Measuring Institutional Investors' Skill from Their Investments in Private Equity

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Abstract

Using a large sample of institutional investors' private equity investments in venture and buyout funds, we estimate the extent to which investors' skill affects their returns. We first consider whether investors have differential skill by comparing the distribution of investors' returns to a bootstrapped distribution that would occur if funds were randomly distributed across investors. We find that the variance of actual performance is higher than that of the bootstrapped distribution, suggesting that higher and lower skilled investors consistently outperform and underperform. We then extend the Bayesian approach of Korteweg and Sorensen (2015) to estimate the incremental effect of skill on performance. The results imply that a one standard deviation increase in skill leads to about a three percentage point increase in returns, suggesting that variation in institutional investors' skill is an important driver of their returns.

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1. Introduction

Institutional investors have become the most important investors in the U.S. economy, controlling more than 70% of the publicly traded equity, much of the debt, and virtually all of the private equity. Their investment decisions have far reaching consequences for their beneficiaries: universities' spending decisions, pension plan funding levels and consequent funding decisions by states and corporations, as well as the ability of foundations to support charitable endeavors all depend crucially on the returns they receive on their investments. For this reason, the highest paid individuals in these organizations are often their investment officers. This high level of pay is often controversial, and it is not clear from existing evidence whether these compensation decisions are optimal.[1] If investment performance is random, then it is hard to justify this high level of pay; however, if higher quality investment officers lead to better returns, then it potentially makes sense to pay high salaries to attract them.

One place where investment officers' skill is potentially important is their ability to select private equity funds. The private equity industry has experienced dramatic growth since the 1990s, bringing the total assets under management to more than $3.4 trillion in June 2013 (*Preqin*). Most of the money in this industry comes from institutional investors, and private equity investments represent a substantial portion of their portfolios. Moreover, the variation in returns across private equity funds is large; the difference between top quartile and bottom quartile returns has averaged approximately nineteen percentage points. Evaluating private equity partnerships, especially new ones, requires substantial judgment from potential investors, who much assess a partnership's strategy, talents, experience, and even how the various partners interact with one another. Consequently, the ability to select high-quality partnerships is one place where an institutional investor's talent is likely to be particularly important. However, it is not known whether different institutional investors on average receive different returns. Moreover, it is not clear whether any

[1] For example, Harvard University pays its top 5 endowment officers more than $100m annually, a pay package that has generated much negative attention recently (see Bloomberg, August 27, 2014).

differences in returns across investors reflect the investors' skill, their access to better private equity groups, or just random luck.

In this paper, we consider a large sample of limited partners' (LPs') private equity investments in venture and buyout funds and estimate the extent to which manager skill affects the returns from their private equity investments. Our sample includes 12,043 investments made by 630 unique LPs, each of which have at least four private equity investments in either venture capital or buyout funds during the 1991 to 2006 period. We first test the hypothesis that skill in fund selection, in addition to luck, affects investors' returns. We then estimate the importance of skill in determining returns. Our results imply that an increase of one standard deviation in skill leads to about a 3% increase in IRR. The magnitude of this effect suggests that variation in skill is an important driver of institutional investors' returns.

Our initial test of whether there is differential skill in selecting private equity investments is model-free. We use a bootstrap approach to simulate the distribution of LPs' performance under the assumption that all LPs are identically skilled (i.e., that there is no differential skill and all differences in performance reflect random luck). We measure performance first in terms of the proportion of an LP's investments that are in the top half of the return distribution for funds of the same type in the same vintage year, and then in terms of average returns across all of the LP's private equity investments. The comparisons with the bootstrapped distributions suggest that more LPs do consistently well (above median) or consistently poorly (below median) in their selection of private equity funds than what one would expect in the absence of differential skill. Furthermore, statistical tests of the standard deviation of LP performance shows that there is more variation in performance than what one would expect in the absence of differential skill. These results hold when restricting the analysis to various subsamples by time period, fund and investor type. These analyses suggest that there are more LPs who are consistently able to earn abnormally high returns than one would expect by chance. Some LPs appear to be better than other LPs at selecting the GPs who will subsequently earn the highest returns.

To quantify the magnitude of this skill, we extend the method of Korteweg and Sorensen (KS) (2015) to measure LP skill. The KS model assumes that the net-of-fee return on a private equity fund consists of three main components: a firm-specific persistent effect, a firm-time random effect that applies to each year of the fund's life, and a fund-specific random effect, as well as other controls. We first use this model to estimate the firm-specific component that measures the skill of each GP managing the private equity funds in our sample. We use these estimates to strip away any idiosyncratic random effects from the returns on each fund, thereby adjusting them so that they reflect only the skill of the GP. Then, using Bayesian regressions, we estimate the extent to which LPs can pick high ability GPs for their investments. The estimation is done by Bayesian Markov chain Monte Carlo techniques, and allows us to measure the extent to which more skillful LPs earn higher returns.

The results from the extended KS model imply that a one-standard-deviation increase in LP skill leads to an expected three-percentage-point increase in annual IRR from their private equity investments. The effect is even larger for venture capital investments, in which a one-standard-deviation increase in skill leads to a three-and-a-half-percentage-point to five-percentage-point increase in returns. The large magnitude of these estimates highlights the importance of skill in earning returns from private equity investments.

An alternative explanation for the results we report is that LPs have different risk preferences. LPs with higher risk tolerance would tend to take riskier investments that would lead to higher average returns. Without data on individual LPs' risk preferences, we cannot directly test how much of the difference in returns occurs because of differing risk preferences. However, LPs within the same type are more likely to have the same risk preferences and investment objectives. Accordingly, we divide LPs into endowments, pension funds, and all others. Within each type, we also observe more variation in LP performance than would be expected if LPs had no differential skill. Therefore, at least to the extent that risk preferences are driven by investor type, differing risk preferences do not appear to be driving the observed differences in returns across LPs.

In addition, it is possible that some LPs receive pressure to invest in particular funds that could affect their investment decisions and hence their returns. In particular, Hochberg and Rauh (2013) find that public pension funds tend to concentrate their investments in local funds, while Barber, Morse and Yasuda (2016) document that a number of LPs receive pressure to invest in "impact funds" that undertake socially responsible investments. Both of these practices tend to lower returns. Of the LPs in our sample, public pension funds are the most prone to be subject to pressure to take these kinds of investments. To evaluate the importance of political pressure in explaining the difference in returns across LPs, we reestimate our model using a specification that allows for the possibility that public pension funds receive systematically different returns from other investors. The results using this specification suggest that public pension funds do not have systematically different skill-adjusted returns. Therefore, it does not appear that the differences in returns across investors are explained by differences in political pressure.

Another potential explanation for the differences in performance across LPs is that different LPs have different access to funds, so that certain LPs can invest in higher quality LPs than others can. Both the bootstrap and Bayesian tests we present assume that LPs are able to invest in any fund they select. However, some of the most successful general partnerships limit investments in their funds to their favorite LPs and do not accept capital from others. Consistent with the importance of limited access, Sensoy, Wang, and Weisbach (2014) argue that access to better performing venture capital funds likely explains endowments' outperformance in 1990s.

To evaluate the extent to which limited access explains the differential performance across investors, we compare LPs' average returns with bootstrapped returns using first-time funds only, because first-time funds generally accept commitments from any investor willing to make one. If the main results were driven by differential access as opposed to differential selection skill, we would not expect to find any systematic differences across LPs in the performance of their investments in first-time funds. Contrary to this explanation, we find that more LPs do consistently well or poorly in first-time venture and buyout funds compared to hypothetical first-time investments made randomly. The standard deviation of LPs' average returns in first-time funds is also significantly higher than those obtained from bootstrap simulations. In addition, estimates from the extended Korteweg-Sorensen (2015) model restricted to first-time funds suggest that skill remains an important determinant of performance. Consequently, the systematic differences in returns across LPs do not appear to occur only because those LPs have better access to the best private equity funds. Better access does appear to help explain some of the superior performance, such as that of endowments' investments in venture capital during the 1990s (Lerner, Schoar, and Wongsunwai, 2005). However, the evidence of some LPs' systematic outperformance goes well beyond established venture capital partnerships during this period, and appears to exist in first time funds, in buyout funds and in other time periods as well.

In summary, our results suggest that skill is an important factor in the performance of institutional investors in their private equity investments. Relative to their peers, some LPs perform consistently well, while some perform consistently poorly. This outperformance exists for these LPs' investments in both buyout and venture investments, and the differences are economically meaningful.

Although there is no prior work analyzing the performance of individual institutional investors in private equity, this paper is related to previous work analyzing the performance of portfolio managers. One of the classic literatures in finance, beginning with Jensen (1968), measures abnormal performance and performance persistence of mutual funds. Recent contributions in this literature have taken a Bayesian approach similar to that used here to evaluate the performance of hedge funds and mutual funds.[2]

In the private equity area, Kaplan and Schoar (2005) are the first to apply persistence tests to measure ability, but the ability they measure is of the GPs who manage the funds, not the institutional investors who choose between GPs. Korteweg and Sorensen's (2015) estimates suggest that there is long-term persistence at the GP level, but also that past performance is a noisy measure of GP skill. Relatedly, Hochberg, Ljungqvist, and Vissing-Jorgensen (2014) argue that the process of learning GP skill is one

[2] See Baks, Metrick and Wachter (2001), Pastor and Stambaugh (2002a,b), Jones and Shanken (2005), Avramov and Wermers (2006), and Busse and Irvine (2006).

reason why GP performance persists over time. Evaluation of GPs' ability appears to be particularly difficult, consistent with our conclusion about the value of LP skill.

These papers measure the abilities of portfolio managers, while our work measures the performance of investors who choose between these managed portfolios. As such, this work is related to Lerner, Schoar, and Wongsunwai (2007) and Sensoy, Wang and Weisbach (2014), who study limited partners' investments in private equity funds. However, these papers focus on differences across *classes* of investors, while our focus is on the individual LPs and their choices.

2. Sample description

2.1. Data Sources

To examine LPs' private equity investments, we construct a sample of LPs using data obtained from two sources: *VentureXpert* provided by Thompson Economics and S&P's *Capital IQ*. While these two sources do not provide a complete list of LPs' investments, we identify a large sample of 32,599 investments of LPs in private equity funds starting from 1991.

For each investment, we match fund-level information with venture and buyout returns data from *Preqin*. Funds raised after 2006 are excluded to provide sufficient time to observe the realization of the fund's return. Since we rely on internal rates of return (IRR) as our primary measure of LP performance, we drop investments with missing IRR or fund size. These restrictions leave a sample containing 14,380 investments made by 1,852 LPs. In addition, we restrict our sample of LPs to those making more than 4 investments in either venture or buyout funds. Our final sample contains 12,043 investments made by 630 unique LPs in 1,195 unique funds.

As a supplement to IRR, we also calculate an "implied public market equivalent (PME)" generated from fund IRRs and multiples, using the method described in Harris, Jenkinson, and Kaplan (2014).[3] The

[3] Although *Preqin* reports fund IRRs and multiples, it does not report PMEs and calculating them requires the underlying cash flow data, which we do not have. Therefore, to compute the implied PME, we rely on regression coefficients reported by Harris, Jenkinson, Kaplan, and Stucke (2013) to impute PMEs from IRRs and multiples.

PME approach is an increasingly popular method of measuring performance of illiquid assets (see Korteweg and Nagel, 2016, and Sorensen and Jagannathan, 2015, for discussions of methodological issues). The results from the tests using implied PMEs are similar to the ones discussed below and are available from the authors on request.

2.2. Sample Characteristics

Table 1 reports summary statistics for all funds, venture funds, and buyout funds at both the LP level and fund level. Panel A shows the number of observations, mean, median, Q1, and Q3 values of each LP characteristic. On average, each LP invests in 19.12 funds. Because we restrict our sample to LPs with at least 4 investments, the first quartile value for *Number of investments* per LP is 5 funds. The average return of LPs' investments shows an IRR of 10.59%. Buyout funds are also larger than venture funds, on average.

Panel B reports summary statistics of LPs' investments at the fund level. The average IRR is 11.02% and average implied PME is higher than the benchmark S&P 500. Buyout funds have higher returns than venture funds and are larger. On average, there are 10.12 LPs in each fund over the entire sample. Since venture funds tend to be smaller than buyout funds, venture funds have fewer LPs, with an average of 7.62 LPs for the venture funds in our sample, and 12.58 LPs for the buyout funds. The average performance of funds in our final sample is close to that of all funds with performance information available in *Preqin*, suggesting that our sample is representative of the universe of private equity funds.

While the sample comprises a large number of LPs and their investments, it does not necessarily include all investments made by any particular LP, nor does it include all of the LPs in a given fund. The coverage is better for later periods as well as for public entities, such as public pension funds and public universities, whose investments are subject to federal and state Freedom of Information Acts. Another drawback of the sample is the lack of commitment data, which precludes us from calculating LPs' total

When a private equity firm raises multiple funds in a given year, we aggregate all funds in that year and compute size-weighted PME.

returns. Instead, we use the reported IRRs of the funds in which the LPs invest. We calculate these returns both equally weighting the returns and weighting them by the log of the fund's capital under management.

3. Model-free Tests of Differential Skill in Selecting Private Equity Funds

3.1. Qualitative Assessment

In this section, we evaluate whether LPs appear to have differential skill in picking private equity investments. If LPs differ in their ability to select private equity funds, then the more able LPs should consistently outperform, and the less able LPs should consistently underperform. This persistence in performance should be greater than what would be expected by chance.

Such persistence could occur because of factors other than skill, such as access to top-performing GPs or differences in risk tolerances. We consider these alternative explanations explicitly in Section 5. The results presented there suggest that differential access or risk tolerances are unlikely to explain the main results. Consequently, until Section 5, for brevity of exposition we refer to evidence of differences in LP performance beyond what would be predicted by chance as evidence of LP skill.

While there is no literature measuring the skill of individual LPs of private equity funds, there is a large literature measuring the skill of other portfolio managers. The conventional approach to measuring skill in other contexts has been to estimate a regression of returns on lagged returns. This approach measures skill by the extent to which returns from the previous fund are predictive of returns from the next fund. Although this approach has some appeal as a simple, intuitive test, it takes a relatively narrow, short-term view of skill, and ignores longer-term patterns of returns. For instance, an LP who makes five outperforming investments in a row, followed by five underperforming investments, is unlikely to be more skillful than an LP who alternates the same number of outperforming and underperforming investments.[4]

[4] See Korteweg and Sorensen (2015) for a critique of the merits of the regression approach.

We measure skill for each LP using approaches that are not dependent on the particular timing of the investments' returns. We first calculate the percentage of an LP's investments in the top half of funds of a particular type (e.g., venture or buyout) for a given vintage year.[5] We assess whether different LPs have differential skill by examining the distribution of this measure across LPs, which we refer to as the "distribution of LP persistence". The more variation there is in skill among LPs, the more variance there should be in the distribution of LP persistence.

In the next subsection, we conduct formal tests of differential skill based on the variance of the distribution of LP persistence. However, in boiling the distribution down to a single summary statistic, we risk losing potentially useful information. Therefore, we begin with a qualitative comparison of the empirical distribution of LP persistence with the hypothetical distribution that would occur if LP investments were made randomly.

If the only source of variation in returns were random chance, then every investment would have a 50% chance of being in the top half of the return distribution for its year, regardless of the identity of the LP making it. Therefore, the distribution of LP persistence would be approximately bell shaped.[6] In contrast, the empirical distribution, shown in Figure 1, is negatively skewed with fat tails in both directions. This pattern suggests that there are more LPs with persistently good and bad performance than what one would expect by chance.

Figure 1 also characterizes LPs' investments in venture capital and buyout funds separately. The distribution of LP persistence in venture capital funds is similar to that in all investments. The figure shows negative skewness and fat tails on both sides in the distribution of LP persistence in venture capital funds. The distribution for buyout funds is more symmetric, and the tails are thinner compared to what we observe

[5] We could extend the analysis to quartiles or deciles, but a finer cutoff would make the comparisons more difficult to interpret.
[6] The actual distribution should be a mixture of binomial distributions depending on the number of investments made by each LP.

for venture funds. However, the tails on both sides are still fatter than what one would expect from a bell-shaped distribution.

In summary, Figure 1 suggests that LPs' performance differs from what would be expected if variation in returns were due to chance alone. There are more LPs at the top and the bottom of the distribution of returns than what would occur if returns were randomly distributed across LPs. This pattern appears to exist for both venture and buyout funds. While some of these LPs could have been merely lucky (or unlucky), this pattern suggests that some of them achieved their persistence through something other than just chance performance, such as skill.

3.2. Bootstrap Simulations of LP Persistence

For a formal test of whether individual LPs have differential skill, we compute the standard deviation of the distribution of LP persistence. We construct a statistical test by bootstrapping the sampling distribution of that test statistic under the null hypothesis that there is no differential skill. An observed standard deviation higher than what would be expected by chance (i.e., one far enough in the right-hand tail of the sampling distribution) would suggest that there is differential skill among LPs.

The null hypothesis is that there is no differential skill, so LPs select funds uniformly at random from the universe of possible investments. Accordingly, in each iteration of the bootstrap, we randomly assign funds to each LP, with the restriction that the fund assignments match the fund types and vintage years of the LPs' actual investments. So, an LP that actually invested in four venture capital funds in 1999 receives a random assignment of four venture capital funds with that vintage year. When we construct the bootstrapped sample, we draw from the entire distribution of funds from the *Preqin* database, not just the funds that are in our sample. Using the *Preqin* universe instead of funds in our actual sample gives our tests more power and does not limit the scope of analyses we run when we restrict our actual sample to smaller subperiods and subsamples. Since small funds tend to have fewer LPs than large funds, we weight the selection probability by fund size. In each iteration, we compute the "persistence" of each LP (i.e., the percentage of the LPs investments for which returns were in the top half relative to funds of the same time in the same vintage year) and the standard deviation of LP persistence. Then, across 1000 iterations, we obtain the distribution of the standard deviation of LP persistence under the assumption that each LP chooses its private equity investments randomly (i.e., the null-hypothesis distribution). We compute the null-hypothesis distribution separately for venture funds, buyout funds, and all funds. Sensoy, Wang, and Weisbach (2014) show that LP returns changed dramatically in the 1999 to 2006 period. Therefore, we also compute our null-hypothesis distribution separately for subperiods from 1991 to 1998, 1999 to 2006, and the full sample.

The results from the bootstrap simulations are reported in Panel A of Table 2. The column labeled *Actual* shows the standard deviation of LP persistence, while the column labeled *Boot* shows the mean of the standard deviations of the bootstrapped samples. The variable *% > Actual* is defined as the percentage of bootstrapped samples with standard deviations greater than what we observe in the actual sample. We perform our tests separately for the subperiods from 1991 to 1998 and from 1999 to 2006. For all of the fund types in each subperiod, we find that the standard deviation of LP persistence is higher than in the vast majority of bootstrapped samples. In other words, if LPs had chosen investments randomly, the distribution of LP persistence would not be as variable as we observe it to be.

To evaluate the statistical significance of these results, we rely on the *% > Actual* value, which has the same interpretation as a p-value in a classical hypothesis test: the likelihood that the actual results would have occurred were the null hypothesis true and the variation in the data due to random chance. In these results from Panel A of Table 2, for each group of funds and each time period, the *% > Actual* is less than 5% and in all except the buyouts for the latter period it is less than 1%. The implication of these low values of *% > Actual* is that it is highly unlikely that random chance alone could cause the standard deviation of LP persistence to be as high as it is.

3.3. Bootstrapping LPs' Returns

We next repeat the above analysis using an LP's average returns instead of the fraction of its investments in the top half of the return distribution. We compute the standard deviation of LPs' average returns, both weighted by the log of fund size and equally weighted, in the actual sample and in every bootstrapped sample. The mean of the bootstrapped standard deviations is an estimate of what the standard deviation would be if there were no differential skill, hence we refer to it as the "bootstrapped estimate" of the standard deviation. We report comparisons of the actual standard deviation and the bootstrapped estimate for log size-weighted and equally-weighted average IRR in Panels B and C of Table 2.

For the full sample period, the standard deviation of LPs' average returns, both weighted by the log of fund size and equally weighted, is higher than the bootstrapped estimate. However, the difference between them is not statistically significant, since the *% > Actual* is around 30% for each. The difference between the actual standard deviation and the bootstrapped estimate is significantly different for the latter (1999-2006) subperiod but not for the earlier period, when the bootstrapped estimate of the standard deviation is actually higher than in the actual sample.

When we divide the sample into venture funds and buyout funds, in each case, the actual standard deviation is greater (or equal in one case) than the bootstrapped estimate for the full sample period. For the later subperiod, the actual standard deviation is statistically significantly higher than the bootstrapped estimate for venture funds but not for buyout funds. Neither is significantly higher for the earlier subperiod. The lack of significance for most of the subgroups and subperiods could be an indication that skill is not a particularly important driver of returns, or it could be the result of noise in returns reducing the power of this test. We address this issue later by using the Korteweg and Sorensen (2015) Bayesian approach with year fixed effects and firm-time random effects.

3.4. The Distribution of LPs' Returns

An alternative to looking at the standard deviation of returns is to consider the details of the distribution more carefully. The standard deviation of LP returns, while informative, is not sufficient for evaluating whether certain LPs systematically outperform others, especially given that the distribution of private equity returns is highly skewed. For example, the larger standard deviation in the actual distribution could be due to a few investors doing exceptionally well, or a few doing exceptionally poorly, or both. It could also be due to the majority of investors doing either moderately well or moderately poorly, but few performing near average (i.e., a bimodal distribution). This distinction speaks in turn to the nature of differential skill and how it affects returns. It could be that there is a small number of highly skilled institutional investors who vastly outperform the field, or there could be subgroups of slightly more- and slightly less-skilled institutional investors.

For this reason, instead of looking at a uni-dimensional measure of the spread of the distribution, we examine exactly where the distribution of LP returns differs from the bootstrapped distributions. To do so, we construct a frequency distribution of LPs' average returns by aggregating returns into evenly spaced bins. Bins in the full sample and the later subsample period are based on increments of five percentage points. Bins in the earlier subsample period are based on increments of ten percentage points because a large number of funds, especially venture funds, had unusually high returns during that period.

For each bin we count the number of LPs whose average returns fall in that bin. We do this for the actual sample, and for each bootstrapped sample, using both equal-weighted and log(size)-weighted returns. Table 3 presents the frequency of LPs in each bin for the actual sample, as well as the tenth and ninetieth percentiles of the frequencies in the bootstrapped samples. Figures 2 and 3 correspond to the size- and equal-weighted average IRR results presented in Table 3, respectively. In each figure, the bars represent the actual count of LPs in each bin, and the horizontal lines represent the cutoffs for top and bottom 10^{th} percentile of the bootstrapped samples. In interpreting these results, it is useful to focus on venture and buyout funds in different subperiods separately, since their returns were very different from one another in different subperiods, with venture doing better in the 1991-1998 period and buyouts better in the 1999-2006 period.

The magnitude of differential returns across LPs is particularly evident for venture funds in the early sample period (middle row, middle column of Figures 2 and 3). In this subsample, relative to bootstrap expectations, there are far fewer LPs with an average IRR in the middle range (e.g., between 20% and 50%), and far more in the right tail (e.g., greater than 70%) and left tail (between -10% and +20%). Relative to venture funds, returns from buyout funds in the early sample period (middle row, right column of Figures 2 and 3) are lower and much more homogeneous. The vast majority of LPs obtained an average IRR between 0% and 20% in both the actual sample and the bootstrap, and we do not observe the same fat tails that were so apparent in the distribution for venture funds. Nevertheless, a similar pattern holds for buyouts as for venture funds, in that there were fewer LPs with an average IRR in the middle range (between 0% and 20%) than the bootstrap expectations. The frequency of LPs with an average IRR greater than 30% exceeded the bootstrap expectations, but the only bin that exceeds the 90th percentile of expectations is from 30% to 40%. Even the most skilled LPs could not obtain the spectacular returns on buyout funds that were possible with venture funds during this period.

In the later sample period (bottom row of Figures 2 and 3), average returns are much more homogenous than in the early sample period. As a result, the distributions for both venture and buyout funds are heavily concentrated around their modes (between -5% and 0% for venture funds and between 0% and 5% for buyout funds) with little sign of the fat tails found in the early sample period. However, the bootstrapped estimates are also heavily concentrated around the mode, especially for venture funds. In the case of venture funds, the number of LPs in the modal class (between -5% and 0%) is below the 10th percentile of the bootstrapped estimate, and the number of LPs in the tails meets or exceeds the 90th percentile of the bootstrapped estimates for the majority of bins (see the bottom panel of Table 3 for details). In the case of buyout funds, we see the opposite pattern: more LPs than expected near the mode and fewer in the tails. This could be interpreted as evidence against differential skill for buyout funds in the later sample period, but it does not rule it out. This pattern could result from negative correlation between skill and luck for these investors in that time period, or simply from type-2 error due to a small effect size and a small sample size. We revisit this issue with the parametric analysis in the next section.

4. Parametric Estimates of LP Skill

The bootstrap analyses of LP performance in the previous sections show that the distribution of LP performance is significantly different than what one would expect if all LPs drew their returns from the same distribution, suggesting that there is an LP-specific factor in determining returns. The bootstrap analysis has the advantage that it is a model-free procedure that imposes no structure on the data. The disadvantages of the bootstrap are that model-free estimates are less powerful than those that parameterize the data, they cannot quantify the magnitude of differences across LPs, and they cannot identify the LPs that consistently earn the highest returns through greater skill.

To address these issues, we extend the model of Korteweg and Sorensen (KS, 2015) to incorporate LP investments. The KS model is designed to measure the differential skill of private equity firms, i.e. GPs. The idea of the KS model is to think of the net-of-fee return on fund u managed by firm i, denoted y_{iu}, as consisting of three components (conditional on appropriate controls): a firm-specific persistent (fixed) effect γ_i, a firm-time random effect η_{it} that applies to each year of the fund's life, and a fund-specific random effect ε_{iu}. We use the KS model to decompose the variance of fund returns into three variance components, one for each of these three effects. The part of the variation due to the firm-specific effects γ_i measures the extent of persistent heterogeneity in private equity firms' skill. When there is greater variation in γ_i, there should be greater differences in skill between firms. The firm-time random effects adjust for, among other things, the fact that a given private equity firm could be managing multiple funds at the same time. We use the version of the model presented by KS that includes fund-vintage-year fixed effects. These fixed effects perform a full risk-adjustment with respect to any set of observed or unobserved risk factors, such as a market or liquidity factor, under the assumption that the relevant risk loadings are common to all funds of a given type (venture capital or buyout) and vintage year.

Although the KS model is designed to measure GP skill, we extend it to measure an LP's ability to invest in high-skill GPs. We extend the model by first using the KS model to decompose the returns from each fund as described above, and then subtracting the random components to isolate the portion of returns that can be attributed to the skill of the GP. We then estimate a Bayesian regression of the adjusted fund returns on LP-specific fixed effects. Since differences in the adjusted fund returns can be attributed to differences in GP skill, the LP-specific fixed effects defined in this way capture differences in an LP's ability to invest in high-skill GPs. We also modify this procedure to allow the LP-specific fixed effects to also incorporate the fund-specific random component of returns. In doing so, the LP fixed effects measure both the LP's ability to invest in high-skill GPs and the LP's ability to select the higher-performing funds of a given GP. In the next subsection we describe the KS model and our extension of it in more detail.

4.1. Model

Under the simplifying assumption that all private equity funds have 10-year lives, the total log return of fund *u* of firm *i* is given by:

$$y_{iu} = 10 * ln(1 + IRR_{iu}). \qquad (1)$$

As described above, KS model this return as:

$$y_{iu} = X_{iu}\beta + \sum_{\tau = t_{iu}}^{t_{iu}+9}(\gamma_i + \eta_{i\tau}) + \varepsilon_{iu}, \qquad (2)$$

where X_{iu} is a vector of vintage year fixed effects, β represents the coefficients on them, and other parameters are as described above.

Following KS, we estimate the model using Bayesian Markov chain Monte Carlo (MCMC) techniques. Although Equation (2) can in principle be estimated using classical techniques such as maximum likelihood, the Bayesian approach offers several advantages for our purpose. It avoids assumptions about the homoscedasticity and normality of the error term that are especially likely to be violated given the skewness of private equity returns. It also avoids small-sample bias in estimation of the fixed effects that are key to the model. Moreover, the Bayesian approach is well suited to estimating the variances in the model, such as that of the GP fixed effects, from relatively small samples, while incorporating reasonable prior beliefs about these parameters, which are of key theoretical importance. Korteweg and Sorensen (2015) elaborate further on the advantages of the Bayesian approach to estimating models like this one.

The estimation proceeds in two steps. For each MCMC cycle g, the first step is to obtain a parameter draw for the distribution of firm fixed effects γ_i and the idiosyncratic errors ε_{iu}. To do so, we estimate the KS model by following the procedure described in sections A1 to A5 of their appendix.[7] We use priors and starting values described in section A7 of the KS appendix. In this step, we use all funds available in *Preqin*, not only those in which the LPs in our sample have invested.

At the end of the first step, we adjust each fund's total return to control for the firm-time random effects and the vintage year fixed effects sampled from the posterior distribution following the KS appendix.

$$\widehat{y_{iu}}^{(g)} = y_{iu} - X_{iu}\beta^{(g)} - \sum_{\tau=t_{iu}}^{t_{iu}+9} \eta_{i\tau}^{(g)} \quad (3)$$

Because some LPs tend to invest in subsequent funds of a given private equity firm, subtracting the firm-year random effects is important to control for overlap. These random effects will tend to be positive (negative) for funds that have a lot of overlap with other funds that have relatively high (low) returns. The adjusted returns obtained in this way are equal to a parameter draw from the posterior distribution for each firm fixed effect (times ten) plus the fund-specific error. Keeping the fund-specific error allows our estimates to appropriately credit LPs who invest in the more successful funds of a given GP, that is, display within-GP selection ability. Estimates based on Equation 3 are referred to as "Model 1". We also present estimates in which Equation (3) also adjusts for the fund-specific error, so that they only reflect the ability of an LP to pick a specific GP ("Model 2"). Comparing the two allows us to infer how much of LPs' differential skill stems from selection among GPs and how much from selection among the funds of a given GP.

The second step, still within the same MCMC cycle g, consists of estimating a Bayesian regression of the adjusted fund returns on LP-specific fixed effects and a set of constants, which consists of either a single intercept for all LPs or a set of LP-type (endowment, pension fund, etc.) fixed effects. The regression can be estimated using BO and VC data together or separately, and for endowments, pension funds and

[7] In KS, the random effects η_{it} are redefined so that their mean is the firm effect γ_i. We instead leave them as mean zero to ease interpretation of the second step of our estimation.

others together or separately.

Specifically, the regression is:

$$\widehat{y_{iuj}} = X_{LP_j}\beta_{LP} + 10\lambda_j + \pi_{iuj}, \qquad (4)$$

where j indexes LPs and we suppress the MCMC index g. Because all LPs in a fund earn the same return, $\widehat{y_{iuj}} = \widehat{y_{iu}}$ for all LP j. In equation (4), X_{LP_j} is the appropriate constant term, consisting of either a single "intercept" for all LPs or LP-type fixed effects. λ_j is the LP-specific fixed effect, and π_{iuj} is a fund-LP specific random effect. Each of these parameters has an intuitive interpretation. In regressions in which the constant term is a common intercept for all LPs, it captures the extent to which the sample LPs (for which we have investment data) outperform or underperform the universe of LPs investing in *Preqin* funds. In other words, the common intercept captures the average ability of the sample's LPs (endowments, pension funds and other LPs) to select funds in the *Preqin* universe. In regressions in which the constant terms are LP-type fixed effects, the omitted category serves this function of controlling for selection "bias" in the LP sample and the other fixed effects estimate the extent to which some types of sample LPs (e.g., endowments) outperform other types.

Regarding the LP-specific fixed effects, LPs whose investments are more frequently in funds whose GPs have high firm fixed effects will have higher LP fixed effects. In this sense, the LP-specific fixed effects capture differences in LP skill, where LP skill is thought of as the ability to invest in high-skill GPs. Part of such skill may in fact stem from differences in access to top-tier private equity firms, a possibility we investigate further below. The fund-LP-specific random effects account for the adding up constraint that results from the fact that all LPs in the fund receive the same return. For instance, if an LP with a high LP-specific fixed effect and one with a low LP-specific fixed effect both invest in the same fund, the former fund-LP-specific random effect must be low and the latter high.

For each MCMC cycle g, Appendix 1 describes how we sample from the posterior distribution of the parameters in equation (4) and their variances. A key parameter is σ_λ, the standard deviation of the LP effects. A high σ_λ means that there is evidence of persistent long-term heterogeneity in the true ability of

LPs to invest with skilled GPs. As in KS, each MCMC cycle g yields a draw of the parameters in equations (2) and (4). The sequence of draws over a large number of cycles forms a Markov chain, the stationary distribution of which is the posterior distribution, from which the marginal posterior distribution of parameters of interest can be obtained.

Each MCMC cycle *g* yields a vector of estimated LP effects that has a certain variance. The overall estimated variance of the LP effects is the average of the estimated variances in each of the 100,000 MCMC cycles. This is the model's estimate of the extent of variation in LP skill.

4.2. Bayesian Estimates of LP Skill

The main results are displayed in Table 4. Panel A displays results for the full sample of funds raised between 1991 and 2006, while Panels B and C focus on funds raised 1991-1998 and 1999-2006, respectively. In each table, results in odd-numbered columns include the fund-specific error (Model 1), while results in even-numbers columns do not include this error (Model 2).

First, the standard deviation of the LP effects, σ_λ, is highly statistically and economically significant,[8] averaging about three percentage points of IRR for the full sample period and for buyout and venture capital funds taken together (columns (1) and (2) of Panel A). This result means that an LP that is one standard deviation more skilled than average earns about 3 percentage points higher IRR on its private equity investments.

Second, consistent with the greater variability of returns to venture capital funds compared to buyouts, there is evidence of stronger LP skill in venture capital investments. The standard deviation of the LP effects for buyout funds is 2.7 to 3.2 percentage points of IRR, compared to 3.5 to 5.0 percentage points when considering venture capital funds only.

Finally, consistent with prior work (Lerner, Schoar, and Wongsunwai, 2007; Sensoy, Wang, and Weisbach, 2014), endowments perform significantly better than other LP types, but this result is driven by

[8] Statistical significance in this context means more than two Bayesian standard errors from zero. Although a standard deviation cannot be negative, the mean estimate could still be within two standard errors of zero if the posterior distribution were sufficiently skewed.

investments in venture capital funds raised in the 1991-1998 period. In this period, the standard deviation of LP effects in venture capital investment is very high: eleven percentage points of IRR without adjusting for fund-specific error and four percentage points with the adjustment.

In the later 1999-2006 period, endowments perform similarly to other LP types, and the standard deviation of LP effects for venture capital funds drops to just over three percentage points of IRR, with or without the adjustment for fund-specific error. In their investments in buyout funds, endowments do not outperform in any sample period, with estimated coefficients similar to those of pension funds and other LP types. The standard deviation of LP effects is likewise stable for buyout funds at just below three percentage points of IRR for both sample periods.

Overall, estimates from the Bayesian KS model are consistent with the tests using the nonparametric bootstrap approach. The ability of LPs to pick GPs is not random, and better LPs outperform less skilled LPs. The magnitude of the performance difference is substantial, amounting to about three additional percentage points of IRR per year for a change in one standard deviation of skill. The magnitude of performance difference was even greater in the earlier sample period, driven mostly by the spectacular performance of endowments' investments in venture funds.

4.3. Estimates of Individual LP Skill

The estimates presented so far suggest that there are systematic differences across LPs in the quality of funds in which they invest. However, they do not provide any guidance into the skill of any particular LP. The measure of an individual LP's skill in this estimation procedure is given by λ_j, the LP-specific fixed effect. We present the λ for each LP in our sample in Appendix 2.[9] Since we estimate equation (4) in logarithmic form, we convert each λ so that it measures the LP's abnormal return. Consequently, if an LP's λ is estimated to be .01, then the model predicts that the LP's private equity investments have 1% higher

[9] We focus our discussion here on the λ's from Model 2, which adjusts for fund-specific errors, and so measures the ability to choose between alternative GPs, but not the ability to pick between funds offered by a given GP. A number of prominent LPs have the strategy of investing in all of a GPs' funds to maintain their relationships. A model that incorporates the ability to distinguish between funds of a given GP would obscure the skill of such LPs.

IRR than a typical LP.

Figure 4 presents a histogram that summarizes the estimated λ for a number of prominent LPs. The number of LPs in each IRR bin is shown on top of the bars. The figure is hump-shaped because of the assumption built into our estimation that the λ's are distributed normally. On this figure, we highlight the λs of 20 prominent LPs. Fifteen of these LPs are among the largest investors in private equity and the other 5 are the largest endowments as of 2015.[10] Of these 20 LPs, the one with the highest estimated λ is MIT, with a λ of 1.17%, and the lowest is CALPERS, with a λ of -1.23%.

4.4. Comparisons of the Estimates

If the estimates of λ we report really reflect skill and not some other factor, then a higher λ should consistently lead to higher returns. A way to evaluate the quality of these estimates is by comparing these estimates across models, with other measures of performance such as IRR, and across subperiods. Positive correlations would indicate that there is some consistent factor such as skill driving returns, while low or zero correlations would suggest that the λ's are relatively noisy and could reflect other factors.

Panel A of Table 5 presents a rank correlation of the estimated skill measures (λ) across the two models. We split the analysis by time period and by LP type. For the full sample, two subsample periods, and different LP types, λ's from the two models are strongly positively correlated. This positive correlation suggests that the LPs who are best at identifying skilled GPs are also best at selecting the best funds within a given GP.

Panel B of Table 5 shows Pearson's correlation between LPs' estimated λ and their average IRR. We present this correlation for each type of investor and for each time period. The correlations are all positive, mostly between .6 and .8, and are all statistically significant. The fact that the correlations are positive and substantial suggests that the estimated λ's do measure skill.

Panel C presents the rank correlation analysis of LPs' IRRs and estimated λ across the two

[10] We identify these LPs based on *Private Equity International's* ranking of LPs for 2015.

subperiods, 1991-1998 and 1999-2006. The correlations for IRR across the two periods are mostly negative, suggesting that returns do not persist across time periods. The negative correlation of IRRs across periods further cautions against using realized performance as the sole measure of an LP's skill, and highlights the importance of a model such as the one we present.

The correlation for estimated λ from Model 1 is relatively small but positive, suggesting that skill does persists across time periods. By far, the highest correlation across periods is from the estimated λ from Model 2. It appears that an LP's ability to identify the most skilled GPs persists across time periods and is much stronger than an LP's ability to select among the funds of a given GP.

5. Interpreting Differences in LP Performance

5.1. Differences in Risk Preferences and Political Pressure

The preceding analyses suggest that there are substantial and statistically significant differences in average returns across LPs, which are consistent with the notion that LPs differ in their skill at selecting private equity funds. An alternative explanation for the observed differences is that LPs could have different risk tolerances, so that LPs with higher risk tolerance tend to select funds that have both higher risk and higher expected returns. It is difficult to test this explanation directly since LP risk preferences are unobservable. The difficulty in estimating fund-level measures of systematic risk in private equity makes the issue doubly difficult.

However, to shed some light on this issue, we repeat our model-free analysis separately for different classes of LPs, specifically endowments, pension funds, and all other types.[11] To the extent that LPs of a given type have similar investment objectives and are benchmarked against one another, risk preferences should be similar across LPs of a given type. If differential skill were the primary explanation for our main

[11] Our Bayesian parametric analysis already had fixed effects for each LP type (endowment, pension fund, and other), so it is not necessary to repeat the analysis separately for each type. The fact that the standard deviation of LP skill (σ_λ) is still statistically and economically significant, even after accounting for different classes of LP that may have different risk preferences (as shown in Table 4), further supports the argument that the observed differences in average returns cannot be explained by risk preferences alone.

results, we should still see evidence of fat tails within LP types. If instead the main results were due to differences in risk-taking across classes of LPs, we would not expect to find such evidence within LP types.

Table 6 shows results for the persistence of LP performance (recall, defined as the percentage of an LP's fund investments that perform above median among a fund type and vintage year), broken down by LP type. For each LP type and fund type, the variability of persistence is significantly higher than what we expect by chance for each LP type.

In addition to differences in risk preferences, it is possible that LPs could also face differences in political pressure. In particular, Hochberg and Rauh (2013) find that public pension funds tend to be more likely to invest in locally run funds, and these funds tend to be worse performers. Similarly, Barber, Morse and Yasuda (2016) find that a number of LPs, especially public pension funds and international LPs, tend to invest more in "impact funds", who tilt their portfolios toward socially responsible investments. These investments tend to underperform. It is possible that differences in LPs' performance could reflect, rather than their skill, their susceptibility to political pressure to invest in particular types of funds.

To evaluate this hypothesis, it is important to distinguish between public and private investors, since public investors face substantially more political pressure than private ones. For this reason, we re-estimate our Bayesian model with fixed effects for private endowments, public endowments, private pensions, public pensions, and all other LPs. Of these types of investors, public pension funds are likely to face the most pressure to distort their investment objectives from return maximization, even more than public endowments. Public endowments have a fiduciary responsibility to maximize returns. In contrast, public pension funds do not have this fiduciary responsibility and are free to pursue whatever objectives they wish, which could potentially include a preference for local or politically powerful investors.

The estimates of this equation are reported in Table 7. The results in this table indicate that the β for public pension funds is not noticeably or statistically different from the β's for the other types of investors. In addition, the estimated impact of skill remains similar to that reported in Table 4 (i.e., σ_λ is the same here as it was in Table 4). These estimates suggest that skill-adjusted returns for public pension funds are not meaningfully different from those achieved by other investors, so it is unlikely that differing political pressure explains the systematic differences in returns we observe across investors.

5.2. Differences in Access to Funds

The most successful GPs often limit the quantity of capital they will take in a particular fund, resulting in oversubscription of many funds (i.e., limited access). Consequently, some of the most successful LPs have policies of reinvesting in all funds of GPs they like to retain access to the GPs' future funds.[12] Sensoy, Wang, and Weisbach (2014) provide evidence suggesting that access to the highest quality venture funds was an important factor contributing to endowments' outperformance in the 1990s.

To evaluate the extent to which differential access explains the observed differences in LPs' performance, we repeat our analysis using only first-time funds. First-time funds are generally considered to be extremely difficult to raise, and typically take commitments from any LPs willing to invest (see Lerner, Hardymon and Leamon, 2011). Consequently, access is unlikely to play much of a role in any potential differential LP performance in investments in first-time funds.

To perform the bootstrap analysis on first time funds, we take LPs who invested in first-time funds more than once during the sample period and simulate their investments using all first-time funds in *Preqin*.[13] We compute the standard deviations of LPs' return persistence as well as each LP's average IRR and compare them to the distributions of the same statistics in the bootstrap simulations, as before. However, because the sample of investments in first-time funds is much smaller than the entire of sample of LP investments, we only present the results for the full sample period. There are not enough observations in each of the subperiods to perform meaningful comparisons.

These bootstrap analyses are presented in Table 8. The results in this table are noisier than those in Table 2 because of the smaller sample size. Nevertheless, as before with the full sample, LPs in first

[12] See Lerner and Leamon (2011).

[13] We also restrict our sample to LPs with three or more investments in first-time funds, and we rerun the same simulation using these LPs. Results (untabulated) are similar to those using LPs' with two or more investments in first-time funds. We have also replicated the analysis comparing decile values for the subsample of first time funds, with similar results to those reported in Table 3.

time venture and buyout funds separately have significantly higher-than-expected persistence. In addition, there is a sharp disparity between the standard deviations for LPs' average returns in first-time venture funds and first-time buyout funds. With first-time venture funds, as with the full sample, the actual standard deviation is significantly higher than those from bootstrap simulations. With first-time buyout funds, on the other hand, there is no statistically significant difference between the standard deviations of the actual and bootstrapped samples.

We also estimate our Bayesian Models 1 and 2 for first-time funds. The estimates are presented in Table 9. Even among first-time funds, the standard deviation of LP fixed effects is statistically significant, whether estimated on the full sample that pools all funds together or for the venture and buyout subsamples separately. Moreover, the estimate of skill is of approximately the same magnitude as the results for all funds shown in Table 4, with a standard deviation increase in skill leading to about a three percentage-point difference in expected fund IRR. This evidence suggests that differential access is not the main factor leading to systematic differences in returns across LPs. Instead, the persistent differences in performance across LPs seem most likely to be a consequence of differential LP skill in selecting GPs, and in identifying the funds of a particular GP that are most likely to perform well.

5.3. Limitations of the Analysis

This paper provides the first estimates of the ability of institutional investors to choose between private equity funds. The estimates we present suggest that investor skill is an important factor affecting the returns LPs receive from their private equity investments. However, we emphasize that there are a number of limitations of the analysis.

First, our data on institutional investors' portfolios are incomplete. Our knowledge of LPs' private equity investments is limited to those investments reported by *VentureXpert* and *Capital IQ*. These sources contain a large number of investments for each LP, but not the entire portfolio, especially for private LPs not subject to FOIA.

Second, we do not have any data on the amount of capital each LP commits to each fund. Therefore, we must make an assumption about the amount each LP contributes to each fund. We assume either that they contribute the same amount to each fund or that they do so in proportion to the fund size or the log of fund size.

Third, we assume that LPs buy each fund at origination and hold it for the fund's life. In fact, there is now an active secondary market for buying and selling funds (see Nadauld et al. 2016). Therefore, the returns an LP receives on any particular investment could differ from those reported in *Preqin*. Our estimates of an LPs' skill could be affected if they transact in this market frequently. For example, OPERs, the Ohio Public Employees Retirement System, had a policy of buying funds at substantial discounts in the secondary market during our sample period. Since our analysis assumes that they hold their private equity investments for their entire life, the reported estimated λ of -0.04% for OPERs could be misleading and understate the true ability of OPERs' managers, since a portion of their returns come from purchasing funds at a discount.

6. Conclusion

Pension plans, insurance companies, foundations, endowments and other institutional investors all depend crucially on their investment income to fund their activities. Consequently, the investment manager is often one of the most important and highly paid employees in these organizations. Yet, there has been surprisingly little work devoted to evaluating the performance of these managers, or even measuring the extent to which there is meaningful variation in their skill. This paper evaluates the extent to which institutions' investment officer skill systematically leads institutional investors to have higher returns, using a large database of LPs' investments in private equity.

Our results suggest that some LPs consistently invest in the top half of funds while some are consistently in the bottom half of funds. There are more LPs with this type of persistence in performance than one would expect by chance, since the standard deviation of the number of investments in the top half of the return distribution is significantly higher than those in bootstrapped samples. This result holds in different time periods for all funds, as well as for venture and buyout funds separately. This pattern of results suggests that there is some LP-specific attribute contributing substantially to private equity returns. This LP-specific attribute potentially reflects LPs' differential skill at picking private equity funds.

We adapt the Bayesian method of Korteweg and Sorensen (2015) to quantify the effect of skill on LP returns. Our approach assumes that there is an underlying unobservable skill level that affects an LP's ability to pick quality GPs. It uses the Markov chain Monte Carlo method to estimate the level of skill for each LP, as well as the variance in skill across LPs. Our estimates indicate that the variance in skill is substantial, and that a one standard deviation increase in LP skill leads to about a three-percentage point difference in annual IRR on the LP's private equity investments. The effect is even larger for investments in venture capital funds, with a one standard deviation difference in ability leading to a five-percentage point difference in the annual IRR they earn.

We consider alternative explanations for why returns could differ systematically across LPs. One possibility is that some LPs have higher risk tolerance or are subject to more political pressure than others. However, the differences across LPs within different classes of LPs appear to be similar to those in the full sample. Since differences in risk preferences are likely to be more salient across different types of LPs than within particular types, this pattern suggests that different risk preferences are unlikely to be the main factor leading to differences in returns across LPs. In addition, returns to public pension funds, which are the most susceptible to political pressure among the investor types in our sample, are similar to returns to other types of investors.

Another possibility is that some LPs have better access to the funds of higher quality GPs, and the higher return they receive results from this superior access. To evaluate this possibility, we repeat our analysis on the sample of first time funds, which generally do not limit their access. Our results suggest that higher quality LPs tend to outperform in first time funds by about the same amount as they do in their investments in funds from established partnerships. Consequently, it does not appear that superior access is the major reason why some LPs earn higher returns than others.

Overall, the results suggest the performance of LPs' private equity investments is not random, and that the ability to identify and invest with private equity partnerships that have the best potential to earn the highest returns is an important skill of institutional investors. Therefore, it makes sense for institutional investors to spend resources acquiring high quality investment officers, and that superior investment officers can generate value that is much higher than their relatively high salaries. While the results in this paper concern only private equity investments, it seems likely that such skill affects managers' other investments as well, especially in other types of alternative assets in which evaluating GP skill is important.

An important limitation is of this study is that we do not have data on the structure of the investment offices in our sample. It would be useful to know identities of the officers picking the private equity funds, their backgrounds, experience and the extent to which they have a professional team helping them. Such data could potentially lead to implications about the way these offices should be set up, who they should hire and how they should go about picking funds. Unfortunately, we do not have access to such data, so while we can document the existence of more skillful and less skillful investment managers, it is difficult to draw conclusions about the factors that affect the skill of a particular manager.

Given the prevalence of institutional investors in the economy and the effect that their performance has on so many different organizations, understanding this investment process seems relatively understudied. How prevalent are differences in skill across institutional investors? Does it vary across different types of institutions and across investment in different asset classes? Does the compensation structure of different investment managers across organizations efficiently sort the better managers into the higher paying positions? How much do differences in pay translate to higher investment performance? Does the structure of investment officers' compensation affect investment performance directly through the incentives they provide? This paper studies some of these issues. While the analysis here is suggestive that skill differences are important, much more work is needed to understand their implications more fully. Given the importance of institutional investors' performance, such research seems like a task worth pursuing.

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Table 1. Summary Statistics at the LP and Fund Levels

The table shows the number of observations (*N*), mean, median, first quartile (*Q1*), and third quartile (*Q3*) values of the characteristics of LPs' investments in all funds, venture funds, and buyout funds. Our sample is restricted to LPs making four or more investments during the years 1991-2006. Panel A reports the statistics at the LP level, and Panel B reports the statistics at the fund level. *No. of investments per LP* reflects the total number of investments made by each LP. All performance measures are as of the end of 2011. *No. of LPs* in Panel B is the total number of LPs in each fund.

Panel A: LP level

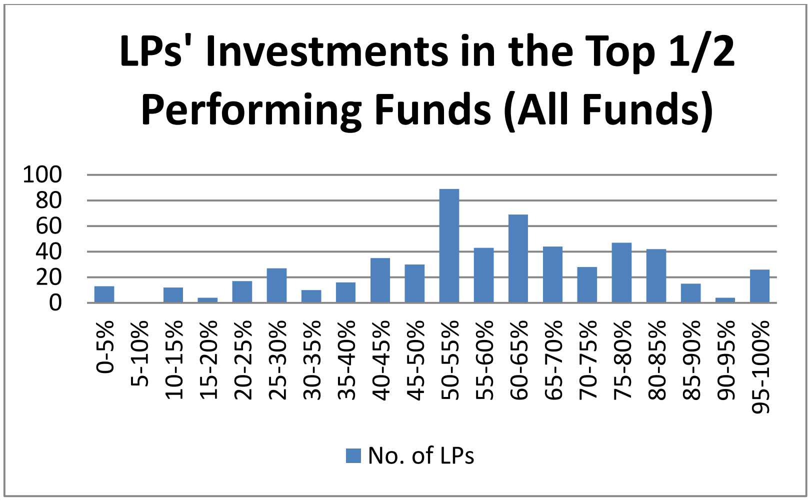
	All Funds					Venture Funds					Buyout Funds				
	N	Mean	Median	Q1	Q3	N	Mean	Median	Q1	Q3	N	Mean	Median	Q1	Q3
No. of investments per LP	630	19.12	10	5	27	379	11.86	8	5	16	528	14.3	9	5	20
IRR	12,043	10.59	6.60	-3.70	18.00	4,494	9.97	0.30	-7.20	9.20	7,549	10.96	10.00	-0.10	21.30
Fund size	12,043	1653.38	700	300	2000	4,494	515.08	335	175	665.23	7,549	2,331.02	1,050	500	3,200
Fund sequence	12,043	3.55	3	2	5	4,494	3.46	3	2	5	7,549	3.6	3	2	4

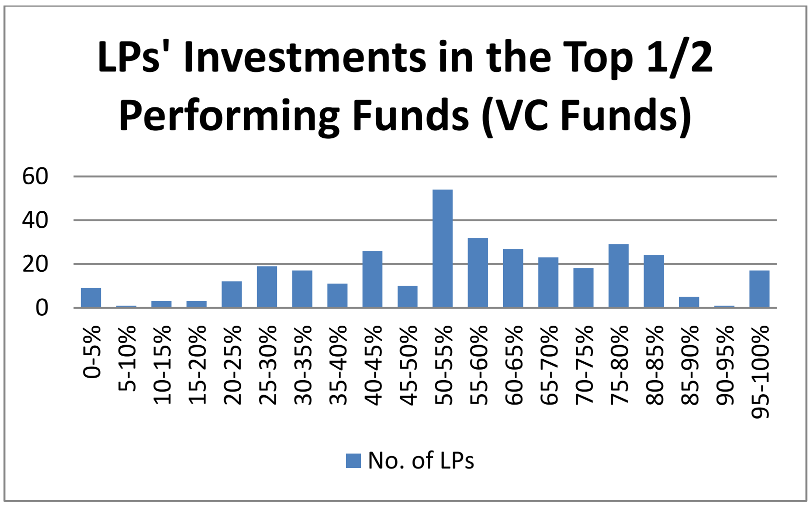
Panel B: Fund level

	All Funds					Venture Funds					Buyout Funds				
	N	Mean	Median	Q1	Q3	N	Mean	Median	Q1	Q3	N	Mean	Median	Q1	Q3
IRR	1,195	11.02	6	-5.2	18.8	590	9.75	-0.38	-8.4	10.3	605	12.27	11	0.8	22.6
Fund size	1,195	728.80	300	136	710	590	293.94	178	88	350	605	1,152.89	515	252	1,200
Fund sequence	1,195	2.36	2	1	3	590	2.33	2	1	3	605	2.38	2	1	3
No. of LPs	1,195	10.12	6	2	13	590	7.62	5	2	10	605	12.58	8	3	17

Figure 1. The Distribution of the Frequency of LPs' Investments in Top Half of Funds

The figures show the distribution of the frequency of LPs' investments in top half performing funds given their vintage years and fund types. For each LP, we calculate the percentage of the LP's investments that are in the top half of funds of the same type (venture capital or buyout) from the same vintage year. Then we count the number of LPs in each percentage group. The percentage groups are divided into increments of five. The x-axis shows the percentage groups, and the y-axis shows the number of LPs in each group for all funds, venture funds, and buyout funds.


LPs' Investments in the Top 1/2 Performing Funds (All Funds)
100
80
60
40
20
0
0-5%
5-10%
10-15%
15-20%
20-25%
25-30%
30-35%
35-40%
40-45%
45-50%
50-55%
55-60%
60-65%
65-70%
70-75%
75-80%
80-85%
85-90%
90-95%
95-100%
No. of LPs


LPs' Investments in the Top 1/2 Performing Funds (VC Funds)
60
40
20
0
0-5%
5-10%
10-15%
15-20%
20-25%
25-30%
30-35%
35-40%
40-45%
45-50%
50-55%
55-60%
60-65%
65-70%
70-75%
75-80%
80-85%
85-90%
90-95%
95-100%
No. of LPs

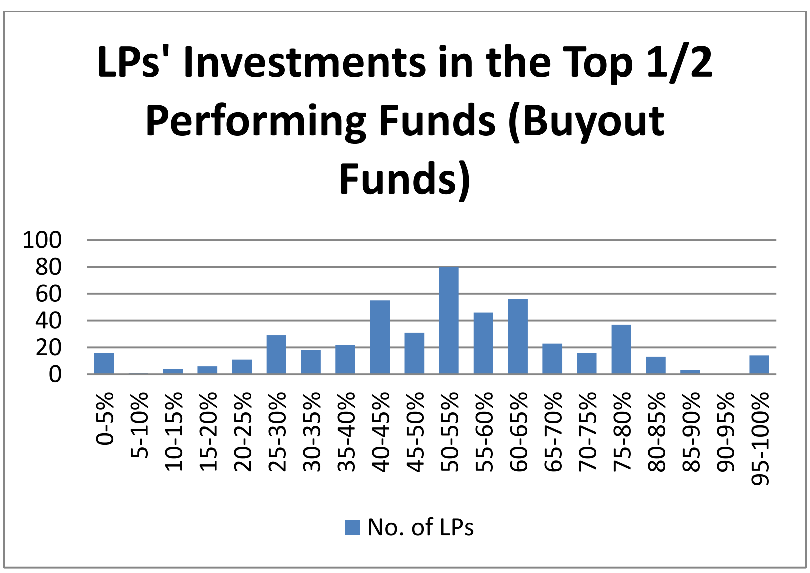

LPs' Investments in the Top 1/2 Performing Funds (Buyout Funds)
100
80
60
40
20
0
0-5%
5-10%
10-15%
15-20%
20-25%
25-30%
30-35%
35-40%
40-45%
45-50%
50-55%
55-60%
60-65%
65-70%
70-75%
75-80%
80-85%
85-90%
90-95%
95-100%
No. of LPs

Table 2. Tests of Differential Skill based on Persistence and Average Returns

This table compares the distributions of LPs' persistence and average returns between the actual and bootstrapped samples. Panel A shows tests for differential skill based on the standard deviation of LPs' persistence, measured as the percentages of times LPs' investments fall in top half of funds. For each LP in the actual sample, we calculate the percentage of times the LP's investments are in the top half of funds given the vintage years and fund types. Then we compute the standard deviation of those percentages. We do the same for each bootstrapped sample. Column *Actual* shows statistics from the actual sample. Column *Boot* reports the mean values of the same test statistics across 1,000 bootstrapped samples. Column *% > Actual* shows the percentage of bootstrapped samples with test statistics greater than those in the actual sample. Panels B shows tests of the standard deviations of LPs' average IRR weighted by the logarithm of fund size, and Panel C reports the same tests based on equal-weighted average IRR. Results are reported for the full sample (1991-2006) and two subsample periods (1991-1998 and 1999-2006). Statistically significant values, highlighted in bold, are those for which *% > Actual* is less than 10% or greater than 90%.

Panel A: Tests of the standard deviation of the distribution of LPs' persistence

	Full Sample			1991-1998			1999-2006		
	Actual	Boot	% > Actual	Actual	Boot	% > Actual	Actual	Boot	% > Actual
All funds	**0.20**	0.17	0.0%	**0.34**	0.32	0.0%	**0.23**	0.21	0.0%
Venture funds	**0.22**	0.18	0.0%	**0.37**	0.34	0.0%	**0.25**	0.22	0.0%
Buyout funds	**0.20**	0.18	0.3%	**0.34**	0.32	0.7%	**0.23**	0.22	4.4%

Panel B: Tests of the standard deviation of LPs' average IRR weighted by log (fund size)

	Full Sample			1991-1998			1999-2006		
	Actual	Boot	% > Actual	Actual	Boot	% > Actual	Actual	Boot	% > Actual
All funds	9.48	9.14	31.3%	23.62	27.44	77.3%	**8.63**	7.97	2.4%
Venture funds	14.36	12.89	12.7%	45.7	46.49	50.5%	**6.26**	4.75	0.0%
Buyout funds	6.86	6.82	50.9%	12.05	11.35	19.8%	7.57	7.90	84.4%

Panel C: Tests of the standard deviation of LPs' equal-weighted average IRR

	Full Sample			1991-1998			1999-2006		
	Actual	Boot	% > Actual	Actual	Boot	% > Actual	Actual	Boot	% > Actual
All funds	10.13	9.74	30.9%	24.38	28.04	77.0%	**8.85**	8.07	0.9%
Venture funds	15.83	14.17	11.8%	45.85	46.48	50.0%	**6.36**	5.01	0.0%
Buyout funds	7.02	6.78	17.6%	12.07	11.39	20.6%	7.66	7.82	66.3%

Table 3. Frequency Distribution of LPs' Average IRR

The table shows the frequency distributions of LPs' average size- and equal-weighted IRR for all funds, venture funds, and buyout funds. Size-weighted average IRR is computed by weighting each IRR by the logarithm of fund size. Equal-weighted average IRR assigns equal weights to each IRR. LPs in the actual and every bootstrapped sample are divided to 10 groups based on their average IRR (*Avg IRR).* Column *Actual* represents the number of LPs in each *Avg IRR* group from the actual sample. Columns *10% Boot* and *90% Boot* show the bottom 10% and top 90% of the bootstrapped frequencies, respectively. For the full sample period (1991-2006) and 1999-2006 subsample period, *Avg IRR* groups are based on increments of 5%. *Avg IRR* groups in the 1991-1998 subperiod are based on increments of 10% due to higher returns from this period.

Pane A: Full Sample (1991-2006)

	Size-Weighted IRR									Equal-Weighted IRR								
	All Funds			Venture Funds			Buyout Funds			All Funds			Venture Funds			Buyout Funds		
	Actual	10% Boot	90% Boot	Actual	10% Boot	90% Boot	Actual	10% Boot	90% Boot	Actual	10% Boot	90% Boot	Actual	10% Boot	90% Boot	Actual	10% Boot	90% Boot
Avg IRR ≤ -10%	6	2	9	9	2	9	6	0	6	8	2	9	11	3	10	8	0	6
-10% < Avg IRR ≤ -5%	13	11	21	35	20	33	13	0	11	9	10	21	32	21	34	9	0	10
-5% < Avg IRR ≤ 0%	50	41	58	95	78	98	50	11	29	52	40	56	92	74	93	52	9	27
0% < Avg IRR ≤ 5%	108	100	124	82	81	104	108	46	77	112	97	119	78	75	98	112	41	72
5% < Avg IRR ≤ 10%	182	178	207	43	50	68	182	130	176	170	170	198	41	48	66	170	118	171
10% < Avg IRR ≤ 15%	136	133	160	33	31	47	136	125	178	126	134	160	40	32	48	126	139	185
15% < Avg IRR ≤ 20%	66	52	72	19	19	32	66	42	76	65	59	78	17	20	34	65	47	82
20% < Avg IRR ≤ 25%	42	18	31	24	10	21	42	9	28	43	21	35	16	12	23	43	8	30
25% < Avg IRR ≤ 30%	11	6	15	16	5	14	11	1	12	23	7	17	20	6	15	23	0	12
Avg IRR > 30%	16	8	17	23	13	24	16	0	7	22	10	20	32	17	29	22	0	8

Panel B: 1991-1998 subperiod

	Size-Weighted IRR									Equal-Weighted IRR								
	All Funds			Venture Funds			Buyout Funds			All Funds			Venture Funds			Buyout Funds		
	Actual	10% Boot	90% Boot	Actual	10% Boot	90% Boot	Actual	10% Boot	90% Boot	Actual	10% Boot	90% Boot	Actual	10% Boot	90% Boot	Actual	10% Boot	90% Boot
Avg IRR ≤ -10%	9	6	15	8	6	14	9	4	12	9	6	15	7	6	14	9	4	12
-10% < Avg IRR ≤ -5%	46	24	39	25	11	22	40	24	39	42	25	39	23	11	22	34	25	39
-5% < Avg IRR ≤ 0%	122	113	137	43	28	43	147	142	168	123	111	135	45	28	43	150	139	164
10% < Avg IRR ≤ 20%	126	139	165	42	27	42	140	151	177	120	136	161	44	28	43	142	151	177
20% < Avg IRR ≤ 30%	78	73	95	18	30	46	44	35	50	81	74	96	16	31	46	46	37	53
30% < Avg IRR ≤ 45%	50	32	48	24	27	43	26	7	16	48	33	50	24	27	42	27	7	17
40% < Avg IRR ≤ 50%	22	13	25	26	21	35	9	0	6	27	14	26	22	21	35	8	1	6
50% < Avg IRR ≤ 60%	20	8	18	28	17	30	2	0	4	19	9	19	33	17	30	1	0	5
60% < Avg IRR ≤ 70%	5	2	10	13	9	20	0	0	0	8	3	10	14	9	19	0	0	0
Avg IRR > 70%	20	13	24	49	33	49	1	0	3	21	13	24	48	33	48	1	0	4

Panel C: 1999-2006 subperiod

	Size-Weighted IRR									Equal-Weighted IRR								
	All Funds			Venture Funds			Buyout Funds			All Funds			Venture Funds			Buyout Funds		
	Actual	10% Boot	90% Boot	Actual	10% Boot	90% Boot	Actual	10% Boot	90% Boot	Actual	10% Boot	90% Boot	Actual	10% Boot	90% Boot	Actual	10% Boot	90% Boot
Avg IRR ≤ -10%	14	7	17	22	10	20	2	3	10	17	8	17	28	12	23	3	2	9
-10% < Avg IRR ≤ -5%	28	23	37	67	53	73	9	6	16	25	23	36	65	57	77	7	5	14
-5% < Avg IRR ≤ 0%	64	75	95	159	170	195	13	24	38	70	74	94	155	163	188	12	21	35
0% < Avg IRR ≤ 5%	164	157	184	94	84	106	70	66	87	164	161	188	93	82	104	65	63	83
5% < Avg IRR ≤ 10%	188	163	189	22	12	24	174	139	164	181	158	185	23	14	26	163	137	163
10% < Avg IRR ≤ 15%	95	74	96	7	1	7	160	126	152	86	74	94	7	1	8	160	132	158
15% < Avg IRR ≤ 20%	39	31	47	4	0	3	60	56	76	45	32	48	4	0	3	73	59	80
20% < Avg IRR ≤ 25%	18	12	23	1	0	2	18	20	33	21	13	23	0	0	0	24	21	34
25% < Avg IRR ≤ 30%	4	3	11	1	0	1	5	6	15	5	4	11	2	0	1	4	6	15
Avg IRR > 30%	13	2	9	1	0	1	14	3	11	13	2	9	1	0	1	14	3	10

Figure 2. Frequency Distribution of Average Size-Weighted IRR

The graphs show the frequency distributions of LPs' average IRR weighted by the logarithm of fund size for all funds, venture funds, and buyout funds. LPs in the actual and every bootstrapped sample are divided to 10 groups based on their average IRR (*Avg IRR).* Each column in the figures represents the number of LPs in each *Avg IRR* group from the actual sample. The horizontal lines for each column show the 10% and 90% of the bootstrapped frequencies for the same group. For the full sample and 1999-2006 subsample period, *Avg IRR* groups are based on increments of 5%. Due to higher returns from the earlier period, *Avg IRR* groups in the 1991-1998 subperiod are based on increments of 10%.

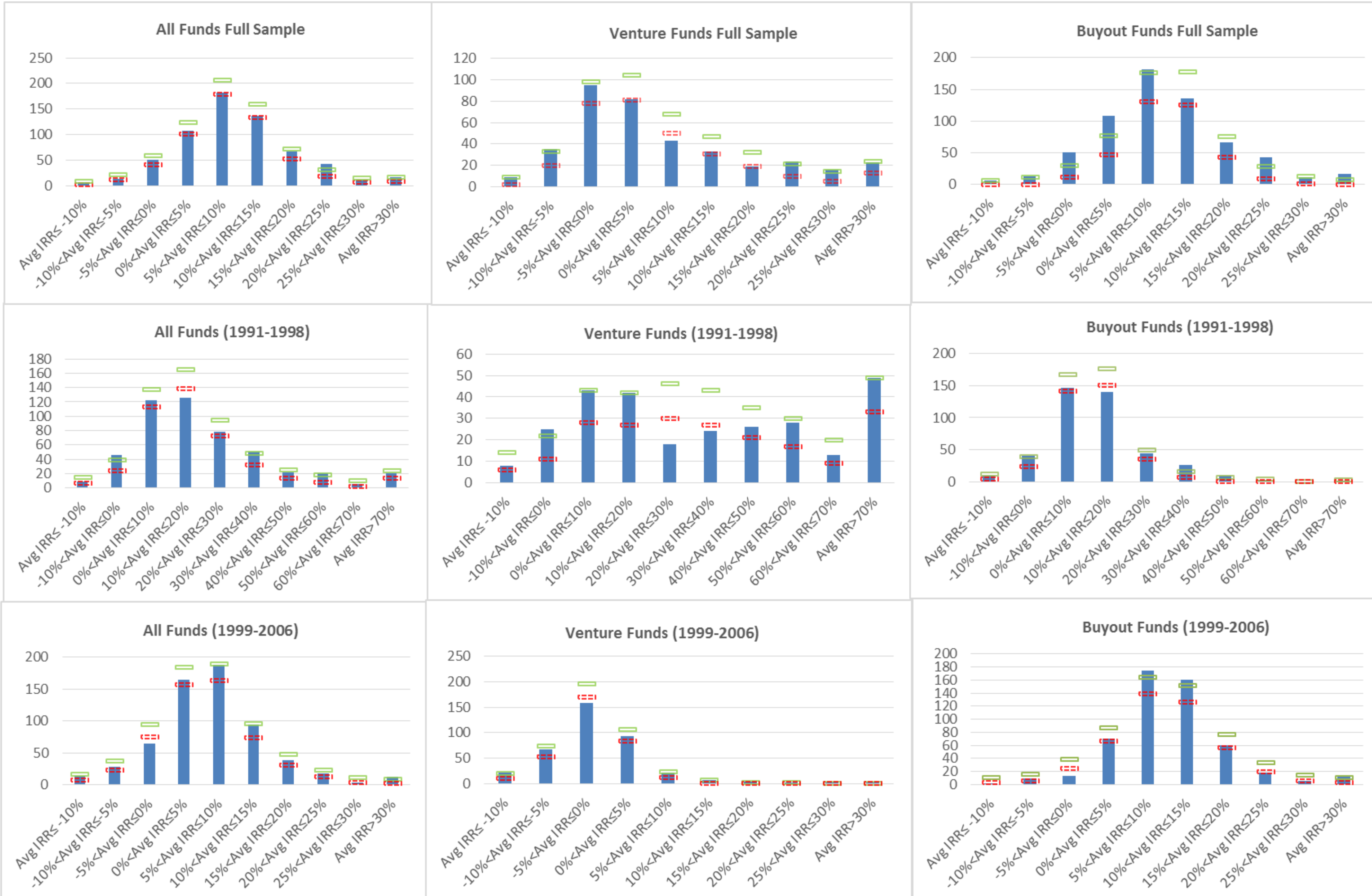

All Funds Full Sample
Avg IRR≤ -10%
-10%<Avg IRR≤-5%
-5%<Avg IRR≤0%
0%<Avg IRR≤5%
5%<Avg IRR≤10%
10%<Avg IRR≤15%
15%<Avg IRR≤20%
20%<Avg IRR≤25%
25%<Avg IRR≤30%
Avg IRR>30%
Venture Funds Full Sample
Buyout Funds Full Sample
All Funds (1991-1998)
Avg IRR≤ -10%
-10%<Avg IRR≤0%
0%<Avg IRR≤10%
10%<Avg IRR≤20%
20%<Avg IRR≤30%
30%<Avg IRR≤40%
40%<Avg IRR≤50%
50%<Avg IRR≤60%
60%<Avg IRR≤70%
Avg IRR>70%
Venture Funds (1991-1998)
Buyout Funds (1991-1998)
All Funds (1999-2006)
Venture Funds (1999-2006)
Buyout Funds (1999-2006)

Figure 3. Frequency Distribution of Average Equal-Weighted IRR

The graphs show the frequency distributions of LPs' average equal-weighted IRR for all funds, venture funds, and buyout funds. LPs in the actual and every bootstrapped sample are divided to 10 groups based on their average IRR (*Avg IRR).* Each column in the figures represents the number of LPs in each *Avg IRR* group from the actual sample. The horizontal lines for each column show the 10% and 90% of the bootstrapped frequencies for the same group. For the full sample and 1999-2006 subsample period, *Avg IRR* groups are based on increments of 5%. Due to higher returns from the earlier period, *Avg IRR* groups in the 1991-1998 subperiod are based on increments of 10%.

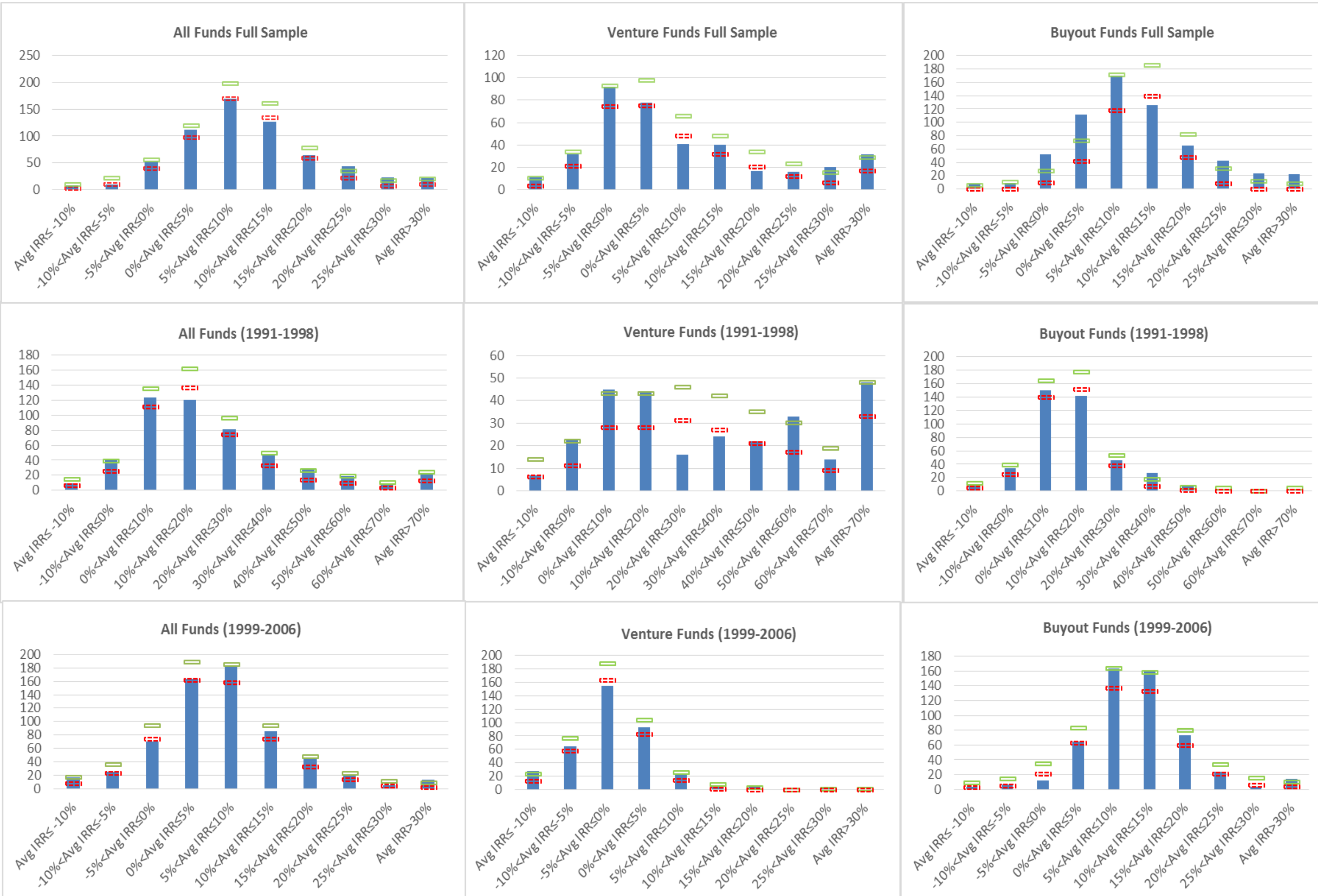

All Funds Full Sample
Avg IRR≤ -10%
-10%<Avg IRR≤-5%
-5%<Avg IRR≤0%
0%<Avg IRR≤5%
5%<Avg IRR≤10%
10%<Avg IRR≤15%
15%<Avg IRR≤20%
20%<Avg IRR≤25%
25%<Avg IRR≤30%
Avg IRR>30%
Venture Funds Full Sample
Buyout Funds Full Sample
All Funds (1991-1998)
Avg IRR≤ -10%
-10%<Avg IRR≤0%
0%<Avg IRR≤10%
10%<Avg IRR≤20%
20%<Avg IRR≤30%
30%<Avg IRR≤40%
40%<Avg IRR≤50%
50%<Avg IRR≤60%
60%<Avg IRR≤70%
Avg IRR>70%
Venture Funds (1991-1998)
Buyout Funds (1991-1998)
All Funds (1999-2006)
Venture Funds (1999-2006)
Buyout Funds (1999-2006)

Table 4. Bayesian Model Estimates of Differences in LP Skill

This table displays the results of the Bayesian models described in Section IV. Panel A shows results for the full sample period, Panel B includes only funds with vintage years between 1991 and 1998, and Panel C includes only funds with vintage years between 1999 and 2006. Odd-numbered columns are based on Model 1, in which adjusted returns are computed as in Equation (3). These estimates pick up LPs' abilities to select funds within a GP family. Even-numbered columns are based on Model 2, which further adjusts returns by subtracting fund-specific errors in addition to the other non-skill-related effects in Equation (3). σ_λ is the estimated standard deviation of LP fixed effects, which is our measure of differential LP skill. σ_π is the estimated standard deviation of the fund-LP random effects. $\beta_{LP\ (all)}$ is the estimated common constant term for all LPs. This parameter measures the difference in performance between the funds invested by our sample LPs and the *Preqin* universe. We also estimated a separate version of the model that included LP-type effects. $\beta_{LP\ (endow)}$, $\beta_{LP\ (pension)}$, and $\beta_{LP\ (other)}$ are the estimated constant terms for endowments, pension funds, and all other LPs, respectively. Estimates of σ_λ and σ_π in this version of the model are nearly identical to the values already reported here for the model with a single intercept, so we do not include them in the table. All estimates are IRRs with Bayesian standard errors reported below the estimates in parentheses.

Panel A: Full Sample (1991-2006)

	All Funds		Buyout Funds		Venture Funds	
	(1)	(2)	(3)	(4)	(5)	(6)
σ_λ	0.032	0.030	0.027	0.032	0.050	0.035
b.s.e.	(0.003)	(0.004)	(0.003)	(0.005)	(0.005)	(0.006)
σ_π	1.630	0.833	1.364	0.845	1.987	0.835
b.s.e.	(0.033)	(0.078)	(0.049)	(0.108)	(0.046)	(0.108)
$\beta_{LP\ (all)}$	0.193	0.202	0.178	0.209	0.203	0.174
b.s.e.	(0.096)	(0.124)	(0.118)	(0.156)	(0.138)	(0.165)
$\beta_{LP\ (endow)}$	0.361	0.301	0.193	0.293	0.547	0.285
b.s.e.	(0.116)	(0.144)	(0.142)	(0.185)	(0.177)	(0.194)
$\beta_{LP\ (pension)}$	0.139	0.207	0.148	0.209	0.119	0.191
b.s.e.	(0.109)	(0.144)	(0.128)	(0.173)	(0.156)	(0.182)
$\beta_{LP\ (other)}$	0.187	0.197	0.219	0.227	0.129	0.136
b.s.e.	(0.091)	(0.117)	(0.115)	(0.148)	(0.134)	(0.158)
Obs	12,037	12,037	7,548	7,548	4,489	4,489
No. of LPs	630	630	528	528	379	379

Panel B: 1991-1998 subperiod

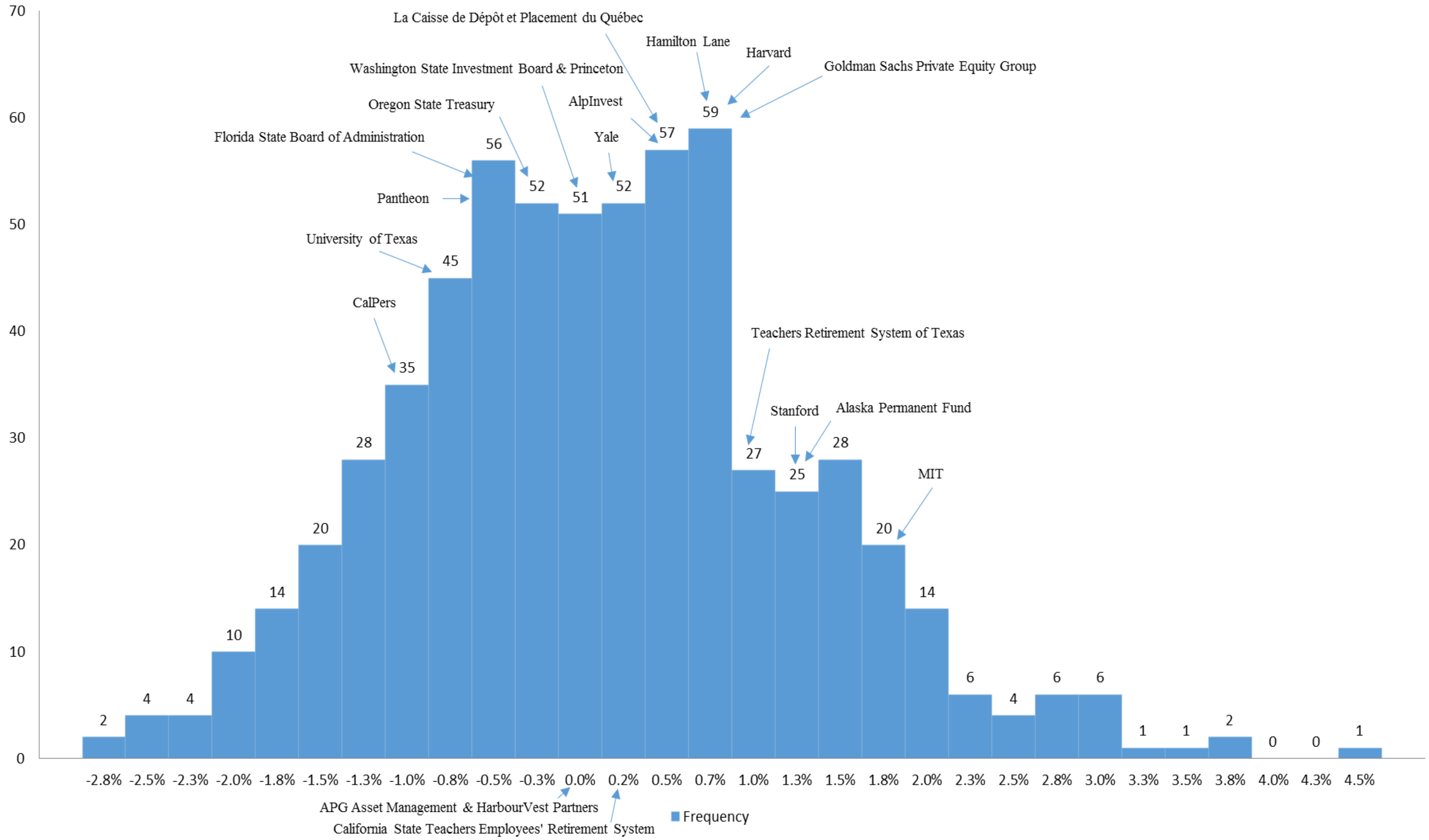
	All Funds		Buyout Funds		Venture Funds	
	(1)	(2)	(3)	(4)	(5)	(6)
σ_λ	0.063	0.032	0.036	0.0326	0.111	0.041
b.s.e.	(0.007)	(0.004)	(0.004)	(0.005)	(0.016)	(0.007)
σ_π	2.292	0.854	1.384	0.847	3.237	0.884
b.s.e.	(0.091)	(0.096)	(0.085)	(0.124)	(0.141)	(0.134)
$\beta_{LP\ (all)}$	0.306	0.127	0.080	0.075	0.733	0.213
b.s.e.	(0.141)	(0.139)	(0.156)	(0.166)	(0.239)	(0.211)
$\beta_{LP\ (endow)}$	0.879	0.251	0.087	0.103	1.776	0.412
b.s.e.	(0.198)	(0.161)	(0.198)	(0.191)	(0.362)	(0.250)
$\beta_{LP\ (pension)}$	0.131	0.079	0.041	0.051	0.338	0.139
b.s.e.	(0.165)	(0.154)	(0.175)	(0.184)	(0.299)	(0.222)
$\beta_{LP\ (other)}$	0.231	0.109	0.105	0.081	0.478	0.157
b.s.e.	(0.147)	(0.137)	(0.162)	(0.168)	(0.270)	(0.209)
Obs	3,046	3,046	1,970	1,970	1,076	1,076
No. of LPs	498	498	418	418	276	276

Panel C: 1999-2006 subperiod

	All Funds		Buyout Funds		Venture Funds	
	(1)	(2)	(3)	(4)	(5)	(6)
σ_λ	0.027	0.026	0.028	0.029	0.038	0.033
b.s.e.	(0.002)	(0.004)	(0.003)	(0.004)	(0.004)	(0.006)
σ_π	1.271	0.806	1.335	0.808	1.175	0.833
b.s.e.	(0.045)	(0.082)	(0.060)	(0.111)	(0.073)	(0.117)
$\beta_{LP\ (all)}$	0.126	0.199	0.189	0.254	0.042	0.163
b.s.e.	(0.104)	(0.126)	(0.134)	(0.165)	(0.154)	(0.170)
$\beta_{LP\ (endow)}$	0.127	0.286	0.196	0.322	0.045	0.226
b.s.e.	(0.135)	(0.146)	(0.181)	(0.200)	(0.183)	(0.195)
$\beta_{LP\ (pension)}$	0.102	0.227	0.152	0.237	0.000	0.197
b.s.e.	(0.129)	(0.147)	(0.153)	(0.183)	(0.175)	(0.190)
$\beta_{LP\ (other)}$	0.150	0.202	0.209	0.244	0.059	0.126
b.s.e.	(0.103)	(0.119)	(0.131)	(0.158)	(0.152)	(0.164)
Obs	8,991	8,991	5,578	5,578	3,413	3,413
No. of LPs	626	626	525	525	377	377

Figure 4. IRR Contribution of Estimated Skill

The figure shows the distribution of estimated skill contribution to IRR. For each LP, we obtain a Bayesian estimate of λ and compute the IRR equivalent (i.e. the skill contribution to IRR). We divide LPs to bins based on their estimated skill contribution to IRR and count the number of LPs in each bin. The upper limit of each bin is shown on the x-axis. The frequency count for each bin is shown on top of each bar. We highlight 20 LPs in the figure below. These are the largest LPs for which we have data and the largest university endowments in 2015. The average Bayesian standard error for the highlighted LPs is approximately 2.7% IRR. Returns are adjusted for vintage-year fixed effects, firm-time random effects, and fund specific errors (i.e., Model 2).



Average b.s.e. for highlighted LPs is approximately 2.7%

Table 5. Correlation Analysis of Estimated Skill and Returns

The table shows correlation analyses of estimated skill (average λ) and IRRs across models and time periods for all LPs and within three LP types. Panel A shows rank correlations between estimated λ from Models 1 and 2. Panel B shows Pearson's correlation of estimated λ in each model with IRR. Panel C shows rank correlations of LPs' average IRR and estimated λ between two subsample periods: 1991-1998 and 1999-2006. Column *Avg IRR* shows correlations for average IRRs. Column *Model 1* λ and *Model 2* λ show correlations for estimated λ of Model 1 and Model 2, respectively. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Rank correlations between λ from two models

	Full Sample	1991-1998	1999-2006
Endowments	0.82***	0.84***	0.69***
Pensions	0.80***	0.80***	0.73***
Others	0.78***	0.73***	0.69***
All LPs	0.80***	0.79***	0.69***

Panel B: Pearson's correlation of λ with IRR

	Full Sample		1991-1998		1999-2006	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Endowment	0.78***	0.70***	0.81***	0.74***	0.63***	0.44***
Pensions	0.68***	0.53***	0.77***	0.66***	0.59***	0.38***
Others	0.78***	0.66***	0.78***	0.56***	0.73***	0.62***
All LPs	0.752***	0.640***	0.79***	0.64***	0.67***	0.51***

Panel C: Correlation analysis of Avg IRR and λ across subsample periods

	Avg IRR	Model 1 λ	Model 2 λ
Endowments	-0.220**	0.13	0.62***
Pensions	-0.103	0.22**	0.59***
Others	0.028	0.06	0.49***
All LPs	-0.076*	0.109**	0.539***

Table 6. Tests of Persistence within Different LP Types

This table shows tests of the standard deviation of persistence within different LP types. Persistence is measured as the percentages of times LPs' returns fall in the top half of funds given their vintage years and fund types. LPs are divided to endowments, pensions, and all other LPs. For each LP type, standard deviations are computed for the actual sample and all bootstrapped samples. Column *Actual* reports the standard deviation from the actual sample. Column *Boot* reports the average standard deviation across 1,000 bootstrapped samples. Column *% > Actual* shows the percentage of bootstrapped samples with standard deviations greater than that of the actual sample. Statistically significant values, highlighted in bold, are those for which *% > Actual* is less than 10% or greater than 90%.

LP Type	All Funds			Venture Funds			Buyout Funds		
	Actual	Boot	% > Actual	Actual	Boot	% > Actual	Actual	Boot	% > Actual
Endowments	**0.21**	0.17	0.1%	**0.22**	0.18	0.4%	**0.21**	0.18	0.6%
Pensions	**0.20**	0.15	0.0%	**0.21**	0.16	0.0%	**0.20**	0.16	0.5%
Other LPs	**0.21**	0.18	0.0%	**0.22**	0.19	0.2%	**0.20**	0.19	4.9%

Table 7. Bayesian Estimates of Differential Skill Controlling for Private and Public LPs

This table displays the results of the Bayesian estimate of skill with five LP-type fixed effects: Private endowments, public endowments, private pensions, public pensions and all other LPs for the full sample period. σ_λ is the estimated standard deviation of LP fixed effects. $\beta_{LP\ (Private\ Endow)}$, $\beta_{LP\ (Public\ Endow)}$, $\beta_{LP\ (Private\ Pension)}$, $\beta_{LP\ (Public\ Pension)}$ and $\beta_{LP\ (other)}$ are the estimated constant terms for private endowments, public endowments, private pension funds, public pension funds, and all other LPs, respectively. All results adjust for firm-time random effects and vintage-year fixed effects. Odd-numbered columns are based on Model 1 and even-numbered columns are based on Model 2. All estimates are IRRs with Bayesian standard errors reported below the estimates in parentheses.

	All Funds		Buyout Funds		Venture Funds	
	(1)	(2)	(3)	(4)	(5)	(6)
σ_λ	0.031	0.029	0.028	0.031	0.047	0.033
b.s.e.	(0.002)	(0.004)	(0.003)	(0.005)	(0.004)	(0.006)
$\beta_{LP\ (Private\ Endow)}$	0.389	0.300	0.187	0.292	0.639	0.305
b.s.e.	(0.127)	(0.152)	(0.158)	(0.193)	(0.187)	(0.204)
$\beta_{LP\ (Public\ Endow)}$	0.231	0.240	0.175	0.227	0.281	0.221
b.s.e.	(0.154)	(0.159)	(0.176)	(0.193)	(0.244)	(0.223)
$\beta_{LP\ (Private\ Pension)}$	0.075	0.156	0.052	0.117	0.128	0.227
b.s.e.	(0.117)	(0.128)	(0.138)	(0.155)	(0.195)	(0.189)
$\beta_{LP\ (Public\ Pension)}$	0.155	0.216	0.167	0.223	0.107	0.165
b.s.e.	(0.118)	(0.153)	(0.139)	(0.176)	(0.176)	(0.203)
$\beta_{LP\ (Other)}$	0.179	0.188	0.210	0.213	0.119	0.133
b.s.e.	(0.093)	(0.115)	(0.114)	(0.138)	(0.136)	(0.163)
Obs	12037	12037	7548	7548	4489	4489
No. of LPs	630	630	528	528	379	379

Table 8. Actual vs. Bootstrapped Persistence and Average Returns for First-Time Funds

This table shows comparisons of the distributions of LPs' persistence and average returns between the actual and bootstrapped samples for first-time funds only. Column *Standard Deviation of Persistence* reports the standard deviations of LP persistence, measured as the percentages of times LPs' returns fall in the top half of funds given their vintage years and fund types. Column *Standard Deviation of Size-Weighted IRR* reports the standard deviations of LPs' averaged returns weighed by the logarithm of fund size, and column *Standard Deviation of Equal-Weighted IRR* shows the same standard deviations when each fund return is weighed equally. Due to the smaller sample size, tests are only performed for the full sample period from 1991 to 2006. All other variables are the same as those described in Table 2. Bold numbers indicate that the actual and bootstrapped samples are significantly different, with *% > Actual* either smaller than 10% or greater than 90%.

	Standard Deviation of Persistence			Standard Deviation of Size-Weighted IRR			Standard Deviation Equal-Weighted IRR		
	Actual	Boot	% > Actual	Actual	Boot	% > Actual	Actual	Boot	% > Actual
All funds	0.26	0.26	33.9%	14.28	14.58	53.5%	15.1	15.36	50.2%
Venture funds	**0.28**	0.27	4.8%	**28.12**	23.21	3.6%	**29.12**	24.8	8.0%
Buyout funds	**0.28**	0.26	5.3%	9.61	9.92	71.3%	9.5	9.91	75.8%

Table 9. Bayesian Model Estimates of Differential Skill Using First-Time Funds

This table displays the results of the Bayesian estimates of differential LP skill using their investments in first-time funds in the full sample (1991-2006). The estimation follows the Bayesian model described in Section IV. All variables are defined in Table 4. Odd-numbered columns do not adjust for fund-specific errors in Equation (3) (i.e., Model 1). Even-numbered columns do perform this adjustment (i.e., Model 2). $\beta_{LP\ (endow)}$, $\beta_{LP\ (pension)}$, and $\beta_{LP\ (other)}$ are estimated in a separate Bayesian regression from the other listed parameters. All estimates are IRRs with Bayesian standard errors reported below the estimates in parentheses.

	All Funds		Buyout Funds		Venture Funds	
	(1)	(2)	(3)	(4)	(5)	(6)
σ_λ	0.038	0.025	0.036	0.028	0.058	0.031
b.s.e.	(0.004)	(0.002)	(0.003)	(0.003)	(0.009)	(0.003)
σ_π	1.915	0.894	1.437	0.922	2.532	0.845
b.s.e.	(0.052)	(0.097)	(0.068)	(0.137)	(0.098)	(0.106)
$\beta_{LP\ (all)}$	-0.002	0.005	0.089	0.036	-0.136	-0.035
b.s.e.	(0.090)	(0.084)	(0.110)	(0.116)	(0.145)	(0.117)
$\beta_{LP\ (endow)}$	0.126	0.051	0.105	0.083	0.120	-0.003
b.s.e.	(0.157)	(0.124)	(0.174)	(0.171)	(0.278)	(0.172)
$\beta_{LP\ (pension)}$	-0.114	-0.019	0.020	0.005	-0.454	-0.088
b.s.e.	(0.117)	(0.102)	(0.129)	(0.128)	(0.222)	(0.140)
$\beta_{LP\ (other)}$	0.046	0.019	0.124	0.043	-0.068	-0.023
b.s.e.	(0.098)	(0.091)	(0.120)	(0.124)	(0.168)	(0.126)
Obs	2,470	2,470	1,582	1,582	888	888
No. of LPs	539	539	448	448	318	318

Appendix 1

The regression model (step 2) is

$$\widehat{y_{iuj}} = X_{LP_j}\beta_{LP} + 10\lambda_j + \pi_{iuj}$$

Where $\widehat{y_{iuj}}$ is the return of Limited Partner j's investment in the u[th] fund of the i[th] PE firm adjusted for firm-time random effects and demeaned at the vintage year level:

$$\widehat{y_{iu}} = y_{iu} - X_{iu}\beta - \sum_{\tau = t_{iu}}^{t_{iu}+9} \eta_{i\tau}$$

Definitions

The parameter vector we want to estimate is $\theta^{LP} \equiv (\beta_{LP}, \sigma_\lambda^2, \sigma_\pi^2)$.

Let U_j^{LP} be the number of PE investments made by Limited Partner j, let $U^{LP} = \sum_j U_j^{LP}$, and let N^{LP} be the number of LPs in the sample.

X^{LP} is a $U^{LP} \times 1$ vector or a $U^{LP} \times 3$ matrix that contain either a single intercept or a LP category (endowment, pension fund, other) indicator, respectively.

L is a $U^{LP} \times N^{LP}$ matrix where each row represent a LP-fund return pair and each column represents a LP. Each row contains an indicator which is equal to 10 in the column of the corresponding LP.

A1 LP (random) effects

We sample the LP effects, λ_j, using a Bayesian regression. The prior is

$$\lambda_j \sim \mathcal{N}(0, \sigma_\lambda^2)$$

The posterior from which we sample is

$$\lambda_j | \{\widehat{y_{iu}}\}, \theta^{LP}, data \sim \mathcal{N}(\mu_\lambda, \sigma_\pi^2 B^{-1})$$

where

$$B = \frac{\sigma_\pi^2}{\sigma_\lambda^2}\, \mathbb{I}_{N^{LP}} + L'L$$

$$\mu_\lambda = B^{-1}(L'(\hat{Y} - X_{LP}\beta_{LP}))$$

A2 Variance of error term and β_{LP} coefficient

In this step we condition on the latent variables $\{\lambda_j\}$ sampled in the previous step. With the conjugate prior

$$\sigma_\pi^2 \sim I\mathcal{G}(o_0, p_0)$$
$$\beta_{LP}|\sigma_\pi^2 \sim \mathcal{N}(\mu_{LP_0}, \sigma_\pi^2 \Sigma_{LP_0}^{-1})$$

the posterior distribution is

$$\sigma_\pi^2|\{\lambda_j\}, data \sim I\mathcal{G}(o, p)$$
$$\beta_{LP}|\sigma_\pi^2, \{\lambda_j\}, data \ \sim \mathcal{N}(\mu_{LP}, \sigma_\pi^2 \Sigma_{LP}^{-1})$$

where

$$o = o_0 + U^{LP}$$
$$p = p_0 + \left(\hat{Y} - L\lambda - X_{LP}\beta_{LP}\right)'\left(\hat{Y} - L\lambda - X_{LP}\beta_{LP}\right) + (\mu_{LP} - \mu_{LP_0})'\Sigma_{LP_0}(\mu_{LP} - \mu_{LP_0})$$
$$\Sigma_{LP} = \Sigma_{LP_0} + X_{LP}{}'X_{LP}$$
$$\mu_{LP} = \Sigma_{LP}^{-1}(\Sigma_{LP_0}\mu_{LP_0} + X_{LP}'\left(\hat{Y} - L\lambda\right))$$

A3 Variance of LP effects

Using the inverse gamma prior

$$\sigma_\lambda^2 \sim I\mathcal{G}(l_0, m_0)$$

the posterior distribution from which we sample is

$$\sigma_\lambda^2|\{\lambda_j\}, data \sim I\mathcal{G}(l, m)$$

where

$$l = l_0 + N^{LP}$$
$$m = \ m_0 + \lambda'\lambda$$

A4 Priors and starting values

We use diffuse priors for all the parameters in the LP model. For the variance of the error term, we set $o_0 = 2.1$ and $p_0 = 1$. For the variance of the LP effects, we set $l_0 = 2.1$ and $m_0 = 0.15^2$. For the beta coefficients, we set Σ_{LP_0} equal to the identity matrix and μ_{LP_0} equal to 0 (or to a zero-valued vector for the case of LP category β). We initialize all the variables at their prior means. We do not need starting values for the LP effects since they are the first variables we simulate. The choice of the priors is in the spirit of section A7 in the KS appendix.

Appendix 2: Skill Estimates of Individual LPs

The table shows the IRR equivalent of estimated λ_j for each LP. Results are adjusted for vintage-year fixed effects, firm-time random effects, and fund specific errors. Bayesian estimates of λ_j are transformed to IRR using $e^{\lambda_j} - 1$. For each LP, Column λ shows the IRR equivalent of the average λ across all MCMC cycles. Column *Standard Error* is the IRR equivalent of Bayesian standard error for λ_j.

LP Name	λ	Standard Error	LP Name	λ	Standard Error	LP Name	λ	Standard Error
3i Group	-0.46%	2.69%	Allianz	0.33%	2.59%	AT&T	-0.76%	2.72%
3M	-1.18%	2.95%	Allianz Capital Partners	0.69%	3.01%	ATP PE Partners	-0.38%	2.28%
747 Capital	2.88%	3.28%	Allstate Insurance	-1.21%	2.83%	Auda Private Equity	-0.33%	2.01%
AA Capital Partners	0.34%	3.01%	Alpha Associates	-0.69%	2.35%	Avadis Anlagestiftung	-0.51%	1.85%
ABB Group Investment	0.26%	3.10%	AlpInvest Partners	0.48%	2.33%	Avery Dennison	-1.64%	2.74%
Abbey National Financial	0.59%	2.90%	Altira Heliad Mgmt	0.59%	2.97%	Aviva International Ins	1.72%	3.54%
Abbey National Treasury	0.58%	2.70%	Amanda Capital	1.09%	2.53%	Aviva Investors Global	0.24%	2.80%
Abbott Capital Mgmt	1.38%	1.98%	AmBex Venture Group	2.32%	3.37%	AXA	-0.11%	2.58%
Abu Dhabi Invest Authority	1.39%	3.38%	American Beacon Advisors	-0.56%	2.72%	AXA Financial	1.20%	3.36%
Access Capital Partners	-0.78%	2.85%	American Family Insurance	-0.81%	2.75%	Ardian	0.15%	2.52%
Adams Street Partners	-0.83%	2.15%	American International	-0.23%	2.91%	Bahrain Middle East Bank	1.72%	3.51%
Adveq Mgmt	-1.12%	2.33%	American PE Partners	-0.92%	2.65%	BAML Capital Partners	-0.86%	2.11%
Aegon USA Investment Mgmt	0.71%	2.99%	Ameritech	-1.37%	2.45%	BancBoston Investments	1.04%	2.28%
Aetna Investment Arm	-0.88%	2.45%	Amherst College	2.73%	2.46%	Bank Gutmann	0.68%	2.75%
Aetna Life Insurance	0.49%	3.15%	AMR Investment Services	-0.89%	2.59%	Bank Leumi	-0.42%	2.82%
AIG Global Investment	-0.45%	2.30%	Andrew W. Mellon FDN	1.71%	2.40%	Bank of America	-1.02%	2.35%
Akina	-0.13%	2.95%	Antares Capital	-0.39%	2.23%	Bank of America Merrill Lynch	0.70%	3.00%
Alaska Permanent Fund	1.05%	1.94%	Aon Advisors	-0.70%	2.81%	Bank of New York Mellon	-2.23%	2.87%
Alaska Retirement Mgmt Board	0.71%	2.87%	Aon Group	-0.55%	3.36%	Bank Of Nova Scotia	-1.01%	2.79%
Alaska State Pension	1.61%	1.82%	AP Fonden 2	0.67%	2.67%	Bank One Capital Markets	-1.28%	2.80%
Alcoa	-0.95%	2.73%	APEN AG	0.50%	2.17%	Bank Vontobel	-0.65%	2.38%
Alfred I. duPont Testamentary	0.28%	2.17%	APG Asset Mgmt US	-0.25%	2.90%	Barclays Bank	-1.02%	2.35%
Alfred P. Sloan Foundation	0.41%	2.93%	Arizona State Retirement	0.93%	2.77%	Baxter International	0.42%	3.00%
All State Venture Capital	1.11%	3.00%	Arkansas TRS	-0.50%	2.74%	Bayer	-0.49%	2.44%
AllianceBernstein	1.50%	3.10%	Arle Capital Partners	-1.68%	3.41%	BC Investment Mgmt	-0.15%	2.52%

LP Name	λ	Standard Error	LP Name	λ	Standard Error	LP Name	λ	Standard Error
BDC Venture Capital	-2.76%	3.44%	Carnegie Mellon University	0.36%	2.59%	Commercial Union Ins	0.14%	2.95%
Bear Stearns	-0.06%	2.89%	Carolina Power & Light	-0.17%	3.03%	Commonfund Capital	-0.23%	1.97%
Belmont Global Advisors	0.35%	2.96%	Case Western Reserve Univ	0.60%	2.96%	Commonwealth Fund	-0.23%	1.97%
Berea College	3.73%	3.40%	Catholic Charities Chicago	0.16%	3.31%	Connecticut State Retire	-1.15%	2.10%
Bessemer Invest Mgmt	-0.62%	2.15%	Caxton Associates	-0.37%	3.35%	Conversus Capital	-0.18%	1.65%
BHF-Bank	1.66%	3.52%	Cazenove Capital Mgmt	0.75%	2.70%	Cornell University	1.73%	2.03%
Bio*One Capital	-1.06%	3.04%	CDC Group	-1.38%	2.82%	Corning	1.16%	2.83%
BIP Investment Partners	0.09%	3.10%	CDPQ	0.44%	2.87%	Covera Ventures	-1.29%	3.15%
BlackRock	-1.44%	2.87%	Charles Schwab Group	-0.86%	2.85%	CPP Investment Board	-1.05%	2.28%
BMO Capital	0.01%	3.03%	Charles Schwab Bank	0.04%	2.99%	Cramer Rosenthal McGlynn	-1.06%	2.92%
Bmp	0.32%	2.64%	Chrysler Master Retire	-1.68%	2.32%	Credit Agricole	-0.93%	2.95%
Boeing	-1.15%	2.49%	Church Pension Fund	0.22%	2.55%	Credit Suisse	-0.36%	2.63%
Bombardier Pension	0.98%	3.43%	CIBC	-0.20%	2.89%	CSFB Private Equity	-1.52%	2.14%
Bowdoin College	0.83%	3.13%	Cincinnati Bell	1.21%	3.29%	CSGN	-1.66%	2.54%
BP America	-0.89%	3.19%	Cisco Systems	2.40%	3.01%	Customized Fund Investment	-1.15%	2.72%
BP Pension	-0.18%	2.85%	Citi	-0.05%	2.15%	Cuyahoga Capital Partners	1.37%	3.26%
Bramdean Asset Mgmt	0.63%	3.09%	Citigroup Private Equity	-0.62%	2.33%	Daimler	1.62%	3.03%
Brinson Partners	-0.08%	2.64%	City of Boston Retirement	-0.84%	2.66%	Daiwa Corporate Invest	-0.98%	3.07%
Bristol-Myers Squibb	0.49%	1.84%	City of Philadelphia	-0.45%	2.89%	Danske Bank	1.83%	3.14%
Brown Brothers Harriman	0.20%	2.71%	City of Worcester Retirement	0.51%	3.04%	Danske Private Equity	-0.51%	2.36%
Brown University	-0.98%	2.85%	Clal Industries and Investments	1.43%	3.07%	Dartmouth College	3.03%	2.30%
Buckeye Venture Partners	0.31%	2.80%	Claude Worthington Benedum	-0.11%	2.77%	Davidson College	2.18%	3.47%
Bure Equity	1.28%	3.42%	Cleveland Foundation	1.33%	3.32%	Dayton Power and Light	0.66%	3.12%
Cal Tech	1.05%	2.35%	CMS Fund Advisers	0.85%	2.00%	DeA Capital	0.34%	2.17%
CalPERS	-1.23%	1.56%	CNA Financial	-0.51%	3.37%	Deere & Company	-0.92%	2.80%
CalSTRS	0.08%	1.61%	CNP	0.25%	2.94%	Delaware State Board Pension	2.18%	3.19%
Cambridge Retirement	-0.69%	2.51%	Colby College	1.57%	2.77%	Delta Air Lines	-2.66%	2.83%
CIBC World Markets	-0.20%	2.89%	Colgate University	1.66%	2.79%	Denison University	0.87%	3.08%
Capital Access Funds	-2.06%	2.79%	Colorado PERA	-1.92%	1.91%	Denver PSR	-1.20%	2.59%
Capvent	-1.00%	2.77%	Columbia University	1.80%	2.59%	Deutsche Bank Alex. Brown	0.01%	3.01%
Carleton College	1.74%	2.91%	Commercial Union Ins	0.14%	2.95%	Deutsche Bank Trust Corp	-0.03%	2.91%

LP Name	λ	Standard Error	LP Name	λ	Standard Error	LP Name	λ	Standard Error
Deutsche Beteiligungs	0.46%	3.13%	Fire & Police San Antonio	-0.97%	3.08%	Grove Street Advisors	-0.53%	1.98%
District of Columbia Retire	-1.05%	2.99%	First Chicago Investment	-0.58%	2.77%	Grupo Guayacan	1.44%	2.01%
DKA Capital	-2.57%	3.36%	FLAG Capital Mgmt	-0.32%	2.15%	GTE Investment Mgmt	-0.65%	3.12%
DLJ Merchant Banking Part	-1.84%	2.77%	Fleet Equity Partners	-0.36%	2.75%	Halyard Capital	-0.71%	2.80%
Dow Chemical	-1.97%	2.65%	Florida State Board of Admin	-0.62%	2.21%	Hamilton Lane (Singapore)	0.56%	2.90%
DSM Venturing	-0.30%	3.05%	Fondinvest Capital	-0.68%	2.75%	Hamilton Lane Advisors	-0.04%	1.96%
Duke Power	2.30%	3.44%	Ford Foundation	1.51%	2.03%	Harald Quandt Holding	0.77%	3.21%
Duke University	0.77%	1.86%	Ford Motor	-0.44%	3.12%	HarbourVest Partners	-0.29%	2.04%
Dunedin Capital Partners	1.87%	3.43%	Fort Washington Capital	0.72%	1.95%	Harvard University	0.70%	2.05%
DuPont Capital Mgmt	-1.45%	2.87%	FPPA Colorado	-0.13%	1.95%	Heller Financial	-0.63%	2.54%
Duquesne Light	0.34%	3.04%	Frank Russell	-0.12%	2.95%	Hellman & Friedman	1.27%	3.29%
E.I. DuPont De Nemours	0.74%	2.53%	Fresno County ERA	-0.84%	3.04%	Henderson Equity Partners	-0.72%	2.54%
EDS Retirement	1.26%	2.62%	GE Asset Mgmt	-0.02%	2.66%	Henry J. Kaiser Family FDN	-0.47%	2.67%
EES Acquisition Fund II	0.88%	2.81%	GE Global Sponsor Finance	0.13%	2.91%	Henry Luce Foundation	0.09%	3.37%
Electricite de France	-1.41%	3.22%	General American Investors	-1.38%	3.26%	Hewlett-Packard	0.61%	2.77%
Electrolux	-0.90%	3.19%	General Electric	-1.56%	2.56%	HFRRF	-0.68%	2.93%
Eli Lilly	0.62%	3.19%	General Mills	-0.41%	2.75%	Hillman Company	-2.23%	2.81%
Emory University	-0.49%	2.88%	Georgia Tech	1.46%	2.95%	Hillman Foundation	-0.21%	3.00%
Equitrust	-1.05%	2.60%	GIC Special Investments	0.36%	2.01%	HLM Venture Partners	-1.11%	3.40%
ERS Hawaii	0.46%	2.70%	GIMV	-1.74%	2.87%	Hoffmann-La Roche	0.90%	2.87%
ERS Texas	-1.05%	2.60%	Goldman Sachs Asset Mgmt	-1.93%	2.41%	Horsley Bridge Partners	2.50%	2.16%
ERS RI	1.92%	3.24%	Goldman Sachs Merch Bank	-0.96%	2.36%	Hospitals of Ontario Pension	-0.51%	2.88%
Eurazeo	-0.38%	2.72%	Goldman Sachs PE Group	0.58%	2.60%	Houston HMEPS	-1.68%	2.95%
eValue Europe	-1.32%	2.89%	Goodyear	-1.82%	2.96%	Houston Police Pension	-0.04%	1.93%
Evangelical Lutheran Church	2.01%	2.80%	Gov of Singapore Invest	-0.43%	2.55%	Howard Hughes Med. Inst.	-0.35%	2.08%
Ewing M. Kauffman FDN	-0.23%	2.29%	Granite Hall Partners	0.69%	2.78%	HRJ Capital	-0.73%	2.83%
Exxon	0.23%	2.93%	Graphite Capital Mgmt	0.62%	2.65%	HSBC France	1.69%	3.53%
F & C Private Equity Trust	-2.02%	2.81%	Greater Manchester Pension	1.28%	3.10%	IBM Retirement	1.34%	2.29%
F & C Asset Mgmt	-0.44%	2.73%	Greenspring Associates	1.36%	2.24%	IDInvest Partners	-1.65%	2.78%
FFP	0.08%	2.96%	Groupama Private Equity	0.34%	2.37%	Illinois Municipal Retire	0.01%	1.60%
Finnish Industry Investment	1.52%	2.80%	Groupe IDI	0.05%	2.97%	Illinois State Board of Invest	-1.20%	2.27%

LP Name	λ	Standard Error	LP Name	λ	Standard Error	LP Name	λ	Standard Error
ID Holding Partners	-0.13%	2.46%	KeyCorp	0.24%	2.75%	Massachusetts Mutual Life	-0.33%	2.68%
Indiana PRS	1.39%	1.78%	KKR PEI Investments	-0.18%	3.10%	Massachusetts PRIT	0.08%	2.00%
Indiana University	-1.72%	2.83%	Knightsbridge Advisers	2.70%	2.82%	Mayo Foundation	-1.79%	2.43%
ING Investment Mgmt	-0.39%	2.92%	König & Cie	0.15%	2.74%	MBTA	-0.62%	2.37%
International Finance	-1.16%	2.79%	Koor Corporate Venture Capital	-0.62%	3.06%	MC Financial Services	-0.89%	3.04%
Invesco Advisers	-0.76%	2.85%	Kresge Foundation	0.65%	2.69%	MD Dept of Bus and Econ Dvlpmnt	-1.66%	2.98%
Investco Private Capital	1.25%	2.04%	Kuwait Financial Private Equity	0.35%	2.08%	Mead	-2.08%	3.09%
Invest Fund for Foundations	1.26%	2.34%	Kuwait Investment Authority	0.87%	2.66%	Meadows Foundation	-1.63%	2.21%
Iowa PERS	1.03%	1.90%	LA City Employees' Retirement	0.31%	2.20%	Merrill Lynch Ventures	0.90%	3.16%
ITAA Retirement	-0.31%	2.03%	LA County Employees' Retire	0.60%	1.91%	MERS of Michigan	0.05%	2.49%
Itochu	-0.59%	3.03%	LA Fire & Police Pension	0.44%	2.08%	Mesirow Financial Hld	1.14%	2.85%
Itochu Tech Venture Investment	-0.57%	2.93%	Landmark Partners	-0.52%	2.61%	Metropolitan Life Ins	-0.20%	2.43%
J. Paul Getty Trust	1.25%	3.21%	Länsförsäkringar	1.61%	3.23%	Metropolitan Museum of Art	1.91%	2.91%
J.F. Shea	1.93%	2.96%	Lehman Brothers PE	0.95%	2.54%	Meyer Memorial Trust	-0.92%	2.78%
J.P. Morgan Asset Mgmt	-0.13%	2.08%	Lexington Partners	-0.43%	2.63%	MIC Capital	-0.51%	3.10%
J.P. Morgan Partners	-1.40%	2.03%	LGT Capital Partners	0.70%	2.08%	Michelin North America	-1.80%	2.41%
JAFCO	-0.84%	2.86%	Liberty Mutual Holding	0.46%	1.87%	Michigan Dept of Treasury	0.47%	1.93%
James Irvine Foundation	0.19%	2.89%	Liberty Mutual Insurance	0.66%	1.91%	Michigan State University	2.75%	3.49%
J.D. & C.T. MacArthur FDN	0.28%	2.73%	Lifespan	-0.24%	2.85%	Middlebury College	0.00%	2.88%
John A. Hartford FDN	2.84%	3.51%	Lincoln National	-0.68%	3.04%	Minnesota Mutual Life Ins	-2.98%	2.94%
John Deere Pension	-0.86%	2.91%	LMS Capital	-0.60%	2.66%	Minnesota Board of Invest	-0.81%	2.05%
John Hancock Life Insurance	0.63%	2.82%	Lockheed Martin	0.71%	2.99%	Missouri PSRS	1.05%	2.63%
John S. & James Knight FDN	-0.08%	2.73%	Louisiana SERS	1.69%	1.96%	Missouri MOSERS	-0.19%	2.96%
Johnson & Johnson	-1.29%	2.62%	Lucent Technologies	-1.34%	2.76%	MIT	1.17%	2.03%
JPMP Capital	-1.82%	2.25%	Lynde & Harry Bradley FDN	-1.41%	2.96%	MITIMCo Private Equity	0.12%	2.36%
K & E Partners	0.02%	3.19%	M.J. Murdock Charitable Trust	4.30%	3.28%	Mitsui & Co. (USA)	0.12%	2.36%
Kansas PERS	-0.32%	1.97%	Macquarie Private Capital	0.26%	2.94%	Mitsui & Co.	-1.72%	2.80%
KBC	-1.73%	3.04%	Madison Dearborn Partners	0.41%	3.21%	Montana Board of Invest	-0.68%	2.35%
Kenmont Capital Partners	-0.08%	2.88%	Martin Currie Investment Mgmt	-0.58%	2.84%	Montreal Police Pension	-0.61%	2.89%
Kentucky Retire Systems	-0.10%	2.86%	Maryland SRPS	0.75%	2.79%	Morgan Stanley	-0.71%	2.77%
Kenyon College	-1.48%	2.43%	Masco	0.02%	3.06%	Morgan Stanley Alt Invest	0.57%	2.73%

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Mousse Partners	0.54%	2.94%	Northwestern University	-1.09%	2.11%	Pantheon Ventures	-0.61%	2.05%
MPC Münch. Petersen A.	0.06%	2.99%	Notre Dame Endowment	2.73%	2.08%	Parallel Private Equity	0.01%	3.04%
Mutual of NY Life Ins	0.05%	2.49%	Novartis Vaccines & Diag.	-0.91%	3.02%	Parish Capital Advisors	-1.11%	2.89%
Mutual of Omaha Insurance	-1.19%	2.56%	NPRF (Ireland)	1.49%	2.75%	Park Street Capital	-0.09%	1.90%
National City Bank	1.35%	3.18%	NY City Police Pension	-0.05%	2.97%	Partners Group Holding	0.29%	2.39%
National City Equity Part	0.66%	2.18%	NY City Retirement	-1.10%	2.05%	Pathway Capital Mgmt	0.10%	1.98%
National Grid	-1.16%	2.51%	NY Common Retirrement Fund	-0.27%	1.90%	Paul Capital France	-0.99%	3.04%
Nationwide	-1.49%	2.16%	NY Life Capital Partners	-0.26%	2.35%	Paul Capital Partners	-0.30%	2.61%
Natixis Private Equity	-0.51%	3.03%	NY STRS	1.07%	2.08%	Penn Mutual Life Insurance	-0.97%	2.63%
Nautic Partners	0.54%	2.56%	NYS OSC	0.06%	2.59%	Pennsylvania State University	0.83%	2.93%
NB Alternatives Advisers	1.26%	2.10%	Oberlin College	0.83%	2.95%	Peppertree Capital Mgmt	0.09%	2.74%
NB Private Equity Partners	0.29%	2.44%	OCERS	-0.97%	2.22%	Peppertree Partners	0.67%	2.36%
Nestle	1.27%	2.66%	Ohio OBWC	-1.68%	2.37%	Performance Equity Mgmt	1.20%	2.91%
Neuberger Berman	0.32%	2.63%	Ohio Capital Fund	0.80%	2.85%	PERS Colorado	-0.60%	2.09%
Nevada PERS	0.72%	2.83%	Ohio Carpenters H & W	0.90%	3.13%	PERSI Idaho	0.39%	2.96%
New Hampshire Retirement	-2.03%	2.35%	Ohio Police & Fire Pension	-2.28%	2.42%	Pew Charitable Trusts	-0.97%	2.81%
New Jersey Division of Invest	-0.08%	2.53%	Ohio State University	-0.56%	2.98%	Pfizer	0.13%	2.31%
New Mexico Edu Retire. Board	0.22%	2.77%	Oklahoma Capital Invest Board	-1.27%	3.04%	PGGM	0.83%	2.56%
New Mexico St Invest Counc.	-0.60%	1.81%	Olayan Group	0.56%	3.14%	Philadelphia Pension	0.40%	2.21%
New York Life Insurance	-0.05%	2.97%	OMERS	0.52%	2.98%	Phillips Academy	2.83%	3.52%
NIB Capital Private Equity	-1.10%	2.05%	Ontario Teachers' Pension	-0.50%	2.19%	Phoenix Life Insurance	-1.65%	2.14%
NIBC Holding	-0.26%	2.35%	OPERS	-0.04%	2.01%	PNC Equity Partners	-1.14%	2.17%
Nippon Venture Capital	-0.54%	2.29%	OPPRS	-1.69%	2.98%	Pohjola Bank	1.82%	3.19%
North Sky Capital	0.56%	2.42%	Oregon PERS	-0.55%	1.93%	Pomona Capital	0.44%	2.03%
Northeastern University	3.47%	2.74%	Oregon State Treasury	-0.30%	2.08%	Pomona College	1.98%	2.47%
Northleaf Capital Partners	1.13%	2.54%	ORS Michigan	-1.08%	2.35%	Portfolio Advisors	0.27%	1.85%
Northrop Grumman	-0.90%	3.17%	Owens-Illinois	1.42%	3.05%	PPM America	-0.71%	2.81%
Northwestern Insurance	-0.29%	2.75%	PA Employees' Retirement	-1.29%	1.89%	Princess Mgmt	0.10%	1.94%
Northwestern Invest Mgmt	-0.20%	2.11%	Pacific Life Insurance	0.50%	2.79%	Princess Private Equity	0.52%	1.89%
Northwestern Memorial Hosp	1.15%	2.14%	PacifiCorp	-0.76%	1.84%	Princeton University	-0.12%	2.18%
Northwestern Mutual Life	0.18%	2.16%	Pamlico Capital	-1.90%	2.68%	Private Advisors	0.72%	2.94%

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Progress Energy	-0.15%	3.05%	Sal. Oppenheim jr. & Cie.	0.48%	2.00%	Starling International Mgmt	0.46%	2.76%
Progress Investment Mgmt	-2.37%	3.11%	Santander UK	-0.42%	2.95%	State Farm Life	1.72%	3.55%
Promark Global Advisors	1.10%	1.86%	SBC Communications	-0.09%	2.72%	State Farm Mutual Auto	0.41%	3.24%
Promark Invest Advisors	-0.17%	2.21%	Scottish Investment Trust	-1.04%	2.97%	State of WI Invest Board	-0.88%	1.78%
Providence Employees' Retire	0.17%	2.83%	Scottish Widows Investment	-0.99%	2.65%	Stichting Pensioenfonds	1.54%	3.02%
Provident Bank	1.93%	3.76%	SDCERA	0.49%	2.18%	Stonehenge Partners	0.01%	3.18%
Prudential Insurance	0.58%	2.69%	Sears Investment Mgmt	1.38%	2.86%	Strategic Investment Solutions	-1.24%	2.26%
PSEG Resources	-0.27%	3.30%	SEB Asset Mgmt	-0.24%	2.64%	STRS Ohio	-1.43%	1.97%
PSPRS AZ	0.97%	2.84%	SERS Ohio	-1.24%	2.21%	Sun Life Financial	-1.27%	2.97%
Public Service Enterprise	1.94%	3.12%	SF City and County Retire	0.36%	2.50%	SunAmerica Ventures	-1.30%	2.64%
Pyxis Capital	-0.39%	2.67%	SFERS	1.55%	2.15%	SunTrust Banks	-0.28%	2.91%
Qwest Asset Mgmt	-1.28%	2.81%	SGAM Alternative Invest	-0.20%	3.22%	SURS Illinois	-0.32%	2.02%
RBC Venture Partners	0.30%	3.10%	ShaPE Capital	0.73%	2.24%	SVB Capital	2.20%	2.44%
RCP Advisors	1.02%	2.65%	Shell Oil	-0.50%	2.92%	SVB Financial Group	-0.86%	2.83%
RDV	-1.38%	3.01%	Sherman Fairchild FDN	-0.29%	2.97%	SVB Silicon Valley Bank	-0.67%	2.80%
Rensselaer Polytech Institute	-1.00%	2.65%	Siemens Venture Capital	0.27%	2.73%	SVG Advisers	0.17%	2.85%
Rho Capital Partners	0.92%	3.25%	Siguler Guff	0.52%	1.86%	SVG Capital	1.01%	2.09%
RI Treasury	0.22%	2.14%	SilverHaze Partners	-0.15%	2.80%	Swarthmore College	-1.38%	2.88%
Richard King Mellon FDN	-0.79%	3.00%	Sitra Investment Arm	0.32%	2.54%	SIFEM	0.05%	2.84%
Riverside Church	-2.30%	3.03%	Sjätte AP	1.29%	3.44%	Swiss Life Private Equity	0.26%	2.70%
Robeco Group	-0.14%	2.13%	Skandia Liv Asset Mgmt	0.68%	2.82%	Swiss Re Private Equity	0.25%	2.00%
Robert Wood Johnson FDN	1.18%	2.69%	SL Capital Partners	0.94%	2.15%	Swiss Reinsurance	-2.49%	2.70%
Rockefeller Br. Fund	-0.21%	2.89%	Source Capital Group	2.34%	3.45%	TA Associates	0.67%	2.96%
Rockefeller Fam Trust	1.78%	2.95%	South Carolina Retirement	0.52%	2.80%	TD Capital	0.80%	2.27%
Rockefeller University	0.61%	2.57%	South Dakota Invest Counc.	-0.39%	2.70%	Teachers' Private Capital	-0.32%	2.61%
RogersCasey	0.41%	2.44%	Southern Company	-1.44%	3.07%	Temasek Capital	-0.65%	2.60%
Royal Bank of Canada Capital	0.23%	2.92%	Spelman College	1.36%	3.32%	Texas A&M	1.51%	3.73%
Rush University Med Center	-0.75%	2.97%	SR One	-2.04%	2.86%	Textron	-2.05%	3.01%
RWB RenditeWertBeteiligung	-0.29%	2.39%	St. Paul Venture	-0.46%	2.83%	The Glenmede Trust Co	0.71%	1.87%
S. C. Johnson & Son	-0.79%	2.97%	Standard Life	-1.80%	2.45%	The GS Group	-0.43%	2.58%
Safeguard Scientifics	-1.66%	3.26%	Stanford University	1.00%	2.17%	The Key Corporation	1.39%	3.29%

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Thomas Weisel Capital Mgmt	0.85%	2.38%	United Technologies	-0.21%	2.27%	Virginia Tech	-0.95%	2.80%
Thrivent Financial Lutherans	-0.41%	3.05%	University of California	-1.16%	2.09%	Vontobel Holding	0.23%	3.11%
TIAA-CREF Invest Mgmt	-0.22%	3.07%	University of Chicago	0.21%	2.81%	Vulcan Capital	-1.10%	2.78%
TIF Ventures	0.33%	2.77%	University Of Colorado	-1.16%	2.65%	Vulcan Materials	0.99%	3.21%
Time Warner	-0.67%	3.08%	University of Michigan	1.11%	1.96%	W.K. Kellogg Foundation	-0.63%	3.12%
Tokio Marine & Nichido Fire Ins	2.09%	3.29%	University of Minnesota	2.23%	2.77%	Wachovia	0.12%	2.95%
Toronto-Dominion Bank	0.16%	2.94%	University of North Carolina	-1.98%	2.16%	Walt Disney	1.98%	3.08%
Travelers Insurance	-0.65%	3.04%	University of Pennsylvania	0.94%	2.79%	Washington State Invest Board	-0.20%	1.70%
Tredegar	-2.70%	2.77%	University of Pittsburgh	-0.30%	2.20%	Washington University	-0.54%	1.95%
Tri-State Ventures	-1.40%	2.86%	University of Richmond	-1.66%	2.67%	Wellesley College	-1.73%	2.16%
Triton Systems	2.53%	3.56%	University of Texas	-0.82%	1.76%	Weome Trust	1.32%	2.97%
TRS Illinois	-2.19%	1.98%	University of Toronto	0.71%	2.93%	Wesleyan University	-0.02%	2.97%
TRS Louisiana	-0.28%	2.28%	University of Virginia	0.43%	2.47%	West Midlands Pension	1.45%	2.90%
TRS texas	0.97%	1.92%	University of Washington	1.82%	2.22%	West Yorkshire Pension	-1.25%	3.02%
Trust Plan	-2.61%	2.76%	University Of Wisconsin	0.14%	3.03%	WestLB Private Equity	0.19%	2.75%
Tunisie Leasing	-0.73%	3.12%	USC	0.60%	2.63%	William & Flora Hewlett FDN	3.60%	2.49%
Twin Bridge Capital Partners	-0.87%	2.80%	Utah Capital Investment	-0.85%	2.77%	Williams College	0.65%	2.78%
U.S. Bancorp	-0.25%	2.91%	Utah Retirement Systems	0.68%	1.97%	Wilshire Associates	-1.15%	1.92%
U.S. Steel & Carnegie Pension	0.09%	2.89%	Vanderbilt University	1.21%	2.58%	Wilton Asset Mgmt	-0.60%	2.74%
U.S. West Investment Mgmt	0.34%	3.08%	Vassar College	-0.15%	3.02%	Wisconsin Alumni Research FDN	-1.87%	2.49%
UBS Capital	0.69%	3.05%	VenCap International	2.89%	2.42%	World Bank Group	0.15%	2.84%
UMWA Health & Retire	-0.18%	2.44%	Verizon Communications	0.56%	2.78%	Y.M.C.A. Retirement Fund	-0.72%	2.04%
Unisys	0.40%	2.05%	Virginia Retirement System	0.88%	1.97%	Yale University	0.17%	2.06%
Thomas Weisel Capital Mgmt	0.85%	2.38%	United Technologies	-0.21%	2.27%	Virginia Tech	-0.95%	2.80%