, 84(2):571–626.

Kanniainen, V. and Keuschnigg, C. (2003). The optimal portfolio of start-up firms in venture capital finance. *Journal of Corporate Finance*, 9(5):521–534.

Kanniainen, V. and Keuschnigg, C. (2004). Start-up investment with scarce venture capital support. *Journal of Banking & Finance*, 28(8):1935–1959.

Kaplan, S. (1989). The effects of management buyouts on operating performance and value. *Journal of financial economics*, 24(2):217–254.

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

Kaplan, S. N. and Strömberg, P. (2001). Venture capitals as principals: Contracting, screening, and monitoring. *American Economic Review*, 91(2):426–430.

Kaplan, S. N. and Strömberg, P. (2003). Financial contracting theory meets the real world: An empirical analysis of venture capital contracts. *The Review of Economic Studies*, 70(2):281–315.

Korteweg, A. and Nagel, S. (2016). Risk-adjusting the returns to venture capital. *The Journal of Finance*, 71(3):1437–1470.

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

Korteweg, A. G. (2011). Markov chain monte carlo methods in corporate finance. *Available at SSRN 1964923.*

Korteweg, A. G. and Westerfield, M. M. (2022). Asset allocation with private equity. *Available at SSRN 4017858.*

Lerner, J. (1995). Venture capitalists and the oversight of private firms. *the Journal of Finance*, 50(1):301–318.

Lindsey, L. (2008). Blurring firm boundaries: The role of venture capital in strategic alliances. *The Journal of Finance*, 63(3):1137–1168.

Lopez-de Silanes, F., Phalippou, L., and Gottschalg, O. (2015). Giants at the gate: Investment returns and diseconomies of scale in private equity. *Journal of Financial and Quantitative Analysis*, 50(3):377–411.

Marquez, R., Nanda, V., and Yavuz, M. D. (2015). Private equity fund returns and performance persistence. *Review of Finance*, 19(5):1783–1823.

Norton, E. and Tenenbaum, B. H. (1993). Specialization versus diversification as a venture capital investment strategy. *Journal of Business venturing*, 8(5):431–442.

Robinson, D. T. and Sensoy, B. A. (2013). Do private equity fund managers earn their fees? compensation, ownership, and cash flow performance. *The Review of Financial Studies*, 26(11):2760–2797.

Sahlman, W. A. (1990). The structure and governance of venture-capital organizations. *Journal of Financial Economics*, 27(2):473–521.

Sørensen, M. (2007). How smart is smart money? a two-sided matching model of venture capital. *The Journal of Finance*, 62(6):2725–2762.

Sorensen, M. and Jagannathan, R. (2015). The public market equivalent and private equity performance. *Financial Analysts Journal*, 71(4):43–50.

Sorenson, O. and Stuart, T. E. (2001). Syndication networks and the spatial distribution of venture capital investments. *American Journal of Sociology*, 106(6):1546–1588.

Sorenson, O. and Stuart, T. E. (2008). Bringing the context back in: Settings and the search for syndicate partners in venture capital investment networks. *Administrative Science Quarterly*, 53(2):266–294.

Spaenjers, C. and Steiner, E. (2021). The value of specialization in private equity: Evidence from the hotel industry. *HEC Paris Research Paper No. FIN-2020-1410.*

Van Nieuwerburgh, S. and Veldkamp, L. (2009). Information immobility and the home bias puzzle. *The Journal of Finance*, 64(3):1187–1215.

Van Nieuwerburgh, S. and Veldkamp, L. (2010). Information acquisition and under-diversification. *The Review of Economic Studies*, 77(2):779–805.

Figures

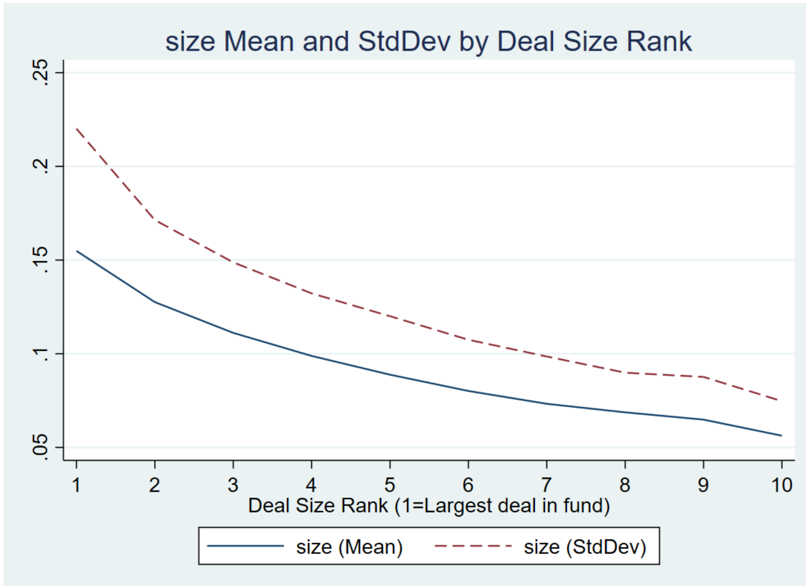


Figure 1: Deal Size by Deal-Size Rank in the Fund

Note: This figure plots the mean and standard deviation of deal sizes in each rank category. The horizontal axis is the rank of the deal (*Deal-Size-Rank*). The vertical axis is the mean (Mean, blue solid line) or standard deviation (StdDev, red dashed line) of the deal size in a given rank category. Deal size is measured in USD billions. *Deal-Size-Rank* is the rank of deal within the fund, sorted by size. 1 to 10 refers to the largest to the smallest. E.g., rank 1 means that the deal is the largest in the fund that it belongs to. Rank 2 means that the deal is the second largest in the fund. We group deals with ranks larger than 10 into one single category: rank 10.

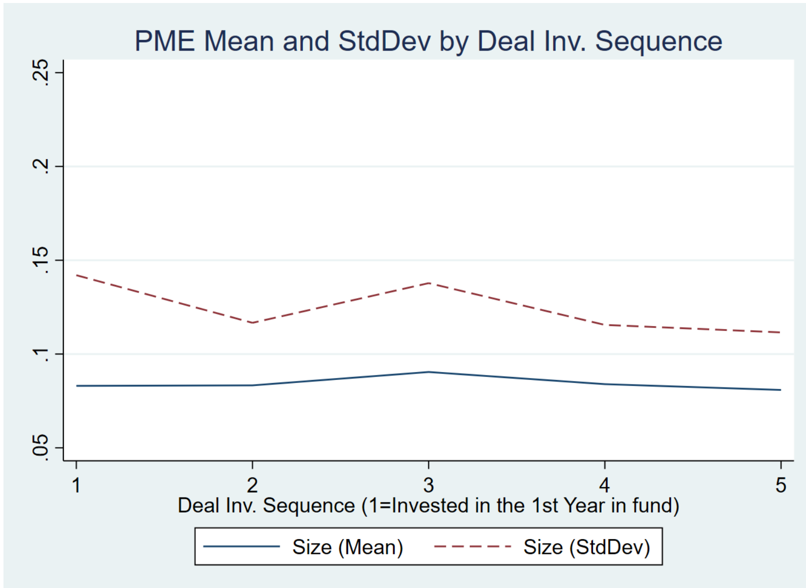
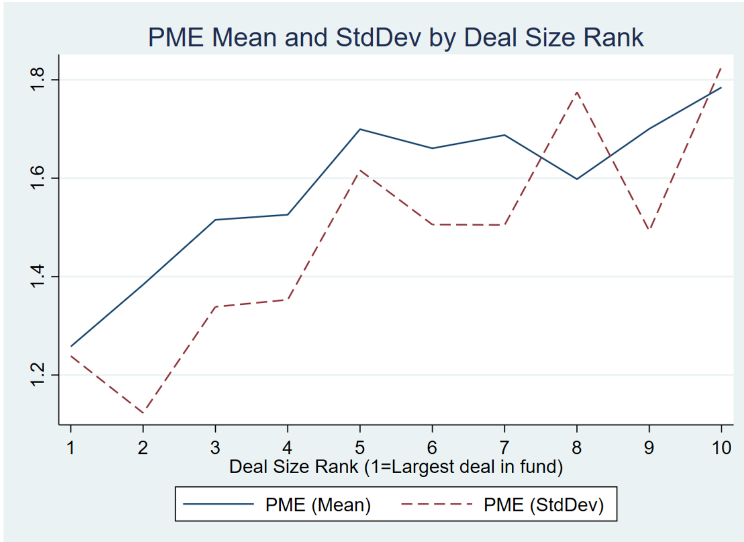
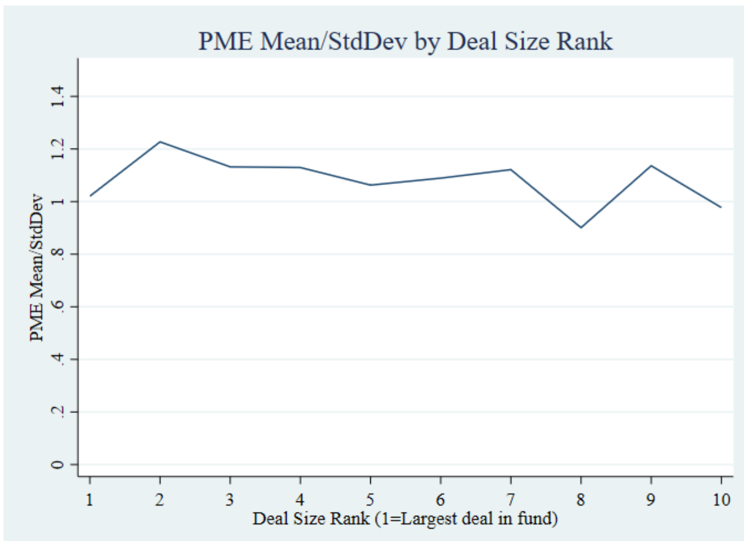


Figure 2: Deal Size by Deal Timing Sequence in the Fund

Note: This figure plots the mean and standard deviation of deal sizes in each timing sequence category. The horizontal axis is the sequence of the deal (*Deal Inv. Sequence*). The vertical axis is the mean (Mean, blue solid line) or standard deviation (StdDev, red dashed line) of the deal size in a given rank category. Deal size is measured in USD billions. *Deal Inv. Sequence* is the timing sequences of deal within the fund, sorted by investment year. One to five refers to the earliest to the latest. E.g., sequence one means that the deal is made in the first year when the fund begins to make investments. Sequence two means that the deal is made in the second year of the fund's investment period. We sequence deals to the year level due to data availability. We group deals with sequences larger than five into one single category: rank five.



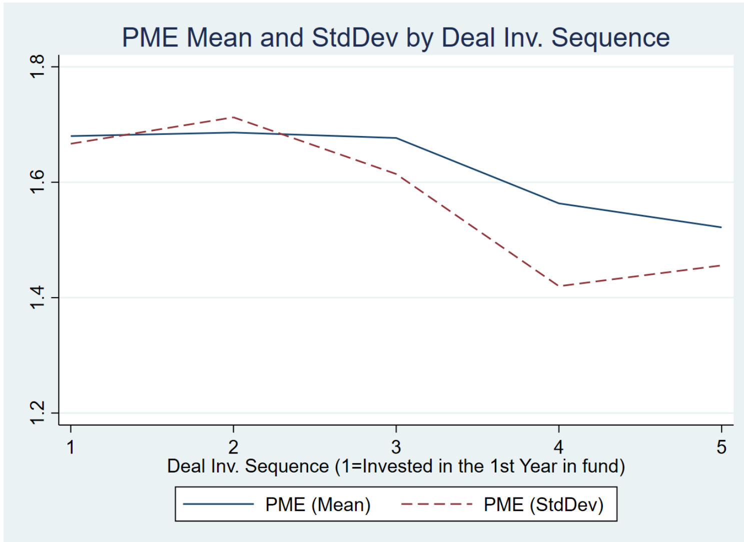
(a) Mean and S.D.



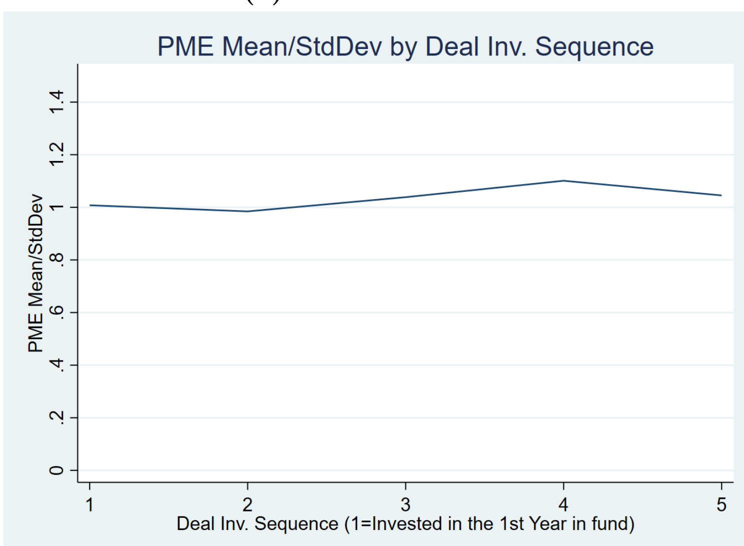
(b) Mean/S.D.

Figure 3: Deal PME by Deal-Size Rank in the Fund

Note: This figure plots the mean and standard deviation of deal PME in each deal-size rank category. The horizontal axis is the rank of the deal (*Deal-Size-Rank*). In Panel (a), the vertical axis is the mean (Mean, blue solid line) or standard deviation (StdDev, red dashed line) of the deal PMEs in a given rank category. In Panel (b), the vertical axis is the mean of the deal PMEs divided by the standard deviation of the deal PMEs. *Deal-Size-Rank* is the rank of deal within the fund, sorted by size. 1 to 10 refers to the largest to the smallest. E.g., rank 1 means that the deal is the largest in the fund that it belongs to. Rank 2 means that the deal is the second largest in the fund. We group deals with ranks larger than 10 into one single category: rank 10.



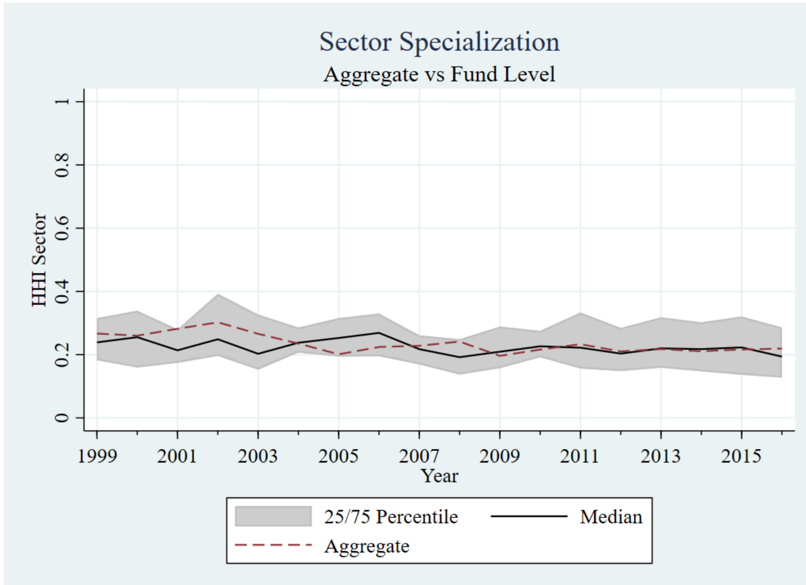
(a) Mean and S.D.



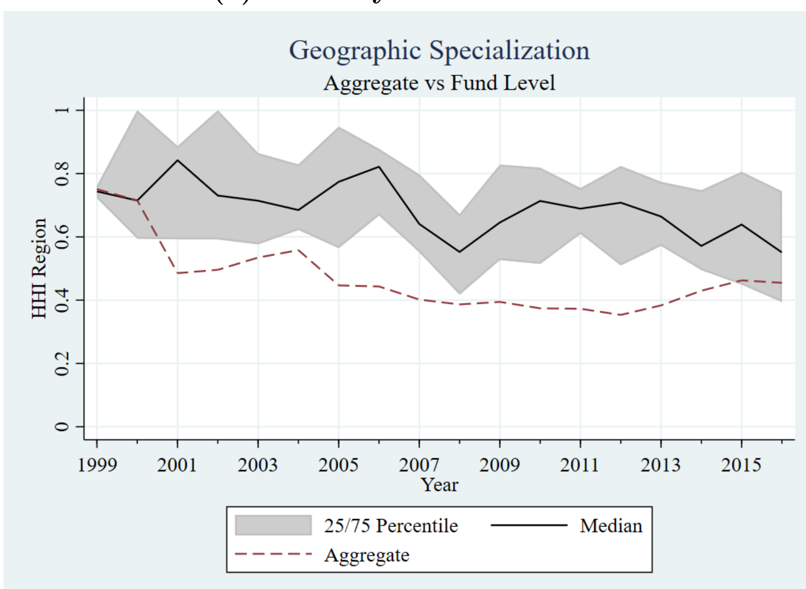
(b) Mean/S.D.

Figure 4: Deal PME by Deal Timing Sequence in the Fund

Note: This figure plots the mean and standard deviation of deal PME in each deal timing sequence category. The horizontal axis is the sequence of the deal (*Deal Inv. Sequence*). In Panel (a), the vertical axis is the mean (Mean, blue solid line) or standard deviation (StdDev, red dashed line) of the deal PMEs in a given sequence category. In Panel (b), the vertical axis is the mean of the deal PMEs divided by the standard deviation of the deal PMEs. *Deal Inv. Sequence* is the timing sequences of deal within the fund, sorted by investment year. One to five refers to the earliest to the latest. E.g., sequence one means that the deal is made in the first year when the fund begins to make investments. Sequence two means that the deal is made in the second year of the fund's investment period. We sequence deals to the year level due to data availability. We group deals with sequences larger than five into one single category: rank five.



(a) Industry Concentration



(b) Geographic Concentration

Figure 5: Industry/Geographic Specialization: Fund-Level v.s. Aggregate-Level

Note: This figure shows the industry specialization degree (Panel (a)) and the region specialization degree (Panel (b)) in each deal entry year/fund vintage. The solid black line represents the median fund level and the grey shade ranges from the 25th percentile to the 75th percentile fund-level concentration degree. The dashed red line is for the aggregate-level (over the entire deal sample) specialization indices.

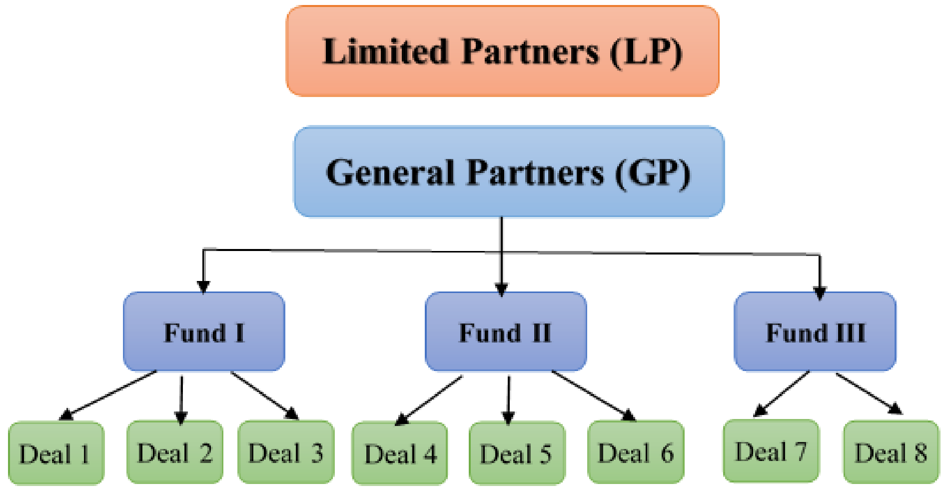


Figure 6: Hierarchical Structural of the Private Equity Industry

Note: This figure gives a graphic illustration of the hierarchical structural of the PE industry, with General Partners (GPs) at the top, managing funds in the middle that invest in deals at the bottom.

Tables

Table 1: Summary Statistics and Correlations

This table provides summary statistics and correlations for the primary variables utilized in our analysis. Panel A reports the summary statistics for deal-level variables and Panel B for fund-level variables. Panel C provides Pearson correlation coefficients among the deal-level variables and Panel among the fund-level variables. Variable definitions are provided in Appendix Table A1. *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels, respectively.

Panel A: Deal-Level Summary Statistics								
Variables	N	Mean	S.D.	Min	5th per.	Median	95th per.	Max
Deal PME	5,925	1.63	1.59	0.00	0.00	1.27	4.38	15.45
Deal TVPI	5,925	2.18	2.11	0.00	0.00	1.70	5.97	13.40
Deal-Size Rank	5,925	6.52	3.19	1.00	1.00	7.00	10.00	10.00
Deal Size (billion, USD)	5,925	0.08	0.13	0.00	0.01	0.04	0.30	2.06
Deal Entry Year	5,925	2012	5.06	1999	2003	2014	2019	2020
Deal Exit Year	3,199	2014	4.32	2001	2006	2015	2020	2020
Deal Duration	5,925	5.79	2.81	1.00	2.00	5.00	11.00	20.00
Exit Dummy	5,925	0.54	0.50	0.00	0.00	1.00	1.00	1.00
Panel B: Fund-Level Summary Statistics								
Variables	N	Mean	S.D.	Min	5th per.	Median	95th per.	Max
PME (Value-Weighted)	467	1.54	0.54	0.21	0.77	1.46	2.51	4.61
PME Volatility	467	1.35	0.74	0.19	0.50	1.19	2.92	6.05
TVPI (Value-Weighted)	467	2.08	0.79	0.33	1.04	1.92	3.56	5.07
TVPI Volatility	467	1.78	0.95	0.21	0.61	1.56	3.70	4.89
Gini Index	467	0.26	0.10	0.05	0.12	0.25	0.42	0.69
HHI Sector	467	0.26	0.15	0.04	0.10	0.22	0.59	1.00
HHI Region	467	0.65	0.21	0.08	0.29	0.66	1.00	1.00
Fund Vintage	467	2,010	4.65	1,999	2,001	2,012	2,016	2,016
I(North American Fund)	467	0.32	0.47	0.00	0.00	0.00	1.00	1.00
Fund Size (billion, USD)	467	1.20	1.77	0.04	0.12	0.60	4.54	17.52
Fraction Invested	467	0.86	0.15	0.34	0.59	0.87	1.11	1.30
Value-Weighted Duration	467	5.23	2.18	0.82	2.06	5.04	9.18	12.73
N. of Deals	467	12.69	6.12	4.00	6.00	11.00	25.00	49.00

Table 1. Summary Statistics and Correlations (Cont.)

Panel C: Deal-Level Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) Deal PME	1.00					
(2) Deal TVPI	0.93***	1.00				
(3) Deal Size	-0.05***	-0.04***	1.00			
(4) Deal-Size Rank	-0.08***	-0.06***	0.20***	1.00		
(5) Deal Duration	-0.14***	0.01	0.10***	0.14***	1.00	
(6) Exit Dummy	0.16***	0.19***	-0.06***	-0.09***	0.17***	1.00

Panel D: Fund-Level Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) PME v.w.	1.00											
(2) PME Volatility	0.58***	1.00										
(3) TVPI v.w.	0.86***	0.49***	1.00									
(4) TVPI Volatility	0.51***	0.89***	0.61***	1.00								
(5) Gini Index	-0.09**	0.15***	-0.06	0.10***	1.00							
(6) HHI Sector	0.05	0.06	0.14***	0.13***	0.07	1.00						
(7) HHI Region	0.06	0.12**	0.19***	0.21***	0.01	0.44***	1.00					
(8) I(North American)	-0.04	-0.05	0.16***	0.07	-0.14***	0.23***	0.27***	1.00				
(9) Fund Size	-0.04	-0.08*	-0.03	-0.08*	0.16***	-0.08*	-0.09*	-0.23***	1.00			
(10) Fund Duration	-0.02	0.08*	0.14***	0.20***	0.15***	0.43***	0.74***	-0.04	0.14***	1.00		
(11) Fraction Invested	-0.07	0.15***	0.17***	0.28***	0.24***	0.21***	0.45***	-0.04	0.10**	0.68***	1.00	
(12) N. of Deals	-0.01	0.08*	0.02	0.10**	0.36***	-0.08*	0.07	-0.25***	0.43***	0.29***	0.21***	1.00

Table 2: Deal Level: Summary Statistics of PME by Deal-Size Rank

This table shows the summary statistics of the deal-level *PME* within each deal-size rank category. *PME* is the Kaplan-Schoar Public Market Equivalence performance measure. *Deal-Size Rank* is the rank of deal within the fund, sorted by size. 1 to 10 refers to the largest to the smallest. E.g., rank 1 means that the deal is the largest in the fund that it belongs to. Rank 2 means that the deal is the second largest in the fund. We group deals with ranks larger than 10 into one single category: rank 10. More details on the variable calculation as well as the sample restrictions are in Appendix Table A1.

		Deal PME									
Deal-Size Rank	N	Mean	S.D.	Min	5th per.	25th per.	Median	75th per.	95th per.	Max	$\frac{\text{Mean}}{\text{S.D.}}$
1	467	1.26	1.24	0.00	0.00	0.39	1.01	1.74	3.55	11.55	1.01
2	467	1.39	1.13	0.00	0.00	0.47	1.26	1.94	3.47	5.81	1.23
3	467	1.51	1.33	0.00	0.00	0.61	1.17	2.10	3.86	7.51	1.14
4	467	1.52	1.35	0.00	0.00	0.61	1.27	2.07	3.95	9.26	1.13
5	464	1.68	1.58	0.00	0.00	0.62	1.32	2.23	4.20	12.63	1.06
6	456	1.68	1.54	0.00	0.00	0.72	1.34	2.21	4.08	15.43	1.09
7	440	1.68	1.51	0.00	0.00	0.75	1.31	2.29	4.81	9.93	1.12
8	402	1.60	1.77	0.00	0.00	0.57	1.18	2.09	4.06	15.45	0.90
9	360	1.71	1.51	0.00	0.01	0.77	1.40	2.22	4.06	13.56	1.13
10+	1935	1.78	1.82	0.00	0.00	0.64	1.35	2.30	5.06	14.41	0.98

Table 3: Deal Level: Summary Statistics of PME by Deal Timing Sequence

This table shows the summary statistics of the deal-level *PME* within each deal timing sequence category. *PME* is the Kaplan-Schoar Public Market Equivalence performance measure. *Deal Seq.* is the sequence of deal within the fund, sorted by investment year. One to five refers to the earliest to the latest. E.g., Sequence one means that the deal is invested in the first year in the fund that it belongs to. Sequence two means that the deal is invested in the second year in the fund. We group deals with sequences larger than five into one single category: sequence five. More details on the variable calculation as well as the sample restrictions are in Appendix Table A1.

Panel A: Deal PME											
Deal Seq.	N	Mean	S.D.	Min	5th per.	25th per.	Median	75th per.	95th per.	Max	Mean / S.D.
1	1157	1.68	1.67	0.00	0.00	0.53	1.33	2.33	4.52	15.45	1.01
2	1324	1.69	1.71	0.00	0.00	0.54	1.31	2.25	4.93	15.43	0.98
3	1226	1.68	1.61	0.00	0.00	0.65	1.31	2.23	4.31	14.41	1.04
4	1030	1.56	1.42	0.00	0.00	0.68	1.26	2.02	4.20	13.93	1.10
5+	1188	1.52	1.46	0.00	0.00	0.67	1.18	1.93	4.01	12.77	1.05
Panel B: Deal Size (USD, Billions)											
Deal Seq.	N	Mean	S.D.	Min	5th per.	25th per.	Median	75th per.	95th per.	Max	Mean / S.D.
1	1157	0.08	0.14	0.00	0.00	0.02	0.04	0.09	0.27	2.06	0.58
2	1324	0.08	0.12	0.00	0.01	0.02	0.04	0.09	0.30	0.95	0.71
3	1226	0.09	0.14	0.00	0.01	0.02	0.04	0.10	0.31	1.75	0.66
4	1030	0.08	0.12	0.00	0.01	0.02	0.04	0.09	0.32	1.05	0.73
5+	1188	0.08	0.11	0.00	0.01	0.02	0.04	0.09	0.27	1.16	0.72

Table 4: Deal Level: Within-Fund Deal Size Rank, Timing Sequence and PME

This table reports the cross-sectional regressions about within-fund deal size rank and PME and within-fund deal sequence and PME. The sample period spans from 1999 to 2016 (both included). The dependent variable is *Deal PME* which is the Kaplan-Schoar Public Market Equivalence performance measure at the deal level. The first key independent variable is *Deal-Size Rank* which is the rank of deal within the fund, sorted by size. 1 to 10 refers to the largest to the smallest. E.g., rank 1 means that the deal is the largest in the fund that it belongs to. Rank 2 means that the deal is the second largest in the fund. We group deals with ranks larger than 10 into one single category: rank 10. The second key independent variable is *Deal Seq.*, which is the sequence of deal within the fund, sorted by investment year. One to five refers to the earliest to the latest. E.g., Sequence one means that the deal is invested in the first year in the fund that it belongs to. Sequence two means that the deal is invested in the second year in the fund. We group deals with sequences larger than five into one single category: sequence five. More details on the variable calculation and the sample restrictions are in Appendix Table A1. Fixed effects for GP, industry, and geographic location are indicated in each column. Standard errors are clustered at GP level. t statistics are reported in parentheses. *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
			Deal PME			
Deal-Size Rank	0.05***	0.04***	0.03***	0.05***	0.05***	0.04***
	(6.18)	(5.61)	(4.07)	(6.82)	(5.83)	(4.61)
Deal Seq.	-0.05***	-0.05***	-0.05***	-0.05***	-0.05***	-0.06***
	(-2.63)	(-2.62)	(-3.02)	(-2.70)	(-2.70)	(-3.29)
Absolute Deal Size		-0.41*	0.06		-0.22	0.37
		(-1.77)	(0.19)		(-0.85)	(1.10)
Exit Dummy			0.56***			0.57***
			(11.91)			(9.55)
Fund Size			-0.02			-0.06
			(-1.06)			(-1.33)
Deal Duration			-0.09***			-0.09***
			(-11.89)			(-9.54)
GP FE	N	N	N	Y	Y	Y
Industry FE	N	N	Y	N	N	Y
Geography FE	N	N	Y	N	N	Y
Observations	5925	5925	5925	5925	5925	5925
Adjusted R^2	0.010	0.011	0.077	0.040	0.039	0.094

Table 5: Fund Level: Concentration, Specialization and PME

This table reports the cross-sectional regressions on the fund level between deal concentration and industry/geographic specialization degree and PME at the fund level. The sample period spans from 1999 to 2016 (both included). In columns (1) to (4), the dependent variable is *value-weighted PME* which is the weighted average of the Kaplan-Schoar Public Market Equivalence (PME) performance measure of all deals in a given fund. Weights are the dollar value invested in the deal. In columns (5) to (8), the dependent variable is *S.D. of Deal PME* which is the standard deviation of deal PMEs in a given fund. The key independent variables are *Gini Index*, *HHI Sector* and *HHI Region*. More details on the variable calculations and the sample restrictions are in Appendix Table A1. Fund vintage fixed effects are indicated in each column. Standard errors are clustered at GP level. t statistics are reported in parentheses. *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Value-Weighted PME				S.D. of Deal PME			
Gini Index	-0.38			-0.43	0.97**			0.95*
	(-1.39)			(-1.58)	(1.98)			(1.94)
HHI Sector		0.47***		0.48***		0.52**		0.41*
		(2.84)		(2.98)		(2.34)		(1.95)
HHI Region			0.50***	0.46**			0.58**	0.59**
			(2.60)	(2.39)			(2.17)	(2.21)
N. of Deals	-0.00	-0.00	-0.01	-0.00	0.00	0.01	0.01	0.01*
	(-0.91)	(-1.09)	(-1.34)	(-0.28)	(0.36)	(1.55)	(1.38)	(0.80)
Fund Size	0.00	0.00	0.01	0.01	-0.05**	-0.04**	-0.04*	-0.04*
	(0.19)	(0.32)	(0.62)	(0.72)	(-2.27)	(-2.13)	(-1.94)	(-1.88)
Fund Duration	0.76***	0.54**	0.21	-0.02	0.49	0.15	-0.25	-0.40
	(2.90)	(2.17)	(0.73)	(-0.05)	(1.49)	(0.45)	(-0.66)	(-1.02)
Fraction Invested	-0.18***	-0.19***	-0.19***	-0.18***	-0.12***	-0.11***	-0.10***	-0.11***
	(-5.95)	(-6.39)	(-6.27)	(-6.19)	(-3.21)	(-3.05)	(-2.86)	(-3.24)
I(North American)	-0.07	-0.10	-0.13*	-0.16**	-0.09	-0.14*	-0.17*	-0.19**
	(-1.16)	(-1.56)	(-1.90)	(-2.34)	(-1.20)	(-1.67)	(-1.87)	(-2.06)
Fund Vintage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	467	467	467	467	467	467	467	467
Adjusted R^2	0.126	0.134	0.135	0.148	0.129	0.124	0.125	0.141

Table 6: Fund Level: Concentration, Specialization and TVPI

This table reports the cross-sectional regressions on the fund level between deal concentration and industry/geographic specialization degree and PME at the fund level. The sample period spans from 1999 to 2016 (both included). In Panel A, the dependent variable is *value-weighted TVPI* which is the weighted average of the Kaplan-Schoar Public Market Equivalence (PME) performance measure of all deals in a given fund. Weights are the dollar value invested in the deal. In Panel B, the dependent variable is *S.D. of Deal TVPI* which is the standard deviation of deal PMEs in a given fund. The key independent variables are *Gini Index*, *HHI Sector* and *HHI Region*. More details on the variable calculations and the sample restrictions are in Appendix Table A1. Fund vintage fixed effects are indicated in each column. Standard errors are clustered at GP level. t statistics are reported in parentheses. *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Value-Weighted TVPI				S.D. of Deal TVPI			
Gini Index	-0.58			-0.68*	0.93			0.85
	(-1.50)			(-1.78)	(1.56)			(1.46)
HHI Sector		0.68***		0.72***		0.73**		0.64**
		(2.86)		(3.11)		(2.41)		(2.14)
HHI Region			0.34	0.28			0.45	0.44
			(1.34)	(1.09)			(1.33)	(1.31)
N. of Deals	-0.00	-0.00	-0.00	0.00	0.01	0.01*	0.01	0.01
	(-0.31)	(-0.43)	(-0.74)	(0.27)	(0.63)	(1.66)	(1.36)	(1.04)
Fund Size	0.01	0.02	0.02	0.02	-0.05**	-0.05**	-0.05**	-0.04*
	(0.57)	(0.70)	(0.77)	(0.88)	(-2.28)	(-2.15)	(-2.06)	(-1.96)
Fund Duration	1.01***	0.71*	0.67	0.32	0.84*	0.40	0.26	0.00
	(2.68)	(1.95)	(1.52)	(0.71)	(1.93)	(0.92)	(0.46)	(0.01)
Fraction Invested	-0.15***	-0.17***	-0.16***	-0.15***	-0.07*	-0.07*	-0.06	-0.07*
	(-3.86)	(-4.25)	(-4.08)	(-3.96)	(-1.80)	(-1.66)	(-1.44)	(-1.83)
I(North American)	0.27***	0.23***	0.24***	0.19**	0.15	0.09	0.09	0.06
	(3.11)	(2.70)	(2.62)	(2.12)	(1.45)	(0.87)	(0.76)	(0.48)
Fund Vintage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	467	467	467	467	467	467	467	467
Adjusted R^2	0.212	0.220	0.210	0.225	0.185	0.187	0.181	0.193

Table 7: Bayesian Model Estimations of Differences in GP Skill (GP-Fund Two-Layer Model)

This table reports posterior means of parameters of Bayesian models described in section 6. The model specification is the GP-Fund two-layer model. Panel A shows the parameter estimates, and Panel B reports the variance decomposition estimates for the same parameters. Specifications where we also include Fund Vintage fixed effects as covariates are indicated in each column. The model is estimated by Markov chain Monte Carlo (MCMC) using ten thousand burn-in cycles followed by 100,000 samples, saving every tenth draw. signal to noise (skill%), overlap effect%, and error% are defined in Equation 7. The fund life N is fixed to ten. Return is measured in TVPI. More details on the variable calculations and the sample restrictions are in Appendix Table A1. Posterior standard deviations (Bayesian standard errors) are in brackets.

	(1)	(2)
Panel A: Parameter estimates		
$\sigma(GPRE)$	0.033	0.033
	(0.003)	(0.003)
$\sigma(GPYearRE)$	0.063	0.059
	(0.012)	(0.010)
$\sigma(\epsilon)$	0.397	0.363
	(0.034)	(0.032)
Vintage Year FE	N	Y
N. of GPs	315	315
N. of Funds	467	467
Panel B: Variance decomposition		
$N^2\sigma^2(GPRE)$	0.113	0.108
	(0.021)	(0.020)
$N\sigma^2(GPYearRE)$	0.041	0.036
	(0.016)	(0.012)
$\sigma^2(\epsilon)$	0.159	0.133
	(0.027)	(0.024)
$\sigma^2(FundReturn)$	0.312	0.277
	(0.032)	(0.027)
signal to noise (skill%)	36.24%	39.14%
	(0.058)	(0.061)
overlap effect%	13.01%	12.99%
	(0.049)	(0.042)
noise%	50.75%	47.88%
	(0.065)	(0.065)

Table 8: Bayesian Model Estimations of Differences in GP Skill (GP-Deal Two-Layer Model)

This table reports posterior means of parameters of Bayesian models described in section 6. The model specification is the GP-deal two-layer model. Panel A shows the parameter estimates, and Panel B reports the variance decomposition estimates for the same parameters. Specifications where we also include deal entry year and deal exit year fixed effects as covariates are indicated in each column. The model is estimated by Markov chain Monte Carlo (MCMC) using ten thousand burn-in cycles followed by 100,000 samples, saving every tenth draw. signal to noise (skill%), overlap effect%, and error% are defined in Equation 7. The deal life N is the deal life which is calculated as deal exit year-deal entry year+1. Return is measured in TVPI. More details on the variable calculations and the sample restrictions are in Appendix Table A1. Posterior standard deviations (Bayesian standard errors) are in brackets.

	(1)	(2)	(3)	(4)
Panel A: Parameter estimates				
$\sigma(GPRE)$	0.034	0.037	0.037	0.033
	(0.003)	(0.004)	(0.004)	(0.003)
$\sigma(GPYearRE)$	0.194	0.170	0.166	0.107
	(0.016)	(0.016)	(0.015)	(0.015)
$\sigma(\epsilon)$	1.023	1.030	1.024	1.023
	(0.013)	(0.013)	(0.013)	(0.012)
Deal Entry Year FE	N	Y	N	Y
Deal Exit Year FE	N	N	Y	Y
N. of GPs	315	315	315	315
N. of Deals	5925	5925	5925	5925
Panel B: Variance decomposition				
$N^2\sigma^2(GPRE)$	0.048	0.057	0.058	0.047
	(0.009)	(0.012)	(0.012)	(0.009)
$N\sigma^2(GPYearRE)$	0.221	0.169	0.161	0.067
	(0.037)	(0.032)	(0.028)	(0.019)
$\sigma^2(\epsilon)$	1.047	1.062	1.049	1.046
	(0.027)	(0.027)	(0.026)	(0.025)
$\sigma^2(DealReturn)$	1.316	1.287	1.269	1.160
	(0.040)	(0.036)	(0.033)	(0.028)
signal to noise (skill%)	3.66%	4.41%	4.60%	4.01%
	(0.007)	(0.009)	(0.009)	(0.007)
overlap effect%	16.72%	13.06%	12.70%	5.80%
	(0.025)	(0.023)	(0.021)	(0.016)
noise%	79.62%	82.53%	82.71%	90.20%
	(0.024)	(0.022)	(0.020)	(0.016)

Table 9: Bayesian Model Estimations of Differences in GP Skill (Largest Deal Within Fund) (GP-Deal Two-Layer Model)

This table reports posterior means of parameters of Bayesian models described in section 6. The model specification is the GP-deal two-layer model. In particular, we limited to the deals that are the largest one within the fund. Panel A shows the parameter estimates, and Panel B reports the variance decomposition estimates for the same parameters. Specifications where we also include deal entry year and deal exit year fixed effects as covariates are indicated in each column. The model is estimated by Markov chain Monte Carlo (MCMC) using ten thousand burn-in cycles followed by 100,000 samples, saving every tenth draw. signal to noise (skill%), overlap effect%, and error% are defined in Equation 7. The deal life N is the deal life which is calculated as deal exit year-deal entry year+1. Return is measured in TVPI. More details on the variable calculations and the sample restrictions are in Appendix Table A1. Posterior standard deviations (Bayesian standard errors) are in brackets.

	(1)	(2)	(3)	(4)
Panel A: Parameter estimates				
$\sigma(GPRE)$	0.058	0.056	0.064	0.059
	(0.009)	(0.010)	(0.011)	(0.010)
$\sigma(GPYearRE)$	0.116	0.107	0.138	0.117
	(0.043)	(0.036)	(0.054)	(0.045)
$\sigma(\epsilon)$	0.830	0.838	0.824	0.833
	(0.062)	(0.062)	(0.072)	(0.062)
Deal Entry Year FE	N	Y	N	Y
Deal Exit Year FE	N	N	Y	Y
N. of GPs	315	315	315	315
N. of Deals	467	467	467	467
Panel B: Variance decomposition				
$N^2\sigma^2(GPRE)$	0.181	0.171	0.220	0.187
	(0.059)	(0.060)	(0.076)	(0.067)
$N\sigma^2(GPYearRE)$	0.101	0.083	0.144	0.103
	(0.081)	(0.059)	(0.109)	(0.084)
$\sigma^2(\epsilon)$	0.693	0.706	0.684	0.698
	(0.104)	(0.106)	(0.120)	(0.104)
$\sigma^2(DealReturn)$	0.976	0.960	1.048	0.988
	(0.115)	(0.116)	(0.138)	(0.123)
signal to noise (skill%)	18.58%	17.81%	20.99%	18.88%
	(0.056)	(0.057)	(0.067)	(0.061)
overlap effect%	10.20%	8.54%	13.50%	10.16%
	(0.075)	(0.057)	(0.096)	(0.076)
noise%	71.22%	73.65%	65.52%	70.96%
	(0.078)	(0.073)	(0.092)	(0.083)

Table 10: Bayesian Model Estimations of Differences in GP Skill (Deals In Year One of The Fund) (GP-Deal Two-Layer Model)

This table reports posterior means of parameters of Bayesian models described in section 6. The model specification is the GP-deal two-layer model. In particular, we limited to the deals that are invested in the first year of the fund. Panel A shows the parameter estimates, and Panel B reports the variance decomposition estimates for the same parameters. Specifications where we also include deal entry year and deal exit year fixed effects as covariates are indicated in each column. The model is estimated by Markov chain Monte Carlo (MCMC) using ten thousand burn-in cycles followed by 100,000 samples, saving every tenth draw. signal to noise (skill%), overlap effect%, and error% are defined in Equation 7. The deal life N is the deal life which is calculated as deal exit year-deal entry year+1. Return is measured in TVPI. More details on the variable calculations and the sample restrictions are in Appendix Table A1. Posterior standard deviations (Bayesian standard errors) are in brackets.

	(1)	(2)	(3)	(4)
Panel A: Parameter estimates				
$\sigma(GPRE)$	0.056	0.056	0.058	0.053
	(0.008)	(0.008)	(0.008)	(0.008)
$\sigma(GPYearRE)$	0.103	0.100	0.097	0.091
	(0.029)	(0.029)	(0.025)	(0.025)
$\sigma(\epsilon)$	1.141	1.133	1.122	1.110
	(0.033)	(0.033)	(0.029)	(0.029)
Deal Entry Year FE	N	Y	N	Y
Deal Exit Year FE	N	N	Y	Y
N. of GPs	315	315	315	315
N. of Deals	1157	1157	1157	1157
Panel B: Variance decomposition				
$N^2\sigma^2(GPRE)$	0.165	0.164	0.176	0.146
	(0.047)	(0.048)	(0.051)	(0.042)
$N\sigma^2(GPYearRE)$	0.077	0.071	0.066	0.059
	(0.045)	(0.042)	(0.035)	(0.034)
$\sigma^2(\epsilon)$	1.304	1.286	1.260	1.233
	(0.074)	(0.074)	(0.066)	(0.065)
$\sigma^2(DealReturn)$	1.545	1.521	1.502	1.438
	(0.083)	(0.084)	(0.076)	(0.073)
signal to noise (skill%)	10.61%	10.72%	11.68%	10.10%
	(0.028)	(0.029)	(0.031)	(0.027)
overlap effect%	4.94%	4.67%	4.38%	4.09%
	(0.029)	(0.027)	(0.023)	(0.023)
noise%	84.45%	84.61%	83.94%	85.81%
	(0.033)	(0.034)	(0.032)	(0.031)

Table 11: Bayesian Estimation of GP-Fund-Deal Three-Layer Hierarchical Linear Model (First Stage)

This table reports posterior means of parameters of Bayesian models described in section 6. The model specification is the GP-fund-deal three-layer model and we report the first stage results in this table. Panel A shows the parameter estimates, and Panel B reports the variance decomposition estimates for the same parameters. Specifications where we also include deal entry year and deal exit year fixed effects as covariates are indicated in each column. The model is estimated by Markov chain Monte Carlo (MCMC) using ten thousand burn-in cycles followed by 100,000 samples, saving every tenth draw. signal to noise (skill)%, overlap effect%, and error% are defined in Equation 7. The fund life N is the deal life which is calculated as deal exit year-deal entry year+1. Return is measured in TVPI. More details on the variable calculations and the sample restrictions are in Appendix Table A1. Posterior standard deviations (Bayesian standard errors) are in brackets.

	(1)	(2)	(3)	(4)
Panel A: Parameter estimates				
$\sigma(FundRE)$	0.033	0.037	0.041	0.035
	(0.003)	(0.004)	(0.004)	(0.003)
$\sigma(FundYearRE)$	0.189	0.161	0.151	0.094
	(0.016)	(0.017)	(0.016)	(0.016)
$\sigma(\epsilon)$	1.017	1.026	1.019	1.020
	(0.013)	(0.013)	(0.013)	(0.012)
Deal Entry Year FE	N	Y	N	Y
Deal Exit Year FE	N	N	Y	Y
N. of Funds	467	467	467	467
N. of Deals	5925	5925	5925	5925
Panel B: Variance decomposition				
$N^2\sigma^2(FundRE)$	0.046	0.056	0.069	0.052
	(0.009)	(0.012)	(0.015)	(0.010)
$N\sigma^2(FundYearRE)$	0.209	0.152	0.134	0.053
	(0.036)	(0.032)	(0.029)	(0.018)
$\sigma^2(\epsilon)$	1.034	1.052	1.038	1.041
	(0.027)	(0.027)	(0.026)	(0.025)
$\sigma^2(DealReturn)$	1.289	1.260	1.242	1.146
	(0.037)	(0.034)	(0.031)	(0.027)
signal to noise (skill%)	3.55%	4.44%	5.59%	4.52%
	(0.007)	(0.009)	(0.012)	(0.009)
overlap effect%	16.14%	12.05%	10.80%	4.62%
	(0.025)	(0.024)	(0.022)	(0.015)
noise%	80.30%	83.51%	83.62%	90.87%
	(0.024)	(0.022)	(0.019)	(0.014)

Table 12: Bayesian Estimation of GP-Fund-Deal Three-Layer Hierarchical Linear Model (Second Stage)

This table reports posterior means of parameters of Bayesian models described in section 6. for the second stage of the GP-fund-deal three-layer. Columns (1) to (4) report the result of Model 1 where the adjusted returns are computed by subtracting fund random effects fund-year random effects. Columns (5) to (8) report the result of Model 2 where the adjusted returns are computed by subtracting fund-year random effects and deal-specific random effects. Panel A shows the parameter estimates, and Panel B reports the variance decomposition estimates for the same parameters. The model is estimated by Markov chain Monte Carlo (MCMC) using ten thousand burn-in cycles followed by 100,000 samples, saving every tenth draw. signal to noise (skill%), overlap effect%, and error% are defined in Equation 7. The fund life N is the deal life which is calculated as deal exit year-deal entry year+1. Return is measured in TVPI. More details on the variable calculations and the sample restrictions are in Appendix Table A1. Posterior standard deviations (Bayesian standard errors) are in brackets.

	Model 1				Model 2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Parameter estimates								
$\sigma(GPRE)$	0.026	0.027	0.027	0.031	0.021	0.028	0.028	0.032
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)	(0.004)	(0.006)
$\sigma(GPYearRE)$ 0.054	0.073	0.078	0.114	0.077	0.105	0.113	0.117	
	(0.008)	(0.012)	(0.013)	(0.015)	(0.008)	(0.015)	(0.015)	(0.022)
$\sigma(\epsilon)$	1.017	1.024	1.013	1.014	0.070	0.102	0.108	0.123
	(0.012)	(0.012)	(0.012)	(0.012)	(0.006)	(0.025)	(0.024)	(0.045)
N. of GPs	315	315	315	315	315	315	315	315
N. of Deals	5925	5925	5925	5925	5925	5925	5925	5925
Panel B: Variance decomposition								
$N^2\sigma^2(GPRE)$	0.052	0.057	0.058	0.076	0.034	0.062	0.065	0.083
	(0.008)	(0.010)	(0.010)	(0.015)	(0.005)	(0.020)	(0.019)	(0.037)
$N\sigma^2(GPYearRE)$	0.017	0.031	0.036	0.077	0.035	0.065	0.075	0.082
	(0.005)	(0.010)	(0.012)	(0.020)	(0.007)	(0.019)	(0.020)	(0.033)
$\sigma^2(\epsilon)$	1.034	1.049	1.027	1.028	0.005	0.011	0.012	0.017
	(0.025)	(0.025)	(0.024)	(0.025)	(0.001)	(0.007)	(0.006)	(0.015)
$\sigma^2(DealReturn)$	1.103	1.138	1.121	1.181	0.074	0.138	0.152	0.182
	(0.027)	(0.030)	(0.029)	(0.039)	(0.011)	(0.042)	(0.041)	(0.080)
signal to noise (skill%)	4.68%	5.03%	5.15%	6.43%	46.39%	44.87%	42.58%	45.69%
	(0.007)	(0.008)	(0.008)	(0.012)	(0.039)	(0.044)	(0.045)	(0.044)
overlap effect%	1.58%	2.74%	3.21%	6.51%	46.92%	47.40%	49.58%	45.79%
	(0.005)	(0.009)	(0.010)	(0.016)	(0.037)	(0.043)	(0.042)	(0.045)
noise%	93.74%	92.22%	91.64%	87.06%	6.69%	7.73%	7.85%	8.53%
	(0.009)	(0.013)	(0.014)	(0.021)	(0.006)	(0.020)	(0.018)	(0.033)

Appendix

Table A1: Sample Restrictions and Variable Definitions

Panel A: Sample Restrictions

We pose the following sample restrictions for the fund to be included in this paper:
1) fund vintage year is between 1999 and 2016 (both included);
2) all the deals in the fund have deal size information (no missing values);
3) the fund have made at least three deals, but less than 50 deals;
4) $0.25 < \frac{\Sigma DealSize_i}{FundSize} < 2$.

Panel B: Variable Definition (Alphabet Order) – Used in Regression Analysis

Variable	Definition
Deal Duration	For exited deals: the number of years between the exited year and investment year. For active deals: the number of years between 2020, the latest year of the valuation data update, and investment year.
Deal PME	Public market equivalence (PME) is calculated in a coarse way using the July as the entry month and June as the exit month as Burgiss does not disclose the exact date of investment entry and exit. The benchmark indices for PME are chosen in the following way: Russell 3000 for holdings in North America, the Asia & Pacific MSCI performance index for Asian & Pacific holdings, the Europe MSCI performance index for European holdings, and MSCI World performance index for other holdings. All indices are in USD. Investment multiples (MOIC) used in the PME calculation are the ratio of total value (market value + total proceeds) to total investment amount, which is directly reported by Burgiss. The total value is the actual realized value (including escrow) for realized deals and the latest reported market value for unrealized deals.
Deal-Size Rank	Generated according to the size of the deal within the same fund. E.g., rank 1 means the deal is the largest in terms of deal size in the fund that it belongs to. We group ranks larger than 10 into one single rank category: rank 10.
Deal Sequence	The deal's investment year $-min_{j \in f}$investment year$_j$ + 1; deals made after the 5th year of the first investment of the fund are grouped together into one single sequence category: sequence five.
Exit Dummy	A dummy that equals to one when the deal is exited and zero is the deal status is active.
Fraction Invested	The sum of deal sizes by the fund divided by fund size.
Fund Duration	Deal-size-weighted sum of deal duration where the weights are Deal-to-Fund-Size.

Table A1. Sample Restrictions and Variable Definitions (Cont.)

Variable	Definition
Fund Duration (Alt.)	Deal-size-weighted sum of deal duration where the weights are $\frac{DealSize_i}{max\{FundSize_f, \Sigma_{i\in F} DealSize_i\}}$
Fund PME	The weighted sum of deal PME held by the fund where the weights are the deal size divided by the sum of deal sizes.
Fund TVPI	The weighted sum of deal TVPI held by the fund where the weights are the deal size divided by the sum of deal sizes.
Fund Size	The total amount of money committed by limited partners (USD Billions).
Gini Index	Calculated using the standard Gini Index formula (Atkinson et al. (1970)) where the inputs are deal sizes in the fund.
HHI Sector	The sum of squared weights of deals in each sector s held by the fund where weights are deal size relative to fund size, i.e. $\Sigma_{s\in S}(\frac{\Sigma_{i\in s} DealSize_i}{max\{FundSize_f, \Sigma_{i\in F} DealSize_i\}})^2$.
HHI Sector (Alt.)	The sum of squared weights of deals in each sector s held by the fund where weights are deal size relative to fund size, i.e.$\Sigma_{s\in S}(\frac{\Sigma_{i\in s} DealSize_i}{FundSize_f})^2$.
HHI Region	The sum of squared weights of deals in each region r held by the fund where weights are deal size relative to fund size, i.e.$\Sigma_{r\in R}(\frac{\Sigma_{i\in r} DealSize_i}{max\{FundSize_f, \Sigma_{i\in F} DealSize_i\}})^2$.
HHI Region (Alt.)	The sum of squared weights of deals in each region r held by the fund where weights are deal size relative to fund size, i.e. $\Sigma_{r\in R}(\frac{\Sigma_{i\in r} DealSize_i}{FundSize_f})^2$.
I(North American)	A dummy that equals to one if the fund invests all deals in North America.
N. of Deals	The number of deals held by the fund.
S.D. of Deal PME	The standard deviation of deal PME held by the fund.
S.D. of Deal TVPI	The standard deviation of deal TVPI held by the fund.

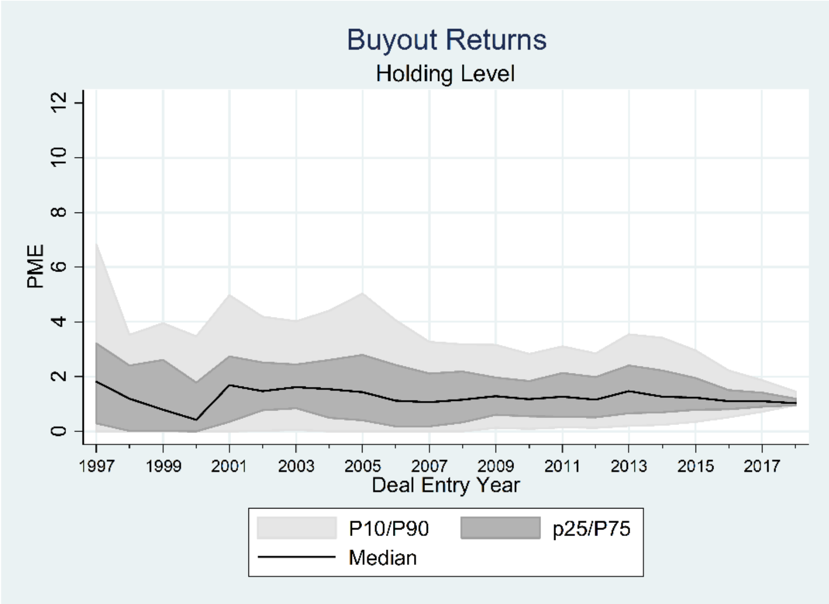
Table A1. Sample Restrictions and Variable Definitions (Cont.)

Panel C: Variable Definition – Used in Hierarchical Linear Model	
Variable	Definition
$\sigma(GPRE)$	standard deviation of GP-specific random effect
$\sigma(GPYearRE)$	standard deviation of GP-time random effect
$\sigma(\epsilon)$	standard deviation of error term
$\sigma(FundReturn)$	standard deviation of fund return
$\sigma(DealReturn)$	standard deviation of deal return
N	Fund/Deal life
Signal to Noise (Skill%)	$\frac{N^2\sigma^2(GPRE)}{\sigma^2(Fund/DealReturn)}$
Overlap Effect%	$\frac{N\sigma^2(GPYearRE)}{\sigma^2(FundReturn)}$
Luck%	$\frac{\sigma^2(\epsilon)}{\sigma^2(FundReturn)}$

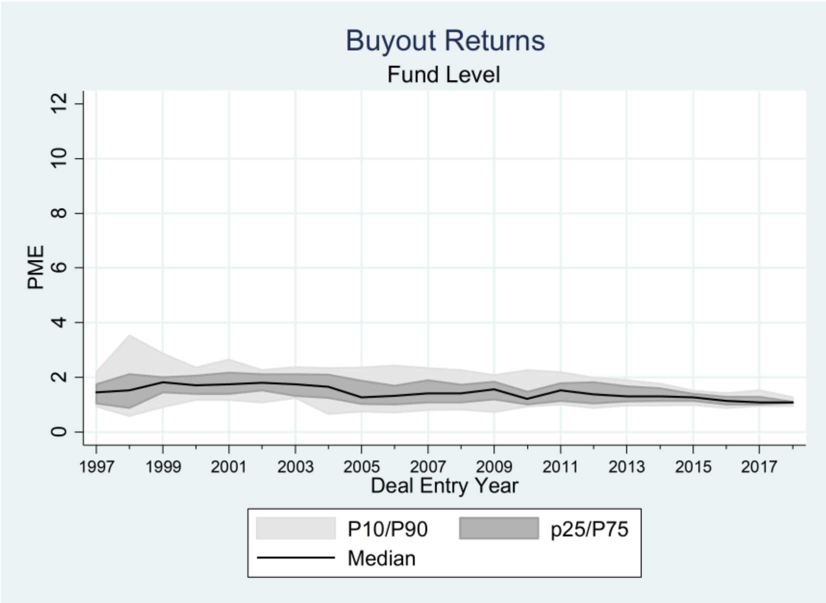
Table A2: Sector and Region Distributions

Sector	Freq.
Communication Services	318
Consumer Discretionary	1158
Consumer Staples	445
Energy	112
Financials	352
Health Care	794
Industrials	1282
Information Technology	987
Materials	350
Other	38
Real Estate	45
Utilities	44
Region	**Freq.**
Africa	21
Asia	228
Caribbean	18
Central America	4
Eastern Europe	66
Middle East	57
North America	3085
South America	105
South Pacific	172
Southeast Asia	138
Western Europe	2031

Internet Appendix A. Additional Figures



Panel (a)



Panel (b)

Figure A1: Return Dispersion: Fund-Level v.s. Deal-Level

This figure shows the dispersion of the holding (Panel (a)) and fund (Panel (b)) level returns in each holding entry year/fund vintage. The dispersion is represented by the gap between the 90th and 10th percentiles and the 75th and 25th percentiles.

Internet Appendix B. Additional Tables

Table B1. Summary Statistics by Deal-Size Rank

This table shows the summary statistics deal-level variables within each rank category. *Deal-Size-Rank* is the within fund rank based on deal size. E.g., rank 1 means that the deal is the largest in terms of deal size in the fund. We group ranks larger than 10 into one single rank category: rank 10. Details on the variable definition and calculation as well as the sample restrictions can be found in Table A1 in the Appendix A.

Panel A: Deal Size

		Deal Size (USD, Billions)								
Rank	N	Mean	S.D.	Min	5th per.	25th per.	Median	75th per.	95th per.	Max
1	467	0.15	0.22	0.01	0.02	0.05	0.08	0.17	0.55	2.06
2	467	0.13	0.17	0.01	0.02	0.04	0.07	0.13	0.46	1.41
3	467	0.11	0.15	0	0.01	0.03	0.06	0.12	0.41	1.33
4	467	0.10	0.13	0	0.01	0.03	0.05	0.1	0.38	1.19
5	464	0.09	0.12	0	0.01	0.03	0.05	0.09	0.31	1.05
6	456	0.08	0.11	0	0.01	0.02	0.04	0.09	0.29	0.95
7	440	0.07	0.1	0	0.01	0.02	0.04	0.08	0.27	0.78
8	402	0.07	0.09	0	0.01	0.02	0.04	0.07	0.25	0.61
9	360	0.06	0.09	0	0.01	0.02	0.03	0.07	0.25	0.6
10+	1935	0.06	0.07	0	0	0.01	0.03	0.07	0.21	0.58

Panel B: Deal Size/Fund Size

		Deal Size/Fund Size								
Rank	N	Mean	S.D	Min	5th per.	25th per.	Median	75th per.	95th per.	Max
1	467	0.15	0.06	0.04	0.08	0.11	0.14	0.18	0.24	0.62
2	467	0.12	0.04	0.04	0.07	0.09	0.11	0.14	0.19	0.31
3	467	0.10	0.03	0.01	0.06	0.08	0.1	0.12	0.16	0.28
4	467	0.09	0.03	0.01	0.05	0.07	0.09	0.11	0.14	0.18
5	464	0.08	0.02	0	0.04	0.07	0.08	0.09	0.12	0.15
6	456	0.07	0.02	0.01	0.04	0.06	0.07	0.08	0.1	0.14
7	440	0.06	0.02	0	0.03	0.05	0.06	0.07	0.09	0.11
8	402	0.05	0.02	0	0.03	0.04	0.05	0.06	0.08	0.11
9	360	0.05	0.01	0	0.02	0.04	0.05	0.06	0.07	0.1
10+	1935	0.03	0.01	0	0.01	0.02	0.03	0.04	0.05	0.08

Panel C: Deal Duration

						Deal Duration				
Rank	N	Mean	S.D.	Min	5th per.	25th per.	Median	75th per.	95th per.	Max
1	191	7.54	3.03	1	3	5	8	10	13	15
2	233	6.96	2.99	2	3	5	7	9	12	14
3	212	7.04	3.04	2	3	5	6	9	13	16
4	233	6.35	2.68	1	3	5	6	8	11	15
5	229	6.30	2.67	1	3	4	6	8	11	15
6	242	6.37	2.82	2	3	4	6	8	12	15
7	229	6.21	2.8	1	3	4	6	8	11	20
8	214	6.07	2.63	1	3	4	6	8	11	14
9	198	6.35	3.05	1	2	4	6	8	13	16
10+	1,218	5.70	2.51	1	2	4	5	7	10	17

Panel D: Fund Age at Deal Entry

						Fund Age at Deal Entry				
Rank	N	Mean	S.D.	Min	5th per.	25th per.	Median	75th per.	95th per.	Max
1	467	2.97	1.56	-1	1	2	3	4	6	8
2	467	3.11	1.54	0	1	2	3	4	6	8
3	467	3.22	1.68	-1	1	2	3	4	6	8
4	467	3.09	1.62	0	1	2	3	4	6	9
5	464	3.15	1.58	0	1	2	3	4	6	8
6	456	3.08	1.71	0	1	2	3	4	6	8
7	440	3.24	1.72	-1	1	2	3	4	6	9
8	402	3.21	1.84	0	1	2	3	5	6	8
9	360	3.15	1.84	-1	1	2	3	4	6	13
10+	1,935	3.15	1.74	-1	1	2	3	4	6	13

Panel E: Deal Entry Year

					Deal Entry Year					
Rank	N	Mean	S.D.	Min	5th per.	25th per.	Median	75th per.	95th per.	Max
1	467	2,012	4.78	1,999	2,004	2,008	2,014	2,016	2,018	2,020
2	467	2,013	4.77	1,999	2,004	2,009	2,014	2,016	2,018	2,020
3	467	2,013	4.83	1,999	2,004	2,009	2,014	2,016	2,019	2,020
4	467	2,013	4.89	1,999	2,004	2,008	2,014	2,016	2,019	2,020
5	464	2,013	4.64	1,999	2,004	2,009	2,014	2,016	2,019	2,020
6	456	2,013	4.81	1,999	2,004	2,009	2,014	2,016	2,019	2,020
7	440	2,013	4.87	1,999	2,003	2,009	2,014	2,016	2,019	2,020
8	402	2,012	4.97	1,999	2,003	2,008	2,014	2,016	2,019	2,020
9	360	2,012	4.94	1,999	2,004	2,008	2,014	2,016	2,019	2,020
10+	1,935	2,011	5.41	1,999	2,001	2,007	2,012	2,016	2,018	2,020

Panel F: Deal Exit Year

					Deal Exit Year					
Rank	N	Mean	S.D.	Min	5th per.	25th per.	Median	75th per.	95th per.	Max
1	191	2,015	3.5	2,005	2,008	2,013	2,016	2,018	2,019	2,020
2	233	2,015	3.7	2,004	2,007	2,013	2,016	2,018	2,020	2,020
3	212	2,015	3.57	2,005	2,008	2,013	2,016	2,018	2,020	2,020
4	233	2,015	4.23	2,003	2,006	2,012	2,016	2,018	2,019	2,020
5	229	2,015	3.92	2,003	2,007	2,012	2,015	2,018	2,019	2,020
6	242	2,015	3.88	2,002	2,007	2,013	2,016	2,018	2,019	2,020
7	229	2,015	4.05	2,003	2,007	2,012	2,016	2,018	2,020	2,020
8	214	2,014	4.22	2,001	2,006	2,012	2,016	2,018	2,019	2,020
9	198	2,015	4.25	2,004	2,006	2,012	2,016	2,018	2,020	2,020
10+	1,218	2,013	4.74	2,001	2,005	2,010	2,014	2,017	2,019	2,020

Table B2. Deal Level: Within-Fund Deal Size Rank, Timing Sequence and PME (Robustness –Fraction Invested ≥80%)

This table reports the robustness check results where we restrict to deals held by funds that has a Fraction Invested ratio ≥ 80%. The results are for the cross-sectional regressions about within-fund deal size rank and PME and within-fund deal sequence and PME. The sample period spans from 1999 to 2016 (both included). The dependent variable is Deal PME which is the Kaplan-Schoar Public Market Equivalence performance measure at the deal level. The first key independent variable is Deal-Size Rank which is the rank of deal within the fund, sorted by size. 1 to 10 refers to the largest to the smallest. E.g., rank 1 means that the deal is the largest in the fund that it belongs to. Rank 2 means that the deal is the second largest in the fund. We group deals with ranks larger than 10 into one single category: rank 10. The second key independent variable is Deal Seq., which is the sequence of deal within the fund, sorted by investment year. One to five refers to the earliest to the latest. E.g., Sequence one means that the deal is invested in the first year in the fund that it belongs to. Sequence two means that the deal is invested in the second year in the fund. We group deals with sequences larger than five into one single category: sequence five. More details on the variable calculation and the sample restrictions are in Appendix A1. Fixed effects for GP, industry, and geographic location are indicated in each column. Standard errors are clustered at GP level. *t* statistics are reported in parentheses. *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels, respectively.

	(1) Deal PME	(2) Deal PME	(3) Deal PME	(1) Deal PME	(2) Deal PME	(3) Deal PME
Deal-Size Rank	0.04***	0.04***	0.03***	0.05***	0.04***	0.04***
	(4.98)	(4.45)	(3.09)	(5.44)	(4.51)	(3.51)
Deal Seq.	-0.04*	-0.04*	-0.04*	-0.03	-0.03	-0.05**
	(-1.68)	(-1.67)	(-1.93)	(-1.42)	(-1.42)	(-2.14)
Absolute Deal Size		-0.30	0.21		-0.19	0.41
		(-1.32)	(0.66)		(-0.75)	(1.23)
Exit Dummy			0.50***			0.45***
			(9.91)			(6.47)
Fund Size			-0.02			-0.08*
			(-1.32)			(-1.82)
Deal Duration			-0.09***			-0.09***
			(-11.11)			(-8.20)
GP FE	No	No	No	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No	Yes
Geography FE	No	No	Yes	No	No	Yes
Observations	4484	4484	4484	4484	4484	4484
Adjusted R^2	0.008	0.009	0.072	0.038	0.038	0.088

Table B3. Deal-Level: Deal Size Position and PME

This table reports the results for the cross-sectional regressions about within-fund deal size rank and PME. The sample period spans from 1999 to 2016 (both included). Panel A covers all funds. In Panel B, we restrict to deals held by funds that has a Fraction Invested ratio ≥ 80%. The dependent variable is Deal PME which is the Kaplan-Schoar Public Market Equivalence performance measure at the deal level. The key independent variable is Deal-Size Rank which is the rank of deal within the fund, sorted by size. 1 to 10 refers to the largest to the smallest. E.g., rank 1 means that the deal is the largest in the fund that it belongs to. Rank 2 means that the deal is the second largest in the fund. We group deals with ranks larger than 10 into one single category: rank 10. More details on the variable calculation and the sample restrictions are in Appendix A1. Fixed effects for GP, industry, and geographic location are indicated in each column. Standard errors are clustered at GP level. *t* statistics are reported in parentheses. *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels, respectively.

Panel A: All Funds

	(1)	(2)	(3)	(4)	(5)	(6)
	Deal PME	Deal PME	Deal PME	Deal PME	Deal PME	Deal PME
Deal-Size Rank	0.05***	0.04***	0.03***	0.05***	0.05***	0.04***
	(6.14)	(5.55)	(4.11)	(6.84)	(5.84)	(4.74)
Absolute Deal Size		-0.41*	0.10		-0.21	0.42
		(-1.74)	(0.33)		(-0.82)	(1.24)
Exit Dummy			0.58***			0.61***
			(12.14)			(10.42)
Fund Size			-0.02			-0.06
			(-1.24)			(-1.36)
Deal Duration			-0.09***			-0.08***
			(-11.54)			(-9.15)
GP FE	No	No	No	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No	Yes
Geography FE	No	No	Yes	No	No	Yes
Observations	5925	5925	5925	5925	5925	5925
Adjusted R^2	0.009	0.010	0.075	0.038	0.038	0.091

Panel B: Fraction Invested ratio ≥ 80%

	(1)	(2)	(3)	(4)	(5)	(6)
	Deal PME	Deal PME	Deal PME	Deal PME	Deal PME	Deal PME
Deal-Size Rank	0.04***	0.04***	0.03***	0.05***	0.04***	0.04***
	(4.98)	(4.45)	(3.19)	(5.48)	(4.55)	(3.67)
Absolute Deal Size		-0.30	0.25		-0.18	0.47
		(-1.30)	(0.78)		(-0.71)	(1.37)
Exit Dummy			0.52***			0.48***
			(10.17)			(7.32)
Fund Size			-0.03			-0.08*
			(-1.43)			(-1.80)
Deal Duration			-0.09***			-0.09***
			(-10.87)			(-8.11)
GP FE	No	No	No	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No	Yes
Geography FE	No	No	Yes	No	No	Yes
Observations	4484	4484	4484	4484	4484	4484
Adjusted R^2	0.007	0.008	0.071	0.038	0.037	0.086

Table B4. Deal-Level: Deal Timing Sequence and PME

This table reports the results for the cross-sectional regressions about within-fund deal timing sequence and PME. The sample period spans from 1999 to 2016 (both included). Panel A covers all funds. In Panel B, we restrict to deals held by funds that has a Fraction Invested ratio ≥ 80%. The dependent variable is Deal PME which is the Kaplan-Schoar Public Market Equivalence performance measure at the deal level. The key independent variable is Deal Seq., which is the sequence of deal within the fund, sorted by investment year. One to five refers to the earliest to the latest. E.g., Sequence one means that the deal is invested in the first year in the fund that it belongs to. Sequence two means that the deal is invested in the second year in the fund. We group deals with sequences larger than five into one single category: sequence five. More details on the variable calculation and the sample restrictions are in Appendix A1. Fixed effects for GP, industry, and geographic location are indicated in each column. Standard errors are clustered at GP level. *t* statistics are reported in parentheses. *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels, respectively.

Panel A: All Funds						
	(1) Deal PME	(2) Deal PME	(3) Deal PME	(4) Deal PME	(5) Deal PME	(6) Deal PME
Deal Seq.	-0.04**	-0.04**	-0.06***	-0.05***	-0.05***	-0.07***
	(-2.54)	(-2.53)	(-3.08)	(-2.69)	(-2.70)	(-3.45)
Absolute Deal Size		-0.66***	-0.48*		-1.02***	-0.44
		(-2.72)	(-1.70)		(-3.35)	(-1.52)
Exit Dummy			0.59***			0.58***
			(12.34)			(9.75)
Fund Size			0.01			-0.01
			(0.63)			(-0.32)
Deal Duration			-0.10***			-0.10***
			(-12.15)			(-10.08)
Industry FE	No	No	Yes	No	No	Yes
Geography FE	No	No	Yes	No	No	Yes
Observations	5925	5925	5925	5925	5925	5925
Adjusted R^2	0.001	0.004	0.074	0.029	0.032	0.090
Panel B: Fraction Invested ratio ≥ 80%						
	(1) Deal PME	(2) Deal PME	(3) Deal PME	(4) Deal PME	(5) Deal PME	(6) Deal PME
Deal Seq.	-0.04*	-0.04*	-0.04**	-0.03	-0.03	-0.05**
	(-1.69)	(-1.68)	(-2.04)	(-1.47)	(-1.48)	(-2.30)
Absolute Deal Size		-0.54**	-0.23		-0.85***	-0.25
		(-2.26)	(-0.88)		(-3.09)	(-0.90)
Exit Dummy			0.52***			0.46***
			(10.11)			(6.54)
Fund Size			-0.00			-0.05
			(-0.11)			(-1.10)
Deal Duration			-0.09***			-0.10***
			(-11.36)			(-8.75)
Industry FE	No	No	Yes	No	No	Yes
Geography FE	No	No	Yes	No	No	Yes
Observations	4484	4484	4484	4484	4484	4484
Adjusted R^2	0.001	0.003	0.070	0.030	0.032	0.085

Table B5. Deal Level: Within-Fund Deal Size Rank, Timing Sequence and PME

(Robustness – Not Grouping Rank and Sequence Category)

This table reports the robustness check results where we use the original sequence number and rank number of the deals (i.e., we do not group deals with rank higher than ten together, similarly, we do not group deals with a sequence later than five together). We conduct the cross-sectional regressions about within-fund size rank, sequence and PME at the deal level. The sample period spans from 1999 to 2016 (both included). Panel A covers all funds. In Panel B, we restrict to deals held by funds that has a Fraction Invested ratio ≥ 80%. More details on the variable calculation and the sample restrictions are in Appendix Table A1. Fixed effects for GP, industry, and geographic location are indicated in each column. Standard errors are clustered at GP level. *t* statistics are reported in parentheses. *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels, respectively.

Panel A: All Funds

	(1) Deal PME	(2) Deal PME	(3) Deal PME	(1) Deal PME	(2) Deal PME	(3) Deal PME
Deal-Size Rank	0.02^{***}	0.02^{***}	0.01^{**}	0.03^{***}	0.03^{***}	0.02^{***}
	(3.93)	(3.48)	(2.14)	(5.18)	(4.50)	(2.91)
Deal Seq.	-0.04^{**}	-0.04^{**}	-0.04^{***}	-0.04^{**}	-0.04^{**}	-0.05^{***}
	(-2.32)	(-2.34)	(-2.77)	(-2.22)	(-2.23)	(-2.92)
Absolute Deal Size		-0.47^{**}	-0.03		-0.23	0.28
		(-1.98)	(-0.10)		(-0.93)	(0.81)
Exit Dummy			0.57^{***}			0.57^{***}
			(12.40)			(9.71)
Fund Size			-0.02			-0.06
			(-0.87)			(-1.16)
Deal Duration			-0.09^{***}			-0.09^{***}
			(-12.07)			(-9.69)
GP FE	No	No	No	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No	Yes
Geography FE	No	No	Yes	No	No	Yes
Observations	5925	5925	5925	5925	5925	5925
Adjusted R^2	0.008	0.009	0.075	0.038	0.038	0.092

Panel B: Fraction Invested ratio ≥ 80%

	(1) Deal PME	(2) Deal PME	(3) Deal PME	(1) Deal PME	(2) Deal PME	(3) Deal PME
Deal Seq.	-0.03^{*}	-0.03^{*}	-0.04^{**}	-0.02	-0.02	-0.04^{**}
	(-1.68)	(-1.70)	(-1.98)	(-1.32)	(-1.34)	(-2.12)
Deal-Size Rank	0.02^{***}	0.02^{**}	0.01	0.03^{***}	0.02^{***}	0.01^{*}
	(2.83)	(2.42)	(1.23)	(3.79)	(2.97)	(1.67)
Absolute Deal Size		-0.38	0.05		-0.28	0.20
		(-1.61)	(0.14)		(-1.11)	(0.56)
Exit Dummy			0.51^{***}			0.45^{***}
			(10.38)			(6.53)
Fund Size			-0.02			-0.07
			(-0.90)			(-1.47)
Deal Duration			-0.09^{***}			-0.09^{***}
			(-11.45)			(-8.56)
GP FE	No	No	No	Yes	Yes	Yes
Industry FE	No	No	Yes	No	No	Yes
Geography FE	No	No	Yes	No	No	Yes
Observations	4484	4484	4484	4484	4484	4484
Adjusted R^2	0.005	0.006	0.070	0.036	0.036	0.086

Table B6. Fund-Level: Concentration, Specialization and PME (Alternative Measures)

This table reports the cross-sectional regressions on the fund level between deal concentration and industry/geographic specialization degree and PME at the fund level. The sample period spans from 1999 to 2016 (both included). In columns (1) to (4), the dependent variable is *value-weighted PME* which is the weighted average of the Kaplan-Schoar Public Market Equivalence (PME) performance measure of all deals in a given fund. Weights are the dollar value invested in the deal. In columns (5) to (8), the dependent variable is *S.D. of Deal PME* which is the standard deviation of deal PMEs in a given fund. The key independent variables are *Gini Index*, *HHI Sector* and *HHI Region*. *Gini Index* is calculated using the standard Gini Index formula (Atkinson (1970)) where we use the deal size as the input variable and fund as the unit of calculation. *HHI Sector* (*HHI Region*) is the sum of squared weights of deals in each sector (region) held by the fund where weights are deal size (USD) relative to fund size (USD), i.e. $\sum\left(\frac{\sum_{i\in s} deal\ size_i}{fund\ size_f}\right)^2$. More details on the variable calculations and the sample restrictions are in Appendix Table A1. Fund vintage fixed effects are indicated in each column. Standard errors are clustered at GP level. *t* statistics are reported in parentheses. *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Fund PME (Value-Weighted)				S.D. of Deal PME			
Gini Index	-0.31			-0.43	1.01**			0.87*
	(-1.10)			(-1.59)	(2.03)			(1.78)
HHI Sector		0.41**		0.45***		0.52**		0.43**
		(2.44)		(2.80)		(2.48)		(2.10)
HHI Region			0.40**	0.41***			0.64***	0.62***
			(2.55)	(2.67)			(2.85)	(2.82)
N. of Deals	-0.00	-0.00	-0.01	-0.00	0.00	0.01	0.01	0.01
	(-1.08)	(-1.22)	(-1.38)	(-0.28)	(0.31)	(1.56)	(1.47)	(0.95)
Fund Size	0.00	0.00	0.01	0.01	-0.05**	-0.05**	-0.04*	-0.04*
	(0.01)	(0.14)	(0.47)	(0.63)	(-2.36)	(-2.21)	(-1.87)	(-1.80)
Fund Duration	0.98***	0.74***	0.42	0.05	0.58	0.12	-0.50	-0.64
	(3.44)	(2.67)	(1.36)	(0.16)	(1.58)	(0.32)	(-1.09)	(-1.35)
Fraction Invested	-0.19***	-0.19***	-0.19***	-0.18***	-0.11***	-0.09**	-0.08**	-0.10***
	(-6.04)	(-6.43)	(-6.36)	(-5.97)	(-2.80)	(-2.46)	(-2.32)	(-2.65)
I(North American)	-0.08	-0.11*	-0.12*	-0.16**	-0.10	-0.14*	-0.18**	-0.19**
	(-1.38)	(-1.74)	(-1.95)	(-2.48)	(-1.30)	(-1.76)	(-2.05)	(-2.24)
Fund Vintage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	467	467	467	467	467	467	467	467
Adjusted R^2	0.130	0.137	0.137	0.148	0.128	0.122	0.127	0.142

Table B7. Fund-Level: Concentration, Specialization and TVPI (Alternative Measures)

This table reports the cross-sectional regressions on the fund level between deal concentration and industry/geographic specialization degree and TVPI at the fund level. The sample period spans from 1999 to 2016 (both included). In columns (1) to (4), the dependent variable is *value-weighted TVPI* which is the weighted average of the total value to paid-in performance measure of all deals in a given fund. Weights are the dollar value invested in the deal. In columns (5) to (8), the dependent variable is *S.D. of Deal TVPI* which is the standard deviation of deal TVPIs in a given fund. The key independent variables are *Gini Index*, *HHI Sector* and *HHI Region*. *Gini Index* is calculated using the standard Gini Index formula (Atkinson (1970)) where we use the deal size as the input variable and fund as the unit of calculation. *HHI Sector* (*HHI Region*) is the sum of squared weights of deals in each sector (region) held by the fund where weights are deal size (USD) relative to fund size (USD), i.e. $\sum\left(\frac{\sum_{i\in s} deal\ size_i}{fund\ size_f}\right)^2$. More details on the variable calculations and the sample restrictions are in Appendix Table A1. Fund vintage fixed effects are indicated in each column. Standard errors are clustered at GP level. *t* statistics are reported in parentheses. *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Fund TVPI (Value-Weighted)				S.D. of Deal TVPI			
Gini Index	-0.51			-0.68^{*}	0.92			0.70
	(-1.31)			(-1.79)	(1.53)			(1.20)
HHI Sector		0.62^{**}		0.69^{***}		0.82^{***}		0.75^{***}
		(2.54)		(2.92)		(2.84)		(2.62)
HHI Region			0.27	0.28			0.77^{**}	0.75^{**}
			(1.18)	(1.28)			(2.54)	(2.53)
N. of Deals	-0.00	-0.00	-0.00	0.00	0.01	0.01^{*}	0.01	0.01
	(-0.43)	(-0.52)	(-0.81)	(0.27)	(0.66)	(1.79)	(1.53)	(1.34)
Fund Size	0.01	0.01	0.02	0.02	-0.05^{**}	-0.05^{**}	-0.04^{*}	-0.04^{*}
	(0.49)	(0.62)	(0.69)	(0.87)	(-2.37)	(-2.21)	(-1.88)	(-1.75)
Fund Duration	1.23^{***}	0.87^{**}	0.89^{**}	0.33	0.78^{*}	0.14	-0.47	-0.85
	(3.12)	(2.26)	(2.03)	(0.67)	(1.69)	(0.30)	(-0.81)	(-1.38)
Fraction Invested	-0.16^{***}	-0.17^{***}	-0.16^{***}	-0.15^{***}	-0.05	-0.04	-0.03	-0.04
	(-4.18)	(-4.49)	(-4.44)	(-4.05)	(-1.15)	(-0.81)	(-0.65)	(-0.93)
I(North American)	0.26^{***}	0.23^{***}	0.24^{***}	0.19^{**}	0.14	0.08	0.06	0.02
	(3.00)	(2.65)	(2.76)	(2.18)	(1.38)	(0.79)	(0.53)	(0.17)
Fund Vintage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	467	467	467	467	467	467	467	467
Adjusted R^2	0.215	0.222	0.213	0.227	0.183	0.188	0.188	0.201

Table B8. Fund-Level: Bayesian Model Estimations of Differences in GP Skill

This table reports posterior means of parameters of Bayesian models described in Section 6. The model specification is the GP-Fund two-layer model. Panel A shows the parameter estimates, and Panel B reports the variance decomposition estimates for the same parameters. Specifications where we also include Fund Vintage fixed effects as covariates are indicated in each column. The model is estimated by Markov chain Monte Carlo (MCMC) using ten thousand burn-in cycles followed by 100,000 samples, saving every tenth draw. signal to noise (skill%)= $\frac{N^2\sigma^2(GP\ RE)}{\sigma^2(\text{fund return})}$, overlap effect%= $\frac{\text{N}\sigma^2(\text{GPYear RE})}{\sigma^2(\text{fund return})}$, and error%= $\frac{\sigma^2(\varepsilon)}{\sigma^2(\text{fund return})}$. The fund life N is fixed to ten. Return is measured in TVPI. More details on the variable calculations and the sample restrictions are in Appendix Table A1. Posterior standard deviations (Bayesian standard errors) are in brackets. Though we use a Bayesian estimator, we discuss results using standard frequentist terminology: our point estimate is the mean of the posterior distribution, and our standard error is the standard deviation of the posterior distribution. A parameter is statistically significant, at a given level, when zero is not contained in the corresponding symmetric credible interval. *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels, respectively.

	(1)	(2)
Panel A: Parameter estimates		
σ(GP RE)	0.033	0.033
	(0.003)	(0.003)
σ(GP-Year RE)	0.063	0.059
	(0.012)	(0.010)
σ(ε)	0.397	0.363
	(0.034)	(0.032)
covariates		
Vintage Year FE	N	Y
N. of GPs	315	315
N. of Funds	467	467
Panel B: Variance decomposition		
$N^2\sigma^2$(GP RE)	0.113	0.108
	(0.021)	(0.020)
$N\sigma^2$(GPYear RE)	0.041	0.036
	(0.016)	(0.012)
$\sigma^2(\varepsilon)$	0.159	0.133
	(0.027)	(0.024)
σ^2(fund return)	0.312	0.277
	(0.032)	(0.027)
signal to noise (skill%)	36.24%	39.14%
	(0.058)	(0.061)
overlap effect%	13.01%	12.99%
	(0.049)	(0.042)
error%	50.75%	47.88%
	(0.065)	(0.065)

Table B9. Deal-Level: Bayesian Model Estimations of Differences in GP Skill (GP-Deal Two-Layer Model)

This table reports posterior means of parameters of Bayesian models described in Section 6. The model specification is the GP-deal two-layer model. Panel A shows the parameter estimates, and Panel B reports the variance decomposition estimates for the same parameters. Specifications where we also include deal entry year and deal exit year fixed effects as covariates are indicated in each column. The model is estimated by Markov chain Monte Carlo (MCMC) using ten thousand burn-in cycles followed by 100,000 samples, saving every tenth draw. signal to noise $(\text{skill\%}) = \frac{N^2\sigma^2(GP\ RE)}{\sigma^2(\text{fund return})}$, overlap effect% $= \frac{N\sigma^2(\text{GPYear RE})}{\sigma^2(\text{fund return})}$, and error%$= \frac{\sigma^2(\varepsilon)}{\sigma^2(\text{fund return})}$. *N* is the deal life which is calculated as deal exit year-deal entry year+1. Return is measured in TVPI. More details on the variable calculations and the sample restrictions are in Appendix Table A1. Posterior standard deviations (Bayesian standard errors) are in brackets. Though we use a Bayesian estimator, we discuss results using standard frequentist terminology: our point estimate is the mean of the posterior distribution, and our standard error is the standard deviation of the posterior distribution. A parameter is statistically significant, at a given level, when zero is not contained in the corresponding symmetric credible interval. *, **, and *** denote significance at the 90%, 95%, and 99% confidence levels, respectively.

	(1)	(2)	(3)	(4)
Panel A: Parameter estimates				
σ(GP RE)	0.034	0.037	0.037	0.033
	(0.003)	(0.004)	(0.004)	(0.003)
σ(GP-Year RE)	0.194	0.170	0.166	0.107
	(0.016)	(0.016)	(0.015)	(0.015)
σ(ε)	1.023	1.030	1.024	1.023
	(0.013)	(0.013)	(0.013)	(0.012)
covariates				
Deal Entry Year FE	N	Y	N	Y
Deal Exit Year FE	N	N	Y	Y
N. of GPs	315	315	315	315
N. of Deals	5925	5925	5925	5925
Panel B: Variance decomposition				
$N^2\sigma^2$(GP RE)	0.048	0.057	0.058	0.047
	(0.009)	(0.012)	(0.012)	(0.009)
$N\sigma^2$(GP-Year RE)	0.221	0.169	0.161	0.067
	(0.037)	(0.032)	(0.028)	(0.019)
$\sigma^2(\varepsilon)$	1.047	1.062	1.049	1.046
	(0.027)	(0.027)	(0.026)	(0.025)
σ^2(deal return)	1.316	1.287	1.269	1.160
	(0.040)	(0.036)	(0.033)	(0.028)
signal to noise (skill%)	3.66%	4.41%	4.60%	4.01%
	(0.007)	(0.009)	(0.009)	(0.007)
overlap effect%	16.72%	13.06%	12.70%	5.80%
	(0.025)	(0.023)	(0.021)	(0.016)
error%	79.62%	82.53%	82.71%	90.20%
	(0.024)	(0.022)	(0.020)	(0.016)

Internet Appendix C. Two-Layer Hierarchical Linear Model

C.1 GP-Fund Two-Layer Model

In this section, we briefly present the fund-level hierarchical linear model developed in Korteweg and Sorensen (2017). Formally, the KS model is a two-layer hierarchical linear model at the GP-Fund level that uses variance decomposition technics to separate the variation in the net-of-fee fund return into variances of three components (conditional on appropriate covariates, i.e. controls): a GP-specific random effect, a GP-time random effect that applies to each year of the fund's life, and a fund-specific random effect.

$$FundReturn_{iu} = X_{iu}'\beta + \sum_{\tau=t_{iu}}^{t_{iu}+N_u} (GPRE_i + GPYearRE_{i\tau}) + \varepsilon_{iu} \tag{3}$$

Where *i* stands for GP firms, *u* stands for funds, X_{iu} are the observed covariates, t_{iu} denotes the fund's first year of operation (vintage year), N_u denotes the fund life, $GPRE_i$ is the GP-specific random effect, $GPYearRE_{i\tau}$ is the GP-time random effect, and ε_{iu} is the fund-specific random effect. Fund return is measured using value-weighted TVPI.[1] As PE funds do not have a clear exit time, we set the fund life the same to ten for all funds (as in the original KS model).

At birth, each PE firm receives an independent draw of $GPRE_i$ from a normal distribution $N(0, \sigma^2(GPRE))$. This GP-specific component remains constant for all funds managed by the GP firm. If we think of GP skills as the intrinsic value of the GP firm that is along with the firm all the time, then the part of the variation in returns due to this GP-specific random effect measures the extent of return persistent heterogeneity in GP skills. The larger the variation in GP-specific random effects, the greater the differences in skill level between GPs. Without loss of generality, we normalize the mean of the distribution to zero. The industry level of expected return is captured by the intercept term in X_{iu}. The GP-specific effect enters the model once each year along with fund life (i.e., ten times) and thus $GPRE_i$ is the annualized abnormal performance for firm *i* relative to its peers.

[1] Using the PME measure is not appropriate in the estimation because the time-specific variation is directly modeled.

The GP-time effect captures an overlapping effect, and is assumed to be independent and identically distributed (i.i.d.) from a normal distribution $N(0, \sigma^2(\text{GPYearRE}))$. The original purpose of the KS model is to test whether a large part of return persistence in return is due to the overlap of consecutive funds that are managed by the same PE firm (overlapping effect or spurious persistence in their terminology). Partially overlapping funds are exposed to the same market conditions during the overlap period, and are very likely to make investments in the same holding companies. When the spurious persistence due to overlapping deals and common risk exposures is larger, the estimated variance of GP-time effect is large.

The final random effect, the fund-specific effect, or the error term ε_{iu} captures fund-specific idiosyncratic performance shocks. It is assumed to be i.i.d. across funds, across GPs, and over time. Because performance in PE is skewed, we model ε_{iu} using a mixture-of-normals distribution where we follow the original KS model by setting the number of a mixture to two.

Table B8 reports the estimates of the GP-fund two-layer model. Panel A shows the magnitudes of the three random effects as measured by their standard deviations σ(GP RE), σ(GP-Year RE), and σ(ε) and the beta estimates of our concentration and specialization measures, *Gini Index*, *HHI Sector* and *HHI Region* that are covariates. In specifications in even columns, we also include fund vintage years as covariates. The results on the concentration and specialization measures are consistent with the findings in regression analysis in previous sections. *Gini* is negatively related to fund return and *HHIs* are positively related to fund return.

Panel B reports the variance decomposition which is easier to interpret. The top part of Panel B shows the magnitude of the decomposed variance of the three random effects ($N^2\sigma^2$(GP RE), $N\sigma^2$(GPYear RE), and $\sigma^2(\varepsilon)$) and the total variance of the fund returns. The bottom part of Panel B shows the percentages of each random effect in explaining the total variance, which are the skill, overlap effect, and luck we define in equations (5) to (7). Following KS (2017), we discuss results using standard frequentist terminology for easy understanding of readers, though we use a Bayesian estimator.

Results are close in specifications with and without the concentration and specialization measures as covariates. For example, in the specification with concentration and specialization measures as covariates in column (5), the variance decomposition shows that 36.16% of the total variance in fund returns is due to skill, 12.98% is due to overlap effect, and 50.80% is due to luck. The component due to skills is slightly smaller after controlling for fund concentration and specialization. For example, in the specification with no covariates in column (1), the variance decomposition shows that 36.24% of the total variance in fund returns is due to skill, 13.01% is due to overlap effect, and 50.75% is due to luck. This suggests that concentration and specialization have a positive but small contribution to GP skills.

In specifications where we include vintage year fixed effects as covariates, the importance of skills and overlap effects in explaining return variation increases slightly, and the importance of luck decreases. For example, in the specification with concentration and specialization measures and vintage fixed effects as covariates in column (6), 38.37% of the total variance in returns is due to skill, 13.19% is due to overlap effect, and 48.02% is due to luck. This is consistent with that part of the noise in returns (luck) is due to market conditions in different years.

Comparing our results to the estimates in KS (2017), the variances are smaller in our sample, probably due to different sample periods. The sample in KS (2017) is 1969 to 2001. We look at a much more recent period, from 1999 to 2016.[2] Take the specification with vintage year fixed effects as an example (column (4)), the level of skill ($N^2\sigma^2$(GP RE)) estimated using our sample is 0.105 and 0.316 in KS, the level of overlap effect ($N\sigma^2$(GPYear RE)) is 0.036 our sample and 0.203 in KS, and the level of luck ($\sigma^2(\varepsilon)$) is 0.130 in our sample and 1.225 in KS. Interestingly, in terms of relative importance, skills explain 25% more of the total variance of returns in our sample (38.77%) than in KS (14.1%). Luck accounts for 19% less of the total variance of returns in our sample (48.02%) than in KS (66.80%). The part due to overlap effects is closer in our sample (13.22%) and KS (19.17%).

C.2 GP-Deal Two-Layer Model

The first straightforward extension of the KS model is to change the GP-Fund structure in KS to the GP-Deal structure since we observe deal-level returns. This provides information on GP skills in terms of returns they achieve for individual deals.

GP skills estimated at the deal-level returns may or may not be larger than skills estimated at the fund-level returns. On the one hand, more granular return data can partially solve the overlap issue. For example, the mechanical overlapping degree attributed to different funds investing in the same company is largely reduced. The likelihood of mechanical deal overlapping (i.e., different deals of the same GP in the same year refer to the same company) is much lower than at the fund level.[3] Yet, risk exposure to

[2] Harris et. al. (2020) show that for the post-2000 period, performance persistence decreases largely for buyout funds, especially for the top quartile performance, though they use the AR(1) analyses.

[3] In our dataset, the deal id is generated by assigning a unique id to each GP-Fund-Deal observation. Although we cannot tell whether two deals are related to the same company in our data, it should be very rare that two deals of the same GP in the same year is related to the same company in private equity. PE firms cannot take arbitrage shares of the company and are very unlikely to make separate investments into the same company simultaneously. In addition, in this study, we look at the main funds, not GP co-investments (Braun et. al. (2020), Fang et. al. (2015) or alternative vehicle investments (Lerner et. al. (2022) where multiple investments into the same company are likely to happen.

common market conditions still exists. This implies that the variance in GP-year effect is likely to be smaller at the deal level than at the fund level. In other words, estimating the (original two-layer) KS model at the deal level instead of at the fund level reallocates the mechanical overlap effect of the same investment by different funds into the GP skill and error random effects. The overlap effects in the GP-deal hierarchical model mainly capture risk exposure to common market conditions. This is a more appropriate way to understand the relative importance of skill, overlap effects, and luck as the mechanical overlap effect may not be very interesting.

On the other hand, return is noisier at the deal level than at the fund level. As a result, the variance in the error term can be larger, leaving GP skills explaining less of the total variance of return. That is to say, GPs may be harder to use their intrinsic skill to achieve high returns at the deal level than at the fund level because there is much more riskiness at the deal level. Moreover, as pointed out in Merton (1980), expected returns (i.e., differences in means) are no better measured with higher frequency observations. Therefore, it is an open question how skillful GPs are at making individual deals, which makes it worthy to estimate the GP-Deal level model to gain more insights into GP skills.

The GP-Deal level model is the following,

$$DealReturn_{ij} = X_{ij}'\beta + \sum_{\tau=t_{ij}}^{t_{ij}+DealLife_{ij}} (GPRE_i + GPYearRE_{i\tau}) + \varepsilon_{ij} \tag{8}$$

Where *i* stands for GP firms, *j* stands for deals, X_{ij} are the observed covariates, t_{ij} denotes the deal's first year (entry year), $DealLife_{ij}$ denotes the deal life which is the number of years from the deal entry to the deal exit, $GPRE_i$ is the GP-specific random effect, $GPYearRE_{i\tau}$ is the GP-time random effect, and ε_{ij} is the fund-specific random effect. Deal return is measured using TVPI.

The assumptions on the parameter distribution are the same in the GP-Fund level model. $GPRE_i$ follows a normal distribution $N(0, \sigma^2(GPRE))$. The GP-time effect is i.i.d. across GPs and over time, and follows a normal distribution $N(0, \sigma^2(GPYearRE))$. The error term ε_{iu} is i.i.d. across deals, across GPs, and overtime and follows a mixture-of-normals distribution with the number of a mixture equal to two.

Table B9 reports the estimates of the GP-deal two-layer model. Panel A shows the magnitudes of the GP-specific, the GP-year specific, and error term random effects and the beta estimates of the covariate (size-based deal rank). Specifications also differ in whether deal entry year and exit year fixed effects are controlled for, which are indicated in the table. The results on the deal rank are consistent with the findings in regression analysis in previous sections. We find that larger deals within the fund (smaller rank) have lower returns. Panel B reports the variance decomposition results.

Results are close in specifications with and without the deal rank as the covariate. For example, in column (1) where we have no covariates, the variance decomposition shows that 3.66% of the total variance in fund returns is due to skill, 16.72% is due to overlap effect, and 79.62% is due to luck. In the specification with deal rank as covariates in column (5), the variance decomposition shows that 3.65% of the total variance in fund returns is due to skill, 16.48% is due to overlap effect, and 79.87% is due to luck. Specifications with and without deal rank as covariates having similar estimates on the variance decomposition are consistent with our findings in the regression analyses. In the regression analysis, our findings also suggest that the risk-return balancing between deals of different sizes is a pattern shared by all GPs.

Including deal entry and exit year fixed effects as covariates decreases the overlap component by more than half, and increases the importance of both the skill and luck components. For example, comparing column (1) where we have no covariates and column (4) where we have deal entry and exit year fixed effects as covariates, the part due to overlap effect decreases from 16.72% to 5.80%. The part due to skill increases from 3.66% to 4.01%. The part due to luck increases from 79.62% to 90.20%. The large decrease in the overlap effect after controlling for year fixed effects suggests that a large part of the time overlap effect is because of the market condition. The rest overlap effect means that after controlling for the market condition for *all* GPs, 5.80% of the return variation is due to time-dependent risk exposures to all deals invested by the *same* GP. The 0.35% increase in the skill component means that a small part of the reason that we see a lack of GP skills (if we look at return variations) is that common risk exposure for deals in the same year washes out the detection of the skill component. The more than 10% increase in the luck component implies that variation in the market condition adds a lot of noise (luck) to the return variations.

Comparing the results on the deal and fund levels can shed more light on whether learning at the more granular deal level can provide more information on the GP skills. The absolute level of variation in GP-specific random effect (σ(GP RE)) is almost the same, 0.033, in the fund-level and deal-level models. However, (as expected), the deal-level return is much noisier, with the error term ($\sigma(\varepsilon)$) being 0.363 at the fund level and 1.023 at the deal level in the comparable specifications with year fixed effects as controls. This leaves, for example in Table 8 column (4) with both deal entry and exit year fixed effects, skills account for 4.01%, overlap effect accounts for 5.80%, and luck accounts for 90.20% of the total variance in returns at the deal level. This is in striking contrast with the decomposition using GP-fund level models. In the comparable specification in Table 7 column (2) with vintage year fixed effects, skills account for 39.14%, overlap effect accounts for 12.99%, and luck accounts for 47.88% of the total variance in returns at the fund level.

This comparison has three implications. First, it explains why we seem to not observe GP skills in the return data (but in other studies discussing the selection and monitoring role of GP managers). The observation that luck explains a large part of return variation in the literature tends to be due to the nature of the PE industry that consists great degree of idiosyncratic risks at the deal level rather than GPs having no value-added role. In other words, the high risks in the PE industry make it unpreventable that some deals outperform other deals even conditional on market conditions and GP-time specific effects. But this does not mean GPs have no skills. Rather, it could be that if these uncontrollable idiosyncratic risks at the deal level are washed out, we would find that GP skills explain a large part of the return variations. (In other words, it is too harsh to say GP skills do not matter if we take all these deal-level risks into the calculation.)

Second, it also provides more insights on what the GP-year specific term captures. It is common that different funds of the *same* GP contain the same deals (holding companies) (Braun et. al. (2016)). The part of the overlap effect due to this mechanical overlap of funds is of less economic insights. Indeed, the change of the overlap effect from 12.99% at the fund level to 5.80% at the deal level implies that such a mechanical overlap effect is quite large. However, the fact that we still have an overlap effect at the deal level suggests that common strategies and common risk exposures (as stated in KS (2017)) also contribute to the overlap effect.

Third, it answers the question of whether estimating the hierarchical model using more granular individual deal performance instead of aggregate fund performance is more informative. As conjectured in KS (2017), more granular data does not necessarily give more information. One reason is the finding of Merton (1980) that expected returns are no better measured with higher frequency observations. Another reason is the existence of a large degree of noise at the deal level, as discussed above, which can mask the relative importance of GP skills in return variation. In addition, although the mechanical overlap effect can be addressed using deal-level data, the effect due to common strategies and risk exposures is still there in deal-level models. Indeed, we find that the absolute level of variation in GP skill is almost the same. Due to the large increase in the idiosyncratic risks, deal level estimation shows lower relative importance in GP skills.