Measuring Institutional Investors' Skill at Making Private Equity Investments

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Abstract

Using a large sample of institutional investors' investments in private equity funds raised between 1991 and 2011, we estimate the extent to which investors' skill affects their returns. Bootstrap analyses show that the variance of actual performance is higher than would be expected by chance, suggesting that some investors consistently outperform. Extending the Bayesian approach of Korteweg and Sorensen (2017), we estimate that a one standard deviation increase in skill leads to an increase in annual returns of between one and two percentage points. These results are stronger in the earlier part of the sample period and for venture funds.

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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, the ability of pension plans to fund promised benefits, and the ability of foundations to support charitable endeavors all depend crucially on the returns they receive on their investments. Yet, it is surprising that there has been little work done measuring differences in investment skill across institutional investors.

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.

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 27,283 investments made by 1,209 unique LPs, each of which have at least four private equity investments in either venture capital or buyout funds during the 1991 to 2011 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 main results imply that an increase of one standard deviation in skill leads to an increase in IRR of approximately one to two percentage points. 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. 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, and when imposing different reasonable sampling restrictions to create the bootstrap distributions. Overall, the bootstrap 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) (2017) 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 between a one and two 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 between and a 2 and 4.5 percentage-point increase in returns. Moreover, the effects declines as the sample period progresses, consistent with related work on the maturing of the private equity industry (Sensoy, Wang, and Weisbach, 2014). These estimates highlight 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. To evaluate whether differences in risk preferences could lead to the differences in returns across LPs, we first evaluate whether the differences in performance differ within types investors; presumably, LPs within the same type are more likely to have the same risk preferences and investment objectives. Within each type, we also observe more variation in LP performance than would be expected if LPs had no differential skill. Second, we conduct a test similar to Andonov, Hochberg, and Rauh (2017) by breaking down the entire distribution of returns by estimated skill level. If LPs with the highest estimated skill are simply taking more risk, they should have the most risky or spread-out distribution of returns. However, this is not the case. LPs we estimate to have high skill outperform LPs estimated to have low skill throughout the distribution of returns, not just at the high end. Therefore, it does not appear that the pattern we document of some LPs systematically outperforming others occurs because the high performing LPs invest in riskier funds with higher expected returns.

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 likely to be the most subject to these pressures, since there is direct evidence that their boards influence the selection of private equity funds negatively for reasons of political expediency (Andonov, Hochberg, and Rauh, 2017). To evaluate the importance of political pressure in explaining the difference in returns across LPs, we first reestimate our model using a specification that allows for the possibility that public funds, public pension funds in particular, receive systematically different returns from other investors. The results using this specification suggest that public pension funds do not have systematically different returns from other types of investors. We also reestimate our model on subsamples of LPs of each particular type. These estimates suggest that the variation in skill *within* each LP type is even larger than that of the full sample. For this reason, it does not appear that the differences in returns across investors are explained by differences in political pressure or any other factor that varies systematically by type of investor.

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.

To evaluate whether limited access can explain differential performance across investors, we estimate the Bayesian model for first-time funds and, separately, reinvested funds, as LPs are usually given the option to reinvest in GPs' follow-on funds. Our estimates 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, 2007; Sensoy, Wang, and Weisbach, 2014). 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 reinvested 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 began with Jensen (1968) and 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.[1]

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 (2017) 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 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. This paper is also related to Hochberg and Rauh (2013), Andonov, Hochberg, and

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

Rauh (2017), and Barber, Morse, and Yasuda (2016), who study investment pressures that LPs face and their impact on performance. However, these papers focus on differences across *classes* of investors, while our focus is on the individual LPs and their choices.

2. Sample description

To examine LPs' private equity investments, we construct a sample of LPs using data obtained from three sources: Preqin, VentureXpert provided by Thompson Economics and S&P's *Capital IQ*. While these three sources do not provide a complete list of LPs' investments, we identify a large sample of 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 2011 are excluded to provide sufficient time to observe the realization of most of the fund's return. The returns data are as of the end of 2016. For funds that are not liquidated by this time, the final observed NAV is treated as a liquidating distribution by *Preqin* to compute returns. 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.[2] These restrictions leave a sample containing 30,915 investments made by 2,314 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 27,283 investments made by 1,209 unique LPs in 2,238 unique funds.

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, first quartile (Q1), and third quartile (Q3) values of each LP characteristic. On average, each LP invests in 22.57 funds. Because we restrict our sample to LPs with at least 4 investments, the first quartile value for *Number of investments* per

[2] We also run our main tests using cash multiples, with similar conclusions.

LP is 6 funds. The average return of LPs' investments shows an IRR of 12.01%. Buyout funds are also larger than venture funds, on average.

Panel B reports summary statistics of LPs' investments by LP type: endowments, pensions, and all other LPs. Pensions have the highest number of funds per LP (30.95) and invest in the largest funds. Endowments have the highest average IRR (13.01%) and invest in the most experienced funds, with an average sequence number of 4.15.

Panel C reports summary statistics of LPs' investments sorted by type of fund. Buyout funds tend to be larger than venture funds and have higher IRRs. On average, there are 12.19 LPs in each fund over the entire sample. Venture funds have fewer LPs than buyout funds, with an average of 8.43 LPs for the venture funds in our sample and 15.11 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 that information on the dollar amount invested by an LP in a given fund (the LP's commitment) is missing for most of the sample, which precludes us from calculating total returns for most LPs. Instead, we focus on LPs' median and equally-weighted returns of their invested funds, which we can calculate for the full sample.

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

3.1. The Distribution of LP Persistence

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 not a literature measuring the skill of individual LPs of private equity funds, there is a large literature measuring the skill of other types of portfolio managers. The conventional approach to measuring skill in asset management 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, i.e. returns "persist". Although this approach has some appeal as a simple, intuitive test, it 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.[3]

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.[4] We call this measure "top-half persistence," and emphasize that it differs from the type of 'persistence' that is typically analyzed in the mutual fund literature in that it does not depend on a regression model. Formally, let $IRR_{j,t,x,u}$ be the return to LP j on their u^{th} investment of type x in year t. Let $M_{t,x}$ be the median return of funds of type x in year

[3] See Korteweg and Sorensen (2017) for a critique of the merits of the regression approach.
[4] We could extend the analysis to quartiles or deciles, but a finer cutoff would make the comparisons more difficult to interpret.

t, and let N_j denote the total number of investments made by LP j during the sample period. Then, the top-half persistence of LP j is defined by:

$$p_j = \frac{\sum_t \sum_x \sum_u [IRR_{j,t,x,u} > M_{t,x}]}{N_j}$$

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.

We note that this approach only picks up a certain kind of skill. In particular, it measures the ability of a particular LP to select funds, conditional on their investing in a particular type of private equity fund in a particular year. In other words, we assume that fund managers are constrained to invest in either a venture or buyout fund in a given year and then measure the quality of the fund they pick. This minimizes concerns about risk differences across investments. Alternatively, an LP's skill could be in knowing when to be in the market and when to leave the market, or in rotating between buyout and venture funds; for example, an LP who knew to invest in venture capital in 1994 and knew not to reinvest in 1999 would be particularly high quality, even if he was not unusually good at picking the particular venture funds to invest in. To the extent that our tests do not incorporate this latter type of skill, we potentially underestimate the importance of LP skill.

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 and type, regardless of the identity of the LP making it. Therefore, the distribution of LP persistence would be approximately bell shaped.[5] In contrast, the empirical distribution, shown in Figure 1, is slightly positively 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.

[5] The actual distribution should be a mixture of binomial distributions depending on the number of investments made by each LP.

Figure 1 also characterizes LPs' investments in venture capital and buyout funds separately. The distribution of LP persistence in buyout funds is similar to that in all investments. The figure shows slight positive skewness and fat tails on both sides in the distribution of LP persistence in buyout funds. The distribution for venture capital funds is more symmetric, and the tails are slightly thinner compared to what we observe for buyout funds. However, the tails on both sides are still fatter than what one would expect from a bell-shaped distribution.

In summary, these results suggest 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 LP persistence 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 statistical test of whether there is more variability in top-half persistence than what we would expect by chance, we use a bootstrapping approach. We begin by noting that the observed top-half persistence by a given LP can be regarded as a statistical estimate of their true underlying probability of being in the top-half on each investment. The more investments we have in our sample for a given LP, the better the estimate of their true top-half persistence. Therefore, to account for differences in the number of investments made by each LP in our sample, we compute the z-score of p_j relative to a baseline (chance) proportion of 0.5:

$$z_j = \frac{p_j - 0.5}{\sqrt{0.5(1-0.5)/N_j}}.$$

Under this transformation, LPs with top-half persistence greater than 0.5 have positive z-scores, while LPs with top-half persistence lower than 0.5 have negative z-scores. The normalizing constant in the z-score is the standard error of p_j, so LPs cannot have z-scores in the tails of the distribution unless we have a large number of their investments in the sample. For example, an LP whose return was in the top-half on three out of four investments would have $p_j = 0.75$ and $z_j = 1.0$, while an LP whose return was in the top-half on 30 out of 40 investments would have $p_j = 0.75$ and $z_j = 3.16$.

Under the assumption of no differential skill among LPs, z_j is a standard normal random variable, so the mean and standard deviation of the z-scores in our sample should be 0.0 and 1.0, respectively. If, on the other hand, there were differential skill among LPs then the standard deviation of z_j should be greater than 1.0. In our sample, across all LPs, the standard deviation of the z-scores is 1.15. Considering venture and buyout funds separately, the standard deviations are 1.21 and 1.09, respectively. The fact that the standard deviations are greater than 1.0 suggests that there is more variability in the z-scores of top-half persistence than what would be expected by random variation alone.

To assess whether these differences in the standard deviation are statistically significant, we use a bootstrap approach. The statistic of interest in the bootstrap is the standard deviation of the distribution of z-scores of top-half persistence, defined as:

$$s_z = \sqrt{\frac{\sum_j (z_j - \bar{z})^2}{n-1}},$$

where $\bar{z}$ is the average z-score in the sample, and n is the number of LPs in the sample. We bootstrap the sampling distribution of this statistic under the null hypothesis that there is no differential skill among LP's.

An observed s_z that is higher than what would be expected by chance (i.e., one far enough in the right-hand tail of the sampling distribution) would be considered statistically significant and suggest that there is differential skill among LPs.

We operationalize the null hypothesis in our test by assuming that 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.[6] 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 of the bootstrap, we compute s_z. Then, across 1000 iterations, we obtain the distribution of s_z 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 of LP investments made from 1991 to 1998, 1999 to 2006, 2007 to 2011, as well as the full sample.

The results from the bootstrap simulations are reported in Panel A of Table 2. The column labeled *Actual* shows the observed s_z in our sample, while the column labeled *Boot* shows the mean of s_z across the bootstrapped samples. As expected, the mean of the bootstrapped s_z is approximately 1.0 for each subsample as well as the full sample. The variable *% > Actual* is defined as the percentage of bootstrapped samples with s_z greater than what we observe in the actual sample. This value has the same interpretation as a p-value in a classical hypothesis test: it equals 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 the full sample the *% > Actual* is less than 1% for each group of funds. In the early and middle subperiods, the *% > Actual* is less than 1% for each group of funds as well, while for the latter (post

[6] This random assignment gives the bootstrap the most power. However, we also have performed alternative bootstraps by excluding fund of funds and by restricting LPs to invest in funds of similar sizes and industry and to reinvest in the follow-on funds of the GPs with similar results. See Table IA-1 in the Internet Appendix.

financial crisis) subperiod, it is less than 1% for the venture capital funds but not for the whole sample of funds or for buyout funds. The implication of these low values of *% > Actual* is that it is highly unlikely that random chance alone could cause the standard deviation of the z-scores to be as high as it is.

As an additional test of whether our sample is consistent with chance performance by LPs, we use the Kolmogorov-Smirnov test. The null hypothesis in the Kolmogorov-Smirnov test is that both the actual sample and the bootstrapped sample are drawn from the same underlying probability distribution. A rejection of the null hypothesis indicates that our sample differs significantly from what would be expected if LPs chose their private equity investments randomly. The column labeled *% reject* in panel A of Table 2 shows the proportion of bootstrapped samples (of z-scores) in which the null hypothesis was rejected. We find that the rejection rates are quite high, even in the latter sample.

3.3. Bootstrapping LPs' Returns

We next repeat the above bootstrap analysis, focusing an LP's average IRR instead of the fraction of its investments in the top half of the return distribution. In each bootstrapped sample, and in the actual sample, we compute both the median IRR and the equal-weighted average IRR for each LP. Then, we compute the standard deviations of these values across LPs. We compare the standard deviation in the actual sample with the distribution of bootstrapped standard deviations to determine if our sample deviates significantly from what would be expected if there were no differential skill. In particular, the mean of the bootstrapped standard deviations is an estimate of the expected standard deviation 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 median and equal-weighted average IRR in Panels B and C of Table 2, respectively.

For the full sample period, the standard deviation of LPs' median IRR is higher than the bootstrapped estimate. The difference is statistically significant, since the *% > Actual* is less than 0.1% (i.e., the p-value less than 0.001). The result is the same when we divide the sample by fund type, with p-values of 0.003 venture funds and 0.004 for buyout funds. Considering each sample period separately, we find the same pattern of results in the middle period (1999-2006) and later period (2007-2011) but not in the earlier period (1991-1998), when the bootstrapped estimate of the standard deviation is actually slightly higher than in the actual sample. The difference in the early period is not statistically significant.

Moving to equal-weighted average IRR, we find that the actual standard deviation is higher than the bootstrapped estimate for all funds, as well as for most subgroups and subperiods, although the differences are not significant in some subgroups and subperiods. The lack of significance 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 (2017) Bayesian approach with year fixed effects and firm-time random effects.

As with the previous bootstrap analysis, we also consider the Kolmogorov-Smirnov test on both median IRR and equal-weighted average IRR. These are reported in the columns labeled *% reject* in Panels B and C of Table 2. Without separating by fund type and sample period, we find 100% of the bootstrapped samples to be significantly different from the actual sample. The result is similar for all subgroups and most subperiods. The exception is the earlier period, in which the test is significant for only 27.5% of the bootstrapped samples for all funds, 14.7% of the bootstrapped samples for venture funds, and 6.6% of buyout funds. Again, the lack of significance could be explained by a lack of statistical power, since the earlier sample period was the smallest of the three.

3.4. The Distribution of LPs' Returns

An alternative to focusing on only the standard deviation of returns is to consider the entirety of the distribution of returns. The standard deviation of LP returns (either median or average), 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 than in the bootstrapped one 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, 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 (and median) returns by aggregating returns into evenly spaced bins. Bins in the full sample, middle subsample, and later subsample periods 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 (respectively, median) returns fall in that bin. We do this for the actual sample, and for each bootstrapped sample. 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. These cutoffs can be interpreted as lower and upper bounds on where we would expect the actual counts to fall if there were no differential skill. For example, consider the number of LPs with a median IRR less than -10% among all funds in the full sample period. Panel A of Table 3 shows that there were 7 such LPs in the actual sample, while 10% of the bootstrap samples had no such LPs, and 90% of the bootstrap samples had 3 or fewer such LPs.

In this panel, the most salient difference between the actual sample and the bootstrap simulations is in the 'middle' range of returns (e.g., between 0% and 15% average IRR for venture funds, or between 10% and 20% average IRR for buyout funds), where there the counts in the bootstrap simulations far exceeded the numbers in the actual sample. For venture funds, the actual frequency in each bin between 0% and 15% median IRR, and between 0% and 10% average IRR, was below the tenth percentile cutoff for the bootstrap simulations. For buyout funds, the actual frequency in each bin between 10% and 20%

average IRR, and the same range of median IRR, was below the tenth percentile cutoff in the bootstrap simulations.

Far more LPs than expected had returns just below the middle of the distribution. Considering venture funds separately, the number of LPs with either median or average IRR between -10% and 0% was nearly double that in the majority of bootstrap simulations. A similar result holds considering buyout funds separately. The number of LPs with median or average IRR between 5% and 10% on buyout funds was nearly double that in the majority of bootstrap simulations.

Unlike the distributions of top-half persistence in Figure 1, the distributions' average and median returns do not have obvious "bumps" in the tails. Nevertheless, although the absolute frequencies were low, the number of LPs at the extreme top and bottom ends of the distribution was high relative to the bootstrap simulations. Considering venture and buyout funds separately, or all funds combined, the number of LPs with an equal-weighted average IRR either greater than 30% or lower than -10% met or exceeded the 90th percentile of bootstrap simulations.

Taken together, these results indicate that he increased standard deviation in the actual distribution, relative to the bootstrap simulations, is not driven by a small number of LPs performing exceptionally well, or exceptionally poorly. Rather, far fewer LPs than expected achieved "typical" average returns, and slightly more LPs than expected achieved average returns at many different levels both above and below average.

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 from what one would expect if all LPs drew their returns from the same distribution. This pattern suggests 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 approach are that it is less powerful than those that parameterize the data, it cannot quantify the magnitude of differences across LPs, and it cannot identify the LPs that consistently earn the highest returns through greater skill.

To address these issues, we extend the KS model 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 effect γ_i, a firm-time effect η_{it} that applies to each year of the fund's life, and a fund-specific effect ε_{iu}. The KS model decomposes 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' (GPs') skill. When there is greater variation in γ_i, there are greater differences in skill between firms. The firm-time 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.

We extend the KS model by first decomposing the returns from each fund as described above in order to isolate the portion of returns that can be attributed to the skill of the GP. We then estimate a hierarchical regression of the adjusted fund returns on LP-specific effects and set of controls. Since differences in the adjusted fund returns can be attributed to differences in GP skill, the LP-specific effects defined in this way capture differences in an LP's ability to invest in high-skill GPs. We also consider a second version of the model in which the LP-specific effects also incorporate the fund-specific random component of returns. In that version, the LP-specific 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:

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

KS model this return as:

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

where X_{iu} is a vector of vintage year fixed effects, and β represents the coefficients on them. The γ_i term is constant for all funds managed by the same GP. It captures long-term persistence in returns (i.e., GP skill). The $\eta_{i\tau}$ term captures the covariance in the returns of partially overlapping funds. Two overlapping funds that are managed by the same PE firm share an $\eta_{i\tau}$ term for each year of overlap. Finally, the ε_{iu} term captures fund-specific idiosyncratic performance shocks and is *i.i.d*. across funds, across firms, and over time.

Equation 2 specifies the return on a single fund raised by a given GP. Although one could estimate the parameters of the equation separately for each GP, the estimates would have high standard errors due to the small sample size of funds for most GPs. Therefore, the KS model utilizes a random effects framework that allows the parameters to be estimated simultaneously for every GP. In particular, it constrains the parameters to follow parametric distributions, so that the estimate for each individual GP is informed by the estimates for every other GP. The GP-specific effect is assumed be distributed as $\gamma_i \sim N(0, \sigma_\gamma^2))$ *i.i.d.*, so that a GP with average skill has $\gamma_i = 0$. The firm-time specific effect is distributed as $\eta_{i\tau} \sim N(0, \sigma_\eta^2)$ *i.i.d.* Finally, the error term is modeled using a mixture of three normal distributions, which allows the return distribution to be skewed. The three variances parameters: σ_γ^2, σ_η^2 and σ_ε^2, are estimated jointly with β, γ_i, and $\eta_{i\tau}$ in Equation 2.

Our model begins with obtaining estimates of the vintage year fixed effects and firm-time random effects in Equation 2. We then use these estimates to isolate the part of each fund return that can be attributed to GP skill. Specifically, we compute the *adjusted return* of each fund by subtracting these components from the actual return:

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

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 the GP-specific 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.

To estimate LP skill, we estimate an equation predicting the adjusted fund returns as a function of LP-specific fixed effects and a set of constants, which consist of either a single intercept for all LPs or a set of LP-type (endowment, pension fund, etc.) fixed effects. Specifically, the equation is:

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

where j indexes LPs. Because all LPs in a fund earn the same return, $\widehat{y_{iuj}} = \widehat{y_{iu}}$ for all LP j. The equation can be estimated using buyout and venture data together or separately, and for endowments, pension funds and others together or separately. 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. The λ_j term is the LP-specific effect, and π_{iuj} is a fund-LP specific effect. Each of these parameters has an intuitive interpretation. When the constant term is a common intercept for all LPs, β_{LP} 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 effects, LPs whose investments are more frequently in funds whose GPs have high firm-specific effects will have higher LP-specific effects. In this sense, the LP-specific 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 effect (π_{iuj}) is essentially the error term in the second-stage regression. It accounts 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 effect and one with a low LP-specific effect both invest in the same fund, the former fund-LP-specific random effect must be low and the latter high.

As in the first-stage model, we use a random effects framework to estimate the LP-specific effects. Specifically, we assume $\lambda_j \sim \mathcal{N}(0, \sigma_\lambda^2)$, so that $\lambda_j = 0$ represents average skill, and the variance parameter σ_λ^2 measures the degree of differential skill among LPs. We assume $\pi_{iuj} \sim \mathcal{N}(0, \sigma_\pi^2)$, *i.i.d.*, and estimate the variance parameters σ_λ^2 and σ_π^2 jointly with λ_j and β_{LP}. A large value of σ_λ^2 means that there is evidence of persistent long-term heterogeneity in the true ability of LPs to invest with skilled GPs.

4.2. Bayesian Estimation Algorithm

Following KS, we estimate the model using Bayesian Markov chain Monte Carlo (MCMC) techniques. Although the hierarchical regression parameters can in principle be estimated using classical techniques such as maximum likelihood, the Bayesian approach offers several advantages for our purpose. For one, the variance parameters in the model must be non-negative, and the Bayesian estimator is well suited to imposing such constraints. The Bayesian estimator also avoids small-sample bias in estimation of the firm-specific and LP-specific effects, while incorporating reasonable prior beliefs about these parameters, which are of key theoretical importance. Finally, it is better able to handle non-normality of the error term, which is important for private equity returns, since they can be highly skewed.

A schematic of our estimation algorithm is provided in section A5 of the Appendix. To summarize, each MCMC cycle *g* in the algorithm consists of two steps. The first step is to obtain a draw of each parameter in 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. The priors are sufficiently diffuse to allow the results to be driven by the data rather than prior assumptions. 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 according to Equation 3 to control for the firm-time random effects and the vintage year fixed effects. This process leads to one possible set of adjusted returns among the distribution of possible values predicted by the first-stage model. Then, conditioned on the adjusted returns in the current cycle, we obtain a draw of each parameter in Equation (4), and their variances. The appendix describes the technical details of how this is done. As in the first step, the priors in the second step are also diffuse so as to allow the results to be driven by the data rather than prior assumptions.

Each completed cycle yields a single draw from the joint posterior distribution of each parameter from both stages of the model. The first cycle is initiated using a set of starting values drawn from the prior distribution for conditional sampling. Subsequent cycles *g+1* are then initiated using the output of the previous cycle *g*. The sequence of draws over a large number of cycles forms a Markov chain, the stationary distribution of which is the joint posterior distribution, from which the marginal posterior distribution of parameters of interest can be obtained.

4.3. Estimates of Differential Skill

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

We present estimates of this model in Table 4. Panel A displays results for the full sample of funds raised between 1991 and 2011, while Panels B, C, and D focus on funds raised 1991-1998, 1999-2006, and 2007-2011, respectively. In each panel, 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).

The rows labeled σ_λ show the estimated standard deviation of the LP-specific effect, which measures the variability of the LP effect. If we presume the source of this variation is LP skill, then the standard deviation of the fixed effect will measure the importance of LP skill. According to Model 1, for the full sample period and for buyout and venture capital funds taken together (Column 1 of Panel A), the estimated value of σ_λ is 2.3 percentage point of IRR. This result implies that an LP that is one standard deviation more skilled than average earns about 2.3 percentage points higher IRR on its private equity investments.

In addition, consistent with the greater variability of returns to venture capital funds compared to buyouts, the estimates suggest that LP skill is more important in venture capital investments than in buyouts. The estimated standard deviation of the LP effects for buyout funds is 1.7 percentage points of IRR (Column 3 of Panel A), compared to 4.5 percentage points for venture capital funds (Column 5 of Panel A).

Model 2 consistently yields lower estimates of σ_λ than does Model 1. This pattern follows from the fact that there is less total variance in the adjusted returns in Model 2, which subtracts the fund-specific errors from the first-stage regression, than in Model 1. Conceptually, the difference between the estimates for the two models reflects the fact that Model 1 reflects the extent to which variability in skill is due to LPs' ability to select the best fund from a given GP, in addition to their ability to identify and invest in funds from the most skilled GPs. In contrast, Model 2 measures only the latter. For the full sample period and for buyout and venture capital funds taken together, the estimated standard deviation within Model 2 is 1.3 percentage points of IRR.

The other parameters of interest in the Table 4 are the LP-type fixed effects, which measure the difference in performance between the sample group and all investors in the Preqin universe. Consistent with prior work (Lerner, Schoar, and Wongsunwai, 2007; Sensoy, Wang, and Weisbach, 2014), we find that endowments perform significantly better than other LP types. In the estimates in both Model 1 and Model 2, the estimated fixed effect for Endowments, $\beta_{LP\ (endow)}$, is the larger than the estimated fixed effects for other types of investors. This difference is driven by investments in venture capital funds raised in the 1991-1998 period. In this period, the standard deviation of LP effects in venture capital investment (Columns 5 and 6) is also very high, equal to 12 percentage points of IRR without adjusting for fund-specific errors and 2.5 percentage points with the adjustment.

In the 1999-2006 period, endowments perform similarly to other LP types, and the standard deviation of LP effects for venture capital funds drops to 2.9 percentage points of IRR without the adjustment for fund-specific error, and 2.0 percentage points of IRR with 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.

In the 2007-2011 period, the effects are similar to the full sample. For all funds, the estimates of σ_λ are 1.9 and 1.3 percentage points. The estimates for buyout funds are almost identical to the full sample (1.9 and 1.3 percentage points) and are somewhat larger for venture funds (3.4 and 2.2 percentage points). Comparing across subsamples, the estimates of σ_λ decline over time, consistent with the idea that LP skill becomes more homogenous over time as the private equity industry matures (Sensoy, Wang, and Weisbach 2014).

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 one to two 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.

4.4. Variance Decomposition

Our model decomposes the total variance in adjusted returns into two parts: that which can be explained by persistent, long-term heterogeneity among LPs (i.e., differential skill), and that which is attributed to transitory random noise. Formally, the total variance is the sum of the variances of the two random effects in the model:

$$\sigma_{\hat{y}}^2 = 100\sigma_\lambda^2 + \sigma_\pi^2.$$

This decomposition allows us to compute the signal-to-noise ratio, which is proportion of the total variance that can be explained by differential skill:

$$s_\lambda = \frac{100\sigma_\lambda^2}{\sigma_{\hat{y}}^2}.$$

We report point estimates of the signal-to-noise ratio in each panel of Table 4. The signal-to-noise ratio is highest in the early sample period (1991-1998), and is generally higher for venture capital funds than for buyouts. Even though there is more total variance in adjusted returns among venture capital funds, LP skill appears to play a greater role in explaining that variance than it does for buyout funds.

Similarly, despite σ_λ being smaller under Model 2 than under Model 1, LP skill actually explains a larger proportion of the variance in adjusted returns under Model 2 than under Model 1. This suggests that LP skill is relatively more effective at selecting GPs than at distinguishing between the funds of a given GP.

4.5. 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 effect.[8] We present the λ for each LP in our sample in the Internet Appendix Table IA-3.[9] Consequently, if an LP's λ is estimated to be .01, then the model predicts that the LP's private equity investments have 1%

[8] Since we estimate equation (4) in logarithmic form, we convert each λ so that it measures the LP's abnormal return.
[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.

higher IRR than a typical LP.

Figure 2 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%, and the lowest is CALPERS, with a λ of -0.5%. The average standard error of these estimates is 1.2%, so very few are statistically distinguishable from zero. The model rejects the hypotheses that all LPs are equally skilled but has limited power to say anything definitive about the skill of any given LP.

4.6. Comparisons of the Estimates

If the estimates of λ we report really reflect skill and not random fluctuations, then a higher λ should consistently lead to higher returns. A way to evaluate the quality of these estimates is by correlating 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 positively correlated, with correlations between 0.48 and 0.70. 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 the Pearson correlation between LPs' estimated λ and their average IRR. We present this correlation for each type of investor and for each time period. For all time periods and the

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

full sample, the correlations are all positive, mostly between 0.3 and 0.8, 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 sample periods. The correlations for IRR across periods are all small and mostly negative, suggesting that returns do not persist across time periods. The negative correlation of IRRs across periods 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 correlations for estimated λ from Model 1 are relatively small but mostly positive, suggesting that skill does persists across time periods. By far, the highest correlation across periods is from the estimated λ from Model 2. An LP's ability to identify the most skilled GPs persists across time periods much more strongly than does an LP's ability to select among the funds of a given GP.

5. Interpreting Differences in LP Performance

The preceding analyses suggest that there are substantial and statistically significant differences in average returns across LPs. Underlying the "LP skill" interpretation is the notion that GP's abilities are not competed away by increased fundraising in the manner described by Berk and Green (2004). Existing evidence suggests that differences in GP returns are persistent (see Kaplan and Schoar, 2005; Korteweg and Sorensen, 2017; and Harris, Jenkinson, and Kaplan, 2017). Moreover, Rossi (2017) estimates that within the range of observed fund sizes, decreasing returns to scale, the main driver of the Berk and Green (2004) effect, are minimal in the private equity industry.

The question of why GPs do not increase fund sizes and/or fees to the point suggested by Berk and Green (2004), in which net-of-fee expected returns are equalized across funds, is a puzzle, perhaps the most pressing one in our understanding of the private equity industry. Part of the answer could be that private equity GPs are compensated with a nonlinear carried interest formula that penalizes managers for sacrificing returns for fund size. In the model of Axelson, Strömberg, and Weisbach (2009), this compensation system sometimes leads GPs to leave rents on the table for LPs, leading the LPs to earn abnormal returns that cannot be captured by GPs through higher fees. Hochberg, Ljungqvist, and Vissing-Jorgensen (2012) present a model and evidence suggesting that LP rents stem in part from incumbent LPs' ability to hold up the GP given their superior soft information during fundraising periods. In addition, GPs appear to be particularly concerned about their reputations as good investors, and are unwilling to sacrifice this reputation in exchange for the fees they could potentially earn on a fund that is larger than appropriate. Regardless of the reason, however, it is evident from both academic evidence and discussions with practitioners that GPs' abnormal returns do persist over time.

5.1. Risk Tolerance

Given that GPs' abnormal returns do persist over time, it is possible that more skillful LPs could consistently choose better funds in which to invest. However, there are a number of alternative explanations for the differences in performance across LPs. One such alternative explanation 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.

To shed some light on this issue, we first repeat our model-free analysis separately for different classes of LPs, specifically endowments, pension funds, and all other types. 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 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 z-scores of LP persistence (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. Moreover, the standard deviation of the estimated λ's is approximately the same for each LP type (Table 9), which is inconsistent with the idea that differences in risk tolerances across LP types translates into differences in estimated λ's. Consequently, the differences in estimated λ's do not reflect differences in type of investor, since they exist within each type and are similar across types. To the extent that risk tolerance varies by type of investor, the estimated λ's do not appear to reflect these differences.

In addition, if the differences in investors' estimated λ's reflect differences in risk tolerance rather than skill, then we expect that the higher λ LPs should be investing in riskier funds. An implication of this view is that the distribution of returns for high λ LPs should be more diffuse than the distribution of returns for low λ LPs. To evaluate this implication, we present the distribution of excess returns for LPs broken down by quartile of estimated λ in Table 7.[11] Excess returns are adjusted for the average returns of funds raised in the same vintage years and of the same types

The returns presented in Table 7 suggest that the superior performance of the LPs with the highest λ's does not occur because invested in more risky funds. The 4th quartile (high λ) LPs outperformed the 1st quartile (low λ) not just at the top of the return distribution, but throughout the distribution. Using estimates of λ from each model, the excess returns for the funds in each percentile shown in Table 7 for the 4th quartile are higher than for the 1st quartile (the 1st, 5th, 10th, 25th, 50th, 75th, 90th, 95th, and 99th percentiles). In other words, the high λ LPs did not outperform the low λ LPs by taking more risky investments; if they did so, their bad investments would be worse performers than the bad investments of the low λ LPs, but in fact, the high λ LPs outperform the low λ LPs throughout the distribution of returns.

5.2. Political Pressure

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

[11] Note that the quartiles are constructed by LP, each of which has a different number of funds in which it invests, so the quartiles have different numbers of funds in them. This analysis is similar to "the value at risk analysis" presented in Table 7 of Andonov, Hochberg, and Rauh (2017).

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 adding a dummy variable for public LPs (i.e. public endowments and public pensions) and an interaction term between public LPs and endowments. Of all 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. Adding the interaction term allows us to test whether public endowments and public pensions perform differently.

The estimates of this equation are reported in Table 8. The results in this table indicate that the β for public LPs is negative but not statistically different from zero. The interaction term between public pensions and endowments show that there is no significant statistical difference between the performance of public pensions and public endowments. In addition, the estimated impact of skill (σ_λ) remains similar to that reported in Table 4. These estimates suggest that skill-adjusted returns for public LPs are not meaningfully different from those achieved by other investors.

We further re-estimate our Bayesian model within different LP types for the full sample. Due to the smaller number of observations, we group public and private endowments together. Results reported in Table 9 show that within each LP type, there is a large variation in skill. σ_λ estimated within endowments only, public pensions, private pensions, and all other LPs is higher than that of the full sample. Therefore, it is unlikely that differing political pressure explains the systematic differences in skill we observe across investors.

5.3. 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.

We reestimate the Bayesian model for first-time funds only. The estimates are presented in Table 10. 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 1.4 to 3.2 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.

Another way to analyze LPs' ability to pick GPs, independent of any differences in access to funds, is to evaluate their reinvestment decisions, since existing investors are usually given the option of reinvesting in a GPs' follow-on funds (Lerner, Schoar, and Wonsunwai, 2007). Therefore, we also estimate our Bayesian model using the subsample made up of just reinvested funds. Estimates of this equation are reported in Table 11. Among reinvested funds, the magnitude of skill differences across LPs is close to those reported in Table 4. Using a sample of reinvestment decisions for all funds, a one standard deviation

[12] See Lerner and Leamon (2011).

increase in skill leads to a 2.3 percent increase in IRR for Model 1 and 1.6 percent increase in IRR for Model 2. The magnitude of skill differences is similar to the full sample for buyout funds, and somewhat larger for venture funds. Overall, our tests with first-time and reinvested funds show that there are persistent differences in performance across LPs even in circumstances for which access to potential investments is likely to be similar. Therefore, it is unlikely that the persistent differences across LPs in the quality of their private equity investments is due to differential access.

Additionally, we find that LPs' estimated skill in the full sample is highly correlated with the estimates for first-time funds and the reinvested subsample, again suggesting that the estimated λ's capture something fundamental about the selection process, likely the skill of the institutions picking the funds.

5.4. 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 *Preqin, 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 much data on the amount of capital each LP commits to each fund most of the investments in our sample.[13]

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. 2017). Therefore, the

[13] We have estimated our Bayesian models for the subsample of 9,774 investments for which we do have commitment data, weighting each investment by the size of the commitment. These estimates are two to three times larger than those reported elsewhere in the paper and are presented in the Internet Appendix,Table IA-2. We also reestimate our original Bayesian models (i.e. weigh each investment equally) using the subsample of LPs with commitment data. The results are similar to those reported in Table 4.

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 -0.4% 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.

Fourth, LPs often negotiate discounts and when they invest in funds. Since our data assumes all LPs pay the same fees, it will misstate the returns LPs actually receive. It is impossible to know which LPs actually received discounts and how much they are. However, conversations with practitioners who manage private the private equity positions for large institutional investors indicate that discounts are too small to meaningfully affect our estimates. For example, a large LP in our sample has a policy of always trying to negotiate a discount of 20% on both fees and carry. They are successful at receiving these discounts about 20% of the time. If the fund charges a 2% management fee and a 20% carry, and earns a 15% return, then the discount would amount to about 1% difference in the net return. Given that they only receive discounts 20% of the time, it would not appear that discounts are not large enough to make a meaningful difference in the estimates.[14]

6. Conclusion

Pension plans, insurance companies, foundations, endowments and other institutional investors all depend crucially on their investment income to fund their activities. Yet, there has been surprisingly little work measuring the extent to which there is meaningful variation in the skill of these organizations at

[14] LPs also negotiate coinvestment opportunities. To the extent that these are positive NPV investments, our analysis ignores their value to the LPs.

selecting investments. This paper evaluates the extent to which institutions' investment officers' skill systematically leads institutional investors to have higher returns on their investments in private equity.

Our results suggest that there are more LPs who consistently invest in the top half of funds than one would expect by chance, since the standardized 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 (2017) 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 between a one and two-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 two to four-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. 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. 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. Moreover, the empirical distribution of returns of the funds picked by LPs suggests that the returns of high quality LPs are not more risky than the returns of other 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. In addition, we repeat our analysis on decisions to reinvest in a fund in which an LP already has invested, which LPs almost always are able to do. Our results suggest that higher quality LPs tend to outperform in first time funds and reinvested funds by about the same amount as they do in their investments in the full sample. 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. 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 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.

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 to 2011. Panel A reports the statistics at the LP level, and Panel B reports the same statistics by three LP types: endowments, pensions, and all other LPs. Panel C shows 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 C 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	1,209	22.57	12	6	27	756	10.97	7	4	14	1,084	17.52	10	5	21
IRR	27,283	12.01	10.10	1.60	18.00	8,294	10.41	3.30	-5.10	12.60	18,989	12.71	12.00	6.20	19.30
Fund size	27,283	2,251.17	808	340	2789.66	8,294	480.89	304	175	600	18,989	3,024.39	1,500	592.13	3,841
Fund sequence	27,283	3.73	3	2	5	8,294	3.62	3	2	5	18,989	3.77	3	2	5

Panel B: LP type

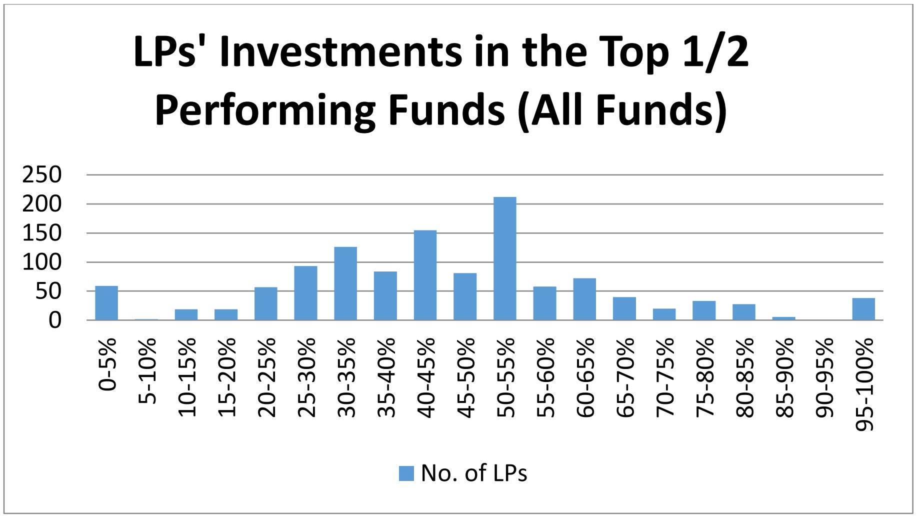
	Endowments					Pensions					Others				
	N	Mean	Median	Q1	Q3	N	Mean	Median	Q1	Q3	N	Mean	Median	Q1	Q3
No. of investments per LP	212	15.91	10	5	18.5	370	30.95	15.5	7	38	627	19.87	10	5	23
IRR	3,373	13.01	9	1	17.9	11,452	12.10	10.70	2.60	18.10	12,458	11.66	10	1.20	18
Fund size	3,373	2,115.34	803.15	350	2500	11,452	2,471.67	915	375	3175.06	12,458	2,085.24	750	313	2,593.92
Fund sequence	3,373	4.15	4	2	6	11,452	3.87	3	2	5	12,458	3.48	3	2	5

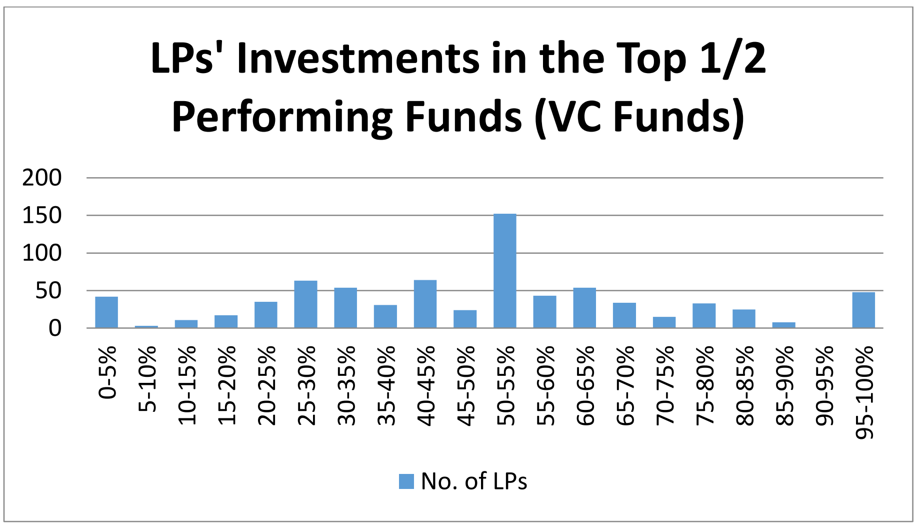
Panel C: Fund level

	All Funds					Venture Funds					Buyout Funds				
	N	Mean	Median	Q1	Q3	N	Mean	Median	Q1	Q3	N	Mean	Median	Q1	Q3
IRR	2,238	12.65	9.7	0.3	19.1	982	10.97	4.6	-4.9	15.2	1,256	13.97	12.5	6	20.6
Fund size	2,238	766.84	300	133	680	982	261.23	170.5	82.72	315	1,256	1162.14	476.44	225	1128.09
Fund sequence	2,238	2.53	2	1	3	982	2.48	2	1	3	1,256	2.56	2	1	3
No. of LPs	2,238	12.19	7	3	15	982	8.43	5	2	11	1,256	15.11	8	3	19

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)
250
200
150
100
50
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)
200
150
100
50
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

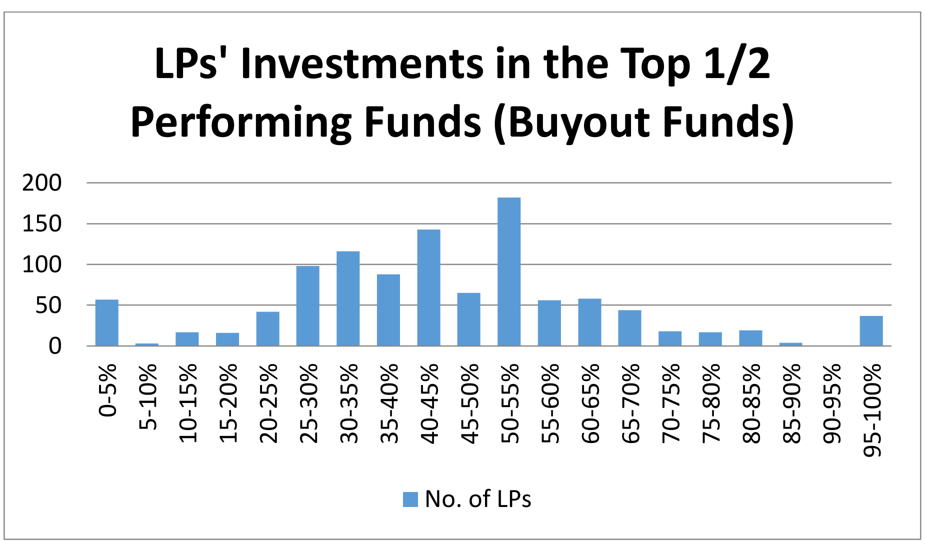

LPs' Investments in the Top 1/2 Performing Funds (Buyout Funds)
200
150
100
50
0
0-5%
5-10%
10-15%
15-20%
20-25%
25-30%
30-35%
35-40%
40-45%
45-50%
50-55%
55-60%
60-65%
65-70%
70-75%
75-80%
80-85%
85-90%
90-95%
95-100%
No. of LPs

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 standardized tests for differential skill based on the standard deviation of the z-statistics 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. To standardize those percentages, we compute the z-statistics for each LP. Then we compute the standard deviation of those z-statistics. 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. We also perform the Kolmogorov-Smirnov test to compare the actual and bootstrapped distributions. *% reject* reports the percentage of bootstrapped distributions that reject the test with p-values less than 0.05. Panels B shows tests of the standard deviations of LPs' median IRR, and Panel C reports the same tests based on equal-weighted average IRR. Results are reported for the full sample (1991-2011) and three subsample periods (1991-1998, 1999-2006, and 2007-2011). Statistically significant values, highlighted in bold, are those for which *% > Actual* is less than 10% or greater than 90%.

Panel A: Standardized tests of persistence

	Full Sample				1991-1998				1999-2006				2007-2011			
	Actual	Boot	% > Actual	% Reject	Actual	Boot	% > Actual	% Reject	Actual	Boot	% > Actual	% Reject	Actual	Boot	% > Actual	% Reject
All funds	**1.15**	0.99	0.0%	100%	**1.12**	0.99	0.0%	95.5%	**1.16**	0.98	0.0%	99.6%	1.00	0.98	24.8%	96.6%
Venture funds	**1.21**	0.99	0.0%	100%	**1.19**	0.99	0.0%	100%	**1.14**	0.99	0.0%	97.6%	**1.00**	0.98	0.0%	94.2%
Buyout funds	**1.09**	0.98	0.0%	100%	**1.08**	0.98	0.0%	56.7%	**1.09**	0.98	0.0%	79.2%	1.00	0.98	25.8%	37.1%

Panel B: Tests of the standard deviation of LPs' median IRR

	Full Sample				1991-1998				1999-2006				2007-2011			
	Actual	Boot	% > Actual	% Reject	Actual	Boot	% > Actual	% Reject	Actual	Boot	% > Actual	% Reject	Actual	Boot	% > Actual	% Reject
All funds	**6.33**	4.31	0.0%	99.9%	25.83	26.04	46.2%	26.5%	**8.64**	6.97	0.2%	100%	**5.63**	4.17	2.5%	99.9%
Venture funds	**9.50**	5.98	0.3%	100%	49.26	45.13	26.0%	26.3%	**7.43**	6.06	2.3%	100%	**10.38**	6.20	0.2%	100%
Buyout funds	**5.36**	4.18	0.4%	89.2%	12.41	13.01	68.7%	62.4%	**7.37**	5.92	0.9%	100%	**4.99**	3.93	2.4%	89.2%

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

	Full Sample				1991-1998				1999-2006				2007-2011			
	Actual	Boot	% > Actual	% Reject	Actual	Boot	% > Actual	% Reject	Actual	Boot	% > Actual	% Reject	Actual	Boot	% > Actual	% Reject
All funds	**7.59**	5.75	0%	100%	27.52	27.82	47.4%	27.5%	**8.86**	7.31	0.2%	100%	5.93	5.12	10.7%	94.7%
Venture funds	**13.61**	7.21	0%	100%	49.25	46.28	30.6%	14.7%	**7.87**	6.38	2.1%	100%	**10.60**	6.77	0.3%	98.3%
Buyout funds	**5.57**	4.82	1.7%	100%	12.46	13.51	83.7%	6.6%	**7.44**	6.02	0.9%	100%	5.21	5.12	27.1%	86.1%

Table 3. Frequency Distribution of LPs' IRR

The table shows the frequency distributions of LPs' median and average IRR for all funds, venture funds, and buyout funds. Average IRR assigns equal weights to each IRR. LPs in the actual and every bootstrapped sample are divided to 10 groups based on their median or average IRR (*Avg IRR)*. Column *Actual* represents the number of LPs in each 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 (1991-2011), 1999-2006 and 2007-2011 subsample periods, *Median IRR* and *Avg IRR* groups are based on increments of 5%. The 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)

	Median 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%	7	0	3	15	2	9	1	0	2	7	0	4	17	3	10	1	0	2
-10% < Avg IRR ≤ -5%	17	2	9	62	14	26	5	0	2	8	2	9	38	12	24	2	0	3
-5% < Avg IRR ≤ 0%	55	19	31	145	80	102	10	0	5	45	16	27	114	63	84	11	0	7
0% < Avg IRR ≤ 5%	125	69	90	217	224	254	40	3	20	109	57	75	160	163	190	40	7	25
5% < Avg IRR ≤ 10%	360	341	377	165	231	261	258	143	194	272	224	258	132	179	209	230	100	143
10% < Avg IRR ≤ 15%	481	538	576	82	84	106	554	576	641	437	516	557	128	119	146	488	492	555
15% < Avg IRR ≤ 20%	120	128	154	44	28	42	161	166	220	198	215	248	54	56	75	210	260	319
20% < Avg IRR ≤ 25%	26	23	38	10	4	12	31	27	55	77	54	74	42	25	40	69	42	79
25% < Avg IRR ≤ 30%	7	3	10	4	1	7	8	1	15	29	15	28	19	13	25	20	7	22
Avg IRR > 30%	11	1	7	12	8	16	16	0	8	27	15	27	52	32	47	13	0	12

Panel B: 1991-1998 subperiod

	Median 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%	16	14	26	20	8	18	13	6	24	14	15	28	16	8	17	12	9	27
-10% < Avg IRR ≤ 0%	57	45	64	36	31	47	53	27	55	52	45	64	33	25	39	45	33	61
0% < Avg IRR ≤ 10%	246	233	265	83	68	89	232	215	264	191	172	202	67	45	63	232	176	231
10% < Avg IRR ≤ 20%	255	263	297	72	57	77	238	220	276	216	222	254	59	45	65	236	215	273
20% < Avg IRR ≤ 30%	92	79	100	39	49	68	74	34	70	126	125	152	37	51	70	75	56	94
30% < Avg IRR ≤ 40%	56	30	46	31	36	54	39	8	26	91	56	75	39	46	64	50	9	30
40% < Avg IRR ≤ 50%	26	17	29	32	25	40	12	2	14	36	26	41	43	36	53	12	2	14
50% < Avg IRR ≤ 60%	22	7	16	38	14	26	7	0	7	27	12	23	43	21	36	6	0	7
60% < Avg IRR ≤ 70%	9	5	14	17	14	26	2	0	4	14	7	17	16	15	28	2	0	4
Avg IRR > 70%	18	17	28	49	36	53	1	0	5	30	22	35	64	46	65	1	0	5

Panel C: 1999-2006 subperiod

	Median 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%	21	4	13	41	17	30	3	0	4	18	5	13	42	19	32	2	0	4
-10% < Avg IRR ≤ -5%	38	11	21	109	40	57	6	0	5	33	11	22	98	44	64	7	0	4
-5% < Avg IRR ≤ 0%	100	46	63	212	170	199	21	0	9	98	47	65	237	190	221	19	0	10
0% < Avg IRR ≤ 5%	241	130	154	205	280	310	79	9	30	224	125	149	200	261	293	81	12	34
5% < Avg IRR ≤ 10%	338	367	402	89	98	122	289	149	198	339	304	338	78	85	108	257	102	144
10% < Avg IRR ≤ 15%	269	337	374	12	13	25	415	409	474	247	342	380	12	15	27	359	326	394
15% < Avg IRR ≤ 20%	90	116	143	12	3	10	123	188	243	119	165	194	11	3	11	185	289	354
20% < Avg IRR ≤ 25%	28	41	59	3	0	4	32	61	95	45	50	69	1	0	4	60	75	113
25% < Avg IRR ≤ 30%	14	10	20	2	0	2	20	11	30	16	11	22	3	0	3	21	12	32
Avg IRR > 30%	26	5	14	5	0	3	32	4	20	26	6	14	8	0	4	29	3	20

Panel D2007-2011 subperiod

	Median 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%	2	0	4	9	0	4	2	0	3	7	1	7	9	0	4	2	0	3
-10% < Avg IRR ≤ -5%	9	1	7	11	2	8	8	0	7	4	1	8	9	1	8	7	0	7
-5% < Avg IRR ≤ 0%	3	1	7	5	1	7	1	0	6	20	13	24	7	1	8	1	0	7
0% < Avg IRR ≤ 5%	14	8	18	41	8	18	12	2	16	113	122	150	33	11	22	12	6	22
5% < Avg IRR ≤ 10%	118	149	178	63	95	117	110	121	165	386	408	444	59	85	106	108	96	138
10% < Avg IRR ≤ 15%	400	392	428	112	156	181	367	326	377	194	140	168	133	158	185	352	342	396
15% < Avg IRR ≤ 20%	194	140	168	147	83	105	167	116	158	37	20	34	121	82	104	178	110	156
20% < Avg IRR ≤ 25%	28	18	31	16	16	28	27	12	30	15	2	10	26	18	31	31	9	32
25% < Avg IRR ≤ 30%	12	2	9	8	2	10	10	0	8	4	1	8	11	3	11	12	0	9
Avg IRR > 30%	2	1	6	11	1	8	2	0	6	0	0	0	15	2	9	3	0	7

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, Panel C includes only funds with vintage years between 1999 and 2006, and Panel D includes only funds with vintage years between 2007 and 2011. 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. *Signal-to-noise* is the proportion of total variance in adjusted returns that can be attributed to LP skill, computed as $\frac{100\sigma_\lambda^2}{100\sigma_\lambda^2+\sigma_\pi^2}$. All estimates are IRRs with Bayesian standard errors reported below the estimates in parentheses.

Panel A: Full Sample (1991-2011)

	All Funds		Buyout Funds		Venture Funds	
	(1)	(2)	(3)	(4)	(5)	(6)
σ_λ	0.023	0.013	0.017	0.013	0.045	0.020
b.s.e.	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
σ_π	1.302	0.404	0.941	0.362	1.852	0.484
b.s.e.	(0.018)	(0.030)	(0.024)	(0.036)	(0.030)	(0.042)
$\beta_{LP\ (all)}$	0.051	0.082	0.007	0.076	0.127	0.088
b.s.e.	(0.033)	(0.034)	(0.039)	(0.043)	(0.054)	(0.045)
$\beta_{LP\ (endow)}$	0.157	0.107	0.001	0.095	0.407	0.126
b.s.e.	(0.049)	(0.045)	(0.056)	(0.058)	(0.092)	(0.060)
$\beta_{LP\ (pension)}$	0.042	0.080	0.002	0.076	0.101	0.089
b.s.e.	(0.040)	(0.041)	(0.045)	(0.048)	(0.067)	(0.050)
$\beta_{LP\ (other)}$	0.026	0.073	0.013	0.072	0.041	0.071
b.s.e.	(0.035)	(0.032)	(0.041)	(0.041)	(0.059)	(0.045)
Signal-to-noise	0.030	0.099	0.031	0.114	0.056	0.145
Obs	26,830	26,830	18635	18635	8195	8195
No. of LPs	1209	1209	1084	1084	756	756

Panel B: 1991-1998 subperiod

	All Funds		Buyout Funds		Venture Funds	
	(1)	(2)	(3)	(4)	(5)	(6)
σ_λ	0.067	0.017	0.030	0.018	0.119	0.025
b.s.e.	(0.004)	(0.001)	(0.002)	(0.001)	(0.011)	(0.002)
σ_π	2.280	0.418	1.273	0.377	3.188	0.484
b.s.e.	(0.042)	(0.035)	(0.051)	(0.041)	(0.069)	(0.050)
$\beta_{LP\ (all)}$	0.460	0.057	-0.045	0.042	1.443	0.080
b.s.e.	(0.078)	(0.037)	(0.074)	(0.046)	(0.143)	(0.058)
$\beta_{LP\ (endow)}$	1.021	0.097	-0.056	0.050	2.464	0.161
b.s.e.	(0.127)	(0.055)	(0.113)	(0.061)	(0.276)	(0.088)
$\beta_{LP\ (pension)}$	0.328	0.046	-0.101	0.029	1.158	0.076
b.s.e.	(0.098)	(0.042)	(0.085)	(0.052)	(0.197)	(0.065)
$\beta_{LP\ (other)}$	0.373	0.050	0.010	0.048	1.247	0.045
b.s.e.	(0.087)	(0.039)	(0.081)	(0.049)	(0.203)	(0.059)
Signal-to-noise	0.080	0.147	0.051	0.177	0.122	0.204
Obs	4550	4550	2993	2993	1557	1557
No. of LPs	796	796	671	671	416	416

Panel C: 1999-2006 subperiod

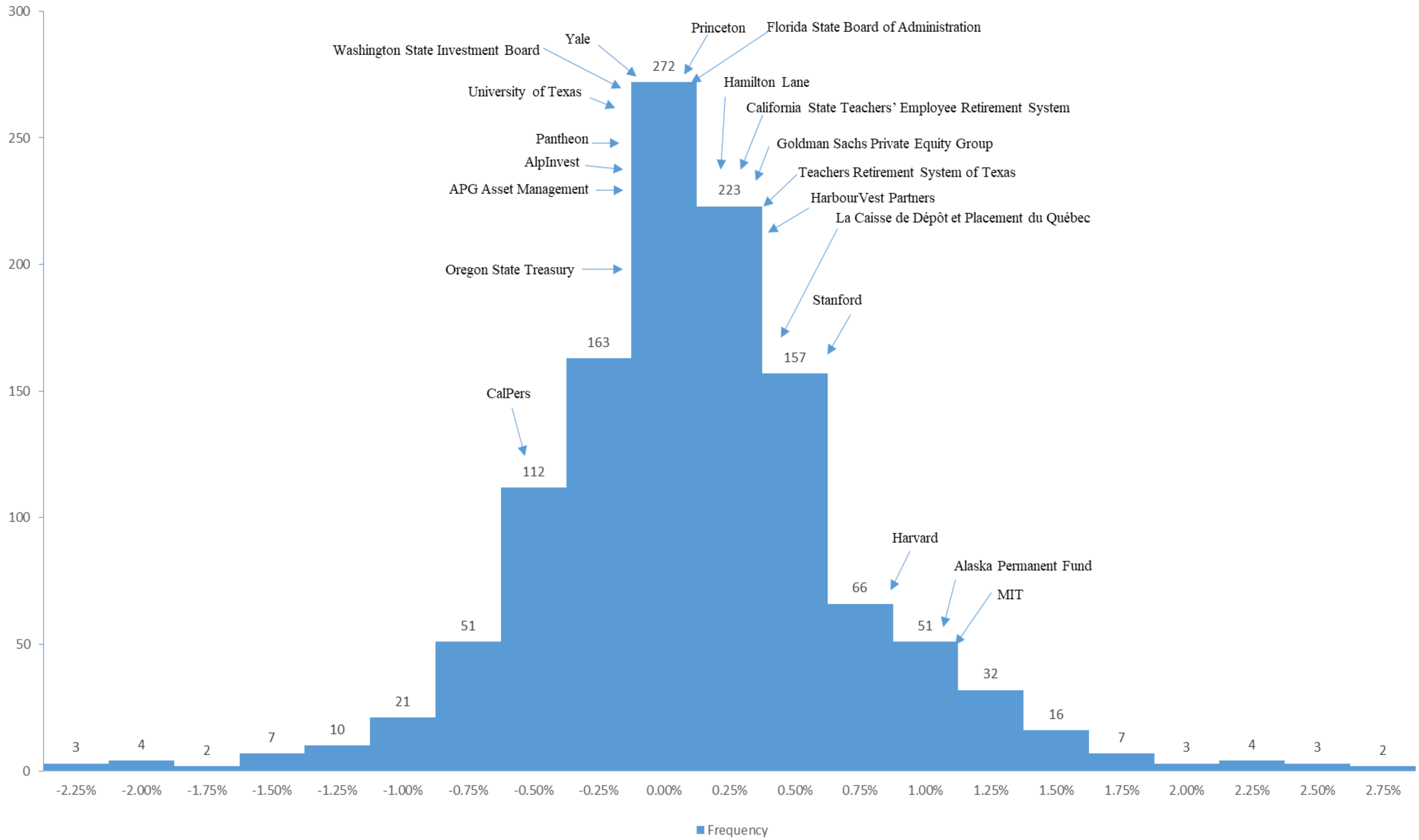
	All Funds		Buyout Funds		Venture Funds	
	(1)	(2)	(3)	(4)	(5)	(6)
σ_λ	0.020	0.014	0.020	0.014	0.029	0.020
b.s.e.	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
σ_π	0.971	0.406	0.912	0.359	1.063	0.484
b.s.e.	(0.021)	(0.030)	(0.029)	(0.036)	(0.028)	(0.044)
$\beta_{LP\ (all)}$	-0.067	0.083	-0.003	0.080	-0.200	0.090
b.s.e.	(0.042)	(0.034)	(0.052)	(0.043)	(0.062)	(0.047)
$\beta_{LP\ (endow)}$	-0.086	0.113	-0.025	0.099	-0.179	0.132
b.s.e.	(0.060)	(0.045)	(0.074)	(0.060)	(0.085)	(0.063)
$\beta_{LP\ (pension)}$	-0.086	0.075	-0.021	0.074	-0.228	0.086
b.s.e.	(0.048)	(0.038)	(0.059)	(0.047)	(0.072)	(0.052)
$\beta_{LP\ (other)}$	-0.052	0.076	0.016	0.078	-0.189	0.078
b.s.e.	(0.041)	(0.033)	(0.052)	(0.042)	(0.062)	(0.047)
Signal-to-noise	0.041	0.101	0.045	0.126	0.067	0.142
Obs	14969	14969	9966	9966	5003	5003
No. of LPs	1165	1165	1020	1020	690	690

Panel D: 2007-2011 subperiod

	All Funds		Buyout Funds		Venture Funds	
	(1)	(2)	(3)	(4)	(5)	(6)
σ_λ	0.019	0.013	0.019	0.013	0.034	0.022
b.s.e.	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
σ_π	0.858	0.390	0.760	0.358	1.126	0.485
b.s.e.	(0.024)	(0.029)	(0.030)	(0.034)	(0.040)	(0.047)
$\beta_{LP\ (all)}$	0.037	0.093	0.053	0.092	-0.021	0.093
b.s.e.	(0.052)	(0.033)	(0.060)	(0.038)	(0.083)	(0.054)
$\beta_{LP\ (endow)}$	0.086	0.108	0.097	0.113	0.057	0.086
b.s.e.	(0.070)	(0.048)	(0.085)	(0.058)	(0.120)	(0.074)
$\beta_{LP\ (pension)}$	0.049	0.107	0.076	0.098	-0.062	0.109
b.s.e.	(0.055)	(0.038)	(0.067)	(0.044)	(0.097)	(0.068)
$\beta_{LP\ (other)}$	0.012	0.077	0.017	0.077	0.002	0.081
b.s.e.	(0.055)	(0.033)	(0.063)	(0.038)	(0.094)	(0.057)
Signal-to-noise	0.049	0.106	0.057	0.119	0.085	0.171
Obs	7311	7311	5676	5676	1635	1635
No. of LPs	824	824	729	729	446	446

Figure 2. 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 1.2% 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 LPs is approximately 1.2%

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 subsample periods: 1991-1998 and 1999-2006 (Column *period 1&2),* 1999-2006 and 2007-2011 (Column *period 2&3)*. Column *Avg IRR* shows correlations for average IRRs. Columns *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	2007-2011
Endowments	0.60***	0.51***	0.62***	0.55***
Pensions	0.61***	0.70***	0.48***	0.60***
Others	0.53***	0.57***	0.49***	0.63***
All LPs	0.57***	0.61***	0.50***	0.60***

Panel B: Pearson's correlation of λ with IRR

	Full Sample		1991-1998		1999-2006		2007-2011	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Endowments	0.76***	0.37***	0.81***	0.45***	0.55***	0.12*	0.74***	0.42***
Pensions	0.78***	0.47***	0.77***	0.50***	0.61**	0.18***	0.68***	0.30***
Others	0.70***	0.36***	0.69***	0.26***	0.67***	0.26***	0.74***	0.59***
All LPs	0.72***	0.39***	0.73***	0.36***	0.65***	0.22***	0.71***	0.44***

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

	Avg IRR		Model 1 λ		Model 2 λ	
	period 1&2	period 2&3	period 1&2	period 2&3	period 1&2	period 2&3
Endowments	-0.30***	0.07	0.10	0.04	0.63***	0.14
Pensions	-0.07	-0.03	0.08	0.04	0.52***	0.38***
Others	0.05	-0.11*	0.06	-0.08	0.43***	0.23***
All LPs	-0.06*	-0.08**	0.07*	-0.03	0.50***	0.27***

Table 6. Tests of Persistence within Different LP Types

This table shows tests of the standard deviation of standardized 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. To standardize those percentages, we compute the z-statistics for each LP. Then we compute the standard deviation of those z-statistics. LPs are divided to endowments, pensions, and all other LPs. For each LP type, z-statistics are computed for the actual sample and all bootstrapped samples. Column *Actual* reports the z-statistics from the actual sample. Column *Boot* reports the average z-statistics across 1,000 bootstrapped samples. Column *% > Actual* shows the percentage of bootstrapped samples with z-statistics 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%. Column *% Reject* reports the percentage of bootstrapped distributions that reject the Kolmogorov-Smirnov test with p-values less than 0.05.

	All Funds				Venture Funds				Buyout Funds			
	Actual	Boot	% > Actual	% Reject	Actual	Boot	% > Actual	% Reject	Actual	Boot	% > Actual	% Reject
Endowments	**1.10**	0.98	0.6%	89.1%	**1.07**	0.99	4.4%	52.4%	**1.07**	0.98	3.5%	83.6%
Pensions	**1.22**	0.98	0.0%	99.9%	**1.25**	0.98	0.0%	99.8%	**1.14**	0.98	0.0%	98.7%
Others	**1.16**	0.99	0.0%	100%	**1.17**	0.99	0.0%	100%	**1.10**	0.98	0.0%	80.7%

Table 7. Skill Estimates and the Return Distribution

This table presents the distribution of returns for four quartiles of LPs based on their estimated skill (λ_j). This test resembles a value-at-risk analysis. Quartile 1 represents LPs in the lowest quartile of λ_j, and 4 represents those in the highest quartile. Column *Number of Funds* shows the number of LP-investment observations. Columns *1% - 99%* are the percentile cutoffs for LPs' returns measured by excess IRR. Excess IRR is net IRR adjusted for the average returns of funds raised in the same vintage years and of the same types. Panel A presents results using λ_j estimated from model 1 (i.e. net IRRs in stage 1 are adjusted for vintage year vintage-year fixed effects and firm-time random effects). Panel B presents results using λ_j estimated from model 2 with additional adjustments of fund specific errors in stage 1.

Panel A: Model 1

LP Quartile	Number of Funds	1%	5%	10%	25%	50%	75%	90%	95%	99%
1	8,790	-49.69	-29.79	-21.32	-11.49	-3.48	3.22	9.78	14.51	33.62
2	5,769	-38.22	-22.02	-16.09	-8.15	-1.99	4.24	10.63	16.04	35.51
3	5,099	-36.88	-21.07	-14.98	-6.82	-0.83	5.29	12.19	18.2	45.71
4	7,625	-36.78	-22.23	-15.39	-6.85	-0.22	6.92	19.72	38.03	113.01

Panel B: Model 2

LP Quartile	Number of Funds	1%	5%	10%	25%	50%	75%	90%	95%	99%
1	6,345	-50.29	-30.62	-22.02	-12.15	-4.05	3.19	10.51	16.42	48.73
2	6,235	-40.12	-22.96	-16.92	-8.09	-1.55	4.35	11.41	18.94	42.20
3	8,485	-38.49	-23.02	-15.87	-7.62	-1.28	5.06	12.21	19.23	55.91
4	6,218	-35.76	-21.69	-15.2	-6.82	-0.45	6.19	15.72	27.86	93.82

Table 8. Bayesian Estimates of Differential Skill Controlling for Private and Public LPs

This table displays the results of the Bayesian estimate of skill with LP-type fixed effects for endowments, pensions, and all other LPs, as well as dummies for public LPs and a Public*Endowment interaction. Estimates are for the full sample period. Other estimates are virtually identical to those in Table 4, so we omit them here. $\beta_{LP\ (Endowment)}$, $\beta_{LP\ (Pension)}$, $\beta_{LP\ (Other)}$, $\beta_{LP\ (Public)}$, and $\beta_{LP\ (Public\times Endowment)}$ are the estimated constant terms for endowments, pensions, all other LPs, public LPs, and the Public×Endowment interaction, 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	0.023	0.013	0.017	0.013	0.045	0.020
b.s.e.	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
$\beta_{LP\ (Endowment)}$	0.176	0.111	-0.003	0.093	0.490	0.138
b.s.e.	(0.054)	(0.048)	(0.061)	(0.059)	(0.104)	(0.065)
$\beta_{LP\ (Pension)}$	0.046	0.074	-0.011	0.061	0.157	0.105
b.s.e.	(0.043)	(0.039)	(0.045)	(0.044)	(0.090)	(0.057)
$\beta_{LP\ (Other)}$	0.025	0.072	0.014	0.073	0.043	0.071
b.s.e.	(0.034)	(0.032)	(0.040)	(0.041)	(0.057)	(0.044)
$\beta_{LP\ (Public\times Endowment)}$	-0.074	-0.026	-0.014	-0.019	-0.203	-0.023
b.s.e.	(0.090)	(0.048)	(0.076)	(0.053)	(0.187)	(0.083)
$\beta_{LP\ (Public)}$	-0.012	0.014	0.023	0.026	-0.098	-0.026
b.s.e.	(0.044)	(0.029)	(0.042)	(0.032)	(0.104)	(0.045)

Table 9. Bayesian Model Estimates within LP Types

This table displays the results of the Bayesian models described in Section IV within four LP types. Estimates are obtained using the full sample period from 1991 to 2011. Panel A includes results for endowments only. Panels B and C show results for public pension funds and private pension funds only, respectively. Panel D shows results for all other LPs. Odd-numbered columns are based on Model 1, in which adjusted returns are computed as in Equation (3) but without LP type indicators. 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 Model 1. For brevity, we only report estimates of σ_λ. Bayesian standard errors are reported in parentheses.

Panel A: Endowments

	All Funds		Buyout Funds		VC Funds	
	(1)	(2)	(1)	(2)	(1)	(2)
σ_λ	0.032	0.020	0.026	0.021	0.054	0.027
b.s.e.	(0.003)	(0.002)	(0.002)	(0.002)	(0.006)	(0.003)
Obs	3341	3341	2039	2039	1302	1302

Panel B: Public pension funds

	All Funds		Buyout Funds		VC Funds	
	(1)	(2)	(1)	(2)	(1)	(2)
σ_λ	0.031	0.018	0.025	0.018	0.057	0.025
b.s.e.	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)	(0.003)
Obs	6845	6845	4918	4918	1927	1927

Panel C: Private pension funds

	All Funds		Buyout Funds		VC Funds	
	(1)	(2)	(1)	(2)	(1)	(2)
σ_λ	0.027	0.019	0.024	0.019	0.043	0.027
b.s.e.	(0.002)	(0.001)	(0.002)	(0.002)	(0.005)	(0.003)
Obs	4294	4294	2936	2936	1358	1358

Panel D: All other LPs

	All Funds		Buyout Funds		VC Funds	
	(1)	(2)	(1)	(2)	(1)	(2)
σ_λ	0.024	0.015	0.020	0.015	0.042	0.022
b.s.e.	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
Obs	12350	12350	8742	8742	3608	3608

Table 10. LP Skill Using First-Time Funds

This table shows results of the Bayesian estimates of differential LP skill using their investments in first-time funds in the full sample. 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	0.032	0.014	0.027	0.015	0.053	0.021
b.s.e.	(0.003)	(0.001)	(0.002)	(0.001)	(0.007)	(0.002)
σ_π	1.671	0.436	1.121	0.382	2.346	0.518
b.s.e.	(0.027)	(0.032)	(0.040)	(0.036)	(0.047)	(0.052)
$\beta_{LP\ (all)}$	-0.106	-0.008	-0.092	-0.001	-0.151	-0.024
b.s.e.	(0.038)	(0.022)	(0.042)	(0.025)	(0.078)	(0.040)
$\beta_{LP\ (endow)}$	-0.016	-0.005	-0.084	-0.009	0.054	-0.002
b.s.e.	(0.090)	(0.041)	(0.092)	(0.046)	(0.183)	(0.075)
$\beta_{LP\ (pension)}$	-0.150	-0.016	-0.115	-0.001	-0.259	-0.051
b.s.e.	(0.057)	(0.026)	(0.054)	(0.031)	(0.118)	(0.052)
$\beta_{LP\ (other)}$	-0.096	-0.006	-0.075	0.000	-0.137	-0.011
b.s.e.	(0.049)	(0.026)	(0.051)	(0.029)	(0.096)	(0.047)
Obs	4859	4859	3141	3141	1718	1718
No. of LPs	1000	1000	853	853	594	594

Table 11. Bayesian Model Estimates of Differential Skill Using Reinvested Funds

This table displays the results of the Bayesian estimates of differential LP skill using only their reinvestments in follow-on funds from the same GP (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	0.023	0.016	0.022	0.016	0.036	0.024
b.s.e.	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
σ_π	1.147	0.397	0.875	0.358	1.569	0.467
b.s.e.	(0.020)	(0.032)	(0.027)	(0.039)	(0.033)	(0.045)
$\beta_{LP\ (all)}$	0.064	0.111	0.024	0.102	0.155	0.128
b.s.e.	(0.043)	(0.043)	(0.054)	(0.053)	(0.066)	(0.059)
$\beta_{LP\ (endow)}$	0.129	0.138	0.017	0.123	0.326	0.167
b.s.e.	(0.067)	(0.058)	(0.080)	(0.074)	(0.111)	(0.081)
$\beta_{LP\ (pension)}$	0.067	0.111	0.027	0.098	0.152	0.136
b.s.e.	(0.050)	(0.049)	(0.060)	(0.059)	(0.080)	(0.067)
$\beta_{LP\ (other)}$	0.042	0.100	0.022	0.098	0.089	0.106
b.s.e.	(0.043)	(0.041)	(0.054)	(0.051)	(0.076)	(0.056)
Obs	10333	10333	7091	7091	3242	3242
No. of LPs	1099	1099	951	951	588	588

Appendix

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

$$\sigma_\pi^2 \sim \mathcal{IG}(o_0, p_0)$$

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

the posterior distribution is

$$\sigma_\pi^2 | \{\lambda_j\}, data \sim \mathcal{IG}(o, p)$$

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

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

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

the posterior distribution from which we sample is

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

where

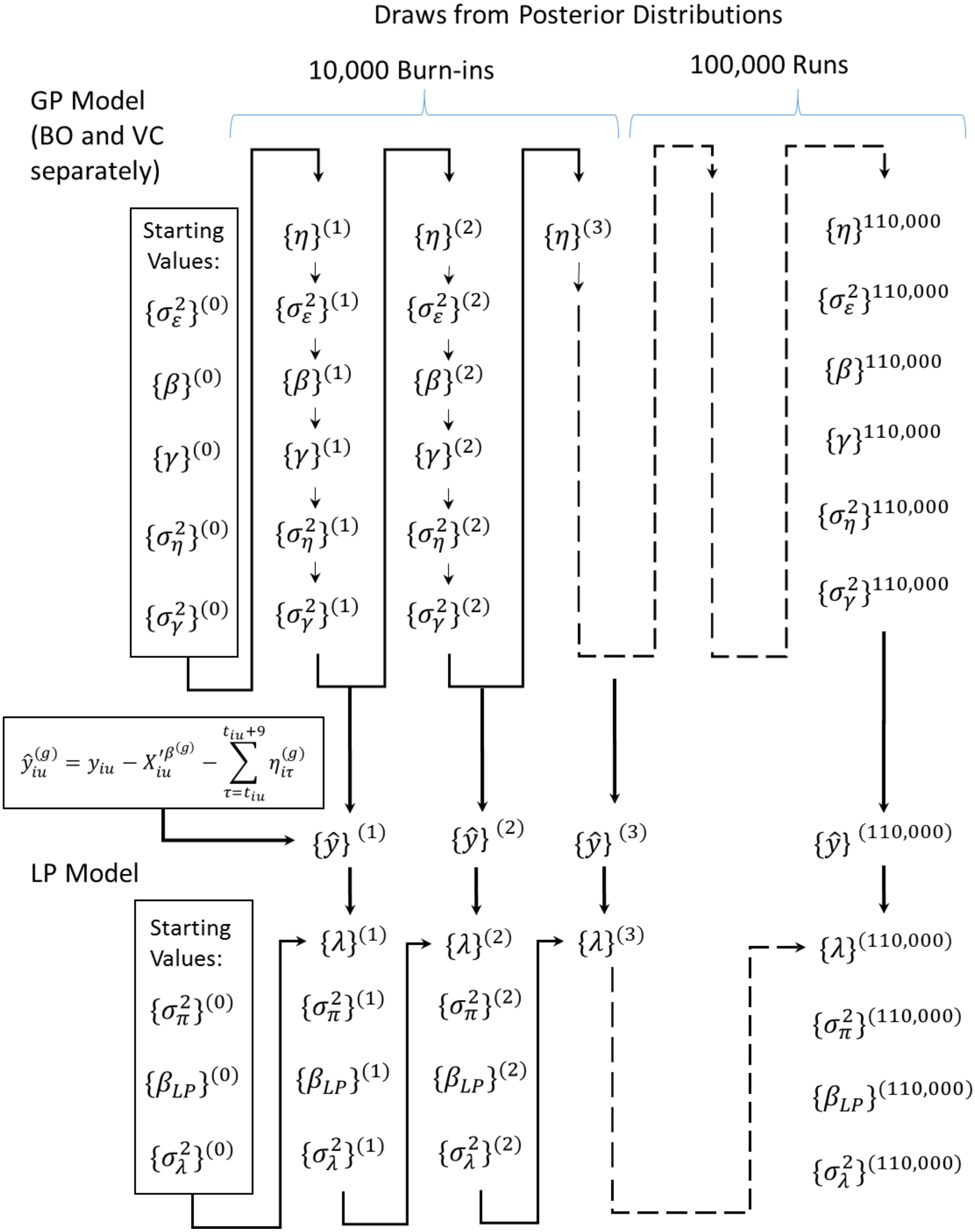
$$l = l_0 + N^{LP}$$

$$m = m_0 + \lambda'\lambda$$

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.

A5 MCMC Sampling Algorithm Schematic



Internet Appendix

This appendix provides supplementary material to the paper *Measuring Institutional Investors' Skill at Making Private Equity Investments*. Table IA-1 shows our main tests of persistence using four alternative bootstrap resampling schemes: 1. reinvest in the follow-on funds of GPs, 2. Invest in funds of similar sizes 3. invest in funds in the same industry, and 4. exclude fund of funds. Table IA-2 shows Bayesian estimates of skill using a subsample of LP investments with commitment data. Finally, Table IA-3 shows the average skill estimates of individual LPs from Model 2 and the number of investments made by each LP.

Table IA-1. Tests of Persistence using Alternative Bootstrap Restrictions

This table shows the main tests of differential skill with additional bootstrap restrictions. In addition to the main bootstrap restrictions described in the paper, Panel A restricts LPs to reinvest in the same GP if a follow-on fund is raised in the year of the LP's investment. If multiple GPs raised follow-on funds in the same year, then the reinvestment choice is random. Panel B shows standardized tests (z-statistics) of persistence restricted to fund size. We divide funds to big and small using the median value for each fund type and vintage year. Panel C shows the z-statistics with four categories of industry restrictions: IT, healthcare, both IT and healthcare, and neither IT nor healthcare. Panel D shows z-statistics excluding fund of funds as LPs. Statistically significant values (*% > Actual* is either less than 10% or greater than 90%) are highlighted in bold.

Panel A: Standardized tests of persistence with reinvestment restriction

	Full Sample			1991-1998			1999-2006			2007-2011		
	Actual	Boot	% > Actual	Actual	Boot	% > Actual	Actual	Boot	% > Actual	Actual	Boot	% > Actual
All funds	**1.15**	1.00	0.0%	**1.13**	1.00	0.0%	**1.16**	1.01	0.0%	1.00	0.98	19.8%
Venture funds	**1.21**	0.98	0.0%	**1.19**	0.99	0.0%	**1.14**	0.98	0.0%	**1.00**	0.95	8.3%
Buyout funds	**1.09**	1.00	0.0%	**1.08**	1.00	0.0%	**1.09**	1.01	0.0%	1.00	0.98	15.8%

Panel B: Standardized tests of persistence with fund size restriction

	Full Sample			1991-1998			1999-2006			2007-2011		
	Actual	Boot	% > Actual	Actual	Boot	% > Actual	Actual	Boot	% > Actual	Actual	Boot	% > Actual
All funds	**1.15**	1.00	0.0%	**1.13**	1.00	0.0%	**1.16**	1.08	0.0%	1.00	1.00	50.4%
Venture funds	**1.21**	0.99	0.0%	**1.19**	0.99	0.0%	**1.14**	1.09	0.0%	1.00	0.99	36.8%
Buyout funds	**1.09**	1.00	0.0%	**1.08**	1.00	0.0%	**1.09**	1.01	0.0%	1.00	1.00	43.5%

Panel C: Standardized tests of persistence with industry restriction

	Full Sample			1991-1998			1999-2006			2007-2011		
	Actual	Boot	% > Actual	Actual	Boot	% > Actual	Actual	Boot	% > Actual	Actual	Boot	% > Actual
All funds	**1.15**	0.99	0.0%	**1.13**	1.00	0.0%	**1.16**	0.99	0.0%	1.00	0.97	11.4%
Venture funds	**1.21**	0.99	0.0%	**1.19**	1.00	99.8%	**1.14**	0.99	0.0%	1.00	0.99	27.0%
Buyout funds	**1.09**	0.98	0.0%	**1.08**	0.98	0.0%	**1.09**	0.98	0.0%	**1.00**	0.97	0.0%

Panel D: Standardized tests of persistence excluding fund of funds

	Full Sample			1991-1998			1999-2006			2007-2011		
	Actual	Boot	% > Actual	Actual	Boot	% > Actual	Actual	Boot	% > Actual	Actual	Boot	% > Actual
All funds	**1.04**	0.99	8.0%	**1.09**	0.99	0.0%	**1.07**	0.99	7.0%	0.95	**0.98**	94.1%
Venture funds	**1.07**	0.99	1.7%	**1.14**	0.99	0.0%	1.00	0.99	37.4%	0.99	0.99	51.7%
Buyout funds	**1.05**	0.99	3.2%	**1.08**	0.99	0.2%	**1.04**	0.99	3.6%	0.96	0.98	75.6%

Table IA-2. Bayesian Model Estimates Weighted by LP Commitment

This table displays the results of the Bayesian models with returns weighted by the dollar amount of LPs' commitment. Results are estimated for the full sample period. Only investments with commitment data are included in this subsample. Odd-numbered columns are based on Model 1, in which adjusted returns are computed as in Equation (3). Even-numbered columns are based on Model 2, which further adjusts returns by subtracting fund-specific errors in addition to the adjustments in model 1. All variables are described in Table 4. Bayesian standard errors reported in parentheses.

	All Funds		Buyout Funds		Venture Funds	
	(1)	(2)	(3)	(4)	(5)	(6)
σ_λ	0.059	0.036	0.066	0.037	0.077	0.037
b.s.e.	(0.025)	(0.011)	(0.031)	(0.013)	(0.007)	(0.007)
σ_π	1.678	0.662	1.499	0.677	2.067	0.604
b.s.e.	(0.408)	(0.210)	(0.588)	(0.268)	(0.076)	(0.153)
$\beta_{LP\ (all)}$	-0.318	0.071	-0.404	0.148	-0.185	-0.044
b.s.e.	(0.442)	(0.267)	(0.506)	(0.304)	(0.237)	(0.184)
$\beta_{LP\ (endow)}$	-0.008	0.086	-0.037	1.177	-0.147	0.345
b.s.e.	(0.479)	(0.292)	(0.698)	(0.000)	(0.306)	(0.000)
$\beta_{LP\ (pension)}$	-0.509	-0.009	-0.617	0.509	-0.197	-0.220
b.s.e.	(0.516)	(0.294)	(0.539)	(0.000)	(0.318)	(0.000)
$\beta_{LP\ (other)}$	-0.103	0.140	-0.061	0.650	-0.173	-0.715
b.s.e.	(0.442)	(0.296)	(0.572)	(0.000)	(0.307)	(0.000)
Obs	9751	9751	6845	6845	2906	2906
No. of LPs	363	363	334	334	236	236

Table IA-3. 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 *No* shows the number of investments made by each LP, and 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	No	λ	Standard Error	LP Name	No	λ	Standard Error	LP Name	No	λ	Standard Error
3i Group	11	-0.22%	1.30%	Aetna	29	-0.27%	0.97%	Allianz Capital Partners	39	0.07%	1.13%
3M	36	-0.53%	1.20%	Aetna Life Insurance	4	0.00%	1.29%	Allianz Global Corp	13	0.45%	1.10%
50 South Capital	14	0.01%	1.09%	Aetna retirement	8	0.02%	1.17%	Allstate Insurance	5	-0.61%	1.33%
57 Stars	21	-0.59%	1.02%	AFA	12	-0.02%	1.18%	Allstate invest. mgmt	68	0.08%	0.74%
747 Capital	7	0.00%	1.36%	Agilent Technologies	34	-0.58%	1.14%	Alpha Associates	22	-0.99%	0.98%
AA Capital Partners	5	0.17%	1.28%	AIG Global invest.	28	0.16%	0.98%	Alphawood FDN	8	0.25%	1.40%
ABB Group	5	0.07%	1.38%	AIG Pension	77	-0.16%	0.67%	AlpInvest Partners	72	0.00%	0.81%
Abbey National Financ.	13	-0.41%	1.21%	Akina	20	-0.35%	1.04%	Altamar PE	21	0.24%	0.96%
Abbey National Treasury	6	-0.33%	1.15%	Alameda County ERA	12	0.43%	1.14%	Altira Heliad mgmt	4	0.02%	1.36%
Abbott Capital mgmt	65	1.11%	0.77%	Alaska Permanent Fund	79	0.91%	0.65%	Altshuler Shaham	5	1.53%	1.48%
Aberdeen	73	0.39%	0.65%	Alaska State Pension	71	1.12%	0.74%	Amanda Capital Oyj	20	0.48%	1.17%
ABP	6	0.02%	1.19%	Albert & Margaret Alkek	25	-0.66%	0.91%	AmBex Venture Group	9	1.47%	1.50%
Abu Dhabi invest. Athrty	7	0.84%	1.49%	Alberta Enterprise	5	-0.01%	1.40%	American Airlines	40	-0.76%	0.89%
Access Capital Partners	25	-0.11%	0.95%	Alcatel-Lucent	162	0.31%	0.61%	American Beacon Advisors	8	-0.19%	1.19%
Ace & Company	7	0.11%	1.19%	Alcoa	22	0.03%	0.98%	American Electric Power Sys.	6	-0.17%	1.36%
ACG Capital	49	-0.05%	0.74%	Alcyon	16	0.09%	1.26%	American Family Insurance	25	-0.22%	1.13%
ACP invest. Group	51	-0.27%	0.73%	Alfred I. duPont Trust	13	-0.55%	1.02%	American Financial Group	4	-0.50%	1.35%
Adams Street Partners	228	0.27%	0.63%	Alfred P. Sloan FDN	16	0.11%	1.37%	American International Grp.	10	0.17%	1.33%
Advantus Capital mgmt	43	-0.89%	0.94%	All Souls College Oxford	6	-0.13%	1.34%	American Nat'l Red Cross retire.	11	-0.61%	1.09%
Adveq	19	-0.40%	1.09%	All State VC Corp.	5	0.08%	1.38%	American PE Partners	7	-0.73%	1.14%
Adveq mgmt	23	-0.20%	1.12%	Allegheny County Retire.	4	0.50%	1.36%	American Sugar Refining Group	5	-0.21%	1.23%
Aegon	4	0.09%	1.20%	AllianceBernstein	12	0.01%	1.35%	Amherst College	29	0.36%	1.06%
Aegon USA invest. mgmt	4	-0.15%	1.37%	Allianz	12	0.17%	1.22%	AMNH	4	-0.3%	1.3%

LP Name	No	λ	Standard Error	LP Name	No	λ	Standard Error	LP Name	No	λ	Standard Error
AMR invest. Services	23	-0.4%	1.1%	AT&T	211	0.2%	0.5%	Baptist Comm. Ministries	11	0.4%	1.2%
Anadarko Petroleum	7	0.6%	1.3%	ATP PE Partners	69	0.2%	0.8%	Barclays	19	-0.1%	1.1%
Andrew W. Mellon FDN	53	1.1%	1.0%	Auburn University	4	0.1%	1.3%	Barr FDN	5	0.7%	1.2%
Antares Capital	28	-0.1%	1.0%	Auda PE	44	0.2%	0.9%	Battelle	5	0.8%	1.4%
Anverse	11	-0.2%	1.1%	Australia APSS	32	-0.6%	1.0%	Baxter International	22	0.8%	1.1%
Aon Advisors	12	-0.5%	1.3%	AustralianSuper	7	0.8%	1.2%	Bayer (US)	13	-0.8%	1.1%
Aon Group	4	0.2%	1.6%	Avadis Anlagestiftung	43	-0.1%	0.7%	BBVA	7	-0.2%	1.2%
AP Pension	4	-0.5%	1.3%	Aviva International	5	1.0%	1.6%	BDC VC	9	-1.2%	1.5%
APEN AG	45	0.2%	0.9%	Aviva Investors Global	8	0.1%	1.2%	BVK Zürich	4	0.0%	1.3%
AP-Fonden 2	16	-0.1%	1.1%	Aviva Life and Pensions	5	-0.3%	1.3%	Bear Stearns	4	-0.4%	1.3%
AP-Fonden 3	33	-0.5%	0.9%	AXA Financial	8	0.0%	1.4%	Belmont Global Capital Partners	7	0.3%	1.3%
AP-Fonden 4	6	-0.2%	1.4%	AXA US	70	-0.7%	0.7%	Berea College	6	2.4%	1.7%
AP-Fonden 6	17	-0.5%	1.2%	BAE Systems	7	0.0%	1.2%	Berkeley mgmt Co.	9	0.6%	1.2%
APG - All Pensions Group	18	-0.4%	1.1%	Bahrain Middle East Bank	5	1.1%	1.6%	Bessemer invest. mgmt	38	-0.8%	0.9%
APG Asset mgmt US	7	-0.2%	1.4%	Bakery&Confection. Union	18	-0.8%	1.0%	Bessemer Trust	14	-0.2%	1.1%
Arcano Capital	15	0.1%	1.0%	Bâloise Holding	9	-0.1%	1.2%	BHF-Bank Aktiengesellschaft	5	1.0%	1.5%
Ardian	76	-0.4%	0.6%	BAML Capital Partners	40	-0.2%	1.0%	Bio*One Capital	4	-0.6%	1.7%
Argentum Asset mgmt	15	-0.5%	1.1%	BancBoston invest.	16	0.5%	1.1%	BIP invest. Partners	4	0.2%	1.4%
Arizona PSPRS	27	-0.3%	1.0%	Bank Gutmann Group	15	-0.1%	1.1%	BJC pension	4	-0.2%	1.4%
Arizona State retire.	32	0.0%	0.8%	Bank Gutmanninvest. Arm	8	0.2%	1.2%	BlackRock PE Partners	57	-0.1%	0.6%
Arkansas TRS	20	0.1%	1.0%	Bank Leumi Group	8	0.7%	1.3%	Blandin FDN	13	-0.2%	1.5%
Arle Capital Partners	5	-0.1%	1.5%	Bank of America	29	-0.9%	1.0%	BMO Global Asset mgmt	36	-0.2%	0.8%
ARMB	127	0.8%	0.8%	Bank of A. Merrill Lynch	6	2.6%	1.5%	bmp AG	7	0.0%	1.3%
Art Institute of Chicago	4	-0.2%	1.2%	Bank of New York Mellon	19	0.4%	1.2%	BNP Paribas Capital Partners	9	-0.3%	1.2%
ARTS ET BIENS	5	0.0%	1.5%	Bank Of Nova Scotia	11	-0.4%	1.2%	BNP Paribas Fortis	6	-0.3%	1.3%
Ascension Health Master	10	-0.3%	1.2%	Bank of Tokyo-Mitsubishi	5	-0.2%	1.2%	Boeing	90	-0.2%	0.7%
Ascension invest. mgmt	11	-0.3%	1.2%	Bank One Capital Markets	4	-0.3%	1.3%	Bombardier	4	0.5%	1.6%
Assicurazioni Generali	7	-0.1%	1.2%	Bank Vontobel AG	25	0.1%	1.1%	Boston City retire.	30	-0.7%	1.0%

LP Name	No	λ	Standard Error	LP Name	No	λ	Standard Error	LP Name	No	λ	Standard Error
Boston University	17	-0.3%	1.1%	Cambridge retire.	4	0.9%	1.5%	Church Comm. for England	12	0.2%	1.3%
Bowdoin College	6	0.4%	1.4%	Cambridgeshire County	10	1.3%	1.4%	Church Pension Group	12	0.0%	1.2%
Boy Scouts of America	6	1.0%	1.1%	Camden Partners	25	-0.2%	1.0%	CIBC Capital Partners	9	0.1%	1.3%
BP America	76	-0.3%	0.7%	Capital Access Funds	9	-1.4%	1.3%	CIBC Merchant Banking	13	-0.3%	1.1%
BP Pension	20	0.0%	0.9%	Capital Dynamics	41	-1.3%	0.9%	Cigna pension	5	-0.5%	1.3%
Brazilian Nat'l Devt Bank	4	-0.1%	1.7%	Capital Guidance	5	0.7%	1.2%	Cinnati retire.	7	-2.2%	1.7%
Brederode	55	0.4%	0.7%	Capvent AG	14	-0.4%	1.2%	Cisco Systems	4	1.6%	1.6%
Bregal invest	12	0.0%	1.1%	CareSuper	5	0.1%	1.3%	Citigroup PE	26	-0.4%	1.0%
Brinson Partners	15	-0.2%	1.3%	Carleton College	12	1.9%	1.4%	Citigroup	79	0.3%	0.7%
Bristol-Myers Squibb	83	0.3%	0.7%	Carnegie corp of NY	53	0.5%	0.9%	City of Boston Retirement Board	10	0.0%	1.2%
British Airways	12	-0.2%	1.2%	Carnegie Mellon	15	0.0%	1.2%	City of Detroit General retire.	9	-0.7%	1.4%
British Coal Staff	6	-0.1%	1.2%	Carolina Power & Light	4	-0.1%	1.5%	City of Philadelphia	5	-0.1%	1.2%
British Columbia invest.	69	0.4%	1.0%	Case Western Reserve	5	0.4%	1.5%	City of Worcester retire.	9	0.2%	1.6%
Broad FDN	4	-0.3%	1.3%	Casey Family Programs	9	0.5%	1.2%	City of Zurich Pension	13	-0.5%	1.1%
Brockton Contributory	8	0.3%	1.3%	Castle PE	90	0.9%	0.6%	Civil Aviation Authority	4	0.2%	1.3%
Brown Advisory	14	0.4%	1.1%	Catholic CharitiesChicago	4	0.3%	1.5%	Clal Industries and invest.	4	0.8%	1.5%
Brown Brothers Harriman	9	0.8%	1.3%	Caxton Associates	4	-0.9%	1.6%	Clal insurance	22	0.3%	1.0%
Brown University	9	-0.3%	1.2%	Cazenove Capital mgmt	10	-0.8%	1.3%	Claremont McKenna College	5	-0.1%	1.4%
Buckeye Venture Partners	8	0.8%	1.3%	CDC Group	12	-0.5%	1.2%	Claude Worthington Benedum	8	-0.5%	1.2%
Bure Equity	4	0.4%	1.5%	CDIB Capital	19	-0.2%	1.0%	Cleveland FDN	5	-0.1%	1.5%
Burroughs Weome Fund	4	0.2%	1.5%	Central pension	18	0.1%	1.0%	Clwyd	20	0.2%	1.1%
Bush FDN	12	-0.4%	1.3%	CenturyLink pension	55	-0.8%	0.8%	CM-CIC	4	-0.1%	1.4%
Caisse de Depot Quebec	107	-0.3%	0.7%	Charles Stewart Mott	12	0.4%	1.4%	CMS Companies	7	0.2%	1.3%
Caisse de Pensions de EV	5	-0.2%	1.2%	Chicago PSTR	13	-0.1%	1.2%	CMS Fund Advisers	29	0.1%	0.9%
Caisse Intercommunale	5	-0.1%	1.3%	Chicago Transit Authority	7	-0.4%	1.4%	CNA Financial corp	4	0.3%	1.5%
Cal Tech	10	0.2%	1.2%	China invest. corp	5	-0.2%	1.3%	CNP Assurances	23	-0.1%	1.0%
Caledonia invest.	7	0.0%	1.1%	Chipstone FDN	17	-0.7%	1.2%	Colby College	9	1.6%	1.4%
CalPers	548	-0.5%	0.4%	Chrysler Master Retire.	33	-0.8%	1.0%	Colgate University	5	0.9%	1.3%
CalSTRS	209	0.1%	0.5%	Chubb insur of Europe	4	-0.3%	1.4%	Coller Capital	75	-0.7%	0.7%

LP Name	No	λ	Standard Error	LP Name	No	λ	Standard Error	LP Name	No	λ	Standard Error
Colorado PERA	138	-0.7%	0.6%	Cummins US pension	7	0.6%	1.6%	Deutsche Bank	8	-0.1%	1.3%
Columbia University	23	2.2%	1.2%	CUNA Mutual Life Ins.	9	-0.5%	1.2%	Deutsche Bank Alex. Brown	5	0.1%	1.4%
Commonfund Capital	45	0.2%	0.7%	Customized Fund invest.	7	-0.8%	1.3%	Deutsche Beteiligungs	4	0.3%	1.5%
Commonwealth Financ. PA	10	0.0%	1.3%	Cuyahoga Capital Partners	4	-0.1%	1.5%	DEVK Insurance	6	-0.2%	1.2%
Commonwealth Fund	17	1.6%	1.3%	CWA/ITU	5	-0.3%	1.3%	Diageo UK pension	10	-0.2%	1.2%
Commonwealth Superannu.	14	0.2%	1.2%	Daido Life Insurance	10	-0.5%	1.2%	DIRECTV pension	5	0.0%	1.3%
Compagnia di San Paolo	13	0.4%	1.1%	Daiwa Corporate invest.	4	-0.5%	1.6%	District of Columbia Retire.	8	-1.0%	1.4%
Connecticut CRPTF	108	-0.6%	0.6%	Dancap PE	12	-0.1%	1.1%	DKA Capital	5	-0.9%	1.6%
Conso. Electrical Distri.	8	-0.4%	1.3%	Danica Pension	13	0.0%	1.3%	DLJ Merchant Banking Partners	9	-0.9%	1.3%
Constitution Capital	9	0.0%	1.2%	Daniels Fund	13	0.0%	1.2%	DNB PE	19	-0.4%	1.0%
Continental Casualty	10	0.0%	1.3%	Danish Growth Fund	6	0.7%	1.6%	Dominion Resources pension	14	-0.1%	1.2%
Conversus Capital	27	0.3%	0.6%	Danske Bank	6	0.4%	1.4%	Doris Duke Charitable FDN	18	-0.2%	1.1%
Co-op retirement	4	-0.6%	1.3%	Danske PE	26	0.2%	0.9%	Dow Chemical	68	-1.2%	1.1%
Cornell University	14	0.4%	0.9%	Dartmouth College	17	0.4%	1.0%	DSM Venturing	5	1.2%	1.6%
Corning pension	58	0.3%	1.1%	Darwin Ventures	17	0.1%	1.2%	DTE Energy Retirement	4	-0.2%	1.4%
County Fund of Co	12	-0.9%	1.1%	David and Lucile Packard	4	0.9%	1.2%	Duke	34	0.9%	0.8%
Covera Ventures	4	-0.9%	1.7%	Davidson College	5	1.3%	1.5%	Duke Energy Company pension	10	0.0%	1.2%
Cox Enterprises Trust	19	0.4%	1.2%	Dayton Power and Light	14	0.2%	1.4%	Duke Faculty & Staff Retire.	58	-0.2%	0.8%
CPP invest. Board	90	-0.1%	0.8%	DB PE	84	-0.1%	0.6%	Duke Power Company	5	2.4%	1.7%
Cramer Rosenthal	5	-0.7%	1.4%	DeA Capital	34	0.1%	1.0%	Duke University	21	0.5%	1.0%
Crédit Agricole	12	0.0%	1.3%	Deere & Company	18	-0.8%	1.3%	Dunedin Capital Partners	4	-0.6%	1.5%
Credit Suisse asset mgmt	6	-0.5%	1.5%	Delaware pension	18	0.2%	1.3%	Dunedin Enterprise invest. Trust	6	-0.3%	1.3%
Credit Suisse	5	-0.5%	1.1%	Delta Air Lines	42	-0.7%	1.0%	DuPont Capital mgmt	7	-0.5%	1.2%
Credit Suisse Place. FDN	13	0.0%	1.1%	Delta Lloyd Insurance	4	0.5%	1.3%	Duquesne Light Co	4	-0.3%	1.6%
Crescent International	15	-0.2%	1.1%	Denison University	5	0.7%	1.5%	Dyson FDN	9	-0.5%	1.2%
Crown Holdings US	8	-0.4%	1.1%	Denver FDN	5	0.1%	1.4%	E.I.Du Pont De Nemours	46	0.0%	0.9%
Crystal Springs FDN	5	0.5%	1.5%	Denver Public Schools	19	-0.2%	1.2%	East Sussex County Coun.	5	1.2%	1.6%
CSFB PE	32	-1.0%	1.0%	Derigo	61	0.2%	0.7%	Eastman Kodak (US)	12	-0.1%	1.2%
Cubera PE	5	-0.2%	1.4%	Deseret Mutual Benefit	7	-0.9%	1.4%	Eastman Retire.	6	0.4%	1.3%

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EDBI	6	-0.9%	1.3%	Ewing Marion Kauffman	61	0.3%	1.0%	Ford Motor	66	-0.1%	0.7%
EDS retirement	20	0.8%	1.2%	Excellence Nessuah	4	0.4%	1.2%	Forethought Life Insurance	5	0.1%	1.3%
EES Acquisition Fund II	4	0.2%	1.3%	Exelon	10	0.1%	1.2%	Fort Washington Capital	35	0.3%	0.8%
El Paso Firemen & Police	5	0.7%	1.3%	Exxon Mobil US	5	-0.6%	1.4%	Fort Worth Employees' Retire	28	0.5%	0.8%
Eli Lilly	27	0.3%	1.1%	F & C PE Trust	7	-0.5%	1.3%	Frank Russell	4	0.6%	1.5%
Elo Mutual Pension Insur.	17	0.5%	1.0%	F&C Asset mgmt	9	-0.3%	1.2%	Franklin Park	12	1.0%	1.1%
Emerg Svcs & State Super	4	0.0%	1.4%	Fairfax Financial	7	-2.0%	1.4%	Fresno County ERA	6	-0.4%	1.3%
Emerson Electric	8	0.2%	1.2%	Fairview Capital Partners	31	0.2%	0.8%	Friends Life	4	-0.1%	1.4%
Emory University	8	0.3%	1.4%	Fan Fox & Leslie Samuels	8	-0.1%	1.5%	Frist FDN	5	-0.3%	1.3%
Energy Super	76	-0.1%	0.7%	FCA Master Retire.	66	-0.6%	0.7%	Funds SA	9	-0.3%	1.3%
Environment Agency	15	-1.6%	1.2%	Fennia	10	0.0%	1.3%	Furuholmen Invest	4	-0.3%	1.5%
eQ Asset mgmt	36	-0.4%	0.9%	FFP	4	0.1%	1.3%	Gain Capital Participations	5	-0.1%	1.3%
Equitrust	18	-0.3%	1.1%	Finnfund	4	-0.3%	1.5%	Gannett pension	11	0.3%	1.4%
Erie Indemnity	18	-0.1%	1.1%	Finnish Industry invest.	16	-0.1%	1.1%	GCM Grosvenor Private Mkt	91	-0.2%	0.6%
Ernst Russ AG	10	-0.1%	1.2%	Finnish Innov Fund (Sitra)	10	-0.8%	1.3%	GE Asset mgmt	16	0.4%	1.4%
ERS Hawaii	97	1.0%	0.7%	Finnish State pension	5	0.0%	1.4%	GE Global Sponsor Finance	31	-0.8%	1.0%
ERS Rhode Island	74	-0.2%	0.8%	Fire & Police Colorado	70	-0.3%	0.7%	General American Investors Co	5	-0.8%	1.4%
ERS Texas	36	-0.2%	0.9%	Firefighters' Pension NO	5	-0.8%	1.4%	General electric	90	-0.5%	0.7%
Essex County Council	19	0.2%	1.0%	First Chicago invest. Corp	4	-0.4%	1.3%	General Mills	24	0.0%	1.1%
Essex Regional Retire.	7	0.1%	1.4%	FLAG Capital mgmt	34	0.4%	1.0%	Generali invest.	9	-0.5%	1.2%
Etera Mutual Pension Insur.	4	0.2%	1.4%	Fleet Equity Partners	4	0.1%	1.2%	George Kaiser Family FDN	11	0.1%	1.3%
Eurazeo	9	1.1%	1.4%	Florida St. Brd of Admin	80	-0.1%	0.7%	Georgia Tech FDN	11	1.7%	1.4%
Euro PE	6	0.3%	1.2%	FM Global	7	-0.2%	1.5%	GIC Special invest.s	39	0.6%	0.9%
European invest. Bank	7	0.1%	1.5%	Fondaction	4	-0.1%	1.3%	Gill FDN	5	-0.5%	1.3%
European invest. Fund	67	-0.4%	0.8%	Fondazione Cariplo	4	-0.1%	1.4%	GIMV NV	9	-2.2%	1.6%
eValue Europe	5	-0.6%	1.4%	Fondinvest Capital	5	-0.1%	1.2%	Gjensidige Forsikring	8	-0.3%	1.2%
Evangelical Lu Ch US	15	2.1%	1.3%	Fonds de Sol. Québec	12	-0.6%	1.4%	Glenmede	9	0.3%	1.2%
Everest Reinsurance	5	-0.1%	1.4%	Ford Family FDN	14	0.6%	1.1%	Global Vision PE Partners	24	-0.1%	1.0%
Eversource retire.	13	-0.2%	1.2%	Ford FDN	69	0.3%	0.9%	Glouston Capital Partners	4	0.5%	1.2%

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GM invest. mgmt corp	21	0.0%	1.0%	HarbourVest Partners	282	0.2%	0.6%	HLM Venture Partners	5	-0.2%	1.7%
Golden LEAF FDN	6	-0.5%	1.3%	Harris corp retirement	15	-0.6%	1.1%	Hoffmann-La Roche	14	1.2%	1.6%
Golding Capital Partners	32	0.2%	1.0%	Hartford ERS	4	0.2%	1.4%	Hollyport Capital	14	0.2%	1.1%
Goldman Sachs Asset Mg	75	-0.6%	0.7%	Hartford Financial Svcs	35	0.0%	0.9%	Honeywell International	33	-0.3%	0.8%
Goldman Sachs FDN	12	-0.2%	1.0%	Harvard Mgmt Company	41	0.7%	0.8%	Horsley Bridge Partners	27	1.2%	0.9%
Goldman Sachs PE Group	13	0.0%	1.3%	Harvard University retire	18	1.0%	0.9%	Hospitals of Ontario pension	6	-0.3%	1.2%
GoldPoint Partners	38	0.0%	0.8%	Hatteras Funds	30	-0.5%	0.9%	Houston Firefighters' Retire.	19	-0.3%	1.3%
Goodyear Tire & Rubber	5	-0.6%	1.3%	Haverhill retire.	5	-0.5%	1.3%	Houston MEPS	28	-0.2%	1.1%
Gordon and Betty Moore	16	0.6%	1.3%	HBM Partners	5	0.6%	1.4%	Houston Police Officers' Pension	59	0.0%	0.8%
Gothic corp	5	0.2%	1.3%	Healthcare of Ontario	10	-0.2%	1.2%	Howard Hughes Medical Inst	22	0.2%	1.0%
Govern of Singapore invest.	34	0.2%	0.9%	Hearst corp retirement	14	-0.6%	1.1%	Howard University	30	0.7%	0.9%
Grable FDN	11	0.9%	1.2%	H-E-B invest. and retire.	19	-0.5%	1.0%	HQ Capital International	32	0.3%	0.9%
Granite Hall Partners	11	0.3%	1.2%	Heinz	36	-0.2%	0.9%	HRJ Capital	4	-0.6%	1.5%
Graphite Capital mgmt	11	0.4%	1.2%	Heller Financial	19	-0.4%	1.1%	HSBC France	5	1.1%	1.6%
Greater Manchester pension	22	0.5%	1.1%	Helvetia Group	5	-0.7%	1.2%	HVB Group	21	0.0%	1.1%
Great-West Insurance	7	0.2%	1.6%	Henderson Equity Partners	16	0.0%	1.1%	Hyams FDN	5	0.8%	1.4%
Greenspring Associates	54	1.1%	0.9%	Henkel KGaA	4	-1.6%	1.7%	I.A.M. National pension	63	0.0%	0.7%
Groupama	20	1.2%	1.1%	Henry J. Kaiser FDN	16	-0.2%	1.2%	IBM	81	0.0%	0.8%
Grove Street Advisors	28	0.0%	0.8%	Herbert &Grace Dow	7	-1.1%	1.6%	IBRD retirements	23	0.4%	1.0%
Grupo Guayacán	39	0.7%	0.8%	Hermes GPE	29	-0.2%	0.8%	ICG Enterprise Trust	24	0.1%	1.0%
GTE invest. mgmt	5	-0.4%	1.4%	Hershey Trust	4	0.1%	1.3%	IDEA Capital Funds	6	-0.4%	1.3%
Guardian Home Office	17	-0.7%	1.1%	Hertfordshire Cty Coun	6	0.1%	1.4%	IDI Emerging Markets	8	-1.2%	1.3%
Guardian Life Insurance	32	-0.8%	1.0%	Hess FDN	6	-0.2%	1.3%	Idinvest Partners	19	-1.3%	1.1%
Gulf invest. corp	4	0.3%	1.3%	Hewlett Packard	64	0.4%	0.8%	IFM Investors	6	0.1%	1.2%
Hall Family FDN	17	0.0%	1.1%	Hexagon invest	9	-0.8%	1.3%	Illinois Municipal Retire	207	0.4%	0.5%
Hallmark Cards retirement	4	-0.7%	1.3%	Highland Street FDN	12	-0.7%	1.1%	Illinois State Brd of invest.	55	-0.4%	0.9%
Halyard Capital	6	-0.6%	1.3%	Highmark	7	-1.4%	1.4%	Illinois St Treasury - Tech	4	-0.5%	1.3%
Hamilton Lane	70	0.0%	0.7%	Hillman Family FDNs	8	0.4%	1.4%	Ilmarinen Mutual	54	-0.1%	0.8%
Hampshire County Coun	11	-0.2%	1.2%	HirtleCallaghan & Co.	5	0.5%	1.3%	Independence Hld Partners	15	-0.2%	1.1%

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Indiana PRS	117	0.1%	0.6%	Jaidah Motors and Trading	4	0.0%	1.4%	Knightsbridge Advisers	5	1.2%	1.4%
Indiana University	4	-1.8%	1.4%	James Irvine FDN	13	-0.2%	1.1%	Koch Industries	13	-0.2%	1.1%
Industrial Bank of Kuwait	8	-0.3%	1.4%	James S. McDonnell FDN	6	-0.1%	1.3%	König & Cie.	9	0.0%	1.2%
Industry Pension Insurance	10	-0.1%	1.2%	Jarir invest.	7	0.1%	1.2%	Koor Corporate VC	4	0.3%	1.4%
Industry Ventures	32	0.1%	1.1%	Jasper Ridge Partners	61	-0.8%	0.8%	Koret FDN	4	-0.3%	1.3%
ING invest. mgmt	4	-0.1%	1.4%	John A. Hartford FDN	5	-0.5%	1.7%	Kresge FDN	28	0.0%	1.2%
Ingleside Investors	4	-0.1%	1.3%	John&Catherine MacArth	82	0.3%	1.1%	Kroger	55	0.5%	0.8%
Innotech Advisers	5	0.0%	1.3%	John Deere Pension	5	-0.1%	1.4%	Kuwait Financial Centre PE Arm	40	-0.3%	0.9%
INPRS	86	1.0%	0.7%	John Hancock Life	8	0.1%	1.2%	Kuwait invest. Authority	16	0.2%	1.0%
Intel	7	-0.1%	1.3%	John&James Knight FDN	28	-0.9%	1.0%	Kuwait invest. Office	5	0.1%	1.3%
Inter-Ikea	4	-0.4%	1.3%	Johns Hopkins University	5	0.5%	1.2%	LA84 FDN	9	-0.4%	1.2%
International Finance corp	10	0.0%	1.2%	Joyce FDN	13	0.1%	1.3%	Laborers' District Coun of Oh	43	0.2%	0.9%
International Paper Co (US)	19	-0.2%	1.0%	JPEL PE Limited	19	-1.0%	1.1%	Lancashire County Council	52	-0.2%	0.8%
Invesco Advisers	6	-0.3%	1.4%	JPMP Capital	29	-0.3%	1.0%	Landmark Partners	4	0.0%	1.1%
Invesco Private Capital	44	0.2%	0.9%	K & E Partners	5	0.2%	1.4%	Länsförsäkringar	10	0.2%	1.3%
Investar Financial	4	-0.3%	1.2%	Kaleva Mutual insurance	6	-0.3%	1.3%	Lehman Brothers PE Division	15	1.3%	1.1%
Investor AB	4	-0.2%	1.6%	Kamehameha Schools	33	-0.1%	0.9%	Lexington insurance	15	-0.1%	1.0%
Iowa PERS	150	1.3%	0.7%	Kansas PERS	58	0.0%	0.8%	Lexington Partners	56	0.3%	1.0%
Ireland Strategic invest.	23	0.3%	1.0%	Kansas State University	6	0.7%	1.5%	LGT Capital Partners	118	0.4%	0.7%
Israel Discount Capital Mkt	7	0.9%	1.4%	KBC PE NV	4	-1.6%	1.5%	LGV Capital Ltd	4	-0.6%	1.5%
ITOCHU corp	6	0.4%	1.5%	Kensington	12	0.0%	1.2%	Liberty Mutual Insurance	104	0.8%	0.7%
Itochu Tech Venture	5	0.3%	1.4%	Kentucky retire	32	0.2%	1.1%	Liberty Mutual Retire.	27	1.8%	1.0%
J. Paul Getty Trust	73	0.2%	0.9%	Kentucky TRS	4	0.3%	1.2%	Lifespan corp	5	-0.2%	1.4%
J.C. Penney	74	0.9%	0.7%	Kenyon College	8	-0.4%	1.2%	Linoln Financial Group	4	0.1%	1.5%
J.F. Shea Co.	7	-0.2%	1.4%	Keva	30	0.2%	0.9%	Linoln National Life insur	18	-0.2%	1.0%
J.P. Morgan Asset mgmt	67	0.0%	0.6%	KeyCorp	15	0.1%	1.3%	LMS Capital	13	-0.2%	1.2%
J.P. Morgan (US)	18	-2.2%	1.1%	KfW Banking Group	6	-1.0%	1.2%	Locals 302 & 612 of IUOE	10	-0.7%	1.2%
Jackson National Life	100	-0.3%	0.6%	KIRKBI	9	-0.3%	1.2%	LocalTapiola Group	11	0.4%	1.2%
JAFCO Co.	10	1.4%	1.4%	KKR PEI invest	4	0.1%	1.4%	Lockheed Martin	25	0.2%	1.0%

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London Borough of Enfield	6	1.4%	1.7%	Massachusetts Pension	208	1.0%	0.6%	Milwaukee County ERS	28	-0.9%	1.0%
London Boro of Hounslow	5	-0.2%	1.4%	Mathile Family FDN	26	-0.1%	1.1%	Minnesota Life insurance	18	-1.3%	1.1%
Los Angeles City ERS	120	0.0%	0.7%	Mayo FDN	23	-0.3%	1.2%	Minnesota State Board of invest.	65	-0.8%	0.8%
Los Angeles County ERA	179	0.5%	0.7%	Mayo pension	65	0.0%	0.9%	Missouri SERS	13	0.2%	1.2%
Los Angeles Fire and Police	165	0.2%	0.6%	MC Capital	13	-1.0%	1.2%	MIT	21	1.0%	0.9%
Louisiana ERS	106	1.1%	0.8%	MC Financial Services .	7	-0.1%	1.3%	MIT Basic retirement	67	0.4%	0.7%
Lowell Milken Family	7	0.2%	1.4%	Mead	4	-1.3%	1.3%	Mithras Capital Partners	8	-0.4%	1.3%
Lucent Technologies	9	-0.3%	1.3%	Meadows FDN	12	0.1%	1.3%	MITIMCo PE	21	0.0%	1.2%
Lumina FDN for Education	15	0.3%	1.1%	MEAG Munich Ergo	8	0.0%	1.1%	Mitsubishi corp	4	-0.4%	1.3%
M&G Private Funds invest.	4	-0.3%	1.3%	Meitav invest. House	4	0.5%	1.3%	Mitsui & Co	4	1.3%	1.4%
Macomb County retire.	35	-0.2%	0.8%	Memorial Sloan-Kettering	9	0.3%	1.2%	Mizuho Bank	14	0.0%	1.1%
Madison Dearborn Partners	5	0.2%	1.5%	Menora Mivtachim	20	0.9%	1.1%	MJ Murdock Charitable Trust	12	0.6%	1.3%
Maine PERS	10	0.7%	1.1%	Merifin Capital	4	-0.2%	1.3%	MLC	8	-0.2%	1.3%
Makena Capital mgmt	4	-0.3%	1.2%	Merseyside	33	0.2%	0.9%	MN	18	0.3%	1.0%
Mandatum Life insurance	6	-0.3%	1.3%	Merton College Oxford	5	-0.1%	1.2%	Modern Woodmen of America	4	-0.3%	1.3%
Manulife Financial	42	-0.5%	0.8%	Mesirow Financial invest.	9	1.0%	1.2%	Monsanto	7	0.7%	1.3%
Marathon Oil Group Trust	12	0.0%	1.3%	Mesirow Financial PE	70	1.0%	0.7%	Montana Board of invest.s	39	-0.2%	0.9%
Marathon Petroleum	12	0.0%	1.2%	MetLife insurance	126	0.1%	0.7%	Montauk TriGuard	4	-0.1%	1.3%
Marble House Capital	5	-0.2%	1.2%	Metropolitan Mus of Art	11	1.1%	1.3%	Montgomery County ERS	8	0.6%	1.2%
Maritime Super	13	-0.2%	1.2%	Meyer Memorial Trust	19	-1.0%	1.3%	Montreal Urban ComPolice	8	-0.8%	1.3%
Mars pension	24	0.1%	1.0%	MIC Capital	5	0.2%	1.4%	Morgan Stanley Alt invest.	35	-0.5%	1.1%
Marsh & McLennan Master	46	0.0%	0.8%	Michelin North America	26	-1.2%	1.2%	Morgan Stanley Wealth mgmt	6	0.8%	1.2%
Martin Currie invest. mgmt	8	0.5%	1.3%	Michigan Dept of Treas	214	0.2%	0.7%	Mount Yale Capital Group	10	0.3%	1.1%
Maryland State Retire	67	0.0%	0.7%	Michigan Laborers	6	0.1%	1.3%	Mousse Partners	6	0.2%	1.3%
Masco corp	7	-0.1%	1.3%	Michigan State University	39	0.8%	1.1%	MPC Capital	6	-0.1%	1.2%
Mass Bay Transportation	39	-1.1%	1.1%	Middlebury College	4	-0.1%	1.3%	MTAA Superannuation	4	0.4%	1.3%
Mass Housing Finance	4	0.9%	1.6%	Middlesex County retire.	22	-1.4%	1.2%	Muller & Monroe Asset	4	-0.6%	1.5%
Massachusetts Laborers	17	-0.2%	1.1%	Migdal Makefet	8	0.6%	1.3%	Muni ERS of Michigan	14	0.0%	1.1%
Massachusetts Mutual	62	-0.3%	0.8%	Milken Family FDN	7	0.2%	1.4%	Museum of Modern Art	4	-0.3%	1.3%

LP Name	No	λ	Standard Error	LP Name	No	λ	Standard Error	LP Name	No	λ	Standard Error
Mutual of New York Life	20	0.6%	1.1%	New Zealand Superann.	8	0.3%	1.1%	NY Life insurance	98	0.2%	0.8%
Mutual of Omaha insurance	19	-1.7%	1.2%	NIB Capital PE	19	-0.4%	1.1%	NY State Common Retire	161	-0.1%	0.7%
MWRA retire.	7	0.2%	1.5%	Nina Mason Pulliam	4	0.3%	1.3%	NY State Nurses' Association	46	0.5%	0.8%
Naomi & Nehemiah Cohen	4	-0.1%	1.3%	Nippon VC Co..	4	-0.2%	1.4%	NY St Teamsters Conference	29	0.6%	0.9%
Nashville & Davidson Cty	4	0.2%	1.4%	Nord Holding	4	-0.1%	1.3%	Nykredit	6	-0.1%	1.4%
National Auto Sprinkler	29	-0.6%	0.9%	Nordea Bank	7	-0.3%	1.3%	NY-Presbyterian Hospital	16	0.3%	1.1%
National City Equity	36	0.1%	0.9%	Nordea Life & s	21	-0.2%	1.0%	NYSTRS	89	0.4%	0.7%
National Grid	5	0.0%	1.2%	Nordea PE	13	-0.2%	1.1%	Oberlin College	4	1.3%	1.6%
National Industries Group	6	-0.3%	1.3%	Norfolk County retire.	10	-2.5%	1.4%	Ohio Bureau of Workers' Comp	18	-0.7%	1.1%
National Life Group	17	-0.4%	1.2%	Norfund	8	-0.3%	1.5%	Ohio Capital Fund	4	0.4%	1.5%
Nat'l Res Fund (Ireland)	10	0.3%	1.3%	Norhukin Bank	14	0.3%	1.0%	Ohio Carpenters Hlth & Welfare	38	0.4%	0.9%
National Railroad	11	0.2%	1.1%	Norsk Hydro	5	0.0%	1.3%	Ohio Police & Fire	30	-0.7%	1.1%
National Retirement Fund	7	-1.0%	1.2%	North Carolina Treasurer	62	-0.4%	0.8%	Ohio State University	4	-0.2%	1.2%
Nationwide Insurance	42	-0.9%	0.9%	North Dakota State invest.	4	0.3%	1.4%	Ohio University	5	-0.8%	1.6%
Nationwide retirement	5	0.3%	1.3%	North East Scotland	5	-0.7%	1.3%	Oklahoma Capital invest. Board	6	-1.1%	1.5%
Nautic Partners	21	-0.1%	1.1%	North Sky Capital	12	-1.1%	1.1%	Oklahoma Police	16	-0.5%	1.2%
NAXS Nordic Access	6	0.0%	1.3%	Northeastern University	4	1.5%	1.3%	Oklahoma TRS	4	-0.2%	1.3%
NB Alternatives	44	0.3%	0.9%	Northleaf Capital Partners	14	0.1%	1.2%	Old Mutual PE	12	0.4%	1.1%
NB PE Partners.	13	-0.3%	1.0%	Northrop Grumman	49	-0.2%	0.8%	Omaha SER	13	-0.3%	1.3%
Nebraska invest. Council	10	-0.2%	1.1%	Northwestern Memorial	9	0.2%	1.2%	OMERS	14	-0.2%	1.0%
Nestlé USA	19	0.3%	1.0%	Northwestern Mem Hos	30	0.6%	1.0%	Ontario Teachers'	40	-0.4%	0.9%
Netherlands Development	7	0.0%	1.3%	Northwestern Mutual Life	135	-0.1%	0.6%	OP Life Assurance Company	6	-0.3%	1.2%
Neubauer Family FDN	4	0.6%	1.3%	Northwestern University	36	-0.2%	0.9%	OPERS	63	-0.4%	0.8%
New England Carpenters	31	0.3%	0.9%	Novartis Vacc. & Diag.	4	-0.6%	1.6%	Orange County ERS	100	0.5%	1.0%
New England Teamsters	4	-0.4%	1.4%	Nuclear Electric Insurance	24	-0.3%	1.0%	Oregon Growth Board	9	-1.6%	1.3%
New Hampshire retire.	24	-2.3%	1.1%	NY City Employees' retire	114	-0.7%	0.7%	Oregon PERS	151	-0.6%	0.6%
New Jersey Div of invest.	32	0.1%	0.9%	NY City Fire Department	99	-0.8%	0.6%	ORIX corp	4	-0.2%	1.4%
New Mexico Edu Retire	21	-0.4%	1.0%	NY City Police	109	-0.6%	0.7%	ORS Michigan	25	-0.4%	1.1%
New Mexico State invest.	136	-1.1%	0.7%	NY Life Capital Partners	35	-0.3%	1.0%	Overseas Private invest.	5	-0.4%	1.3%

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Owens-Illinois	14	1.2%	1.5%	Pfizer	59	0.6%	0.8%	Producer-Writers Guild of Am.	25	0.3%	1.0%
Pacific Life insurance	17	0.7%	1.1%	PGGM	20	0.2%	1.1%	Progress Energy	4	-0.1%	1.4%
PacifiCorp	86	-0.9%	0.8%	Philadelphia Brd of Retire	54	0.0%	0.9%	Progress invest. mgmt	5	-1.2%	1.3%
Pamlico Capital	11	-0.8%	1.3%	Phillips Academy Ando.	10	1.8%	1.6%	Promark Global Advisors	67	0.4%	0.8%
Pantheon	174	-0.2%	0.7%	Phoenix Companies	74	-0.1%	0.7%	Promark invest. Advisors	30	0.5%	0.9%
Parallel PE	4	-0.4%	1.4%	Phoenix insurance	13	-0.2%	0.9%	Proparco	4	0.9%	1.7%
Parish Capital Advisors	4	-1.2%	1.5%	Pictet Alternative Advisors	16	0.0%	1.3%	Providence ERS	22	-0.4%	1.3%
Park Street Capital	16	0.3%	0.8%	PineBridge invest.s	27	-0.1%	0.9%	Prudential Financial	115	0.2%	0.6%
Partners Group	209	0.4%	0.6%	PKA AIP	13	-0.6%	1.2%	PSEG Resources	4	0.8%	1.4%
Partners Healthcare System	31	1.0%	1.0%	Plan de es de .España	11	-0.1%	1.1%	PSRS Missouri	36	0.5%	0.9%
Parvilla	4	-0.4%	1.3%	Plymouth County Retire	9	-0.4%	1.4%	PSRS St. Louis	5	-0.8%	1.3%
Pathway Capital mgmt	25	0.5%	0.8%	PNC Equity Partners	47	-0.9%	1.0%	Public Service Enterprise Group	16	0.3%	1.4%
Paul Capital France	5	0.6%	1.7%	PNC Financial Services	9	0.2%	1.2%	Purdue University	30	0.9%	1.0%
Paul Capital Partners	14	0.5%	1.3%	PNC	7	1.3%	1.7%	Pyxis Capital	9	-0.4%	1.3%
PaulHastingsJanofsky & W	11	-0.2%	1.2%	Pohjola Bank	5	0.4%	1.4%	QIC	4	0.2%	1.2%
Pavilion Alternatives Group	9	0.3%	1.2%	Pohjola Insurance	13	-0.4%	1.1%	Quilvest PE	34	-0.4%	0.9%
Penn Mutual Life insurance	25	-0.4%	1.2%	Polk Brothers FDN	11	0.1%	1.3%	Qwest Asset mgmt	5	-0.7%	1.2%
Pennsylvania PSERS	118	-0.5%	0.7%	Pomona Capital	52	0.4%	0.8%	Railway Industry	5	0.1%	1.3%
Pennsylvania SERS	228	0.2%	0.5%	Pomona College	13	1.0%	1.1%	Railways Trustee Company	13	-0.4%	1.1%
Pennsylvania State U	17	0.4%	1.2%	Portfolio Advisors	60	0.2%	0.7%	Rashed Abdul Rahman Al-Ra.	6	-0.1%	1.3%
Pensioenfonds PNO Media	11	0.1%	1.2%	Portico Benefit Services	23	0.7%	1.2%	Rasmuson FDN	18	0.1%	1.2%
Danmark	17	-0.2%	1.1%	PPM America Capital	7	0.1%	1.2%	Raytheon Co	13	0.2%	1.2%
Peppertree Capital mgmt	9	-0.1%	1.3%	Pre George's County	9	-0.4%	1.2%	RBC Venture	6	0.5%	1.4%
Peppertree Partners	18	0.2%	1.1%	Press mgmt Limited	52	0.1%	0.8%	RCP Advisors	30	0.1%	0.9%
PERA New Mexico	21	0.5%	1.0%	Preton Theological Sem.	7	-0.1%	1.2%	RDV corp	4	-0.6%	1.4%
Performance Equity mgmt	15	1.4%	1.2%	Preton University	19	-0.1%	1.0%	Realdania	6	-0.6%	1.5%
PERSI	60	-0.3%	0.9%	Priem Family FDN	5	-0.6%	1.4%	Reiman FDN	15	-0.4%	1.2%
Pew Charitable Trusts	5	-0.4%	1.5%	Private Advisors	14	0.0%	1.2%	Reinsurance Grp of Ame.	4	0.3%	1.3%
PFA	12	-0.3%	1.2%	Procific	5	-0.6%	1.3%	Renaissance VC Partners	5	0.5%	1.6%

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Rensselaer Polytechnic Inst	9	-0.5%	1.3%	S. D. Bechtel Jr FDN	6	-0.2%	1.3%	Sheet Metal Workers National	7	-0.8%	1.3%
Retirw - Saudi Arabian Oil	4	0.3%	1.3%	Safeguard Scientifics	9	-0.9%	1.7%	Shell Asset mgmt	27	-0.3%	1.0%
Retraites Populaires	5	-0.2%	1.3%	Sal. Oppenheim jr. & Cie.	7	0.4%	1.2%	Shell Contributory UK	5	0.1%	1.4%
Reynolds American	41	0.5%	0.8%	Samford University	4	0.8%	1.8%	Shelter Insurance	5	-0.5%	1.5%
Rho Capital Partners	4	0.7%	1.7%	Sam	20	-0.1%	1.1%	Sherman Fairchild FDN	68	-0.2%	1.1%
Richard H. Driehaus FDN	4	-0.9%	1.4%	San Antonio Fire&Police	14	-0.1%	1.1%	Shinsei Bank	4	0.2%	1.3%
Richard King Mellon FDN	42	0.8%	1.4%	San Bernardino Cty ERA	16	0.0%	1.0%	Sidney E. Frank FDN	5	0.5%	1.3%
Riverside Church invest.	5	-0.7%	1.4%	San Diego City ERS	11	0.1%	1.2%	Siemens VC	7	-0.5%	1.4%
Robeco Group N.V.	35	-0.5%	1.0%	San Diego County ERA	35	-0.1%	0.9%	SIFEM	5	-0.5%	1.4%
RobecoSAM PE	59	-0.4%	0.7%	Santander PE	4	0.0%	1.3%	Siguler Guff	20	-0.4%	0.9%
Robert & Myra Kraft Fam	9	0.1%	1.2%	Santander UK	4	0.2%	1.3%	Sihl invest. FDN	13	-0.6%	1.2%
Robert Wood Johnson FDN	68	0.2%	1.0%	SBC Communications	13	-0.2%	1.2%	Silicon Valley Bank	4	-0.4%	1.4%
ROC Partners	54	-0.2%	0.7%	Scandinavian PE Partners	6	-0.3%	1.3%	Silicon Valley Community FDN	5	0.8%	1.3%
Roche USA	43	0.2%	0.8%	Schlumberger	8	0.4%	1.4%	SilverHaze Partners	9	1.3%	1.5%
Rockefeller FDN	71	0.8%	0.8%	Scotiabank PE invest.	11	-0.6%	1.1%	Sirius Group	4	-0.3%	1.3%
Rockefeller University	7	0.9%	1.2%	Scottish Widows invest.	10	-0.4%	1.3%	Sitrainvest. Arm	21	-1.6%	1.2%
RogersCasey	29	0.3%	1.1%	SDRS South Dakota	22	0.0%	1.0%	Sjätte AP-fonden	4	0.4%	1.5%
Rolls-Royce	5	-0.4%	1.3%	Searle Freedom Trust	10	-0.6%	1.2%	Skandia Life insurance	13	0.0%	1.2%
Rose Community FDN	5	-0.2%	1.3%	Sears Holdings	10	0.5%	1.2%	Skandia Liv Asset mgmt	5	0.3%	1.3%
Rose Hills FDN	7	0.4%	1.5%	Sears invest. mgmt	19	0.9%	1.3%	Skoll FDN	20	0.0%	1.1%
Royal Bank of Scotland	4	0.4%	1.4%	Seattle ERS	4	0.6%	1.3%	SL Capital Partners	54	0.0%	0.9%
Royal Cty of Berkshire	4	0.1%	1.4%	SEB Asset mgmt	13	-0.5%	1.2%	Sofina	11	0.3%	1.1%
Royal London Asset mgmt	4	-0.2%	1.3%	SEIU	4	-0.1%	1.3%	Sony Life Insurance	11	0.5%	1.2%
RSA Group	7	0.4%	1.4%	Sentry Insurance	50	0.8%	0.9%	Sound retirement	6	0.1%	1.3%
Rush Pres-St. Luke's Med.	6	-0.7%	1.3%	Sequoia FDN	4	-0.6%	1.6%	Source Capital Group	5	2.4%	1.7%
Rush University Med	5	-0.1%	1.3%	SERS Ohio	44	-0.1%	0.8%	South Carolina SCRS	13	-0.2%	1.1%
RWB Private Capital	48	-0.5%	0.8%	SFERS	145	0.4%	0.7%	South Dakota invest. Cou.	10	-0.4%	1.2%
RWB RenditeWertB	18	-0.1%	1.0%	SGAM Alternative invest	5	0.1%	1.4%	South Yorkshire s	16	-0.5%	1.1%
S. C. Johnson & Son	9	-0.6%	1.3%	ShaPE Capital	34	0.2%	0.9%	Southern California Edison	9	-0.1%	1.3%

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Southern Co	17	-0.6%	1.1%	Strategic Partners Fund	48	-1.4%	0.9%	Teachers' Private Capital	12	0.0%	1.3%
Southern Farm Bureau Life	5	0.2%	1.4%	Strathclyde	15	-0.3%	1.1%	Teachers' Retire. Allowances	4	-0.6%	1.5%
Southern Methodist U	12	-0.6%	1.3%	STRS Ohio	88	-0.1%	0.8%	Telstra Super	4	0.7%	1.3%
Southwest Carpenters	6	0.2%	1.2%	Stuart FDN	14	0.3%	1.1%	Temasek Capital	13	-0.2%	1.3%
Spelman College	4	0.0%	1.5%	Sumitomo corp	4	-0.7%	1.5%	Temasek Holdings	15	0.0%	1.1%
SPF Beheer	14	0.0%	1.2%	Sumitomo Mitsui Banking	6	-0.1%	1.3%	Tennessee Consolidated retire.	10	1.0%	1.3%
Spice PE	108	-0.2%	0.6%	Sumitomo Mitsui Trust	10	0.5%	1.2%	Texas County & District retire.	44	0.9%	0.8%
Spider mgmt Company	6	-0.5%	1.3%	Sun Life Financial	6	-0.8%	1.2%	Textron	12	-0.3%	1.1%
Spur Capital Partners	5	-0.6%	1.4%	SunAmerica Ventures	16	0.3%	1.3%	The Glenmede Trust	64	0.3%	0.8%
SR One	9	-2.1%	1.5%	Sunoco	14	0.4%	1.1%	The Henry Luce FDN Fund	4	2.1%	2.0%
St. Catherine's College	5	-0.2%	1.3%	SunSuper	4	0.3%	1.2%	The Hillman Co	8	-0.6%	1.2%
St. Paul VC	4	-0.4%	1.3%	SunTrust Banks	8	-0.2%	1.3%	The invest. Fund for FDNs	24	0.6%	1.1%
Standard Life European PE	41	0.1%	0.9%	Surdna FDN	16	-0.1%	1.0%	The Key corp	4	-0.1%	1.5%
Stanford mgmt Company	10	0.4%	1.1%	Surrey County Council	7	-0.2%	1.4%	The Lynde & Harry Bradley	5	-0.7%	1.3%
Starling Group	20	0.5%	1.1%	SURS Illinois	16	0.4%	0.8%	The Olayan Group	5	-0.1%	1.4%
Starling International mgmt	18	0.3%	1.3%	Sutter Health	10	0.3%	1.2%	The Provident Bank	7	0.0%	1.7%
Starr FDN	7	0.0%	1.2%	SVB Capital	65	1.1%	0.8%	The World Bank Group	8	-0.1%	1.3%
State Farm Insurance Asset	5	1.0%	1.6%	SVB Financial Group	7	-1.0%	1.5%	Thomas Weisel Capital mgmt	24	0.0%	1.1%
State Farm Mutual Auto	11	-0.6%	1.6%	SwanCap Partners	12	0.0%	1.2%	Thrivent Financial	21	0.0%	1.2%
State General Reserve Fund	7	0.0%	1.3%	Swarthmore College	6	-0.6%	1.2%	TIAA	111	0.0%	0.6%
State of Wisconsin invest.	153	-0.1%	0.6%	SWEN Capital Partners	4	-0.4%	1.3%	TIF Ventures	7	0.8%	1.3%
StepStone Group	56	0.0%	0.8%	Swift Capital Partners	16	-0.1%	1.1%	TIFF	67	0.5%	0.7%
Stewardship FDN	7	0.4%	1.3%	Swiss Life PE Partners	7	-1.2%	1.4%	Time Warner	4	0.3%	1.5%
Stichting Pensioen	8	0.5%	1.3%	Swiss Re	7	-1.2%	1.4%	Timken Company	4	0.0%	1.3%
Stonehage Fleming	37	-0.2%	0.8%	Syracuse University	5	-0.5%	1.3%	Toa Reinsure. of America	4	0.00%	1.40%
Stonehenge Partners	5	-0.3%	1.4%	TA Associates	4	0.3%	1.3%	Tokio Marine&Nichido F	13	1.10%	1.40%
Stonetree Capital mgmt	12	-0.2%	1.3%	Talanx Asset mgmt	16	0.6%	1.2%	Tokio Marine Asset mgmt	13	-0.60%	1.00%
Storebrand Asset mgmt	26	-0.3%	0.9%	Target	7	-0.6%	1.3%	Top Tier Capital Partners	9	0.60%	1.30%
Strategic invest. Group	4	-1.5%	1.1%	TD Capital	31	-0.3%	1.0%	Toronto-Dominion Bank	10	-0.20%	1.30%

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Total Finance USA	4	-0.40%	1.70%	Union Pacific corp	19	-0.10%	1.20%	USC	5	-0.4%	1.2%
Transamerica	20	-0.10%	0.90%	Unisys	23	-0.30%	0.90%	Utah Capital invest. corp	19	0.3%	1.1%
Travelers Companies	14	0.00%	0.70%	United Food&Com. Wrk	6	-0.50%	1.30%	Utah retirement system	26	0.5%	0.8%
Tredegar	16	-2.40%	1.40%	United St Steel&Carnegie	10	0.10%	1.20%	VAH PE	6	0.1%	1.3%
Tri-State Growth Capital	8	0.00%	1.30%	United Technologies	53	-0.20%	0.80%	Vanderbilt University	15	1.4%	1.2%
Tri-State Ventures	9	-1.70%	1.50%	Univ. Superannuation	9	-0.20%	1.10%	Vantage Asset mgmt	4	0.3%	1.3%
Triton Systems	6	2.60%	1.90%	University of California	156	0.20%	0.60%	Varma Mutual insurance	36	-0.1%	0.9%
TRS Illinois	76	-0.80%	0.70%	University of Chicago	16	0.10%	1.30%	Vega-Invest	9	-0.2%	1.1%
TRS NY	100	-0.80%	0.60%	University of Cinnati	11	-0.10%	1.20%	VenCap International	14	1.4%	1.1%
TRS of Texas	84	0.20%	0.70%	University of Colorado	15	-0.20%	1.20%	Verizon	117	0.2%	0.6%
TRSL Louisiana	39	-0.30%	0.80%	University of Georgia	4	0.50%	1.30%	Verizon invest. mgmt corp	68	-0.1%	0.8%
Trust Plan	14	-1.00%	1.20%	University of Illinois	11	0.10%	1.10%	Virginia G. Piper	6	0.1%	1.2%
Tunisie Leasing	4	-0.10%	1.90%	University of Michigan	162	0.70%	0.70%	Virginia retirement	157	1.1%	0.8%
Twin Bridge Capital	13	-0.10%	1.10%	University of Minnesota	23	0.10%	1.00%	Virginia Tech	4	-0.6%	1.5%
U.S. Bancorp	6	0.00%	1.40%	Univ of Missouri Retire	6	-0.60%	1.30%	Vontobel Holding	4	1.6%	1.6%
U.S. West invest. mgmt Co.	4	-0.30%	1.40%	Univ of Missouri System	9	-0.50%	1.20%	Voya Financial	14	-0.2%	1.1%
UA Local 467	11	0.70%	1.50%	University of Nevada Re	6	0.00%	1.20%	Vulcan Capital	5	0.1%	1.4%
UBS	11	-0.70%	1.30%	University of New Mexico	4	1.00%	1.50%	Vulcan Materials	5	0.8%	1.6%
UFCW - Northern Cal	7	-0.60%	1.40%	University of Notre Dame	23	0.40%	1.60%	W.K. Kellogg FDN	27	0.7%	1.2%
UFCW International Union	27	0.10%	1.00%	University of Oklahoma	5	0.40%	1.30%	WA Super	4	0.3%	1.3%
UJA Federation of NY	4	0.80%	1.30%	University of Oregon	4	0.10%	1.50%	Wachovia	25	0.7%	1.1%
UMWA Health	29	0.00%	1.00%	Univ of Pennsylvania	9	0.30%	1.20%	Walt Disney	50	0.3%	1.0%
UNICare retirement	4	-0.30%	1.40%	University of Pittsburgh	5	-0.20%	1.00%	Washington State invest. Board	182	0.0%	0.6%
UNC Chapel Hill	13	-1.20%	1.00%	University of Richmond	15	-1.1%	1.3%	Washington State U	6	0.0%	1.3%
UniCredit Bank Austria	8	0.3%	1.3%	University of Texas	157	-0.1%	0.7%	Washington U in St. Louis	4	-0.4%	0.9%
Unigestion	46	-0.20%	0.80%	University of Virginia	17	0.3%	1.1%	Wealth mgmt Capital	10	0.0%	1.3%
UniHealth FDN	5	-0.30%	1.30%	University of Washington	80	0.7%	0.9%	Wega Support	6	0.0%	1.3%
Union Carbide	62	-0.20%	0.80%	University of Wisconsin	10	1.2%	1.2%	Wellesley College	5	0.8%	1.3%
Union Fidelity Life ins.	6	-0.50%	1.30%	UPMC retirement	19	0.0%	1.0%	Wells Fargo	20	-0.6%	1.2%

LP Name	No	λ	Standard Error	LP Name	No	λ	Standard Error	LP Name	No	λ	Standard Error
Wenner-Gren FDN	6	0.1%	1.4%	Weyerhaeuser	67	-0.3%	0.8%	Wilshire Private Markets	40	-0.3%	0.8%
Weome Trust	39	-0.5%	1.0%	William & Flora Hewlett	13	1.0%	1.0%	Wilton Asset mgmt	8	-0.2%	1.3%
Wesleyan University	4	0.9%	1.5%	William H. Miner FDN	21	0.0%	1.1%	Wisconsin Alumni Research FD	6	-0.7%	1.1%
West Midlands	108	0.4%	0.8%	William K. Warren FDN	4	-0.1%	1.4%	Worcester retirement	19	0.3%	1.1%
West Virginia invest. mgmt	14	0.6%	1.0%	William Randolph Hearst	12	-0.4%	1.2%	Workers Comp Fund of Utah	4	-1.1%	1.5%
West Yorkshire	8	-0.2%	1.4%	William T. Grant FDN	4	0.4%	1.4%	WorkSafe Victoria	4	0.0%	1.3%
Western & Southern Life	17	-0.4%	1.1%	Williams College	6	0.3%	1.3%	Yale University	47	-0.2%	0.9%
WestLB AG - PE	6	0.1%	1.2%	Willowridge Partners	7	0.0%	1.3%	Yale University retirement	20	1.1%	1.1%
WestRock	14	-0.7%	1.3%	Wilshire Associates	53	-0.7%	0.8%	YMCA Retirement Fund	42	0.2%	0.9%