Portfolio Management in Private Equity*

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Abstract

We study how private equity general partners (GPs) make portfolio management decisions. Using a novel deal-level dataset of 5,925 global investments from 1999 to 2016, we take a portfolio view of private equity funds to reconcile various findings in the PE literature. We document several new findings consistent with GPs trading off the benefits of focusing their skills on a relatively small number of portfolio companies with high levels of (especially idiosyncratic) risk. First, we find that a higher degree of industry or geographic concentration is associated with both higher fund returns as well as a higher fund risk. Second, we find that instead of betting more on high-returning "best ideas" as is common in portfolios of public companies (Antón, Cohen, and Polk, 2021), the largest investments in PE portfolios have the lowest returns on average but are also the lowest risk in the fund. Third, extending the Bayesian estimation of hierarchical models in Korteweg and Sorensen (2017), we find that skill only accounts for 4%-6% of the total return variation of a typical investment and that almost all remaining variation is idiosyncratic. However, GP skill accounts for more than 40% of the return variation at the fund level (i.e., after accounting for diversifiable deal-level risk) consistent with fund structures reducing skill-related information asymmetry between LPs and GPs. Overall, our findings suggest that GPs carefully consider how they construct their portfolios in an attempt to generate high risk-adjusted fund-level returns that maximize their long-run franchise value.

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1 Introduction

Private equity as an asset class has grown over the last forty years from a relatively niche investment segment to a $six 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 through the lens of the *investor's* portfolio management decision; asking, for example, how a retirement system balances private equity commitments against 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)).

Yet there is another, perhaps more important, portfolio management decision in private equity, one that is intrinsic to the delegated nature of the investment process itself. General partners (GPs), who are responsible for investing the capital committed by limited partners (LPs), invest their fund's capital in a portfolio of individual deals. Indeed, the very term *portfolio company*, which is used to refer to the companies in which a GP invests, reflects the fact that the GP is forming a portfolio of investments when they raise a fund and deploy the capital.

In spite of the centrality of the issue to our understanding of the risk and return of private equity as an asset class, almost no work to date has focused on the GPs portfolio formation decision.[1] 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. No paper connects individual GP investment decisions through the lens of portfolio choice. Under what conditions are specialist GPs better than generalist GPs? How is the capital committed to a fund allocated across investments, and what are the implications of this for risk and return?

[1]The primary exception we are aware of is Lopez-de Silanes et al. (2015), which documents the decreasing returns to scale of buyout funds and Spaenjers and Steiner (2021) showing evidence of better performance by specialized funds. In venture capital, Gompers et al. (2009) and Hochberg et al. (2015) investigate the specialization of funds.

The goal of this paper is to take a first step at filling this gap. Using a novel research-quality dataset of deal-level returns and portfolio composition, we explore the individual investments made by a GP in a given private equity fund and connect the characteristics of these investments to deal-level and fund-level performance.

We first provide a framework to characterize the trade-offs faced by GPs when making portfolio composition decisions. The unique nature of PE, where transactions typically take a controlling ownership stake, suggests that GP faces stronger trade-offs than in public companies where ownership is typically a minority stake and more passive. Benefits from adding value to operations has increasing returns to scale – deal partners have to get deep into a company to add value and deal partners cannot be spread too thin or they run the risk of becoming ineffective (see., Fulghieri and Sevilir (2009)). Likewise, beneficial information asymmetries (for example, Kacperczyk et al. (2016)), resource exchanges and spillovers among portfolio companies can provide further gains to specialization (see., González-Uribe (2020)).[2] In addition, there are substantial fixed costs associated with a PE deal (e.g., legal and administrative) and once acquired a portfolio company has very low liquidity. These factors suggest a specialized and highly concentrated portfolio is optimal.

However, PE deals have very high idiosyncratic risk which GPs are reluctant to bear due to the franchise value of the GP which depends substantially on returns generated by future funds (see Barber and Yasuda (2017); Brown et al. (2019)). Consequently, a fund with a small number of deals experiencing bad luck would imply the GP is unlikely to raise a next fund and the franchise value would collapse. In this way, the franchise value of the GP is like a down-and-out call option whose value will not be monotonically increasing in risk. In addition, GPs are often individuals with significant personal capital at risk, and thus their financial risk-aversion will seek them to limit portfolio concentration. There are three ways that GPs can control the level of risk in a fund. First, they can diversify idiosyncratic risk by making a larger number of smaller investments which, as just discussed, likely comes at a cost to the ability to add value. Second, GPs can diversify across industries and/or regions to benefit from lower correlations between portfolio companies. Third, GPs can choose to

[2] A related literature in public equity discusses the impact of common ownership (e.g., Azar et al. (2018)).

invest in less risky companies or structure their investments so they are less risky.[3] However, the range of control is limited compared to sizing risk in a public company which is effectively continuous (Giommetti and Sorensen (2021); Gredil et al. (2020)).

Altogether, these trade-offs suggest that GPs will want to specialize to maximize their value-added but only to the point where the costs of idiosyncratic risks do not outweigh the benefits of specialization. In short, GPs face several constraints that motivate them to carefully choose the composition of their portfolio under management.

Our empirical analysis utilizes a novel dataset on PE buyout fund portfolio companies provided by Burgiss. We examine a sample of 5,925 global deals by 467 buyout funds managed by 315 GP firms. The fund vintage years are from 1999 to 2016 and the investment and return information is updated through 2020. We do not consider fund vintages after 2016 since most newer funds will still be in their investment period. We impose other restrictions to limit our sample to funds where we can observe primarily the fully-realized investment activity of the funds. 52% of the portfolio companies in our sample are located in North America, 34% in Western Europe, and the remainder are in other global regions. The sample covers companies operating in all 11 GICS sectors such as consumer discretionary, health care, information technology, etc. Our primary measure of deal-level performance is market-adjusted return multiple (e.g., PMEs) using regional public market benchmarks. For robustness, we also examine unadjusted multiples (i.e., total value to paid in capital or TVPI) and find very similar results.[4]

Our main results are as follows: First, we study how GPs allocate the money inside the portfolio to different investments. We rank deals by their size inside of their fund[5] (i.e., by their portfolio weights – not across all funds) and find that the largest positions have on average the lowest returns. This is in contrast to mutual funds and hedge funds which

[3]GPs have some limited control over deal-level idiosyncratic risks by adjusting financial terms (e.g., deal leverage) and size of equity commitment through club deals and co-investment.

[4]In some ways it is more reasonable to use unadjusted risk when discussing riskiness of the portfolio. We thank Arthur Korteweg for pointing this out.

[5]Another way of thinking about the portfolio held by the GP is all the deals that the GP is managing at a given time (Lopez-de Silanes et al. (2015)). However, given that we can observe both the GP and the fund for our deals, we can examine the economic mechanisms on the composition of the funds (e.g., some funds invest in specific industries or regions; core funds outperform non-core funds (Harris et al. (2020)). Consequently, our analysis using funds as a middle layer is more economically insightful.

invest in public companies and have their highest returns for outsized positions in their "best ideas" (Antón et al. (2021)). In fact, we find that deal performance within a typical PE fund improves monotonically as the investment 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.[6] We find the negative relationship between within-fund deal size and deal return to be strong even after controlling for fund size and deal duration.

This raises the question as to why PE buyout funds would make outsized bets in 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 deal. 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, buyout fund managers will take on a large investment (on average 15% of fund size for the largest investment) but only if the risk is lower, 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.[7] 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, GPs actually allocate a large proportion of their funding to "safest ideas" instead of "best ideas."

Second, we examine the relation between investment concentration and funds' risk-return profiles. We find a negative relationship between the size concentration, measured in a Gini-style index, and fund return. As to the risk-return trade-off related to concentration, we find that a higher level of portfolio concentration is related to higher risks. This implies that even if large deals are less risky, the overall effect on the fund-level risk of a concentrated portfolio appears to be positive. Overall, our results are consistent with the argument that focusing on a smaller number of deals, but not risking too much on a single deal, makes better use of limited human capital which is rewarded by higher returns (but at the cost of higher risk).

[6] 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.

[7] We do not know whether managers are mitigating risk by forgoing risky projects or adjusting deal characteristics, such as applying less leverage to large deals (or other risk-mitigating strategies). This is an interesting avenue to pursue with data availability.

We also examine sector and geographic specialization and find that more focused funds, measured using Herfindahl-Hirschman-style indices, 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 risks consistent with these sorts of trade-offs.

Our regression analyses suggests a nuanced set of portfolio decisions undertaken by GPs that incorporates expected returns, investment risk, and the franchise value of the GP. However, we do not know how much of the return variation is attributed to the portfolio management skill of GPs. To investigate this issue, we extend the model of Korteweg and Sorensen (2017) (henceforth, *KS model*) 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.

More specifically, the private equity industry clearly features a hierarchical structure, with the GP firms being at the top of the tree, funds as branches, and portfolio company deals being the bottom nodes. Taking advantage of our dataset, we extend the GP-fund two-layer KS model to a GP-fund-deal three-layer model. As in Cavagnaro et al. (2019), we develop two extensions of the KS model, one with and one without taking into account deal-level idiosyncratic risks, which helps us to distinguish between portfolio management skills and deal selection skills.[8] 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. This allows us to have a richer set of results on the risk-return trade-off. Using the Bayesian estimation approach, 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

[8] 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.

deal return entering the second stage. In the first extension, we adjust the deal return by only subtracting the fund-year-specific effect from the actual deal return. In the second extension, we subtract the fund-year-specific and fund-deal-specific effects from the actual deal return. The difference in the estimated GP-specific effect between the two extensions reflects the GP's fund management skills.

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 addition, the model also sheds more light on the "best ideas" finding. We find that when taking risk exposures to the market condition into account, best ideas within funds are typically with *smaller* allocations (as estimated in the first stage). However, after subtracting the component for risk exposures to market conditions, best ideas are typically larger investments (as estimated in the second stage). This provides additional support for the hypothesis that portfolio risk management concerns result in GPs limiting risk exposure in larger deals.

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 size 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. 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.[9] However,

[9]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).

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 understanding 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),[10] 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.[11]

[10] 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).

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

3 Data

3.1 Data Source

In this study, we rely on a new dataset of deal-by-deal investment and return information from Burgiss, a global provider of data management services for the limited partner community. Additional information on the Burgiss deal-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 deal-level dataset from Burgiss, fund-level data from Burgiss have been used extensively in recent academic work.[12].

Because including funds with incomplete deal holdings 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 deals in the fund have deal size information (no missing values), ii) the fund made at least three deals, but less than 50 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

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

measure of size, and we refer to the capital committed by the fund as *Deal Size* just to simplify the exposition.

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.[13] 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.[14]

We also look at the ratio of total fund value to paid-in capital (TVPI), which is defined as

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

[14] 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.

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 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

In this section, we study how private equity funds allocate assets to different investments inside their portfolios. 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" (Antón et al. (2021)). 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.

4.1 Measures of Relative Deal Size

We use two measures to capture the within-fund size of deals. Our first measure is *Deal-Size Rank*, which is the rank of deal size within a given fund as measured by the dollar value invested by the fund. 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. 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]

Our second measure is *Deal-to-Fund-Size* which is the ratio of the fund's equity commitment of a deal to the total fund size as measured by total fund capital commitments, i.e., $\frac{DealSize_{i,f}}{FundSize_f}$, where i stands for deal and f stands for fund. The larger the *Deal-to-Fund-Size* ratio, the larger the deal is relative to the fund size. Panel A of Table 1 shows that the mean (median) *Deal-to-Fund-Size* is 0.07 (0.06) and the interquartile range is 0.03 to 0.09. *Deal-Size Rank* and *Deal-to-Fund-Size* capture very similar information about the relative size of investments and for expositional reasons we focus mostly on *Deal-Size Rank*.

We emphasize that both measures are relative measures that take the variation in fund size *per se* 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. Therefore, the actual magnitude of deal size (not relative to fund size) will reflect most of the performance variation related to size. This is largely a separate question but we examine it to see if absolute size drives some or all of our results. In fact, we document a small negative correlation between deal size and deal PME that accounts for about 10% of the relative size affect we document subsequently. Consequently, we are careful to also control for absolute deal size in our regression analysis.

4.2 Illustrative Results

We rank deals by their size within the fund (i.e., by *Deal-Size Rank*) from the largest (rank 1) to the smallest (rank 10 and higher). Figure 2 plots average deal PMEs as the solid blue line and Table 2 reports summary statistics of deal PMEs for each *Deal-Size Rank* category. The results indicate that on average a fund's largest deal has the lowest return with a mean (median) PME of 1.26 (1.01). 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.

[INSERT Table 2 AROUND HERE]

The finding that larger deals have lower returns is in contrast to the findings for mutual 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 Panel (a) of Figure 2 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 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 for each group. Results are shown in the last column of Table 2 and plotted in Panel (b) of Figure 2 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 that that there are unlikely to be significant agency costs associated with GP risk-aversion as it pertains to deal sizing.

[INSERT Figure 2 AROUND HERE]

We also examine other characteristics by *Deal-Size Rank* group.[15]. The mean (median) deal size decreases from 0.15 (0.08) billion USD in the first rank group to 0.06 (0.03) billion USD in the last rank group. The Deal Size-to-Fund-Size ratio has a mean (median) that ranges from 0.15 (0.14) in the first rank group to 0.03 (0.03) in the last rank group. These results imply that 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

[15] Detailed results are provided in Internet Appendix Table B1

at deal entry, deal entry year, or deal exit year by *Deal-Size Rank*.

4.3 Regression Results: Deal Return (PME)

In this section we use a regression approach to further investigate the relation between deal size rank deal return in the presence of other deal characteristics. In particular, we examine other variables that measure if the investment is fully exited, the size of the fund, and the duration of the deal as well as fixed effects for the deal year, industry, and geographic region. Table 3 reports results from regressions with deal PMEs as the dependent variable.

[INSERT Table 3 AROUND HERE]

Panel A reports the results of specifications without GP fixed effects. As was the case in the univariate analysis, the regressions indicate that larger deals tend to have lower returns. Columns (1) to (3) report results when using*Deal-Size Rank* as the measure of relative deal size. In column (1), we look at the simple OLS regression of deal PME on *Deal-Size Rank*. 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. Column (2) adds a dummy variable that equals one if the deal is fully exited since these may have higher returns (e.g., if value creation is still occurring or interim valuations are conservative). Column (3) shows the results with the full set of control variables and fixed effects. We find that the strong, and statistically significant, positive relationship between PME and *Deal-Size Rank* persists after controlling for the exit dummy and the full set of other control variables. However, the other variables moderate the magnitude of the relation. For example, in specification (3), a one-notch increase in rank is associated with a 0.03 increase in PME. Coefficients for other control variables are of expected signs: we find that on average exited deals tend to have significantly higher PMEs, larger funds have slightly lower PMEs, and longer duration deals have lower PMEs.

Columns (4) – (6) mirror the first three columns but with *Deal-to-Fund-Size* instead *Deal-Size Rank* as the measure of relative deal size, which leads to qualitatively similar results that larger deals have significantly lower PMEs on average. For example, the results in column (6) indicate that a one standard deviation increase in the *Deal-to-Fund-Size* is related to a 0.11 decrease in PME, which represents a large effect in economic magnitude. The effects of other variables on deal PMEs are almost unchanged.

Panel B reports the specifications with GP fixed effects. We observe the same relationship that larger deals have lower returns. All coefficients on deal size position are positive 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-to-Fund-Size* are even larger after controlling for GP fixed effects, suggesting that the negative relationship between deal return and size is stronger after controlling for GP specific factors.

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. The deal-level data do not allow us to accurately determine whether this is done through deal selection, capital structure, or a combination. The finding stands in contrast to the"best ideas" findings in mutual funds and hedge funds where relatively large positions have higher returns on average.

4.4 Regression Results: Deal Duration

Deal duration is potentially another lens through which we can gain insights regarding the nature of different deal sizes. Table 4 reports the regression results on the relation between deal duration and deal size. We restrict to the sub-sample of fully-exited deals because these are the only deals with meaningful duration which is defined as the number of years between the entry and exit years.

[INSERT Table 4 AROUND HERE]

Panel A shows the results without GP fixed effects. In columns (1) and (2), the independent variable of interest is *Deal-Size Rank*. We find strong evidence that larger deals have a longer duration. For example, in the specification with the full set of controls in column (2), a one-notch change in *Deal-Size Rank* is associated with a 0.16 year decrease in the holding duration. In columns (3) and (4), the independent variable of interest is *Deal-to-Fund-Size*. Similarly, a one standard deviation increase in the Deal-to-Fund-Size is related to a 0.5 year increase in the holding duration.

Panel B reports the results where we control for GP fixed effects. The results that larger deals have longer duration remain. For example, in column (2) where we have a full set of control variables, a one-notch increase in *Deal-Size Rank* is associated with a 0.17 year decrease in the deal duration, slightly more negative compared to the same specification but without GP fixed effects. Similarly, in the specifications using *Deal-to-Fund-Size* as the independent variable in columns (3) and (4), we have slightly larger magnitude of effects with GP fixed effects. These findings imply that the association between deal size and duration is not mainly driven by manager-level time-invariant differences, such as personal preference and risk tolerance.

Take together, our results suggest that larger deals are also owned longer by GPs, which are likely to involve more valuation creation efforts in operational performance improvements (e.g., Eaton et al. (2020), Fracassi et al. (2022)). Previous research suggests such valuation creation deals appear to have more stable returns and a smaller likelihood of extremely high returns (see, Lopez-de Silanes et al. (2015)). Our findings is consistent with that the longer duration is on average associated with deals that are more likely to require GP expertise to drive meaningful operational and other improvements (as opposed to "quick flips").

4.5 Robustness

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 B1 and B2).

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).[16] 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 (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.

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

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 Concentration and Specialization 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 3 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 3 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 relationship between the *Gini Index* and *value-weighted PME*, indicating a lower return for more concentrated funds. However, the negative relation is moderated by the inclusion of control variables and no longer statistically significant.

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 the results with 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 0.97 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*. The specifications mirror that analysis in columns (1) to (4) for the return-concentration analysis. 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 0.41 (0.59) 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 mostly robust to using TVPI as an alternative performance measure.

5.3 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 fund size and the sum of deal sizes. As an alternative measure, we calculate the concentration indices using the total capital commitment. The alternative measures of fund size also affect the calculation of the HHI indices. In a similar way, we calculate the HHI sector index and the HHI region index using the fund size. Results are similar (and reported in Online Appendix Table B3 for PME and B4 for TVPI).

6 Parametric Estimation of the Hierarchical Linear Model

The OLS regression analyses in the previous sections show that GP firms balance among deals of different sizes within the fund; the fund concentration and specialization degrees are related to the fund performance. These patterns suggest that portfolio management at the fund level is important. The regression analyses have the advantage that it is easy to interpret the findings. However, we do not learn about how important the fund-level portfolio effect is from such analyses. In this section, we quantify the portfolio effect by separating the (fund-level) portfolio management dimension and deal selection dimension (conditional on the same fund) of GP skills.

[INSERT Figure 4 AROUND HERE]

To study these questions, we adopt hierarchical linear models to our GP-Fund-Deal level dataset. As shown in Figure 4, the private equity industry features a clear hierarchical structure, with the GP firms being the top of the tree, funds as middle layers, 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 are first introduced to study PE return in Korteweg and Sorensen (2017) (KS model henceforth) and extended in Cavagnaro et al. (2019) (CSWW henceforth) to the LP-Fund-GP setting to study the skills of LPs.

Using the same modeling and estimation technics in Korteweg and Sorensen (2017) and Cavagnaro et al. (2019), we extend the KS model to the GP-Fund-Deal setting to exploit our novel deal-level dataset. As to be discussed in detail below, by extending the two-layer GP-Fund KS model to a three-layer GP-Fund-Deal model, we can separate the GP's value-added at the fund and the deal level.

6.1 The Model

6.1.1 GP-Fund Two-Layer Model

Before we present the deal-level extension of the KS model, we first briefly present the fund-level hierarchical linear model developed in Korteweg and Sorensen (2017). We can learn about the relative importance of GP intrinsic value to the fund-level idiosyncratic risks (luck) in explaining fund return. The KS model also contains a GP-time specific term that tells us how much covariance in the returns of funds with overlapping fund life is due to common exposure to market conditions and investment strategy.

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.

$$FundReturn_{iu} = X_{iu}^{'}\beta + \Sigma_{\tau=t_{iu}}^{t_{iu}+N_{iu}}(GPRE_i + GPYearRE_{i\tau}) + \epsilon_{iu} \tag{3}$$

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.[17] 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).

6.1.2 GP-Deal Two-Layer Model

The first extension is to use a GP-Deal structure to take advantage of our deal-level return data. This estimates GP skills in the sense of variation in deal-level value.

GP skills estimated using the deal-level returns can be different than skills estimated using the fund-level returns for a couple of reasons. First, more granular return data can partially solve the overlap issue by largely reducing the mechanical overlapping degree attributed to

[17] Using the PME measure is not appropriate here because the time-specific variation is directly modeled.

different funds investing in the same company.[18] Estimating the two-layer version of the KS model at the deal level instead of at the fund level reallocates the mechanical overlap effect into the GP-specific and error random effects. The overlap effect in the GP-deal hierarchical model mainly capture risk exposure to common market conditions. As a result, the estimated GP-specific effect is likely to be larger in the deal-level model than in the fund-level model. Second, 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. 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 empirical question how much we can learn from deal-level data on GP skills.

The GP-Deal level model is the following,

$$DealReturn_{ij} = X'_{ij}\beta + \Sigma_{\tau=t_{ij}}^{t_{ij}+DealLife_{ij}}(GPRE_i + GPYearRE_{i\tau}) + \epsilon_{ij} \tag{4}$$

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.

6.1.3 GP-Fund-Deal Three-Layer Model

The second extension is to a three-layer GP-Fund-Deal hierarchical regression model. The estimation of the KS model at the GP-Deal level in the previous section cannot tell us about one important dimension of GP skills, namely portfolio management. Using the three-layer model, we quantify the variation across GPs in their value-added in terms of portfolio management.

[18]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.

As discussed in section 2, there are various reasons that GPs can be different in their skills in portfolio management. First, information asymmetry between the GP and the portfolio company plus the resource constraint of the managers implies that the due diligence and monitoring costs can differ if investing in a different portfolio of companies. Some GPs may be better at allocating their resources. In addition, some GPs may have better multi-task ability than others. These can lead to the variance across GPs in the portfolio effect. Second, deals within the portfolio may not be independent of each other. Spillovers and resource exchanges among the companies invested by the same GP can also lead to different portfolios having different levels of value-added. Some GPs may be more capable to facilitate the resource exchange and thus achieve a higher overall return.

[INSERT Figure 5 AROUND HERE]

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 reduction in return dispersion at the fund level than at the deal level.[19] Figure 5 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 due to portfolio management and a mechanical reduction in return dispersion at a higher level. The difference between the GP-Fund and GP-Deal model in the previous sections captures both effects. Using a three-layer GP-Fund-Deal hierarchical regression model in this section, we provide estimates of the first effect, the non-mechanical portfolio effect.

One way of thinking about a portfolio is all the deals that the GP is in charge of in the same time period (Lopez-de Silanes et al. (2015)). We define portfolio in another way by considering a fund as a portfolio managed by the GP due to a couple of reasons. First, we have the advantage that our data provides clear structure of the GP-Fund-Deal. Second, there are economic reasons how funds are composed of portfolio companies (e.g., some funds

[19] 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.

invest in specific industries or regions) and thus analyses using funds as the mid-layer is more economically insightful.

Formally, we use a two-stage version of the GP-fund-deal level hierarchical linear model, which provides more results than using a single three-layer model. For example, as to be discussed in the result section below, we learn different information about the relation between the deal-size position and return at the first and the second stages. Similar to CSWW, we do two different models at the second stage so that we could compare GP's value-added at the deal-level (conditional on the fund-level) and at the fund-level (i.e. portfolio management). The specifications are as follows,

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.

$$DealReturn_{iuj} = X'_{uj}\beta + \Sigma_{\tau=t_{iuj}}^{t_{iuj}+DealLife_{iuj}}(FundRE_u + FundYearRE_{u\tau}) + \epsilon_{uj} \tag{5}$$

Where u stands for funds, j stands for deals, X_{uj} are the observed covariates, 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.

$$\widehat{DealReturn}_{iuj} = X'_{ij}\delta + \Sigma_{\tau=t_{iuj}}^{t_{iuj}+DealLife_{iuj}}(GPRE_i + GPYearRE_{i\tau}) + \nu_{ij} \tag{6}$$

Where i stands for GP firms, u stands for funds, j stands for deals, X_{iuj} are the observed covariates, 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 do two models that differ in how the *adjusted* deal return is calculated. The difference in the estimated GP-specific effect ($GPRE_i$) from Model 1 and Model 2 tells how skillful GPs are at managing funds.

In the first version of the model (Model 1), we compute the adjusted return for each deal by subtracting the estimated effects of covariates and estimated fund-year-specific effect from the *actual* deal returns (Equation 7). The variation left in the *adjusted* deal returns reflects GP's skills to achieve high return deals (the fund-level deal-specific effect ϵ_{uj}) and to manage funds well (the fund-specific effect $FundRE_u$).

$$\widehat{DealReturn}_{iuj} = DealReturn_{iuj} - X'_{uj}\hat{\beta} - \Sigma_{\tau=t_{iuj}}^{t_{iuj}+DealLife_{iuj}} \widehat{FundYear}RE_{u\tau} \tag{7}$$

Where $\widehat{FundYear}RE_{iu\tau}$ is the estimated fund-time random effect.

In a second version of the model (Model 2), when computing the *adjusted* return for each deal, we subtract the estimated effects of covariates, estimated fund-year-specific effect, and the fund-level deal-specific effect from the *actual* deal return (Equation 7′). The variation left in the adjusted deal returns reflects the GP's value-added to manage funds well (the fund-specific effect $FundRE_u$).

$$\widehat{DealReturn}_{iuj} = DealReturn_{iuj} - X'_{uj}\hat{\beta} - \Sigma_{\tau=t_{iuj}}^{t_{iuj}+DealLife_{iuj}} \widehat{FundYear}RE_{u\tau} - \widehat{\epsilon}_{uj} \tag{7′}$$

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

6.1.4 Model Assumptions and Variance Decomposition

In this section, we discuss the assumptions of the model and the variance decomposition, taking the GP-Fund two-layer model as an example. Other extensions follow similar assumptions and variance decomposition.

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 expected return of the entire PE industry 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.

The GP-time effect captures an overlapping effect, and is assumed to be independent and identically distributed (i.i.d.) from a normal distribution $N(0, \sigma^2(GPYearRE))$. 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 noise 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.

The total variance in $FundReturn_{iu}$ is the sum of the variances of the above discussed three random effects,

$$\sigma^2(FundReturn) = N^2\sigma^2(GPRE) + N\sigma^2(GPYearRE) + \sigma^2(\epsilon) \tag{8}$$

And we further define the percentage of skill (or signal to noise in the terminology in Bayesian estimation), overlap effect, and luck as follows,

$$SignaltoNoise(Skill\%) = \frac{N^2\sigma^2(GPRE)}{\sigma^2(FundReturn)} \tag{9a}$$

$$OverlapEffect\% = \frac{N\sigma^2(GPYearRE)}{\sigma^2(FundReturn)} \tag{9b}$$

$$Noise\% = \frac{\sigma^2(\epsilon)}{\sigma^2(FundReturn)} \tag{9c}$$

6.2 Bayesian Estimator

Following KS and CSWW, we estimate our model using a Bayesian estimator and techniques of Markov chain Monte Carlo (MCMC) and Gibbs sampling. Details on the estimation procedure and fitness of the Bayesian estimator to the PE setting are discussed in KS (2017) and CSWW (2019). Korteweg (2011) has a book chapter-length review on the MCMC method in finance. 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.

In the two-layer models, we follow the algorithm developed in KS. In the three-layer models, we extend the algorithm similarly as in CSWW to our GP-Fund-Deal structure. More specifically, we first use the KS algorithm (steps A1 to A5 in their appendix) to estimate at the Fund-Deal level. Following CSWW, we also modify the KS algorithm so as that the mean of the fund random effect. We use the priors and starting values described in section A7 in the KS appendix. The choice of the priors aims to have sufficiently diffused parameter starting values so that the results are driven by the data rather than prior assumptions.

6.3 Results

6.3.1 GP-Fund Two-Layer Model

[INSERT Table 7 AROUND HERE]

Table 7 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 $\sigma(GPRE)$, $\sigma(GPYearRE)$, and $\sigma(\epsilon)$ 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 *HHI*s 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 ($N^2\sigma^2(GPRE)$, $N\sigma^2(GPYearRE)$, and $\sigma^2(\epsilon)$) 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 noise we define in Equation 9. Following KS (2017), we discuss results using standard frequentist terminology for easy understanding of readers, though we use a Bayesian estimator.

Noise explains around half of the return variation. For example, in our preferred specification in column (5) with concentration and specialization measures as covariates, 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 noise. 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 noise decreases. For example, in column (6) where the specification is with a full set of covariates , 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 noise. This is consistent with that part of the noise in returns is due to market conditions in different years.

We study a recent period, from 1999 to 2016, while Korteweg and Sorensen (2017) focus on a sample from 1969 to 2001. Comparing our results to the estimates in KS (2017), all variances are smaller in our sample, probably due to the different sample periods.[20] Take

[20] 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.

the specification with vintage year fixed effects as an example (column (4)), the level of skill ($N^2\sigma^2(GPRE)$) estimated using our sample is 0.105 and 0.316 in KS, the level of overlap effect ($N\sigma^2(GPYearRE)$) is 0.036 our sample and 0.203 in KS, and the level of luck ($\sigma^2(\epsilon)$) is 0.130 in our sample and 1.225 in KS. Interestingly, in terms of relative importance, skills explain more of the total variance of returns in our sample (38.77%) than in the KS sample (14.1%). On the other hand, noise accounts for less of the total variance of returns in our sample (48.02%) than in the KS sample (66.80%). The part due to overlap effects is closer in our sample (13.22%) and the KS (19.17%) sample.

6.3.2 GP-Deal Two-Layer Model

[INSERT Table 8 AROUND HERE]

Table 8 reports the estimates of the GP-Deal two-layer model. Panel A shows the magnitudes of the GP-specific, the GP-year specific, and noise 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. Compared to estimates from the GP-Fund model, skill explains less while noise explains more for the total variation of return in the GP-Deal model. The part due to overlap also increases slightly. For example, in our preferred specification in column (5) where we have the deal rank as covariates, 3.65% of the total variance in deal return is due to skill (32.51% less), 16.48% is due to overlap effect (3.5% more), and 79.87% is due to noise (29.07% more).

It is interesting to notice that the absolute level of variation in GP-specific random effect ($\sigma(GPRE)$) is almost the same, 0.033, in the fund-level and deal-level models. The changes in the relative importance of skill and noise come from the fact that the noise term ($\sigma(\epsilon)$) increase from 0.363 in the GP-fund model to 1.023 in the GP-deal model. 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 noise components. For example, comparing column (1) (without covariates) and column (4) (with covariates), the part due to overlap effect decreases from 16.72% to 5.80%, suggesting that the market condition contributes a large part of the overlap effect. The rest of the 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 part due to skill increases from 3.66% to 4.01%. The part due to luck increases from 79.62% to 90.20%, implying that variation in the market condition adds a large amount of noise to the variation of return.

Comparing the results on the deal and fund levels have several implications that can shed more light on our understanding of the PE industry. First, it shows that, in the GP-fund model, the mechanical overlap effect due to same holding issue is quite large. It is common that different funds of the *same* GP invest in the same holding company (Braun et al. (2017)). Indeed, we find that the overlap effect decreases from 12.99% at the fund level to 5.80% at the deal level. However, the fact that we still observe an overlap effect at the deal level (5.8%) suggests that common strategies and common risk exposures (as discussed in Korteweg and Sorensen (2017)) also contribute to the overlap effect.

Second, it answers the question of whether estimating the hierarchical model using the individual deal return data instead of aggregate fund return data is more informative. As conjectured in Korteweg and Sorensen (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 the larger degree of noise at the deal level masks the relative importance of GP skills in return variation. Indeed, we find that the absolute level of variation in GP skill is almost the same. Due to the large increase in the noise part, deal level estimation shows lower relative importance of GP skills.

6.3.3 GP-Fund-Deal Three-Layer Model

In this section, we present the results of the three-layer model where we quantify the relative importance of portfolio effect. More specifically, we estimate how much of the return variation is due to the variation across GPs in their intrinsic value that adds to *all* deals within the fund and to *individual* deals (conditional on the fund).

[INSERT Table 9 AROUND HERE]

Table 9 shows the results estimated from the first stage of the model (Equation 5), 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 the deal-level decomposition in the two-layer GP-deal model, as reported in Table 8. We find that noise accounts for 80% to 90% (depending on specifications) of the deal-level total return variation. This implies that idiosyncratic risks at the deal-level account for a large part of return variation either when we use fund (Table 9) or use GP (Table 8) as the level of aggregation.

[INSERT Table 10 AROUND HERE]

Table 10 reports the results of second-stage estimates of Model 1 where we only subtract fund-year-specific effect when adjusting the deal return that enters the second-stage estimation (Equation 7). This tells us how GP's skills affect deal returns if we take into account both fund-specific effects (i.e., how good GPs are at portfolio management) and deal-specific effect (i.e., how good GPs are selecting deals conditional on funds). We find that skills only account for 6.11% of the total variance of returns. Similar to the results of the two-layer GP-deal model reported in Table 8, we find that noise accounts for a large part, more than 91%, of the return variation. The part of return variation due to the overlap effect is smaller, around 2.41%, in the three-layer model. This is reasonable because after subtracting fund-year-specific effect that can contain effects rising from common fund strategies, the overlap effect here only captures the GP level common strategies (e.g., management team year specific effect) and common risk exposures to the market conditions.

[INSERT Table 11 AROUND HERE]

Table 11 reports the results of second-stage estimates of Model 2 where we subtract both fund-year-specific and fund-level deal-specific effects when adjusting the deal returns entering the second-stage estimation (Equation 7′). In Model 2, we learn how much return variation is due to variation across GPs in their intrinsic when referring to fund-specific effects (i.e., GP's portfolio management skills). We find that skill accounts for a much larger part of the return variation, 46.55%, in this case. This implies that GPs differ to a large degree in their portfolio management skills. The overlap effect is also larger in Model 2 than in Model 1, accounting for 46.71% of the total variance in returns. Noise only accounts for 6.74% of the return variation. This implies that after subtracting fund-deal specific error term, there is only a small proportion of return variation attributed to GP-deal specific error term. Overall, the estimation from Model 2 implies that GP skills in the sense of fund management (portfolio effect) account for a large part of the return variation (conditional on deal-level idiosyncratic risks).

Another interesting result is that we find that the coefficients before deal rank are positive in the first-stage estimation but negative in the second-stage estimation. This provides direct support that the risk management concern of the GPs drive the opposite finding on "best idea" in private equity than in mutual funds. The positive relation between size rank and return in the first stage means that larger deals have lower returns than smaller deals in the *same* fund, when taking risks into account. In the second stage, we use the adjusted return which does not include fund-year-specific effects (and deal-specific effects). Therefore, the negative relation between size rank and return in the second stage means that larger deals have higher return after separating out risk exposures to market condition (and deal-level idiosyncratic risks). That is to say, we observe the same pattern in private equity as in mutual funds regarding "best idea" if the GPs did not bare high level of risks.

Taken together, using the three-layer GP-fund-deal model, we first provide novel evidence on quantifying the relative importance of portfolio management in private equity. Consistent with the literature, we find that noise (luck in the expression in Korteweg and Sorensen (2017) and other follow-on papers) explains a large part of return variation. However, conditional on the deal-specific "luck" effect, GPs show a large variation in their skills in portfolio management. In addition, we find that while best ideas within funds are invested with a smaller amount if accounting for risks (in contrast with findings on mutual funds), best ideas are invested with a larger amount after controlling for risk exposures common to the deals in the same year in the same fund such as market conditions (the same as for mutual funds).

7 Conclusion

There is a long debate on whether GP managers in private equity have skills. At a first glance, it is true that the realized returns seem to have a large degree of noise (luck). Careful variance decomposition in Korteweg and Sorensen (2017) shows that luck accounts for more than 66% of the fund return variation for buyout funds. Therefore, follow-on literature argues that initial luck can lead to future success due to a reputational effect. However, if GP skills do not matter, why the PE industry can remain to charge investors (limited partners) high fees? To think of the question in another way, if much of the success in PE investment is due to initial luck that is transferred to the entire investment history of the fund manager, why limited partners do not simply make random bets on themselves? In addition, there is long-dated literature demonstrating the value-added role of PE managers and their skills in asset selection and timing.

In this paper, we take a portfolio management view and provide new insights on the question that can reconcile different findings in the literature. On one hand, we also find that idiosyncratic risks explain a large part of the total variance of return, even more (90%) at the deal level in our sample period (1999 to 2006) than in the fund-level sample (1969 to 2001) in Korteweg and Sorensen (2017). On the other side, if we restrict GP skills in portfolio management (by subtracting the idiosyncratic risks from the estimation), GP skills account for more than 40% of the return variation.

In the more intuitive regression analyses, our findings suggest that GPs exert efforts on portfolio management and deliberately choose the deals in their funds to balance the risk-return tradeoff. First, we find that instead of betting more on “best ideas” as shown in mutual funds, PE managers bet more on “safest ideas”. Second, we find that a higher degree of industry or geographic concentration is associated with both higher fund returns as well as a higher fund risk, which is similar to findings in mutual funds (Coval and Moskowitz (1999, 2001), Kacperczyk et al. (2005)) and in venture capital (Gompers et al. (2009).

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Figures

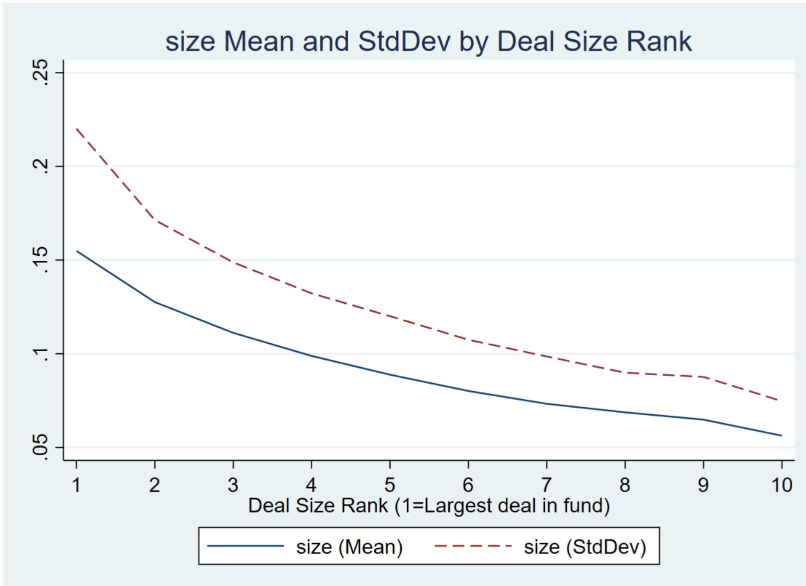
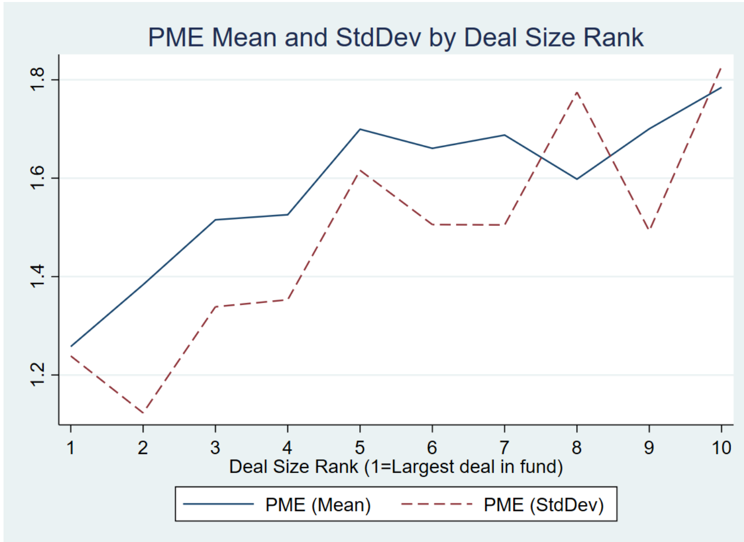
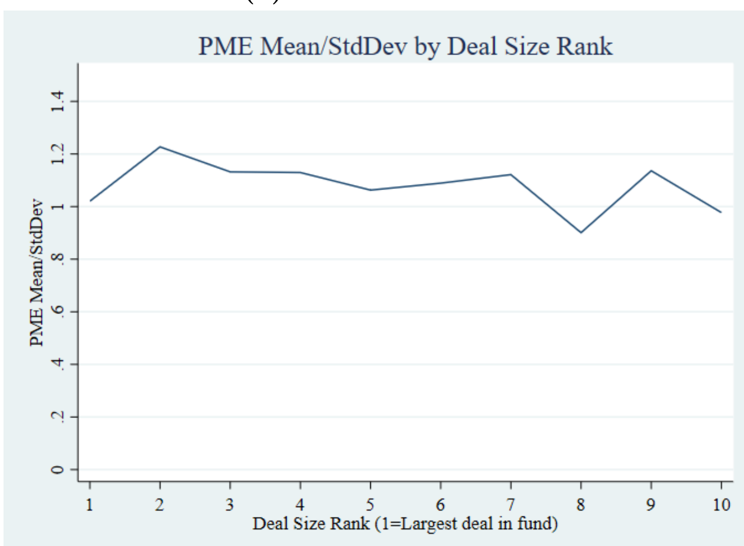


Figure 1: Deal Size by Deal-Size Rank in the Fund

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.



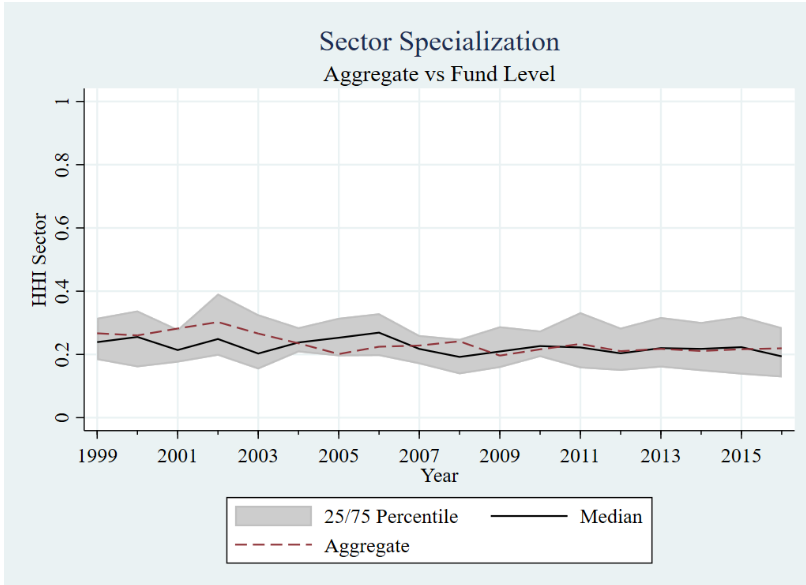
(a) Mean and S.D.



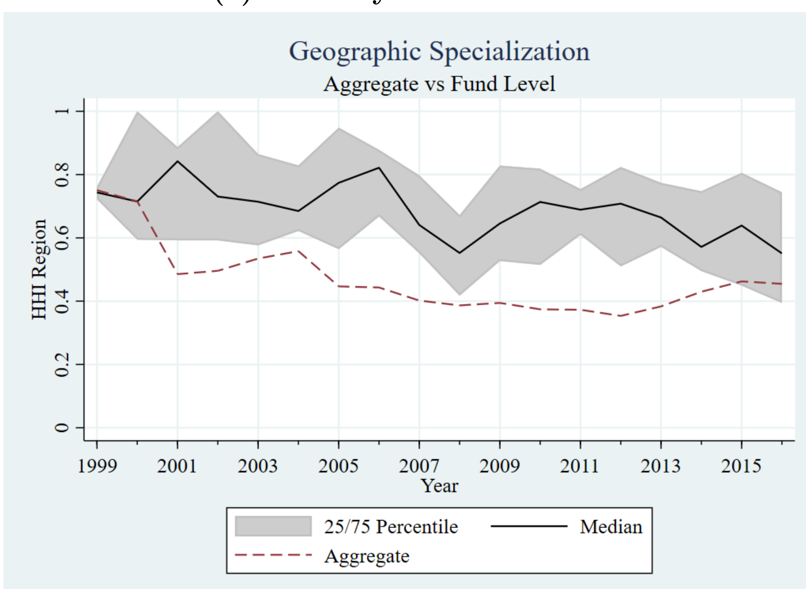
(b) Mean/S.D.

Figure 2: Deal PME by Deal-Size Rank in the Fund

Note: This figure plots the mean and standard deviation of deal PME in each 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) Industry Concentration



(b) Geographic Concentration

Figure 3: 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.

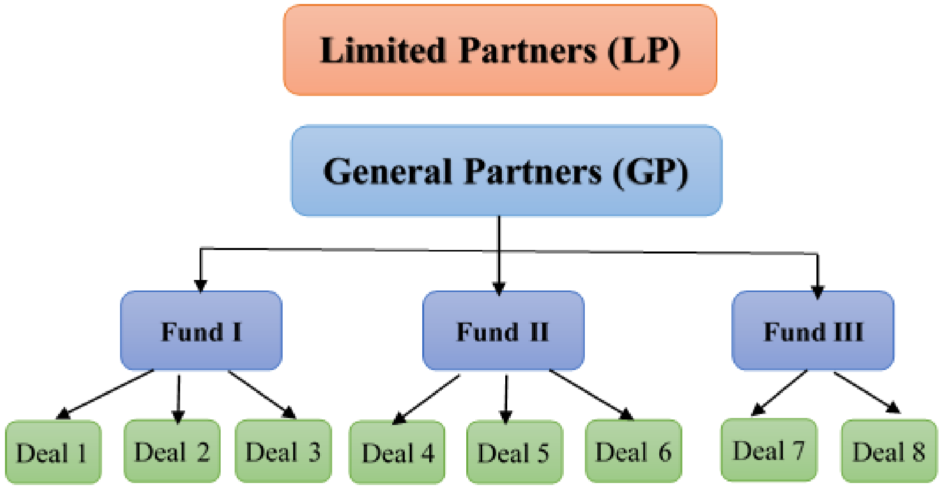
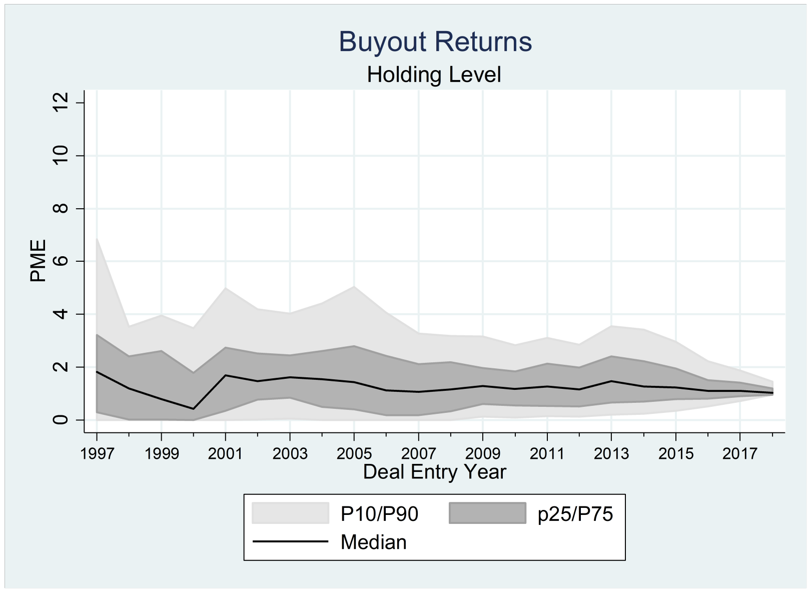
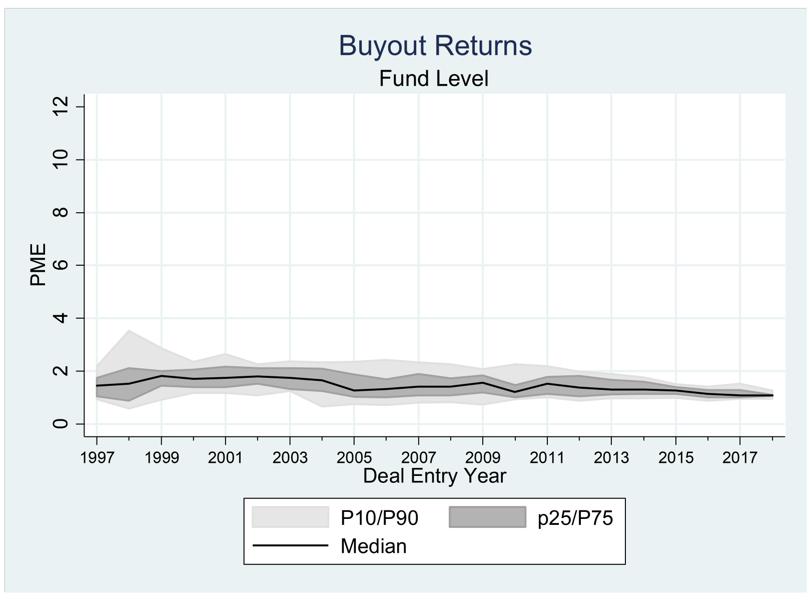


Figure 4: Hierarchical Structural of the Private Equity Industry



(a) Deal Level Return Dispersion



(b) Fund Level Return Dispersion

Figure 5: Return Dispersion: Fund-Level v.s. Deal-Level

Note: 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.

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-to-Fund-Size	5,925	0.07	0.05	0.00	0.01	0.06	0.15	0.62
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)	(7)
(1) Deal PME	1.00						
(2) Deal TVPI	0.93***	1.00					
(3) Deal Size	-0.05***	-0.04***	1.00				
(4) Deal-to-Fund-Size	0.09***	0.08***	-0.23***	1.00			
(5) Deal-Size Rank	-0.08***	-0.06***	0.20***	-0.81***	1.00		
(6) Deal Duration	-0.14***	0.01	0.10***	-0.10***	0.14***	1.00	
(7) Exit Dummy	0.16***	0.19***	-0.06***	0.13***	-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: Within-Fund Size Position and PME

This table reports the cross-sectional regressions about within-fund position and PME at the deal level, where the within-fund position is measured using the rank/deal-to-fund ratio based on size. Size is the amount of fund (USD) invested in the holding company. 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. Panel A reports results without GP fixed effects. Panel B reports results with GP fixed effects. In each panel, in columns (1) to (3), the key independent variable is *Deal-Size Rank* which is the within-fund rank sorted by deal size. In columns (4) to (6), the key independent variable is *Deal-Fund-Size* which is the ratio of the deal size to the fund size. More details on the variable calculation and the sample restrictions are in Appendix Table A1. Fixed effects for GP, deal investment year, 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: Without GP FE						
	(1)	(2)	(3)	(4)	(5)	(6)
			Deal PME			
Deal-Size Rank	0.05***	0.04***	0.03***			
	(6.12)	(4.94)	(4.44)			
Deal-to-Fund-Size				-2.87***	-2.41***	-2.14***
				(-5.25)	(-4.39)	(-4.41)
Exit Dummy		0.48***	0.45***		0.49***	0.45***
		(9.95)	(5.65)		(10.15)	(5.62)
Fund Size			-0.0**			-0.02**
			(-2.04)			(-2.17)
Deal Duration			-0.12***			-0.12***
			(-8.57)			(-8.63)
Deal Inv. Year FE	-	-	Yes	-	-	Yes
Industry FE	-	-	Yes	-	-	Yes
Geography FE	-	-	Yes	-	-	Yes
Observations	5925	5925	5925	5925	5925	5925
Adjusted R^2	0.009	0.031	0.095	0.007	0.031	0.095

Table 3. Deal Level: Within-Fund Size Position and PME

Panel B: With GP FE						
	(1)	(2)	(3)	(4)	(5)	(6)
			Deal PME			
Deal-Size Rank	0.05***	0.05***	0.04***			
	(6.83)	(5.89)	(4.63)			
Deal-to-Fund-Size				-3.84***	-3.40***	-2.78***
				(-6.19)	(-5.48)	(-4.45)
Exit Dummy		0.63***	0.42***		0.64***	0.41***
		(10.84)	(4.89)		(10.99)	(4.85)
Fund Size			-0.01			-0.01
			(-0.31)			(-0.43)
Deal Duration			-0.12***			-0.12***
			(-8.25)			(-8.34)
GP FE	Yes	Yes	Yes	Yes	Yes	Yes
Deal Inv. Year FE	-	-	Yes	-	-	Yes
Industry FE	-	-	Yes	-	-	Yes
Geography FE	-	-	Yes	-	-	Yes
Observations	5925	5925	5925	5925	5925	5925
Adjusted R^2	0.038	0.065	0.110	0.037	0.065	0.110

Table 4: Deal Level: Deal Size Position and Duration

This table reports the cross-sectional regressions about within-fund position and duration at the deal level, where the within-fund position is measured using the rank/deal-to-fund ratio based on size. Size is measured in dollar value (USD) invested in the holding company. The sample period spans from 1999 to 2016 (both included). We include only *exited* deals. The dependent variable is *Deal Duration*. Panel A reports results without GP fixed effects. Panel B reports results with GP fixed effects. In each panel, in columns (1) and (2), the key independent variable is *Deal-Size Rank*. In columns (3) and (4), the key independent variable is *Deal-Fund-Size*. More details on the variable calculation and the sample restrictions are in Appendix Table A1. Fixed effects for GP, deal investment year, 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: Without GP FE				
	(1)	(2)	(3)	(4)
		Deal Duration		
Deal-Size Rank	-0.16***	-0.16***		
	(-10.60)	(-10.88)		
Deal-to-Fund-Size			11.52***	10.92***
			(8.37)	(8.03)
Fund Size		0.11***		0.12***
		(5.01)		(5.00)
Deal Inv. Year FE	-	Yes	-	Yes
Industry FE	-	Yes	-	Yes
Geography FE	-	Yes	-	Yes
Observations	3199	3199	3199	3199
Adjusted R^2	0.033	0.247	0.038	0.246
Panel B: With GP FE				
	(1)	(2)	(3)	(4)
		Deal Duration		
Deal-Size Rank	-0.20***	-0.17***		
	(-11.11)	(-9.79)		
Deal-to-Fund-Size			15.18***	12.57***
			(8.95)	(7.58)
Fund Size		0.14**		0.18**
		(2.02)		(2.44)
GP FE	Yes	Yes	Yes	Yes
Deal Inv. Year FE	-	Yes	-	Yes
Industry FE	-	Yes	-	Yes
Geography FE	-	Yes	-	Yes
Observations	3199	3199	3199	3199
Adjusted R^2	0.160	0.254	0.165	0.254

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. We include our concentration and specialization measures, *Gini Index*, *HHI Sector* and *HHI Region*, as covariates. 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 9. 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)	(3)	(4)	(5)	(6)
Panel A: Parameter estimates						
$\sigma(GPRE)$	0.033	0.033	0.033	0.032	0.033	0.032
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
$\sigma(GPYearRE)$	0.063	0.059	0.063	0.059	0.062	0.060
	(0.012)	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)
$\sigma(\epsilon)$	0.397	0.363	0.392	0.360	0.395	0.363
	(0.034)	(0.032)	(0.032)	(0.031)	(0.033)	(0.030)
covariates						
β(Gini)			-0.516	-0.783	-0.614	-0.801
			(0.303)	(0.296)	(0.310)	(0.306)
β(HHI Sector)					0.295	0.270
					(0.252)	(0.254)
β(HHI Region)					0.410	0.251
					(0.142)	(0.145)
Vintage Year FE	N	Y	N	Y	N	Y
N. of GPs	315	315	315	315	315	315
N. of Funds	467	467	467	467	467	467
Panel B: Variance decomposition						
$N^2\sigma^2(GPRE)$	0.113	0.108	0.112	0.105	0.112	0.106
	(0.021)	(0.020)	(0.020)	(0.019)	(0.020)	(0.019)
$N\sigma^2(GPYearRE)$	0.041	0.036	0.041	0.036	0.040	0.038
	(0.016)	(0.012)	(0.015)	(0.012)	(0.014)	(0.013)
$\sigma^2(\epsilon)$	0.159	0.133	0.155	0.130	0.157	0.133
	(0.027)	(0.024)	(0.026)	(0.023)	(0.026)	(0.022)
$\sigma^2(FundReturn)$	0.312	0.277	0.308	0.271	0.309	0.276
	(0.032)	(0.027)	(0.031)	(0.026)	(0.031)	(0.026)
signal to noise (skill%)	36.24%	39.14%	36.42%	38.77%	36.16%	38.37%
	(0.058)	(0.061)	(0.057)	(0.060)	(0.057)	(0.059)
overlap effect%	13.01%	12.99%	13.32%	13.22%	12.98%	13.19%
	(0.049)	(0.042)	(0.046)	(0.042)	(0.045)	(0.045)
noise%	50.75%	47.88%	50.27%	48.02%	50.80%	48.02%
	(0.065)	(0.065)	(0.061)	(0.065)	(0.063)	(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. We include our size-based *Deal Rank* as covariates. 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 9. 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)	(5)	(6)	(7)	(8)
Panel A: Parameter estimates								
$\sigma(GPRE)$	0.034	0.037	0.037	0.033	0.034	0.037	0.037	0.033
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)
$\sigma(GPYearRE)$	0.194	0.170	0.166	0.107	0.193	0.168	0.165	0.108
	(0.016)	(0.016)	(0.015)	(0.015)	(0.016)	(0.016)	(0.014)	(0.015)
$\sigma(\epsilon)$	1.023	1.030	1.024	1.023	1.023	1.030	1.025	1.022
	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)	(0.012)
covariates								
β(Deal Rank)					0.021	0.019	0.012	0.006
					(0.006)	(0.006)	(0.006)	(0.005)
Deal Entry Year FE	N	Y	N	Y	N	Y	N	Y
Deal Exit Year FE	N	N	Y	Y	N	N	Y	Y
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								
$N^2\sigma^2(GPRE)$	0.048	0.057	0.058	0.047	0.048	0.056	0.058	0.047
	(0.009)	(0.012)	(0.012)	(0.009)	(0.009)	(0.012)	(0.012)	(0.009)
$N\sigma^2(GPYearRE)$	0.221	0.169	0.161	0.067	0.217	0.165	0.160	0.069
	(0.037)	(0.032)	(0.028)	(0.019)	(0.035)	(0.031)	(0.027)	(0.019)
$\sigma^2(\epsilon)$	1.047	1.062	1.049	1.046	1.047	1.062	1.050	1.045
	(0.027)	(0.027)	(0.026)	(0.025)	(0.026)	(0.027)	(0.026)	(0.025)
$\sigma^2(DealReturn)$	1.316	1.287	1.269	1.160	1.311	1.283	1.267	1.161
	(0.040)	(0.036)	(0.033)	(0.028)	(0.039)	(0.036)	(0.033)	(0.028)
signal to noise (skill%)	3.66%	4.41%	4.60%	4.01%	3.65%	4.37%	4.57%	4.03%
	(0.007)	(0.009)	(0.009)	(0.007)	(0.007)	(0.009)	(0.009)	(0.007)
overlap effect%	16.72%	13.06%	12.70%	5.80%	16.48%	12.83%	12.57%	5.93%
	(0.025)	(0.023)	(0.021)	(0.016)	(0.023)	(0.022)	(0.020)	(0.015)
noise%	79.62%	82.53%	82.71%	90.20%	79.87%	82.80%	82.86%	90.04%
	(0.024)	(0.022)	(0.020)	(0.016)	(0.023)	(0.022)	(0.019)	(0.015)

Table 9: Bayesian Model Estimations of Differences in GP Skill (GP-Fund-Deal Three-Layer 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. We include our size-based *Deal Rank* as covariates. 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 9. 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)	(5)	(6)	(7)	(8)
Panel A: Parameter estimates								
$\sigma(GPRE)$	0.033	0.037	0.041	0.035	0.033	0.036	0.040	0.035
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)
$\sigma(GPYearRE)$	0.189	0.161	0.151	0.094	0.186	0.159	0.152	0.093
	(0.016)	(0.017)	(0.016)	(0.016)	(0.017)	(0.017)	(0.018)	(0.017)
$\sigma(\epsilon)$	1.017	1.026	1.019	1.020	1.018	1.025	1.019	1.021
	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)	(0.012)
covariates								
β(Deal Rank)					0.019	0.018	0.010	0.005
					(0.006)	(0.006)	(0.006)	(0.005)
Deal Entry Year FE	N	Y	N	Y	N	Y	N	Y
Deal Exit Year FE	N	N	Y	Y	N	N	Y	Y
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								
$N^2\sigma^2(GPRE)$	0.046	0.056	0.069	0.052	0.046	0.056	0.068	0.052
	(0.009)	(0.012)	(0.015)	(0.010)	(0.009)	(0.012)	(0.015)	(0.010)
$N\sigma^2(GPYearRE)$	0.209	0.152	0.134	0.053	0.203	0.149	0.135	0.051
	(0.036)	(0.032)	(0.029)	(0.018)	(0.036)	(0.032)	(0.031)	(0.018)
$\sigma^2(\epsilon)$	1.034	1.052	1.038	1.041	1.036	1.051	1.039	1.043
	(0.027)	(0.027)	(0.026)	(0.025)	(0.027)	(0.027)	(0.026)	(0.025)
$\sigma^2(DealReturn)$	1.289	1.260	1.242	1.146	1.284	1.256	1.241	1.146
	(0.037)	(0.034)	(0.031)	(0.027)	(0.037)	(0.034)	(0.031)	(0.026)
signal to noise (skill%)	3.55%	4.44%	5.59%	4.52%	3.55%	4.44%	5.48%	4.56%
	(0.007)	(0.009)	(0.012)	(0.009)	(0.007)	(0.009)	(0.012)	(0.009)
overlap effect%	16.14%	12.05%	10.80%	4.62%	15.75%	11.81%	10.84%	4.46%
	(0.025)	(0.024)	(0.022)	(0.015)	(0.025)	(0.023)	(0.023)	(0.015)
noise%	80.30%	83.51%	83.62%	90.87%	80.70%	83.75%	83.68%	90.99%
	(0.024)	(0.022)	(0.019)	(0.014)	(0.024)	(0.021)	(0.020)	(0.014)

Table 10: Bayesian Model Estimations of Differences in GP Skill (GP-Fund-Deal Three-Layer Model 1, Second 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 1, in which adjusted returns are computed by only subtracting fund random effects and effects of covariates. We report the results of the second stage in this table. Panel A shows the parameter estimates, and Panel B reports the variance decomposition estimates for the same parameters. We include our size-based *Deal Rank* as covariates. 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 9. 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)	(5)	(6)	(7)	(8)
Panel A: Parameter estimates								
$\sigma(GPRE)$	0.027	0.028	0.030	0.030	0.027	0.027	0.030	0.030
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
$\sigma(GPYearRE)$	0.063	0.066	0.086	0.075	0.062	0.063	0.075	0.068
	(0.011)	(0.012)	(0.016)	(0.014)	(0.012)	(0.012)	(0.016)	(0.012)
$\sigma(\epsilon)$	1.024	1.035	1.025	1.020	1.024	1.034	1.025	1.019
	(0.013)	(0.013)	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)	(0.012)
covariates								
β(Deal Rank)					-0.430	-0.635	-0.859	-0.954
					(0.228)	(0.237)	(0.234)	(0.222)
Deal Entry Year FE	N	Y	N	Y	N	Y	N	Y
Deal Exit Year FE	N	N	Y	Y	N	N	Y	Y
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								
$N^2\sigma^2(GPRE)$	0.058	0.062	0.072	0.070	0.058	0.059	0.069	0.070
	(0.010)	(0.011)	(0.014)	(0.013)	(0.010)	(0.010)	(0.013)	(0.013)
$N\sigma^2(GPYearRE)$	0.024	0.026	0.045	0.034	0.023	0.023	0.034	0.027
	(0.009)	(0.010)	(0.017)	(0.013)	(0.009)	(0.009)	(0.014)	(0.010)
$\sigma^2(\epsilon)$	1.049	1.070	1.051	1.040	1.048	1.069	1.051	1.039
	(0.026)	(0.027)	(0.026)	(0.024)	(0.026)	(0.026)	(0.026)	(0.024)
$\sigma^2(DealReturn)$	1.131	1.158	1.168	1.144	1.129	1.151	1.154	1.136
	(0.029)	(0.031)	(0.034)	(0.030)	(0.029)	(0.030)	(0.033)	(0.029)
signal to noise (skill%)	5.13%	5.30%	6.18%	6.13%	5.11%	5.09%	5.96%	6.11%
	(0.008)	(0.009)	(0.011)	(0.010)	(0.008)	(0.008)	(0.011)	(0.011)
overlap effect%	2.08%	2.26%	3.80%	2.97%	2.03%	2.03%	2.91%	2.41%
	(0.008)	(0.008)	(0.014)	(0.011)	(0.008)	(0.008)	(0.012)	(0.009)
noise%	92.80%	92.44%	90.03%	90.90%	92.86%	92.87%	91.13%	91.47%
	(0.012)	(0.013)	(0.018)	(0.015)	(0.012)	(0.012)	(0.017)	(0.014)

Table 11: Bayesian Model Estimations of Differences in GP Skill (GP-Fund-Deal Three-Layer Model 2, Second 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 2, in which adjusted returns are computed by subtracting deal-specific errors in addition to fund random effects and effects of covariates. We report the results of the second stage in this table. Panel A shows the parameter estimates, and Panel B reports the variance decomposition estimates for the same parameters. We include our size-based *Deal Rank* as covariates. 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 9. 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)	(5)	(6)	(7)	(8)
Panel A: Parameter estimates								
$\sigma(GPRE)$	0.020	0.022	0.024	0.022	0.020	0.022	0.023	0.021
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\sigma(GPYearRE)$	0.077	0.086	0.096	0.079	0.077	0.084	0.095	0.079
	(0.008)	(0.009)	(0.010)	(0.007)	(0.008)	(0.009)	(0.010)	(0.007)
$\sigma(\epsilon)$	0.069	0.075	0.082	0.072	0.069	0.075	0.082	0.072
	(0.006)	(0.007)	(0.008)	(0.006)	(0.006)	(0.007)	(0.008)	(0.006)
covariates								
β(Deal Rank)					-0.071	-0.102	-0.151	-0.127
					(0.045)	(0.054)	(0.065)	(0.058)
Deal Entry Year FE	N	Y	N	Y	N	Y	N	Y
Deal Exit Year FE	N	N	Y	Y	N	N	Y	Y
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								
$N^2\sigma^2(GPRE)$	0.033	0.037	0.044	0.037	0.033	0.037	0.042	0.036
	(0.005)	(0.006)	(0.008)	(0.006)	(0.005)	(0.006)	(0.007)	(0.006)
$N\sigma^2(GPYearRE)$	0.035	0.043	0.054	0.036	0.035	0.042	0.052	0.036
	(0.007)	(0.009)	(0.011)	(0.007)	(0.007)	(0.009)	(0.011)	(0.007)
$\sigma^2(\epsilon)$	0.005	0.006	0.007	0.005	0.005	0.006	0.007	0.005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\sigma^2(DealReturn)$	0.073	0.086	0.104	0.078	0.073	0.084	0.101	0.078
	(0.011)	(0.015)	(0.018)	(0.012)	(0.011)	(0.014)	(0.018)	(0.012)
signal to noise (skill%)	45.64%	43.80%	42.21%	47.09%	45.72%	43.90%	41.88%	46.55%
	(0.040)	(0.041)	(0.041)	(0.039)	(0.040)	(0.040)	(0.040)	(0.038)
overlap effect%	47.85%	49.58%	51.23%	46.26%	47.75%	49.26%	51.47%	46.71%
	(0.038)	(0.039)	(0.038)	(0.036)	(0.038)	(0.038)	(0.038)	(0.036)
noise%	6.51%	6.61%	6.56%	6.65%	6.53%	6.84%	6.65%	6.74%
	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)

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-to-Fund-Size	The fraction of the deal size to the fund size of the deal, i.e., $\frac{DealSize_{i,f}}{FundSize_f}$, where i stands for deal and f stands for fund.
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