Estimating Skill in Private Equity Performance using Market Data

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ABSTRACT

There is ongoing debate about whether the returns earned by private equity (PE) firms are persistent. However, recent research has raised concerns about the integrity of both the data and the empirical methods that are commonly used in the PE persistence literature. I address these concerns by studying skill using a comprehensive sample of publicly traded listed private equity entities (LPEs) representing Buyout, Mezzanine, Venture, and Funds-of-Funds. LPEs can be viewed as closed-end funds with indefinite life, and using tests developed in the funds literature, Buyout LPEs exhibit short-term persistence (0.67% per month), and investors anticipate short-term managerial performance. Short-term persistence disappears in the period 2005-2010, but recovers strongly in 2010-2015. Tests for long-term persistence show that substantial skill remains after controlling for luck, and skilled LPEs outperform unskilled ones by up to 1.2% per month. Finally, using the value that LPEs extract from private markets as the measure of skill, the median LPE generates about $16 million per year. These results are the first estimates of private equity skill derived directly from observed stock market data.

Keywords: Private equity; closed-end; persistence; skill.

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I. Introduction

In the private equity literature, there is ongoing debate about whether private equity firms (General Partners or GPs) are skilled[1]. The seminal study by Kaplan and Schoar (2005) was the first of a number to show that the funds of some GPs earn persistently higher returns than those of other GPs. However, recent research, such as that by Harris, Jenkinson, and Kaplan (2014a), has shown that reliable, unbiased data on private equity firm performance is difficult to obtain. As a result, estimates of PE performance (on which measures of PE persistence rely) vary widely[2], with some studies finding substantial outperformance and others finding substantial underperformance. Furthermore, the nature of PE funds and fundraising (funds of about 10 years duration, raised every 3 to 5 years) poses methodological challenges for researchers. Korteweg and Sorensen (2015) argue that methodologies commonly used to measure PE persistence have empirical limitations that could affect the interpretation of results derived using those methodologies.

Private equity firms are famously protective of information relating to their fund performance. Thus many studies of PE performance and persistence rely on data provided by commercial providers such as Venture Economics, Preqin, and Burgiss. However, each of these databases has data integrity or completeness issues. Venture Economics data, used for over two decades by practitioners and academics to benchmark PE performance, has been shown by Stucke (2011) to have systematic and persistent errors that increase noise and cause significant downward bias in performance measures. Preqin data is based on fund manager and investor reports, which Ang, Chen, Goetzmann, and Phalippou (2014) argue are potentially subject to reporting and selection biases. Fund-level cashflow data from Burgiss may not have major biases, but as Braun, Jenkinson, and Stoff (2015) point out, will inevitably have gaps in the fund sequences, reflecting investors choices about which funds to

[1]See Section II for a detailed literature review.

[2]Driessen, Lin, and Phalippou (2012) estimate the alpha of unlisted PE to be -12%, while Cochrane (2005) reports a value of 32%.

invest in. This is less important for analysis of PE returns, but is a serious constraint when analyzing persistence. Some studies use data provided by PE investors or fund managers, and as a result are potentially exposed to reporting and selection biases. Jegadeesh, Kräussl, and Pollet (2015), on the other hand, show that these data integrity issues can be overcome by using market data that is publicly available for listed private equity (LPE), from which market-based estimates of PE risk and expected performance can be made.

In addition to data integrity challenges, research on the persistence of traditional PE faces methodological issues. Almost all major studies of PE persistence measure persistence either by regressing a PE firm's fund n returns on the firm's fund $n-1$ returns, or by using Markov chain transition matrices, or both. Korteweg and Sorensen (2015) show that regressing fund n returns on fund $n-1$ returns is equivalent to an AR(1) timeseries[3] process that does not distinguish skilled firms from lucky ones, and which has the undesirable property that it converges to the same distribution, implying no long-term performance differences. Estimating Markov chain transition probabilities (the probability that the (quartile) performance ranking of a PE firm's fund n will be the same as the firm's fund $n-1$) is also a commonly used persistence measurement technique. However Korteweg and Sorensen (2015) argue that Markov chains do not provide necessary or sufficient conditions to imply the absence or otherwise of persistence. To overcome these methodological issues, Korteweg&Sorensen measure long-term persistence in PE using a robust, but complex, variance decomposition model estimated using a Bayesian procedure.

In this paper, I use LPE to analyze skill and luck in private equity performance. LPE comprises the firms and funds engaged in private equity activities that are traded on international stock markets. Like closed-end funds[4], LPEs raise capital in an Initial Public Offering (IPO) which they then use to invest in private companies, either directly by taking con-

[3]The AR(1) process $y_{i,n} = \alpha + \beta y_{i,n-1} + \epsilon_{i,n}$ converges to $E[y] = \frac{\alpha}{1-\beta}$. Under an AR(1) model of persistence where $y_{i,n}$ is the performance of fund n raised by firm i, then by construction, all funds raised by all firms have the same expected performance, which is not realistic.

[4]Closed-end funds are funds whose share price may vary independently of their NAV, unlike open-end funds whose share price is by law the same as their NAV per share.

trolling equity (Buyout) or debt (Mezzanine) positions in established firms, or indirectly by investing as Limited Partners (LPs) in a number of traditional private equity funds (Funds-of-Funds). LPEs may also be be investors in early-stage firms (Venture). Some GPs have also chosen to list, allowing shareholders gain exposure to fees and other income earned by these traditional PE fund managers (in this study, I generally use the term LPE to refer to listed private equity firms and funds other than GPs). Unlike the typical 10-year life of traditional PE funds, there are no limits on LPE life, or on the duration that they hold their investments.

The LPE asset class has grown rapidly in recent years. In 1990 there were 31 LPE vehicles with combined assets under management (AUM) of around \$57.5 billion; in 2015 there were 174 LPEs with AUM of about \$950 billion. This compares with \$3.8 trillion AUM for the PE universe in 2014 reported by Preqin (2015). Furthermore, LPE is increasingly seen as representative of the general private equity asset class; for example, the Committee of European Insurance and Occupational Pension Supervisors (CEIOPS) has adopted a listed private equity index as the private equity benchmark for Solvency II, the European Union's flagship project to modernize and harmonize insurance supervision.

LPE has a number of attractive features for private equity researchers. Firstly, reliable, complete and unbiased data is readily available. My LPE sample consists of the constituents of publicly available indices of LPE firms and funds whose stock prices and financial history are accessible via the standard databases used in financial research. Secondly, LPE Net Asset Value (NAV) returns are highly correlated with those of unlisted PE. Preqin and LPX Group (2012) show that the correlation is 0.94. Thus LPE performance can be considered a good proxy for unlisted PE performance. Finally, LPEs behave like closed-end funds (CEFs) of private equity investments. Many LPEs choose to list as regulated CEFs (in the United States this is the only structure that LPEs may legally take). Regulated CEFs may enjoy tax advantages, at the expense of facing restrictions on distributions, leverage, fees, and diversification. Other LPEs choose to list as normal public limited companies. Irrespective of their structural form, LPE firms and funds raise and invest capital in a similar way.

I take advantage of the fund nature of LPE to apply tests of fund manager persistence to my LPE sample. The debate on mutual fund manager skill has been ongoing at least since the 1960s (see Treynor (1965), for example), much longer than the debate on PE firm skill, and many robust tests for fund manager skill have been developed.

Firstly, I measure short-term persistence using the classic test[5] by Carhart (1997), which defines skill as the 4-factor alpha for a winner-minus-loser portfolio constructed using lagged 12-month returns and held for 12 months. I find positive winner-minus-loser alpha of 0.67% per month (about 8% per year) using price returns for Buyout LPEs. Using changes in NAV as the measure of skill, I find positive and statistically significant winner-minus-loser NAV returns for Buyout and Mezzanine LPEs (7.8% and 8.7% per year, respectively).

Chay and Trzcinka (1999) show that the NAV premium (the difference between the NAV per share and the share price) for CEFs that hold equities is a strong predictor of short-term changes in NAV; in other words, the NAV premium captures short-term market expectations of manager skill. I confirm that Chay and Trzcinka (1999)'s findings hold for my LPE sample for all LPE types except Funds of Funds; Buyout, Venture and Mezzanine LPEs with larger NAV premiums have larger NAV changes 12 months later. This result is evidence not only that certain LPEs have short-term skill, but also that investors can identify these skilled LPEs.

Secondly, I apply tests to separate skilled LPEs from lucky ones. Fama and French (2010) argue that Carhart's short-term persistence measure picks up noise in that it ranks funds by short-term past performance, thus some funds with short-term persistence may just be lucky rather than truly skilled. To separate luck from skill, Kosowski, Timmermann, Wermers, and White (2006) generate a cross-sectional bootstrapped distribution where the true alpha is zero by construction, and which captures the case where all funds have equal skill, but some funds may have significant alpha by luck alone. Applying this technique to LPE, I find

[5] Carhart adopted his methodology from Hendricks, Patel, and Zeckhauser (1993).

strong evidence of skill - the number of positive alpha LPEs in the sample is nearly 33% more than would be expected if the true alpha for the sample was zero. Barras, Scaillet, and Wermers (2010) use another data-driven technique to separate skilled funds from lucky ones - the False Discovery Rate. Using this approach with LPE suggests that for Buyout and Mezzanine LPEs, there is a large proportion of truly skilled funds in the sample (13% and 11% respectively). Furthermore these tests highlight the fact that few LPEs are truly unskilled.

These tests also give give insights into the long-term returns to investors who can identity skilled LPEs. For the full sample, there is a difference in risk-adjusted returns of over 1.2% per month between the LPE at the 80th percentile and the LPE at the 20th percentile. For the Buyout subsample, the difference is over 1%, for Mezzanine it is about 0.9%, it is over 1.2% for Venture, and 0.7% for FoFs.

Finally, following the arguments first set out by Berk and Green (2004), Berk and van Binsbergen (2015) argue that risk-adjusted returns (net or gross alpha) are not in fact measures of fund manager skill (they suggest that if alpha is positive then markets are inefficient, and if alpha is negative then investors are irrational). Instead they propose that the dollar value taken by the fund from the markets is a true measure of skill. Applying their methodology, I find that the median value-added generated by LPEs is $16 million per year.

I perform a range of robustness checks to verify that my findings hold up under alternative specifications. These include controlling for short-term post-IPO LPE performance, using value-weighted instead of equal-weighted portfolios, applying the Fama and French (2010) specification for the cross-sectional bootstrap, and tracking changes in short-term persistence over time.

The major contributions of this paper are threefold. Firstly, I use a novel dataset, Listed Private Equity. Using LPE overcomes the data integrity issues that affect studies of traditional private equity, and permits analysis of private equity using market-based data. Secondly, I apply a battery of empirically robust tests from the mutual fund and closed-end fund literature that are not possible to use with unlisted PE fund data. These tests include classic measures of short-term persistence, measures which separate skill from luck, and tests which quantify the value generated by LPEs. Finally, this study seems to be the first to examine the performance of Mezzanine private equity. Most PE studies focus on Buyout and Venture funds, but as the results of this study will show, Mezzanine is a PE subclass that deserves more careful attention from researchers and investors.

The major findings of this study are that there is a large amount of persistence in LPE returns, and much of that persistence is due to skill. Furthermore, LPEs generate value. Buyout and Mezzanine LPEs perform best in most tests. There is little evidence of skill for Venture LPEs. Looking at the left tail, there is evidence that many LPEs with negative alphas may just be unlucky - fewer LPEs have negative alphas than would be expected if the true alpha is zero.

A further insight is that, consistent with studies of unlisted Buyout PE persistence, short-term Buyout LPE persistence declined during the 2000-2010 period. This decline has been interpreted by Braun et al. (2015) to be a sign of the increasing competition for deals among PE firms. However in the period 2010-2015, short-term persistence for Buyout LPE has rebounded significantly. Competition for deals declined during the 2007-2008 financial crisis, allowing skilled LPEs to differentiate themselves from unskilled ones, and to deliver strong returns in the years following the crisis.

A study close to this one is by Jegadeesh et al. (2015) who use LPE to determine the risk and expected returns of private equity. My paper may be viewed as a follow-on to their study in that I use LPE to examine persistence in private equity returns. While the main focus of Jegadeesh *et al* is to directly determine the *ex ante* expected alpha of the unlisted PE funds that are held by FoFs, they also study a sample of LPEs that invest directly in private companies. They find that the expected alpha for direct LPEs is not dramatically different from that of the unlisted funds held by FoFs. In this paper, I do not attempt to directly estimate the skill of the PE funds underlying FoFs, but Jegadeesh *et al*'s findings are further evidence that conclusions regarding LPE skill may reasonably be transfered to unlisted PE.

Also, the study of unlisted PE persistence by Korteweg and Sorensen (2015) has similar objectives to mine. Korteweg&Sorensen separate luck from skill by measuring long-term persistence and investable persistence for Buyout, Venture (and Other) PE investment styles. They use a Bayesian procedure to overcome the methodological challenges facing tests of traditional PE persistence, however they rely on Preqin data, so data integrity may still be a concern. Given the methodological and data differences between my study and theirs, the findings are not directly comparable. Nonetheless, there are similarities - Korteweg&Sorensen too find substantial evidence of long-term persistence. Their estimate of the difference in returns for skilled and unskilled PE firms is 7% to 8% per year, which is close to what I find for LPE (8% to 14% per year). They find little evidence of investable persistence, especially not for Venture funds - the signal-to-noise ratio is too high, and investors are unable to identify skilled PE firms. For LPE, I show that there is little evidence of persistence for Venture LPEs, but some investors are able to identify skilled LPEs of all types (except FoFs) and set the NAV premium for these LPEs in accordance with their expectations.

This paper is structured as follows: Section II summarises the literature on private equity and mutual fund persistence; in Section III I describe listed private equity and the LPE dataset. The results for the short-term and long-term persistence tests are presented in Section IV and Section V respectively. In Section VI I describe a number of robustness checks. I discuss results and future research in Section VII, and Section VIII concludes.

II. Persistence in Private Equity and Mutual Funds

Many studies of traditional, unlisted, private equity (PE) find that the funds of certain GPs yield persistently higher or persistently lower returns than those of other GPs. Kaplan and Schoar (2005) find evidence of significant heterogeneity in performance across PE funds, and that persistence was strong for Venture and Buyout funds raised in the 1980s and 1990s. Robinson and Sensoy (2011) obtain similar results for a sample of Buyout funds, again raised largely in the 1980s and 1990s. Chung (2012) studies Buyout and Venture funds raised through 2000 and finds somewhat less persistence than the other papers. Harris, Jenkinson, Kaplan, and Stucke (2014b) find that PE persistence for Buyout and Venture funds was strong pre-2000, and post-2000 Venture persistence is unchanged, but for Buyouts it is weaker post-2000 especially at the upper end of the performance spectrum. Braun et al. (2015) also show that Buyout PE firm returns are persistent, but that this persistence has declined post-2000. Korteweg and Sorensen (2015) find a large amount of long-term PE persistence which they believe reflects the average outperformance of more skilled private equity firms, but that it is difficult for investors to separate these skilled private equity firms from just lucky ones. They confirm that persistence declined somewhat post-2000, but in contrast to Harris et al. (2014b), they find that Venture persistence declined the most whereas Buyout persistence held up well.

However, as described in the Introduction to this paper, nearly all studies of traditional PE persistence either use data whose integrity is susceptible to bias, or use measures of persistence that have theoretical limitations, or both. Studying LPE avoids the data integrity issues faced by traditional PE as reliable LPE stock prices and returns are widely available. Also, there is a rich body of literature describing robust methodologies for measuring persistence in mutual funds that can be applied to LPE. I summarize some of these techniques briefly here, but the detailed implementation is discussed in later sections.

Carhart (1997)'s landmark study of persistence in open-end US mutual fund returns is the main inspiration. In that paper, Carhart argues that persistence in mutual fund performance does not reflect superior stock-picking skill. Rather, common factors in stock returns (particularly the momentum factor introduced by Carhart) and persistent differences in mutual fund expenses and transaction costs explain almost all of the predictability in mutual fund returns.

Kosowski et al. (2006) and Fama and French (2010) both use a bootstrap approach to estimating the likelihood that US open-end mutual fund returns are due to skill rather than luck. This approach has the advantage that it does not assume returns follow a normal distribution. Fama and French (2010) find that few funds earn benchmark-adjusted expected returns sufficient to cover their costs. Kosowski et al. (2006) on the other hand find that a sizable minority of managers pick stocks well enough to more than cover their costs. Moreover, the superior alphas of these managers persist.

Barras et al. (2010) also employ a data-driven approach to separate skill from luck in mutual funds returns. Barras *et al* use the False Discovery Rate, a statistical technique developed by Storey (2002) which estimates the proportion of funds whose true alpha is zero, but which have significant alpha by luck alone. They find that about 2% of their sample have long-term skill, and 23% are unskilled. They also show that the proportion of skilled funds diminished significantly in the period 1990-2010, and the proportion of unskilled funds increased substantially.

Berk and van Binsbergen (2015) challenge the long-held assumption that risk-adjusted returns (net or gross alpha) is an appropriate measure of mutual fund manager skill. Net alpha, they argue, is determined in equilibrium by competition between investors and not by the skill of managers. Gross alpha is a return measure, not a value measure, and therefore not a measure of skill either. Instead, Berk and van Binsbergen (2015) propose the dollar value of what a fund adds over its benchmark as the measure of skill. They find that the average mutual fund has added value by extracting about $3.2 million a year from financial markets, and that cross-sectional differences in value added are persistent for as long as ten years.

Pástor, Stambaugh, and Taylor (2015) measure skill as the estimated mutual fund fixed effect from a panel regression of fund performance on fund size. They find that individual fund manager skill has actually increased in the period 1979-2011, but this upward trend in skill coincides with industry growth, which precludes the skill improvement from boosting fund performance. They also find that new funds entering the industry are more skilled, on average, than the existing funds.

An international sample of LPE stocks is used in my study, so it is important to consider international determinants of performance. Ferreira, Keswani, Miguel, and Ramos (2012) analyse open-end mutual fund performance in 27 countries, and find that country characteristics such as liquid stock markets and strong legal institutions may explain performance.

While the studies discussed above focus on open-end mutual funds, the literature on closed-end funds also debates managerial performance. Chay and Trzcinka (1999) ask if the closed-end premium, the difference between the market value of the fund and its NAV, is a predictor of the fund's future NAV returns. They find that equity funds that trade at a larger premium (or a smaller discount) have higher NAV returns one year later. However for funds that hold debt, the premium does not predict NAV returns.

Berk and Stanton (2007) present a dynamic model that predicts the findings of Chay and Trzcinka (1999). In this model, the premium is driven by the tradeoff between managerial ability and fees. Managerial ability adds value to the fund, so, if there were no fees, competitive investors would be willing to pay a premium over NAV to invest in the fund. Fees subtract value from the fund, so, if managers had no ability, investors would only be willing to invest if they could buy shares in the fund at a discount. In the presence of both fees and managerial ability, the fund may trade at either a premium or a discount to NAV depending on whether fees or ability dominate. Because the price of an open-end fund is forced to equal NAV at the end of each day, investors react to changes in their beliefs about managerial ability and fees by moving capital in and out of the fund. With closed-end funds, the assets under management remain fixed, so investors' updates of managerial ability and fees cause price changes. I discuss the Berk&Stanton model in detail in Section VII.

Cherkes, Sagi, and Stanton (2009) link closed-end fund performance to the liquidity benefits provided by CEFs. They argue that investors who trade illiquid assets directly (such as private equity investors) incur potentially large transaction costs. On the other hand, if investors trade the assets indirectly, by buying or selling the relatively liquid shares of a CEF like an LPE, the underlying illiquid assets do not change hands, and the investors avoid these large illiquidity costs. The liquidity benefits represent the liquidity difference between the CEF shares and its underlying assets. Liquidity benefits may be amplified using leverage, and may vary over time. Cherkes et al. (2009) outline a model similar to that of Berk and Stanton (2007), except the NAV premium set by investors is driven by the tradeoff between the investors' assessment of the liquidity benefits provided by the CEF (which drive up NAV premia) and of the CEF manager's fees (which drive down NAV premia). CEFs choose to IPO when liquidity benefits are high so they can launch at a premium to NAV and thus recuperate their IPO costs.

III. Listed Private Equity

In parallel with the significant financial growth in LPE documented in the Introduction, there is increasing interest in the topic among academics, practitioners and regulators. For example, Jegadeesh et al. (2015) use LPE to infer risk and returns to traditional, unlisted, private equity funds. Sender and Foley (2015), writing in in the Financial Times, report that traditional fund managers, frustrated at having to pass up on good investment opportunities to cater to the whims of nervous investors, are looking to LPE as a source of "permanent capital". The Economist (2014) reports that LPE is being seen by some regulators as a solution to the problem of transferring risk from institutions with government insured funding, such as deposits at banks, to ones with more stable, loss absorbing backers, such as the shareholders of LPEs. After an exhaustive analysis with input from PE industry stakeholders, the European insurance regulatory body has adopted LPE as its private equity benchmark (EIOPA (2013)).

Bergmann, Christophers, Huss, and Zimmermann (2009) classify LPE firms by three types of investment style: direct private equity, funds of funds, and fund managers. The two main types of direct LPE firms are those that make direct private equity investments or direct mezzanine debt investments. Mezzanine capital is any capital between equity and debt e.g. subordinated debt, convertible debt or loans with equity kickers. Indirect LPE vehicles commit capital to unlisted private equity limited partnerships. These are typically closed-end funds known as funds of funds (FoFs). Jegadeesh et al. (2015) note that the unlisted PE funds in which LPE FoFs invest represent a large fraction of the unlisted PE fund universe. Finally, a number of traditional PE fund management firms (GPs) such as Kohlberg Kravis Roberts, Blackstone and Apollo have chosen to list on public exchanges, enabling investors to access the fees and other income earned by GPs from their private equity funds.

To create the LPE sample used for my tests, I start by identifying a large sample of all LPEs, the LPE universe. The LPE universe includes Business Development Companies (closed-end funds of PE investments which are regulated by the Securities and Exchange Commission in the United States), private equity Investment Trusts (closed-end funds of PE investments run by members of the AIC in the United Kingdom), and the constituent lists of publicly available LPE indices and ETFs. The main LPE indices are the S&P Listed Private Equity index, the Société Générale Privex index, and the ALPS-RedRocks Global Listed Private Equity index. I also include the constituents of the ProShares Global Listed Private Equity ETF which tracks the LPX Direct Listed Private Equity Index.

Using equities included in the LPE indices has a number of advantages, including the screening of firms and funds for private equity activities, and also ensuring minimum levels of stock liquidity. However some of the indices include derivative entities, and a small number of firms and funds that are classified as non-financial (industrials, infrastructure, consumer staples etc). In this study I wish to focus on index-listed public financial investment firms and funds that most closely resemble traditional unlisted PE, including buyout, venture, and mezzanine, so I exclude derivative entities, and LPEs that are not LPE index constituents, and non-financial LPEs, from the final sample.

The LPE indices came into existence in the 2000s, and as the time-period for this study includes the 1990s, there is a possibility that the LPE sample excludes LPEs that were active during this period but which failed to survive through to the 2000s, thus introducing a potential survivorship bias. To identify and quantify the extent of any survivorship bias, I examine company and transaction details in the CapitalIQ database[6]. I find that the LPEs which drove the vast majority of buyout transactions during the 1990s are already included in my sample. Not surprisingly, given the dot-com boom and bust, 74% of the LPEs that were active in the 1990s but failed to survive through to the mid-2000s are venture LPEs. Only one firm not included in the LPE sample made mezzanine investments during the 1990s and has since exited. Thus there may be a bit of survivorship bias in the final sample for venture LPEs, but buyout and mezzanine should be robust.

[Table I about here.]

Summary statistics are provided in Table I. While the LPE universe comprises 194 firms and funds, the LPE sample used in this study (public financial entities, excluding infrastructure, that are included on LPE indices) comprises 124 firms and funds. Using information hand-collected from LPE websites and annual reports, the sample is broken down into subsamples according to the activity of the LPE using the categorization outlined by Bergmann et al. (2009): Buyout, Mezzanine, Venture, Funds-of-Funds (FoF). I also give summary statistics for GPs, but I do not include them in the persistence tests. The period of the study is January 1st 1990 through to December 31st 2015. Monthly prices and annual asset values are retrieved from Datastream. I use US dollar denominated currency values throughout the

[6]I create the following screens in CapitalIQ: a) leveraged buyout and management buyout transactions by public investment companies and public funds in the 1990s; b) public investment companies and public funds that made private placements of venture capital or growth/PE capital during the 1990s and that subsequently went out of business or were acquired. 29 of a total of 41 LPE exits were Venture LPEs; c) public investment companies and public funds that have the keyword "mezzanine" in their business description and that closed transactions in the 1990s.

paper, which presumes that investors can costlessly hedge deviations from purchasing power parity, or can ignore such deviations.

A Fama-French-Carhart 4-factor model (using market, size, value and momentum factors) is used to compute risk-adjusted monthly excess returns (alpha). As the sample is an international one, I first evaluate the fit of 6 different sets of international factors. I use 4 sets of factors (Global, Global ex-US, North American, European) downloaded from Ken French's website, and also UK factors from Gregory, Tharyan, and Christidis (2013), and French's North American factors plus a Liquidity factor downloaded from Ľuboš Pástor's website. In each case the 1-month US Treasury bill is used as the risk-free rate. The results of the factor regressions and their R^2 estimates are provided in Table II. The Global factors have the greatest explanatory power (largest R^2 value), and thus I use these for the tests which follow.

[Table II about here.]

[Table III about here.]

The alpha and factor coefficients for the 4-factor regression of the full LPE sample and each of the four subsamples are presented in Table III. Excess returns are positive for all samples and significant at the 5% level for the full LPE sample and for the Buyout and Mezzanine subsamples. Venture LPEs have the highest market factor loading which is unsurprising given that these LPEs invest in highly risky assets; they also have the highest positive loading on size (SMB) and the highest negative loading on value (HML) factors, which is again intuitive as Venture LPEs invest in high-growth businesses that tend to be smaller and valued at a large premium to their asset values. Buyout LPEs have a market factor loading of about 1 and positive loadings on size and value. Mezzanine and Funds of Funds LPEs have the smallest market factor loadings, suggesting these are the least risky LPEs. All subsamples load negatively on the momentum factor (WML). The constant (alpha) is positive for all subsamples and is statistically significant at the 10% level for the full sample, and for Venture.

LPEs potentially provide liquidity benefits to investors because the underlying PE investments are illiquid. My estimates of alpha incorporate any illiquidity premium earned by the LPEs' underlying unlisted PE investments that is not captured by a risk premium associated with the factor loadings.

My paper may be viewed as a follow-on to Jegadeesh et al. (2015) who use LPE to infer risk and returns to unlisted PE. My LPE sample differs somewhat from theirs in that I use stocks of both public limited companies and closed-end funds that are included in major LPE indices (and thus meet minimum stock liquidity requirements), whereas they focus on LPEs that are organized as funds and that are not necessarily listed on LPE indices. I repeat the 4-factor regression with the subsample of my dataset that most closely matches that of Jegadeesh *et al* (i.e. just closed-end funds, for the period 1994-2008, using value-weighted portfolios, and North American factors). I find very similar factor loadings to those reported in Table 6 of Jegadeesh *et al*.

IV. Short-term Persistence

In this section, I measure LPE persistence up to one year out following Carhart (1997), and following Chay and Trzcinka (1999) I measure how well the NAV premium for LPEs predicts NAV changes one year later.

A. Carhart (1997)

Using the LPE sample, I reproduce Table III ("Portfolios of Mutual Funds Formed on Lagged 1-Year Return") from Carhart (1997)'s landmark study of mutual fund persistence. The test is performed twice, for price returns and for NAV returns.

Using price returns, stocks are grouped by returns over a 12-month formation period (following the standard practice of skipping the most recent month to avoid short-term microstructure effects) to create 5 equal-weighted quintile portfolios. I use overlapping periods to increase the number of observations. The portfolios are then held for 12 months and the holding period price return is calculated. A 4-factor Fama-French-Carhart model is estimated for each of the quintile portfolios, and for the winner-minus-loser (5-1) portfolio. The constant (alpha) from these regressions measures the manager's contribution to performance. The alpha for the winner-minus-loser portfolio thus represents the difference in contribution between skilled and unskilled managers.

[Table IV about here.]

[Table IV about here.]

The excess price returns and factor coefficients for the quintile and winner-minus-loser (5-1) portfolios are provided in Table IV. Results are provided for the full LPE sample, and for the Buyout, Mezzanine, Funds-of-Funds and Venture subsamples. As the regressions use overlapping monthly returns, so the number of lags for the Newey-West standard errors equals the overlap in the dependent returns. The excess return for the 5-1 portfolio can be interpreted as a measure of persistence, the 4-factor alpha as a measure of skill, ie the return achieved by winner LPEs in excess of the losers that is not explained by common risk factors. Only Buyout LPEs achieve positive and significant persistence and skill. For the other subsamples, the 5-1 alpha is positive but not significant.

I repeat the procedure using NAV returns. Stocks are grouped by past one year NAV return to create equal-weighted tercile portfolios, and the NAV return for each portfolio for the following year is estimated. NAV is measured for each firm fiscal year as total assets minus total liabilities. Datastream[7] report balance sheet information on an annual basis, so the number of NAV observations available is smaller than for price returns, so I create three portfolios for NAV instead of five.

The results are reported in Table V. The winner-minus-loser (3-1) spread is positive for all subsamples except Venture, ranging from 6% per year for Funds of Funds to almost 9% per

[7]Bloomberg provide quarterly balance sheet information, but data is missing for some firms.

year for Mezzanine LPEs, and is statistically significant for Buyouts (at the 5% level) and for Mezzanine (at the 1% level). The negative 3-1 NAV return for Venture seems economically large (-16%), but is statistically insignificant.

Two key findings emerge from these tests. The first is that Buyout LPEs clearly demonstrate short-term persistence, showing up with significant winner-minus-loser returns in both the price-return and NAV-return tests. The second is that Mezzanine LPEs have large and statistically significant winner-minus-loser NAV returns, suggesting that these LPEs are truly skilled (or unskilled), however this persistence vanishes in the price-return test. This apparent puzzle is discussed further in Section VII.

[Table V about here.]

B. Chay and Trzcinka (1999)

The studies by Chay and Trzcinka (1999) and Berk and Stanton (2007) show that the NAV premium (the difference between the NAV per share and the share price) for closed-end funds predicts future NAV returns. Specifically, Chay and Trzcinka (1999) present empirical evidence that there is a significant and positive relation between NAV premia and NAV performance over the following year. In other words, NAV premia reflect the market's assessment of anticipated managerial performance. Chay and Trzcinka (1999)'s finding holds for funds that hold equities but not for funds that hold bonds (debt), and is robust to fund fees.

Following Chay and Trzcinka (1999), I show that the NAV premium for LPEs is a good predictor of future NAV returns. LPEs are grouped each year by their NAV premium into 3 portfolios. For each portfolio I estimate the average NAV premium and the average NAV return one year later. The results are presented in Table VI. The pattern is clear: portfolio 3 comprises the LPEs with the largest NAV premium, and for every subsample (except Funds of Funds), the average NAV return one year later for portfolio 3 is higher than for the other portfolios. Similarly, for portfolio 1 which comprises LPEs with the smallest NAV premium, the NAV return one year later is smaller than for the other portfolios for all subsamples (except FoFs).

For Funds-of-Funds, the opposite effect is evident - FoFs with the largest NAV premium have the smallest NAV changes one year later (and *vice versa*). FoFs hold LP positions in unlisted private equity funds, so it may be the case that FoF investors have difficulty discerning the future performance of these underlying PE funds and thus can not adjust the NAV premium accordingly.

[Table VI about here.]

V. Separating Skill from Luck

In the previous section, I present results for tests of short-term persistence where returns from one 1-year period are compared with returns from the following 1-year period. While the results of these tests are interesting and informative, they do not necessarily separate skilled LPEs from those that may just be lucky. For example, Carhart (1997) suggests that mutual fund managers that have strong short-term persistence hold momentum stocks, but they are not following a momentum strategy - these funds must just be holding momentum stocks by accident. In this section I implement two tests that aim to separate luck from skill for LPEs to give a true measure of long-term persistence.

A. Kosowski et al. (2006)

To separate skill from luck, Kosowski et al. (2006) use a bootstrapping approach that uses the existing sample of fund returns to generate 1000 new samples of pseudo-funds whose true alpha is zero by construction. This cross-sectional bootstrapped zero-alpha distribution captures the case where all funds have equal skill, but some funds may have significant alpha by luck alone. They estimate the number of pseudo-funds that have significant alpha in each of the 1000 bootstrap samples and take the average - this is the number of pseudo-funds that have significant alpha by luck alone. They compare this estimate with the number of real funds in their original sample that have significant alpha. They find that the number of actual funds with significant alpha exceeds the number that have significant alpha by luck alone. They conclude that funds do not all have equal skill; some funds are truly skilled and some are truly unskilled.

Applying their test to my LPE sample, I generate 1000 bootstrap samples of pseudo-LPEs which have zero alpha by construction. I find that the actual alpha is greater than zero for 75 LPEs in my original sample, while in the 1000 bootstrap samples, the average number of pseudo-LPEs that have alpha greater than zero is 57. Thus 18 LPEs, about 16% of the actual LPE sample, are truly skilled. On the other hand, 39 LPEs in the actual sample have negative alpha, compared with an average of 57 pseudo-LPEs in the bootstrap samples. Figure 1 illustrates the results graphically.

[Figure 1 about here.]

[Table VII about here.]

Furthermore, Kosowski *et al* estimate cross-sectional bootstrap p-values for individual LPEs at specific percentiles of the actual distribution. For example, a cross-sectional bootstrap p-value of 0.04 at the 80th alpha percentile means that the alpha of the pseudo-LPE at the 80th alpha percentile for 40 of the 1000 bootstrap samples is greater than the alpha of the actual LPE at that alpha percentile. Estimating the p-value in this way overcomes the assumption of normality that is associated with p-values which are calculated parametrically.

Table VII details the distribution of alpha (Panel A) and the t-statistics of alpha (Panel B) for the LPE sample. Looking at the bootstrap p-values for the right-tail (alpha percentiles 60 to 99), for the full sample, there is evidence of skill; for example, the LPE at the 80th alpha percentile has an alpha of 0.96 which is not statistically significant using the normal parametric p-value (0.14) but has a statistically significant bootstrap p-value (0.04). Buyout LPE alphas have significant bootstrap p-values above the 90th alpha percentile, while for

Mezzanine LPEs, the alphas are significant at the 60th alpha percentile and above. For Venture LPEs the non-normality of returns is evident in that for the LPEs at the 60th, 70th and 80th alpha percentile, the bootstrap p-values are significant, but not at the higher percentiles. For Funds-of-Funds the alphas are not significant except at the 99th percentile.

Looking at the left tail (alpha percentiles 1 to 40), for the full sample, non-normality is even more starkly evident in that none of the LPEs have significant bootstrap p-values. This is in contrast to the parametric normal p-values which are highly significant below the 5th alpha percentile. For each of the subsamples, only the LPE fund at the extreme 1st alpha percentile is significantly negative using the bootstrap p-value.

The results also give insights into the long-term returns to investors who can identity skilled LPEs. For the full sample, there is a difference of over 1.2% per month between the alpha of the LPE at the 80th percentile and the alpha of the LPE at the 20th percentile. For Buyouts the difference is over 1%, for Mezzanine it is about 0.9%, it is over 1.2% for Venture, and 0.7% for FoFs.

Using the t-statistic of alpha instead of just alpha as the skill measure allows for cross-sectional variation in risk-taking by LPEs, and also for survivorship bias in the sample. The picture for the t-statistics (Panel B of Table VII) of the LPE alpha is similar to that for the alpha. Bootstrap p-values are significant throughout the right tail for Buyout and Mezzanine LPEs, but not so much for Venture or Funds-of-Funds, while in the left tail it is only in the extreme tail that alpha t-statistics become significantly negative.

Overall, the Kosowski *et al* test shows that Buyout and Mezzanine LPEs earn significantly positive 4-factor alpha, much more than would be expected if the true alpha (or t-statistic for the alpha) for these LPEs was zero. Furthermore LPE returns do not follow a normal distribution.

[Figure 2 about here.]

B. *Barras et al. (2010)*

Barras et al. (2010) use another technique to separate skilled funds from lucky ones using a simple statistical methodology, the False Discovery Rate (FDR), developed by Storey (2002).

The False Discovery Rate can be somewhat intuitively explained as follows. Consider a 10-bar histogram of p-values, the height of each bar representing the proportion of LPEs in the sample with p-values in the range 0 to 0.1, 0.1 to 0.2,..., 0.9 to 1. Figure 2 presents the histogram of Buyout LPE p-values. If the true alpha of all LPEs was zero, then the distribution of p-values in the sample would be uniform and all the bars would have equal height. Even if the true alpha of all LPEs is not zero (the bars have different heights), the LPEs with p-values closer to 1 are still highly likely be true zero-alpha LPEs. Therefore by estimating the average height of the bars for p-values above a certain value λ, 0.5 say, it can be inferred that this average height is a reasonable estimate of the proportion (height) π_0 of zero-alpha funds in all bars. Then for the LPEs with p-values representing LPEs with alpha that is significant at a particular level γ, say 10% (represented by the bar for 0 to 0.1 in the histogram), subtracting π_0 from the total height of the bar gives the proportion of truly skilled or truly unskilled funds $T_{\gamma=0.1}$.

The value for λ can be chosen using a bootstrapping technique described by Barras et al. (2010), although they also suggest that any value in the range 0.3 to 0.7 should produce reasonable results. The significance level γ used to estimate the number of LPEs with significant alpha can also be chosen using a bootstrapping technique. The proportion of truly skilled LPEs π_+ can be estimated as the proportion S^+ of LPEs with t-statistics greater than the t-statistic for the chosen significance level γ, less the proportion of lucky zero-alpha LPEs ($\pi_+ = S^+ - \pi_0 * \gamma/2$). The proportion of truly unskilled LPEs π_- can be calculated in a similar manner, as the proportion S^- of LPEs with t-statistics less than the negative of the t-statistic for the chosen significance level γ, less the proportion of unlucky zero-alpha LPEs ($\pi_- = S^- - \pi_0 * \gamma/2$). See Barras et al. (2010) for further implementation details.

[Table VIII about here.]

Table VIII gives the proportion of zero-alpha LPEs π_0, the proportion of truly skilled LPEs π_+ and the proportion of truly unskilled LPEs π_- for the various LPE samples. For the full sample, 94% of the LPEs are zero-alpha, 4% are truly skilled and 2% are truly unskilled. The Buyout subsample has the lowest proportion of zero-alpha LPEs 78%, 13% of the subsample are truly skilled and 9% are truly unskilled. Zero-alpha LPEs account for 88% of the Mezzanine subsample, and 11% are truly skilled and 1% are truly unskilled. For Venture and Funds-of-Funds LPEs, practically all LPEs are zero-alpha with virtually no truly skilled or unskilled LPEs.

The results for the False Discovery Rate test are consistent with my previous findings in that skill is evident for Buyout and Mezzanine LPEs, and the proportion of truly unskilled LPEs is small.

C. Berk and van Binsbergen (2015)

For the final test of LPE skill, I consider the ideas proposed by Berk and van Binsbergen (2015). They assert that abnormal returns are not a true measure of investment manager skill, arguing that alpha is evidence of market inefficiency if it is positive or investor irrationality if it is negative. Instead they propose that a better measure of skill is the dollar value that the manager extracts from the market. For mutual funds, for example, they conclude that the average manager extracts $3.2 million per year. Their findings reject the hypotheses that no managers are skilled, or that the average fund manager is unskilled.

Berk and van Binsbergen (2015) define their mutual fund skill measure, which they call value-added, as the product of the fund's assets under management and its gross alpha. Following Berk & van Binsbergen, I estimate the alpha earned each year by each LPE as the annual return for the LPE in excess of its benchmark return. The benchmark return for an LPE is the systematic risk component of its return, estimated using 4-factor Fama-French-Carhart portfolios. The LPE alpha is net alpha in that price returns reflect all fees incurred by the LPE, so the LPE value-added will underestimate somewhat the true value-added. I then estimate LPE value-added as follows: each year t, for each LPE, the total assets of the LPE in year $t-1$ is multiplied by its alpha in year t; value-added for the LPE is the mean annual value of this product. Berk and van Binsbergen (2015) compute the cross-sectional mean value-added as the average value-added of all funds, and the cross-sectional weighted mean value-added as the mean value-added of surviving funds (i.e. the average value-added is estimated by weighting each fund by the number of periods that it appears in the sample).

Table IX gives the results for the LPE samples. The cross-sectional distribution of value-added is clearly skewed with large extreme values, and in this situation the median is often considered a more robust measure of the central tendency (von Hippel (2005)). The median value-added for all LPEs is about $16 million per year. For the LPE subsamples, Mezzanine LPEs have the largest cross-sectional median value-added ($42 million per year), and the cross-sectional weighted median is also large ($34 million). Venture LPEs have the lowest cross-sectional median value-added ($1.3 million per year or $1.9 million cross-sectional weighted). For Buyout LPEs, the unweighted median value-added is $8 million, and the weighted value-added is $11 million. Funds-of-Funds have the second largest cross-sectional median value-added of about $18 million per year ($21 million weighted median).

[Table IX about here.]

These results suggest that LPEs overall exhibit skill by generating positive value-added, and Mezzanine LPEs are the most skilled in that they generate the largest amount of value-added. Somewhat surprisingly, the value-added for FoF LPEs is the next highest. Buyout LPEs also generate large positive value-added.

VI. Robustness Checks

The previous two sections present results for five tests which differ significantly from each other in their approach (winner-minus-loser return, cross-sectional bootstrap, false discovery rate, value-added), their timeframe (short-term, long-term), the skill metric used (NAV, NAV premium, alpha, t-statistic of alpha, dollar value-added), and the structure of the data (portfolios, individual stocks). Thus each of the tests provides an independent view of LPE persistence, and taken together they paint a consistent and complementary picture. Nonetheless, I outline in this section a range of further checks to ensure that the persistence test results are robust to a number of alternative specifications and interpretations.

A. Short-term Post-IPO Performance

Weiss (1989) show that there is a consistent and substantial decline in NAV premiums following the IPO of a closed-end fund. To control for any possible impact of such a decline in my LPE sample, I follow Jegadeesh et al. (2015) and rerun the tests that use NAV returns as the skill measure, omitting the NAV return for the first year that the LPE appears in my dataset. The results for the Carhart test using NAV returns and for the Chay&Trczinka test do not change significantly, and the findings described in Section IV above are unaffected.

B. Value-weighted Portfolios

In Table II in Section III, I present the R^2 estimates for equal-weighted portfolios of LPEs regressed on 6 different sets of international factors. Global factors have the highest R^2 value (0.71) so these factors are used in the persistence tests. However, using value-weighted LPE portfolios could yield a different result. To evaluate the possible benefits of using value-weighted portfolios instead of equal-weight ones, I repeat the six regressions in Table II using value-weighted portfolios. The R^2 value drops significantly for all specifications. The Global ex-US factors have the largest R^2 value (0.55) with the value-weighted portfolios, which is significantly smaller than the R^2 for the regression using Global factors and equal-weight portfolios. Therefore, given the much larger explanatory power of the equal-weight portfolios with the Global factors, using this combination for the persistence tests seems justified.

C. Fama-French Cross-Sectional Bootstrap

Fama and French (2010) implement a cross-sectional bootstrap procedure that differs in a number of aspects to that used by Kosowski et al. (2006). Kosowski *et al* regress their zero-alpha pseudo-LPE returns on the same historical sequence of explanatory returns. Fama&French, on the other hand, randomly select (with replacement) the sequence of months to use in a bootstrap sample, and use the same monthly sequence for all funds. They then regress the zero-alpha pseudo-LPE return for those months on the explanatory factor returns for those same months. The advantage of this approach, they argue, is that it preserves cross-correlation that arises in the estimates of the alphas of different funds. The disadvantage is that the number of months for a fund in a simulation run does not always match the fund's actual number of months of returns.

However, applying the Fama-French version of the cross-sectional bootstrap to the LPE sample, using t-statistic of alpha as the skill measure, yields similar bootstrap p-values to the original Kosowski *et al* methodology. If anything, the bootstrap p-values are marginally smaller using the Fama-French approach; e.g. for Mezzanine LPEs, the 90% bootstrap p-value is 0.07 using the Kosowski approach, and 0.06 using the Fama-French approach.

D. Changes Over Time

Table X gives a picture of changes in short-term LPE skill during the sample period (1990-2015) using the Carhart winner-minus-loser portfolio 4-factor alpha as the skill measure. Overall, short-term LPE skill has been weakest during the financial crisis (2005-2010) and strongest in the period following it (2010-2015). The largest skill measure for Buyout and

Venture LPEs was recorded in the period 2000-2005, but for the 2010-2016 Venture skill is negative and not statistically significant while for Buyouts it is positive and significant. Mezzanine LPEs were uncommon before 2005, and 2005-2010 they recorded negative short-term skill; however since 2010 skilled Mezzanine LPEs strongly outperformed unskilled ones in terms of both the magnitude and significance of returns. Skilled FoFs did relatively well in the 1990s, but did poorly in the 2000s. Since 2010 skilled FoFs again outpaced unskilled one by a significant margin.

[Table X about here.]

VII. Discussion

Overall, the tests detailed in the previous sections paint a consistent picture. There is substantial evidence of skill for LPE, irrespective of which measure of skill is used. In the tests of short-term persistence, the Carhart winner-minus-loser alpha is significant for Buyout and Mezzanine LPEs; furthermore investors appear to be able to identify LPEs with short-term skill and adjust the NAV premium accordingly. The tests for long-term skill by Kosowski *et al* and Barras *et al* show that more Buyout and Mezzanine LPEs demonstrate skill than could be expected if all LPEs had the same level of skill but some happened to be luckier than others. Finally, LPEs, particularly Mezzanine LPEs, generate significant and positive value over and above a 4-factor benchmark.

Buyout and Mezzanine LPEs dominate most of the skill measures. Venture LPEs seem to have little or no skill, either in the short- or long-term. This finding is consistent with research for unlisted PE such as that of Korteweg and Sorensen (2015). They find that Buyout PE funds show the largest skill differences, implying the greatest long-term persistence, and Venture PE performance is noisy implying the smallest amount of investable persistence.The evidence for skill by Fund-of-Funds LPEs is mixed. The short-term tests for FoF s do not yield significant results overall, but this may be due to FoF weakness during the 2000-2010 period. FoFs exhibit positive and significant short-term skill in the 1990s and in the 2010-2015 period. In the long-term tests, FoFs do not perform well, but in the value-added test they achieve the second highest score after Mezzanine LPEs.

The changes in short-term skill over time yield an interesting insight. A number of studies of unlisted PE persistence, including Harris et al. (2014a) and Braun et al. (2015) find that Buyout PE persistence declined after 2000. Braun *e*t al interpret this decline as a symptom of the increasing competition for deals and evidence of the commoditization and maturing of the PE asset class. My findings confirm this trend for Buyout LPE, short-term persistence was weak in the period 2000-2010, disappearing completely in 2005-2010. However in the 2010-2015 period, Buyout LPE persistence recovered strongly. Thus competition for Buyout deals may have declined significantly since 2005-2010 enabling skilled LPEs to differentiate themselves from unskilled ones.

Two of the tests for short-term persistence use changes in LPE NAV as a measure of LPE skill. However NAV is an estimate by the LPE of the fair value of the assets in its portfolio, and fair value accounting is a controversial topic especially since the financial crisis. Thus, some researchers may choose to be cautious in interpreting the results of tests which use reported NAVs. However recent research on unlisted PE NAV reporting by Jenkinson, Landsman, Rountree, and Soonawalla (2015) suggest that reported NAVs are extremely good predictors of future economic performance, and thus are relatively unbiased indicators of the fund's true economic value. There is little reason to believe this is not also the case for LPEs.

A notable finding in my tests is that relatively few LPEs are truly unskilled. Barras et al. (2010) find that the negative returns to active mutual fund management are driven by a surprisingly large number of truly unskilled funds, but this is not the case for LPEs. The test by Kosowski *et al* indicates that there are about 31% fewer LPEs in the full sample with negative alpha than would be expected if the true alpha of the LPEs in the sample was zero, while the Barras *et al* test shows that the proportion of truly unskilled LPEs is about half that of skilled ones.

A number of inconsistencies or puzzles surface in the tests. In the Carhart tests for short-term persistence, the winner-minus-loser alpha using price returns for Mezzanine funds is not statistically significant, while using NAV returns it is very significant. The sample period for the Mezzanine LPEs used in this test (2002-2015) envelopes the financial crisis, so perhaps it may be that their short-term price returns were particularly noisy during this time, thus confounding the test. This explanation stands up if the results from the tests which separate luck from skill are considered, where it is evident that many Mezzanine LPEs demonstrate true skill rather than luck.

Another puzzle arises in the Chay&Trczinka test where the size of NAV premia for Buyout, Mezzanine and Venture LPE subsamples predict the size of future NAV returns, but for Funds-of-Funds almost the reverse effect is observed: the larger the FoF NAV premium in year t, the smaller the change in NAV one year later. It may be that investors are simply not able to predict future NAV changes for unlisted PE funds. This explanation would be consistent with Korteweg and Sorensen (2015) who find little evidence of what they call investable persistence in unlisted PE, that is, the PE persistence that investors can identify and trade on. They show that investors would need to be able to observe the returns for an inordinate number of PE funds raised by the same firm to determine if the firm is truly skilled.

The cross-sectional bootstrap and False Discovery Rate tests yield puzzle-free results, but the value-added test poses one last surprise. As in all the previously discussed tests, Buyout and Mezzanine LPEs both perform well, and in this test this is also the case, but surprisingly FoF LPEs also perform well. If FoFs are skilled in that they add substantial value, why is this skill not also apparent in the tests that use price or NAV returns? This could be an interesting question for future research.

A. Future Research

That net-of-fee outperformance by both PE and LPE is not competed away by investors runs contrary to the prediction by Berk and Green (2004), who argue that rents should accrue fully to the manager. Korteweg and Sorensen (2015) posit that skilled PE firms are scarce, but investors with the ability to identify these skilled firms may also be scarce, therefore these skilled investors should earn rents. Another explanation may lie in the nature of the managerial contracts held by PE firms and LPEs. In their study of CEFs, Berk and Stanton (2007) model three types of manager contract - a short term contract (the manager's pay continuously adjusts so that his fee always equals the value he adds), a long-term contract (the manager's fee is a constant fraction of assets under management and the manager commits never to leave the fund) and an insurance contract (which is like a long-term contract, but the manager can capture the benefit he provides by negotiating a pay increase). In the Berk&Stanton model, the NAV is fixed at the amount of funds raised in the IPO, and, given a fixed dividend rate, long-term returns are driven by increases in the NAV premium. NAV premiums (or discounts) arise due to investor assessment of manager skill and investor expectations of manager fees. Under the short-term contract, investors expect the manager to adjust fees instantaneously to capture any rents generated by his skills, so investors set the NAV premium to zero. Under the long-term contract, investors do not expect the manager to adjust fees, so they allow the NAV premium to monotonically increase in ability: funds with good managers trade at large premia, and funds with bad managers trade for discounts. For the insurance contract, the relation between ability and the premium is monotonic, up to a point. Very high ability does not translate into very high long-term returns because investors believe that for these very skilled managers, there is a higher likelihood that the manager will increase his fees, either now or in the near future. In this case investors cause the NAV premium (and hence returns) to fall.

Applying Berk&Stanton's interpretation to the evidence presented in this paper, managerial contracts used by LPEs are sufficiently long-term, or the skill threshold at which managers demand fee increases is sufficiently high, or both, to allow investors that can identify skilled firms or funds to earn rents. For LPEs, the form of the managerial contract is inextricably linked to the organization structure chosen by the LPE. LPEs organized as public limited companies have different managerial contracts from those organized as funds; and LPE funds that are externally managed (that is, the fund's board outsources the investment activities of the fund to an external investment manager) have different managerial contracts compared to LPE funds that are internally managed. Furthermore, the domicile of the LPE may also be a factor - for example, fees incurred by regulated CEFs may be subject to local government regulations (as is the case for LPEs domiciled in the United States). Hence LPEs of equal skill, but differing organization structure or domicile, may have different fees according to the norms and regulations governing their chosen structure or domicile. Thus a hypothesis that could be examined further in future research is that these organizational and regional norms (frictions) may limit LPE flexibility around adjusting fees in order to capture rents, leaving some net alpha on the table for investors that can identify skilled LPEs.

Other areas for future research could include identifying the channels through which skilled LPEs differentiate themselves from unskilled ones. It could be that skilled LPEs hold their investments for a longer period, or they are located in a particular geographical region, or focus on particular industries. Also, differences in organizational structure could lead to variation in performance between LPEs organized as closed-end funds or as public limited companies - legal restrictions on leverage, distributions, fees, and diversification of LPEs organized as closed-end funds could impact their performance. This line of investigation could be extended to include a comparison of LPE and unlisted PE performance. Because unlisted PE funds have a finite life, the GP must approach investors periodically to raise money for the next generation of unlisted PE funds. These ongoing interactions create pressures (cf Arcot, Fluck, Gaspar, and Hege (2015)) that could potentially differentiate unlisted PE fund performance from LPE performance.

VIII. Conclusions

It is clear that LPE is a relatively unexplored dataset that has significant potential to shed new light on many contentious issues regarding PE generally. LPE is gaining increasing acceptance as being representative of the PE universe. Traditional PE research is hampered by data integrity issues, such as self-reported returns by investors and fund managers. Using market data which are readily available for LPE firms and funds help overcome many of the data integrity problems.

The main contribution of this study is to use LPE to address a common question in private equity research: do fund managers have skill. The closed-end fund nature of LPE means that robust tests for persistence and skill developed in the closed-end and mutual fund literature can be applied, including tests from Carhart (1997), Chay and Trzcinka (1999), Kosowski et al. (2006), Barras et al. (2010) and Berk and van Binsbergen (2015). These tests overcome methodological issues, such as AR(1) convergence, which arise in tests of persistence used in many previous studies of traditional private equity.

In the short-term, Buyout and Mezzanine LPEs exhibit skill, in that skilled LPEs in these categories persistently achieve the largest increases in their firm's net asset values. Nonetheless investors for all LPE categories (except Funds-of-Funds) are able to set the NAV premium for LPEs in anticipation of managerial performance. Funds-of-Funds investors do not seem to be able to anticipate managerial performance in the same way, perhaps because they have difficulty assessing the future performance of the underlying unlisted private equity fund holdings for these LPEs.

Short-term persistence tests are informative, but suffer from the disadvantage that they are noisy and may confound skill and luck. Long-term tests that separate skill from luck have appeared in recent mutual fund literature, and applying two of them to my LPE sample confirms that there is large cross-sectional variation in LPE skill. By these measures, Buyout and Mezzanine LPEs again perform well, and significant proportions of these LPEs have alphas that are truly different from zero. Finally, Mezzanine and Buyout LPEs, along with FoFs, generate large value-added.

However Berk and van Binsbergen (2015) suggest that while their value-added measure is a true measure of skill, it may be of little use to investors - skilled managers simply adjust their fees to capture all the rents generated by their skill, leaving investors with little or no net alpha. For mutual funds there is evidence that net alpha may be close to zero, but the tests reported here show that substantial net alpha exists for LPE. Berk *et al* would probably argue that this is the result of (possibly temporary) market inefficiency, however the results for the tests separating skill from luck, which are essentially tests of longer-term skill, suggest that LPE alphas are not a short-term effect. Korteweg and Sorensen (2015) measure long-term persistence in traditional unlisted PE, and their results are similar to mine. They too find substantial evidence of long-term persistence for PE, but this persistence is not investable as it is difficult for investors to identify skilled PE firms. Therefore, they hypothesize that the small number of investors with the ability to identify skilled PE firms should earn rents. Another possible explanation why investors may earn rents lies in the managerial contracts used by PE firms and LPEs. In their model of CEFs, Berk and Stanton (2007) show that the performance of a CEF increases monotonically in the skill of the CEF manager, provided the manager commits to a long-term contract with fixed fees. Managerial contracts used by PE firms and LPEs may be sufficiently long-term, or the skill threshold at which managers demand fee increases may be sufficiently high, or both, to allow investors that can identify skilled firms or funds to earn rents. Future research could examine what frictions, if any, affect the adjustment of PE and LPE fees.

While LPE is accepted as representative of the PE universe, precisely identifying and quantifying the advantages and disadvantages of the traditional PE model versus the LPE model is another area for future research. Jensen (2007) raises concerns about giving PE firms permanent public capital (in other words, listed private equity). He argues that, as traditional PE firms have their reputations on the line, are forced to repay investors, and must regularly raise new funds, they are incentivized to do good deals and make them work. He fears that these incentives would be weakened or lost in LPE. However recent research (such as that by Arcot et al. (2015)) shows that the traditional PE model also puts PE firms under pressure to make deals, even if they are bad. Unlike traditional PE fund managers, LPEs have considerable flexibility in timing the entry and exit of their deals, and this may allow skilled LPEs to differentiate themselves from unskilled ones in a way that skilled traditional PE fund managers cannot. The flexibility of the LPE model may enable skilled LPEs perform better, or unskilled LPEs perform worse, or both, than would be possible in the traditional PE model.

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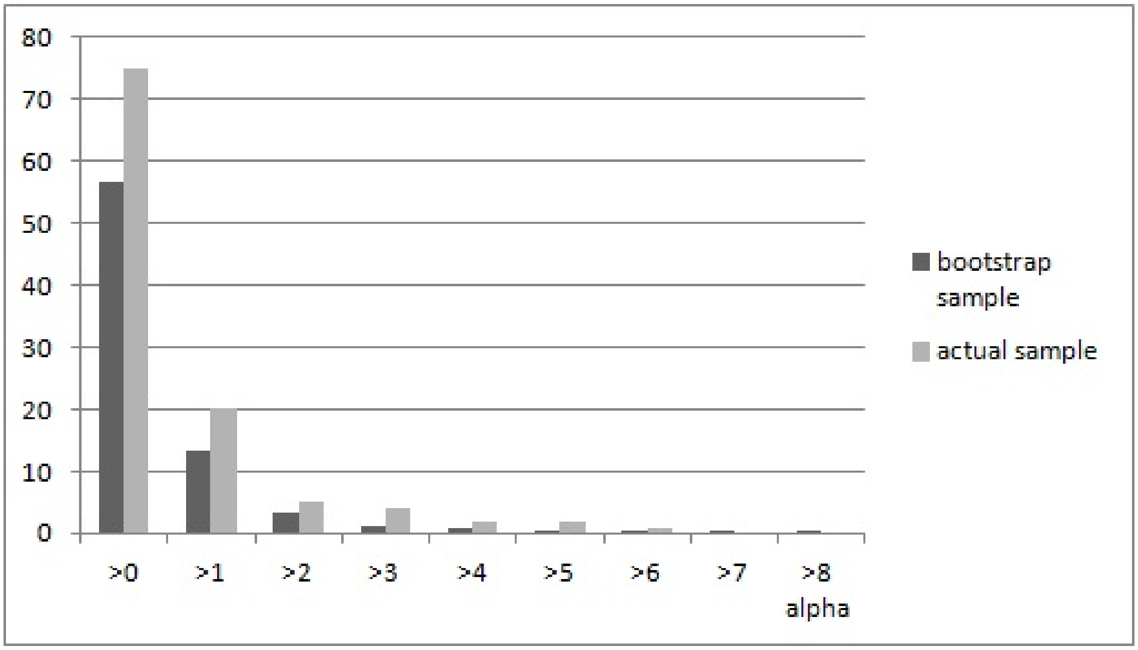
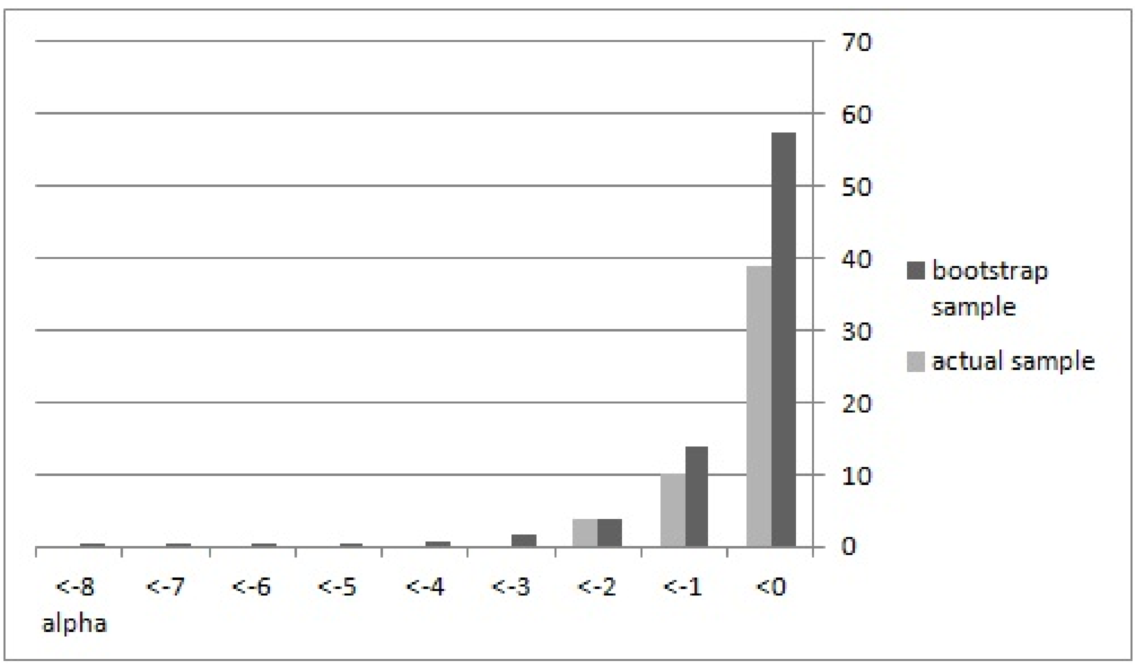


(a) Positive alpha count



(b) Negative alpha count

Figure 1. Funds above and below certain alpha levels

This figure presents the number of funds from the actual and the bootstrapped cross-sectional distributions (as vertical bars) that surpass (Panel A) or lie below (Panel B) various unconditional four-factor alpha levels.

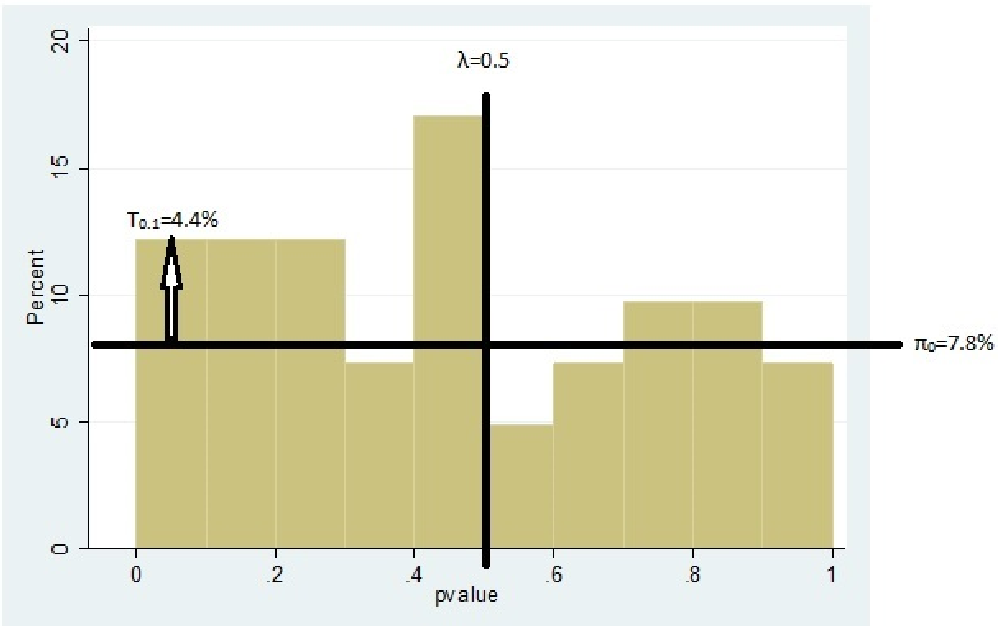


Figure 2. False Discovery Rate - Buyout LPEs

This figure presents a histogram of the p-values for Buyout LPEs. The proportion of true zero-alpha LPEs in the sample π_0 *is estimated as the mean height of the bars to the right of the line indicated by* λ*.* $T_{0.1}$ *is the number of truly skilled (or unskilled) LPEs where the significance level* γ *is 10%, and is estimated as the height of the first bar minus* π_0*.*

Table I LPE Summary Statistics

This table presents summary statistics including firm/fund count and asset values for Listed Private Equity. The LPE Universe consists of the constituents of the S&P Listed Private Equity index, Société Générale Privex index, and the ALPS-RedRocks Global Listed Private Equity index, and also SEC registered Business Development Companies in the US, and private equity Investment Trusts that are members of the AIC in the UK. The final LPE sample used in the study is a subset of the LPE Universe that includes all index-listed stocks, excluding non-financials and infrastructure. LPEs in the final sample are classified by type: Buyout, Mezzanine, Venture, Funds-of-Funds (FoF) and General Partners (GPs); and by region United States & Canada, Europe, Rest of World (RoW); and by structure: public limited companies (PLCs), closed-end funds (CEFs). Total (Net) Assets are the sum of the total (net) assets of all LPEs as of 31 December, 2014. The Net Assets of an LPE are estimated as its Total Assets minus its Total Liabilities (i.e. Total Shareholder Equity).

	LPE Universe	LPE Sample	Buyout	Mezzanine	Venture	FoF	GP	PLCs	CEFs
Count	193	114	41	26	16	25	6	68	46
US & Canada	83	32	4	22	3	0	3	6	25
Europe	98	75	34	4	11	23	3	52	23
RoW	12	7	3	0	2	2	0	7	0
PLCs	102	68	29	4	14	14	6		
CEFs	91	46	12	22	2	11	0		
Net Assets ($millions, 2014)	366,744	166,465	26,756	26,756	5,407	10,234	89,064	74,580	91,884
Total Assets ($millions, 2014)	956,764	308,904	90,501	45,928	6,425	10,811	155,749	182,479	126,424

Table II Regional Factor R^2 Estimates

This table presents the coefficients and adjusted R^2 statistics for regressions of the excess returns for an equal-weight portfolio consisting of the full LPE sample stocks on regional factors for market (RMRF), size (SMB), value (HML) and momentum (WML) risk. The Global, Global ex-US, North American, and European factors are from Ken French's website. The UK factors are from Gregory et al. (2013). The liquidity factor (LIQ) is from Lubos Pastors Research website. The 1-month US Treasury bill is used as the risk-free rate. t-statistics using robust standard errors are in parentheses.

	RMRF	SMB	HML	WML	LIQ	Constant	Adj R^2
Global Factors	1.094	0.773	-0.086	-0.082		0.457	0.715
	(12.75)	(6.13)	(-0.59)	(-0.62)		(2.20)	
Global ex-US Factors	0.989	0.40	-0.34	0.007		0.731	0.656
	(15.65)	(3.25)	(-1.88)	0.24		(3.13)	
European Factors	1.028	0.51	-0.34	-0.002		0.533	0.705
	(17.50)	(4.89)	(-2.44)	-0.14		(2.69)	
UK Factors	0.087	0.61	-0.08	-0.007		0.699	0.112
	(1.10)	(3.73)	(-0.58)	-0.05		(1.70)	
North American Factors	0.905	0.62	0.09	-0.029		0.235	0.588
	(11.97)	(4.99)	(0.95)	-1.26		(1.02)	
North American Factors plus Liquidity	0.917	0.63	0.10	-0.03	0.08	0.194	0.592
	(11.94)	(4.88)	(1.03)	-1.28	(1.47)	(0.79)	

Table III 4-factor Coefficients for the LPE samples

This table presents the monthly returns in excess of the risk-free rate (in percent) and regression coefficients for equal-weight portfolios of the LPE samples. The 4 factors (market RMRF, size SMB, value HML, and momentum WML) are the Global factors downloaded from Ken French's website. The Buyout subsample represents LPE firms and funds that take controlling equity stakes in their portfolio firms. The Mezzanine subsample represents firms and funds that provide mezzanine debt capital to portfolio firms. Funds of Funds are LPE funds that hold several LP investments in unlisted PE funds. GPs are the stocks of private equity fund managers. The sample period is 1990-2015. t-statistics using Newey-West standard errors (6 lags) are in parentheses.

	Monthly Excess Return	RMRF	SMB	HML	WML	Constant	Adj R^2	Obs
Full	0.885	1.094	0.773	-0.086	-0.082	0.457	0.715	18938
	(1.98)	(12.75)	(6.13)	(-0.59)	(-0.62)	(2.20)		
Buyout	0.813	1.074	0.561	0.382	-0.108	0.282	0.685	7701
	(1.89)	(14.33)	(4.48)	(4.07)	(-0.85)	(1.21)		
Mezzanine	0.911	0.901	0.528	0.309	-0.204	0.451	0.364	3085
	(2.06)	(7.49)	(3.77)	(2.41)	(-2.42)	(1.44)		
Venture	1.28	1.567	1.884	-1.802	-0.05	1.15	0.478	2822
	(1.33)	(8.62)	(5.22)	(-3.97)	(-0.13)	(2.12)		
FoF	0.844	0.887	0.581	0.108	-0.095	0.417	0.517	4626
	(1.92)	(7.89)	(5.27)	(0.87)	(-0.84)	(1.22)		
GP	1.159	1.3	0.554	1.119	-0.137	0.224	0.533	704
	(1.41)	(9.44)	(1.92)	(3.41)	(-0.72)	(0.51)		

Table IV Portfolios of LPE stocks formed on Lagged 1-Year Price Return

This table presents the results of 4-factor regressions of the monthly excess returns of the quintile portfolios formed by ranking all stocks in the sample by past 12-month price returns (skipping the most recent month), held for 12 months, and the winner-minus-loser (5-1) portfolio. Stocks with the highest 1-year past return comprise the quintile 5 portfolio and stocks with the lowest 1-year past return comprise quintile 1. t-statistics using Newey-West standard errors (11 lags) are in parentheses.

Panel A - Full Sample

Portfolio	Monthly Excess Return	RMRF	SMB	HML	WML	Constant	Adj R^2
1 (low)	0.200	0.12	0.18	-0.285	-0.16	0.331	0.110
	(0.39)	(3.16)	(1.68)	(-2.68)	(-2.38)	(0.68)	
2	0.601	0.15	0.12	-0.108	-0.10	0.626	0.103
	(1.44)	(4.42)	(1.57)	(-1.46)	(-2.30)	(1.55)	
3	0.666	0.13	0.12	-0.096	-0.07	0.672	0.097
	(1.84)	(3.34)	(1.91)	(-1.69)	(-1.71)	(1.89)	
4	0.751	0.13	0.10	-0.085	-0.01	0.717	0.065
	(1.98)	(3.84)	(1.49)	(-1.07)	(-0.20)	(1.93)	
5 (high)	0.543	0.18	0.19	-0.103	0.04	0.455	0.082
	(1.07)	(4.43)	(2.16)	(-0.82)	(0.73)	(0.95)	
5-1 spread	0.342	0.06	0.01	0.182	0.19	0.123	0.053
	(0.84)	(1.71)	(0.10)	(1.63)	(4.10)	(0.31)	

Panel B - Buyout

Portfolio	Monthly Excess Return	RMRF	SMB	HML	WML	Constant	Adj R^2
1 (low)	0.163	0.12	0.08	0.074	-0.08	0.124	0.128
	(0.37)	(2.75)	(0.80)	(0.86)	(-1.43)	(0.28)	
2	0.442	0.12	0.12	-0.048	-0.06	0.427	0.135
	(1.15)	(3.73)	(2.00)	(-0.63)	(-1.70)	(1.14)	
3	0.719	0.13	0.06	-0.046	-0.05	0.699	0.123
	(1.99)	(3.20)	(0.79)	(-0.70)	(-1.08)	(1.92)	
4	0.855	0.10	0.11	-0.043	-0.02	0.826	0.118
	(2.37)	(3.29)	(1.57)	(-0.59)	(-0.63)	(2.30)	
5 (high)	0.914	0.18	0.22	0.045	0.01	0.791	0.088
	(1.96)	(4.24)	(2.75)	(0.45)	(0.16)	(1.79)	
5-1 spread	0.751	0.07	0.15	-0.029	0.09	0.667	0.078
	(2.27)	(2.30)	(2.02)	(-0.29)	(2.18)	(2.16)	

Table IV - continued

Panel C - Mezzanine

Portfolio	Monthly Excess Return	RMRF	SMB	HML	WML	Constant	Adj R^2
1 (low)	-0.087	0.07	0.56	-0.391	-0.46	0.105	0.175
	(-0.09)	(0.76)	(2.56)	(-1.25)	(-2.89)	(0.12)	
2	0.327	0.14	0.38	-0.249	-0.27	0.388	0.166
	(0.43)	(2.96)	(2.50)	(-1.07)	(-3.41)	(0.59)	
3	0.237	0.12	0.25	-0.180	-0.28	0.306	0.170
	(0.33)	(2.04)	(1.95)	(-1.10)	(-3.67)	(0.48)	
4	0.314	0.11	0.29	-0.173	-0.17	0.341	0.098
	(0.48)	(2.48)	(1.75)	(-1.30)	(-3.21)	(0.59)	
5 (high)	0.063	0.13	0.18	-0.163	-0.14	0.062	0.061
	(0.08)	(2.59)	(1.21)	(-1.02)	(-2.58)	(0.09)	
5-1 spread	0.150	0.06	-0.38	0.228	0.32	-0.043	0.145
	(0.25)	(0.76)	(-2.54)	(1.08)	(2.50)	(-0.07)	

Panel D - Funds of Funds

Portfolio	Monthly Excess Return	RMRF	SMB	HML	WML	Constant	Adj R^2
1 (low)	-0.456	0.14	0.21	-0.145	-0.22	-0.334	0.078
	(-0.64)	(2.15)	(1.60)	(-1.15)	(-3.01)	(-0.50)	
2	0.599	0.18	0.19	-0.168	-0.09	0.624	0.103
	(1.06)	(4.13)	(2.21)	(-1.71)	(-1.39)	(1.16)	
3	0.639	0.12	0.08	-0.161	-0.06	0.673	0.061
	(1.33)	(2.37)	(0.91)	(-2.28)	(-0.90)	(1.39)	
4	0.630	0.20	0.13	-0.166	-0.02	0.599	0.119
	(1.29)	(3.89)	(1.53)	(-2.29)	(-0.29)	(1.28)	
5 (high)	0.443	0.18	0.10	-0.080	-0.01	0.384	0.062
	(0.76)	(3.51)	(1.31)	(-0.59)	(-0.16)	(0.67)	
5-1 spread	0.899	0.04	-0.11	0.066	0.21	0.718	0.022
	(1.32)	(0.70)	(-0.88)	(0.33)	(2.70)	(1.14)	

Panel E - Venture

Portfolio	Monthly Excess Return	RMRF	SMB	HML	WML	Alpha	Adj R^2
1 (low)	-0.556	0.25	0.40	-0.873	0.02	-0.393	0.193
	(-0.43)	(3.04)	(2.38)	(-3.10)	(0.17)	(-0.37)	
2	-0.370	0.16	0.38	-0.495	-0.11	-0.239	0.094
	(-0.36)	(2.56)	(1.99)	(-3.47)	(-1.11)	(-0.26)	
3	-0.374	0.22	0.03	-0.340	-0.10	-0.277	0.064
	(-0.41)	(4.19)	(0.17)	(-2.35)	(-1.54)	(-0.32)	
4	-0.282	0.23	0.22	-0.319	-0.03	-0.279	0.080
	(-0.31)	(3.59)	(1.26)	(-1.76)	(-0.31)	(-0.33)	
5 (high)	-0.382	0.19	-0.04	-0.489	0.01	-0.266	0.078
	(-0.37)	(2.91)	(-0.21)	(-2.55)	(0.07)	(-0.28)	
5-1 spread	0.173	-0.06	-0.43	0.384	-0.01	0.127	0.114
	(0.31)	(-1.02)	(-3.08)	(2.97)	(-0.20)	(0.26)	

Table V Portfolios of LPE stocks formed on Lagged 1-Year NAV Return

This table presents the annual NAV returns of the tercile portfolios formed by ranking all stocks in the full sample, and in the each of the subsamples, by their past one-fiscal-year NAV return and held for one fiscal year, and the winner-minus-loser (3-1) portfolio. Stocks with the highest 1-year past return comprise the tercile 3 portfolio and stocks with the lowest 1-year past return comprise tercile 1. t-statistics using robust standard errors are in parentheses.

	Full	Buyout	Mezzanine	Venture	FoF
1 (low)	9.178	6.114	4.422	21.829	9.408
	(2.39)	(1.75)	(1.51)	(1.10)	(2.90)
2	9.757	10.457	8.011	1.918	13.570
	(3.53)	(3.09)	(3.67)	(0.35)	(3.17)
3 (high)	13.367	13.916	13.195	5.239	15.440
	(3.84)	(3.76)	(3.12)	(0.65)	(2.67)
3-1 spread	4.189	7.802	8.772	-16.590	6.032
	(1.31)	(2.39)	(3.39)	(-0.82)	(1.36)

Table VI Lagged NAV Premium and NAV Return

This table presents the average NAV premium at the end of year t and the average NAV return in year t+1 for portfolios of LPEs grouped by NAV premium. Premia are winsorized at the 5% level.

Portfolio Ranked by Year t NAV Premium	Full		Buyout		Venture		Mezzanine		FoF	
	Year t Premium	Year t+1 NAV change	Year t Premium	Year t+1 NAV change	Year t Premium	Year t+1 NAV change	Year t Premium	Year t+1 NAV change	Year t Premium	Year t+1 NAV change
1 (low)	-46.13%	8.47%	-51.53%	10.73%	-29.92%	-2.55%	-35.91%	1.59%	-43.41%	11.60%
2	-16.61%	8.37%	-22.57%	10.67%	21.14%	-4.39%	-7.48%	7.22%	-24.51%	10.90%
3 (high)	53.49%	12.58%	26.03%	14.21%	110.14%	19.09%	21.90%	12.54%	12.81%	6.36%

Table VII Cross Section of LPE Alphas and Alpha t-statistics

In this table, LPEs are ranked by their 4-factor alpha (Panel A) or by the t-statistic of their alpha (Panel B), estimated monthly using price returns. The average alpha (alpha t-statistic), the p-values of the t-statistic based on standard critical values, and the cross-sectionally bootstrapped p-values of the alpha (alpha t-statistic) are given for the individual LPE located at each percentile in the distribution and for the individual LPEs with smallest and the largest alpha (alpha t-statistic). The cross-sectionally bootstrapped p-value is based on the distribution of the best (worst) LPEs in 1,000 bootstrap resamples. The t-statistics of alpha are based on heteroskedasticity- and autocorrelation-consistent standard errors.

percentile	min	1%	5%	10%	20%	30%	40%	50%	60%	70%	80%	90%	95%	99%	max
Panel A - Cross Section of LPE Alpha															
								Full							
alpha	-2.80	-2.68	-1.41	-0.81	-0.26	-0.02	0.12	0.22	0.34	0.54	0.96	1.51	1.99	5.26	6.55
p-value (1-tail)	<0.01	0.03	0.03	0.16	0.38	0.49	0.45		0.26	0.08	0.14	0.09	0.11	0.04	0.16
b-p-value	0.87	0.88	0.81	0.93	0.99	0.99	0.97		0.15	0.16	0.05	0.04	0.08	<0.01	0.23
								Buyout							
alpha	-2.68	-2.68	-1.71	-1.13	-0.50	-0.41	-0.15	0.10	0.28	0.42	0.56	1.83	3.42	6.55	6.55
p-value (1-tail)	0.03	0.03	0.1	0.11	0.1	0.33	0.42		0.21	0.13	0.23	0.22	<0.01	0.16	0.16
b-p-value	0.76	<0.01	0.73	0.71	0.84	0.57	0.65		0.20	0.28	0.44	0.02	<0.01	0.01	0.20
								Mezzanine							
alpha	-2.8	-2.8	-0.50	-0.12	0.12	0.15	0.22	0.39	0.73	0.94	0.99	1.50	1.53	1.62	1.62
p-value (1-tail)	<0.01	<0.01	0.15	0.44	0.45	0.41	0.35		0.25	0.27	0.10	0.05	0.03	<0.01	<0.01
b-p-value	0.06	<0.01	0.98	1	0.99	0.97	0.93		0.02	0.03	0.07	0.05	0.10	0.18	0.49
								Venture							
alpha	-1.77	-1.77	-1.77	-0.23	0.04	0.15	0.20	0.44	0.76	1.16	1.29	1.51	2.28	2.28	2.28
p-value (1-tail)	0.05	0.05	0.05	0.43	0.49	0.43	0.4		0.31	0.13	0.28	0.09	0.11	0.11	0.11
b-p-value	0.78	<0.01	<0.01	1	0.99	0.99	0.95		0.05	0.05	0.09	0.24	0.17	0.17	0.54
								FoF							
alpha	-1.41	-1.41	-1.39	-0.81	-0.15	-0.04	0.07	0.18	0.31	0.36	0.55	0.82	0.97	1.99	1.99
p-value (1-tail)	0.03	0.03	0.23	0.16	0.41	0.47	0.46		0.32	0.19	0.24	0.05	0.10	0.11	0.10
b-p-value	0.57	<0.01	0.59	0.73	0.93	0.9	0.82		0.23	0.32	0.36	0.30	0.33	0.06	0.30
Panel B - Cross Section of LPE Alpha t-statistics															
								Full							
alpha t-stat	-2.76	-2.28	-1.29	-1.00	-0.35	-0.02	0.15	0.32	0.55	0.74	1.14	1.54	1.85	2.70	2.83
p-value (1-tail)	<0.01	0.01	0.10	0.16	0.36	0.49	0.44		0.29	0.23	0.13	0.06	0.03	<0.01	<0.01
b-p-value	0.73	0.91	0.97	0.94	0.99	0.99	0.96		0.10	0.17	0.10	0.13	0.14	0.04	0.30
								Buyout							
alpha t-stat	-2.28	-2.28	-1.29	-1.22	-0.77	-0.37	-0.20	0.11	0.53	0.76	1.11	1.57	2.09	2.83	2.83
p-value (1-tail)	0.01	0.01	0.10	0.11	0.22	0.36	0.42		0.30	0.22	0.13	0.06	0.02	<0.01	<0.01
b-p-value	0.75	<0.01	0.96	0.78	0.75	0.80	0.68		0.12	0.13	0.09	0.07	0.02	0.01	0.10
								Mezzanine							
alpha t-stat	-2.76	-2.76	-1.05	-0.14	0.15	0.25	0.36	0.40	0.66	1.07	1.21	1.85	2.18	2.70	2.70
p-value (1-tail)	<0.01	<0.01	0.15	0.45	0.44	0.40	0.36		0.26	0.14	0.12	0.03	0.02	<0.01	<0.01
b-p-value	0.12	<0.01	0.93	1.00	0.99	0.98	0.94		0.13	0.09	0.11	0.07	0.05	0.02	0.15
								Venture							
alpha t-stat	-1.64	-1.64	-1.64	-0.35	0.03	0.14	0.23	0.26	0.35	0.55	0.59	1.25	1.33	1.33	1.52
p-value (1-tail)	0.05	0.05	0.05	0.36	0.49	0.44	0.41		0.37	0.29	0.28	0.11	0.09	0.09	0.06
b-p-value	0.74	<0.01	<0.01	1.00	0.99	0.99	0.96		0.20	0.31	0.43	0.20	0.37	0.37	0.53
								FoF							
alpha t-stat	-1.86	-1.86	-1.00	-0.99	-0.24	-0.07	0.08	0.26	0.59	0.69	0.90	1.27	1.43	1.63	1.63
p-value (1-tail)	0.03	0.03	0.16	0.16	0.41	0.47	0.47		0.28	0.25	0.19	0.10	0.08	0.05	0.05
b-p-value	0.55	<0.01	0.95	0.84	0.94	0.90	0.80		0.19	0.25	0.33	0.28	0.31	0.35	0.68

Table VIII False Discovery Rate

This table gives the proportion of zero-alpha LPEs π_0, truly unskilled LPEs π_-, and truly skilled LPEs π_+ for the full LPE sample and the LPE subsamples. λ denotes the p-value used to demarcate zero-alpha LPEs as described in the text, and γ is the significance level used to identify LPEs with significant 4-factor alpha.

	λ	γ	π_0	π_-	π_+
Full	0.35	0.2	0.94	0.02	0.04
Buyout	0.5	0.2	0.78	0.09	0.13
Mezzanine	0.3	0.2	0.88	0.01	0.11
Venture	0.3	0.2	>0.99	-	-
FoF	0.65	0.2	>0.99	-	-

Table IX LPE Value-Added

This table gives statistical properties of the distribution of the cross-sectional mean annual value-added (Sn) and the cross-sectional weighted mean annual value-added (Sw) for the LPE samples. Values are in thousands of US dollars.

	Total		Buyout		Mezzanine		Venture		FoF	
	Sn	Sw	Sn	Sw	Sn	Sw	Sn	Sw	Sn	Sw
1%	-1,981,045	-1,173,729	-1,981,045	-984,232	-270,583	-181,844	-228,312	-110,697	-152,160	-88,348
5%	-152,160	-117,632	-1,361,052	-429,772	-87,534	-117,653	-228,312	-110,697	-76,825	-62,494
10%	-60,751	-45,423	-104,927	-98,640	-30,984	-70,796	-33,208	-18,784	-54,948	-27,081
25%	-12,642	-10,949	-28,383	-19,275	-5,205	-3,498	-11,567	-10,118	-854	-536
median	16,808	15,947	8,641	11,634	42,507	33,955	1,310	1,985	18,288	21,735
mean	60,605	96,264	-14,756	79,876	170,155	219,279	48,436	96,595	64,676	42,640
75%	84,492	70,437	89,939	104,431	121,119	92,866	48,401	49,018	52,150	79,360
90%	268,081	401,269	224,177	336,484	969,672	1,563,988	418,600	687,189	116,333	124,227
95%	685,323	898,485	520,940	753,426	1,226,590	1,648,642	447,577	811,829	564,854	143,868
99%	1,342,037	2,519,634	1,270,329	2,112,841	1,342,037	1,803,814	447,577	811,829	685,323	394,061

Table X Variation in Short-term LPE Skill Over Time

This table gives the 4-factor alpha for the winner-minus-loser portfolio (Carhart skill measure) for the LPE sample and subsamples for various subperiods. Newey-West standard errors (11 lags) are in brackets, and the number of observations for each subperiod is given in braces.

	1990-2000	2000-2005	2005-2010	2010-2015
Full	0.164	0.12	-0.158	1
	(0.26)	(0.08)	(-0.29)	(5.84)
	{3196}	{2980}	{5140}	{7530}
Buyout	0.59	1.246	-0.028	0.936
	(1.15)	(1.47)	(-0.05)	(2.02)
	{1829}	{1313}	{1991}	{2553}
Venture	-1.727	2.231	-0.967	-0.112
	(-2.46)	(1.88)	(-1.48)	(-0.18)
	{491}	{502}	{793}	{1029}
Mezzanine	-	-	-0.863	1.402
	-	-	(-0.88)	(5.07)
	{134}	{287}	{927}	{1699}
FoFs	2.239	-0.731	-0.322	0.671
	(2.67)	(-0.38)	(-0.50)	(1.92)
	{742}	{833}	{1250}	{1785}