Picking Partners: Manager Selection in Private Equity*

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Abstract

We study the selection of private equity managers (GPs) for over 100,000 capital commitments between 1990 and 2019 by global institutional investors (LPs) choosing from a plausible contemporaneous opportunity set. In addition to chasing GPs with high prior performance, LPs have large propensities to select first-time or young GPs without a performance history. LPs also have tendencies to follow their peers' investment decisions, to reinvest with the same GP, and to invest with GPs domiciled in the same state/country. These selection criteria, however, do not provide information material for future performance, and in the case of first-time GPs are associated with lower future performance.

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1. Introduction

We study the selection of investment managers (GPs) to fulfil allocations to private equity (PE). There are two reasons for our inquiry. First, capital commitments to private equity have become globally ubiquitous and significant in magnitude. Second, private equity funds have a closed-end structure with performance visible only after long holding periods. Unlike allocations to public equity and fixed income in which investment vehicles can be liquidated at will and transitioned to other portfolios relatively quickly, investment in private equity funds locks up capital for up to 10 years.[1] The selection process is, therefore, even more consequential for private equity.

We take the perspective of an institution (LP) seeking to place an investment mandate with a GP raising capital for a specific fund in a particular asset class at a point in time.[2] The pertinent question for such an investor then becomes which GP to select from the candidate set, and the consequences thereof. To study these issues, we assemble a database of 100,506 capital commitments originating from 8,801 public and corporate pension systems, endowments, foundations, and sovereign wealth funds over the 1990-2019 period. The source and destination of the capital is global: 27% of commitments originate from non-North-American LPs, and 37% are invested in funds whose geographic focus is outside of North America. Capital commitments are designated to a diverse set of sub-asset classes often referred to as alternatives (buyouts, direct lending, distressed equity, growth, infrastructure, mezzanine financing, natural resources, real estate, and venture capital), all of which use the same closed-end delivery vehicle.

Our analysis unfolds in two steps. First, we estimate selection equations that seek to explain GP choice relative to an opportunity set. For each commitment, we generate the opportunity set

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[1] Closed investment structures can be an equilibrium outcome that manage the tradeoff between liquidity and adverse selection (see, for example, Lerner and Schoar (2004)). An escape hatch for some investors is the secondary market in which investors can sell stakes in private equity funds. Buyers can be other institutions but are most often secondary fund-of-funds created by private equity firms. Secondaries are a small but growing fraction of the industry. See Nadauld, Sensoy, Vorkink, and Weisbach (2019) for details on the market and the costs associated with such transactions.

[2] Although our interest is in allocations by institutional investors, the selection issue takes on added importance for retail investors as well. Registered Investment Advisors (RIAs) increasingly allocate assets of wealthy individual investors to private equity (see, for example, https://www.wealthforge.com/insights/allocations-to-alternatives-results-from-our-ria-survey). Even firms that cater directly to individual investors, such as Vanguard, partner with GPs to allow individual investors to invest in private equity (see https://www.morningstar.com/articles/1041026/vanguard-steps-further-into-private-equity). Finally, newly issued rules by the Department of Labor permit 401K plans to invest in private equity (https://www.natlawreview.com/article/dol-creates-path-401k-plans-to-offer-private-equity-investment-options).

from GPs raising capital in the same sub-asset class, within one year of the actual decision, and comparable in size to the fund that won the capital allocation.[3] We then ask which criteria influence LPs' choices, and use the counterfactual opportunity set to assess post-selection excess performance. This allows us to understand whether the selection criteria used by LPs provide information that is useful for pecuniary payoffs. In each step, we organize our tests around two key selection criteria: (a) prior performance of the GP, and (b) channels by which LPs can acquire information about GPs. These channels include LPs' prior investments, LPs' peers' investments, and geographic proximity between the LPs and the GPs.

Almost 50% of capital commitments in our data are made to GPs without any performance history. Performance history may not exist if the GP is raising capital for the first time, or for younger GPs where insufficient time has passed since the launch of their first fund to observe distributions. We find that GPs without a performance history are 30 percent more likely to be selected than those with observable performance. The tendency to invest in GPs without prior performance is surprising, particularly since three-to five-year track records are standard screening devices in public equity and fixed income. It could, however, be driven by several plausible explanations. For example, it may be that LPs are unable to access funds sponsored by mature well-established GPs and are therefore more likely to select first-time GPs (Sensoy, Wong, and Weisbach (2014)). We perform two tests to determine the importance of this limited access explanation. First, we restrict the sample to undersubscribed funds where access is less likely to drive selection. Second, we estimate regressions for LPs of different sizes under the presumption that access should be of little concern to large LPs. In both tests, the preference for first-time GPs remains high (if anything, the preference for first time GPs increases with LP size). A second possible explanation is that first-time GPs are not true rookies in the sense that their founding partners may be veterans of well-established firms. We use hand-collected data to separate out such firms, but the selection probabilities remain high for both "true" rookies and veteran-founded first-time GPs. A third possibility is that first-time GPs are selected in sub-asset classes with smaller opportunity sets or where non-pecuniary motives may play a role (for example, preferences

[3] The challenge of selection is highlighted by the opportunity set itself. On average, there are approximately 37 GPs in the opportunity set, implying that the unconditional probability of selection is about 2.6%. There is, however, considerable variation in opportunity sets across types of funds, their geographic focus, and over time. The upshot is that in estimating selection effects, it is important to account for variation in fund type, geographic focus, and vintage year.

towards infrastructure or natural resources as shown by Andonov, Kräussl, and Rauh (2021)). However, we observe similar selection effects across all types of funds, including buyout and venture capital. A fourth possibility is that first-time funds offer fee discounts to entice investors. If such fee discounts are large, ceteris paribus, they would imply higher after-fee post-selection performance for first-time funds, relative to funds offered by experienced GPs with even low prior performance. We do not observe such a difference. A fifth possibility is that LPs believe that first-time GPs may deliver superior performance. However, we find that first-time GPs underperform (in the case of true rookies statistically significantly so) even those GPs with poor prior observable performance.

What else then might explain the penchant to select GPs without a performance history? A plausible explanation resides in the increasing weight of private equity in institutional investor asset allocations over time. Ivashina and Lerner (2018) report an increase in average private equity allocations from 4% in 2006 to 15% in 2015, and Burgiss data indicate that private equity assets grew from $130 billion in 1998 to $2 trillion at the end of 2018.[4] With free entry (Cochrane (2005) and Kaplan and Schoar (2005)), this demand for investable funds should result in an increase in the number of new entrants (who, by definition, have no performance history). We observe precisely such patterns in the data.

When prior performance is observable, we find that a GP in the 4th quartile of the distribution of pre-decision IRRs is 33 percent more likely to be selected than a 1st quartile GP. LPs may engage in performance chasing because they believe there is persistence in back-to-back fund performance even though the evidence on persistence is, at best, mixed (Harris, Jenkinson, Kaplan, and Stucke (2020)). However, the average difference in excess IRRs between selected and non-selected funds sponsored by 4th quartile GPs is −1.10% (t-statistic = −0.58), suggesting that winner chasing does not translate into larger future payoffs.[5]

The second class of inputs to selection that we examine is private information acquisition, organized around three conduits. The first conduit is one in which LPs acquire information about GPs through peer networks (Lerner, Schoar, and Wang (2008) and Swensen (2000)). Following a peer can be a rational information acquisition, or it can be inefficient because valuable own

[4] See https://www.kenaninstitute.unc.edu/wp-content/uploads/2019/10/A-new-equilibrium-report.FINAL_.v2-1.pdf.
[5] Our tests pertain to selection in the cross-section and should not be conflated with time series persistence in fund or GP performance (Harris et al. (2020)), or market-timing (Brown, Harris, Hu, Jenkinson, Kaplan, and Robinson (2021)).

information is ignored (Banerjee (1992) and Bikchandani, Hirshleifer, and Welch (1992)). It can also generate social utility via a joint consumption of the asset (Bursztyn, Ederer, Ferman, and Yuchtman (2014)), or serve as protection from headline risk associated with adverse tail outcomes. All the above serve to increase the probability of selection, an effect clearly visible in the data: relative to the unconditional probability of selection, a prior investment by an LP's peer (constructed at the intersection of the LP type and domicile) in a GP increases the likelihood of selection of that GP by approximately 30 percent. It is unlikely that this selection is driven by reputation effects because GP-year fixed effects (which effectively allow us to hold GP reputation constant), leave our conclusions unaltered. With respect to post-selection performance, the average excess IRR of selected funds is statistically indistinguishable from non-selected funds within this group (i.e., GPs that have received commitments from peers in the past); prior hiring experiences by an LP's peers do not seem to convey information to the LP about future performance.

The second conduit is through an LP's own prior investment activity. Lerner, Schoar, and Wongsunwai (2007) argue that reinvestment allows an LP to exploit inside information obtained from earlier investments and report that reinvestment likelihood is about 50% (see also DaRin and Phalippou (2014), Hochberg, Ljungqvist, and Vissing-Jørgensen (2014), Phalippou (2020), and Robinson and Sensoy (2013)). We exploit the opportunity set to quantify the role of prior investment in selection decisions: our regressions indicate that an LP who has invested in a GP's prior fund is almost 16.5% more likely to commit capital to a subsequent fund than the opportunity set. That represents an increase of 634 percent over the unconditional probability.[6] Again, reputation does not appear to be the driver because GP-year fixed effects do not change inferences. Looking at the post selection performance, we find that funds of selected GPs do not outperform funds of non-selected GPs when both groups are drawn from LPs prior investment experiences.[7]

The third conduit for information acquisition that we consider is LPs preference for local GPs because they think they have access to better information, regardless of whether it is true or not. Hochberg and Rauh (2013) report evidence of such a home bias in US LPs by comparing in-

[6] We note that this probability increase over the baseline cannot be inferred from hiring decisions without considering an opportunity set.

[7] Lerner, Schoar, and Wongsunwai (2007) report that for endowments, reinvestment IRRs are substantially larger than initial investment IRRs. They attribute this to information acquisition but Sensoy, Wang, and Weisbach (2014) argue that the superior performance of reinvestment decisions is largely a pre-2000 phenomenon and may be driven by access to superior funds rather than selection or information. We find that the lack of outperformance is true even in the earlier time period.

state and out-of-state GP choices. In our selection regressions, an LP is almost twice as likely to choose a local GP over a non-local GP from the opportunity set. However, the preference for local GPs does not seem to be driven by information as the average excess IRRs of selected funds is statistically indistinguishable from non-selected funds in the same group (i.e., funds of local GPs).

Overall our results suggest that the conduits for information transmission studied above do not convey information relevant for future performance. It could be the case that some types of LPs are able to harness this information, as suggested by Lerner, Schoar, and Wongsunwai (2007). We find that with two exceptions, the selection propensities and post-selection performance of various criteria are similar across different types of LPs. The first exception in the importance of prior investments by peer groups for university endowments. This group is almost twice as likely to follow their peer group compared to other types of LPs, suggesting the influence of the so-called Yale model pioneered by Swensen and Takahashi (Swensen (2000)). The second exception is the underperformance of repeat investments by public pension systems. When reinvesting with the same GP, the difference in excess IRRs between selected and non-selected funds for public pension systems is −5.92% (*t*-statistic = −2.84). Such stark performance differences are not present for other types of LPs. A likely explanation is that advanced by Andonov, Hochberg, and Rauh (2018), who show that political representation on investment committees in public pension plans deleteriously affects performance, either because of suboptimal decision making due to control or corruption issues.

Our tests use IRRs both as a selection criterion and as a performance measure. However, IRRs sometimes cause concerns because of their sensitivity to the timing of cash flows and because they are not returns. When we use multiples instead of IRRs, our conclusions with respect to both selection and post-selection performance remain unaltered. Another concern may be that variation in fees across LPs could influence performance measurement (Begenau and Siriwardane (2021)). There are two reasons why we believe that this does not bias our results. First, Preqin's data collection policies do not suggest a bias because they collect data from both GPs and LPs to generate one fund-level IRR (see Section 2 for details). Second, to the extent that fund-level IRRs are drawn from a mix of high- and low-fee LPs, we may both over- and under-estimate net-of-fee IRRs for LPs. The error associated with this mis-estimation is likely, therefore, diversified away.

Our analysis of the future performance of chosen funds relative to the opportunity set is related to a growing literature examining the performance of LP investments, primarily in buyout and venture capital funds (Andonov, Hochberg, and Rauh (2018), Cavagnaro, Sensoy, Wang, and Weisbach (2019), Lerner, Schoar, and Wongsunwai (2007), and Sensoy, Wang, and Weisbach (2014)). The main focus of these papers is on cross-sectional variation, viz., the performance of various types of LPs.[8] In contrast we focus on selection, and whether selection criteria result in outperformance relative to the opportunity set. Cavagnaro et al. and Barber, Morse, and Yasuda (2021) implicitly consider opportunity sets but their purpose is quite different. Cavagnaro et al. are interested in performance persistence and deploy an unconstrained bootstrap as a counterfactual. Barber, Morse, and Yasuda are concerned with willingness-to-pay for funds with non-pecuniary social or environmental intentions (impact funds). Our purpose is general: we wish to understand selection criteria and compare relative performance within a selection criteria.

Taking stock, we provide a novel set of results that suggest that there are attributes (for example, absence of performance history for first-time funds) and prior investment experiences that are important for selection. But these dispositions do not allow LPs to pick GPs with superior future performance. Since private equity allocations are part of a larger investment process for institutional investors, our results have implications for the wider literature. Broadly speaking, our results are in accordance with those in public equity and fixed income where outcomes associated with manager selection are closer to a random draw (Goyal, Wahal, and Yavuz (2021) and Jenkinson, Jones, and Martinez (2016)). The fact that LPs have limited selection ability is somewhat surprising because private equity is known for opacity and information asymmetry, an environment in which selection decisions should be more material. Of course, we do not mean to imply that the decisions of investment committees and consultants that oversee the selection process do not matter. Indeed, there is enough variation in LP performance relative to feasible choices that the selection process is likely material (see, for example, Binfarè, Brown, Harris, and Lundblad (2021)). Moreover, non-pecuniary benefits such as fraud avoidance, trust, preferences (Barber, Morse, and Yasuda (2021) and Hochberg and Rauh (2013)), or headline risk (Gennaioli, Shleifer, and Vishny (2015)) can also be germane to selection but are not observed.

The remainder of the paper is organized as follows. Section 2 describes the data sources and sample. Section 3 focusses on GP choice. Section 4 examines the performance of selected GPs

[8] A larger set of papers examines the performance of buyout and venture capital using individual funds as the unit of observation. A partial list includes Ang, Chen, Goetzmann, and Phalippou (2018), Harris, Jenkinson, Kaplan, and Stucke (2020), Kaplan and Schoar (2005), Phalippou (2020), Phalippou and Gottschalg (2008), and Robinson and Sensoy (2013). See Harris, Jenkinson, and Kaplan (2014) and Kaplan and Sensoy (2015) for surveys.

relative to the counterfactual, and relative to other choices. Section 5 discusses variation in selection and performance for different types of LPs and funds. Section 6 describes the sensitivity of the primary results to various specifications. Section 7 concludes.

2. Data Sources and Sample

2.1 Data Sources and Sample Construction

We use three customized data files provided by Preqin. The first contains capital commitments from LPs between 1990 and 2019. It includes the vintage year of the fund receiving the commitment, the domicile of the LP, an indicator variable that specifies if fundraising is completed or ongoing, the target and final fund size, and the percentage of the fund that has been called. The sample consists of commitments to different types of private equity funds, well beyond the traditionally studied buyout and venture capital funds. LP coverage is global, encompassing 8,801 LPs from 61 countries. The closest comparison is the database used by Ivashina and Lerner (2018) which includes similar allocations between 2008 and 2017. The second file contains IRRs and multiples of invested capital for all funds in the Preqin universe.[9] Importantly, it contains a time series of this information so that performance information is as would be visible to an LP at a point in time, rather than at the end of the life of a fund. The file also contains information on the geographic focus of each fund, sub-asset class (referred to as fund type), the GP name and location. The third file contains assets under management (in US dollars) for the LPs in our sample.

Brown, Harris, Jenkinson, Kaplan, and Robinson (2015) describe Preqin's data collection methods in considerable detail, so we do not duplicate them here (see also, Begenau, Robles-Garcia, Siriwardane, and Wang (2020)). However, we note two important features relevant to our analysis. First, the data are sourced from both LPs and GPs on a voluntary basis or based on FOIA filings. Some Sovereign Wealth Funds and other private institutions do not report to the database. Therefore, our aggregate statistics likely understate the magnitude of global capital commitments to private equity. Second, some data fields in the two files can sometimes be missing, most likely because the original information provider (LP or GP) did not provide it. For instance, out of the 100,000 capital commitments, the dollar value of the commitment is only available for 39,000 records. We retain records with missing information so as not to introduce unintended biases into

[9] Preqin informs us that if the underlying data for a fund is obtained from both GPs and LPs, then the performance is reported based on GP sourced data. If data are sourced from multiple LPs (but not GPs), then preference is given based on whether the LP is a first-close investor, the timeliness of the source, and the reliability of the source.

the analysis.

From the original Preqin commitment file, we eliminate some obvious data errors, and commitments to Fund of Funds, Co-investment funds, Separate Accounts, Secondaries, and Miscellaneous funds. The fund raising and investment cycle of these three fund types is quite different from other private equity funds, and the destination of the capital can be difficult to verify. We also exclude LPs classified by Preqin as private equity firms, fund of fund managers, infrastructure firms, hybrid firms, and hedge funds.

The capital commitment file is linked to the time series of performance via unique IDs. The net IRR for each fund-quarter is calculated by Preqin as the money-weighted return using the present value of contributed and distributed cash, and the fair market value of unrealized investments. The database also includes two types of multiples: TVPI (computed as total value returned scaled by invested capital), and MOIC (computed as distributed plus residual value scaled by capital calls and fees).

2.2 Sample Description

For reporting purposes, we consolidate each LP's country of domicile into three major regions, North America (US and Canada), Europe (including UK), or rest of the world (ROW). The breadth of investors in the database is demonstrative of the ubiquity and expansion of private equity around the world. For example, the range of LPs varies from behemoth Sovereign Wealth Funds and US-based public pension systems, to UK boroughs and pension funds of small Swiss Cantons. The database contains 8,801 such unique LPs which Preqin classifies into 40 different types, many of which are sparsely populated. We consolidate these into 11 groups that represent economically meaningful differences in structure, purpose, and governance. In doing so, we correct some obvious classification errors in the underlying data. We use these groups in our empirical tests (for example, in constructing peer groups) but for data description purposes, we consolidate further into the following 8 groups: corporate plans, foundations (not including universities), public pension systems, sovereign wealth funds, unions, universities, and a miscellaneous group.[10]

[10] The 11 groups distinguish between public versus private universities, public versus private foundations, and local versus state-level pension systems. Many studies and practitioners aggregate university endowments, private foundations, and public foundations into one endowments-and-foundations category. We intentionally separate out universities motivated by Brown, Dimmock, Kang, and Weisbenner (2014) who discuss the ramifications of illiquid

Table 1 shows the distribution of capital commitments by LP region and type. The first two blocks of data show aggregate dollar value committed by each group and the number of commitments respectively. Since the dollar value of commitments is only available for a subsample of allocations, the aggregate values understate the true magnitude of the private equity in institutional portfolios. The third block shows the median size of commitments (in $ millions). The total value of the 39,000 commitments for which we observe dollar values is $1.9 trillion. If we multiply the remaining 61,000 commitments by the median commitment size ($22 million), the imputed total value of allocations is $3.2 trillion. The last block of data shows the commitment size as a fraction of the fund size.

North American LPs are by far the largest funding source both by dollar amount (about $1.5 trillion out of the observable commitments of $1.9 trillion) and by number (approximately 73,000 out of 100,000 commitments). Despite that, a non-negligible number of capital commitments (over 25,000) originate from non-North American LPs. The median commitment size is also largest for North American LPs. The North American public pension systems account for 66% of aggregate capital flow. Collectively, university systems contribute about $57 billion in capital in 7,475 capital commitments. Across all LPs, the median capital commitment (of $22 million) represents about 3.3 percent of fund size.

Table 2 shows the destination of this capital across different types of private equity funds. Approximately $1.2 trillion out of the $1.9 trillion in capital commitments are routed to funds focused on North American markets. The two most well-studied types of funds, North American buyout and venture capital funds, account for $521 billion and $100 billion respectively. Allocations to North American real estate funds are also quite large ($292 billion). The other categories including direct lending, distressed equity/debt, growth funds, infrastructure, mezzanine, and natural resources together account for $587 billion in global commitments. For readers interested in source-to-destination flow of funds, we provide statistics in Appendix Table A1.

There are several useful points of comparison of our sample relative to the existing literature. Lerner, Schoar, and Wongsunwai (2007) study allocations from 320 institutional investors to buyout and venture capital funds over the 1991-1998 period. Sensoy, Wang, and

investments and financial market shocks for payout policy (see also Barber and Wang (2013). The performance of this group is also of obvious self-interest to us.

Weisbach (2014) examine 14,380 allocations by 1,852 LPs over the 1991-2006 period, sourced from VentureXpert and Capital IQ. Cavagnaro et al. (2019) use combined data from VentureXpert, Capital IQ and Preqin to study 30,915 capital commitments made by 2,314 LPs over the 1991-2011 period. All of the above studies focus solely on buyout and venture capital. Andonov, Kräussl, and Rauh (2021) study allocations to infrastructure funds, examining 3,741 commitments from 1,664 LPs to 243 GPs. In terms of coverage, the closest sample to ours is that of Ivashina and Lerner (2018), who use Preqin-compiled data on allocations from 1,960 pension funds to alternative assets over the 2008-2017 period.

3. Picking GPs

3.1 Opportunity Set

For each capital commitment, we construct a set of plausible investment choices from funds of the same type, with the same geographic focus, and within one year of the vintage year of the fund receiving the capital.[11] Given the substantial variation in fund sizes, we also require that funds in this opportunity set be within ±50 percent of the fund receiving the capital commitment. This accounts for the possibility that funds of different sizes could be preferred by or available to different LPs. In Section 3.2.3. we do robustness tests for the construction of the opportunity set. Although the counterfactual is a particular fund that could receive the capital commitment, many of the observable characteristics are associated with the GP sponsoring the fund. Therefore, the vernacular we use to describe choice is "GP selection" rather than "fund selection."

The first two columns of Table 3 report the number of capital commitments in our sample, and the average number of GPs sponsoring funds in the opportunity set. In the North America region, the opportunity set for buyouts and venture capital is sizeable, 45 and 75 GPs respectively. The opportunity set for real estate is also quite large, at 75 firms. Beyond those three groups, the average number of GPs in the opportunity set ranges from a minimum of 9 (Infrastructure) to 25 (Direct Lending). Unsurprisingly, the opportunity sets in Europe and ROW are smaller, but the pattern across types of funds is largely similar.

[11] For purpose of constructing the opportunity set, we do not use the broad regions shown in Table 2. Instead, we match funds investing in the US, Canada, China, Japan, UK, India, Europe and ROW to those within the same geographic focus. This narrower geographic matching ensures more precision in the opportunity set and allows for better counterfactual comparisons.

At the time of the selection, funds that receive (or could receive) capital commitments are in the fund-raising stage and do not have observable performance. We therefore examine the performance of prior funds sponsored by the same GP. To measure excess performance, we use a three-step procedure. First, we use the time series of fund-level IRRs for each GP reported by Preqin, reported more than five years after the vintage year of the fund. Second, we calculate a benchmark IRR as the median IRR of all funds of the same type, vintage year, and geographic focus. The fund-level excess IRR is then computed as the difference between the fund IRR and the median IRR of the benchmark. Third, we roll-up these fund-level excess IRRs to the GP-level by computing the fund-size weighted excess IRRs of all funds raised by the GP prior to that year. An example is helpful to understand the latter part of the calculation. Consider an LP contemplating a capital commitment to a GP in 2008. At that time, the GP has raised three funds I, II, and III with vintage years 1998, 2000 and 2004. Performance for each fund is available after 2003, 2005 and 2009 respectively. At the time of the capital commitment, the weighted average performance of GP is based on funds I and II.[12]

There are several important features to this process. It ensures that only post-distribution IRRs are used. This avoids strategic issues related to interim IRRs, particularly for young GPs, discussed by Barber and Yasuda (2017) and Chung, Sensoy, Stern, and Weisbach (2012). Unlike Preqin-constructed benchmarks which can often contain very few funds, our custom benchmarks are well-diversified from a controlled comparison set. Most importantly, all excess IRRs are calculable using information available at the time of the capital commitment.

The last two columns in Table 3 show the number of GPs with valid IRRs in the group of selected funds, and the equivalent average number of funds in the opportunity set. For selected funds, the number of GPs with valid excess IRRs is substantially smaller than the number of commitments. For instance, there are 20,373 capital commitments to North American buyout funds but excess IRRs at the time of the selection decision can only be computed for 10,353 of them. A similar pattern is present in the opportunity set, and across other regions. Missing IRRs trace to three sources: (a) the GP is raising capital for the first time, (b) the GP is raising capital in a second or a third fund, but fewer than five years have passed after the first fund, (c) Preqin is unable to calculate IRRs because of lack of cash flow data. Approximately 50 percent of missing IRRs are

[12] The vast majority of GPs stick to their knitting in the sense that they do not sponsor funds of different types. As a result, our GP-level IRR calculation is not contaminated by different fund types.

due to (a) and another 30 percent are traceable to (b). In subsequent tables and text, we use the subscript "First" and "Young" to describe these groups. For (c), we use "Missing" as the subscript.

Table 4 reports averages for three key variables used in subsequent tests. PriorInv is an indicator variable equal to one if an LP has invested in a prior fund sponsored by the GP (and zero otherwise). Similarly, PeerInv is an indicator variable equal to one if an LP's peers have invested with the GP in the past. To calculate this, we define peer groups using a combination of LP domicile and type that cluster similar institutions. For example, US domiciled public university endowments comprise a separate peer group than US domiciled private universities. Details of the classification system are in the Appendix. Local is an indicator variable designed to measure home bias in selection decisions. Following Hochberg and Rauh (2013), for US domiciled LPs, the variable equal to one if the LP and GP-headquarters are in the same state. For non-US LPs, Local is equal to one if the LP and GP are headquartered in the same country.

Three aspects of the data are apparent in Table 4. First, there is a large difference between repeat LP investment among selected funds relative to the opportunity set. Again, using North American buyouts as an illustrative example, 41.8% of funds selected by LPs belong to GPs that have received capital from the same LP in the past. In comparison, the equivalent statistic in the opportunity set is only 6.2%. Second, the percentage of funds selected by LPs that have also been selected by peer institutions in the past is substantially larger than in the opportunity set. In North American buyouts, 70.4% of GPs selected by LPs have also been selected by peer institutions in the past, compared to 49.5% in the opportunity set. Third, irrespective of the type of fund or its geographic focus, the preference for local GPs in selected funds is considerably larger than in the opportunity set. Continuing with the North American buyout example, 13.4% of selected funds are local, compared to 8.2% in the opportunity set.

3.2 Choice Regressions

3.2.1 Methodology

We formally model choice using regressions in which the dependent variable is equal to one (zero) if LP l commits (does not commit) capital to fund f of GP g. Specifications take the following form:

$$\begin{aligned} Commit_{lfg} = \beta_0 + \Sigma_{i=1}^{4}\beta_{1i} IRR_{i,g} + \Sigma_{j=2}^{4}\beta_{2j} IRR_{Qj,g} + \beta_3 \ln GPSize_g \\ + \beta_4 PriorInv_{lg} + \beta_5 PeerInv_{lg} + \beta_6 Local_{lg} + FE + e_{lfg}. \end{aligned} \tag{1}$$

The first two independent variables are related to GP performance. Private equity flows react to prior GP performance, although the relationship between the two is concave (Kaplan and Schoar (2005) and Chung et al. (2012)). Given this non-linearity, we use a piece-wise linear specification where we assign GP excess performance into four quartiles (subscripted j), creating four dummy variables, labelled IRR_{Low}, IRR_{Q2}, IRR_{Q3}, and IRR_{High}. If GP performance is not available, we create a dummy variable labeled IRR_{NA} (subscripted i and subsequently separated into multiple categories). In several specifications, IRR_{Low} is the omitted category in the regressions implying that the coefficients are relative to this quartile. The regression includes independent variables related to prior investment in a GP (PriorInv and PeerInv as defined earlier) and to home bias (Local). We also include the natural logarithm of GP size as a control variable.

With the large number of LPs and GPs, fund types, and geographic foci, there is likely considerable heterogeneity that we cannot observe and that maybe relevant for choice. We account for such unobserved heterogeneity using fixed effects that control for combinations of fund type, geographic focus (the same as that used for the construction of the opportunity set), and vintage year. This combination of fixed effects recognizes distinctions so that, for example, a commitment to a North American buyout fund from 2005 is treated as a separate group than a commitment to a European venture capital fund in 2010. In some specification, we control for individual LP fixed effects, thereby subsuming individual LP preferences in selection. We double cluster standard errors using the same combination as that for fixed effects.

The traditional approach to estimating selection equations is via logit regressions. Angrist and Pischke (2009) argue for the use OLS over nonlinear models especially when the focus is on the marginal effects rather than the latent index variables (see Bertrand, Djankov, Hanna, and Mullainathan (2007) on the use of OLS over logit). The advantage of OLS is that the coefficients are interpretable as marginal effects. We report OLS regressions throughout the paper but note that logit regressions have very little impact on inferences. Finally, since the fund raising process takes between ten and 18 months (Marquez, Nanda, and Yavuz (2015)), we lag all independent variables by two years to ensure that all information is available to LPs at the time of the commitment decision.

3.2.2 Results

Table 5 contains a variety of regressions that hone in on the effects of selection criteria.

Column (1) shows a sparse specification that focusses on the observability of GP performance. The coefficient on IRR_{NA} shows that there is a 0.3% higher probability that GPs without a track record are selected relative to those whose performance is observable. Since the unconditional probability of section is 2.6% (100,506/3,854,659), this represents a 12 percent increase in the probability of selection. Specification (2) augments the regression with indicator variables for performance quartiles two through four (quartile one is the omitted category). Relative to 1st quartile GPs, GPs in the 3rd and 4th quartile are 0.8% and 1.1% more likely to receive a capital commitment. Again, comparing to the unconditional probability, these coefficients imply a 31 to 42 percent increase in selection probabilities. In column (3) we estimate the same specification but add LP-specific fixed effects to control for unobserved heterogeneity across LPs. The coefficient on IRR_{NA} is quite similar.

A. First-time Funds

As noted earlier, IRRs could be missing because this is the first fund raised by the GP, because not enough time has elapsed from prior funds for IRRs to be calculable, or simply because Preqin does not have adequate cash flow data to calculate IRRs. We separate these by defining three new dummy variables: IRR_{First} is equal to one if the GP has no prior funds, IRR_{Young} is equal to one if the IRR is missing and none of the prior funds are more than five years old, and $IRR_{Missing}$ is equal to one if the past IRR is missing but the GP has funds that are more than five years old. In specification (4), the coefficient on IRR_{First} indicates that the probability of a capital commitment to a GP raising a first-time fund is 1.6% higher than that for 1st quartile GPs. Notably, this probability is also higher than that for 4th quartile GPs (1.1%). Similarly, the probability that a young GP receives a capital commitment is about 0.9% higher than that for 1st quartile GPs.

Together, these results suggest a meaningful proclivity among LPs to hire first-time and young GPs. The tendency to invest in GPs without prior performance is somewhat surprising given that three-to five-year track records are standard screening devices in public equity and fixed income. (We consider various plausible explanations of this result in Section 3.2.3 below.) To shed further light on these first-time and young GPs, we do two things. First, we hand collect information on the founding partners of each first-time GP. Our purpose in this is to determine whether these firms are true rookies or whether they are founded by veterans of well-established private equity firms. To do so, we go to the website of each GP and read the background profile of each founder. If the founder has worked at or previously founded another private equity firm in the past, then the first-time GP is labelled "veteran." For some GPs (especially ones that no longer exist), we examine alternative sources such as Crunchbase, Tracxn, Bloomberg, and Pitchbook.[13] With these data are in place, we include indicator variables corresponding to these two groups (labelled $IRR_{First,Rookie}$ and $IRR_{First,Veteran}$) in the regressions. Column 5 shows that selection probabilities for both groups are quite similar, 1.6% and 1.7% respectively. Second, as a descriptive exercise, we investigate who invests in first-time funds and where these funds invest their assets. There are 19,321 such capital commitments in our sample amounting to at least $286 billion in allocations. Over half (10,900) originate from North American LPs with the majority of capital ($105 billion) coming from public pension systems.

B. Prior Investment or Local Experience

There are strong a priori reasons for peer influence in LP decision-making. LPs participate in a variety of industry conferences, often marketed as networking events to meet fellow investors as well as GPs. Such events permit soft information sharing. As Banerjee (1992) and Bikchandani, Hirshleifer, and Welch (1992) emphasize, there is no guarantee that such peer following is efficient because there can be information cascades in which valuable own information is ignored. Beyond this, Bursztyn et al. (2014) suggest that following peers might simply generate social utility, similar in spirit to a keeping up with the Joneses reference dependent utility. It is also possible that following peers serves as protection from headline risk associated with (ex post) ruinous tail outcomes or through a certification effect. The fact that LP performance evaluation is often conducted within peer groups suggest that such an approach is at least plausible.[14] Each of these rationales suggest that the coefficient on PeerInv should be positive, which is the case in all specifications in Table 5. In column (5), which includes LP fixed effects, the point estimate indicates that relative to 1st quartile GPs, LPs are 0.7% more likely to invest in funds managed by GPs that have received capital from peers in the past. Again, comparing this to the unconditional probability of 2.6%, this is a 27 percent increase.

[13] As an example, consider the case of .406 Ventures, founded by Mr. Liam Donohue in 2005. Mr. Donohue was previously a principal at Foster Management, and then co-founded Arcadia Partners. We therefore classify .406 Ventures as founded by industry veterans.

[14] For example, the National Association of College and University Business Officers (NACUBO) annually publishes allocations to private equity and other asset classes, as well as performance information that allows educational institutions to conduct benchmarking.

Lerner, Schoar, and Wongsunwai (2007) report that 51% out of 2,716 LP investments in their sample are with the same GP. These outcomes do not necessarily allow one to infer the role of prior investment decisions on selection probabilities – that is possible only with a feasible opportunity set. To do so, we include PriorInv in the regressions. Across all specifications, the coefficient on this variable is large and statistically significant. In column (5), which includes LP fixed effects, the coefficient implies a 16.5% probability of a repeat investment, which is 634 percent increase over the unconditional probability. An LP's prior experience with a GP is, quite simply, the single most influential determinant of choice.

Hochberg and Rauh (2013) find that US LPs substantially overweight GPs located in their own state. This could be because they have improved access to information, are engaging in self-dealing, or are responding to initiatives that target employment and other benefits to the local economy. Our regressions isolate the effect of this overweighting on selection probabilities. Across all specification, the coefficient on Local is positive with large *t*-statistics. In column (5), the coefficient implies that a 3.4% probability of a commitment to a local GP, an increase of 116 percent over the unconditional probability.

It is interesting to consider the degree to which various selection criterion amplify or attenuate selection probabilities. For example, consider an LP contemplating an allocation to a young GP with whom she has previously invested. Is this LP more likely to reinvest with this GP or allocate to a 4th quartile GP with whom she has no prior experience? We address such joint effects by adding interaction terms between variables of interest. For readers interested in the nuances of such combined selection signals, the detailed results are available in the internet appendix. The gist of those results is that in many cases, combining selection signals is associated with a modest amplification of selection probabilities.

3.2.3 Discussion and Alternative Explanations

Four basic results emerge from the above regressions. First, the lack of a track record does not appear to be a deterrent to capital commitments. Second, there is evidence of performance chasing, in that 4th quartile GPs are more likely to be selected. Third, prior investment by a peer institution, or by the LP itself, seems to matter for GP choice. Fourth, LPs display some degree of home bias as they are more likely to select local GPs. In this section, we discuss various explanations of these results.

A. Reputation Effects

Chasing winners, selecting managers with whom an LP has (or its peers have) prior experience, or even selecting local GPs, is consistent with the idea that these selection criteria are used to glean information pertinent for future performance. But there are other plausible explanations. One possibility is that prior investment reflects accumulated reputation effects. If some GPs are more reputable by virtue of their prestige, brand, etc., and more likely to be hired by LPs, then they will have longer histories and as a result, more LPs have investments with them. In this scenario, reputation affects both the selection decision and the LPs prior experience with the GP, independent of information. To assess this possibility, we control for GP-year fixed effects. This allows us to compare the selection decisions of two LPs with the same GP: one with prior experience with the GP and one without. These fixed effects also control for unobserved time-varying heterogeneity across GPs. Specification (6) of Table 5 shows that even with GP-year fixed effects, PriorInv and PeerInv remain important to the GP selection decision. In the case of repeat investments, the incremental probability is 14.0% and for peer investment, the probability is unchanged at 0.7%.

Another possibility is that reputation influences selection indirectly through its effect on fund size and the opportunity set. Recall that we use fund size to determine the opportunity set, and larger funds have smaller opportunity sets. If more reputable GPs raise larger funds, this generates a higher unconditional probability of selection. Coupled with the fact that more reputable GPs are likely to have longer histories, this also implies that they accumulate more past hiring relationship with LPs, generating a correlation between past investment decisions and the probability of selection. In specification (7) we include fixed effects for each commitment (labelled Commitment ID in the table) to absorb differences between the unconditional probability of selection across commitments. These rather stringent fixed effects also account for any other unobserved heterogeneity across capital commitments. The inclusion of so many fixed effects still has little impact on the coefficients of interest: the coefficients on IRR_{High}, PeerInv, PriorInv, and Local remain quite similar at 0.8%, 0.9%, 17.0%, and 3.8% respectively.

B. Access

Why are LPs willing to allocate capital to GPs without an observable track record? It is widely believed, particularly among practitioners, that access is an important component to private equity selection decisions. Consistent with that, Kaplan and Schoar (2005) and Lerner, Schoar, and Wang (2008) suggest that preferential access to high performing GPs partly accounts for the successful performance of endowments. Sensoy, Wang, and Weisbach (2014), however, show that endowments do not have preferential access over 1999 to 2006 period. Given this, it is possible that differential access accounts for the selection of first-time and young GPs as well as the importance of PriorInv, PeerInv, and perhaps even the predilection to select local GPs.

To understand the role of limited access we perform two tests. First, we restrict the sample to undersubscribed funds where limited access is less likely to drive selection and re-estimate our main regression. This sample includes only undersubscribed funds; we drop observations with missing fund target size. The results are reported in Table 6 under the column labelled "Undersubscribed." The coefficients in this regression are larger because the opportunity sets are smaller. However, coefficients of $IRR_{First,Rookie}$, $IRR_{First,Veteran}$, and IRR_{Young} relative to the unconditional probability remain statistically significant and similar in magnitude. The coefficients on PriorInv, PeerInv, and Local also remain largely similar relative to the unconditional probability.

Second, we estimate regressions for LPs of different sizes under the presumption that access is more likely to be binding for smaller LPs; large LPs should be relatively unconstrained in their choice of funds. We sort LPs into quartiles based on their total assets and estimate separate regressions for each group. The results are reported in columns three through six in Table 6. Even for the very largest LPs in our sample, the coefficients on $IRR_{First,Rookie}$, $IRR_{First,Veteran}$, and IRR_{Young}, and the unconditional probability of selection are similar across the size quartiles. In fact, the point estimates of each of these variables are bigger for large LPs than for small LPs. Interestingly, the coefficients on PriorInv, PeerInv, and Local decrease across LP size quartiles, implying that each of these variables has a smaller impact on selection probabilities for larger LPs. Nonetheless, even in the very largest LPs, the magnitude of the impact on selection probabilities remains economically important. For example, the coefficient on PriorInv still indicates a 12.1% probability of a repeat investment, not far off from the 16.5% probability in column (5) of Table 5. These two tests suggest that access (or lack thereof) is unlikely to explain selection proclivities that we document. It is possible, of course, that GP access still matters for other kinds of LP investments (see, for example, Lerner, Mao, Schoar, and Zhang (2020) for the role of access to alternative vehicles in PE).

Andonov, Kräussl, and Rauh (2021) report that pension funds are more willing to allocate to capital to inexperienced infrastructures funds. Given that evidence, it is possible that first-time GPs are concentrated in sub-asset classes that are less mainstream and where, at the margin, other issues play a role. For instance, it could be that allocations to infrastructure, to real estate, or to natural resources are motivated by non-pecuniary preferences. Figure 1 shows the number of first-time funds of each type over time. The data show that throughout the time series, the fraction of first-time funds originating from these esoteric sub-asset classes is not large. Indeed, buyouts and venture capital still account for a large proportion of first-time funds. We also show in Section 6 that preference for first time funds is similar across fund types.

A simpler explanation for the propensity to invest in first-time funds resides in the evolution of the demand for and supply of private equity funds. Over our sample period, portfolio weights of institutional investors to private equity increase steadily. Ivashina and Lerner (2018) report an increase in allocations to alternatives (which are comparable to the fund types in our sample) from 4% in 2006 to over 15% in 2015. Industry reports and surveys show similar increases in allocations to private equity. In a competitive market with free entry, this rise in demand should entice new entrants and permit incumbent GPs to raise larger funds to satisfy demand.[15] Panel A of Figure 2 shows that the number of new entrants rises over the time series, with the well-known market cycles and peaks associated with 2000 and 2007. Panel B shows an increase in average fund sizes over the same period, again with noticeable increases prior to the financial crisis of 2008. The aggregate data, therefore, appear to be consistent with a simple demand-supply story.

This demand-based explanation suggests that LPs with high growth rates of capital allocated to private equity may be more likely to invest in first-time funds. To test this conjecture, we first compute the annual growth rate of capital commitments for LPs and generate a dummy variable equal to one for LPs in the highest growth rate quartile. We then interact this variable with the first-time fund indicator variables in our selection equations. The sample is limited to only LPs for which we have capital commitments available. In unreported results, even in this limited sample, we find that the coefficients on other variables remain the same as in column (7) of Table 5. More importantly, for these high growth rate LPs, the coefficients on the interactions imply an

[15] One could ask why incumbents do not simply raise still larger funds to thwart entrants. See Hochberg, Ljungqvist, and Vissing-Jørgensen (2014), and Marquez, Nanda, and Yavuz (2015) for possible explanations.

increase in selection probability of 0.19% and 0.27% for first-time rookie and first-time veteran funds respectively. These results are, therefore, consistent with our conjecture that increased demand for private equity allocations is met by first-time funds.

C. Alternative Opportunity Sets

Our selection regressions are centered on an opportunity set that is contemporaneously investable and addresses the question: "what could the LP have reasonably chosen?" In doing so, we impose two restrictions that could potentially influence selection probabilities. The first is that funds in the opportunity set be within 50 percent of the size of the selected fund. Since fundraising in private equity is sequential and may be predicated on the performance of a prior fund, a size restriction could influence selection effects. To investigate this issue, we estimate selection equations where we vary the size tolerance using a 30 percent and 70 percent band. We also remove the restriction entirely. Table 7 shows that, as expected, relaxing or tightening the size restriction decreases or increases the unconditional probability of selection (4.6% for a 30 percent restriction and 1.6% for a 70% restriction, compared to 2.6% in Table 5). More importantly, the increase in selection probabilities for the variables of interest (relative to their unconditional probabilities) are quite similar. If we impose no size restriction, extremely small funds enter the opportunity set. But even here (when the unconditional probability drops to 0.6%), the propensity to invest in first-time funds, 4th quartile GPs, local GPs, and those in which the LP or its peers have invested in the past, remain quite high.

The second restriction of interest is one that recognizes the importance of private equity programs by LPs (often termed "private equity initiatives"). In such programs, an LP allocates a certain amount of capital to private equity and conducts multiple searches. In our baseline econometric setting, each mandate decision is considered independent. Therefore, the opportunity set can appear multiple times for each fund selected in the same program. And a fund selected for an allocation in a program could appear in the choice set for another selection decision in the same program. To determine whether this affects inferences, we use a single opportunity set when an LP allocates capital to multiple GPs in the same region, fund type and vintage year (with no restriction on fund size).[16] The results are reported in the last column of Table 7. The increase in

[16] An example is helpful to explain the structure of such programs and relevance for selection equations. In 2002, the State of Wisconsin Investment Board (SWIB), approved a private equity program to invest $100 million in venture capital funds (https://www.swib.state.wi.us/wisconsin-venture-capital). From that program, SWIB made 3 allocations.

selection probabilities (relative to the new unconditional probability of 1%) for first-time rookie GPs, first-time veteran GPs and 4th quartile GPs are 70, 70 and 40 percent respectively. And the equivalent increases for PriorInv, PeerInv, and Local remain comparable to those in Table 5.

Overall, our results do not seem to be driven by alternative size restrictions on the opportunity set or whether LPs allocate multiple mandates individually or jointly to multiple GPs in the same region, fund type and vintage year.

4. Post-selection Performance

Our tests thus far suggest that explanations related to access, GP size, and reputation are unlikely drivers of selection propensities. What then explains the attention to local GPs, prior hiring decisions, or for that matter, peer hiring decisions? One plausible channel is soft information transmission between LPs and GPs. To explore this and shed light on the economics and rationale of selection mechanisms, we turn to post-selection performance. We note that post-selection performance is also of independent interest from the perspective of an institution attempting to maximize returns subject to constraints, particularly given large portfolio weights to private equity in aggregate asset allocations.

4.1. Methodological Approach

We analyze fund level excess IRRs at the end of 2018 (or at end of life if the fund is liquidated prior to 2018), comparing selected funds to non-selected funds from opportunity set. We require that more than five years elapse from the vintage year to ensure adequate distribution of cash flows so that IRRs are correctly measured. This restriction causes us to lose observations from the latter part of the time series.

We adopt a panel regression approach in which the dependent variable is a fund-level excess IRR as defined in Section 3.1. We maintain a specification identical to the selection equations (i.e., the exact same explanatory variables), which allows us to draw conclusions specific to each selection criterion. Inferences regarding post-selection performance are drawn from the hired indicator variable, which is equal to one for selected funds and zero for not-selected funds, as well as interaction effects. The regression for future excess IRR of fund f after LP l commits

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In our original formulation, each allocation would have its own opportunity set. In this estimation, there is one opportunity set for all three allocations.

(or not) capital to fund f of GP g is:

$$FutureExcessIRR_{lfg} = \beta_0 + \Sigma_{i=1}^{4}\beta_{1i}IRR_{i,g} + \Sigma_{j=2}^{4}\beta_{2j}IRR_{Qj,g} + \beta_3 \ln GPSize_g$$
$$+\beta_4 PriorInv_{lg} + \beta_5 PeerInv_{lg} + \beta_6 Local_{lg} + \beta_7 Hired_{lfg} + [\Sigma_{i=1}^{4}\beta_{8i}IRR_{i,g} + \Sigma_{j=2}^{4}\beta_{9j}IRR_{Qj,g}$$
$$+\beta_{10} \ln GPSize_g + \beta_{11} PriorInv_{lg} + \beta_{12} PeerInv_{lg} + \beta_{13} Local_{lg}] \times Hired_{lfg} + FE + e_{lfg}, \quad (2)$$

We use two sets of fixed effects that account for unobserved heterogeneity (FundRegion×FundType×VintageYear and LP) and cluster standard error using the same groupings.

Before proceeding to the results, it is useful to compare our methodological approach to that of Barber, Morse, and Yasuda (2021) and Cavagnaro et al. (2019). Cavagnaro et al. use a bootstrap in which they ask whether the IRR of LP l making a capital commitment to a fund type x (venture or buyout) in year t is above or below the median. Our regression approach differs from their approach in several ways.[17] First, their benchmark is broad in that it includes all funds of a particular type and vintage year. Our requirement, that fund size be comparable, narrows the opportunity set considerably. Second, our regression approach intentionally conditions on an information set observable at the time of the investment decision. That is, we draw inferences by tightening parameters of the counterfactual based on selection criteria from Table 5. Third, our approach is predicated on the previously estimated selection equations to evaluate the efficacy of the predictor variables; these predictor variables are of direct economic interest. Barber, Morse, and Yasuda's approach is closer to ours in the sense that they use a discrete choice model (which includes an opportunity set) to investigate the willingness-to-pay for impact funds. However, their focus is entirely different in that they model and predict expected returns as a way to understand investment in impact funds, whereas we estimate whether selection criteria provide information that is material for realized returns.

4.2. Returns to Selection Criteria

Since our primary interest is in evaluating outcomes associated with the selection criteria studied in Section 3, we relegate coefficient estimates from regression (2) to Appendix Table A2.[18]

[17] Cavagnaro et al. (2019) find evidence of LP skill in that the ex-post IRRs are higher than could be realized by chance alone. In unreported equivalent regressions where we run specification (2) with just the Hired variable, the coefficient on Hired is 0.44% with a *t*-statistic of 2.13, consistent with the results of Cavagnaro et al.

[18] Of some interest, however, is the coefficient on the Hired indicator variable which contains the average difference in excess IRRs between selected and non-selected funds. That coefficient is −0.13 with a *t*-statistic of −0.06, indicating

Instead, we combine coefficients from the regressions in two ways. First, we examine the difference in excess IRRs within each selection criterion, asking whether selected funds differ from non-selected funds. If the selection criteria provide information material for future returns then LPs should be able to select funds with higher IRRs using the same criteria. We refer to these as within-category differences and report them in Panel A of Table 8. Second, in Panel B of Table 8, we compare excess IRRs of selected funds using one selection criterion to non-selected from another criterion, referred to as across-category comparisons.

The omitted category in the regressions is non-selected 1st quartile GPs, who have an average excess IRR of 0.0006%. Aggregated coefficients in subsequent tables are relative to this group, which is functionally equivalent to comparing them to zero. To illustrate the process of combining coefficients, suppose we are interested in the future excess IRR of selected first-time rookie GPs. That is calculated by adding the coefficients of Hired (−0.13), $IRR_{First,Rookie}$ (−1.03), and the interaction term between the two (−2.93) (the sum is −4.09%). An equivalent combination of coefficients for non-selected first-time rookie GPs is −1.03%, which implies a within-category difference of −3.06%.

In Panel A of Table 8, with one exception, the average excess IRR of selected funds within each criterion is indistinguishable from zero. For example, selected 4th quartile GPs (labelled IRR_{High}) have an excess IRR of 1.09% with a *t*-statistic of 0.59. And selection decisions that are a repeat investment with a GP have an excess IRR of 0.28% with a *t*-statistic of 0.14. The sole exception is selection of first-time rookie GPs which have a large negative excess IRR (−4.09%) with a *t*-statistic of −2.37.

Comparing selected funds to non-selected funds in the same criterion exploits the opportunity set. The differences in excess IRRs are negative for every selection criterion but with varying magnitude and statistical significance. For funds sponsored by first-time rookie and first-time veteran GPs, the differences in excess IRRs between selected and non-selected funds are −3.06% (*t*-statistic = −2.09) and −2.33% (*t*-statistic = −1.70) respectively. For other selection criteria, the point estimates of differences in excess IRRs are negative but with large standard errors. In funds sponsored by 4th quartile GPs, GPs who have previously received an investment, and GPs who have received mandates from peers, and local GPs, the excess IRRs of the non-

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that the excess IRRs of selected funds are no different than those of the opportunity set. Given our large sample, this is not surprising.

selected group are positive (2.20%, 1.11%, 0.81%, and 0.16% respectively). That causes the difference in excess IRRs of each of these groups to be negative, −1.10%, −0.83%, −0.32%, and −0.49% respectively.

In Panel B, we compare excess IRRs of selected funds using one selection criterion to non-selected from another criterion, referred to as across-category comparisons. We use funds sponsored by 4th quartile GPs as the default in such comparisons because quartile breakpoints are widely used in institutional investment management. Such comparisons effectively ask whether an LP selecting a fund using criterion x (for example, reinvesting in a GP's subsequent fund) would have been better off by simply choosing a non-selected fund sponsored by a 4th quartile GP. Once again, each of these across-category comparisons generate negative differences in excess IRRs. The differences are particularly large for first-time rookie, first-time veteran, and young GPs, at −6.29%, −2.87%, and −4.68% respectively.

As with the selection equations, it is possible to ask whether combining selection criteria improves outcomes relative to the opportunity set. To do so, we estimate future excess IRRs regression which contain triple interactions between the hired indicator variable, and combinations of other explanatory variables. As before, drawing inferences requires combining a variety of coefficients. Rather than overwhelm the reader with excessive combinations, we relegate them to the internet appendix but note there is no evidence that combinations of selection criteria generate positive differences in excess IRRs; all excess IRR differences are either negative or statistically indistinguishable from zero.

Overall, regardless of whether we consider selection skill as the ability to select better (future) performing funds within a selection criterion or by employing multiple selection criteria, the answer seems to be the same: there is no clear-cut evidence that LPs can pick private equity funds that deliver future excess IRRs relative to the opportunity set. These results contrast with those in Chung et al. (2012) which are organized around a rational learning model in which information plays a vital role and investors do not engage in return chasing or "dumb money" behavior. It also contrasts with a large literature in which information acquisition is key ingredient to capital allocation in private equity. Rather, our results suggest that information acquired through the channels that are influential in selection do not help LPs in selecting funds with higher future excess IRRs.

4.3. Unsuccessful Fundraising

If a fund has extremely poor performance, its GP may not be able to raise capital for subsequent funds (see, for example, Barber and Yasuda (2017), Chung et al. (2012), and Hochberg, Ljungvist, and Vissing-Jørgensen (2012)). If this is the case, a follow-on fund never appears in our (or any) database. Our selection equations in Tables 5, 6, and 7 ask which criteria are influential in the selection process amongst contemporaneously available funds. Our post-selection tests also ask about performance differentials between funds that were chosen and those that could have been chosen from the same available opportunity set. Therefore, the absence of some follow-on funds does not affect inferences with respect to selection criteria that we study.

Nevertheless, to the extent that unsuccessful follow-on funds reflect willful collective choices by LPs, it is possible that unsuccessful fundraising could affect broader inferences regarding LPs' selection ability. We perform a simple test to assess the importance of this issue. For funds within each type, region, and vintage year, we create two groups: those for which GPs were able raise a follow-on fund and those for which they were not. For the two groups of funds, Panel A of Appendix Table 3 contains end-of-life IRRs measured at the end of the sample period, and interim IRRs measured at the actual time of fund raising for successful GPs and estimated time of fund raising for the failed GPs.[19] In general, and as expected, the end-of-life IRRs of funds that subsequently raise follow-on funds are higher than those for funds that do not raise follow-on funds. But so also are interim IRRs. Panel B contains estimates from a quantile regression of end-of-life IRRs on interim IRRs and an indicator variable that is equal to one if the fund subsequently raises a follow-on fund. The follow-on indicator variable is not statistically significant: LPs collective decision to not provide capital to follow-on funds sponsored by GPs with observable poor interim performance does not imply selection ability.

5. Variation Across Investors and Investment Strategies

Our analysis thus far pools capital commitments from a variety of different types of institutions and across different types of private equity strategies. Since the regressions employ individual LP and fund-type fixed effects, we do not expect any particular subsample to drive inferences. However, examining results for different types of LPs and funds is of independent

[19] The estimated time is the average time of fund raising in the same fund type and geography in our sample rounded to the end of the year.

interest. Several papers examine the performance of specific types of institutions. For example, Andonov, Hochberg, and Rauh (2018) focus on public pension funds while Lerner, Schoar, and Wang (2018) concentrate on university endowments. And since the bulk of evidence in private equity is concerned with US LPs, we also consider it is useful to separately examine non-US LPs. At the minimum, doing so speaks to the generality of the evidence we consider. With respect to types of funds, majority of existing studies focus on buyout and venture capital funds. To prevent cluttering the tables, we only report results for a select group of LPs and fund types, confining ourselves to particular groups of interest and with a sample size large enough to draw meaningful inferences.

Table 9 presents results from choice regressions equivalent to specification (5) in Table 5. The first two columns show estimates for US and non-US LPs. The propensity to select first-time funds or young GPs is quite similar across both groups. While the coefficient on IRR_{High} is large and positive for US LPs, it is indistinguishable from zero for non-US LPs; performance chasing of this manner is largely a US phenomenon. Two other variables of interest (PriorInv and PeerInv) are positive in both subsamples, although the magnitudes differ. Most interesting is the difference in the magnitude of the coefficient on Local. For US LPs, the probability of selecting a GP headquartered in the same state is 1.7%. Compared to an unconditional probability of selection of 2.4%, that represents a 71 percent increase. In contrast, for non-US LPs, the probability of selecting a GP from the same country is 10.1%, which is a 306 percent increase over the unconditional probability (3.3%). One might think that home bias might be larger for non-US public entities where social mores, economically targeted investments, and political influence may be more acceptable. However, the sources of capital in our sample are quite diverse (see Table 1), and in unreported results, the coefficient on Local is similar (about 10%) for both public and non-public non-US LPs. Thus, the data suggest that the large home bias in non-US LPs goes beyond public pension systems.

The next set of columns contain estimates for public pension systems, universities, non-university foundations, and corporate plans. Each of these types of LPs are more likely to hire first-time funds (both rookies and veteran-founded firms), young GPs and 4th quartile GPs. The coefficients on PriorInv and PeerInv are similarly positive. With two exceptions, the magnitude of the selection probabilities are similar across various types of LPs. The first exception is that universities are roughly twice as likely to follow the investment decisions of their peers, compared to other types of LPs. This is suggestive of the influence of the well-publicized "Yale model" popularized by Swensen (2000). A second exception is that non-university foundations (which include both public and private foundations) are almost twice as likely to reinvest with a GP as other types of LPs. The last three columns report results for buyout, venture capital, and real estate funds, which constitute the largest fund types in our sample. There is surprisingly little variation across fund types, suggesting that the economic mechanisms at play are not specific to sub asset classes.

We turn next to post-selection performance for these same groups. We estimate regressions equivalent to those in Table 7, and similarly consolidate coefficients to generate regression-implied differences in future IRRs within- (Panel A) and across-categories (Panel B) in Table 10. There is little meaningful variation in within-category or across-category excess IRRs for US versus non-US LPs; excess IRR differences are generally negative in both groups with varying degrees of statistical significance. This is comforting in the sense that it implies that our results are economically driven and global, not unique to the US institutional setting.

Lerner, Schoar, and Wongsunwai (2007) estimate regressions of (chosen) fund IRRs on indicator variables corresponding to each type of LP. Their estimates indicate that corporate plans substantially underperform public pension plans, and endowments substantially outperform public pension plans. This is a puzzle in the sense that such large heterogeneity is not explained by access to superior funds. In our tests, which compare IRRs to those of the opportunity set, public pension systems stand out as having remarkably different excess IRR differences, compared to other LPs. In every within- and across-category comparison, excess IRR differences for public plans are negative, often by large amounts. Consider the following examples. The difference in excess IRRs between selected versus non-selected funds when both are in the 4th quartile of GP performance is −6.05% with a *t*-statistic of −3.31. For repeat investments in a GP, the equivalent difference is −6.39% (*t*-statistic = −3.29). And if one compares across categories, the difference between selected funds receiving repeat capital commitments and unselected 4th quartile GPs is −7.09% (*t*-statistic = −3.12). The poor selection ability of public plans is also evident in other asset classes (Goyal, Wahal, and Yavuz (2021)), and is consistent with an agency cost explanation. Andonov, Hochberg, and Rauh (2018) present sharp evidence showing that political representation on investment committees in public pension plans negatively affects performance. Our results suggest that the GP selection decision within the opportunity set is the channel by which this takes place.

In contrast to the above, as well as to the evidence in Lerner, Schoar, and Wongsunwai (2007), differences in excess IRRs for corporate plans, universities and foundations are largely indistinguishable from zero. This is true for most within-category and across-category comparisons. Of special interest are reinvestment decisions, where private information transmission is possible. Here too we see no clear-cut evidence that universities or foundations are able to parlay private information gleaned through prior investments to generate excess IRRs thereafter.

The bottom line is that private equity investment by LPs is not a monolith. There are important differences in selection, opportunity sets, and performance across different types of LPs. Lerner, Schoar, and Wongsunwai (2007) argue that these differences arise from variation in investment criteria and sophistication. These include, but are not restricted to, poor or distorted incentive structures, conflicting objectives, and low levels of expertise in an opaque asset class (see, for example, staffing descriptions in DaRin and Phalippou (2014)). It is well known that public pension systems are rife with agency problems (Lakonishok, Shleifer, and Vishny (1992), and underfunding likely exacerbates distorted incentives (Novy-Marx and Rauh (2009)). These are the single largest group of investors in our sample and appear to have the most inferior outcomes relative to their opportunity sets. Interestingly, and notwithstanding the evidence in Lerner, Schoar, and Wongsunwai and Sensoy, Wang, and Weisbach (2014), endowments and foundations do not appear to have particular selection ability relative to the counterfactual.

6. Specification Issues

Our methods require a host of empirical choices in setting up and estimating regressions. We make decisions that, in our view, manage the tradeoff between statistical power and items of economic interest. In this section, we report the sensitivity of our key results to three major issues discussed in the literature.

First, issues associated with IRR computations for private equity funds are well known (Phalippou (2020)). Most of our comparisons are between selected funds and the opportunity set. Therefore, to the extent that there are biases in IRRs at the database level, they are likely prevalent in both groups and should not affect our interpretations. Nonetheless, because IRRs are a noisy measure of performance that are sensitive to timing of cash flows, we follow Harris, Jenkinson, and Kaplan (2014) and replicate the regressions in Tables 5 and 8 using two types of excess multiples instead of IRRs: TVPI and MOIC. TVPI is Total Value to Paid-In Capital, computed as Total Value Returned / Invested Capital. MOIC is Multiple of Invested Capital, computed as (Distributed Value + Residual Value) / (Capital Calls + Fees). We report the results for both selection equations and post-selection performance in Appendix Table A4. As is apparent from the table, the importance of the selection criteria, and the variation in post-selection performance is quite similar. Statistical significance of difference in multiples is, in general, lower than that for difference in IRRs. Nevertheless, we do not find any evidence that selection based on any criteria leads to higher post-hiring multiples.

Second, several papers argue that there is a structural shift in private equity over time and that the results from early in the time series are sometimes no longer present in the latter periods. Therefore, we reproduce our results for subsamples before and after 2002. Since the pre-2002 sample is smaller, we expect larger standard errors but the exercise is still useful in providing a sense of robustness. The selection regressions for the two sample periods appear in the first two columns of Panel A of Appendix Table A5. There are a few differences in the two sample periods. Preference for first time funds seems to have increased over time consistent with the idea that this preference is driven by increasing allocations to private equity. Another interesting finding is that performance chasing, is largely a post-2002 phenomena. This may be somewhat expected because by definition early in the sample LPs do not observe past performance of GPs. The other covariates are largely similar in the two sample periods. In the post-selection results (Panel B), the differences in IRRs are generally similar in both subperiods with very few exceptions. For example, pre-2002 within-category differences in excess IRRs for reinvestments, investments in GPs that peers have prior investment, and investments in local GPs are all positive but not statistically significant.

Third, many of our results based on value-weighted excess IRRs computed from all prior funds raised by the GP. To the extent that IRRs early in the sample period were high, GP-level IRRs may be heavily influenced by those observations. An alternative approach is to use the IRR of the last fund raised by the GP in the selection regressions. The results using the last fund IRR are contained in the last column of Appendix Table A5. Again, selection probabilities and post-selection IRRs are remarkable similar to those reported in the main tables.

Finally, our results are net of fees and carry, and it is possible that variation in fees across LPs complicates inferences (Begenau and Siriwardane (2021)). However, Preqin's data collection policies described in Section 2 do not suggest a bias in the reported IRRs. If fund-level IRRs are calculated from a mix of high- and low-fee LPs, this adds noise but no bias to our analysis.

7. Conclusion

Capital allocation by institutional investors to private markets is enormous; as of June 2019, Preqin (2020) reports global assets under management of over $4 trillion. This aggregate allocation reflects large and increasing allocations of institutions to this asset class. But despite its importance, to our knowledge, there is no systematic evidence on how institutional investors select private equity funds. We attempt to fill that void.

Our empirical tests focus on selection criteria used in choosing GPs, economic mechanisms that underly these criteria, and whether these criteria provide information material to post selection performance. To address these questions, we use a contemporaneous counterfactual opportunity set, and post-selection IRRs earned by LPs relative to this opportunity set. We find that LPs are surprisingly more likely to select GPs without a track record, regardless of whether the founding partner is a rookie or a veteran of a more established private equity firm. This tendency is more apparent in the latter time period of our sample coinciding with LPs' increasing allocations to private equity. LPs also display a predilection to hire GPs in the 4th quartile of performance, local GPs, and those with whom either they or their peers have prior investment experience. None of these selection tendencies, however, translate into positive selection ability and, in the case of investments in first time funds, result in worse outcomes.

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Table 1. Sources of Capital

The sample consists of capital commitments by global LPs between 1990 and 2019. We report the total value of all commitments (in $ billions), the number of commitments, the median commitment size (in $ millions), as well as the median ratio of commitment value to fund size (in percent). Since the dollar value of capital commitments is only available for a subsample, aggregate and median commitment statistics are based on the subsample. The following LPs are shown: Corporate Pension Systems (Corp), Public and Private Foundations (Fndn), Public Pension Systems (Public), Sovereign Wealth Funds (SWF), Unions (Union), Public and Private Universities (Univ), and a miscellaneous category (Misc) for all other LPs. The geographic designations represent the domicile of the LP. North America includes US and Canada. Europe includes Continental Europe and the UK.

LP Domicile	Corp	Fndn	Public	SWF	Union	Univ	Misc	All
	Aggregate commitment (in $ billions)							
North America	22	2	1,286	89	5	57	125	1,586
Europe	18	3	62	9	<1	<1	40	132
ROW	4	<1	13	28	<1	<1	161	206
All	45	5	1,361	126	5	57	325	1,925
	Number of commitments							
North America	14,027	11,589	25,188	695	2,826	7,295	11,485	73,105
Europe	2,353	745	4,083	373	63	161	745	15,540
ROW	492	66	1,742	698	8	19	66	11,861
All	16,872	12,400	31,013	1,766	2,897	7,475	12,400	100,506
	Median commitment (in $ millions)							
North America	25	3	31	60	10	15	14	25
Europe	20	8	17	29	11	15	16	17
ROW	20	2	24	75	34	10	7	8
All	24	5	30	50	10	15	11	22
	Median commitment / fund size (in percent)							
North America	3.0	0.3	3.2	4.0	0.8	2.0	2.2	2.8
Europe	10.4	3.5	2.6	10.0	2.4	2.5	5.7	3.8
ROW	15.2	2.3	8.2	25.7	0.9	8.3	9.3	9.6
All	5.6	0.6	3.1	5.6	0.9	2.0	4.0	3.3

Table 2. Destination of Capital

The sample consists of capital commitments by LPs between 1990 and 2019 to various types of private equity funds. We report the total value of all commitments (in $ billions), the number of commitments, the median commitment size (in $ millions), as well as the median ratio of commitment value to fund size (in percentage). Since the dollar value of capital commitments is only available for a subsample, aggregate and median commitment statistics are based on the subsample. The following nine fund types are shown: Buyouts, Direct Lending, Distressed Debt and Equity (Distress), Growth, Infrastructure, Mezzanine, Natural Resources, Real Estate and Venture Capital. The geographic designations represent the geographic focus on the funds, not the domicile of the LP. North America includes US and Canada. Europe includes Continental Europe and the UK.

Geog. Focus	Buyout	Lending	Distress	Growth	Infra.	Mezz.	Nat. Res.	Real Est.	Venture	All
	Aggregate commitment (in $ billions)									
North America	521	36	93	57	74	42	69	292	101	1,284
Europe	175	11	13	9	39	6	1	67	9	329
ROW	63	1	10	99	22	2	5	52	57	312
All	760	48	115	165	134	50	75	411	167	1,925
	Number of commitments									
North America	20,373	1,171	4,253	3,326	2,606	2,743	4,395	12,142	12,311	63,320
Europe	10,052	448	611	899	1,732	577	70	2,912	2,920	20,221
ROW	2,742	83	493	3,923	917	309	331	1,730	6,437	16,965
All	33,167	1,702	5,357	8,148	5,255	3,629	4,796	16,784	21,668	100,506
	Median commitment (in $ millions)									
North America	25	40	30	20	40	16	25	30	10	25
Europe	30	41	43	20	32	16	27	36	7	28
ROW	27	33	30	15	30	16	30	50	5	12
All	27	40	30	17	35	16	25	30	8	22
	Median commitment / fund size (in percentage)									
North America	2.0	4.5	1.9	3.3	1.8	3.0	1.9	4.4	3.4	2.7
Europe	1.7	2.8	3.1	9.0	3.0	4.2	11.4	5.0	6.7	2.8
ROW	5.0	6.1	5.0	9.8	8.2	9.9	7.3	5.8	9.1	8.1
All	2.0	4.3	2.0	6.0	2.5	3.3	2.1	4.6	5.1	3.3

Table 3. Opportunity Set

For each capital commitment, we construct an opportunity set from non-selected funds of the same type, with the same geographic focus, with a vintage year within one year of the selected fund, and with a fund size within 50 percent of the selected fund. The following designations are used to identify geographic focus: US, Canada, China, Japan, UK, India, Europe and ROW. Statistics for the selected funds and the opportunity set are organized by a broader geographic grouping (North America, Europe, and ROW), and by fund type. The column labeled #GPs contains the average number of GPs in the opportunity set. The table also shows the number of GPs for which excess IRRs are calculable.

		#GPs in	GP IRR available	
Type	#commitments	opportunity set	#commitments	#GPs in opportunity set
	Geographic focus = North America			
Buyout	20,373	45	10,353	16
Dir. Lending	1,171	25	585	10
Distress	4,253	11	2,009	3
Growth	3,326	19	1,558	6
Infra.	2,606	9	246	1
Mezz.	2,743	12	1,264	3
Nat. Res.	4,395	12	1,978	4
Real Est.	12,142	71	4,191	17
Venture	12,311	75	4,950	17
	Geographic focus = Europe			
Buyout	10,052	21	4,339	5
Dir. Lending	448	12	110	4
Distress	611	6	312	2
Growth	899	14	142	1
Infra.	1,732	9	72	<1
Mezz.	577	7	63	<1
Nat. Res.	70	2	9	<1
Real Est.	2,912	24	846	5
Venture	2,920	32	434	2
	Geographic focus = ROW			
Buyout	2,742	12	754	2
Dir. Lending	83	3	8	<1
Distress	493	2	86	<1
Growth	3,923	28	432	2
Infra.	917	7	43	<1
Mezz.	309	3	35	<1
Nat. Res.	331	6	39	1
Real Est.	1,730	13	559	2
Venture	6,437	48	453	1

Table 4: Prior LP Investment Experience, Peer Investment Experience, and Home Bias

PriorInv is a dummy variable equal to one if an LP has invested with a GP in the past, zero otherwise. PeerInv is a dummy variable equal to one if a peer institution has invested with a GP in the past, zero otherwise. Local is an indicator variable equal to one if the LP and GP-headquarters are in the same state for US domiciled LPs. For non-US LPs, Local is equal to one if the LP and GP are headquartered in the same country. Peer institutions are defined in the Appendix. The table shows average LP and peer experience, and local for selection decisions and the opportunity set.

Type	Selected funds			Opportunity set		
	PriorInv	PeerInv	Local	PriorInv	PeerInv	Local
	Geographic focus = North America					
Buyout	0.418	0.704	0.134	0.062	0.495	0.082
Dir. Lending	0.333	0.710	0.100	0.056	0.578	0.054
Distress	0.455	0.775	0.115	0.089	0.602	0.073
Growth	0.420	0.624	0.162	0.041	0.383	0.074
Infra.	0.294	0.586	0.061	0.034	0.371	0.031
Mezz.	0.392	0.700	0.128	0.054	0.487	0.051
Nat. Res.	0.438	0.737	0.081	0.064	0.514	0.049
Real Est.	0.365	0.660	0.121	0.036	0.419	0.059
Venture	0.412	0.584	0.195	0.038	0.346	0.085
	Geographic focus = Europe					
Buyout	0.370	0.681	0.202	0.043	0.395	0.068
Dir. Lending	0.239	0.493	0.243	0.036	0.373	0.088
Distress	0.462	0.728	0.191	0.080	0.466	0.079
Growth	0.265	0.394	0.518	0.009	0.213	0.076
Infra.	0.221	0.441	0.397	0.026	0.304	0.152
Mezz.	0.246	0.515	0.326	0.029	0.277	0.085
Nat. Res.	0.229	0.371	0.243	0.028	0.139	0.056
Real Est.	0.270	0.522	0.230	0.027	0.312	0.081
Venture	0.224	0.366	0.579	0.010	0.189	0.090
	Geographic focus = ROW					
Buyout	0.312	0.535	0.376	0.059	0.389	0.181
Dir. Lending	0.120	0.301	0.265	0.028	0.196	0.063
Distress	0.296	0.552	0.288	0.062	0.386	0.146
Growth	0.210	0.367	0.512	0.013	0.264	0.458
Infra.	0.154	0.325	0.406	0.022	0.263	0.066
Mezz.	0.243	0.583	0.599	0.044	0.425	0.225
Nat. Res.	0.184	0.356	0.254	0.012	0.150	0.041
Real Est.	0.295	0.539	0.203	0.035	0.319	0.069
Venture	0.195	0.406	0.655	0.009	0.317	0.674

Table 5. Choice Regressions

The table contains OLS regressions in which the dependent variable is equal to one if LP l commits capital to fund f of GP g at time t, zero otherwise. IRR_{NA} is equal to one if prior GP IRR is unavailable. IRR_{First} is equal to one if this is the GP's first fund, IRR_{Young} is equal to one if a GP's funds are less than eight years old and GP IRR is missing, and $IRR_{Missing}$ is equal to one if a GP's funds are more than eight years old but the GP's IRR is missing. $IRR_{First,Rookie}$ is equal to one if this is the GP's first fund and the GP partner has no prior PE experience, and $IRR_{First,Veteran}$ is equal to one if this is the GP's first fund and the GP has prior PE experience. IRR_{Q2} through IRR_{High} are equal to one if the asset weighted past IRR of the GP is in the 2nd through 4th quartile of GPs in the same type, geography, and vintage year. PriorInv is equal to one if the LP has previously committed capital to the GP. PeerInv is equal to one if peer institutions have previously committed capital to the GP. Local is an indicator variable equal to one if the LP and GP-headquarters are in the same state for US domiciled LPs. For non-US LPs, Local is equal to one if the LP and GP are headquartered in the same country. t-statistics are based on standard errors clustered using the same grouping as fixed effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IRR_{NA}	0.003	0.008	0.009	—	—	—	—
	(2.77)	(4.74)	(4.95)				
IRR_{First}	—	—	—	0.016	—	—	—
				(8.00)			
$IRR_{First,Rookie}$	—	—	—		0.016	—	0.012
					(7.98)		(6.59)
$IRR_{First,Veteran}$	—	—	—		0.017	—	0.013
					(7.74)		(6.17)
IRR_{Young}	—	—	—	0.009	0.009	—	0.009
				(5.19)	(5.18)		(5.18)
$IRR_{Missing}$	—	—	—	0.007	0.007	—	0.007
				(3.37)	(3.36)		(3.51)
IRR_{Q2}	—	0.002	0.002	0.001	0.001	—	−0.000
		(0.80)	(0.68)	(0.55)	(0.55)		(−0.01)
IRR_{Q3}	—	0.008	0.008	0.008	0.008	—	0.005
		(3.03)	(2.90)	(2.80)	(2.80)		(1.74)
IRR_{High}	—	0.011	0.011	0.011	0.011	—	0.008
		(3.85)	(3.76)	(3.71)	(3.71)		(3.04)
Ln(GPSize)	0.004	0.004	0.004	0.005	0.005	0.015	0.002
	(10.51)	(10.49)	(9.19)	(10.03)	(10.03)	(6.93)	(2.54)
PriorInv	0.160	0.160	0.165	0.165	0.165	0.140	0.170
	(21.05)	(21.03)	(16.37)	(16.37)	(16.37)	(17.56)	(16.07)
PeerInv	0.004	0.004	0.005	0.007	0.007	0.007	0.009
	(6.00)	(6.16)	(6.75)	(9.67)	(9.67)	(12.81)	(9.77)
Local	0.027	0.027	0.034	0.034	0.034	0.031	0.038
	(11.05)	(11.06)	(9.37)	(9.36)	(9.36)	(9.42)	(9.45)
Fixed effects	——————————FundRegion×FundType×VintageYear, and——————————						Commitment
	—	—	LP	LP	LP	LP, GP×Year	ID
Adj-R^2	0.093	0.093	0.095	0.095	0.095	0.238	0.081
# observations	3,854,659	3,854,659	3,854,538	3,854,538	3,854,538	3,853,585	3,852,123

Table 6: Choice Regressions Controlling for Access

We estimate OLS regressions in which the dependent variable is equal to one if LP l commits capital to fund f of GP g at time t, zero otherwise as in Table 5. Regressions in the undersubscribed column are for a subsample of funds in which the final fund size is smaller than the target fund size. We sort all LPs based on their assets under management into four quartile and estimate separate regressions for each quartile (labelled Small LP through Large LP). Unconditional probabilities are computed by dividing the total number of commitments by the total number of observations. All regressions include FundRegion×FundType×VintageYear, and LP fixed effects. t-statistics are based on standard errors clustered using the same grouping as fixed effects.

	Undersubscribed	Small LP	Q2 LP	Q3 LP	Large LP
$IRR_{First,Rookie}$	0.045	0.012	0.014	0.015	0.017
	(4.06)	(4.88)	(6.03)	(6.84)	(7.69)
$IRR_{First,Veteran}$	0.044	0.012	0.014	0.017	0.018
	(4.11)	(4.54)	(5.82)	(7.09)	(8.03)
IRR_{Young}	0.023	0.004	0.007	0.010	0.010
	(2.70)	(1.93)	(3.33)	(4.99)	(5.38)
$IRR_{Missing}$	0.013	0.003	0.006	0.007	0.007
	(1.31)	(1.39)	(2.61)	(3.05)	(3.17)
IRR_{Q2}	0.006	0.002	-0.000	0.002	0.002
	(0.39)	(0.64)	(-0.05)	(0.71)	(0.58)
IRR_{Q3}	0.022	0.004	0.008	0.010	0.007
	(1.16)	(1.29)	(2.92)	(3.16)	(2.22)
IRR_{High}	0.032	0.003	0.012	0.011	0.011
	(1.71)	(1.05)	(3.58)	(3.29)	(3.52)
Ln(GPSize)	0.013	0.003	0.004	0.005	0.006
	(3.98)	(4.68)	(7.69)	(8.67)	(10.35)
PriorInv	0.409	0.428	0.255	0.174	0.121
	(21.87)	(11.67)	(15.63)	(15.50)	(13.84)
PeerInv	0.026	0.011	0.010	0.008	0.005
	(7.07)	(8.31)	(7.41)	(7.89)	(5.87)
Local	0.150	0.050	0.035	0.031	0.028
	(8.75)	(9.28)	(7.86)	(7.28)	(6.01)
Adj-R^2	0.264	0.152	0.119	0.099	0.086
Observations	163,874	470,583	717,911	1,047,334	1,396,354
Uncond. probability	0.103	0.026	0.026	0.026	0.027

Table 7. Choice Regressions: Different Opportunity Sets

We run OLS regressions of PE fund choice by LPs similar to those in Table 5 but with different opportunity sets. Columns (1) and (2) consider funds in the opportunity set if they are withing ±30% and ±70%, respectively of the winning fund size. Column (3) imposes no restriction on fund size. Column (4) considers only one combined opportunity set if an LP allocates to multiple GPs in the same region, type, and vintage year (no restriction is imposed on the size of the funds in the opportunity set). All regressions include FundRegion×FundType×VintageYear and LP fixed effects. Unconditional probabilities are computed by dividing the total number of commitments by the total number of observations. *t*-statistics based on clustered standard errors using the same categories as the fixed effects appear in parentheses. The sample consists of PE mandates from LPs to funds between 1990 and 2019.

	30% around winning fund	70% around Winning fund	No restriction	Single set
	(1)	(2)	(3)	(4)
$IRR_{First,Rookie}$	0.029	0.013	0.004	0.007
	(11.34)	(11.73)	(10.97)	(12.54)
$IRR_{First,Veteran}$	0.032	0.014	0.004	0.007
	(10.47)	(11.24)	(10.62)	(11.75)
IRR_{Young}	0.016	0.007	0.002	0.004
	(7.56)	(6.99)	(6.61)	(7.47)
$IRR_{Missing}$	0.013	0.005	0.002	0.003
	(4.66)	(4.01)	(4.16)	(4.35)
IRR_{Q2}	0.005	0.001	−0.001	−0.001
	(1.39)	(0.37)	(−0.92)	(−1.13)
IRR_{Q3}	0.016	0.005	0.001	0.002
	(3.88)	(2.98)	(1.02)	(1.28)
IRR_{High}	0.019	0.008	0.002	0.004
	(4.21)	(4.12)	(3.15)	(3.30)
Ln(GPSize)	0.006	0.004	0.001	0.001
	(8.39)	(11.65)	(9.19)	(9.09)
PriorInv	0.242	0.119	0.054	0.161
	(18.98)	(14.93)	(12.35)	(25.65)
PeerInv	0.014	0.007	0.005	0.010
	(10.07)	(10.81)	(12.40)	(17.69)
Local	0.055	0.022	0.009	0.017
	(9.90)	(9.04)	(8.95)	(14.30)
Adj-R^2	0.139	0.070	0.033	0.072
# observations	2,186,088	6,204,662	17,960,976	10,285,729
Uncond. probability	0.046	0.016	0.006	0.010

Table 8. Future Excess IRRs

The table shows regression-implied excess IRRs (and differences in excess IRRs) between different categories of funds. Regression coefficients are reported in Table A2. The regression includes FundRegion×FundType×VintageYear and LP fixed effects. The table shows appropriate combinations of coefficients corresponding to each category of funds. Panel A shows excess IRRs for hired funds, not-hired funds, and the difference in each category. Panel B shows differences in excess IRRs between hired funds in a category and not-hired funds from the 4th quartile of GP performance. *t*-statistics based on clustered standard errors using the same categories as the fixed effects appear in parentheses.

Panel A: Future excess IRRs and within category differences in IRRs			
	Hired	NotHired	Difference
$IRR_{First,Rookie}$	−4.09	−1.03	−3.06
	(−2.37)	(−0.84)	(−2.09)
$IRR_{First,Veteran}$	−0.67	1.66	−2.33
	(−0.38)	(1.33)	(−1.70)
IRR_{Young}	−2.49	−1.37	−1.12
	(−1.46)	(−1.32)	(−0.72)
IRR_{High}	1.09	2.20	−1.10
	(0.59)	(2.05)	(−0.58)
PriorInv	0.28	1.11	−0.83
	(0.14)	(4.95)	(−0.42)
PeerInv	0.49	0.81	−0.32
	(0.23)	(2.72)	(−0.15)
Local	−0.33	0.16	−0.49
	(−0.17)	(0.72)	(−0.26)

Panel B: Across category differences in future excess IRRs	
Hired & $IRR_{First,Rookie}$ − NotHired & IRR_{High}	−6.29
	(−3.54)
Hired & $IRR_{First,Vetern}$ − NotHired & IRR_{High}	−2.87
	(−1.61)
Hired & IRR_{Young} − NotHired & IRR_{High}	−4.68
	(−2.54)
Hired & PriorInv − NotHired & IRR_{High}	−1.92
	(−0.81)
Hired & PeerInv − NotHired & IRR_{High}	−1.71
	(−0.70)
Hired & Local − NotHired & IRR_{High}	−2.52
	(−1.10)

Table 9. Subsample Choice Regressions

The table contains subsample regressions equivalent to those in specification (5) of Table 5. All regressions include FundRegion×FundType×VintageYear and LP fixed effects. Unconditional probabilities are computed by dividing the total number of commitments by the total number of observations. *t*-statistics based on clustered standard errors using the same categories as the fixed effects are in parentheses.

	LP types						Fund types		
	US	Non-US	Public	Univ	Fndn	Corp	Buyout	Venture	Real Est.
$IRR_{First,Rookie}$	0.014	0.015	0.018	0.014	0.015	0.012	0.013	0.010	0.014
	(7.44)	(4.15)	(7.46)	(5.65)	(5.59)	(4.74)	(3.55)	(4.42)	(5.12)
$IRR_{First,Veteran}$	0.017	0.012	0.019	0.019	0.017	0.014	0.016	0.009	0.018
	(7.61)	(3.32)	(7.30)	(6.38)	(5.77)	(5.35)	(4.11)	(3.72)	(5.12)
IRR_{Young}	0.009	0.004	0.012	0.014	0.007	0.007	0.008	0.004	0.012
	(5.24)	(1.26)	(5.99)	(5.38)	(2.98)	(2.79)	(2.44)	(2.03)	(5.18)
$IRR_{Missing}$	0.007	0.003	0.009	0.012	0.005	0.003	0.006	0.001	0.010
	(3.26)	(0.72)	(3.66)	(4.19)	(1.85)	(1.08)	(1.71)	(0.43)	(3.26)
IRR_{Q2}	0.001	0.007	0.003	0.003	0.000	-0.002	0.002	−0.000	0.006
	(0.24)	(1.16)	(1.15)	(0.90)	(0.05)	(-0.54)	(0.32)	(−0.00)	(1.66)
IRR_{Q3}	0.009	0.006	0.012	0.014	0.004	0.004	0.003	0.004	0.015
	(3.00)	(1.36)	(3.61)	(3.22)	(1.01)	(1.11)	(0.50)	(1.21)	(3.17)
IRR_{High}	0.013	0.004	0.016	0.014	0.009	0.006	0.013	0.001	0.019
	(4.12)	(0.91)	(4.57)	(3.53)	(2.11)	(1.67)	(2.66)	(0.20)	(2.34)
Ln(GPSize)	0.004	0.006	0.005	0.003	0.005	0.007	0.005	0.004	0.001
	(7.82)	(10.25)	(7.36)	(4.08)	(7.11)	(9.61)	(8.32)	(6.86)	(1.58)
PriorInv	0.153	0.264	0.136	0.186	0.263	0.169	0.146	0.143	0.134
	(16.10)	(15.34)	(13.27)	(7.31)	(9.19)	(8.60)	(13.08)	(8.33)	(12.22)
PeerInv	0.008	0.005	0.009	0.016	0.009	0.005	0.008	0.004	0.009
	(8.35)	(3.27)	(8.85)	(6.52)	(6.28)	(3.33)	(5.99)	(4.52)	(7.14)
Local	0.017	0.101	0.029	0.022	0.025	0.028	0.026	0.039	0.021
	(9.29)	(13.76)	(5.84)	(3.33)	(6.74)	(6.13)	(6.34)	(5.55)	(6.16)
Adj-R^2	0.090	0.126	0.092	0.101	0.132	0.098	0.072	0.069	0.067
# observations	3,013,203	841,295	1,142,739	315,942	487,530	666,191	1,161,935	1,319,973	960,429
Uncond. Probability	0.024	0.033	0.027	0.024	0.025	0.025	0.029	0.016	0.017

Table 10. Subsample Future Excess IRRs

We estimate subsample regressions equivalent to those in Table 8. Panel A shows regression-implied future excess IRRs of different categories. Panel B shows regressions implied differences in future IRRs across groups. All regressions include FundRegion×FundType×VintageYear and LP fixed effects. *t*-statistics based on clustered standard errors using the same categories as the fixed effects appear in parentheses.

	LP Types						Fund Types		
	US	Non−US	Public	Univ	Fndn	Corp	Buyout	Venture	Real Est.
Panel A: Within category differences in future excess IRRs									
Hired & $IRR_{First,Rookie}$	−2.85	−5.16	−6.90	0.13	2.13	1.58	−3.98	0.15	−4.28
− NotHired & $IRR_{First,Rookie}$	(−1.75)	(−3.00)	(−3.99)	(0.04)	(0.83)	(0.61)	(−1.88)	(0.04)	(−1.80)
Hired & $IRR_{First,Veteran}$	−2.09	−4.09	−5.90	3.99	4.09	0.11	−2.40	0.67	−4.13
− NotHired & $IRR_{First,Veteran}$	(−1.40)	(−1.98)	(−3.74)	(1.22)	(1.76)	(0.05)	(−1.38)	(0.16)	(−1.68)
Hired & IRR_{Young}	−0.82	−2.77	−4.78	5.36	4.62	1.82	−2.35	3.22	−6.19
− NotHired & IRR_{Young}	(−0.47)	(−1.69)	(−2.69)	(1.50)	(1.86)	(0.77)	(−1.06)	(0.75)	(−2.90)
Hired & IRR_{High}	−0.68	−3.40	−5.67	7.70	5.54	2.94	−1.86	2.35	−2.14
− NotHired & IRR_{High}	(−0.32)	(−1.47)	(−2.96)	(1.65)	(1.85)	(0.97)	(−0.83)	(0.44)	(−0.80)
Hired & PriorInv	−0.35	−3.13	−5.92	6.63	5.99	3.41	−3.64	9.32	−6.46
− NotHired & PriorInv	(−0.16)	(−1.40)	(−2.84)	(1.53)	(2.03)	(1.14)	(−1.55)	(1.41)	(−2.12)
Hired & PeerInv	0.27	−3.86	−4.01	6.31	7.61	3.84	−2.77	10.18	−7.39
− NotHired & PeerInv	(0.11)	(−1.53)	(−1.72)	(1.42)	(2.26)	(1.17)	(−1.10)	(1.45)	(−2.71)
Hired & Local	−0.29	−2.53	−6.18	8.07	6.57	4.69	−2.05	8.41	−7.79
− NotHired & Local	(−0.14)	(−1.07)	(−3.29)	(1.99)	(2.19)	(1.46)	(−0.84)	(1.37)	(−2.76)
Panel B: Across category differences in future excess IRRs									
Hired & $IRR_{First,Rookie}$	−6.23	−7.05	−11.23	−2.37	−0.65	−1.34	−6.59	−4.87	−3.95
− NotHired & IRR_{High}	(−3.22)	(−3.81)	(−5.99)	(−0.70)	(−0.24)	(−0.49)	(−2.89)	(−1.21)	(−1.01)
Hired & $IRR_{First,Veteran}$	−2.86	−2.80	−7.44	3.66	4.09	0.01	−2.97	0.51	−2.66
− NotHired & IRR_{High}	(−1.50)	(−1.24)	(−4.41)	(1.00)	(1.48)	(0.00)	(−1.63)	(0.10)	(−0.62)
Hired & IRR_{Young}	−4.47	−5.55	−8.62	2.01	1.18	−2.01	−4.47	−3.58	−6.65
− NotHired & IRR_{High}	(−2.21)	(−3.00)	(−4.73)	(0.51)	(0.44)	(−0.76)	(−1.87)	(−0.72)	(−2.11)
Hired & PriorInv	−1.57	−3.95	−6.67	6.01	4.79	1.57	−0.16	4.02	−9.01
− NotHired & IRR_{High}	(−0.60)	(−1.71)	(−2.79)	(1.17)	(1.39)	(0.46)	(−0.06)	(0.51)	(−3.04)
Hired & PeerInv	−1.30	−4.11	−6.63	4.81	5.65	3.31	−0.06	4.97	−10.18
− NotHired & IRR_{High}	(−0.48)	(−1.69)	(−2.72)	(1.03)	(1.55)	(0.84)	(−0.02)	(0.59)	(−3.79)
Hired & Local	−2.49	−2.94	−7.30	5.50	3.57	1.77	0.06	2.54	−11.07
− NotHired & IRR_{High}	(−0.98)	(−1.27)	(−3.20)	(1.23)	(1.09)	(0.50)	(0.02)	(0.34)	(−3.60)

Figure 1: First-time funds

The histogram shows the number of first-time funds (the sum of rookie and veteran first-time funds) for each fund type in each vintage year.

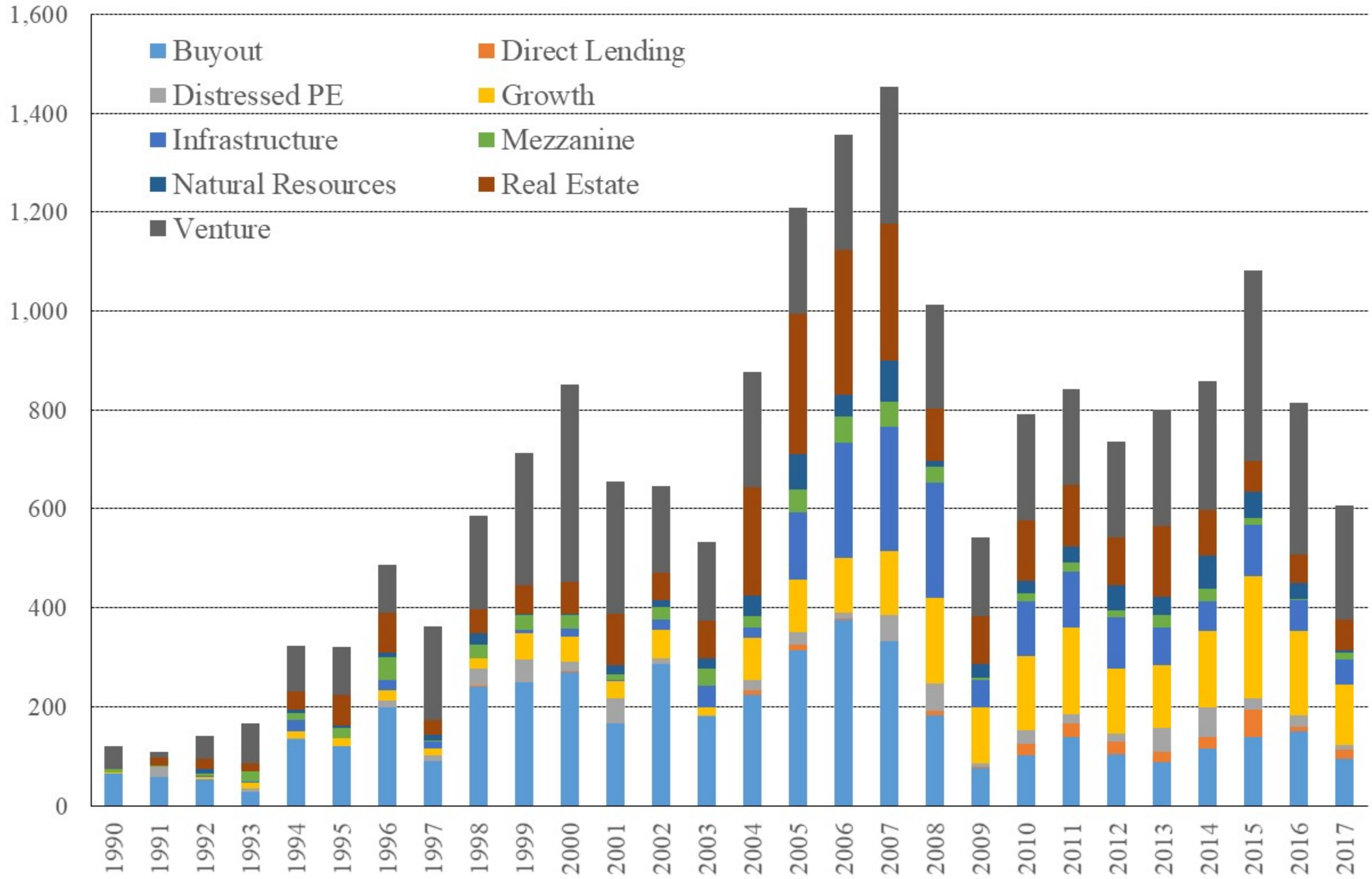
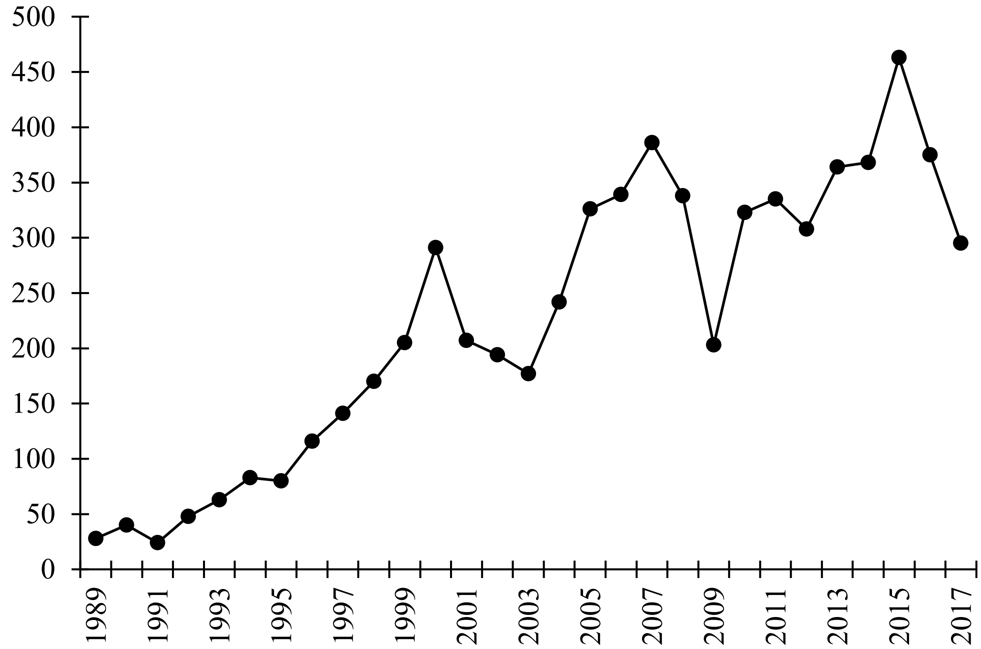


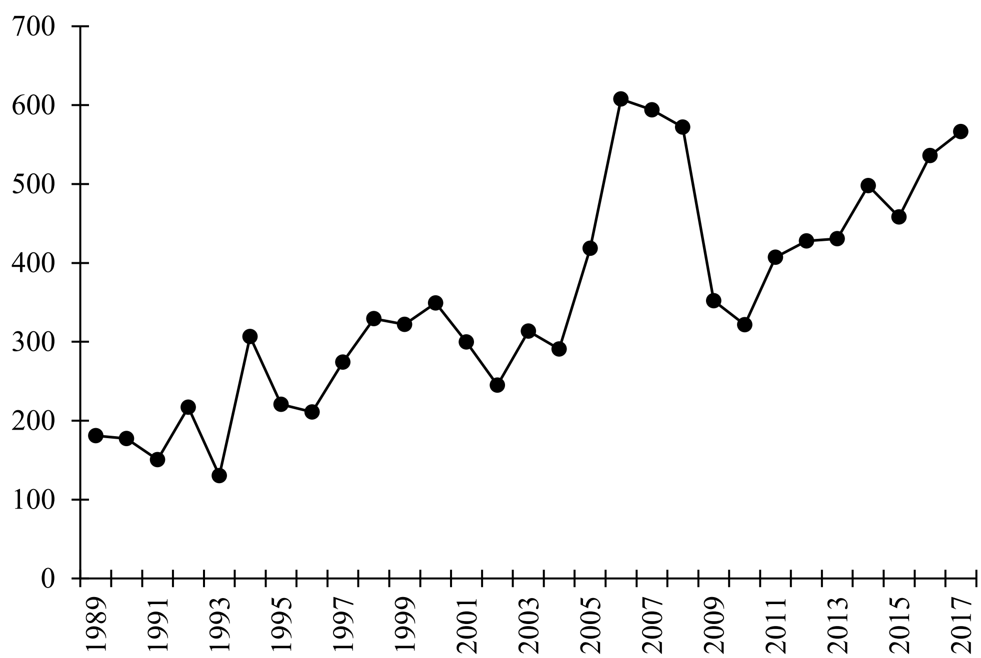
Figure 2: New GPs

Panel A shows the number of new GPs entering the private equity market in each vintage year. Panel B shows the average fund size of all funds in each vintage year.

Panel A: Number of New Entrants



Panel B: Average Fund Size ($M)



Appendix: Peer Construction

We construct peer groups at the intersection of the domicile of the LP and the type of LP. There is substantial variation in the type of LPs across domiciles, so we create country- or region-specific intersections based on the empirical distribution of the LPs. A full list of peer groups appears below.

China:	All LPs
Japan:	Corporate Plans
	Miscellaneous
ROW:	Corporate Plans
	Miscellaneous
	Private Foundations
	Public Foundations
	Public Pension Systems
	Union
UK:	Corporate Plans
	Local Plans
	Miscellaneous
	Private Foundations
	Private Universities
	Public Universities
	Public Pension Systems
US:	Corporate Plans
	Local Plans
	Miscellaneous
	Private Foundations
	Private Universities
	Public Foundations
	Public Universities
	State Pension Systems
	Union Plans
Sovereign Wealth Funds	

Table A1. Flow of Capital from Type of LPs to Types of Funds

The sample consists of private equity mandates from plan sponsors to private equity funds between 1990 and 2019. We report the total value of all mandates (in $ millions). The LP types are Corporate DB (Corp), Foundations (Fndn), Public that includes local and state plans (Public), Sovereign Wealth Funds (SWF), Union (Union), Universities (Univ), and a miscellaneous category (Misc) for all other plans. The fund types are Buyout, Direct lending, Distress, Growth, Infrastructure, Mezzanine, Natural Resources, Real estate, and Venture capital.

LP		Fund type									
Geography	Type	Buyout	Lending	Distress	Growth	Infra.	Mezz.	Nat. Res.	Real Est.	Venture	All
US	Corp	9,882	32	1,915	437	1,739	663	1,258	4,763	1,603	22,292
	Fndn	664	5	184	126	84	18	99	663	384	2,227
	Misc	50,768	923	7,322	8,810	9,268	14,084	3,194	21,561	8,693	124,623
	Public	556,699	38,088	92,945	56,802	55,679	28,454	58,618	312,212	86,421	1,285,917
	SWF	59,867	719	1,572	5,679	4,191	449	4,414	10,196	2,038	89,125
	Union	1,002	20	83	154	1,563	175	435	1,123	276	4,830
	Univ	19,308	1,079	4,308	4,526	2,228	814	4,765	10,858	9,263	57,147
	All	698,190	40,865	108,328	76,533	74,752	44,657	72,784	361,376	108,677	1,586,162
Europe	Corp	1,868	423	30	4,064	5,612	136	103	2,248	3,839	18,324
	Fndn	501	12	–	213	449	31	–	1,482	221	2,909
	Misc	7,245	853	1,058	3,812	14,317	818	377	8,655	2,787	39,923
	Public	19,396	3,875	2,779	1,860	15,919	1,180	1,531	11,304	4,380	62,223
	SWF	2,278	335	111	780	295	32	–	4,491	736	9,058
	Union	–	–	–	13	96	–	–	50	–	159
	Univ	1	27	–	1	184	–	–	50	1	264
	All	31,289	5,524	3,978	10,744	36,872	2,197	2,012	28,280	11,964	132,860
ROW	Corp	334	–	50	1,166	700	53	48	1,477	514	4,342
	Fndn	2	–	–	7	103	–	–	–	1	113
	Misc	18,241	837	1,720	71,083	16,884	2,374	378	6,424	42,633	160,573
	Public	1,717	516	782	323	2,476	310	16	5,633	888	12,661
	SWF	10,374	–	500	4,655	2,602	–	75	7,735	2,357	28,297
	Union	–	–	–	–	97	–	–	55	–	152
	Univ	–	–	–	45	–	–	–	–	24	69
	All	334	–	50	1,166	700	53	48	1,477	514	4,342

Table A2. Future Excess IRRs Regressions

The table shows regression coefficients of future excess IRRs. Hired is a dummy variable is equal to one for the fund chosen by an LP, and zero for funds from the opportunity set. The other independent variables are identified in Table 5. The regression includes FundRegion×FundType×VintageYear and LP fixed effects. *t*-statistics based on clustered standard errors using the same categories as the fixed effects appear in parentheses.

Regression coefficients				
Hired				
−0.13				
(−0.06)				
$IRR_{First,Rookie}$	$IRR_{First,Veteran}$	IRR_{Young}	$IRR_{Missing}$	IRR_{Q2}
−1.03	1.66	−1.37	−0.24	1.90
(−0.84)	(1.33)	(−1.32)	(−0.23)	(1.86)
IRR_{Q3}	IRR_{High}	Ln(GPSize)	PriorInv	PeerInv
−0.47	2.20	−0.59	1.11	0.81
(−0.42)	(2.05)	(−3.05)	(4.95)	(2.72)
Local				
0.16				
(0.72)				
Hired×$IRR_{First,Rookie}$	Hired×$IRR_{First,Veteran}$	Hired×IRR_{Young}	Hired×$IRR_{Missing}$	Hired×IRR_{Q2}
−2.93	−2.20	−0.99	−0.61	−1.18
(−2.25)	(−1.59)	(−1.06)	(−0.64)	(−0.96)
Hired×IRR_{Q3}	Hired×IRR_{High}	Hired×Ln(GPSize)	Hired×PriorInv	Hired×PeerInv
−0.55	−0.97	0.22	−0.70	−0.19
(−0.40)	(−0.82)	(1.06)	(−2.77)	(−0.59)
Hired×Local				
−0.36				
(−0.95)				
Adj-R^2	0.047			
# observations	1,668,163			

Table A3. Unsuccessful Fundraising

We divide funds in each FundRegion×FundType×VintageYear group into two categories – funds for which the GP was able to raise a follow-on fund and funds for which GP was unable to do so. Panel A provides descriptive statistics for these two categories. We report number of funds, median interim excess IRR measured 3 years after the vintage year, and median future IRR measured at the end of the sample period. Panel B reports results of a quantile regression with future IRR as the dependent variable. The independent variables are interim IRR and a dummy for success in raising a follow-on fund and interim IRR. The regression includes fixed effects for FundRegion×FundType×VintageYear. The sample includes only funds for which we observe interim IRR.

Panel A: Descriptive statistics

	Without follow-on fund			With follow-on fund		
	N	Interim IRR	Future IRR	N	Interim IRR	Future IRR
Buyout	152	−6.75	−5.94	393	0.35	0.05
Growth	30	0.00	−1.89	68	0.95	0.17
Mezzanine	33	−1.27	−1.76	60	0.03	−0.07
Venture	29	0.00	0.00	180	3.10	1.75

Panel B: Future IRR as dependent variable

Follow-on fund dummy	0.28
	(0.63)
Interim IRR	0.94
	(59.96)
Constant	−2.77
	(−0.56)
Adj-R^2	0.644
# observations	945

Table A4: Selection and Performance using Multiples

We estimate selection regressions equivalent to those in Table 5 and future performance regressions equivalent to those in Table 7, except that we use multiples instead of IRRs. We use two types of multiples, TVPI and MOIC. TVPI is Total Value to Paid-In Capital, computed as Total Value Returned / Invested Capital. MOIC is Multiple of Invested Capital, computed as (Distributed Value + Residual Value) / (Capital Calls + Fees). Panel A shows regression coefficients from selection regression, Panel B shows regression-implied future excess multiples of different categories, and Panel C shows regressions implied differences in future multiples across categories. All regressions include FundRegion×FundType×VintageYear and LP fixed effects. *t*-statistics based on clustered standard errors using the same categories as the fixed effects appear in parentheses.

	MULT = TVPI	MULT = MOIC
Panel A: Selection regression		
$MULT_{First,Rookie}$	0.015	0.013
	(7.33)	(6.96)
$MULT_{First,Veteran}$	0.016	0.014
	(7.52)	(7.27)
$MULT_{Young}$	0.009	0.006
	(4.50)	(3.77)
$MULT_{Missing}$	0.006	0.004
	(2.74)	(1.95)
$MULT_{Q2}$	0.004	0.001
	(1.41)	(0.57)
$MULT_{Q3}$	0.006	0.000
	(2.17)	(0.15)
$MULT_{High}$	0.008	0.007
	(3.16)	(2.92)
Ln(GPSize)	0.005	0.005
	(9.93)	(9.95)
PriorInv	0.165	0.165
	(16.36)	(16.38)
PeerInv	0.007	0.007
	(9.67)	(9.67)
Local	0.034	0.034
	(9.37)	(9.36)
Adj-R^2	0.095	0.095
# observations	3,854,538	3,854,538
Uncond. Probability	0.026	0.026

	MULT = TVPI	MULT = MOIC
Panel B: Within category differences in future multiples		
Hired & $MULT_{First,Rookie}$ − NotHired & $MULT_{First,Rookie}$	−0.06	−0.02
	(−0.71)	(−0.21)
Hired & $MULT_{First,Vetern}$ − NotHired & $MULT_{First,Vetern}$	−0.08	−0.06
	(−1.02)	(−0.78)
Hired & $MULT_{Young}$ − NotHired & $MULT_{Young}$	−0.01	0.03
	(−0.10)	(0.29)
Hired & $MULT_{High}$ − NotHired & $MULT_{High}$	0.04	0.07
	(0.33)	(0.63)
Hired & PriorInv − NotHired & PriorInv	0.05	0.10
	(0.44)	(0.93)
Hired & PeerInv − NotHired & PeerInv	0.05	0.11
	(0.47)	(0.91)
Hired & Local − NotHired & Local	0.04	0.10
	(0.34)	(0.89)
Panel C: Across category differences in future multiples		
Hired & $MULT_{First,Rookie}$ − NotHired & $MULT_{High}$	−0.29	−0.22
	(−2.95)	(−2.15)
Hired & $MULT_{First,Vetern}$ − NotHired & $MULT_{High}$	−0.12	−0.08
	(−1.12)	(−0.74)
Hired & $MULT_{Young}$ − NotHired & $MULT_{High}$	−0.20	−0.15
	(−1.95)	(−1.35)
Hired & PriorInv − NotHired & $MULT_{High}$	−0.05	0.04
	(−0.42)	−0.29
Hired & PeerInv − NotHired & $MULT_{High}$	−0.05	0.04
	(−0.44)	−0.31
Hired & Local − NotHired & $MULT_{High}$	−0.10	−0.02
	(−0.91)	(−0.17)

Table A5: Selection and Performance: Robustness

We estimate selection regressions equivalent to those in Table 5 and future performance regressions equivalent to those in Table 7, except that we break the sample into pre- and post-2002, and consider an alternative way of calculating GP IRRs in the last column. Panel A shows regression coefficients from selection regression, Panel B shows regression-implied future excess IRRs of different categories, and Panel C shows regressions implied differences in future IRRs across categories. All regressions include FundRegion×FundType×VintageYear and LP fixed effects. *t*-statistics based on clustered standard errors using the same categories as the fixed effects appear in parentheses.

	Pre-2002	Post-2002	Last Fund IRR
	Panel A: Selection regression		
$IRR_{First,Rookie}$	0.010	0.017	0.018
	(2.50)	(7.95)	(8.52)
$IRR_{First,Veteran}$	0.011	0.018	0.019
	(2.54)	(7.68)	(8.52)
IRR_{Young}	0.004	0.010	0.012
	(1.17)	(5.30)	(5.85)
$IRR_{Missing}$	−0.000	0.008	0.010
	(−0.09)	(3.65)	(4.29)
IRR_{Q2}	0.008	0.000	0.005
	(1.30)	(0.05)	(1.94)
IRR_{Q3}	0.003	0.008	0.011
	(0.47)	(2.75)	(3.56)
IRR_{High}	−0.003	0.013	0.012
	(−0.38)	(4.00)	(3.60)
Ln(GPSize)	0.006	0.005	0.005
	(7.34)	(8.64)	(10.36)
PriorInv	0.147	0.169	0.165
	(7.13)	(16.03)	(16.40)
PeerInv	0.010	0.007	0.007
	(3.89)	(9.91)	(9.75)
Local	0.029	0.036	0.034
	(4.64)	(9.13)	(9.36)
Adj-R^2	0.095	0.095	0.095
# observations	835,031	3,019,452	3,854,538
Uncond. Probability	0.025	0.026	0.026

	Pre-2002	Post-2002	Last Fund IRR
Panel B: Within category differences in future IRRs			
Hired & $IRR_{First,Rookie}$ − NotHired & I $IRR_{First,Rookie}$	−1.85	−4.41	−3.22
	(−0.72)	(−2.84)	(−2.24)
Hired & $IRR_{First,Vetern}$ − NotHired & $IRR_{First,Vetern}$	−1.24	−3.92	−2.51
	(−0.50)	(−2.90)	(−1.82)
Hired & IRR_{Young} − NotHired & IRR_{Young}	1.93	−4.10	−1.36
	(0.68)	(−2.88)	(−0.88)
Hired & IRR_{High} − NotHired & IRR_{High}	−1.14	−3.00	−0.08
	(−0.22)	(−1.84)	(−0.04)
Hired & PriorInv − NotHired & PriorInv	3.77	−3.71	−1.56
	(0.80)	(−2.02)	(−0.85)
Hired & PeerInv − NotHired & PeerInv	5.27	−3.80	−1.01
	(1.05)	(−2.10)	(−0.51)
Hired & Local − NotHired & Local	4.27	−3.25	−1.16
	(0.97)	(−1.77)	(−0.64)
Panel C: Across category differences in future IRRs			
Hired & $IRR_{First,Rookie}$ − NotHired & IRR_{High}	−10.50	−6.20	−4.43
	(−2.04)	(−3.39)	(−2.57)
Hired & $IRR_{First,Vetern}$ − NotHired & IRR_{High}	−6.58	−3.45	−1.05
	(−1.27)	(−2.07)	(−0.59)
Hired & IRR_{Young} − NotHired & IRR_{High}	−8.06	−6.04	−3.06
	(−1.46)	(−3.88)	(−1.68)
Hired & PriorInv − NotHired & IRR_{High}	−0.16	−4.27	−0.75
	(−0.02)	(−2.25)	(−0.34)
Hired & PeerInv − NotHired & IRR_{High}	0.79	−4.58	−0.54
	(0.11)	(−2.38)	(−0.24)
Hired & Local − NotHired & IRR_{High}	−0.93	−4.70	−1.41
	(−0.13)	(−2.49)	(−0.67)

Internet Appendix: Joint Effects

It is interesting to consider the degree to which various selection criterion amplify or attenuate selection probabilities. To do so, we re-estimate specification (5) of Table 5 by adding interaction terms between IRR_{Young} and quartiles two through four of performance with PriorInv. We do not report the details of the regression but provide relevant combinations of coefficients in Table IA1 and highlight a few interesting results here. Consider an LP contemplating an allocation to a young GP with whom she has previously invested. Is this LP more likely to reinvest with this GP or allocate to a 4th quartile GP with whom she has no prior experience? The answer is that prior experience trumps 4th quartile performance (Panel C, row 1). Indeed, when LPs have no prior experience with 4th quartile GPs, they are significantly more likely to commit to first-time funds, with whom by definition they have no prior experience (differences in probabilities of hiring are 0.6% for $IRR_{First,Rookie}$ and 0.7% for $IRR_{First,Veteran}$). But if LPs have experience with 4th quartile GPs, they are less likely to select first-time funds (differences in probabilities of hiring are −17.1% for $IRR_{First,Rookie}$ and −17.0% for $IRR_{First,Veteran}$). Overall, both rookie fund and first-time fund chasing is much more likely when LPs have no prior experience with GPs.

As with the selection equations, it is possible to ask whether combining selection criteria improves outcomes relative to the opportunity set. To do so, we estimate future excess IRRs regression which contain triple interactions between the hired indicator variable, and combinations of other explanatory variables. As before, drawing inferences requires combining a variety of coefficients. Rather than overwhelm the reader with excessive combinations, we report the results in Table IA2 and discuss them briefly here. Because of the economic importance of repeat investment decisions as a source of soft information (and its derived influence on selection probabilities), we focus on four conditions: where an LP has a prior investment in both selected and non-selected GPs; where an LP has no prior investment in either selected or non-selected GPs; and where an LP has a prior investment in either the selected or non-selected GP (but not both). Regardless of the condition, there is no evidence that combinations of selection criteria generate positive differences in excess IRRs; all of the excess IRR differences in the Table IA2 are either negative or statistically indistinguishable from zero.

Table IA1. Combined Role of Past Performance and Repeat Investment in Selection

We estimate OLS regressions

$$Commit_{lfg} = \beta_0 + \Sigma_{i=1}^{4}\beta_{1i}IRR_{i,g} + \Sigma_{j=2}^{4}\beta_{2j}IRR_{Qj,g} + \beta_3 PriorInv_{lg} + \beta_4 PeerInv_{lg} + \beta_5 Local_{ig}$$
$$+\beta_6 \ln GPSize_g + \beta_7 IRR_{Young,g} \times PriorInv_{lg} + \Sigma_{j=2}^{4}\beta_{8j}IRR_{Qj,g} \times PriorInv_{lg} + FE + e_{lfg},$$

as in Table 5 except that we include some interaction terms with PriorInv. All regressions include FundRegion×FundType×VintageYear, and LP fixed effects. The table shows consolidated coefficients from such regressions (the individual regression coefficients are not displayed) that reflect the probability of hiring (in Panel A) or differences in probability of hiring (Panels B and C). *t*-statistics are based on standard errors clustered in the same grouping as fixed effects.

Panel A: Prob(Hiring)	
NotPriorInv & $IRR_{First,Rookie}$	0.01
	(7.90)
NotPriorInv & $IRR_{First,Veteran}$	0.01
	(7.78)
NotPriorInv & IRR_{Young}	0.01
	(4.25)
NotPriorInv & IRR_{High}	0.01
	(3.90)
PriorInv & IRR_{Young}	0.21
	(13.33)
PriorInv & IRR_{High}	0.18
	(13.27)
Panel B: Within IRR category differences in Prob(Hiring)	
PriorInv & IRR_{Young} − NotPriorInv & IRR_{Young}	0.21
	(13.12)
PriorInv & IRR_{High} − NotPriorInv & IRR_{High}	0.18
	(13.64)
Panel C: Across IRR category differences in Prob(Hiring)	
PriorInv & IRR_{Young} − NotPriorInv & IRR_{High}	0.21
	(13.15)
PriorInv & IRR_{Young} − PriorInv & IRR_{High}	0.03
	(2.18)
NotPriorInv & IRR_{Young} − NotPriorInv & IRR_{High}	−0.00
	(−1.26)
NotPriorInv & IRR_{Young} − PriorInv & IRR_{High}	−0.18
	(−13.11)
NotPriorInv & $IRR_{First,Rookie}$ − NotPriorInv & IRR_{High}	0.01
	(3.41)
NotPriorInv & $IRR_{First,Rookie}$ − PriorInv & IRR_{High}	−0.17
	(−12.70)
NotPriorInv & $IRR_{First,Veteran}$ − NotPriorInv & IRR_{High}	0.01
	(4.08)
NotPriorInv & $IRR_{First,Veteran}$ − PriorInv & IRR_{High}	−0.17
	(−12.64)

Table IA2: Combined Role of Past Performance and Repeat Investment in Future Excess IRRs

The table shows regression-implied IRR differences between different categories of funds from regression:

$$FutureExcessIRR_{lfg} = \beta_0 + \Sigma_{i=1}^{4}\beta_{1i}IRR_{i,g} + \Sigma_{j=2}^{4}\beta_{2j}IRR_{Qj,g} + \beta_3 \ln GPSize_g$$
$$+\beta_4 PriorInv_{lg} + \beta_5 PeerInv_{lg} + \beta_6 Local_{ig} + \beta_7 Hired_{lfg} + [\Sigma_{i=1}^{4}\beta_{8i}IRR_{i,g} + \Sigma_{j=2}^{4}\beta_{9j}IRR_{Qj,g}$$
$$+\beta_{10} \ln GPSize_g + \beta_{11} PriorInv_{lg} + \beta_{12} PeerInv_{lg} + \beta_{13} Local_{ig}] \times Hired_{lfg}$$
$$+\left[\beta_{14} IRR_{Young,g} + \Sigma_{j=2}^{4}\beta_{15j}IRR_{Qj,g} + \beta_{16} \ln GPSize_g + \beta_{17} Local_{lg}\right] \times PriorInv_{lg}$$
$$+[\beta_{18} IRR_{Young,g} + \Sigma_{j=2}^{4}\beta_{19j}IRR_{Qj,g} + \beta_{20} \ln GPSize_g + \beta_{21} Local_{lg}] \times PriorInv_{lg} \times Hired_{lfg} + FE + e_{lfg},$$

as in Table A3 and Table 7 except that we include a few triple interaction terms. All regressions include FundRegion×FundType×VintageYear and LP fixed effects. *t*-statistics based on clustered standard errors using the same categories as the fixed effects appear in parentheses. The number of observations is 1,668,163.

Panel A: LP has prior investment with both Hired and NotHired	
Hired & IRR_{Young} − NotHired & IRR_{Young}	−1.16
	(−0.77)
Hired & IRR_{High} − NotHired & IRR_{High}	−1.60
	(−0.84)
Hired & IRR_{Young} − NotHired & IRR_{High}	−5.44
	(−2.94)
Panel B: LP does not have prior investment with either Hired or NotHired	
Hired & $IRR_{First,Rookie}$ − NotHired & $IRR_{First,Rookie}$	−3.06
	(−2.09)
Hired & $IRR_{First,Veteran}$ − NotHired & $IRR_{First,Veteran}$	−2.33
	(−1.71)
Hired & IRR_{Young} − NotHired & IRR_{Young}	−1.07
	(−0.69)
Hired & IRR_{High} − NotHired & IRR_{High}	−1.25
	(−0.65)
Hired & $IRR_{First,Rookie}$ − NotHired & IRR_{High}	−6.30
	(−3.54)
Hired & $IRR_{First,Veteran}$ − NotHired & IRR_{High}	−2.88
	(−1.62)
Hired & IRR_{Young} − NotHired & IRR_{High}	−4.62
	(−2.50)
Panel C: LP has prior investment with Hired but not with NotHired	
Hired & IRR_{Young} − NotHired & IRR_{Young}	−0.90
	(−0.57)
Hired & IRR_{High} − NotHired & IRR_{High}	−0.61
	(−0.31)
Hired & IRR_{Young} − NotHired & IRR_{High}	−4.45
	(−2.40)
Panel D: LP does not have prior investment with Hired but does with NotHired	
Hired & IRR_{Young} − NotHired & IRR_{Young}	−1.32
	(−0.89)
Hired & IRR_{High} − NotHired & IRR_{High}	−2.23
	(−1.18)
Hired & $IRR_{First,Rookie}$ − NotHired & IRR_{High}	−7.28
	(−4.05)
Hired & $IRR_{First,Veteran}$ − NotHired & IRR_{High}	−3.86
	(−2.16)
Hired & IRR_{Young} − NotHired & IRR_{High}	−1.32
	(−0.89)