Estimating Skill in Private Equity Performance using Market Data

MAURICE McCOURT*

First Version: May 30, 2016

This Version: January 13, 2017

ABSTRACT

Are private equity (PE) firms that earn persistently higher returns truly skilled, or are they just lucky? I approach the question using a novel dataset: publicly traded listed private equity entities (LPEs) representing Buyout, Venture, Mezzanine, and Funds-of-Funds. LPE enables measures of skill that have been developed in the mutual funds literature to be applied to private equity. I find evidence of both short-term and long-term persistence for Buyout LPEs, and that skill remains after controlling for luck. Mezzanine LPEs also exhibit skill, however the evidence for Venture and Funds-of-Funds is mixed. Furthermore, investors are able to identify skilled LPEs. The approach overcomes concerns about the integrity of both the data and the empirical methods that have been commonly used in studies of PE persistence.

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

JEL classification: G2.

---

*Maurice McCourt is a PhD Candidate with the Finance Department of ESSEC Business School, Paris, France. The author would like to thank Sridhar Arcot and Sofia Ramos for their support and guidance. I am also grateful to Laurent Barras, Romain Boulland, Andras Fulop, Laurence Lescourret, Lorenzo Naranjo, and Olivier Scaillet, and discussants and participants at the 2016 Paris Financial Management Conference and the Eurofidai 2016 Paris December Meeting.

Why would investors put money with private equity managers who aren't that good? It could be that investors herd mindlessly into asset classes. But some of it may also reflect the way the industry manipulates data.

"Every private equity firm you talk to is first quartile", quips the boss of a $58 billion pension fund. Research [by Oliver Gottschalg] shows that 66% of funds can claim to be in the top quartile depending on what vintage year they said their fund was.

–The Economist, January 28, 2012

I. Introduction

In the private equity (PE) literature, there is ongoing debate about whether some PE firms (General Partners or GPs) are skilled. The seminal study by Kaplan and Schoar (2005) was the first of a number[1] to show that the funds of some GPs earn persistently higher (or persistently lower) returns than those of other GPs. The question whether PE firms are skilled is important for a number of reasons. One is the size and phenomenal growth of the PE industry: Preqin, a private equity research firm, estimate that in 2015 there was about $4 trillion invested in PE, which has risen from $2.5 trillion in 2008. This strong growth is expected to continue, with Mellon and Preqin (2016) reporting that 39% of PE fund managers expect their assets under management to grow by at least 50% in the next 5 years. Another reason why understanding PE skill is important is that some critics have begun to question the fees charged by PE firms (Robinson and Sensoy (2013)), arguing that these fees do not seem to reflect PE fund managers' skill in generating returns for their investors. The typical PE contract seems to allow GPs to earn excessive compensation, and does too little to discipline GPs or to provide them with incentives to maximize investor returns.

However, PE researchers face a number of challenges. Firstly, reliable, unbiased data on PE firm performance is difficult to obtain. As a result, estimates of PE performance (on

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

which measures of PE persistence rely) vary widely[2], with some studies finding substantial outperformance and others finding substantial underperformance. Secondly, 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 (2016) argue that methodologies commonly used to measure PE persistence have empirical limitations that could affect the interpretation of results derived using those methodologies.

In this paper, I use listed private equity (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[3], LPEs raise capital in an Initial Public Offering (IPO) which they then use to invest in private companies, either directly by taking controlling 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 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. 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 193 LPEs with AUM of about \$950 billion. This compares with \$3.8 trillion AUM for the PE universe reported by Preqin (2015).

Importantly, LPE is increasingly seen by practitioners, academic researchers, and regulators as representative of the private equity asset class. LPE firms follow the same investment strategies as traditional (unlisted) PE firms, and they both face the same opportunity set. LPE Net Asset Value (NAV) returns have been shown by Preqin and LPX Group (2012)

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

[3]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.

to be highly correlated with those of unlisted PE (Pearson coefficient: 0.94). In academic research, the study by Jegadeesh, Kräussl, and Pollet (2015) shows that the market returns of LPEs predict future self-reported returns of unlisted private equity funds. Thus LPE performance can be considered a good proxy for unlisted PE performance. This view received significant support when, after an extensive consultation process, regulators responsible for supervision of the \$10 trillion[4] insurance and reinsurance industry in Europe[5] adopted LPE as their private equity benchmark (EIOPA (2013)).

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. LPEs behave like listed closed-end funds (CEFs) of private equity investments. I take advantage of the fund nature of LPE to apply tests from the mutual funds literature to measure performance persistence, and to separate skill from luck.

Firstly, I measure short-term persistence using the classic winner-minus-loser alpha test[6] by Carhart (1997). I find positive top-quartile minus bottom-quartile (4-1) alpha of 0.48% per month (about 6% per year) using price returns for Buyout LPEs. Using changes in NAV as the measure of skill, I find positive and statistically significant 4-1 risk-adjusted NAV returns for Buyout and Mezzanine LPEs (about 8% and 9.5% 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 predictor of short-term changes in NAV; in other words, the NAV premium captures short-term market expectations of manager skill. I confirm that Buyout, Venture and Mezzanine LPEs with larger NAV premiums have larger NAV changes 12 months later. This result provides evidence not only that certain LPEs have short-term skill, but also that investors can identify these skilled

[4]Source: www.insuranceeurope.eu, accessed 25.November, 2016.

[5]US regulators are also showing interest in LPE, and how it can help diversify risk - see "Business-development companies: Shadowy developments", The Economist, 22.November, 2014.

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

LPEs. Investors are not able to identify skilled FoFs however.

Secondly, I apply tests to separate skilled LPEs from lucky ones. Short-term persistence measures picks up noise in that they rank 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, I apply the cross-sectional bootstrap test (Kosowski, Timmermann, Wermers, and White (2006)), and the the false discovery rate (Barras, Scaillet, and Wermers (2010)). With the cross-sectional bootstrap, I find 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. Using the false discovery rate with LPE suggests that for Buyout, Mezzanine and FoF LPEs, there is a large proportion of truly skilled funds in the sample (21%, 24% and 22% respectively). Furthermore these tests indicate that few LPEs are truly unskilled. Finally, using the dollar value-added measure (Berk and van Binsbergen (2015)) I find that the median excess 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 liquidity effects, short-term post-IPO LPE performance, 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 as follows. Firstly, I use a novel dataset, Listed Private Equity. 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 literature that are not possible to use with unlisted PE fund data. As a result, I believe this paper is the first to test for persistence and skill in PE performance where both the data and the methods are free from potential bias.

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 and skill in private equity returns. Also, Korteweg and Sorensen (2016) is perhaps the only other study that separates skill from luck in traditional PE persistence, however they use performance data from Preqin which is based on self-reports by PE fund-managers and investors, so data integrity may be a concern.

This paper is structured as follows: Section II summarises the relevant literature on private equity, mutual fund persistence and listed private equity; in Section III I describe the LPE dataset. The results for the persistence tests and the tests to separate skill from luck 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. Literature

This section provides a brief overview of the main literature pertinent to this study, covering potential biases in private equity data and methodologies, studies of persistence in private equity, mutual fund persistence, and listed private equity.

A. Persistence in Private Equity

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, Jenkinson, and Stoff (2015) also show that Buyout PE firm returns are persistent, but that this persistence has declined post-2000. They argue that this decline is due to increased competition for deals among PE firms. Korteweg and Sorensen (2016) 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 relatively well.

B. Potential Bias in Data and 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 Harris, Jenkinson, and Kaplan (2014a) argue are potentially subject to reporting and selection biases. Fund-level cashflow data from Burgiss may not have major biases, but as Braun et al. (2015) point out, will inevitably have gaps in the fund sequences, reflecting investors choices about which funds to invest in. This is less important for analysis of PE returns, but is a serious constraint when analyzing persistence. Instead of using commercial databases, some other studies use data provided by PE investors or fund managers, and as a result are potentially exposed to the same reporting and selection biases that arise when using data from the commercial providers. Jegadeesh et al. (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 performance can be made.

In addition to data integrity challenges, research on the persistence of traditional PE faces methodological issues. Typically, PE persistence is measured 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 (2016) show that regressing fund n returns on fund $n-1$ returns is equivalent to an AR(1) timeseries[7] 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 quantile 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 (2016) 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 variance decomposition model estimated using a Bayesian procedure.

C. *Skill in Mutual Funds*

Listed Private Equity allows the robust methodologies for measuring persistence in mutual funds to be used to estimate PE skill. In this way, I avoid using data whose integrity is susceptible to bias, or using measures of persistence that have theoretical limitations, or both. 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

[7]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.

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 unlisted 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 such as 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.

Note that theBerk and Stanton (2007) and Cherkes et al. (2009) models of closed-end fund performance are not incompatible. In fact Cherkes et al. (2009) point out that managing a portfolio of illiquid assets entails skill, albeit not necessarily "stock-picking" or "market-timing" skill. For instance, the manager will have to possess detailed institutional knowledge and/or industry relationships in order to minimize transaction costs when trading in the underlying investments.

D. Listed Private Equity

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.

Jensen (2007) raises concerns about giving PE firms permanent public capital to invest (in other words, LPE). 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 listed PE. Jensen also expresses fears that taking traditional PE firms (GPs) public puts at risk another of the major competitive advantages of the PE firm. Citing the case of Blackstone, he argues that "the new public holders of the limited partnership [ie shareholders] have virtually no say in the governance of the enterprise".

LPE has also been the subject of numerous articles in the financial press[8], documenting the interest in LPE from private equity firms looking to meet their own desire for longer-term capital, from investors looking for yield in the current low-interest rate environment, and from regulators looking to measure and distribute risk.

III. Data

To create the LPE sample used for my tests, I start by identifying a large sample of all LPEs, the LPE universe for the 20-year period from 1995 to 2015. 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

[8]See, for example, "Permanent capital: Perpetual cash machines", Financial Times, 4.January, 2015; "Business-development companies: Shadowy developments", The Economist, 22.November, 2014; "Private equity for ordinary folk", Reuters, 29.April, 2014.

Investment Trusts (closed-end funds of PE investments run by members of the AIC in the United Kingdom), and the constituents 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 late 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[9]. 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

[9] 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.

venture LPEs, but buyout and mezzanine should be robust.

[Table I about here.]

Summary statistics for the sample are provided in Table I. While the LPE universe comprises 193 firms and funds, the LPE sample used in this study (public financial entities, excluding infrastructure, that are included on LPE indices) comprises 114 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 1995 through to December 31st 2015. Price and NAV returns are estimated using monthly prices and annual asset values are retrieved from Datastream, and are winsorized at the 1% level. I use US dollar denominated currency values throughout the 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 Buyout, Mezzanine and FoF 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 largest positive loading on size (SMB) and the largest 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.

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.

IV. Short-term Persistence

In this section, I implement two tests for short-term LPE persistence up to one year out. In the first I measure the winner-minus-loser alpha (Carhart (1997)), and in the second I measure how well the NAV premium for LPEs predicts NAV changes one year later (Chay and Trzcinka (1999)).

A. *Winner-minus-Loser Alpha*

Using the LPE sample, I implement the short-term persistence test from Carhart (1997)'s landmark study of mutual fund persistence[10]. The test is performed twice, for price returns

[10]Specifically, I reproduce Table III ("Portfolios of Mutual Funds Formed on Lagged 1-Year Return" from Carhart (1997).

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 4 equal-weighted quartile portfolios. I use overlapping periods to increase the number of observations. The portfolios are then held for 12 months and the average return in excess of the risk-free rate is calculated for each month of the holding period. A 4-factor Fama-French-Carhart model is estimated for each of the quartile portfolios, and for the winner-minus-loser (4-1) 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 quartile and winner-minus-loser (4-1) 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. The return for the 4-1 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. For the full sample, the raw 4-1 return is positive and significant at the 10% level, but the risk-adjusted 4-1 return (4-factor alpha) is not significant. Buyout LPEs achieve economically significant persistence and skill measures of about 50 basis points per month, which are statistically significant at the 5% level. For the other subsamples, the 4-1 alphas are not significant.

I repeat the procedure using NAV returns. Stocks are grouped by past one-year NAV return to create equal-weighted quartile 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.

The results are reported in Table V. The raw winner-minus-loser (4-1) spread is positive for all subsamples except Venture, ranging from 7.5% per year for Funds of Funds (statistically significant at the 5% level) to over 11% per year for Buyout and Mezzanine LPEs (statistically significant at the 1% level). The negative 4-1 NAV return for Venture seems economically large (-20%), but is statistically insignificant. For completeness, winner-minus-loser 4-factor coefficients are also reported, but given that the dependent variable is a NAV return and the independent variables are price returns, values and significance levels may just be suggestive rather than definitive.

To sum up this section, two key findings emerge. 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 may be due to noise; the short-term nature of the winner-minus-loser test means that sample 4-1 alpha could be insignificant when the true alpha is actually significant. I address this issue in Section V.

[Table V about here.]

B. Lagged NAV Premium predicts NAV Return

The studies by Chay and Trzcinka (1999) and Berk and Stanton (2007) show that the NAV premium (the difference between the share price and the NAV per share) 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.

I show that the NAV premium for LPEs is a predictor of future NAV returns. LPEs are grouped each year by their NAV premium into 4 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 4 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 4 is higher than for the other portfolios. An unpaired t-test shows that the NAV change for portfolio 4 is significantly larger than that for portfolio 1 for all LPEs, 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*), but the effect is small and not statistically significant. 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. Cross-Sectional Bootstrap

To separate skill from luck in mutual funds, 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.

Using the 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, cross-sectional bootstrap p-values are estimated 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 controls 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 cross-sectional bootstrap 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. *False Discovery Rate*

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 estimated using the bootstrap technique described in Section V.A. 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, 0.4 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, 81% of the LPEs are zero-alpha, 14% are truly skilled and 5% are truly unskilled. Zero-alpha LPEs account for 69% of the Buyout subsample, and 21% are truly skilled and 10% are truly unskilled. The Mezzanine subsample has the lowest proportion of zero-alpha LPEs 71%, 24% of the subsample are truly skilled and 5% are truly unskilled. For Venture LPEs, practically all LPEs are zero-alpha with virtually no truly skilled or unskilled LPEs. Zero-alpha LPEs account for 73% of the Funds of Funds subsample, 22% are truly skilled and 5% are truly unskilled.

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. Dollar Value-Added

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 in excess of their benchmark. 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.

Dollar value-added is defined as the product of the fund's assets under management and its gross alpha. 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:

$$R_{it}^{B} = \beta_i^{mkt} MKT_t + \beta_i^{sml} SML_t + \beta_i^{hml} HML_t + \beta_i^{wml} WML \quad (1)$$

where MKT_t, SML_t, HML_t, and WML_t are the realizations of the four factor portfolios (excess return on the market, small minus big, high minus low, and winners minus losers) and β_i are risk exposures of the ith LPE, which can be estimated by regressing the fund's return on to the factors.

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. Jegadeesh et al. (2015) Sample

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. As a robustness check, I repeat the 4-factor regression from Table III 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 Jegadeesh *et al*[11].

B. *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.

C. *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 (0.81) 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 factors again have the largest R^2 value (0.69) 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

[11]Specifically, Table 6 of Jegadeesh et al. (2015).

portfolios with the Global factors, using this combination for the persistence tests seems justified.

D. Liquidity Factor

It may that the significant alphas reported in Table IV for winner-minus-loser (4-1) portfolios are due to differences in the liquidity of the stocks in the portfolios rather than LPE skill.

In the tests for short-term price persistence, I use 4 Fama-French-Carhart Global factors as these factors have the strongest explanatory power for the sample (see Table II in Section III). However using 4 Fama-French-Carhart North American factors plus Pastor's Liquidity factor also has reasonable explanatory power (R^2 0.69).

I rerun the short-term price persistence tests using the 4 Fama-French-Carhart North American factors plus the Liquidity factor, however the findings remain unchanged. The alpha for the Buyout 4-1 portfolio remains significant at the 5% level, and insignificant for the other LPE types.

E. 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.

F. Changes Over Time

Table X gives a picture of changes in short-term LPE skill during the sample period (1995-2015) 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 (2005-2009) and strongest in the period following it (2010-2015). The largest skill measure for Buyout and Venture LPEs was recorded in the period 2000-2004, but for the 2009-2015 Venture skill is negative and not statistically significant while for Buyouts it is positive and significant. Mezzanine LPEs were uncommon before 2005, and 2005-2009 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

[Table XI about here.]

Overall, the tests detailed in the previous sections paint a consistent picture (see Table XI for an overview of the tests and results). There is substantial evidence of skill for LPE, irrespective of which measure of skill is used. In the tests of short-term persistence, the 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, the cross-sectional bootstrap and the false discovery rate, 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 (2016). 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 I find for skill by Fund-of-Funds LPEs is mixed. The short-term tests for FoFs 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 *et 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 that for Buyout LPE, short-term persistence was weak in the period 2000-2009, disappearing completely in 2005-2009. However in the 2010-2015 period, Buyout LPE persistence recovered strongly. Thus competition for Buyout deals may have declined significantly since 2005-2009 enabling skilled LPEs to differentiate themselves from unskilled ones.

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 cross-sectional bootstrap test 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 false discovery rate test shows that the proportion of truly unskilled LPEs is about half that of skilled ones.

These results also give insights into the rents 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% per month, for Mezzanine it is about 0.9%, it is over 1.2% for Venture, and 0.7% per month for FoFs.

A. What Drives Skill?

As I find evidence that some LPE firms are more skilled than others, the question that then arises is, what are these skilled LPEs doing that makes them perform better than unskilled ones?

In mutual funds, fund-manager skill is typically attributed to stock-picking and market-timing (cf Kacperczyk, Nieuwerburgh, and Veldkamp (2014)). In private equity, performance is driven by the ability to pick good deals and make them work (Jensen (2007)), but the ability to time deals is also important. A number of studies (cf Kaplan and Schoar (2005)) have documented the boom and bust nature of private equity returns, where deals initiated during boom times in private equity fundraising (usually coinciding with hot IPO markets) underperform deals initiated when PE fundraising is weak. One of the main drivers of PE performance are increases in industry valuation multiples (Guo, Hotchkiss, and Song (2011)), which requires the PE firm to have a keen sense of the outlook for the industry in which it is investing.

In addition to being able to time deals, skilled PE firms need to be able to identify good deals. The impact of a certain type of poor deal selection has been documented by Arcot, Fluck, Gaspar, and Hege (2015) who show that GPs who find themselves with unspent committed capital at the end of their fund's investing period (usually the first 5 years of the fund's life) feel pressure to make secondary buyouts from other PE firms, and these deals are often expensive relative to comparable mergers and acquisitions (M&A) transactions. Lopez-de Silanes, Phalippou, and Gottschalg (2015) also argue that deals by PE firms that hold a high number of simultaneous investments tend to underperform substantially, suggesting that these firms select poor deals due to limits to scalability of PE fund manager skill. Furthermore, they suggest that PE fund returns decrease as the size of the fund increases.

After market timing and deal selection, skilled PE firms make their deals work. Financial engineering, such as realized tax benefits from increasing leverage in target companies, also plays an important role, as do operating gains that arise due to PE owners promoting strong management practices (Guo et al. (2011), Bloom, Sadun, and Van Reenen (2015)) or making value-enhancing acquisitions.

The drivers for LPE performance are the same as for traditional PE, except in one important respect - as LPE investment capital is permanent, LPEs do not face the same pressures to invest or divest that traditional PE funds face due to the 10 year life of their funds. Strömberg (2007) finds evidence that LPEs seem to hold their deals for longer than unlisted PE firms.

VIII. Conclusions

This study examines whether some listed Private Equity (LPE) firms exhibit skill. LPE is increasingly seen by practitioners, academic researchers, and regulators as representative of the PE asset class, and a number of significant studies have shown that the performance characteristics of LPE are very similar to those of traditional PE. 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 closed-end fund nature of LPE means that robust measures for persistence and skill developed in the closed-end and mutual fund literature can be estimated, including the winner-minus-loser 4-factor alpha, NAV changes predicted by NAV-premia, cross-sectional zero-alpha bootstrap, false discovery rate, and dollar value-added. These tests overcome methodological issues, such as confounding luck and skill, and AR(1) convergence, which arise in the tests commonly used to measure persistence in private equity.

Thus while a number of prior studies have identified persistence in PE firm performance, these studies have relied on data and methodologies which have been shown to be potentially biased. The main contribution of this study is that it is the first to overcome both data and methodology issues. Furthermore, only a small number of recent studies have attempted to separate skill from luck in PE performance persistence, and my study contributes to this emerging area of research.

In the short-term, I find that 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. This is consistent with Korteweg and Sorensen (2016) who show that there is little persistence in unlisted PE that investors can identify and trade on - 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.

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, I find that 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.

While the dollar 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. However my findings, and those of Korteweg and Sorensen (2016) for unlisted PE, show that the net-of-fee outperformance by both PE and LPE is not competed away. Korteweg and Sorensen (2016) 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 model of closed-end funds, 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. Frictions such as industry norms and reputational[12] concerns may affect the adjustment of PE fees. The 2-and-20 fee structure has become a PE industry norm (PE fund managers charge 2% of committed capital in management fees, and take 20% of profits (carry) earned above a certain hurdle rate, usually 8%). Given the criticism the PE industry has faced regarding fees (Robinson and Sensoy (2013)), it may be that skilled PE firms prefer to avoid the reputational damage that could arise from deviating significantly from these norms, even if their performance may justify such a deviation.

[12]In a similar vein, Huang, Ritter, and Zhang (2016) suggest that PE firms reputational concerns lead to conservative investment and dividend policies after bond offerings by their portfolio companies, in order to avoid being seen as expropriating bondholders.

REFERENCES

Arcot, Sridhar, Zsuzsanna Fluck, José-Miguel Gaspar, and Ulrich Hege, 2015, Fund managers under pressure: Rationale and determinants of secondary buyouts, *Journal of Financial Economics* 115, 102–135.

Barras, Laurent, Olivier Scaillet, and Russ Wermers, 2010, False Discoveries in Mutual Fund Performance: Measuring Luck in Estimated Alphas, *The Journal of Finance* 65, 179–216.

Bergmann, Bastian, Hans Christophers, Matthias Huss, and Heinz Zimmermann, 2009, Listed private equity.

Berk, Jonathan B., and Richard Stanton, 2007, Managerial Ability, Compensation, and the Closed-End Fund Discount, *The Journal of Finance* 62, 529–556.

Berk, Jonathan B., and Jules H. van Binsbergen, 2015, Measuring skill in the mutual fund industry, *Journal of Financial Economics* Forthcoming.

Bloom, Nicholas, Raffaella Sadun, and John Van Reenen, 2015, Do Private Equity Owned Firms Have Better Management Practices?, *The American Economic Review* 105, 442–446.

Braun, Reiner, Tim Jenkinson, and Ingo Stoff, 2015, How Persistent is Private Equity Performance? Evidence from Deal-Level Data, SSRN Scholarly Paper ID 2314400, Social Science Research Network, Rochester, NY.

Carhart, Mark M., 1997, On Persistence in Mutual Fund Performance, *The Journal of Finance* 52, 57–82.

Chay, J. B., and Charles A. Trzcinka, 1999, Managerial performance and the cross-sectional pricing of closed-end funds, *Journal of Financial Economics* 52, 379–408.

Cherkes, Martin, Jacob Sagi, and Richard Stanton, 2009, A Liquidity-Based Theory of Closed-End Funds, *Review of Financial Studies* 22, 257–297.

Chung, Ji-Woong, 2012, Performance Persistence in Private Equity Funds, SSRN Scholarly Paper ID 1686112, Social Science Research Network, Rochester, NY.

Cochrane, John H, 2005, The risk and return of venture capital, *Journal of financial economics* 75, 3–52.

Driessen, Joost, Tse-Chun Lin, and Ludovic Phalippou, 2012, A new method to estimate risk and return of nontraded assets from cash flows: The case of private equity funds, *Journal of Financial and Quantitative Analysis* 47, 511–535.

EIOPA, 2013, Technical Report on Standard Formula Design and Calibration for certain Long-Term Investments, Technical report.

Fama, Eugene F., and Kenneth R. French, 2010, Luck versus Skill in the Cross-Section of Mutual Fund Returns, *The Journal of Finance* 65, 1915–1947.

Ferreira, Miguel A., Aneel Keswani, António F. Miguel, and Sofia B. Ramos, 2012, The Determinants of Mutual Fund Performance: A Cross-Country Study, *Review of Finance* rfs013.

Gregory, Alan, Rajesh Tharyan, and Angela Christidis, 2013, Constructing and Testing Alternative Versions of the Fama–French and Carhart Models in the UK, *Journal of Business Finance & Accounting* 40, 172–214.

Guo, Shourun, Edith S. Hotchkiss, and Weihong Song, 2011, Do Buyouts (Still) Create Value?, *The Journal of Finance* 66, 479–517.

Harris, Robert S., Tim Jenkinson, and Steven N. Kaplan, 2014a, Private Equity Performance: What Do We Know?, *The Journal of Finance* n/a–n/a.

Harris, Robert S., Tim Jenkinson, Steven N. Kaplan, and Rüdiger Stucke, 2014b, Has Persistence Persisted in Private Equity? Evidence from Buyout and Venture Capital Funds, SSRN Scholarly Paper ID 2304808, Social Science Research Network, Rochester, NY.

Hendricks, Darryll, Jayendu Patel, and Richard Zeckhauser, 1993, Hot Hands in Mutual Funds: Short-Run Persistence of Relative Performance, 1974–1988, *The Journal of Finance* 48, 93–130.

Huang, Rongbing, Jay R. Ritter, and Donghang Zhang, 2016, Private Equity Firms' Reputational Concerns and the Costs of Debt Financing, *Journal of Financial & Quantitative Analysis* 51, 29–54.

Jegadeesh, Narasimhan, Roman Kräussl, and Joshua M. Pollet, 2015, Risk and Expected Returns of Private Equity Investments: Evidence Based on Market Prices, *Review of Financial Studies* hhv046.

Jensen, Michael, 2007, The Economic Case for Private Equity (and Some Concerns)–pdf of Keynote Slides, SSRN Scholarly Paper ID 963530, Harvard NOM Working Paper No. 07-02.

Kacperczyk, Marcin, Stijn Van Nieuwerburgh, and Laura Veldkamp, 2014, Time-Varying Fund Manager Skill, *The Journal of Finance* 69, 1455–1484.

Kaplan, Steven N., and Antoinette Schoar, 2005, Private Equity Performance: Returns, Persistence, and Capital Flows, *The Journal of Finance* 60, 1791–1823.

Korteweg, Arthur G., and Morten Sorensen, 2016, Skill and Luck in Private Equity Performance, *Journal of Financial Economics* Forthcoming.

Kosowski, Robert, Allan Timmermann, Russ Wermers, and Hal White, 2006, Can Mutual Fund "Stars" Really Pick Stocks? New Evidence from a Bootstrap Analysis, *The Journal of Finance* 61, 2551–2595.

Lopez-de Silanes, Florencio, Ludovic Phalippou, and Oliver Gottschalg, 2015, Giants at the Gate: Investment Returns and Diseconomies of Scale in Private Equity, *Journal of Financial and Quantitative Analysis* 50, 377–411.

Mellon, BNY, and Preqin, 2016, BNY Mellon report predicts that investor demand for real assets will surge by 2020, Technical report.

Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor, 2015, Scale and skill in active management, *Journal of Financial Economics* 116, 23–45.

Preqin, 2015, 2015 Preqin Global Private Equity and Venture Capital Report-Sample Pages., Technical report, Preqin Ltd.

Preqin, and LPX Group, 2012, Listed Private Equity Highly Correlated with Traditional Closed-End PE Limited Partnerships, Technical report.

Robinson, David T., and Berk A. Sensoy, 2011, Cyclicality, Performance Measurement, and Cash Flow Liquidity in Private Equity, Working Paper 17428, National Bureau of Economic Research.

Robinson, David T., and Berk A. Sensoy, 2013, Do Private Equity Fund Managers Earn Their Fees? Compensation, Ownership, and Cash Flow Performance, *Review of Financial Studies* hht055.

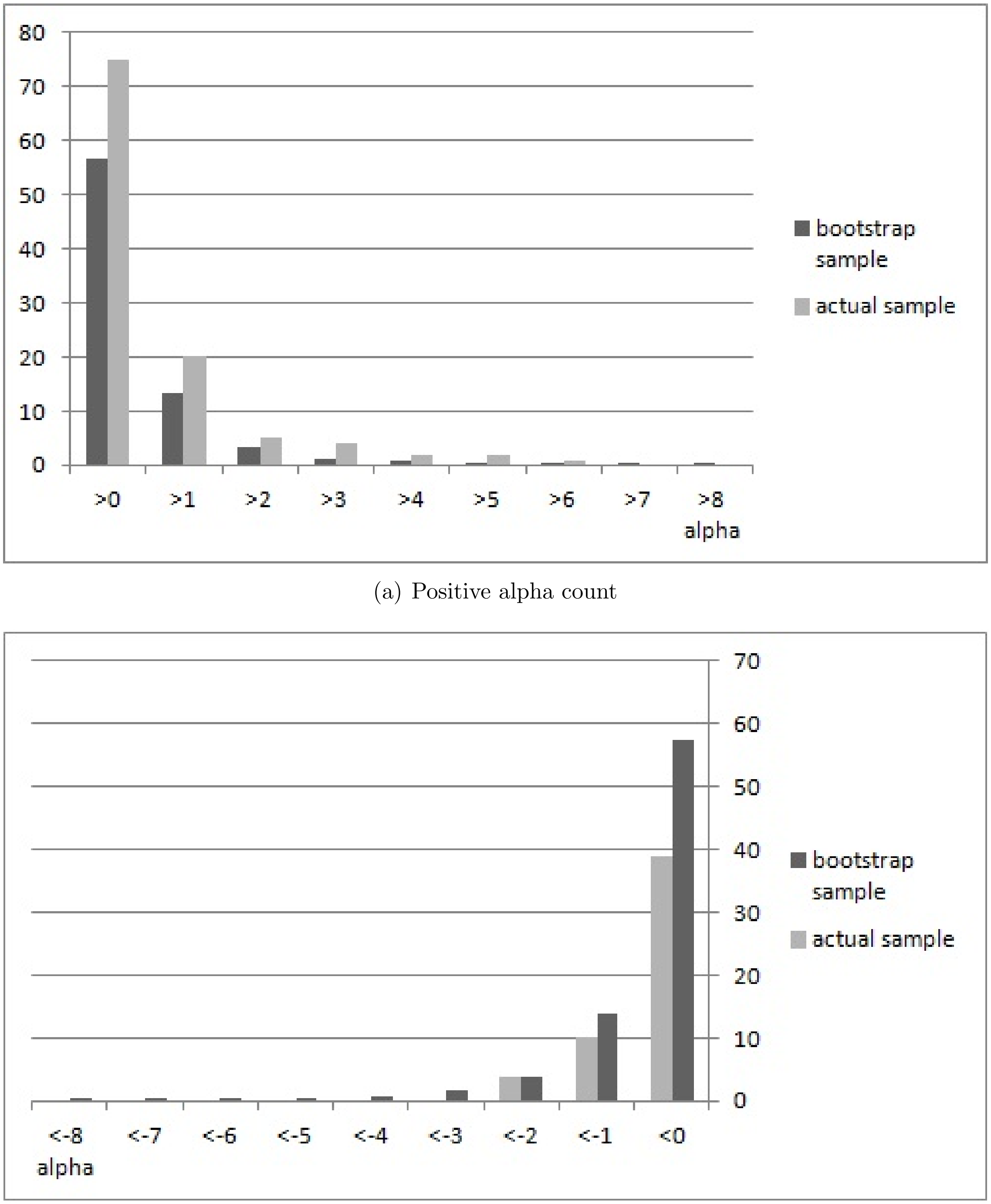
Storey, John D., 2002, A direct approach to false discovery rates, *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 64, 479–498.

Strömberg, Per, 2007, The new demography of private equity .

Stucke, Rüdiger, 2011, Updating history, *Available at SSRN 1967636* .

von Hippel, Paul, 2005, Mean, Median, and Skew: Correcting a Textbook Rule, *Journal of Statistics Education* 13.

Weiss, Kathleen, 1989, The Post-Offering Price Performance of Closed-End Funds, *Financial Management* 18, 57–67.



(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.

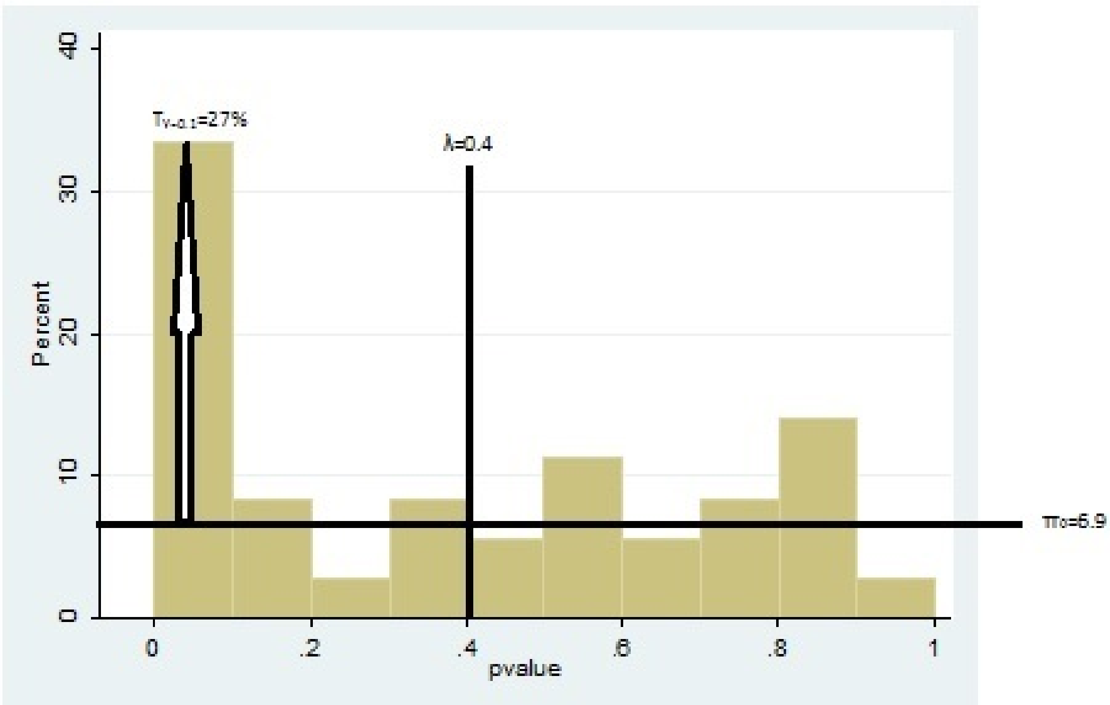


Figure 2. False Discovery Rate - Buyout LPEs

This figure presents a histogram of the p-values for Buyout LPEs, estimated using the bootstrap technique from Section V.A. 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. $T_{\gamma=0.1}$ *is the proportion 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 for the period January 1st 1995 to December 31st, 2015. The LPE Universe consists of the constituents of the S&P Listed Private Equity index, Société Générale Privex index, the ALPS-RedRocks Global Listed Private Equity index, and the ProShares Global Listed Private Equity ETF, 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 December 31st, 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	5	68	46
Count (US & Canada)	83	32	4	22	3	0	3	6	25
Count (Europe)	98	75	34	4	11	23	2	52	23
Count (RoW)	12	7	3	0	2	2	0	7	0
Count (PLCs)	102	68	29	4	14	14	6		
Count (CEFs)	91	46	12	22	2	11	0		
Net Assets ($millions, 2015)	375,955	153,748	38,794	74,883	5,460	10,754	23,853	63,890	89,857
Total Assets ($millions, 2015)	983,073	293,545	102,539	114,664	6,265	11,259	58,816	161,788	131,756

Table II Regional Factor R^2 Estimates

This table presents the coefficients and adjusted R^2 statistics for regressions of the monthly 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	1.052	0.646	-0.010	-0.117		0.259	0.810
	(21.44)	(7.54)	(-0.13)	(-1.71)		(1.56)	
Global Non-US Factors	0.926	0.348	-0.136	0.005		0.465	0.710
	(18.13)	(3.71)	(-1.38)	(0.22)		(2.71)	
European Factors	0.947	0.466	-0.181	-0.001		0.312	0.791
	(23.81)	(6.05)	(-2.48)	(-0.05)		(2.08)	
UK Factors	0.087	0.605	-0.078	-0.007		0.699	0.140
	(1.10)	(3.73)	(-0.58)	(-0.05)		(1.70)	
North American Factors	0.884	0.448	0.150	-0.029		0.059	0.689
	(14.45)	(6.18)	(2.17)	(-1.63)		(0.31)	
North American Factors plus Liquidity	0.895	0.454	0.163	-0.030	0.074	0.091	0.693
	(14.52)	(6.12)	(2.23)	(-1.66)	(1.62)	(1.98)	

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 1995-2015. t-statistics using robust standard errors are in parentheses.

	Monthly Excess Return	RMRF	SMB	HML	WML	Constant	Adj R^2	Obs
Full	0.67	1.05	0.65	-0.01	-0.12	0.26	0.81	17,378
	(1.94)	(21.44)	(7.54)	(-0.13)	(-1.71)	(1.56)		
Buyout	0.81	1.05	0.58	0.34	-0.07	0.26	0.75	6,844
	(2.34)	(19.97)	(5.77)	(4.53)	(-0.91)	(1.36)		
Mezzanine	0.79	0.92	0.52	0.35	-0.16	0.37	0.49	2,990
	(2.06)	(11.25)	(4.05)	(3.15)	(-2.54)	(1.19)		
Venture	0.11	1.37	1.08	-1.41	-0.33	0.12	0.64	2,606
	(0.18)	(13.49)	(4.62)	(-8.03)	(-2.32)	(0.30)		
FoF	0.70	0.92	0.58	0.18	-0.06	0.27	0.64	4,255
	(2.14)	(13.64)	(5.82)	(1.81)	(-0.71)	(1.11)		
GP	1.13	1.28	0.53	1.12	-0.12	0.24	0.53	683
	(1.66)	(11.41)	(1.57)	(3.22)	(-0.67)	(0.49)		

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

This table presents the results of Fama-French-Carhart 4-factor regressions of the monthly excess returns of the quartile 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 (4-1) portfolio. Stocks with the highest 1-year past return comprise the quartile 4 portfolio and stocks with the lowest 1-year past return comprise quartile 1. t-statistics using robust standard errors are in parentheses.

Panel A - Full Sample

Portfolio	Monthly Excess Return	RMRF	SMB	HML	WML	Constant	Adj R^2
1 (low)	0.57	1.14	0.72	-0.26	-0.36	0.28	0.78
	(1.36)	(20.03)	(6.12)	(-2.63)	(-4.93)	(1.37)	
2	0.76	1.04	0.60	0.08	-0.13	0.26	0.79
	(2.17)	(19.52)	(6.37)	(0.95)	(-1.85)	(1.45)	
3	0.78	1.01	0.57	0.08	-0.09	0.28	0.76
	(2.31)	(19.49)	(6.59)	(1.03)	(-1.29)	(1.51)	
4 (high)	0.86	1.11	0.60	-0.12	0.06	0.27	0.77
	(2.34)	(19.41)	(5.59)	(-1.27)	(0.76)	(1.48)	
4-1 spread	0.29	-0.03	-0.11	0.14	0.42	-0.01	0.35
	(1.60)	(-0.92)	(-1.30)	(2.07)	(9.35)	(-0.09)	

Panel B - Buyout

Portfolio	Monthly Excess Return	RMRF	SMB	HML	WML	Constant	Adj R^2
1 (low)	0.64	1.14	0.60	0.42	-0.14	-0.02	0.69
	(1.59)	(17.73)	(4.20)	(3.61)	(-1.52)	(-0.06)	
2	0.64	1.02	0.52	0.34	-0.09	0.04	0.72
	(1.84)	(17.52)	(4.86)	(4.26)	(-1.22)	(0.19)	
3	0.90	1.01	0.53	0.35	-0.07	0.29	0.72
	(2.63)	(18.18)	(5.15)	(4.27)	(-0.96)	(1.50)	
4 (high)	1.17	1.07	0.61	0.36	0.02	0.46	0.71
	(3.23)	(20.30)	(6.11)	(4.30)	(0.37)	(2.27)	
4-1 spread	0.53	-0.06	0.01	-0.06	0.16	0.48	0.08
	(2.84)	(-1.49)	(0.06)	(-0.59)	(2.35)	(2.41)	

Table IV - continued

Panel C - Mezzanine

Portfolio	Monthly Excess Return	RMRF	SMB	HML	WML	Constant	Adj R^2
1 (low)	1.27	0.93	0.60	0.61	-0.50	0.47	0.54
	(2.06)	(9.50)	(2.00)	(1.97)	(-3.13)	(1.03)	
2	1.13	0.86	0.38	0.77	-0.31	0.34	0.56
	(2.11)	(9.68)	(1.65)	(2.74)	(-2.60)	(0.85)	
3	1.11	0.85	0.31	0.75	-0.20	0.31	0.58
	(2.24)	(10.13)	(1.46)	(2.71)	(-1.94)	(0.83)	
4 (high)	0.92	0.82	0.31	0.78	-0.14	0.12	0.56
	(1.93)	(8.99)	(1.45)	(2.72)	(-1.68)	(0.33)	
4-1 spread	-0.35	-0.11	-0.29	0.16	0.36	-0.35	0.16
	(-1.09)	(-1.55)	(-1.22)	(0.81)	(2.60)	(-1.12)	

Panel D - Funds of Funds

Portfolio	Monthly Excess Return	RMRF	SMB	HML	WML	Constant	Adj R^2
1 (low)	0.35	0.98	0.58	0.02	-0.19	-0.06	0.45
	(0.78)	(13.21)	(3.36)	(0.11)	(-2.07)	(-0.16)	
2	0.89	0.90	0.57	0.23	-0.12	0.41	0.60
	(2.58)	(12.71)	(5.13)	(2.24)	(-1.39)	(1.61)	
3	0.80	0.91	0.56	0.23	-0.04	0.26	0.59
	(2.33)	(12.33)	(4.77)	(2.13)	(-0.43)	(0.99)	
4 (high)	0.75	0.91	0.59	0.16	0.03	0.19	0.58
	(2.17)	(11.14)	(5.06)	(1.38)	(0.31)	(0.70)	
4-1 spread	0.40	-0.07	0.01	0.14	0.21	0.24	0.04
	(1.18)	(-1.08)	(0.08)	(0.92)	(2.33)	(0.68)	

Panel E - Venture

Portfolio	Monthly Excess Return	RMRF	SMB	HML	WML	Constant	Adj R^2
1 (low)	-0.38	1.38	0.91	-2.03	-0.66	0.19	0.56
	(-0.45)	(10.43)	(2.43)	(-7.78)	(-3.06)	(0.29)	
2	0.09	1.45	1.01	-1.41	-0.31	0.14	0.64
	(0.13)	(13.37)	(3.91)	(-7.41)	(-2.07)	(0.30)	
3	0.07	1.44	1.20	-1.37	-0.15	0.00	0.64
	(0.09)	(14.31)	(4.94)	(-7.13)	(-1.02)	(0.01)	
4 (high)	0.20	1.37	1.16	-1.17	0.06	-0.05	0.57
	(0.29)	(12.65)	(4.15)	(-5.77)	(0.38)	(-0.12)	
4-1 spread	0.58	0.00	0.26	0.87	0.71	-0.24	0.13
	(0.93)	(-0.04)	(0.74)	(3.24)	(3.61)	(-0.38)	

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

This table presents the annual NAV returns of the winner-minus-loser (4-1) quartile 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. Stocks with the highest 1-year past return comprise the quartile 4 portfolio and stocks with the lowest 1-year past return comprise quartile 1. The results of Fama-French-Carhart 4-factor regressions of the monthly excess returns of the 4-1 portfolios are also given. t-statistics using robust standard errors are in parentheses.

Portfolio	Annual Excess Return	RMRF	SMB	HML	WML	Constant	Adj R^2
Full (4-1)	5.48	0.43	0.81	0.20	0.13	1.24	0.38
	(1.49)	(3.23)	(1.82)	(0.65)	(0.75)	(0.34)	
Buyout (4-1)	11.22	0.42	0.03	0.42	-0.14	7.97	0.26
	(2.97)	(3.00)	(0.09)	(1.88)	(-0.84)	(1.81)	
Venture (4-1)	-20.55	0.01	2.24	-1.45	-3.72	18.62	0.34
	(-1.16)	(0.02)	(0.92)	(-0.99)	(-2.70)	(1.58)	
Mezzanine (4-1)	11.40	0.12	-0.29	-0.26	0.26	9.70	0.26
	(4.06)	(1.49)	(-0.58)	(-0.66)	(1.85)	(3.80)	
FoF (4-1)	7.48	0.39	-0.37	0.62	0.17	0.32	0.37
	(2.50)	(4.11)	(-1.19)	(3.41)	(0.89)	(0.08)	

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. Portfolio 1 includes the LPEs with the lowest NAV permia in year t, portfolio 4 consists of the LPEs with the highest NAV premia. The results of an unpaired t-test comparing the year t+1 NAV changes for portfolio 4 and portfolio 1 are given in the last row. NAV changes and premia are winsorized at the 5% level.

Portfolio	Full		Buyout		Mezzanine		Venture		FoF	
Ranked by Year t NAV Premium	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)	-53.22	3.26	-58.58	3.87	-35.93	0.94	-46.94	-4.49	-48.97	9.35
2	-26.95	6.71	-32.42	8.83	-14.26	2.41	-13.85	-5.74	-31.83	9.92
3	-5.50	2.94	-13.29	6.27	-0.52	3.20	38.90	-7.57	-19.72	8.33
4 (high)	66.68	10.38	31.02	13.15	23.50	6.32	170.45	17.78	17.20	6.34
4-1 t-stat		2.71		2.03		1.67		2.99		-0.74

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-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, 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	0.81	0.05	0.14
Buyout	0.4	0.2	0.69	0.10	0.21
Mezzanine	0.35	0.2	0.71	0.05	0.24
Venture	0.3	0.2	>0.99		
FoF	0.4	0.2	0.73	0.05	0.22

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 monthly excess price return and 4-factor alpha for the winner-minus-loser (4-1) portfolio (Carhart skill measure) for the full LPE sample and its subsamples for various subperiods. t-statistics estimated using robust standard errors are in parentheses, and the number of observations for each subperiod is given in braces.

	1995-1999		2000-2004		2005-2009		2010-2012		2013-2015	
Portfolio	Excess Return	alpha	Excess Return	alpha	Excess Return	alpha	Excess Return	alpha	Excess Return	alpha
Full (4-1)	0.83	0.32	0.44	0.4	-0.29	-0.42	0.58	0.39	1.02	0.68
	(1.85)	(0.66)	(0.68)	(0.67)	(-1.29)	(-2.04)	(2.67)	(1.95)	(2.87)	(1.63)
	{1925}		{2980}		{5140}		{3793}		{3842}	
Buyout (4-1)	0.22	-0.02	0.92	1.04	0.13	0.16	0.09	-0.06	1.63	1.01
	(0.61)	(-0.04)	(2.00)	(1.83)	(0.33)	(0.46)	(0.20)	(-0.18)	(3.25)	(1.69)
	{1066}		{1313}		{1991}		{1323}		{1265}	
Venture (4-1)	1.35	0.82	1.57	-1.20	-0.23	-0.29	-0.71	-0.63	-0.03	-0.23
	(0.75)	(0.48)	(0.79)	(-0.60)	(-0.40)	(-0.56)	(-0.93)	(-0.85)	(-0.02)	(-0.13)
	{314}		{502}		{793}		{523}		{520}	
Mezzanine (4-1)	-	-	-1.58	-1.35	-0.34	-0.41	0.27	0.10	0.72	0.27
	-	-	(-1.81)	(-1.17)	(-0.53)	(-0.68)	(0.67)	(0.27)	(1.82)	(0.72)
	{108}		{287}		{927}		{817}		{906}	
FoFs (4-1)	1.38	1.87	0.85	1.30	-0.59	-0.67	0.81	0.64	0.38	0.33
	(1.19)	(1.20)	(1.17)	(1.60)	(-1.60)	(-1.81)	(2.89)	(2.54)	(1.04)	(0.84)
	{437}		{833}		{1250}		{925}		{885}	

Table XI Results Summary

This table gives a review of the tests performed in this paper and the test results for the full LPE sample and the four subsamples.

Test	Full Sample	Buyout	Mezzanine	Venture	FoF
Short-term 4-1 Price return	-	Significant	-	-	-
Short-term 4-1 NAV return	-	Significant	Significant	-	Significant
Short-term 4-1 NAV Predictability	Significant	Significant	Significant	Significant	-
Cross-sectional bootstrap (alpha)	Significant	Significant	Significant	Significant	-
Cross-sectional bootstrap (t-alpha)	Significant	Significant	Significant	-	-
False Discovery Rate (truly skilled)	14%	20%	24%	-	22%
False Discovery Rate (truly unskilled)	5%	7%	5%	-	5%
Dollar Value-add (USD millions)	16	11.6	34	2	21.7