Why Funds of Funds?

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Private equity funds of funds (FOFs) have become big business. Today, FOFs form 14% of new money raised. I test six explanations for why limited partners (LPs) might use FOFs. First, I find that FOFs do not generally deliver superior returns. They do, however, perform well enough for the limited partners (LPs) that hire them. Second, FOFs allow small LPs to scale upward, to invest in more funds. However, I find that they do not contribute to diversification. What they really do is to provide smaller LPs a way to lower the cost of fund management. Third, FOFs allow large LPs to scale downward, to invest vast amounts over a short duration. However, the mechanism is imperfect because LPs can either use many FOFs and risk coordination problems among these FOFs, or use few FOFs and risk getting held up. Fourth, FOFs are used by LPs with weaker governance structures. Fifth, there is some evidence that LPs use FOFs to learn to invest in new areas, but the support is weak. Last, the use of FOFs is partly due to cyclical booms. These empirics also shed light on theories of financial intermediation, organizational boundaries, and agency mechanisms.

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Why Funds of Funds?

Private equity funds of funds (FOFs) have become big business. Their number tripled over the last three years. The amount raised doubled from $3.3 billion in 2000 to $6.3 billion in 2001, when other types of private equity slumped 60%. Today, FOFs form 14% of new money raised (Hyde (2002)).

This growth is puzzling. FOFs charge fees of 1% to 3% of assets, on top of and with the same magnitude as those by underlying private equity funds. A small number of FOFs, like Hamilton Lane, even have interest carry of up to 15%, on top of the 20 to 30% that venture capitalists (VCs) charge. One limited partner (LP)[2] exclaims: "Too many people are stepping on the money!"

While intermediation is much studied in the context of retail investments and mutual funds (see for example, the work by Chan (1983) and Holmstrom and Tirole (1997)), it is much less well understood in an institutional setting. Indeed, why LPs use FOFs is even more bewildering than why individuals buy mutual funds: unlike retail investors, who might be resource- or skill-challenged, institutions might be expected to need no help from intermediaries. Is it because:

1. FOFs deliver better <u>returns</u> than some LPs can manage on their own?

2. FOFs help small LPs in <u>upward scaling</u>, to achieve diversification over a wider set of funds and to avoid subscale operations?

3. FOFs help big LPs in <u>downward scaling</u>, so that these LPs can ramp up their private equity investments quickly? Downward scaling can also mean that large LPs can collapse many tedious fund-level approvals into an umbrella approval for a FOF, by giving the latter discretionary authority. Finally, the LPs do not have to build enormous capacity during the sparse investment points and capital calls, only to have the capacity underutilized at other times[3].

4. LPs with weaker <u>governance</u> structures use FOFs to shoulder the blame in case of bad performance? Or maybe LPs with *strong* governance but little resources to monitor VC funds want FOFs as additional pairs of eyes on the VC funds?

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[2] Personal communication with European-based LP. I use "institutional investor" and LP interchangeably in this paper. A survey by Asset Alternatives, Inc. shows that the mean management fee is 0.76% to 1%, and the carry is bi-modal, with most firms charging 0% or 5% (with a 8% hurdle rate) (2002).

[3] Upward and downward scaling are suggested by Asset Alternatives (2002), as described in the HBS case study by Hardymon, Lerner, Leamon and Angella (2003).

5. FOFs are learning vehicles, used by new LPs or LPs venturing into new areas?

6. FOFs are a result of too much money chasing too few deals in recent years, a temporary or cyclical phenomenon of the boom?

These explanations need not be exclusive, or even exhaustive. The first contribution of this paper is to document rigorous tests of these explanations for this burgeoning but largely unexplored part of finance, adding to the work of Gompers and Metrick (2001) for institutional funds and others for various types of private equity (e.g., Gompers and Lerner (1996), Mayer, Schoors and Yafeh (2002)). To do this, I take the union of the major datasets used in previous studies of private equity and add to that proprietary data from a major LP that manages over $100 billion, on the same order of magnitude as Calpers' $183 billion, but has a considerably bigger private equity arm that has co-investments with GPs such as Sequoia Capital, Matrix Partners, Summit Ventures, and TA Associates. I also obtain public information and hand-check the data, resolving a number of errors. Also, unlike previous studies (with the prominent exception of Cochrane (2001)), I correct for selection bias in my estimations. This is a problem pointed out by Kaplan and Schoar (forthcoming). The second contribution of the paper is to articulate how the empirics shed light on theories of financial intermediation, organizational boundaries, and agency mechanisms. These contributions are really more modest than they sound, because with such a broad sweep, this paper cannot be deep. The plan is to use the data assembled for this paper as a platform for deeper inquiry in the future.

But first, a word on how I define an FOF in this paper. I define it broadly, to include any fund that its manager calls an FOF and whose manager is not also the LP[4]. Therefore, I exclude activities of advisors or gatekeepers, but include FOFs who do not have discretionary authority. By including non-discretionary FOFs, I get more heterogeneity in my dataset. I also exclude those funds that might occasionally invest in funds but for the most part, their investment charter is to invest directly.

Some FOFs are captive or customized, industry jargon for those set up dedicated to single LPs. A prominent example is Grove Street Advisors' California Emerging Ventures, set up for CalPERS. However, most FOFs are set up like regular VC funds, except that they invest in funds rather than operating companies. An example is Lexington Capital Partners' eponymous fund II, whose LPs include Franz and Frieder Burda, Lakeview Direct Investments, and Pomplemousse, among others. Table 1 shows some examples of FOFs.

The rest of this paper has three parts: (1) theory and key findings, (2) data, and (3) results.

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[4] For example, the Government of Singapore Investment Corporation calls itself a "fund of funds" in the sense that it invests in funds, but it does not accept money from outside the government. It is not considered an FOF in this paper.

THEORY AND KEY FINDINGS

Each of the explanations outlined earlier – returns, downward and upward scaling, governance, learning, and booms – can draw upon a rich set of theories. My focus is on highlighting where theories offer conflicting predictions, so that this paper can shed light on them using the FOF setting.

Returns

Lerner, Schoar and Wong (2004) show that advisors do better than most other types of LPs, except endowments (see their Table 3). Their unit of analysis is the LP who invests in funds, of which one type is "advisors." If this includes FOFs, then their study suggests that FOFs offer potentially high returns. However, my focus is not on LPs who might be FOFs, but LPs who *use* FOFs. Indeed, there are three perspectives of how to compare FOF performance, each answering a distinctive research question. The first is to compare FOFs with other types of funds. For example, this might answer a question from the perspective of an LP: should I invest in an FOF versus directly into a private equity fund? The second is to compare FOFs with other types of LPs. This answers the question, perhaps for the general partner of the LP: are FOFs able to pick funds with better returns than my LP can? Yet, neither of these answers the question of why FOFs exists, since FOFs can exist as long as there are *some* LPs who find it worthwhile using them, even if other LPs do not. This suggests yet another method: compare FOF-using LPss with LPs who do not use FOFs.

I find that the answers to these questions are: (1) compared with other funds (i.e., as a recipient of money), FOFs do less well *on average*, (2) compared with other LP types (i.e., as a selector of funds), *on average*, FOF performance is statistically no different from zero, and (3) most important, *FOF-using* LPs get better returns from their FOF portfolios than their non-FOF portfolios. The exceptions are those FOF-users who are already good fund selectors – i.e., their non-FOF portfolios compare well with the portfolios of non-users. This suggests that, to a select clientele of LPs, FOFs do deliver value.

Where might superior returns come from? One possibility is a <u>size</u> effect. Or perhaps FOFs, as boutique shops, could better attract and retain <u>talent</u>. In particular, they have people who have more <u>experience</u> and the relationships to gain superior <u>access</u> to better funds? As suggested by Hardymon, Lerner, Leamon and Angella (2003), better access could also arise because GPs prefer FOFs because the latter need less hand-holding, unlike inexperienced LPs, and they do not require GPs to fill bulky questionnaires, unlike the gatekeepers so often engaged by pension fund investors. Finally, could FOFs garner superior returns because, unbeknownst to LPs, they simply take more <u>risks</u>?

What do theories predict, and what do I find? Starting with size, a good place to start is to consider the theories on mutual fund performance. In that literature, the size effect has many views. One is that size offers economies of scale. But size can limit the ability of a money manager to make large trades, with its attendant impact on price and liquidity, as pointed out by Chen, Hong, Huang and Kubik (forthcoming). Grinblatt and Titman (1989) find that size has an overall negative impact. Like Kaplan and Schoar (forthcoming), I find that FOF size has a concave relationship with returns, but unlike them, I find this statistically insignificant. The finding adds weight to their theme that size does not have a straightforward linear relationship with performance.

I find that once size is controlled for, the explanatory power of FOF-usage is reduced but does not vanish, so something more is going on. The second possible driver of returns is the ability of FOFs to attract and retain talent, who have the requisite experience and access to better funds. While I do not have data on talent, I have data to test for experience and access. Contrary to popular opinion, I find that FOFs tend to have less experienced staff. This might account for their generally negative performance. In terms of access, FOF-using LPs are less skilled than non-users. Looking at the former's FOF and non-FOF portfolios, I find that their FOF portfolios do show better access than their non-FOF portfolios. In short, FOFs deliver superior access to those with poor access.

A final consideration is risk. Since all the above findings have controlled for observable characteristics such as stage and scope of investment, it appears that risk alone does not explain for the mixed performance of FOFs.

Upward Scaling

In upward scaling, FOFs might help *small* LPs to: (1) achieve diversification over a wider set of funds and (2) avoid subscale operations. The picture I have in mind is in Figure 3. Suppose the minimum efficient scale, however measured (say relative to market practice), has an upward-sloping relationship with the degree of diversification (a measurement which I will describe below). That is, if an LP wants to put money in many funds (diversify), it has to be a big one (large minimum efficient scale). The first question is whether FOFs help LPs move right. The second question is in moving up – i.e., conditional on a desired level of diversification, LPs can be smaller to achieve minimum scale.

The diversification issue has been heavily studied in the context of mutual funds. The received wisdom is that retail investors can diversify by themselves without overly high transaction costs, so diversification cannot be a motive for investment or fund premium. Cumby and Glen (1990) show this for international funds. Indeed, there is an argument for <u>not</u> diversifying, so that fund managers can maximize their informational advantage in narrow sectors. Kacperczyk, Sialm and Zheng (2004) look at mutual funds from 1984 to 1999 and find that controlling for other effects, concentration helps performance in a risk-adjusted sense.

I find that diversification is unlikely to be a motivation for using FOF too, since the non-FOF portfolios of FOF-using LPs are *more* diversified than the portfolios of non-users. Furthermore, conditional on FOF usage, the FOF portfolio is *less* diversified than the non-FOF portfolio.

Although diversification may not be an explanation, what about the other dimension of upward scaling, that sub-scale LPs might use FOFs to get to minimum efficient scale? I find this to be more plausible. This cost-reduction explanation can also be cast in terms of outsourcing, analogous to the case for mutual funds, studied by Chevalier and Ellison (1997) and Chen, Hong and Kubik (2004). They suggest three more predictions. First, FOF-using LPs, as principals, must have the tool to ensure that FOFs as agents indeed exert the appropriate amount of effort. That tool is high-powered incentives. In my case, the specific prediction is that the use of FOFs would increase the chance of an LP not investing in a follow-on FOF in the same series for poor performance, a test suggested by Lerner, Schoar and Wong (2004). This sensitivity should be skewed more toward poor performance. Second, if FOFs operate under higher-powered incentives, they should take less risk, since effort is unobservable but poor performance is. Third, if FOFs take less risk, they ought to get lower return, assuming a reasonably efficient market. This last prediction does not contradict the earlier one which says that I expect *higher* returns for FOF-usage, because that is *after* controlling for risks.

I find that LPs do use higher-powered incentives for FOFs. Specifically, LPs' reinvestment decisions in follow-on FOFs are more performance-sensitive than those for other funds. I also find that FOFs do take lower risks, controlling for other effects. As a consequence, they also have lower returns, adjusted for risks.

Downward Scaling

There is another explanation for the use of FOFs, this time by large LPs. The oft-told story is that of Calpers' need to ramp up its private equity investments. The peculiarity of the situation is that working with multiple FOFs might increase the chance of these FOFs battling with each other, using Calper's money among themselves, to invest in the same portfolio company. Theories on vertical restraints inform this problem, which is often identified with the lack of coordination and free riding among distributors. There are standard industrial organization prescriptions, the most common of which is to reduce the number of distributors or establish exclusive territories, first explored by Telser (1960). This is the exactly analogy of the appointment of Grove Street Advisors as a captive FOF. On the other hand, working with only one FOF makes Calpers subject to holdup problems, especially when it is difficult to monitor the FOF's real effort. I should expect to see some remedial devices, such as the kind of staging solution documented by Gompers (1995). Ironically, this leaves unsolved the original problem of how to rush out large quanta of money into the market. The FOF setting offers an interesting one to see how the empirics turn out, since this issue of rushing out large quantities through exclusive agents might be increasingly important in a world where product lifecycles are shortening. I find empirical support for this tradeoff mechanism.

Downward scaling can also mean that LPs use FOFs so that they can collapse many tedious fund-level approvals into an umbrella approval for FOFs given discretionary authority. This is reminiscent of the Grossman and Hart (1986) argument that ownership of assets and residual rights should optimally be in the hands of the party that has a comparative advantage in capabilities (in this case, in moving fast). By outsourcing to FOFs, LPs also do not have to build enormous capacity during the sparse investment points and capital calls, only to have the capacity underutilized at other times. Both of these are efficiency arguments, and are covered in the previous discussion on outsourcing. Therefore, I do not repeat any testing.

Governance

Lerner, Schoar and Wong (2004) posit that one of the reasons some LPs such as endowments might outperform others is that they have better governance structures in place. Their managers are less likely to be political appointees, and are more likely to have high-powered incentives. I find confirming evidence of this for the use of FOFs too. Specifically, I find that public-sector LPs tend to use FOFs more than any other LP types.

Learning

LPs might also use FOFs as stepping stones into less familiar investment areas. A common learning mechanism is to insist on co-investment rights when signing up the FOF. For example, Grove Street Advisors agree to let Calpers invest alongside GSA's investments, and in stages, reduce the proportion of investment by GSA-managed funds and increase that of Calpers' direct investment into identified portfolio companies. I do not have detailed information about co-investment arrangements. However, if learning were an explanation, I should see that FOF-using LPs tend to be those who are younger or are newer to the area of investing. I use an SUR (seemingly unrelated regression) estimation to control for the many dependant variables (FOF usage by different investment areas like venture capital or buyouts) and independent variables (age, newness to investing, etc.). I find support for the learning proposition, but only when the FOFs concerned are specialized ones. This makes intuitive sense, as learning might be important only for specialized areas and not general ones.

So far, I have not incorporated FOF performance into the learning model. A different prediction of the learning explanation is that FOF-using LPs in say, venture capital, tend to increase their commitment to the same investment scope after a short *positive* experience with FOFs. Figure 5 shows how the learning versus performance stories might look like, in terms of LPs' increased commitment, FOF performance, and the length of experience with FOFs. In the left graph is the performance story. It shows that LPs would manage more funds in-house if their FOFs are not delivering, and out-source more if FOFs deliver. In the right graph is the learning story, which gives the opposite predictions, *but only in the short-term*. In the short-term, if their FOFs do well, LPs would have obtained a positive learning experience and try to do more themselves, reducing out-sourcing. If their FOFs do poorly, LPs might try other FOFs or quit trying to learn to invest in the area. In the longer term, conditional on learning having been saturated, the effect of FOF performance is the same as that of the performance story. Therefore, in testing the learning story, I have to be careful not to confound the short- and long-term.

I find stronger support for the performance story, although again, there is weak support for the learning story for specialized areas.

Temporary or Cyclical Phenomenon

There is a final explanation I can think of to explain the rise of FOFs. They could be popular in the last decade because of the economic boom. I find support for this too.

To summarize, there is unsurprisingly more than one explanation for the use of FOFs. But surprisingly, I find little support for some commonly thought explanations, such as the use of FOFs to take advantage of their experience or for diversification. Even learning is only weakly supported. The general theme appears to be the use of FOFs for more straightforward efficiency reasons.

DATA

I build the sample from several sources.

First, from *SDC Platinum*, I obtain profiles of 1,900 LPs who invest in 8,559 funds, managed by 3,997 GPs (general partners). This is the official database of the National Venture Capital Association, but operated by Thomson Financials.

Second, there is another Thomson Financials database, *VentureXpert*, that turns out to be sufficiently different from the SDC dataset, so I obtain it too.

Third, Thomson Financials also has a print version of the *Directory of Limited Partners* that is yet again slightly different than the first two! I have to hand-code information from this source.

Fourth, from *Private Equity Intelligence*, I obtain a dataset with profiles of funds, GPs, LPs, and the relationships among theses. Importantly, PEI has internal rates of return (IRRs) for 1,782 funds, which are said to be cross-checked between reporting by LPs and GPs. Although I have only IRR as the single measure of performance, Kaplan and Schoar (forthcoming) show that this measure is highly correlated with others they use. These were IRRs calculated with cash in- and out-flows, public market equivalents that benchmark returns against the S&P 500 return, the IRRs reported to Venture Economics at the end of five years after first closing of funds, and the total value of funds to paid-in capital. For FOFs, the IRRs are after fees and carry of the FOF manager.

Fifth, Asset Alternatives' *Galante Directory* provides yet another source.

Sixth, I manage to get IRR and fund profiles *direct* from a number of LPs, and hand-coded these. The following have IRR information: (1) the University of Michigan endowment, (2) CalPERS, (3) California State Teachers' Retirement System, (4) Colorado PERA, (5) Orange County Employees Retirement System, (6) Regents of the University of California, (7) UTIMCO, (8) Washington State Investment Board, (9) Oregon Public Employees' Retirement Fund, (10) Ohio Public Employees Retirement System, (11) Pennsylvania Public School Employees' Retirement System, (12) Idaho Public Employees Retirement System[5], and (13) Illinois Municipal Retirement Fund. The others have only fund information, including their commitments and amount drawn down. Among them, about two dozen have fairly complete and detailed lists of their investments.[6] The primary ones are the National Association of College and University Business Officers (with endowment information) and the Employee Retirement Systems of State and Local Governments Census from the U.S. Census Bureau (with state pension information).

Seventh, I also check in detail the *websites* of over 375 funds, FOFs, and LPs for original material. I use these

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[5] This shows the "time-weighted rate of return in accordance with AIMR's Performance Presentation Standards."

[6] These are: (1) Abbott Capital Management LLC, (2) Alaska State Pension Investment Board, (3) AP2 Sweden, (4) AP3 Sweden, (5) Census, (6) Colorado Fire and Police Pension Association, (7) Delaware State Board of Pension Trustee, (8) Finnish Local Government Pensions Institute, (9) Fondinvest, (10) Indiana State Teachers' Retirement System, (11) Kansas Public Employees Retirement System, (12) Los Angeles City Employees' Retirement, (13) Massachusetts Pension Reserves Investments, (14) Minnesota State Board of Investment, (15) NACUBO, (16) New York State Teachers' Retirement System, (17) Norsk Vekst Forvaltning., (18) Oregon State Treasury, (19) Oregon University System, (20) Pennsylvania State Employees' Retirement, (21) San Diego County Employees Retirement, (22) Virginia Retirement System. I also obtain information from about 40 other LPs, but they have spotty information. Examples are the Hewlett Foundation, the Connecticut Treasury, the European Investment Fund, and the Kern County Employees' Retirement Association.

to confirm what I got from the other sources or to obtain updates or new information. From another 400 plus websites of these similar entities and those of third-parties such as magazines, books, reports, and 44 HBS cases and teaching notes, I find information such as whether two funds belong to the same GP under different names.

Finally, I use Nelson Information's *Investment Managers*. From this, I extract by hand the age, experience, and years-with-firm information for executives in LPs and FOFs. There are over 1,700 money managers in the database, and I randomly select 706 into the dataset.

From these sources (except the last), I construct a union of the datasets, manually matching fund with fund, LP with LP, assigning each a unique identifier. One tricky bit about assembling these datasets is that there is some recursion in the logic, since an FOF can be in a fund dataset as well as an LP dataset. I have to ensure that the entity is correctly identified as the same one in both. With these multiple sources, Table 2 shows that I am able to significantly enlarge the samples of any individual source taken alone. This is important given the sampling biases in individual datasets, as reported by Kaplan, Sensoy and Stromberg (2002).

Table 2 does not, however, show the qualitative improvements in the dataset. Scrubbing using multiple sources and the visual inspection of each observation turns out to be important because each non-original source has its share of errors or issues to resolve. For example, some of these are due to different reporting times (I take the latest) and others to coding errors (e.g., fund's closing date does not match with vintage year). Conversely, some funds have the same label but are really different. For example, there are several entries for an "Allstate Insurance Co." fund, but one was started in 1958 and another 1987. Using discriminating information such as vintage and size, I identify these distinctive entities.

The trickiest is the IRR information, since the differences are mostly genuine – LPs could enter the same funds at different times, often producing dramatically different IRRs. This is highlighted by a stinging letter from HTMF (Hicks Muse Tate & Furst, a GP) to its LPs and the *Financial Times* for reporting CalPERS' return from Fund III as 5%, rather than 14.4%[7]. The complaint is that the *Financial Times* "mis-characterized" the fund's IRR, since CalPERS entered Fund III only in 1997, after the formation of the fund in 1996. The main estimations are done using IRRs for the full investment duration of the funds, but I also conduct robustness checks using LP-specific IRRs from the dozen LPs listed above.

[7] Letter from Mr. Dan H. Blacks, HTMF partner, to the *Financial Times*, July 23, 2001. This appears to be unpublished, as a search in Factiva does not reveal it.

RESULTS

My empirical strategy follows the example set out by Lerner, Schoar and Wong (2004). Table 3 summarizes the dataset of LPs. A few observations stand out. First, there is sufficient heterogeneity among key variables, such as vintage and size (assets under management), overall and even within types of LPs that use or do not use FOFs. Although I do not have many observations where the percent allocation to FOFs is observed, for those observed among FOF users, there is also heterogeneity in allocation, from 0.1% to 100%. There is also heterogeneity in the type of FOF used, captured by the rather awkward "maximum number of LPs in the FOF." Say an LP invests in several FOFs. Each FOF may draw money from any number of LPs. The "maximum number of LPs in the FOF" is the maximum of this last, for an LP's FOF. LPs who use only captive FOFs would have this equal to 1. Among FOF-using LPs, the mean is 2 LPs in their FOFs.

The second observation about Table 3 is that FOF-users *in general* tend to be older. In panel (b), the mean vintage for those FOF-using LPs is 1989, while that for non-users is 1991. Third, the average size of the FOF-using LP is larger than that of the non-users, suggesting that FOF-usage is not confined to ill-endowed small LPs trying to scale up. Fourth, FOF-using LPs in general allocate less of their portfolios to private equity.

Fifth, FOF-usage by LP class is consistent with the earlier observation that large LPs are not averse to using FOFs. Banks and non-financial corporations tend to use FOFs less. This is plausible if we believe that banks have asset management skills and contacts as good as most FOFs'. It is less obvious why non-financial corporations (which include corporate pension funds) use FOFs less – perhaps they are too small to be of interest to FOFs, or perhaps the non-pensions among them are corporate venturing LPs who prefer direct investments of strategic interests. Educational institutions tend to use more. This is somewhat surprising because education institutions tend to be performance-oriented, hinting that FOFs deliver value to some types of LPs. Interesting, some FOFs are LPs themselves, who in turn invest in FOFs. However, this is rare.

Sixth, in terms of usage by geography, FOFs are used slightly more in the Americas than elsewhere. This is to be expected if we believe that the fund management business is more developed in the former. For American LPs, usage has only slight variation by state location, at least among the states with the most LPs.

Table 4 also shows summary statistics, this time for funds, including FOFs as a distinct group. I tabulate FOFs both as LPs and as funds. As LPs, the perspective is interesting as a comparison to previous work on LP performance. As funds, the perspective is more pertinent to this paper, with the LP as a decision-maker looking at FOFs versus regular funds.

Again, several interesting observations stand out in the table. First, FOFs appear to be larger than non-FOFs on the average. One average, the actual size is also closer to the targeted size at fund raising. Second, FOFs tend to be younger. This is expected, since the FOF phenomenon is relatively new. Third, FOFs take longer from closure of financing to the first investment. This is somewhat surprising since I expect that it is easier to find and evaluate funds than portfolio companies. The small number of observations for this statistic may be driving this. The mean time from the first investment to the last is 3 years for FOFs and double that for non-FOFs. This is more consistent with my expectation that it is easier to find and evaluate VCs than to do so for portfolio companies. Fourth, FOFs appear to have bigger sequence numbers in the dataset. Venture Economics provides sequence numbers at the GP level. However, LPs might make follow-on investments in the same fund series, not across series. Therefore, I manually construct another sequence number, based on fund series. I am able to unambiguously identify the number for 2,885 funds. The larger average sequence numbers for FOFs suggest, but do not conclusively imply, that FOFs run "out of fashion" less frequently than the regular private equity fund. Fifth, the investment characteristics of FOFs and non-FOFs appear similar. FOFs tend to invest amounts as large as those for non-FOFs, both per round as well as per portfolio company[8]. The rather large amount by non-FOFs masks the fact that there are buyout funds in that category. For example, the round average for non-FOF buyout funds is $24.6 million. Sixth, and glaringly, the mean IRR for FOFs is lower than that for non-FOFs. I also calculate "excess IRRs," which are IRRs from the benchmark IRR of funds grouped by: (1) vintage, (2) stage (e.g., early versus mezzanine), (3), investment scope (e.g., venture capital versus distressed debt), and (4) continent (e.g., Americas versus Europe). The means of excess IRRs exhibit the same pattern.

The rest of Table 4 does not have sufficient data for FOFs, so I just document them. Because commercial datasets classify FOFs along the same dimension as others in "investment scope," the data does not show the scope of FOFs themselves. The distribution of FOFs by stage is also spotty. There is more information on location, and it is interesting that many FOFs are in Connecticut, relatively speaking.

I next link LPs with funds. Table 5 shows the characteristics of LP-fund observations, following the approach in Lerner, Schoar and Wong (2004).

Once again, I list some observations. First, comparing the overall LP profile of these LP-fund pairs with the profile of just the LPs, I see that the average LP here is much larger, at $20.5 billion rather than $2.7 billion. Therefore, the results in this paper need to account for this bias. The larger size, however, is not significantly larger than the $18.0 billion average in the LP-fund dataset in Lerner, Schoar and Wong (2004). The other characteristics, such as vintage, allocations, and number of investees, are not significantly different from

[8] For FOF's, the data is down to the eventual portfolio company level.

theirs.

Second, continuing on the overall profile into funds, the comparison between fund size here and in the pure fund dataset earlier shows a size bias, with a larger mean here ($792 million) versus there ($239 million). This is comparable with the same in Lerner, Schoar and Wong (2004), who have $777 million versus $406 million. Consistent with those authors' report, the mean sequence numbers are higher for educational and non-profit institutions and consultants, and lower for financial institutions. The IRR is also generally higher for educational institutions. My dataset also has IRRs specific to LPs. Funds of funds seem bludgeoned to death on IRRs. However, I need to check LP-specific returns. This is important as some GPs complain that any IRR disclosed for a LP-fund is specific to the LP due to the LP's timing of entry into the fund. Since Private Equity Intelligence's fund IRRs are at the level of the fund, I check if LP-specific returns are any different. To the extent data is available, the LP-specific returns do look somewhat different. I present results later on the statistical significance of this.

Third, moving onto investments into funds of funds, the table shows that the investing LPs are not strikingly different than those of the general profile. Returns from funds of funds also appear relatively low, compared to the general returns profile earlier.

I also create a smaller dataset for fund vintages 1998 or earlier. This excludes right-truncated observations that might not have performance data, avoiding some of the look-ahead bias described by Carhart and et al. (2002). All the estimations below are repeated with this smaller dataset. Because the results are qualitatively unchanged, I do not report them, except for a few important regressions.

I now test the specific explanations discussed earlier.

Returns

Recall that I propose three perspectives for looking at FOF returns, each answering a distinctive research question. The first is to compare FOFs with other types of funds. The second is to compare with other types of LPs. The third is to compare between FOF-users and non-users, rather than between funds or LP types.

1 – Comparing FOFs with Other Funds. To answer the first question, I compare fund returns under a number of controls. To control for scale differences, I use fund size and sequence numbers. Kaplan and Schoar (forthcoming) show that these can have quadratic relationships. They also control for risk using an indicator for venture capital (VC) funds. In Table 6, Model (1) is my replication of their main result in their Table VIII. My signs are all identical to theirs. However, their estimation has significant coefficients for log(size), $\log(\text{size})^2$, and the VC indicator, while my estimation has only significant coefficients for $\log(\text{size})^2$.

This is despite my having 1,256 observations, compared with their 746. However, the *F* statistic on my two size variables *together* is 14.1, which is a highly significant p-value of 0.000. And like them, I obtain little significance on the sequence variables. Therefore, I believe we have directionally the same results.

As a robustness check, I undertake a second estimation in Model (2) with a different definition of "sequence" - by GP, rather than fund series – and with an additional NASDAQ level control. I also use GP fixed effects. The definition of GP itself poses a problem. It is not obvious whether say, "3i PLC" (from the UK) and "3i (US)," should be considered the same GP. The answer depends on how 3i organizes itself, which is information that is difficult to obtain for all GPs. By inspecting the 4,849 corporate names, location, investment, scope, and vintage, I am able to hand-code two distinct variables: one that classify GPs broadly at the holding group level (*GPglobalID*) and another at the local organizational level (*GPlocalID*). This distinction also happens when a GP morphs, say after acquisitions, from "Adler & Co." to "Adler & Shaykin." Model (2) uses *GPglobalID*. After all this, the results are qualitatively unchanged from those of Model (1). They are also unchanged using *GPlocalID* (unreported).

I now come to the FOF question. Model (3) has the same specification as (2), with a new FOF indicator. The FOF indicator has a positive coefficient, but not significant.

However, I am concerned about two kinds of sample selection bias. The first, pointed out by Kaplan and Schoar (forthcoming), is that GPs might selectively stop or start reporting IRRs. I repeat their test, by regressing the presence of the IRR for a fund on the IRRs for previous funds in the sequence by the same GP. Like them, I find a positive coefficient on the IRR of the previous fund, so bias is a concern. The second source of bias is that *Private Equity Intelligence* might be more likely to get IRRs from bigger funds, more recent funds, funds that invest bigger amounts (so these are likelier to show up in the media), or funds in the major centers (California or Massachusetts) or where PEI has offices (Pennsylvania and London). Table 7, panel (A), shows t-tests that reveal statistically different means between the subsets with and without IRR information, all at the 0.000 significance level. These reasons motivate my sample bias correction below.

Going back to Table 6, in Model (4), I use a two-stage Heckman correction procedure for my estimation. The selection equation is a probit with the following fund-level covariates:

$$ProbabilitySelected = \beta_0 + \beta_1.log(FundSize) + \beta_2.FundVintage + \beta_3.RoundAverage + \Sigma\beta_4.MajorStateIndicator + \beta_5.USorUKindicator + \beta_6.PreviousIRR + \varepsilon.$$

Hopes are dimmed in Model (4). The coefficient on the FOF indicator is negative, albeit still insignificant. The inverse Mills ratio has a significant coefficient, indicating that the uncorrected estimations have sample selection bias.

I have thus far relied on the controls in Kaplan and Schoar (forthcoming). But I can use more specific controls – such as various stages of funds rather than just an indicator for VCs – and indicators for geographic regions and investment scope. Also, besides sequence number, I can use another instrument for risk, which is the average amount per round for each fund. Finally, I add a variable for fund vintage.

The estimation with all these additional controls is in Model (5). Now, the FOF indicator has a negative coefficient that is very significant, at the 1% level.

All the regressions here and in the rest of the paper are repeated with excess IRR as dependant variable, and other measures of the total fund flows, such as the S&P index and sum of private equity flows in place of the NASDAQ. They are also repeated with the smaller pre-1999 dataset. The results are qualitatively unchanged and not reported here.

2 – Comparing FOFs with Other LPs. While these negative performances of FOFs look discouraging, it is only from the perspective of an average LP. But LPs are different, and I next address the second way of looking at FOF returns: compare if FOFs are able to pick funds better than *some* LPs. Table 8 starts with the specification in Lerner, Schoar and Wong (2004), in Model (1)[9]. The results are qualitatively the same as theirs. The more significant coefficients are for educational institutions and foundations, and these are positive.

For the previous reasons, I once again employ a Heckman correction. I first build the selection model. A suggestion of how selection works in the dataset is in Table 7, panel (b). It shows that the distribution of LP type varies significantly between the sub-dataset with IRRs and the one without. The LP-fund pairs that have IRR information tends to associated with younger funds and bigger LPs, so I use the following selection model:

$$ProbabilitySelected = \beta_0 + \beta_1.log(FundSize) + \beta_2.FundVintage + \beta_3.RoundAverage + \Sigma\beta_4.MajorStateIndicator + \beta_5.USorUKindicator + \Sigma\beta_6.LPtypeIndicators + \beta_7.Log(LPsize) + \varepsilon$$

Table 8, Model (2), shows the Heckman corrected estimation. The inverse Mill's ratio is large and significant, confirming that there is sample selection bias. More coefficients for LP types are now significant, although that for "Fund of Funds" is still not. While the top performers in Model (1) are, in order, Educational

[9] These authors also do a robustness check using just funds rather than LP-fund pairs, which might contain too much heterogeneity correlated with returns. I repeat their process here and the results are qualitatively the same (unreported).

Institutions, Foundation, and Government, those for the corrected Model (2) are, also in order, Consultants/Gatekeepers, Government, and Educational Institutions.

3 – Comparing FOF Usage with Non-usage. The previous result is more encouraging in terms of FOF returns, but is still a general answer, such as "FOFs as a class performs better than many other types of LPs." I now take on the third perspective, which asks directly: do FOF-users do better than non-users, controlling for all relevant variables?

In Table 8, Model (3), I show the estimation with an indicator for FOF-usage. That is, unlike the previous indicator for whether an LP is an FOF, this is indicator for whether an LP uses FOFs. Its coefficient is negative and statistically significant. It is also economically significant: one standard deviation of FOF-usage (0.50) decreases IRR by 0.98 basis points; the mean IRR is 5.00 basis points and the standard deviation 40.33.

It is also useful to see how this LP comparison looks like if I add FOF-usage as an orthogonal dimension to LP type. Model (4) shows the interactions between the indicators for FOF-usage and LP type. To see the performance of FOF-usage, I need to conduct joint tests of the indicators for both FOF-usage and LP type. Table 9 shows that all joint tests are significant, both statistically and for most LP types, economically too, and in a negative way.

This is still not the end of the story because thus far, poor performance of FOF-using LPs (versus LPs not using FOFs) could be interpreted in two ways: is the poor performance a cause or effect of FOF-usage? One way to disentangle these competing explanations is to look at compare the non-FOF portfolio of FOF-users and those of non-users. This is what I do next.

In Model (5), I add an indicator for whether the invested fund is an FOF. I interact this indicator with the earlier indicator for FOF usage. Finally, I interact these three – the indicators for FOF fund, FOF usage, and their interaction – with LP type. A picture can help clarify what this is all about. In Figure 1, I lay out the two comparisons we want to address. The first, which I label unimaginatively as "intra-user comparison" is: conditional on FOF usage, how well do LPs' FOF investments do versus their non-FOF investments? The second is called "user-non-user comparison": how well do FOF users do versus non-users in selecting non-FOF (regular) funds? The (b) panel in Figure 1 provides a simplifying picture of these comparisons. I tabulate the answers, by LP type, in Table 10. In general, I observe that those FOF users who are good (can pick non-FOFs as well as the non-users) find that their FOF portfolios do not do as well as their non-FOF portfolios. This is easy to see when I plot same data on a graph, in Figure 2. This answers the question of why some LPs use FOFs: because they are not as strong as other LPs in picking funds. Within any LP type save advisors, the data points are near or below the horizontal axis. Advisors are somewhat special given that some of them run FOFs themselves, so their odd position is understandable.

The analysis and finding are not surprising. However, they are useful because they clarify the appropriate ways to evaluate FOF performance (intra-user) and usage (user-non-user), and they also pose some puzzles, such as why are there some dots positioned to the left of the vertical axis in Figure 2 – i.e., when FOFs do not seem to contribute to performance. The rest of this paper serves to answer puzzles like these, on why FOFs are used.

But first, let us dive deeper, to understand the drivers of returns. Recall that existing theories provide some propositions for why FOFs could do better (or worse) than other funds in the FOF-users' portfolios: size, ability to better attract and retain talent (especially those with experience and relationships to gain access to better funds), and risks taken.

1 – Returns Driven by Size? Continuing with the dataset of LP-fund pairs, a simple OLS regression with log(fund size) as the dependant variable and indicators for FOF-usage, FOF-fund, and the interaction of these two shows that on average, users invest in bigger funds than non-users do. But within users, the FOFs invested are smaller than the regular investments (unreported). I now check if IRRs are affected by this size difference. In Table 11, I first undertake the user-non-user comparison; this means that I confine the sample to investments in regular, non-FOF funds. As a way of showing robustness of earlier results, I now use the pre-1999 dataset. Model (1) is without fund size as a control, and it simply confirms the qualitative results of the earlier user-non-user results. Model (2) is with size as a control. The significance of all the FOF-usage interactions vanishes. However, a joint test on whether all these interactions are *simultaneously* zero is roundly rejected, with a chi-square of 3,300,000 and a *p*-value of zero. Furthermore, the regression as a whole and the size coefficients themselves are insignificant. I interpret this as size explaining part of the user-non-user heterogeneity in performance, but there remain significant portions unexplained. Models (3) and (4) repeat this for the intra-user comparison – that is, I now limit the sample to only FOF-users, and for pre-1999 IRRs. The result is analogous, with the joint test being rejected with a chi-square of 6,500,000 and p-value of zero.

I also use an alternative way of checking the size effect, similar to that used by Lerner, Schoar and Wong (2004) when they test for the effect of investment style. Using a specification that includes fund type, LP type, and vintage, they look at how the adjusted R-square goes up with additional variables. In my case, adding size and size squared increases the adjusted R-square slightly, from 13.8% to 15.5%. The coefficient for FOF-usage maintains its importance, from -3.90 at the 0.003 significance level to -2.81 at the 0.037 significance level.

2 – Returns Driven by Talent? The second possibility, after size, is that FOF firms pay better than FOF-using LPs in attracting, developing, and retaining talent. I do not have pay information, and even if I do, many FOFs have been established only recently, so to the extent their managers' pay have variable components such as interest carry, the pay information might not be useful. Therefore, I focus on two observable elements of talent that are important: experience and access.

My data on experience is also somewhat sketchy, because I do not have executives' experience in the LPs, but only in FOF LPs. However, I do have data for private equity funds and other public-markets money managers. I compare executives in FOFs against those in these outfits. While this provides some insights, the analysis does not correlate experience with returns, holding other variables constant. Table 12 shows a summary of the data. Ten percent of the firms are private equity firms, and 3% are private equity FOFs that are in our earlier dataset. There are 18 in this last group, out of the 709 we have earlier. I check for representativeness, and their sizes and vintages are not particularly skewed (unreported). The striking observation about Table 12 is that the average private equity executive has slightly less experience and is younger than the average money manager, and the one in private equity FOFs has even less. More formal regressions in Table 13 confirm this. While this cannot be said to be confirming evidence that FOF executives are less experienced or younger than those in other *LPs*, and even less indicative of any relationship with returns, the fact that they are so viz-a-viz other private equity funds mildly suggests that the lack of experience might be the reason for FOFs' relatively poor performance.

The measure of talent is access. I use two ways to analyze this. First, I have some data on LP-specific timing of investments into funds. Presumably, only LPs, including FOFs, that have superior access can get into a fund earlier than the generic fund vintage date given by commercial sources like Thomson. This is true *ex ante*, for funds of high or low quality. Therefore, my first method is to check if FOFs enter funds earlier. The second method follows Lerner, Schoar and Wong (2004) by investigating whether any relationship between IRR and FOF usage disappears if the dataset is limited to young funds. For young funds, it is argued, no LP would have superior access through earlier, established relationships. The results of these two methods are qualitatively the same, so I report only that from the first method.

Table 14 shows the summary of the differences in access, measured by (the negative of) lateness, which is in turn defined as the year the LP enters a fund subtracted by the fund vintage year. Some of the lateness figures in the table are very large, and this is due to a number of funds that are open-ended. Since I want to measure access, the appropriate consideration would be only those funds which have a shorter window of entry. I use various cut-offs, from 10, 5, and 3 years[10]. As the table shows, FOF-using LPs tend to be later than non-using LPs when entering regular funds. The difference is significant. This means that FOF-users have poorer access, which might be the reason they employ FOFs. In the intra-user comparison, the FOF-users' FOF portfolios have statistically significant better access than their non-FOF portfolios. The next step is to see if these superior access by non-users and FOFs really contribute to better returns. Table 15 shows that the answer is: likely. Models (1) and (2) show the user-non-user comparison. In Model (1), as a baseline, does not control for lateness. In Model (2), I add lateness and the interaction of lateness with fund size. Without the interaction, the lateness variable has a positive coefficient (unreported). I interpret this finding as masking early entry into low and high quality funds. Rushing into smaller funds, which I suggest is of generally poorer or unknown quality compared with larger funds, does not tend to provide good results. Therefore, I add the interaction variable. The access coefficients are now of the predicted signs, and are statistically significant. Superior access is positively correlated with performance, for bigger (better) funds.

In Models (3) and (4), I analyze the intra-user comparison. The results are qualitatively the same.

3 – Returns Driven by Risk? The final consideration is risk. I only have observable characteristics, such as fund stage, investment scope, and round average amount. These have been either explicitly controlled for or are worked into fixed effects in previous estimations (e.g., see Table 6). Since there are significant coefficients on the other explanatory variables despite these, I conclude that these remaining differences are unlikely to be due to risk.

This completes the discussion of returns by FOF, and the potential reasons behind return heterogeneity. In the next few sections, I consider other reasons why LPs might use FOFs.

UPWARD SCALING

Upscaling is about *smaller* LPs using FOFs to move right (diversify) and up (improve efficiency) in the Figure 3. In Table 3, Panel (b), I observe that, on the average, it is *larger* LPs that use FOFs. So the upward scaling explanation is not starting on a hopeful note. I now dive into the details to see if this pessimism is justified.

1 – Upward Scaling to Diversify? I start with the diversification dimension. In an intra-user comparison, if I see that the non-FOF portfolio of an LP is more diversified – measured in some suitable way – than the FOF portfolio, I can conclude that diversification is not a motive. If the non-FOF portfolio is less diversified, then it is inconclusive as to what is happening, since the lower diversification could be the cause or the result of

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[10] I also Winsorize the data instead of just cutting off the outliers. The result is qualitatively unchanged and unreported.

the more diversification achieved through the FOF portfolio. Similarly, in a user-non-user comparison of non-FOF portfolios, if a user's non-FOF portfolio is more diversified than that of the non-user, controlling for other variables that matter, then I can conclude that diversification is unlikely to be a motive, even if the FOF portfolio of the user is indeed more diversified. Likewise, if it is less diversified, the result is ambiguous. In short, these two tests can only falsify the proposition that diversification is a motive, but not support it. There is a third test that can do the latter. I can check the diversification of the FOF-user right before it invests in FOFs. If the diversification is lower than that afforded by the FOF, this rough event-study can attest to diversification as a possible motive.

I use several measures of diversification. These are the number of non-FOF funds and the number of portfolio companies that an LP gets into, either directly or via FOFs. I also use others like the average, minimum, and maximum round amounts, and the average, minimum, and maximum amounts per portfolio company. Using these last six do not change the qualitative results, so I do not report their tests here. There is yet another measure of diversification, not of funds or portfolio companies, but of investment scope and style. I defer the discussion of this to the section below on "learning," since learning is about going into the uncharted waters of a new scope or style.

In Table 16, Models (1) and (2) show the user-non-user comparisons using the two dependant variables: the logs of number of funds per LP and of the number of portfolio companies per fund in the LP-fund pairs. I control for a number of other effects that might confound my variables of interest. These include the sizes of the LP and fund, whether the LP and GP are in the same state (since non-economic forces might drive the degree of diversification), the NASDAQ level, fund sequence number, and fixed effects for three LP characteristics: the location of their headquarters by state, investment scope, and vintage. In both models, the estimation suggests that the *non-FOF* portfolios of FOF-users are *more* diversified than non-users. This is evidence that diversification might not be a motive for using FOFs.

I conduct another estimation as a robustness check. The diversification motive, if it exists, should be stronger for smaller LPs and might not even exist for larger ones. I add the interaction of the indicator for FOF-users with LP and fund sizes, as shown in Models (1a) and (2a). For Model (1a), the previous result is unchanged: diversification is larger for the non-FOF portfolios of users than non-users, suggesting that it is not a motive for LPs to use FOFs. Indeed, diversification is greater for larger LPs. The negative sign on the coefficient for the interaction of FOF-usage and log fund size suggests that the level of diversification obtained by FOF-users might be outshone by that of non-users. The means of log LP size and log fund size are 7.89 and 5.80, so FOF-users' level of diversification over non-users is $.98 + .11 \times 7.89 - .15 \times 5.80 = .98$ for Model (1a) and $-.41 + .03 \times 7.89 + .04 \times 5.80 = .06$ for Model (2a). That is, both still indicate that FOF-users can diversify easier than non-users, consistent with Models (1) and (2).

In Models (3) and (4), the intra-user comparisons show that that FOF portfolio of users is *less* diversified than that of the non-FOF portfolio, and this is statistically significant. With the interactions in Models (3a) and (4a), I see that for the average LP and fund size, the result is maintained: the FOF-portfolio is less diversified, with the partial at -2.58 - .04*7.89 +.35*5.8 = -.87 for Model (3a) and -3.49 - .11*7.89 +.62*5.8 = -.76 for Model (4a).

Models (5) and (6) are for the third test, comparing diversification before and after LPs' first usage of FOFs. My interpretation is that diversification is reduced after FOFs are used.[11] Models (5) and (6) are univariate, regressing on just the after-event indicator. In Models (7) and (8), I add the same control variables as those in (1) through (4), and although the signs remain unchanged, the results become statistically insignificant.

This finding is somewhat counter to conventional wisdom, but a random check on the marketing pitches of some big FOFs reveals that none actually pitch diversification explicitly[12]. Instead, they pitch their superior ability to identify funds and their disciplined investment processes. Furthermore, a picture correlating LP size with fund size in Figure 4 shows that most small LPs invest only in small FOFs. Why they do not or cannot invest in larger FOFs is probably for the same reason that they do not or cannot invest in larger funds for diversification. This speculation is an interesting proposition for future work.

2 – Upward Scaling for Efficiency? Although diversification may not be an explanation, what about the other dimension of upward scaling, that sub-scale LPs might use FOFs to get to minimum efficient scale? Like the diversification story, this predicts that FOF usage is higher among smaller funds. Unlike diversification, it can be confirmed if I observe that the cost of fund management is higher for smaller LPs. Since I do not have cost data, I look at the next best thing: the relative performance of FOF-users versus non-users for different LP sizes. If FOFs help small LPs in overcoming scale issues in their search for high-performing funds, then I expect that among small LPs, FOF-usage delivers better returns, net of expenses. Table 17, Panel (a), shows the results for this test. Unlike the previous ones, I now compare the overall performance of LPs – FOF investments or not - since I expect that any overhead is spread over both portfolios. All variants of the test do not reject the hypothesis of upward scaling to overcome sub-scale

[11] This is a measure of diversification of both FOF and non-FOF investments by LPs. It would be interesting to see how the level of diversification in the non-FOF portfolio changes with FOF use, but my dataset does not have sufficient number of observations to do this in a fixed effects model.

[12] Although I check the websites of many FOFs for fund profiles, for these pitches specifically, I check only those at Commonfund, Abbott Capital, Thomas Weisel, Great Hill, and Leonard Green.

operations.

As mentioned in the theory section of this paper, upward scaling for efficiency is an out-sourcing story. The story has three further agency predictions: (1) FOF-using LPs should have high-powered incentives when out-sourcing to FOFs, so I expect that using FOFs would increase the chance of an LP not re-investing in a follow-on FOF in the same series for poor performance, (2) if FOFs operate under higher-powered incentives, they should take less risk, since effort is unobservable but poor performance is, and (3) if FOFs take less risk, they ought to get lower return, assuming a reasonably efficient market.

In Table 17, Panel (b) Mode(1), I show the results of the test for reinvestment decisions. I am worried about serial correlation of the disturbance terms, so I cluster on GP identity. I also control for the variables previous discussed, and estimate with a number of effects, such as year and fund stage. The prediction is supported. The intra-user comparison shows that FOF-users' FOF portfolio has a statistically significant, negative (-4.46 + 3.98) effect on reinvesting; the *F* statistic on these the two relevant indicators is 478, with a p-value of 0.000. The other coefficients have the expected signs. For example, the coefficient for IRR is positive, so performance enhances the probability of reinvestment. The interesting one is the user-non-user comparison. For the non-FOF portfolio, FOF users have a significant positive 0.31 coefficient over non-users, suggesting that FOF users are less savvy on their own (non-FOF) portfolio.

Still, the coefficient for the indicator for FOF-fund in Model (1) might be confounded with other characteristics of the LP or the fund. For example, perhaps during times when money is chasing deals, there is less performance sensitivity. Model (2) shows that after controlling for the interactions of IRR with other variables, the partial for FOF funds is still negative (-4.27 + 4.17), with a joint *F* statistic of 661. The signs on the other coefficients are mostly unchanged or turn insignificant (such as "LP and GP in same state"). The curious results, however, are the interactions of FOF-usage and FOF funds with IRR. All are negative, contrary to prediction. The joint significance has a chi-square statistic of 9.65 and a p-value of 0.01. I cannot think of a good agency-based explanation for this that is also consistent with my earlier finding. Having said that, the real effect is small, since the standard deviation of the IRR is 40.33, so one standard deviation results in a change of (-0.0003-0.001)x40.33 = -.052 in the probability of reinvestment, compared with the base change of 0.10x40.33 = 4.33 and the mean IRR of 4.99 percent.

The second and third agency predictions say that FOFs should take lower risks and have lower returns. In Table 17, Panel (b), Models (3) and (4) show the regressions for risk, measured in two ways: the number of portfolio companies per fund and the log of the average round amount per fund. FOFs tend to have larger number of portfolio companies and smaller round amounts, controlling for other variables that might influence these. This supports the risk portion of the prediction. The return portion has been discussed in Table 6, where I provide evidence for FOF's having lower returns than regular funds. This squares with the return portion of the prediction too.

To sum up, the upward scaling story has validity in one area: FOF appears to help smaller LPs reduce their costs by outsourcing to FOFs. It does not appear that these LPs are using FOFs for diversification, or even if they do, the FOFs are not achieving that.

DOWNWARD SCALING

There is another explanation for the use of FOFs, this time by large LPs. This is about how big LPs who need to ramp up their private equity investments need the help of FOFs to spread them around. Such LPs face two problems: (1) spreading the money to many FOFs can lead to inter-FOF competition to the detriment of the LPs themselves, and (2) putting the money with single FOFs subjects the LPs to holdup problems, so the latter might have to manage that by stage-investing into the single FOFs.

Table 18 shows the existence of this trade-off between "spreading out over many FOFs, risking mis-coordination" and "not staging investments in one FOF, risking being held up." The dependant variable is a measure of "staging": the maximum sequence number of the funds an LP put with a GP. The key explanatory variable of interest is "spreading out," measured by the number of FOFs used by a LP at the time of the last staged investment in that GP. It has a significant negative sign, as predicted. To avoid serial correlation, I cluster this estimation on LP identity, and have a number of effects in place. The other control variables have the intuitive signs too. For example, the more other non-FOFs, the less time the LP has to monitor this FOF GP, so the more staging is involved. The higher flow of funds as indicated by the NASDAQ index, the quicker the LP has to capture the hot period, and the shorter the staging. The better performing the average excess IRR for this sequence of funds, the less need to monitor and the shorter the staging too. A particularly intriguing covariate is the indicator for "captive FOF," which is one in which an LP specifies that it is the sole investor into the FOF. Theory does not sign this unambiguously: while the lack of other LPs might make the GP more eager to serve the sole LP, it might also reduce the overall monitoring effort (although that in itself is subject to free-rider problems – e.g., Bolton and Scharfstein (1996)). Empirically, therefore, it appears that the dominant force is the former, leading to a positive coefficient.

What kinds of LPs go for many FOFs with short staging and what for few FOFs with long staging? Unfortunately, I do not have sufficient number of observations to detect this. An unreported regression on the number of FOFs and the maximum sequence number on LP characteristics gives statistically insignificant results.

Downward scaling can also mean that LPs use FOFs so that they can collapse many tedious fund-level approvals into an umbrella approval for a FOF given discretionary authority, and they do not have to build enormous capacity during the sparse investment points and capital calls, only to have the capacity underutilized at other times. Both of these are efficiency arguments, and are covered in the previous discussion on outsourcing. Therefore, I do not repeat any testing here.

GOVERNANCE

Table 3, Panel (b), shows a lot of heterogeneity between FOF-user and non-users by LP type. However, I need to control for other explanations, such as LP size, given the discussion on upward and downward scaling before. Table 19 shows the estimation results. None of the indicators for LP type turns out to be significant, save government, which has a positive coefficient at the 4% significance level. Indeed, given that this is a probit estimation, a government indicator almost certainly correlates with the usage of FOFs. This checks with the argument by Lerner, Schoar and Wong (2004) that government funds are most likely to be associated with a different set of governance structure than other LPs.

LEARNING

Table 20, Panel (a), shows the results. In Model (1), I look at FOF-usage in aggregate, without splitting hairs on the specific type of FOF used. The signs are the reversed of what I would expect from a learning model, and that for LP age is insignificant. But what if learning is more specific, at the level of FOF type? For example, an LP may learn about investing in buyouts only from using buyout FOFs. In Model (2), I repeat the regression on age and "newness" to the investing area, at the investment scope level. Because there might be cross-learning (using buyout FOFs might teach an LP something about VC FOFs), I have to control *across* these FOF types too. An appropriate method is the SUR (seemingly unrelated regression) estimation. Model (2) shows that signs are as predicted only for focused FOFs. This makes intuitive sense, as learning might be important only for specialized areas and not general ones. I repeat Model (2) using FOF stage (seed, mezzanine, etc.) and the result is qualitatively the same.

In Table 20, Panel (b), I test the two competing stories in Figure 5 – performance versus learning. The results show that the learning story is not supported. In Model (1), I look at learning from general experience with FOFs, not specific experience with special types of FOFs – e.g., those specializing in buyout or venture capital investments. The signs of the coefficients for experience, IRR, and the interaction are the opposite of what I would expect from a learning story. In Model (2), I remove the experience variables and the sign for IRR is negative, consistent with the outsourcing story. However, the regression as a whole does not have statistical significance. In Models (3) and (4), I dive into experience with two specific types of FOFs. I have insufficient number of observations for the other two types, focused and mixed, so I cannot afford an SUR regression as before. In the simple fixed effects estimations in these two models, I now find that the signs are consistent with a learning story, although the coefficients are not statistically significant. This repeats the early conclusion in Panel (a): learning in a general way is unsupported, but there is weak support for learning if I look at learning within specialized investment areas.

TEMPORARY OR CYCLICAL PHENOMENON

In the previous estimations, the coefficient on the NASDAQ level and other unreported proxies for fund flows is often negative when the dependant variable is a measure of performance – e.g., Table 8, Table 17 Panel (a). When the dependant variable is FOF-usage, the coefficient is positive – e.g.: Table 19, Table 20 (unreported there). I interpret these as consistent with the explanation that FOF usage is coincident with greater fund flows.

CONCLUSIONS

Given the enormous amount of money going into funds of funds, I hope to have clarified why LPs use FOFs. In the process, the findings could have shed light on many interesting issues in agency theory and industrial organization.

This paper also poses a number of profitable avenues for research. First, it is an intriguing issue as to how the FOF market interacts with other markets, especially those for direct private equity and other institutional money. Second, the FOF setting opens up some interesting issues in industrial organization. For example, one that I discussed is how organizations can build supplier or distributor networks when they have to push large volumes in short periods of time. On the one hand, using many partners can cause coordination problems. On the other hand, using few partners subject an organization to hold-up problems. The obvious solution of staging only returns us to the original problem of not pushing large throughputs. What other creative solutions might there be? Finally, it would be interesting to trace the development of the retail mutual funds market to see what parallels we can or cannot draw.

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APPENDIX

Table 1 - Example Funds of Funds

This table shows a few examples of the larger funds of funds. GP means general partner, LP means limited partner, and vintage means when the fund started.

	GP	Fund	Nation	State	Vintage	Size ($mil)	Example LPs`
1	Capital Z Investment Partners (FKA: Capital Z Partners, Ltd)	Capital Z Investments, L.P.	US	NY	1998	1500	Zurich Financial Services
2	Swiss Life Private Equity Partners Ltd	Swiss Life Private Equity Holding	SZ		1997	1500	Swiss Life
3	Swiss Life Private Equity Partners Ltd (fund now owned by Alpha Assoiates)	5E Holding (Excellence in Eastern Emerging Equity)	SZ		1998	1500	Allgemeine Pensionskasse der SAirGroup, Adroit Investment AG, Basler Lebensversicherungsgesellschaft, Pensionskasse des Basler Staatspersonals
4	Thomas Weisel Partners, LLC	Thomas Weisel Global Growth Partners	US	CA	2000	1300	CalPERS
5	Lexington Capital Partners	Lexington Capital Partners II	US	MA	1999	330	Pomplemousse, L.P. Lakeview Direct Investments, Inc. Franz and Frieder Burda
6	Great Hill Equity Partners, LLC	Great Hill II	US	MA	2000	330	First Union Capital Partners, Inc. Heller Financial, Inc.
7	Auda Securities GmbH (Main Office)	Auda Capital II L.P.	US	NY	1998	312	Henry Luce Foundation, Inc.
8	Goldman, Sachs & Co.	Goldman Sachs Private Equity Partners II, L.P.	US	NY	1998	250	Southern Company Services, Inc. Warner-Lambert Company
9	GTCR Golder Rauner LLC	Golder Thoma Cressey Rauner II	US	IL	1984	235	Security Benefit Life Insurance Co. Pack River Investment Company
10	Leonard Green & Partners	Green Equity Investors III	US	CA	1999	215.7	Citicorp Alternative Investment Strategies Jackson National Life Insurance Co. Grand Avenue Associates, L.P.

Table 2 – Comparison of Datasets by Source

This table compares the number of observations from the main sources used in the table. The column "How many more here?" means the number of times the "dataset in this paper" (last row) is bigger over the source in the row. IRR means "internal rate of return."

	Funds							
	All		With IRRs		LPs		Fund-LP pairs	
Source	N	How many more here?	N	How many more here?	N	How many more here?	N	How many more here?
SDC and VentureXpert (Thomson Financials/Venture Economics)	8,317	1.2x	0	-	1,900	2.1x	5,191	3.0x
Private Equity Intelligence	1,782	5.4x	1,516	1.1x				
Alternative Assets Galante	1,609	6.0x	0	-	404	9.7x	7,003	2.2x
Other sources – e.g.: LPs, websites	3,141*	3.1x	2,077*	0.8x	3,953	1.0x	4,442	3.5x
Dataset in this paper	9,659	1.0x	1,734	1.0x	3,927	1.0x	15,514	1.0x

* Include observations that are also in other sources.

Table 3 – Summary Statistics for LPs

This table summarizes the information about limited partners (LPs). Panel (a) compares LPs who are also funds of funds (FOFs) from those who are not, such as non-financial corporations, government funds, etc. Panel (b) compares in an orthogonal way, showing LPs who use FOFs and those who do not. "Num of PE funds" means the number of private equity funds in which an LP invests. If the LP invests through FOFs, this number includes the private equity funds held by the FOFs. "Num of FOFs" is the number of FOFs employed by an LP. "Col%" are percentages by column and "Row%" are by row. Dollar amounts are in millions unless otherwise stated.

(a) FOFs and non-FOFs

	All					FOFs					Non-FOFs				
Variable	**N**	**Mean**	**S.D.**	**Min**	**Max**	**N**	**Mean**	**S.D.**	**Min**	**Max**	**N**	**Mean**	**S.D.**	**Min**	**Max**
Total obs	3,927					709					3,218				
Year started	2,502	1,991	7	1,935	2,004	588	1,998	4	1,979	2,004	1,914	1,989	7	1,935	2,001
Assets managed	2,628	2,727	12,363	0	300,000	600	335	595	1	6,744	2,028	3,435	13,992	0	300,000
Num of PE funds	2,400	6.6	18.4	1	410	325	9.6	12.8	1	125	2,075	6.2	19.1	1	410
Num of FOFs	2,377	0.5	1.9	0	33	301	0.1	0.3	0	2	2,076	0.5	2.0	0	33
Max num of LPs in FOFs	3,834	2.0	8.2	0	58	616	0.7	3.3	0	27	3,218	2.3	8.8	0	58
Allocation to:															
Stocks	857	46.1	14.5	2	95	0					857	46.1	14.5	2	95
Fixed income	846	31.5	12.5	0	100	1	9.8	.	10	10	845	31.5	12.5	0	100
Private equity	556	5.5	16.5	0	100	9	82.1	36.8	0	100	547	4.2	12.6	0	100
FOFs	89	43.8	37.0	0	100	0					89	43.8	37.0	0	100
LP class		**N**		**% col**			**N**		**% col**			**N**		**% col**	
Non Fin. Corp		862		25.9								862		32.8	
Government		718		21.5								718		27.3	
Fund of Funds		709		21.3			709		100.0						
Investment Banks		385		11.5								385		14.7	
Educational Inst.		176		5.3								176		6.7	
Insurance		145		4.4								145		5.5	
Banks/Fin. Corp.		142		4.3								142		5.4	
Foundation		91		2.7								91		3.5	
Other Non Profits		52		1.6								52		2.0	
Consultants		15		0.5								15		0.6	
Others		40		1.2								40		1.5	
Total		3,335		100.0			709		100.0			2,626		100.0	
Continent	**N**	**Col%**		**Row%**		**N**	**Col%**		**Row%**		**N**	**Col%**		**Row%**	
Americas	3,432	90		100		515	83		15		2,917	91		85	
Europe	348	9		100		98	16		28		250	8		72	
Other	46	1		100		9	1		20		37	1		80	
	3,826	100				622	100				3,204	100			
US state (top few)	**N**	**Col%**		**Row%**		**N**	**Col%**		**Row%**		**N**	**Col%**		**Row%**	
NY	469	14		100		125	24		27		344	12		73	
CA	376	11		100		85	16		23		291	10		77	
MA	307	9		100		68	13		22		239	8		78	
IL	258	8		100		54	10		21		204	7		79	
CT	197	6		100		100	19		51		97	3		49	
TX	163	5		100		15	3		9		148	5		91	

Amounts are in million dollars.

(b) FOF-users and non-users

	All					FOF-users					Non-users				
Variable	**N**	**Mean**	**S.D.**	**Min**	**Max**	**N**	**Mean**	**S.D.**	**Min**	**Max**	**N**	**Mean**	**S.D.**	**Min**	**Max**
Total obs	3,927	4,739	1,704	1	12,639	414	4,705	1,267	2	7,007	3,513	4,743	1,749	1	12,639
Year started	2,502	1991	7	1935	2004	314	1989	8	1935	2001	2,188	1991	7	1936	2004
Assets managed	2,628	2,727	12,363	0	300,000	324	10,656	28,059	1	300,000	2,304	1,612	7,337	0	142,339
Num of PE funds	2,400	6.6	18.4	1	410	413	20.0	37.4	1	410	1,987	3.9	8.5	1	153
Num of FOFs	2,377	0.5	1.9	0	33	414	2.7	3.7	1	33	1,963	0.0	0.0	0	0
Allocation to:															
Stocks	857	46.1	14.5	2	95	171	53.7	14.8	3	89	686	44.2	13.7	2	95
Fixed income	846	31.5	12.5	0	100	172	28.2	11.7	7	84	674	32.4	12.6	0	100
Private equity	556	5.5	16.5	0	100	194	5.4	12.9	0	100	362	5.6	18.1	0	100
FOFs	89	43.8	37.0	0	100	89	43.8	37.0	0	100	0				
Max num of LPs in FOFs	3,834	2.0	8.2	0	58	414	18.6	17.6	0	58	3,420	0.0	0.0	0	0
LP class	**N**	**% row**		**% col**		**N**	**% row**		**% col**		**N**	**% row**		**% col**	
Non Fin. Corp	862	100		26		86	10		21		776	90		26	
Government	718	100		22		93	13		23		625	87		21	
Fund of Funds	709	100		21		31	4		8		678	96		23	
Investment Banks	385	100		12		16	4		4		369	96		13	
Educational Inst.	176	100		5		106	60		26		70	40		2	
Insurance	145	100		4			-				123	85		4	
Banks/Fin. Corp.	142	100		4		15	11		4		127	89		4	
Foundation	91	100		3		17	19		4		74	81		3	
Other Non Profits	52	100		2		11	21		3		41	79		1	
Consultants	15	100		0		1	7		0		14	93		0	
Others	40	100		1		27	68		7		35	88		1	
Total	3,335	100				403	100				2,932	100			
Continent	**N**	**% row**		**% col**		**N**	**% row**		**% col**		**N**	**% row**		**% col**	
Americas	3,432	100		90		366	11		93		3,066	89		89	
Europe	348	100		9		25	7		6		323	93		9	
Other	46	100		1		2	4		1		44	96		1	
Total	3,826			100		393			100		3,433			100	
US state (top few)	**N**	**% row**		**% col**		**N**	**% row**		**% col**		**N**	**% row**		**% col**	
NY	469	100		14		47	10		13		422	90		14	
CA	376	100		11		36	10		10		340	90		11	
MA	307	100		9		26	8		7		281	92		9	
IL	258	100		8		27	10		8		231	90		8	
CT	197	100		6		21	11		6		176	89		6	
TX	163	100		5		18	11		5		145	89		5	

Dollar amounts are in millions unless otherwise stated.

Table 4 – Summary Statistics for Funds

This table summarizes information about private equity funds, including funds of funds (FOFs). “$ in PC” means the amount invested in a portfolio company. If the fund is an FOF, the information like “Round ave” and “$ in PC, ave” are for rounds and portfolio companies via the investee funds of the FOF. “Yrs between close to 1st investment” is the number of years from the close of the fund to the year of its first investment, whether in a private equity firm (for non-FOFs) or fund (for FOFs). “Excess IRRs” are IRRs deviations from the benchmark IRR of funds grouped by: (1) vintage, (2) stage (e.g., early versus mezzanine), (3), investment scope (e.g., venture capital versus distressed debt), and (4) continent (e.g., Americas versus Europe). Dollar amounts are in millions unless otherwise stated.

	All					FOFs					Non-FOFs				
Variable	**N**	**Mean**	**S.D.**	**Min**	**Max**	**N**	**Mean**	**S.D.**	**Min**	**Max**	**N**	**Mean**	**S.D.**	**Min**	**Max**
Total obs.	9,659	6,685	4,109	1	12,776	709	2,558	2,516	1	12,639	8,950	7,012	4,033	277	12,776
Vintage	6,624	1,992	9	1,947	2,004	588	1,998	4	1,979	2,004	6,036	1,991	9	1,947	2,004
Size	8,441	239	1,883	0.100	95,549	600	335	595	0.800	6,744	7,841	231	1,947	0.100	95,549
Size targeted	2,745	264	503	0.200	5,235	208	352	447	5.000	3,200	2,537	257	507	0.200	5,235
Round ave	6,270	5	23	0.002	1,040	136	6	10	0.004	88	6,134	5	23	0.002	1,040
Round max	6,270	20	104	0.002	3,757	136	22	56	0.007	500	6,134	19	105	0.002	3,757
Round min	6,270	2	19	0.000	1,040	136	2	5	0.001	49	6,134	2	19	0.000	1,040
$ in PC, ave	6,270	6	25	0.002	1,040	136	7	11	0.004	88	6,134	6	25	0.002	1,040
$ in PC, max	6,266	21	107	0.002	3,757	136	23	56	0.007	500	6,130	21	108	0.002	3,757
$ in PC, min	6,266	2	19	0.000	1,040	136	2	6	0.001	49	6,130	2	19	0.000	1,040
Num of rounds	6,516	22	37	1	647	140	22	38	1	278	6,376	22	37	1	647
Num of PCs	6,586	13	18	1	310	210	13	18	1	125	6,376	13	18	1	310
Sequence num, by series	9,659	1	1	1	14	709	2	2	1	14	8,950	1	1	1	14
Sequence num, by GP	5,987	4	6	1	67	402	7	7	1	36	5,585	4	6	1	67
Date closed	6887	29oct91	3143	01jan58	28sep04	314	24dec97	1,925	01may78	28sep04	6,573	13jul91	3,150	01jan58	23sep04
Yrs between close to 1st investment	5,376	1	3	-40	35	101	1	3	-13	9	5,275	1	3	-40	35
Yrs between 1st to last investment	5,376	6	7	0	52	101	4	5	0	22	5,275	6	7	0	52
IRR (%)	1,734	6.3	41	-100	535	162	2.7	27	-96	93	1,572	6.7	43	-100	535
Excess IRR (%)	1,734	5.1	41	-100	532	162	2.7	26	-98	88	1,572	5.4	42	-100	532

Invest scope	**N**	**% row**	**% col**	**N**	**% row**	**% col**	**N**	**% row**	**% col**
Advising	2	0.0	100.0			-	2	0.0	100.0
All	927	17.7	100.0	30	10.0	3.2	897	18.1	96.8
Buyout	1,049	20.0	100.0	116	38.5	11.1	933	18.9	88.9
Co-investment	3	0.1	100.0			-	3	0.1	100.0
Development	21	0.4	100.0			-	21	0.4	100.0
Distressed	39	0.7	100.0			-	39	0.8	100.0
Fund of Funds	24	0.5	100.0	22	7.3	91.7	2	0.0	8.3
Industry	86	1.6	100.0			-	86	1.7	100.0
International	3	0.1	100.0			-	3	0.1	100.0
Venture Capital	3,091	58.9	100.0	133	44.2	4.3	2,958	59.8	95.7
Total	5,245	100.0		301	100.0		4,944	100.0	

Stage	**N**	**% row**	**% col**	**N**	**% row**	**% col**	**N**	**% row**	**% col**
Seed	252	3	100	1	1	0.4	251	3	100
Early	2,030	25	100	12	9	1	2,018	25	99
Mezzanine	241	3	100	6	5	2	235	3	98
Expansion	747	9	100	1	1	0.1	746	9	100
Late	2,605	32	100	95	71	4	2,510	31	96
All	2,394	29	100	18	14	1	2,376	29	99
Total	8,269	100		133	100		8,136	100	

Continued…

…continued

	All			FOFs			Non-FOFs		
Owner type	**N**	**% col**		**N**	**% col**		**N**	**% col**	
PRIV	5,628	62					5,628	67	
FINCORP	877	10					877	10	
CORPVEN	815	9					815	10	
SECFOF	709	8		709	100		59	1	
IBANK	708	8					708	8	
INDIV	101	1					101	1	
SBIC	59	1							
DEVEL	39	0.4					39	0.5	
ADV	37	0.4					37	0.4	
PENSION	36	0.4					36	0.4	
GOVT	30	0.3					30	0.4	
ENDOW	20	0.2					20	0.2	
UNIV	14	0.2					14	0.2	
PUBLIC	11	0.1					11	0.1	
EGRN	4	0.0					4	0.1	
Total	9,088	100		709	100		8,379	100	
Continent	**N**	**% row**	**% col**	**N**	**% row**	**% col**	**N**	**% row**	**% col**
Americas	7,183	78	100	515	83	7	6,668	78	93
Europe	1,245	14	100	98	16	8	1,147	13	92
Others	751	8	100	8	751	1	751	8	100
Total	9,179	100		622	100		8,557	100	
US state (top few)	**N**	**% row**	**% col**	**N**	**% row**	**% col**	**N**	**% row**	**% col**
CA	1,668	23	100	CA	85	16	5	CA	1,583
NY	1,440	20	100	NY	125	24	9	NY	1,315
MA	793	11	100	MA	68	13	9	MA	725
CT	392	5	100	CT	100	19	26	TX	340
IL	384	5	100	IL	54	10	14	IL	330
TX	355	5	100	TX	15	3	4	CT	292

Primary investor types:
ADV = advisors who are non-FOFs
CORPVEN = corporate ventures
DEVEL = development programs, including community programs
EGRN = evergreen funds
ENDOW = endowments and foundations
FINCORP = financial corporations, including those of government affiliates
GOVT = government programs, both national and state
IBANK = investment banks and their venture subsidiaries
INDIV = individuals and families
PENSION = pension funds, corporate and public
PRIV = private partnerships
PUBLIC = public firms
SBIC = Small Business Investment Companies, including MESBIC, public SBIC
SECFOF = secondary partnerships and FOFs
UNIV = university programs

Table 5 – Summary of Means for LP-fund Pairs

This table summarizes the means of limited partner (LP) and fund pairs. Panel (a) shows the breakdown by LP type, panel (b) by whether the LP in the LP-fund pair is a user of funds of funds (FOFs). In the "Allocation" columns, "Eq" means equities, "Fixed Inc" fixed income, "Priv Eq" private equity. "# of PC" is the number of portfolio companies in the fund of the LP-fund observation. If the fund is an FOF, then it includes the portfolio companies of the investee funds of the FOF. "Seq num" is the sequence number of the fund, whether by fund series or general partner (GP). "Excess IRRs" are IRRs deviations from the benchmark IRR of funds grouped by: (1) vintage, (2) stage (e.g., early versus mezzanine), (3), investment scope (e.g., venture capital versus distressed debt), and (4) continent (e.g., Americas versus Europe). "Weighted IRR" use commitment by the LP to the fund as a percentage of the total commitment by the LP to private equity funds as weight. Standard errors in brackets are corrected for heteroskedascity. Dollar amounts are in millions unless otherwise stated.
* Although some non-users indicate a link to FOFs, their allocation to them is zero, so I retain their status as non-users.

(a) By LP Type

			LP							Fund								
				Allocation				# of PC			Seq num		IRR			Weighted IRR		
LP type	Fund type	N	Size	Eq	Fixed Inc	Priv Eq	FOF	FOFs	Funds	Size	By series	By GP	For LP	Fund	Excess	For LP	Fund	Excess
Total	All	15,514	20,466.0	52.7	26.3	7.0	18.8	3.9	57.6	792.0	2.0	5.9	8.2	4.7	3.2	21.7	3.2	0.7
	Buyout	5,256	22,951.0	52.6	26.6	7.3	17.8	4.0	62.0	1,333.0	1.7	5.0	10.0	1.9	-1.4	10.4	0.9	-2.5
	Focused	528	24,130.0	52.8	26.3	5.8	15.4	4.2	55.4	1,235.0	1.8	4.7	11.8	9.1	0.1	1.0	9.1	-0.1
	FOF	1,432	24,046.0	54.1	27.5	5.7	27.6	7.1	55.9	692.0	2.4	8.8	-0.4	-1.5	0.9	41.9	-6.8	-9.7
	Mixed	2,446	17,462.0	52.7	26.5	7.4	16.7	3.4	54.5	621.0	2.1	6.6	9.3	5.1	2.5	27.4	-2.1	-5.1
	VC	5,037	17,867.0	52.2	25.7	7.0	17.9	3.2	56.4	347.0	2.3	6.4	9.0	8.7	10.3	25.6	15.0	15.6
Consultants	All	105	2,215.0		9.8	53.5	6.8	0.1	18.6	634.0	2.0	6.1		4.9	3.4			
	Buyout	37	2,364.0		9.8	53.1	6.8	0.1	18.6	1,035.0	1.9	4.3		5.0	1.8			
	Focused	4	2,308.0			37.3	6.8	0.3	14.0	965.0	1.8	7.3		4.7	-4.1			
	FOF																	
	Mixed	19	1,875.0		9.8	47.2		-	20.3	534.0	2.0	6.4		-18.9	-22.0			
	VC	41	2,390.0		9.8	56.9	6.8	0.0	18.6	313.0	2.2	7.4		14.7	15.8			
Educational Inst	All	1,960	19,331.0	45.5	22.2	8.2	9.8	2.6	59.7	750.0	2.3	6.5	12.7	11.0	10.0	23.4	1.9	0.3
	Buyout	539	25,431.0	43.8	20.5	9.3	5.8	2.4	66.7	1,400.0	1.8	5.2	5.0	0.7	-2.4	11.2	20.2	17.1
	Focused	84	24,400.0	44.9	23.0	5.3	5.5	2.6	51.2	1,307.0	1.9	5.1	-6.9	8.1	-0.6	-12.3	11.6	2.7
	FOF	234	11,694.0	55.3	26.1	4.5	31.1	4.2	28.1	455.0	2.1	9.8	10.8	13.5	13.2	48.6	-11.4	-13.1
	Mixed	273	17,909.0	45.7	23.3	7.3	9.4	2.6	62.8	592.0	2.4	6.6	14.8	7.4	4.6	27.0	19.4	16.4
	VC	756	18,377.0	45.1	22.5	8.8	9.0	2.5	62.4	389.0	2.7	7.2	20.6	20.4	22.6	26.3	23.3	22.5
Financial Inst	All	2,498	11,396.0	13.0	70.0	6.5	27.2	1.0	31.4	623.0	1.9	5.3	24.0	4.0	1.9		5.7	3.7
	Buyout	960	11,845.0	14.5	68.6	7.7	26.1	0.9	37.2	1,029.0	1.7	4.6		2.9	-0.4		5.5	2.6
	Focused	66	10,746.0			5.6	34.5	0.8	15.7	815.0	1.7	3.9		5.1	-3.7			
	FOF	137	15,647.0	6.0	76.2	7.6	43.0	3.0	26.5	683.0	2.8	8.7		-9.9	-5.8		-0.6	-2.1
	Mixed	381	11,066.0	18.6	65.1	8.1	18.3	1.2	36.2	451.0	1.8	5.0		3.7	1.0		-3.3	-6.3
	VC	753	10,502.0	13.0	70.0	3.6	22.7	0.9	29.9	288.0	2.0	6.4	24.0	7.0	7.0		14.9	15.6

Continued…

			LP							Fund								
				Allocation				Num of investees			Seq num		IRR			Weighted IRR		
LP type	Fund type	N	Size	Eq	Fixed Inc	Priv Eq	FOF	FOFs	Funds	Size	By series	By GP	For LP	Fund	Excess	For LP	Fund	Excess
Foundation	All	543	2,841.0	51.8	25.6	2.5	26.8	0.8	20.4	701.0	2.1	6.5		10.8	9.4		-10.4	-12.6
	Buyout	156	3,104.0	50.9	26.6	2.7	26.8	0.7	21.1	1,301.0	1.8	5.5		1.6	-1.0		-7.3	-9.9
	Focused	37	1,540.0	51.4	21.3	4.0		0.5	12.1	1,311.0	1.9	4.8		6.3	-2.6			
	FOF	34	2,123.0	57.9	22.7	1.9	35.8	2.1	13.5	777.0	2.7	7.7		-11.1	-8.7		-20.2	-21.9
	Mixed	79	2,737.0	52.9	26.5	1.3	25.2	0.9	21.8	351.0	1.6	6.5		9.8	6.8		-14.2	-17.3
	VC	214	3,183.0	51.2	26.1	2.6	26.3	0.6	23.1	328.0	2.5	7.6		22.2	23.8		-9.3	-8.5
Fund of Funds	All	2,723	422.0		9.8	66.6		0.1	21.7	812.0	2.3	6.1	20.2	-0.3	-0.4		-21.7	-16.3
	Buyout	831	449.0		9.8	65.4		0.2	20.2	1,429.0	1.7	5.1	282.0	-1.0	-4.5			
	Focused	22	623.0			100.0		0.2	19.1	1,759.0	1.7	5.7		11.1	2.0			
	FOF	124	429.0			100.0		0.4	21.6	1,160.0	4.4	7.6	-8.9	-19.1	-10.2			
	Mixed	558	467.0		9.8	70.5		0.1	20.7	660.0	2.5	6.8		1.8	-0.6			
	VC	1,128	377.0		9.8	56.9		0.1	23.1	390.0	2.4	6.4		1.1	4.2		-21.7	-16.3
Government	All	4,669	40,872.0	54.6	27.8	6.0	17.9	10.0	121.6	983.0	2.0	5.8	6.2	3.8	2.1	11.7	2.2	-1.8
	Buyout	1,804	41,272.0	54.4	28.0	6.0	17.3	9.6	118.1	1,525.0	1.8	5.0	9.6	2.2	-1.1	7.8	-0.2	-3.8
	Focused	179	40,773.0	55.6	27.5	5.9	14.5	9.6	115.1	1,311.0	1.6	4.7	14.6	13.4	4.2	9.6	10.6	1.7
	FOF	565	40,845.0	53.4	27.6	5.7	19.8	12.4	106.7	767.0	2.1	8.4	0.2	-3.8	-2.1	-4.4	18.9	-2.4
	Mixed	668	37,946.0	54.1	27.6	6.4	17.0	9.6	120.7	736.0	2.1	7.1	6.4	6.4	3.7	32.7	-9.0	-12.0
	VC	1,225	41,371.0	55.1	27.7	5.7	19.5	10.0	133.8	380.0	2.2	6.0	3.7	6.3	7.5	19.2	16.8	18.0
Non-Fin Corp	All	2,533	13,096.0	60.2	25.5	4.1	21.9	1.6	19.4	663.0	1.8	5.8	24.0	6.5	4.3		3.3	0.5
	Buyout	799	12,567.0	59.7	26.3	3.9	21.4	1.7	23.0	1,152.0	1.7	4.7		3.9	0.8		-1.4	-5.1
	Focused	100	11,841.0	57.2	27.5	3.4	18.6	1.5	19.4	1,232.0	1.9	4.5		6.0	-3.0		12.2	2.3
	FOF	231	15,232.0	60.5	25.7	5.1	35.2	4.2	21.7	604.0	2.1	10.5		2.6	5.2		-2.9	-2.2
	Mixed	412	11,356.0	60.6	25.4	3.6	16.9	1.2	17.1	605.0	1.8	7.2		6.9	4.1		1.1	-2.0
	VC	771	14,578.0	61.0	23.8	4.0	15.4	1.2	19.9	257.0	2.0	6.0	24.0	10.4	11.1		17.2	17.5
Other Non Profits	All	294	4,434.0	49.7	22.9	9.6	23.1	2.7	22.4	851.0	2.2	6.5		3.7	2.3		12.9	10.3
	Buyout	91	4,695.0	50.3	21.0	10.5		2.0	20.9	1,490.0	1.8	6.1		-1.5	-4.3		4.9	2.3
	Focused	22	2,366.0	45.8	29.6	5.7		2.0	15.4	1,036.0	1.6	3.8		5.6	-3.3		7.7	-1.1
	FOF	38	4,391.0	52.0	21.7	12.3	23.1	5.9	24.3	675.0	2.5	10.9		5.8	4.9		15.3	13.6
	Mixed	38	3,224.0	49.5	22.9	7.2	23.1	2.3	21.4	645.0	2.1	6.1		15.3	12.6		46.5	43.4
	VC	103	5,162.0	49.3	23.5	10.2	23.1	2.5	25.2	388.0	2.5	6.9		2.6	4.6		11.7	13.7
Other	All	189	4,404.0	54.6	39.1	0.0	100.0	2.2	10.8	571.0	2.1	6.9		6.8	4.7			
	Buyout	39						0.1	9.7	831.0	1.6	6.7		2.5	-0.6			
	Focused	14						-	7.6	1,259.0	1.9	5.1		5.6	-3.2			
	FOF	68	2,692.0			0.0	100.0	5.9	7.5	472.0	2.3	9.6		4.7	3.7			
	Mixed	18	22,500.0			0.0	100.0	0.1	15.4	653.0	1.8	4.0		-2.9	-5.6			
	VC	46	22,500.0			0.0	100.0	0.3	15.9	252.0	2.6	8.0		15.9	16.2			

(b) By FOF-usage

			LP							Fund								
				Allocation				# of PCs			Seq num		IRR			Weighted IRR		
FOF usage By LPs	Fund type	N	Size	Eq	Fixed Inc	Priv Eq	FOF	FOFs	Funds	Size	By series	By GP	For LP	Fund	Excess	For LP	Fund	Excess
FOF-users	All	8,243	31,134.0	53.0	26.8	6.5	18.8	7.3	90.0	873.9	2.0	6.0	7.6	5.0	3.4	21.7	1.5	-1.1
	Buyout	2,876	33,612.4	52.9	27.1	6.7	17.8	7.4	93.7	1,425.9	1.8	5.0	8.7	1.5	-1.7	1.0	12.2	2.3
	Focused	313	33,420.8	53.3	26.4	5.9	15.4	7.0	84.4	1,249.6	1.7	4.6	11.6	10.7	1.6	41.9	-6.8	-9.7
	FOF	1,284	26,063.9	54.1	27.5	5.8	27.6	7.9	59.5	619.4	1.9	8.4	-0.4	3.1	4.0	27.4	-5.5	-8.5
	VC	2,289	30,723.6	52.6	26.3	6.2	17.9	7.1	98.7	374.3	2.3	6.4	9.0	9.8	11.3	25.6	12.1	12.7
	Mixed	1,141	29,591.9	52.6	26.7	7.1	16.7	7.3	94.4	711.0	2.1	7.1	9.3	5.2	2.6	10.4	1.4	-2.0
Non-users	All	7,271	4,269.0	51.6	24.4	8.4	0.0	0.0	20.8	701.3	2.1	5.9	34.7	4.4	3.1		7.8	5.3
	Buyout	2,380	5,150.7	51.5	24.2	9.3	0.0	0.0	23.8	1,222.8	1.7	4.9	70.0	2.3	-1.0		-0.9	-4.3
	Focused	215	4,202.7	51.1	25.7	5.4	0.0	0.0	13.2	1,217.1	1.9	4.8	21.5	6.4	-2.5		7.7	-1.1
	FOF*	148	2,775.3	53.7	26.4	4.8	0.0	0.0	24.7	1,300.0	6.2	10.0		-20.7	-12.1		-29.8	-26.0
	VC	2,748	4,085.2	50.9	23.6	8.9	0.0	0.0	21.2	326.0	2.3	6.5	9.1	7.7	9.4		19.5	20.1
	Mixed	1,305	3,120.4	53.2	25.8	8.0	0.0	0.0	19.6	544.9	2.1	6.2		5.0	2.4		4.7	1.6
	LP type																	
FOF-users	Consultants/Gatekeepers	4,584	103.4			19.6	6.8	1.0	6.0	44.1	1.7	1.0		20.6	17.8			
	Educational Institutions	4,998	22,790.8	45.3	22.7	7.0	9.8	3.6	69.6	724.2	2.2	6.5	12.7	11.2	10.1		0.4	-1.1
	Financial Institution	4,996	16,728.5	13.0	70.0	5.4	27.2	3.8	42.6	720.6	1.9	5.8		2.1	-0.3		5.9	3.5
	Foundation	4,626	4,703.0	48.8	30.7	1.1	26.8	2.0	30.0	540.6	1.8	6.7		12.9	11.8		-9.1	-11.3
	Fund of Funds	2,292	759.0			100.0		1.3	30.2	1,011.4	2.0	5.4	-8.9	-10.3	-10.5			
	Government	4,868	43,415.6	54.7	27.6	6.2	17.9	11.0	130.3	976.0	1.9	5.8	6.2	4.3	2.5		1.6	-1.9
	Non Financial Corp	4,754	18,831.6	60.2	25.7	4.7	21.9	3.5	35.9	864.5	1.9	6.3		3.4	1.4		1.9	-0.8
	Other Non Profits	4,483	6,535.8	52.2	19.9	13.7	23.1	4.8	32.9	779.6	2.4	7.0		2.7	2.4		18.2	17.9
	Other	6,429	4,578.7			0.0	100.0	5.6	6.7	402.9	1.8	7.8		10.8	10.0			
Non-users	Consultants/Gatekeepers	4,236	2,360.8		9.8	55.9		0.0	19.4	671.7	2.0	6.2		4.5	3.0			
	Educational Institutions	4,690	10,159.9	45.8	21.0	10.9		0.0	33.6	816.8	2.5	6.5		10.5	9.6		22.5	19.9
	Financial Institution	4,759	7,601.4			8.0		0.0	27.3	587.5	1.8	5.1	24.0	4.8	2.7		5.5	3.9
	Foundation	4,640	1,628.7	54.1	21.8	3.3		0.0	14.1	807.8	2.3	6.4		9.6	8.2		-14.5	-17.2
	Fund of Funds	2,865	377.2		9.8	40.9		0.0	20.7	788.8	2.3	6.2	282.0	0.9	0.8		-21.7	-16.3
	Government	4,672	14,130.4	53.2	29.6	3.4		0.0	37.6	1,049.2	2.2	6.0	6.5	-0.6	-2.6		7.3	-0.8
	Non Financial Corp	4,668	4,813.8	60.1	25.0	2.9		0.0	5.6	488.9	1.7	5.4	24.0	9.5	7.2		17.7	14.4
	Other Non Profits	4,420	1,545.8	42.1	32.5	4.0		0.0	8.8	940.2	1.9	6.0		4.9	2.1		12.9	10.3
	Other	4,399	728.8	54.6	39.1	0.1		0.0	13.4	671.8	2.3	6.7		5.9	3.5			

Table 6 – Performance of FOF among Funds

This table uses OLS for models (1) through (3) and the Heckit procedure for (4) through (6), whose selection model is:

$$ProbabilitySelected = \beta_o + \beta_1.log(FundSize) + \beta_2.FundVintage + \beta_3.RoundAverage + \Sigma\beta_4.MajorStateIndicator + \beta_5.USorUKindicator + \beta_6.PreviousIRR + \varepsilon.$$

Standard errors in brackets are corrected for heteroskedascity. Dollar amounts are in millions unless otherwise stated.

Dependant variable: fund IRR	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
FOF indicator			2.46 (4.66)	-13.77 (17.86)	-45.01 (17.77)
Log(size)	1.86 (3.27)	2.66 (4.23)	1.77 (4.14)	-5.16 (11.72)	-1.46 (7.46)
Log(size)^2	-.65 (.31)	-.76 (.42)	-.64 (.41)	.055 (1.086)	-.38 (.70)
Log(seqBySeries)	.25 (4.74)		.30 (5.09)	4.63 (11.59)	2.09 (8.48)
Log(seqBySeries)^2	-.49 (3.27)		-.56 (3.00)		-6.68 (4.17)
Log(seqByGP)		1.68 (4.34)			
Log(seqByGP)^2		.25 (1.55)			
VC indicator	.83 (2.62)	1.13 (2.61)	.93 (2.55)	.53 (6.06)	
NASDAQ level		-.003 (.006)	-.003 (.006)	.011 (.019)	.001 (.006)
Vintage					-
Stage (base is “All”)					
Seed					15.38 (21.42)
Early					41.88 (18.94)
Mezzanine					37.68 (18.85)
Expansion					36.50 (18.62)
Late					46.75 (19.11)
Region (base is “Americas”)					
Europe					12.57 (8.08)
Others					15.33 (12.78)
Investment scope (base is “All”)					
Venture capital					-40.30 (20.16)
Focused					-33.01 (25.15)
Buyout					-54.11 (21.31)
Round average					.03 (.03)
Inverse Mills ratio (lambda)				-31.72 (11.51)	-32.43 (11.46)
GP F.E.	No	Yes	Yes	Yes	Yes
Year F.E	Yes	Yes	Yes	Yes	Yes
N	1,256	1,183	1,253	724	709
Adj R^3 (or pseudo likelihood ratio, for estimations using Heckman correction)	.07	.07	.07	-2320.7	-2225.5
p-value of Wald test	.000	.000	.000	.000	.000

Table 7 – Comparison of Data Subsets with and without IRR Information

This table shows the potential sample selection bias for datasets with IRR information, compared with the subset without the information. Dollar amounts are in millions unless otherwise stated.

(a) Funds dataset

	With IRR Information					Without					t on null that means are the same
	N	Mean	S.D.	Min	Max	N	Mean	S.D.	Min	Max	
Size	1,276	498	794	1	6,500	7,165	193	2,013	0	95,549	-5.34
Vintage	1,379	1987	10	1935	2,004	7,449	1991	9	1936	2,004	15.77
Round ave ($ 000)	984	11,889	32,487	6	460,928	5,286	3,584	20,220	2	1,040,000	-10.59
Fund HQ in one of CA, NY, MA, PA	1,734	.52	.50	0	1	7,925	.40	.49	0	1	-9.42
Fund HQ in US or UK	1,734	.89	.31	0	1	7,925	.77	.42	0	1	-11.34
IRR of previous fund in series	548	14.7	43.7	-94	513	523	1.5	38.4	-100	415	-5.27

(b) LP-fund dataset

	With IRR Information		Without		Z statistic for H_0: same frequencies
LP type	N	Freq	N	Freq	
Banks/Financial Corp.	350	3.2	257	5.5	6.71
Consultants/Gatekeepers	83	0.8	22	0.5	-2.05
Educational Institutions	1,482	13.7	478	10.2	-5.89
Foundation	372	3.4	171	3.7	0.73
Fund of Funds	2,044	18.9	679	14.6	-6.46
Government	3,646	33.6	1,023	21.9	-14.57
Insurance	641	5.9	441	9.5	7.93
Investment/Merchant Banks	473	4.4	335	7.2	7.24
Non Financial Corporations	1,450	13.4	1,083	23.2	15.20
Other Non Profits	204	1.9	90	1.9	0.20
Other	101	0.9	89	1.9	5.07
Total	10,846	100.0	4,668	100.0	

	With IRR Information					Without					t for H_0 : same means
	N	Mean	S.D.	Min	Max	N	Mean	S.D.	Min	Max	
Fund vintage	1,158	1997	5	1978	2004	14,100	1991	9	1978	2004	-21.07
Fund size	10,378	980	1,222	0.5	6,500	4,189	324	562	0.1	7,700	-33.33
Round ave ($ 000)	8,567	20,965	46,282	6	460,928	2,686	9,313	33,444	7	322,772	-12.10
Fund HQ in one of CA, NY, MA, PA	10,846	0.63	0.48	0	1	4,668	0.50	0.50	0	1	-15.23
Fund HQ in US or UK	10,846	0.97	0.16	0	1	4,668	0.79	0.41	0	1	-40.89
IRR of previous fund in series	656	15.4	44.9	-94.2	513.0	246	-5.6	24.8	-100.0	97.2	-6.92
LP committed to fund	768	51	91	0	1,400	4,670	31	64	0	1,500	-7.58
LP drawn from fund	614	21	102	-1,246	400	700	19	57	-291	841	-0.44
LP vintage	1,061	1990	8	1935	2001	12,670	1991	8	1935	2004	3.77
Log(LP size)	1,160	64,252	62,551	72	149,300	11,615	16,093	35,063	0	300,000	-40.75
LP %alloc to equity	976	50	15	25	72	5,829	53	12	3	89	7.73
LP %alloc to fixed inc	976	25	10	9	40	5,848	26	10	2	100	3.09
LP %alloc to pte equity	943	5	3	0	13	7,272	7	14	0	100	4.36
LP %alloc to FOF	515	29	11	7	37	2,438	17	19	0	100	-14.13
Num of funds per LP	1,168	208	136	1	410	14,346	45	56	1	410	-82.12
Num of FOFs per LP	1,168	14	12	0	32	14,346	3	6	0	33	-58.23
LP & GP in same state	1,168	0.24	0.43	0.00	1.00	14,346	0.18	0.38	0.00	1.00	-5.52

Table 8 – Performance of FOFs among LPs

This table shows how the fund IRR in LP-fund observations correlates with a number of explanatory variables. Model (1) uses OLS, while the rest use the Heckit procedure, whose selection model is:

$$ProbabilitySelected = \beta_o + \beta_1.log(FundSize) + \beta_2.FundVintage + \beta_3.RoundAverage + \Sigma\beta_4.MajorStateIndicator + \beta_5.USorUKindicator + \beta_6.PreviousIRR + \varepsilon.$$

Standard errors in brackets are corrected for heteroskedascity. Dollar amounts are in millions unless otherwise stated.

	Dependant var: IRR for LP-fund pairs	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
LP types (base="Consultants")	Educational Institutions	9.69 (6.07)	3.87 (6.54)	4.64 (6.54)	5.41 (6.44)	5.91 (6.28)
	Financial Institution	2.52 (6.09)	-9.03 (8.65)	-8.58 (8.56)	-8.88 (8.40)	-8.84 (8.45)
	Foundation	7.37 (6.37)	1.57 (7.61)	1.84 (7.63)	3.30 (8.34)	3.68 (8.31)
	Fund of Funds	-1.93 (5.97)	-2.63 (6.37)	-2.45 (6.35)	-1.47 (6.19)	-1.21 (6.26)
	Government	5.72 (6.06)	5.60 (6.52)	6.57 (6.35)	6.04 (7.62)	6.13 (7.69)
	Non Financial Corporations	2.38 (6.04)	-6.78 (9.52)	-6.13 (9.36)	-6.64 (10.85)	-6.54 (10.93)
	Other Non Profits	4.55 (6.88)	-2.98 (9.91)	-2.38 (9.78)	.73 (9.34)	.99 (9.31)
Interaction with FOF-usage	Indicator for FOF-usage			-1.41 (.38)	17.33 (6.24)	17.13 (6.22)
	Educational Institutions				-18.98 (6.24)	-18.93 (6.32)
	Financial Institution				-16.77 (7.89)	-16.65 (7.92)
	Foundation				-21.51 (6.96)	-21.52 (6.75)
	Fund of Funds				-22.31 (8.83)	-22.17 (8.76)
	Government				-17.40 (8.59)	-17.28 (8.43)
	Non Financial Corporations				-16.94 (2.77)	-16.70 (2.84)
	Other Non Profits				-24.37 (7.44)	-24.58 (7.26)
Interaction with FOF-fund	Indicator for FOF-fund					-21.13 (6.54)
	Educational Institutions					4.72 (12.83)
	Financial Institution					-.98 (8.80)
	Foundation					20.51 (6.38)
	Fund of Funds					11.87 (2.74)
	Government					20.45 (3.96)
	Non Financial Corporations					13.29 (15.70)
	Other Non Profits					-5.56 (7.87)
Interaction with FOF-usage x FOF-fund	FOF-usage x FOF-fund					4.72 (12.83)
	Educational Institutions					7.53 (13.60)
	Financial Institution					.63 (15.56)
	Foundation					
	Fund of Funds					.59 (9.54)
	Government					-.08 (9.99)
	Non Financial Corporations					
	Other Non Profits					38.05 (16.74)
	LP vintage	-.06 (.08)	-.12 (.04)	-.12 (.04)	-.11 (.04)	-.11 (.04)
	LP and GP in same state	-.56 (1.41)	-.42 (1.16)	-.45 (1.14)	-.41 (1.15)	-.49 (1.16)
	NASDAQ level	-.01 (.00)	-.01 (.00)	-.01 (.00)	-.01 (.00)	-.01 (.00)
	Log(LP size)	-.13 (.29)	.51 (.58)	.57 (.59)	.54 (.59)	.53 (.58)
	Inverse Mill's ratio (lambda)		42.33 (14.56)	42.32 (14.55)	42.33 (14.58)	42.27 (14.62)
	Indicators for LP location by state	Yes	Yes	Yes	Yes	Yes
	Year FE	Yes	Yes	Yes	Yes	Yes
	Fund stage FE	Yes	Yes	Yes	Yes	Yes
	N	7,768	9,628 (uncensored 7,495)	9,628 (uncensored 7,495)	9,628 (uncensored 7,495)	9,628 (uncensored 7,495)
	Pseudo LR ratio	354.6 (Wald)	-41,851	-41,851	-41,848	-41,844
	p-value of Wald test	.000	.001	.001	.001	.000

Table 9 – Statistical and Economic Significance of Joint-tests on FOF-usage and LP Type

This table shows the joint tests of whether the use of funds of funds (FOFs) and limited partner (LP) type are significant. It is for Model (4) in Table 8, where the specification is (Ind = indicator operator):

IRR of LP-fund pair = $\beta_o + \beta_1.Ind(LP\ types) + \beta_2\ Ind(LP\ is\ FOF\text{-}user) + \beta_3.Ind(LP\ types) \times Ind(LP\ is\ FOF\text{-}user) + \beta_4\ LPvintage + \beta_5.Ind(LP\ \&\ GP\ in\ same\ state) + \beta_6.NASDAQlevel + \beta_7.Log(LP\ size) + \varepsilon.$

The Heckman correction procedure is used, with the selection model:

$ProbabilitySelected = \beta_o + \beta_1.log(FundSize) + \beta_2.FundVintage + \beta_3.RoundAverage + \Sigma\beta_4.MajorStateIndicator + \beta_5.USorUKindicator + \beta_6.PreviousIRR + \varepsilon.$

"Economic significance" is based on the mean levels of the appropriate variables concerned. The mean IRR is 4.99%.

Interaction of FOF-usage with LP type indicators	**Statistical Significance X^2 for H_0: both coeff=0**	**p-value**	**Economic Significance ∂IRR/∂FOFusage for FOFusage**
Consultants/Gatekeepers	7.71	0.0055	17.3
Educational Institutions	16.55	0.0003	-1.7
Financial Institution	26.37	0.0000	0.6
Foundation	9.67	0.0079	-4.2
Fund of Funds	9.53	0.0085	-5.0
Government	37.45	0.0000	-0.1
Non Financial Corporations	79.49	0.0000	0.4
Other Non Profits	18.82	0.0001	-7.0

Table 10 – FOF Performance Compared in Two Ways

This table shows two comparisons of FOF performance. In the user-non-user comparison, I compare the performance of the non-FOFs portfolios of FOF-using LPs and non-using LPs. This tells whether FOF-using LPs (disregarding the performance generated by their FOF portfolios) are stronger than non-users. In the intra-user comparison, I compare the performance of the FOF and non-FOF portfolios of FOF-using LPs. This tells whether FOFs deliver value condition on LPs' using them. The full estimation is in Model (5) of Table 8, where the specification is (Ind = indicator operator):

IRR of LP-fund pair = $\beta_o + \beta_1.Ind(LP\ types) + \beta_2\ Ind(LP\ is\ FOF\text{-}user) + \beta_3.Ind(LP\ types) \times Ind(LP\ is\ FOF\text{-}user) + \beta_4\ Ind(fund\ is\ FOF) + \beta_5.Ind(LP\ types) \times Ind(fund\ is\ FOF) + \beta_6\ Ind(fund\ is\ FOF) \times Ind(LP\ is\ FOF\text{-}user + \beta_7.Ind(LP\ types) \times Ind(fund\ is\ FOF) \times Ind(LP\ is\ FOF\text{-}user) + \beta_8\ LPvintage + \beta_9 Ind(LP\ \&\ GP\ in\ same\ state) + \beta_{10}.NASDAQlevel + \beta_{11}.Log(LP\ size) + \varepsilon.$

The Heckman correction procedure is used, with the selection model:

$ProbabilitySelected = \beta_o + \beta_1.log(FundSize) + \beta_2.FundVintage + \beta_3.RoundAverage + \Sigma\beta_4.MajorStateIndicator + \beta_5.USorUKindicator + \beta_6.PreviousIRR + \varepsilon.$

LP type	**User-non-user comparison**: Do FOF-users pick regular funds better than non-users? (IRR bp)	**Intra-user comparison:** Do FOFs do better than non-FOFs? (IRR bp)
Consultants/Gatekeepers	17.1	-16.4
Educational Institutions	-1.8	-4.1
Financial Institution	0.5	-16.7
Foundation	-4.4	4.1
Fund of Funds	Not applicable	Not applicable
Government	-0.1	4.0
Non Financial Corporations	0.4	-3.1
Other Non Profits	-7.4	16.1

Table 11 – Size Effect on Performance

This table uses IRR as the dependant variable. In the user-non-user comparison, I compare the performance of the non-FOFs portfolios of FOF-using LPs and non-using LPs. This tells whether FOF-using LPs (disregarding the performance generated by their FOF portfolios) are stronger than non-users. In the intra-user comparison, I compare the performance of the FOF and non-FOF portfolios of FOF-using LPs. This tells whether FOFs deliver value condition on LPs' using them. The Heckman correction procedure is used, with the selection model:

$$ProbabilitySelected = \beta_o + \beta_1.log(FundSize) + \beta_2.FundVintage + \beta_3.RoundAverage + \Sigma\beta_4.MajorStateIndicator + \beta_5.USorUKindicator + \beta_6.PreviousIRR + \varepsilon.$$

Standard errors in brackets are corrected for heteroskedascity. Dollar amounts are in millions unless otherwise stated.

		User-non-user		Intra-user	
	Dependant var: IRR for LP-fund pairs	**(1)**	**(2)**	**(3)**	**(4)**
LP types (base="Consultants")	Educational Institutions	8.68 (6.30)	5.38 (4.89)	23.19 (25.50)	6.05 (9.40)
	Financial Institution	-8.54 (8.81)	-7.83 (8.56)	3.33 (15.80)	-5.57 (3.17)
	Foundation	6.75 (7.72)	3.73 (7.02)	8.31 (21.29)	3.87 (12.13)
	Fund of Funds	1.16 (6.37)	-1.42 (5.31)	-1.91 (15.49)	-12.74 (3.85)
	Government	6.92 (7.99)	-4.67 (10.11)	18.67 (19.12)	-2.27 (6.37)
	Non Financial Corporations	-7.29 (12.06)	-4.09 (8.85)	7.22 (16.63)	-4.12 (4.62)
	Other Non Profits	1.93 (10.52)	-1.17 (10.58)	5.43 (24.71)	-.76 (7.54)
Interaction with FOF-usage	Indicator for FOF-usage	17.87 (6.45)	-3.11 (11.97)		
	Educational Institutions	-17.31 (5.82)	3.79 (11.17)		
	Financial Institution	-19.78 (9.55)	5.26 (10.34)		
	Foundation	-24.23 (7.80)	4.44 (18.96)		
	Fund of Funds	-22.72 (9.13)	-4.12 (8.23)		
	Government	-18.55 (10.66)	4.71 (12.09)		
	Non Financial Corporations	-16.16 (3.07)	1.93 (12.78)		
	Other Non Profits	-27.52 (8.44)	-.79 (11.52)		
Interaction with FOF-fund	Indicator for FOF-fund			18.46 (3.01)	-4.54 (16.91)
	Educational Institutions			-47.15 (8.83)	-26.80 (19.65)
	Financial Institution			-14.93 (19.56)	
	Foundation				
	Fund of Funds			-16.98 (8.81)	-1.40 (19.39)
	Government			-19.59 (3.67)	1.49 (16.09)
	Non Financial Corporations			-16.85 (13.51)	-1.53 (14.19)
	Other Non Profits				7.09 (22.86)
	Log(LP size)	.56 (.73)	-.62 (.25)	.29 (.46)	-.74 (.59)
	Log(fund size)		2.58 (6.20)		4.82 (6.91)
	$Log(fund size)^2$		-.83 (.73)		-.97 (.78)
	LP vintage	-.16 (.06)	-.10 (.06)	-.04 (.07)	.02 (.11)
	LP and GP in same state	.43 (1.09)	-1.52 (.60)	-1.06 (.77)	-3.54 (1.51)
	NASDAQ level	.002 (.003)	.003 (.003)	.0004 (.0037)	.00 (.00)
	Inverse Mill's ratio (lambda)	47.54 (17.74)	-.90 (.68)	49.17 (19.03)	-.97 (.80)
	Indicators for LP location by state	Yes	Yes	Yes	Yes
	Year FE	Yes	Yes	Yes	Yes
	Fund stage FE	Yes	Yes	Yes	Yes
	N	6,795 (uncensored 5,381)	6,795 (uncensored 5,381)	3,684 (uncensored 3,015)	3,684 (uncensored 3,015)
	Pseudo LR ratio	-30,407	-30,719	-16,976	-17.161
	p-value of Wald test	.000	.333	.000	.378

Table 12 – Summary of Executive Profiles in Money Management Firms, 2004

This table compares the profiles of executives in a random sample of 706 money management firms, out of over 1,700 in the full set in Nelson Information's *Investment Managers*. Data such as age, experience and "years with firm" are in years.

	N	Mean	S.D.	Min	Max
All in dataset					
Private equity or VC firms?	706	10%			
FOF firm?	706	3%			
Age (median among executives)	597	48.9	8.0	27	74
Experience (median)	685	22.4	7.3	2	50
Years with firm (median)	692	9.2	7.0	1	35.5
Age (max among executives)	597	60.7	9.6	27	90
Experience (max)	685	35.5	8.7	2	74
Years with firm (max)	692	18.3	12.1	1	58
Within private equity and VC firms					
FOF firms?	68	34%			
Age (median among executives)	45	48.0	5.0	33	61
Experience (median)	54	20.6	5.0	7.5	32
Years with firm (median)	57	7.0	5.3	1	20
Age (max among executives)	45	57.6	8.1	41	73
Experience (max)	54	32.3	8.1	15	49
Years with firm (max)	57	15.7	10.4	1	42
Within private equity and VC FOFs					
Age (median among executives)	18	46.8	6.0	33	61
Experience (median)	23	20.5	5.0	7.5	32
Years with firm (median)	23	7.2	4.4	1	14
Age (max among executives)	18	55.9	8.7	41	73
Experience (max)	23	31.7	8.7	15	49
Years with firm (max)	23	15.4	7.6	4	32

Table 13 – Test of Equality of Means of Executive Experience and Age

This table does a t-test to see whether the means from the data in Table 12 are significantly different.

	t	p-value
Between those in FOFs and other money managers (private equity/VC or not)		
Age (median among executives)	1.113	.266
Experience (median)	1.308	.191
Years with firm (median)	1.403	.161
Age (max among executives)	2.144	.032
Experience (max)	2.184	.029
Years with firm (max)	1.156	.248
Between those in FOFs and other private equity/VC		
Age (median among executives)	1.306	.199
Experience (median)	0.081	.936
Years with firm (median)	-0.182	.856
Age (max among executives)	1.151	.256
Experience (max)	0.501	.619
Years with firm (max)	0.163	.871

Table 14 – Summary of Differences in Access

In the user-non-user comparison, I compare the performance of the non-FOFs portfolios of FOF-using LPs and non-using LPs. This tells whether FOF-using LPs (disregarding the performance generated by their FOF portfolios) are stronger than non-users. In the intra-user comparison, I compare the performance of the FOF and non-FOF portfolios of FOF-using LPs. This tells whether FOFs deliver value condition on LPs' using them. Each cell shows "access" achieved by the LP (either directly or via FOFs). It is measured by (the negative of) lateness, which is the year an LP gets into a fund minus the year the fund is started. Therefore, the smaller the number (less late), the better the access.
* The cut-off in absolute access is to ensure that the lateness/earliness figures do not become so big that they represent most likely long-term open-ended funds rather than close-end ones.

		Cut-off in absolute access*		
	All	**10 years**	**5 years**	**3 years**
User-non-user comparison				
Non-user mean (N)	15.33 (2,500)	5.06 (686)	-1.45 (336)	0.61 (260)
User mean (N)	15.60 (4,921)	6.05 (1,314)	1.92 (486)	0.88 (599)
t statistic	-0.94	-5.61	-3.29	-2.78
p-value	.347	.000	.001	.0055
Intra-user comparison				
Non-FOF mean (N)	15.60 (4,921)	6.05 (1,314)	1.92 (486)	0.88 (599)
FOF mean (N)	5.86 (571)	0.57 (407)	0.31 (390)	0.17 (371)
t statistic	20.19	28.83	13.66	8.78
p-value	.000	.000	.000	.000

Table 15 – Effect of Access on Performance

This table uses IRR as the dependant variable. In the user-non-user comparison, I compare the performance of the non-FOFs portfolios of FOF-using LPs and non-using LPs. This tells whether FOF-using LPs (disregarding the performance generated by their FOF portfolios) are stronger than non-users. In the intra-user comparison, I compare the performance of the FOF and non-FOF portfolios of FOF-using LPs. This tells whether FOFs deliver value condition on LPs' using them. Access is measured by (the negative of) lateness, which is the year an LP gets into a fund minus the year the fund is started. Therefore, the smaller the number, the better access.
The Heckman correction procedure is used, with the selection model:

$$ProbabilitySelected = \beta_o + \beta_1.log(FundSize) + \beta_2.FundVintage + \beta_3.RoundAverage + \Sigma\beta_4.MajorStateIndicator + \beta_5.USorUKindicator + \beta_6.PreviousIRR + \varepsilon.$$

* The absolute access difference limit is to ensure that the lateness/earliness figures do not become so big that they represent most likely long-term open-ended funds rather than close-end ones.

	User-non-user		Intra-user	
Dependant var: IRR for LP-fund pairs	**(1)**	**(2)**	**(3)**	**(4)**
Indicator for FOF user	.18 (.76)	3.35 (1.96)		
Indicator for FOF fund			-3.62 (5.94)	22.09 (3.07)
Lateness*		1.66 (.24)		2.03 (.26)
Lateness x log(fund size)		-.20 (.04)		-.24 (.04)
LP vintage	-.07 (.06)	.25 (.09)	-.09 (.03)	.09 (.11)
LP and GP in same state	.27 (1.27)	.69 (.95)	-1.45 (.93)	-.79 (1.91)
NASDAQ level	.0009 (.0036)	.01 (.02)	.003 (.005)	.01 (.01)
Log(LP size)	1.04 (.63)	1.74 (1.24)	1.00 (.35)	.76 (.37)
Inverse Mill's ratio (lambda)	47.51 (17.99)	56.13 (23.26)	48.64 (18.91)	56.76 (22.53)
Indicators for LP location by state	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Fund stage FE	Yes	Yes	Yes	Yes
N	6,795 (uncensored 5,381)	4,043 (uncensored 2,629)	3,749 (uncensored 3,075)	2,672 (uncensored 1,998)
Pseudo LR ratio	-30,446	-15,394	-17,275	-11,586
p-value of Wald test	.000	.000	.000	.378

Table 16 – Test of Diversification as a Motive for Using FOFs

This table shows whether a measure of diversification is correlated with the use of funds of funds (FOFs) and other explanatory variables. In the user-non-user comparison, I compare the performance of the non-FOFs portfolios of FOF-using LPs and non-using LPs. This tells whether FOF-using LPs (disregarding the performance generated by their FOF portfolios) are stronger than non-users. In the intra-user comparison, I compare the performance of the FOF and non-FOF portfolios of FOF-using LPs. This tells whether FOFs deliver value condition on LPs' using them. The "before and after FOF" test uses an indicator variable to undertake an event study.
Dollar amounts are in millions unless otherwise stated. "PC" = portfolio company.

	User-non-user		Intra-user						Before and after FOF	
Dependant var (total per LP, logs taken)	**Funds**	**PCs**	**Funds**	**PCs**	**Funds**	**PCs**	**Funds**	**PCs**	**PCs**	**PCs**
	(1)	**(2)**	**(1a)**	**(2a)**	**(3)**	**(4)**	**(3a)**	**(4a)**	**(5)**	**(6)**
Indicator for FOF user	.91 (.03)	.005 (.026)	.98 (.12)	-.41 (.12)						
Indicator for FOF user x log(LP size)			.11 (.01)	.03 (.01)						
Indicator for FOF user x log(fund size)			-.15 (.01)	.04 (.01)						
Indicator for FOF fund					-.77 (.18)	-.51 (.20)	-2.58 (.85)	-3.49 (1.22)		
Indicator for FOF fund x log(LP size)							-.04 (.04)	-.11 (.05)		
Indicator for FOF fund x log(fund size)							.35 (.12)	.62 (.17)		
Indicator for after-event FOF use									-.74 (.29)	-10.13 (2.07)
Indicator for FOF fund x log(fund size)										1.48 (.32)
LP location by state FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Fund stage FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
Investment scope FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
Events FE	No	No	No	No	No	No	No	No	Yes	Yes
N	6,762	5,881	6,762	5,881	3,843	3,346	3,740	3,251	253	250
Adjusted R^2	56.9%	33.2%	58.2%	33.3%	37.8%	33.0%	52.5%	33.1%	2.7%	0.6%
p-value of Wald test	.000	.000	.000	.000	.000	.000	.000	.000	.010	.000

Table 17 – Test of the Sub-scale Explanation

This table looks at whether LPs use FOFs to (successfully) overcome sub-scale operations. Dollar amounts are in millions unless otherwise stated. "PC" = portfolio company.

(a) Do FOFs Deliver Value to Subscale (small) LPs?

Dependant var:	(1) IRR	(2)	(3) Excess IRR	(4)
Indicator for FOF-usage	5.46 (3.12)	8.19 (4.00)	5.13 (3.20)	7.73 (4.00)
Log(LP size)	2.00 (1.18)	.12 (.39)	1.43 (.36)	.11 (.39)
FOF-usage x log(LP size)	-.18 (.42)	-1.11 (1.85)	-.20 (.43)	-1.08 (.51)
Log(fund size)		.13 (1.85)		.22 (1.85)
Log(fund size)^2		-.46 (.15)		-.46 (.15)
LP vintage		-.10 (.08)		-.16 (.08)
LP and GP in same state		-1.63 (1.49)		-1.52 (1.49)
NASDAQ level		-.0047 (.0015)		-.0048 (.0014)
Inverse Mill's ratio (lambda)	49.2 (18.2)	-2.68 (.55)		-2.44 (.56)
Indicators for LP location by state	No	Yes	No	Yes
Year FE	No	Yes	No	Yes
Fund stage FE	No	Yes	No	Yes
N	7,632 (uncensored 6,125)	7,576 (uncensored 5,497)	8,501 (uncensored 6,422)	7,576 (uncensored 5,497)
Pseudo LR ratio	-34,669	-31,975	-36,937	-31,956
p-value of Wald test	.0001	.0001	.000	.378

(b) Are Agency Effects Present?

	Dependant var:	Reinvest in next fund, conditional on a next fund?		Num of PCs in fund	Log (ave round amount)
		(1)	(2)	(3)	(4)
	IRR	.0017 (.0010)	.10 (.15)		
	Indicator for FOF-using LP	.31 (.06)	.31 (.06)		
	Indicator for FOF fund	-4.46 (.29)	-4.27 (.21)	9.30 (3.67)	-.87 (.22)
	Interaction of above two	3.98 (.23)	4.17 (.18)		
x IRR	Indicator for FOF-using LP		-.022 (.008)		
x IRR	Indicator for FOF fund		- .0003 (.0011)		
x IRR	Interaction of above two		-.001 (.005)		
	Log (fund size)	.23 (.16)	.25 (.17)	4.13 (.74)	.39 (.02)
	Log (fund size)^2	-.019 (.016)	-.021 (.016)		
	LP vintage	-.0009 (.0039)	-.0002 (.0042)		
	LP and GP in same state	.013 (.082)	-.004 (.086)		
	NASDAQ	.0022 (.0002)	.002 (.0002)	.001 (.002)	.0001 (.0002)
	Log (LP size)	.06 (.01)	.06 (.02)		
	Indicators for LP location by state	Yes	Yes		
	Indicators for LP type	Yes	Yes		
	Interaction of IRR with all above?	No	Yes		
	Indicators for fund location by state			Yes	Yes
	Fund sequence number			.33 (.11)	.008 (.010)
	Fund vintage			-.20 (.10)	-.01 (.01)
	Inverse Mill's ratio (lambda)	.59 (1.00)	.74 (1.02)		
	Cluster by GP	Yes	Yes	Yes	Yes
	Year FE	Yes	Yes	Yes	Yes
	Fund stage FE	Yes	Yes	No	No
	Investment scope FE	Yes	Yes	Yes	Yes
	N	3,584	3,584	1.823	1,794
	Pseudo R^2	24.9%	25.4%	35.7%	56.3%
	p-value of Wald test	.000	.000	.000	.000

Table 18 – Test of the Downward Scaling Explanation

This table shows the results of a test of whether large LPs face a trade-off in downward scaling, which is to push out large volumes of investments over a short period of time. The trade-off is between spreading investment over many FOFs and risking coordination problems among them, versus not staging investments in one FOF and risking getting held up. "Staging" is measured by the dependant variable, which is the maximum sequence number among the funds run by a GP for an LP. "Spreading out" is measured by the number of FOFs by an LP. "Captive FOFs" are those organized by GPs for single LPs.

Dependant var:	**Max sequence number for GP's funds**
Number of FOFs by LP	-1.13
	(.078)
Number of non-FOFs by LP	.076
	(.0007)
NASDAQ Index	-.0006
	(.0005)
Average excess IRR for sequence of funds by this GP	-.06
	(.020)
Captive FOFs?	.14
	(.0003)
Log (amount LP allocates to private equity)	.58
	(.11)
Log (amount LP allocates to FOFs)	-.51
	(.21)
Indicators for LP location by state	Yes
Indicators for LP state	Yes
Indicators for LP vintage	Yes
Cluster by LP	Yes
N	92
Pseudo R^2	45.5%
p-value of Wald test	.000

Table 19 – Test of the Governance Explanation

This table shows whether the use of funds of funds (FOFs) can be explained by different types of LPs, which have different governance structures.

Dependant var:	**FOF-usage**
Indicators for LP type (based=consultants)	
Educational Institutions	1.37
	(.96)
Financial Institution	.85
	(.74)
Foundation	.65
	(.96)
Fund of Funds	.98
	(.68)
Government	1.76
	(.85)
Non Financial Corporations	1.12
	(.84)
Other Non Profits	1.17
	(.81)
LP vintage	-.001
	(.012)
Log (LP size)	.22
	(.06)
Allocation of private equity	.00049
	(.00885)
NASDAQ level	.0017
	(.0059)
Indicators for LP location by state	No
Year FE	No
N	7,930
Pseudo R^2	21.2%
p-value of Wald test	.000

Table 20 – Test of the Learning Explanation

In panel (a), I test for whether FOF usage can be explained by young LPs or LPs venturing into new areas. The latter is measured by an indicator on whether the LP is a first-timer into new investment areas for a particular LP-year observation. Model (1) uses probit estimation. Model (2) uses SUR (seemingly unrelated regression) estimation. Other controls include log(LP size), log(fund size), LP vintage, whether LP and GP are in the same state, NASDAQ level.

In panel (b), I test whether allocation to private equity without using FOFs changes with the duration of the experience with FOFs and the performance of that FOF experience. Other controls include log(LP size), LP vintage, NASDAQ level.

(a) Who Uses FOFs?

Dependant var:	(1) FOF usage	(2) Usage of FOF by investment scope			
		Mixed	Buyout	Focused	VC
LP age	.0039	.0008	.0028	-.0004	-.0012
	(.0058)	(.0003)	(.0005)	(.0002)	(.0060)
Indicator for being first-timer	-.74				
All types	(.11)				
Mixed		-.210	.032	.0023	.020
		(.012)	(.019)	(.0071)	(.018)
Buyout		.044	-.119	-.025	-.014
		(.011)	(.017)	(.006)	(.016)
Focused		.022	-.439	.47	-.071
		(.019)	(.030)	(.01)	(.028)
VC		.021	-.030	-.002	-.11
		(.010)	(.016)	(.006)	(.02)
Other controls*	Yes	Yes	Yes	Yes	Yes
Indicators for LP type	Yes	Yes	Yes	Yes	Yes
Indicators for LP location by state	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Fund stage FE	Yes	Yes	Yes	Yes	Yes
N	8,917	9,222	9,222	9,222	9,222
Pseudo R^2	38.6%	49.8%	42.0%	20.5%	38.5%
p-value of Wald test	.000	.000	.000	.000	.000

(b) Learning or Outsourcing?

Dependant var: Allocation to non-FOFs	Experience with which type of FOFs?			
	(1) All FOFs	(2) All FOFs	(3) Buyout FOFs	(4) VC FOFs
Log (year since first FOF)	-.100		.0098	.0014
	(.034)		(.0067)	(.0175)
$(\text{IRR of most recent FOF})_{-1}$	-.01	-.003	.00002	.0010
	(.002)	(.001)	(.0010)	(.0016)
Interaction of above	.0037		-.000002	-.0002
	(.0009)		(.0003)	(.0008)
Other controls*	Yes	Yes	Yes	Yes
Indicators for LP type	Yes	Yes	Yes	Yes
Indicators for LP location by state	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
LP FE	Yes	Yes	Yes	Yes
N	899	899	291	138
R^2	27.0%	27.2%	84.9%	52.4%
p-value of Wald test	.02	.61	.01	.00

Figure 1 – FOF Usage and Investments in FOFs

(a) Regression Formulation

$$IRR = \ldots + \alpha.FOFuser+\beta.FOFfund+\gamma.FOFuser x FOFfund + \ldots$$

FOFuser \ FOFfund	1	0
1	$\alpha+\beta+\gamma$	α
0	Not applicable	0

Intra-user comparison:
For FOFusers, how do their FOF investments do versus their non-FOF investments?
∂ IRR / ∂ FOFfund $|_{FOFuser=1} = (\alpha+\beta+\gamma) - \alpha = \beta+\gamma$

User-non-user comparison:
How do FOF users do versus non-users in selecting non-FOF (regular) funds?
∂ IRR / ∂ FOFuse $|_{FOFfund=0} = \alpha - 0 = \alpha$

(b) Mapping Above to a Simplifying Picture

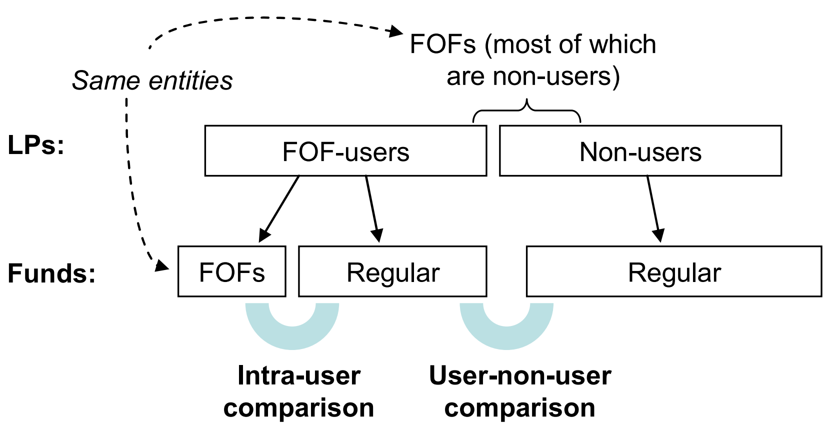
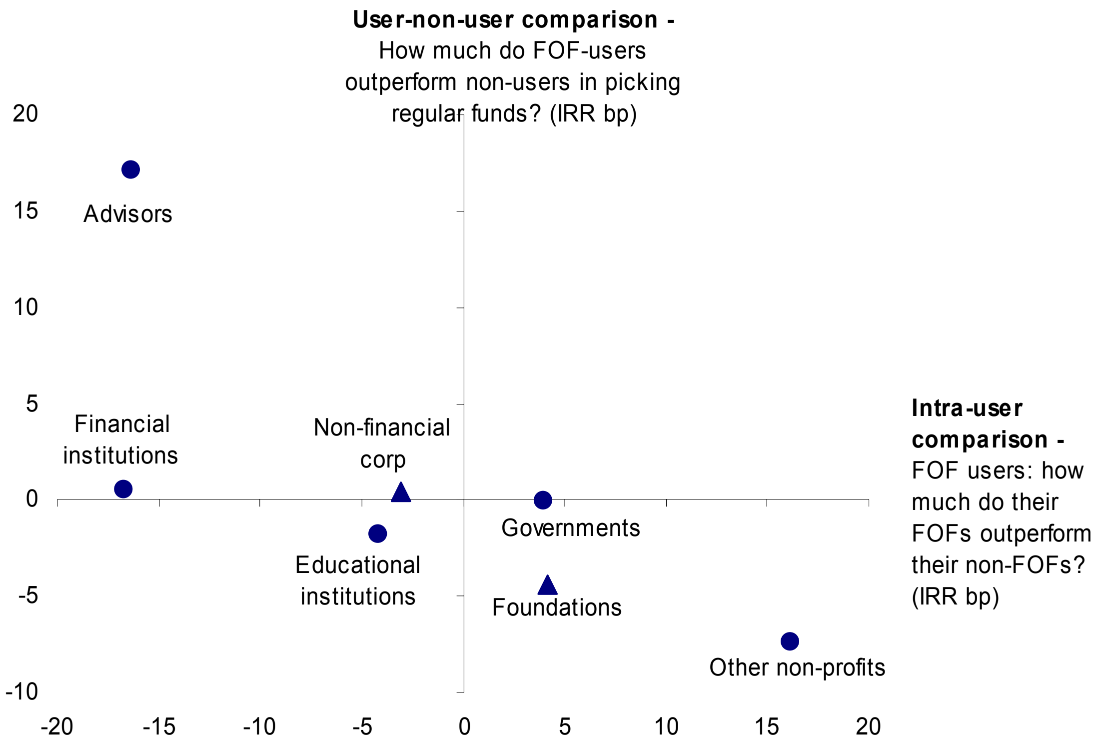


Figure 2 – FOF Usage and Investments in FOFs – Estimation Results by LP Type



Note that "Non-financial corp" and "Foundations," indicated by triangles rather than circles, do not have coefficients for the interaction with FOFusagexFOFfund due to collinearity, and the placement in the plot above assumes a zero coefficient. The plot might be better considered without these two, but I place them here for completeness.

Figure 3 – LP Size and Diversification

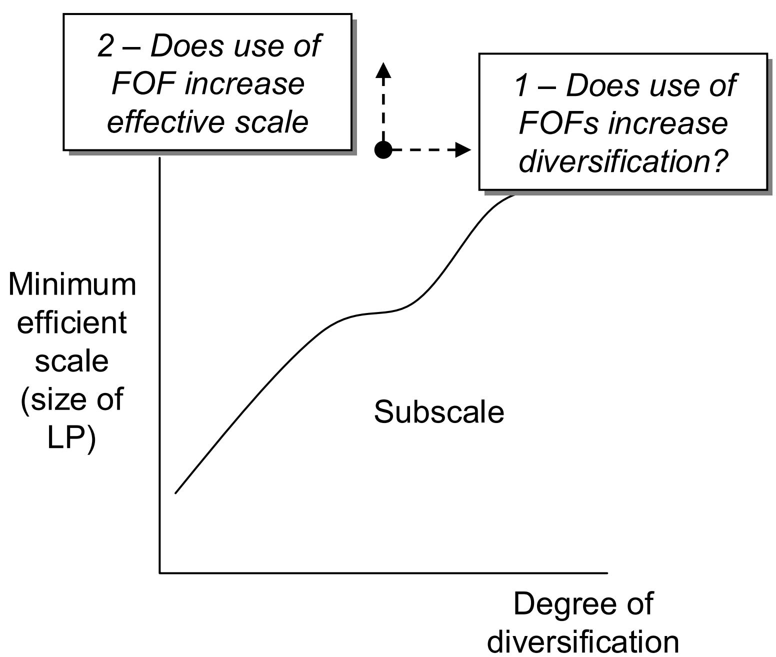


Figure 4 – Correlation of LP size (horizontal axis) and FOF size (vertical axis)

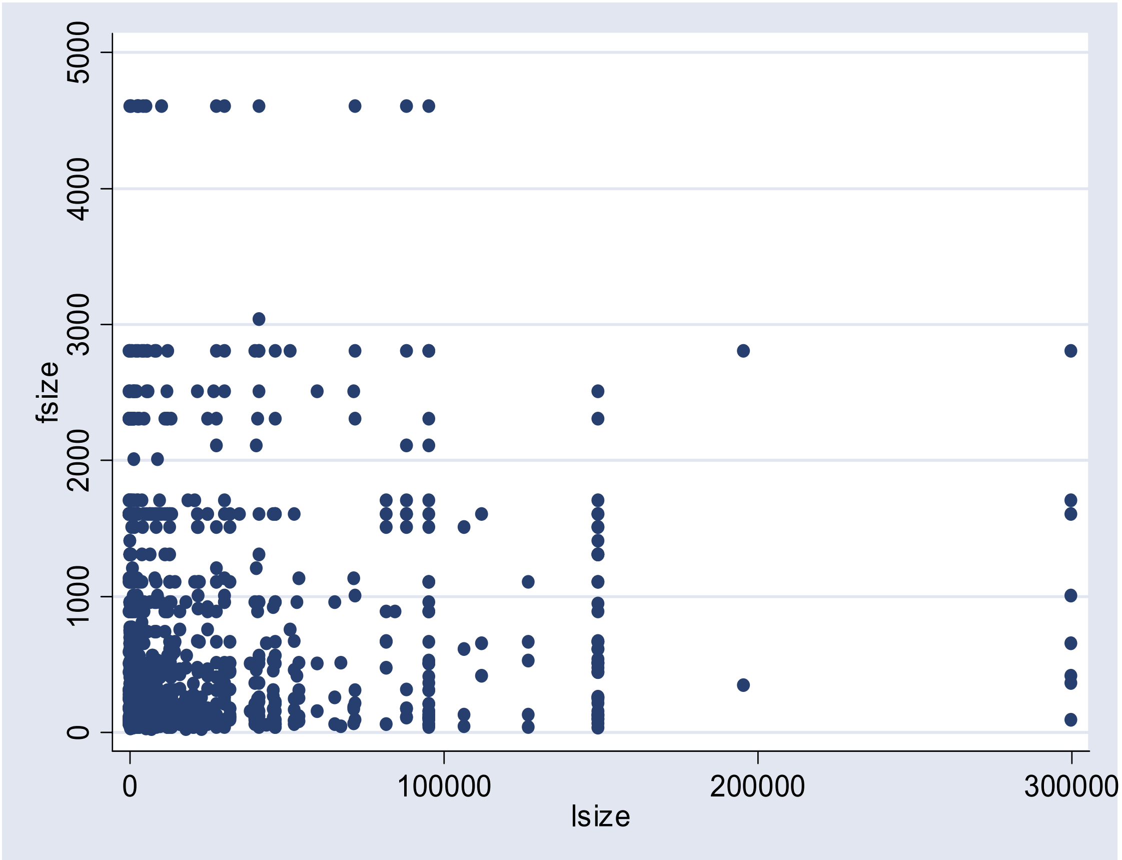


Figure 5 – Performance versus Learning