ESSAYS ON PRIVATE EQUITY AND MUTUAL FUNDS

A dissertation submitted

in partial fulfillment of the requirements for the degree of

PHD IN BUSINESS ADMINISTRATION

and for the degree of

DOCTEUR EN SCIENCES DE GESTION

DE L'ECOLE DOCTORALE

« ECONOMIE, MANAGEMENT, MATHEMATIQUES ET PHYSIQUE »

ED 405

UNIVERSITE PARIS-SEINE

Presented and defended publicly the 19th of June 2018 by

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Acknowledgements

Over the 5-year course of my PhD studies at ESSEC, I have come to realise how much team support is required to get through. In rough chronological order, I am grateful to the people who took the time to assist me with my application to the PhD program - Hitesh Tewari, Dónal O'Mahony, Séamus Kelly, Yanp Zhong and Donatien Hainaut. I am very appreciative of the efforts of Laurence Lescourret, the director of the ESSEC Finance PhD progam, for offering me a position on the program in the first place, and for supporting me through the ups and downs along the way. I owe a huge debt of gratitude to my thesis co-supervisor Sridhar Arcot whose door was always open for lively discussion and advice. I am also very grateful to my second thesis co-supervisor Sofia Ramos who likewise provided inspiration and guidance at key points during my studies. I would also like to acknowledge advice and support generously provided by members of the Finance department, particularly José-Miguel Gaspar, Andras Fulop, Roméo Tédongap, Patrice Poncet, and Lorenzo Naranjo. Lina Prevost and Christine Gil in the PhD Program Office deserve a big thank you for their cheerful assistance with many administrative tasks.

A special word of appreciation is due to the external PhD committee members, Marie Brière, Roland Füss, and Armin Schwienbacher, for generously taking time out of their busy schedule to examine this thesis.

I would also like to acknowledge sources of financial support. ESSEC granted me a tuition waiver throughout the program, and a PhD stipend for years 3 and 4. The ESSEC-Amundi Chair awarded a scholarship for year 5. I also received funding from Inquire Europe for Essay 2 *Do Publicly Listed Private Equity Firms make Bad Deals?*.

Lastly, and most importantly, I would like to thank my wife Inju whose vision and belief inspired me to make this thesis a reality, and I dedicate it to her.

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General Introduction

Investment manager skill is one of the most researched topics in finance, so readers may wonder why there are still theses such as this one which launches three new Essays on the topic. There are two parts to the answer. The first part lies in the fact that the issue is an extremely important one for many people, organizations, and even governments, at all levels of society and in all corners of the globe. The second part of the answer lies in the fact that, despite intensive research going back 50 years at least, investment manager skill is not yet a well understood phenomenon.

For most people, securing the resources required to live is a primordial and never-ending quest. The first priority for people of working age is to secure an income that covers living expenses and provides some level of savings. People save for many reasons, but perhaps the most important is to provide a cushion for the times when they cannot work due to illness or old age. The second priority then is to manage these savings so that they are available when they are needed and are sufficient to meet the person's requirements. It is already at this point that investment management skills come in to play. Even at an individual level, we are all investment managers - we must decide where to place our savings so that they are available and sufficient when we need them.

Managing savings of course is not just a challenge for individuals - households, families, institutions and governments need to manage funds that will provide financial security for their stakeholders in the future. Family offices centralize the management of a significant family fortune. At the institutional level, pension fund managers have the onerous responsibility of managing the pension pots of their individual members, while the investment management success of certain university endowment funds has attracted attention in the financial community. At the government level, sovereign wealth funds such as those of Norway and Abu Dhabi aim to provide a financial buffer for their citizens after oil revenues expire.

Savers today have a wide range of investment management options. They can choose to manage their own savings without any outside assistance. Unsophisticated savers[1] may hold their cash at home. Very sophisticated savers may also manage all or part of their own investments, directly accessing financial instruments such as stock markets or real estate. However most savers are willing to pay intermediaries such as asset management companies to manage their savings. These financial intermediaries typically aggregate the savings of many individuals into mutual funds which are invested by fund managers on the savers' behalf. As well as choosing a financial intermediary, investors may choose an asset class based on their tastes or risk preferences, and decide whether they want to passively track general benchmarks (such as S&P500) for the chosen asset class (passive management), or whether they believe certain individual fund managers have special investment management skills which will enable their savings to grow more quickly than the general benchmarks (active management).

Financial intermediation today is a huge industry. According to ICI Global[2], savers globally had committed $50 trillion (US dollars) to regulated open-end mutual funds at the end of 2017. This figure does not include capital committed to other types of mutual funds, such as closed-end funds, sovereign wealth funds, or alternative investments such as hedge funds, infrastructure funds or private equity. Despite the recent rapid rise in popularity of passively managed funds, the majority (over 90% according to ICI Global) of capital committed to mutual funds is actively managed.

Therefore most savers continue to entrust a very large amount of their hard-earned cash with fund managers who then have discretion to make investments

[1] The World Bank estimates that 2 billion people do not use formal financial services and more than 50% of adults in the poorest households are unbanked. (http://www.worldbank.org/en/topic/financialinclusion, accessed 18 April, 2018)

[2] Source: https://www.iciglobal.org/iciglobal/research/stats/ww/ci.ww_q4_17.global, accessed 16.April.2018.

on their behalf. Furthermore, savers pay these fund managers extremely well; in the mutual fund sample used in Essay 3 of this thesis, the median US equity fund manager charges expenses of 0.12% per month, or 1.4% per year; aggregating that over the global mutual fund industry in 2017, fund managers received over $0.7 trillion in fees from their investors.

Therefore the first reason why fund manager skill has been, is now, and will continue to be an important research topic is that so many people believe active fund managers can help them provide for their future financial security, and therefore give these managers huge sums of money to manage, and compensate them very well for doing so.

The second reason why fund manager skill is a fascinating research topic is that it is difficult to pin down what it is exactly that skilled fund managers do, or even whether they actually exist. In this thesis, Essays 1 and 3 address directly the question whether skill exists in the fund management industry and if so, what is it that skilled fund managers are doing. Specifically, in Essay 1 *Estimating Skill in Private Equity Performance using Market Data* I test for skill in private equity funds, which are essentially actively-managed closed-end funds of investments in private companies, while in Essay 3 *Persistence and Skill in the Performance of Mutual Fund Families* I (along with Sofia Ramos) look at whether some mutual fund families (that is, asset management firms) group together skilled fund managers.

Essays 1 and 3 test the efficient markets hypothesis[3] (EMH) which posits that asset prices fully reflect all available information and that it is impossible to “beat the market” consistently on a risk-adjusted basis since market prices should only react to new information. Thus, according to the EMH, while some investment managers may have a good run for a period of time, and may

[3] The origins of the efficient markets hypothesis can be traced back to the PhD thesis of Bachelier (1900) and the work of Hayek (1945), but it’s modern form is mainly attributed to the work of Eugene Fama (1965, 1970).

appear to have investment selection abilities that are superior to their peers, these managers do not actually have special skills, rather they are just lucky, and given a long enough time period their apparent gains will disappear.

Carhart (1997) and Fama and French (2010) provide evidence supporting the EMH in the US mutual fund industry. They measure skill as α, the abnormal return earned by the fund in excess of a set of passive benchmarks (the Fama-French-Carhart factors). Fama and French advance the notion of equilibrium accounting, which argues that where returns are measured before costs (fees and other expenses), passive investors get passive returns, that is, they have zero α (abnormal expected return) relative to passive benchmarks. This means active investment must also be a zero sum game - aggregate α is zero before costs. Thus, if some active investors have positive α before costs, it is dollar for dollar at the expense of other active investors. After costs, that is, in terms of net returns to investors, active investment must be a negative sum game. Using α as the skill measure, and applying the cross-sectional bootstrap to control for luck, Fama and French (2010) show that indeed there is little evidence that active fund management is not a negative sum game, after fees.

Essay 1 also examines the Berk and Green (2004) model, where a fund is endowed with a permanent α, before costs, but it faces costs that are an increasing convex function of assets under management (AUM). Investors use returns to update estimates of α. A fund with a positive expected α before costs attracts inflows until AUM reaches the point where expected α, net of costs, is zero. Outflows drive out funds with negative expected α. In equilibrium, all active funds (and thus funds in aggregate) have positive expected α before costs and zero expected α net of costs.

Thus Berk and van Binsbergen (2015) argue that using α as a measure of skill is misleading; the skill of a fund manager must take into account the effect of decreasing returns to scale due to the size of their funds. Berk and van

Binsbergen propose an alternative skill measure, dollar-value-added, which is the fund's gross α multiplied by its lagged AUM. Using this measure, they show that the average fund manager has sufficient skill to add value to their funds.

In Essay 3, we explore Pástor et al. (2015)'s measure of skill as the fund fixed effects from a regression of gross α on fund size and industry size. Using this measure, the authors argue that fund managers are skilled, and indeed that skill has been increasing over time. However, they also show that mutual fund industry size has increased over time, and that fund returns are decreasing in industry size due to increased competition; in fact, they argue that it is industry size, not fund size, that has the strongest negative scale effects on fund performance. As a result, mutual fund performance has not improved despite increasing fund manager skill.

While these Essays consider different theories of fund manager skill, they do so primarily in order to determine if skill exists by applying the tests used in the literature to support these theories, to quantify skill, and to examine it's determinants. It is not my objective to conclude that one theory is "right', or that another is "wrong".

Specifically, in Essay 1, I examine the *net* returns of a sample of listed closed-end private equity funds and firms (so-called "permanent" PE, to distinguish them from traditional PE fund managers which raise their investment capital via sequences of fixed-life funds). I test the efficient market hypothesis using α (or its t-statistic) as the skill measure, and I find evidence of skill for Buyout and Mezzanine private equity (the risk-adjusted returns for top-quartile Buyout LPEs exceed bottom-quartile LPE returns by 6-8% per year), but there is little evidence that Venture LPEs exhibit skill. Using the dollar-value-added skill measure, I also find that the median LPE generates \$16 million of value-added per year for investors.

These findings are consistent with prior studies of persistence and skill in traditional private equity funds, including Kaplan and Schoar (2005) and Korteweg and Sorensen (2017). Also, consistent with Braun et al. (2017) and Kartashova (2014), I find that short-term Buyout LPE persistence declined during the 2000-2009 period. This decline has been interpreted by Braun et al. (2017) to be a sign of the increasing competition for deals among PE firms. However in the period 2010-2015, short-term persistence for Buyout LPE has rebounded significantly. Thus competition for deals may have declined since the 2007-2008 financial crisis, allowing skilled LPEs to differentiate themselves from unskilled ones, and to deliver strong returns in the years following the crisis.

The dataset also allows me to examine the determinants of skill for Buyout and Mezzanine LPEs, and I find that firms with higher proportions of solo deals relative to syndicate deals have higher performance measures, while PE firms with relatively large numbers of exits via secondary buyouts and management buyouts tend to underperform. More solo buyouts by a PE firm mean that the PE firm has the resources (such as capital, network or reputation) required to find its own deals in the first place, and that it is confident of deal outcomes and wishes to capture exclusively the rents from the deal. On the other hand, PE deals that are exited via a secondary buyout or a management buyout may be more likely to have been unsuccessful, as the PE firm was unable to bring the portfolio firm to IPO or to find a trade buyer.

Essay 3 *Persistence and Skill in the Performance of Mutual Fund Families* is the most recent of the series. In this Essay, we analyze skill, and the determinants of skill, in the average *gross* fund returns of mutual fund families. While much prior research has focused on individual fund manager skill, there have been very few studies of skill at the mutual fund family level. This seems to be a significant gap, as other research has shown that firm-level policies have a significant effect on the performance of individual fund managers (Berk et al. (2014)). Here we find evidence that fund family performance is persistent, and that some families are truly skilled. We introduce a novel measure for estimating the impact of family characteristics on family skill. The fund families most likely to be skilled are single-fund families that charge higher fees, presumably reflecting the fact that there is self-selection by skilled fund managers to start their own fund family, and that it is costly to acquire and retain skill. We also find that families that have high fund turnover (that is, that close old funds and launch new ones) have higher skill measures, perhaps reflecting higher monitoring of individual fund management by the family, and more active reallocation of funds across managers. This finding is consistent with Berk et al. (2014) who show that fund families reallocate capital among fund managers based on the famliy's private information about the skill of its managers.

Essay 2 *Do Publicly Listed Private Equity Firms make Bad Deals?* does not focus on skill per se, rather it addresses concerns that deals by publicly listed private equity firms may underperform those of more traditional unlisted private equity firms. I use a Heckman selection procedure to impute the deal multiples for deals by public and private PE firms from CapitalIQ transaction data, and as a result I have one of the largest datasets of private equity deal performance. This novel dataset is free of certain biases that affect previous private equity research, can easily be kept up-to-date, and thus has the potential to be the basis for a number of interesting and significant papers on private equity performance. In the paper I ask if deal performance for publicly listed private equity firms is weaker than for private PE firms. I find that this is not the case: the performance of deals by "permanent" private equity firms and funds is not significantly different from the performance of deals by traditional GPs. Furthermore, deals by publicly listed GPs significantly outperform deals by private GPs.

Taken together, these Essays contribute to various streams of the investment management literature by taking a fresh look at skill in asset classes where it is difficult to measure (private equity), or where the topic has not previously been studied in depth (mutual fund families). The findings yield contrasting results in that there is substantial evidence of skill for private equity, even after fees, but less evidence of skill for mutual fund families. Possible reasons for the divergence may include high fund manager incentives in the private equity industry, decreasing returns to scale in the mutual fund industry, search costs for investors (which are high in private equity - see Korteweg and Sorensen (2017)), market sector inefficiency, or some combination of these factors.

These Essays also contain useful information for practitioners and investors. By identifying at least some determinants of skill, practitioners can get a sense of the behaviors which add to (or subtract from) the value of their funds. By quantifying and locating skill in different type of funds, the papers' findings can also aid investors to focus their search for skill, and at least increase the probability of finding a skilled fund manager.

A feature of this thesis is the variety of empirical methodologies that it brings together. These include classic workhorses such as vanilla OLS, Markov transition probabilities, Heckman selection, propensity score analysis, OLS fixed effects, and instrumental variables, but I also apply approaches that have only recently appeared in the financial literature such as cross-sectional bootstrap, false discovery rate, dollar-value-added, and recursive-demeaned fixed effects models. We also introduce a novel method for estimating the impact of fund manager characteristics.

To conclude this Introduction, the topic of skill in fund management is extremely important for many people, yet it is a complex one that still requires much serious research. The best I can hope for is that these Essays shed some new light on some areas of the topic that have not yet been fully explored in the existing literature. On a personal note, I found researching skill a very interesting and challenging task that provided a rich framework for advancing my skills as an empirical financial researcher. I hope you enjoy reading these Essays as much as I enjoyed putting them together.

Maurice McCourt

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Résumé

La compétence des gestionnaires de placements est l'un des sujets les plus étudiés en finance, de sorte que les lecteurs peuvent se demander pourquoi il existe encore des thèses comme celle-ci qui lance trois nouvelles Essais sur le sujet. Il y a deux parties à la réponse. La première partie réside dans le fait que la question est extrêmement importante pour de nombreuses personnes, organisations et même gouvernements, à tous les niveaux de la société et aux quatre coins de la planète. La deuxième partie de la réponse réside dans le fait que, malgré une recherche intensive remontant au moins à 50 ans, la compétence des gestionnaires d'investissement n'est pas encore un phénomène bien compris.

Pour la plupart des gens, obtenir les ressources nécessaires pour vivre est une quête primordiale et sans fin. La première priorité pour les personnes en âge de travailler est de s'assurer un revenu qui couvre les frais de subsistance et fournit un certain niveau d'épargne. Les gens économisent pour de nombreuses raisons, mais le plus important est peut-être de fournir un coussin pour les moments où ils ne peuvent pas travailler. La deuxième priorité est de gérer ces économies afin qu'elles soient disponibles lorsqu'elles sont nécessaires et répondent aux exigences. C'est déjà à ce stade que les compétences en gestion d'investissement viennent jouer. Même au niveau individuel, nous sommes tous des gestionnaires d'investissement - nous devons décider où sauvegarder nos économies.

Bien entendu, la gestion de l'épargne n'est pas seulement un défi pour les individus: les ménages, les familles, les institutions et les gouvernements doivent gérer des fonds qui assureront la sécurité financière de leurs parties prenantes à l'avenir. Les family offices centralisent la gestion d'une fortune familiale importante. Sur le plan institutionnel, les gestionnaires de fonds de pension ont la lourde responsabilité de gérer les caisses de retraite de leurs membres individuels, tandis que le succès de la gestion des placements de certains fonds de dotation universitaires a attiré l'attention de la communauté financière. Au niveau gouvernemental, les fonds souverains tels que ceux de Norvège et d'Abou Dhabi visent à fournir un tampon financier à leurs citoyens après l'expiration des revenus pétroliers.

Les épargnants ont aujourd'hui un large éventail d'options de gestion de placements. Ils peuvent choisir de gérer leurs propres économies sans aucune aide extérieure. Les épargnants non avertis peuvent conserver leur argent à la maison. Les épargnants très sophistiqués peuvent également gérer tout ou partie de leurs propres investissements, en accédant directement à des instruments financiers tels que les marchés boursiers ou l'immobilier. Cependant, la plupart des épargnants sont prêts à payer des intermédiaires tels que des sociétés de gestion d'actifs pour gérer leur épargne. Ces intermédiaires financiers regroupent généralement l'épargne de nombreuses personnes dans des fonds communs de placement qui sont investis par les gestionnaires de fonds au nom des épargnants. Outre le choix d'un intermédiaire financier, les investisseurs peuvent choisir une classe d'actifs en fonction de leurs goûts ou préférences de risque et décider s'ils souhaitent suivre passivement les benchmarks généraux (tels que S & P500) pour la classe d'actifs choisie (gestion passive). Nous croyons que certains gestionnaires de fonds ont des compétences particulières en gestion de placements qui permettront à leur épargne de croître plus rapidement que les indices de référence généraux (gestion active).

L'intermédiation financière est aujourd'hui une industrie énorme. Selon ICI Global, les épargnants à l'échelle mondiale ont engagé 50 000 milliards de dollars américains en fonds communs de placement à capital variable réglementés à la fin de 2017. Ce chiffre n'inclut pas les capitaux engagés dans d'autres types de fonds communs de placement, comme les fonds de placement ou les placements alternatifs tels que les hedge funds, les fonds d'infrastructure ou les fonds de capital-investissement. Malgré la récente montée en popularité rapide des fonds gérés de manière passive, la majorité (plus de 90% selon ICI Global) du capital investi dans des fonds communs de placement est activement gérée.

Par conséquent, la plupart des épargnants continuent de confier une très grande partie de leur argent durement gagné à des gestionnaires de fonds qui ont alors le pouvoir discrétionnaire de faire des placements en leur nom. De plus, les épargnants paient extrêmement bien ces gestionnaires de fonds. Dans l'échantillon de fonds commun de placement utilisé dans l'Essai 3 de cette thèse, le gestionnaire de fonds d'actions américaines médian impute des frais de 0,12% par mois, ou 1,4% par année; en 2017, les gestionnaires de fonds ont reçu plus de $0,7 trillion en frais de la part de leurs investisseurs.

Donc, la première raison pour laquelle la compétence de gestionnaire de fonds a été, est maintenant, et continuera d'être un sujet de recherche important est que beaucoup de gens croient que les gestionnaires de fonds actifs peuvent les aider à assurer leur sécurité financière future. Ils donnent donc à ces gestionnaires d'énormes sommes d'argent à gérer et les paient très bien pour cela.

La deuxième raison pour laquelle les compétences de gestionnaire de fonds est un sujet de recherche fascinant est qu'il est difficile de cerner ce que font exactement les gestionnaires de fonds compétents, ou même s'ils existent réellement. Dans cette thèse, les Essais 1 et 3 abordent directement la question de savoir si les compétences existent dans l'industrie de la gestion de fonds et, dans l'affirmative, qu'est-ce que les gestionnaires de fonds compétents font. Spécifiquement, dans l'Essai 1 «Estimation de la compétence en Private Equity Performance en utilisant les données du marché», je teste les compétences dans les fonds de private equity, qui sont essentiellement des fonds de placement fermés gérés activement dans des sociétés privées. Dans l'Essai 3 «Persistance et compétence dans la performance des fonds communs de placement» (avec Sofia Ramos) je cherche à savoir si certaines familles de fonds communs de placement (c'est-à-dire les sociétés de gestion d'actifs) regroupent des gestionnaires de fonds qualifiés.

Les Essais 1 et 3 testent l'hypothèse des marchés efficients (EMH) qui postule que les prix des actifs reflètent pleinement toutes les informations disponibles et qu'il est impossible de «battre le marché» de façon cohérente ajustée au risque puisque les prix du marché ne devraient réagir qu'aux nouvelles information. Ainsi, selon l'EMH, si certains gestionnaires de placements peuvent avoir une bonne performance pendant un certain temps, et peuvent sembler avoir des capacités de sélection d'investissement supérieures à leurs pairs, ces gestionnaires n'ont pas de compétences spéciales, mais plutôt chanceux, et étant donné une période suffisamment longue, leurs gains apparents disparaîtront.

Carhart (1997) et Fama & French (2010) fournissent des preuves à l'appui de l'EMH dans le secteur des fonds communs de placement aux États-Unis, qui mesurent la compétence en alpha, le rendement anormal gagné par le fonds au-delà d'un ensemble de benchmarks passifs. Fama & French avancent la notion de la comptabilité d'équilibre, qui soutient que lorsque les rendements sont mesurés avant les coûts (frais et autres dépenses), les investisseurs passifs obtiennent des rendements passifs, c'est-à-dire zéro alpha (rendement attendu anormal). Cela signifie que l'investissement actif doit également être un jeu à somme nulle - l'alpha global est égal à zéro avant les coûts. Ainsi, si certains investisseurs actifs ont un alpha positif avant les coûts, c'est dollar pour dollar au détriment des autres investisseurs actifs. En termes de rendement net pour les investisseurs, l'investissement actif doit être un jeu à somme négative. Avec l'alpha comme mesure de compétence, et en appliquant le bootstrap transversal pour contrôler la chance, Fama & French (2010) montrent qu'il y a peu de preuves que la gestion active de fonds n'est pas un jeu à somme négative, après les frais.

L'Essai 1 examine également le modèle de Berk et Green (2004), où un fonds est doté d'un alpha fixe, avant coûts, mais il fait face à des coûts qui sont une fonction convexe croissante des actifs sous gestion (AUM). Les investisseurs utilisent les rendements pour mettre à jour les estimations de l'alpha. Un fonds avec un alpha positif anticipé avant les coûts attire les flux jusqu'à ce que l'actif sous gestion atteigne le point où l'alpha attendu, net des coûts, est nul. Les sorties de fonds chassent les fonds avec un alpha négatif attendu. En situation d'équilibre, tous les fonds actifs (et donc les fonds dans leur ensemble) ont un alpha attendu positif avant les coûts et un alpha net attendu de zéro après les coûts.

Par conséquent Berk & van Binsbergen (2015) soutiennent que l'utilisation de l'alpha comme mesure de compétence est trompeuse: la compétence d'un gestionnaire de fonds doit tenir compte de l'effet de réduction des rendements d'échelle en raison de la taille de leurs fonds. Berk & van Binsbergen proposent une autre mesure de compétence, la valeur ajoutée en dollars, qui est l'alpha brut du fonds multiplié par la valeur retardée de ses actifs sous gestion, ce qui montre que le gestionnaire de fonds moyen possède les compétences suffisantes pour ajouter de la valeur à ses fonds.

Dans l'Essai 3, nous examinons la mesure de la compétence de Pastor, Stambaugh et Taylor (2015), à savoir les effets fixes du fonds découlant d'une régression de l'alpha brut sur la taille du fonds et la taille de l'industrie. En outre, ils montrent que la taille de l'industrie des fonds communs de placement a augmenté au fil du temps et que les rendements des fonds diminuent en raison de l'intensification de la concurrence. En fait, ils soutiennent que c'est la taille de l'industrie, pas la taille du fonds, qui a les effets négatifs les plus importants sur le rendement du fonds, ce qui fait que la performance des fonds communs de placement ne s'est pas améliorée malgré l'amélioration des compétences des gestionnaires de fonds.

Bien que ces Essais examinent différentes théories de la compétence des gestionnaires de fonds, ils le font principalement afin de déterminer si la compétence existe en appliquant les tests utilisés dans la littérature pour soutenir ces théories, quantifier les compétences et examiner ses déterminants. Mon objectif n'est pas de conclure qu'une théorie est «juste», ou qu'une autre est «fausse».

Spécifiquement, dans l'Essai 1, j'examine les rendements nets d'un échantillon de fonds et de sociétés de capital-investissement fermés cotés (PE «permanent», afin de les distinguer des gestionnaires de fonds PE traditionnels qui augmentent leur capital d'investissement via des séquences des fonds à durée fixe). Je vérifie l'hypothèse du marché efficace en utilisant l'alpha (ou sa statistique t) comme mesure de compétence, et je trouve des preuves de compétence pour les capitaux propres Buyout et Mezzanine (les rendements ajustés au risque pour les LPE Buyout du premier quartile dépassent les rendements LPE du quartile inférieur de 6 à 8% par an), mais il y a peu de preuves que les LPE de Venture affichent des compétences. En utilisant la mesure des compétences à valeur ajoutée, je constate également que la LPE médiane génère 16 millions de dollars de valeur ajoutée par an pour les investisseurs.

Ces résultats concordent avec des études antérieures sur la persévérance et les compétences dans les fonds de capital-investissement traditionnels, notamment Kaplan & Schoar (2005) et Korteweg & Sorensen (2017). De plus, d'après Braun et al. (2017) et Kartashova (2014), la persistance à court terme de LPE Buyout a diminué au cours de la période 2000-2009. Cette baisse a été interprétée par Braun et al (2017) comme un signe de la concurrence croissante pour les transactions entre les entreprises de PE. Cependant, sur la période 2010-2015, la persistance à court terme de Buyout LPE a fortement rebondi. Ainsi, la concurrence pour les transactions peut avoir diminué depuis la crise financière de 2007-2008, permettant aux LPE qualifiés de se différencier des non qualifiés, et de générer de solides rendements dans les années qui ont suivi la crise.

L'ensemble de données me permet également d'examiner les déterminants des compétences pour les LPE Buyout et Mezzanine, et je trouve que les entreprises avec des proportions plus élevées de transactions en solo ont des mesures de performance plus élevées, tandis que les entreprises PE avec un nombre relativement élevé de sorties les rachats de gestion ont tendance à sous-performer. Plus de rachats en solo par une société de capital-investissement signifie que la société PE a les ressources (telles que capital, réseau ou réputation) nécessaires pour trouver ses propres offres, et qu'elle est confiante sur les résultats des transactions et souhaite capturer exclusivement les loyers de l'affaire. D'un autre côté, les opérations PE qui sont abandonnées via un rachat secondaire ou un rachat par la direction ont plus de chances d'échouer, car l'entreprise PE n'a pas été en mesure amener à l'introduction en bourse ou de trouver un acheteur.

L'Essai 3 est le plus récent de la série. Dans cet Essai, nous analysons les compétences et les déterminants des compétences dans les rendements moyens des fonds communs de placement. Bien que beaucoup de recherches antérieures se soient concentrées sur les compétences des gestionnaires de fonds individuels, il y a eu très peu d'études sur les compétences au niveau de la famille de fonds communs de placement. Cela semble être un écart important, car d'autres recherches ont montré que les politiques au niveau de l'entreprise ont un effet significatif sur le rendement des gestionnaires de fonds individuels. Nous constatons ici que la performance de la famille de fonds est persistante et que certaines familles sont vraiment qualifiées. Nous introduisons une nouvelle mesure pour estimer l'impact des caractéristiques familiales sur les compétences familiales. Les familles de fonds les plus susceptibles d'être qualifiées sont des familles à fonds unique qui imposent des frais plus élevés, reflétant probablement le fait que les gérants qualifiés choisissent eux-mêmes de créer leur propre famille de fonds et qu'il est coûteux d'acquérir et de conserver des compétences. Nous constatons également que les familles dont le chiffre d'affaires est élevé (c'est-à-dire les anciens fonds proches et qui en lancent de nouveaux) ont des compétences plus élevées, reflétant peut-être davantage la gestion individuelle des fonds par la famille et une réallocation plus active des fonds. Cette constatation est cohérente avec Berk et al. (2017) qui montrent que les familles de fonds réaffectent le capital entre les gestionnaires de fonds sur la base des informations privées de la famille sur les compétences de ses gestionnaires.

L'essai 2 ne se concentre pas sur les compétences en tant que telles, mais s'attaque plutôt aux craintes que les opérations de sociétés de capital-investissement cotées en bourse puissent sous-performer celles des sociétés de capital-investissement non cotées plus traditionnelles. J'utilise une procédure de sélection Heckman pour imputer les multiples de transactions pour les transactions par des sociétés de capital-investissement publiques et privées à partir de données de transactions CapitalIQ, et par conséquent, j'ai l'un des plus grands ensembles de données sur les performances de private equity. Cette nouvelle base de données est exempte de certains biais qui affectent la recherche de private equity précédente, peut facilement être tenue à jour, et a donc le potentiel d'être la base d'un certain nombre d'articles intéressants et significatifs sur la performance du private equity. Dans le document, je demande si la performance des transactions pour les sociétés de capital-investissement cotées en bourse est plus faible que pour les sociétés de capital-investissement privées. Je trouve que ce n'est pas le cas: la performance des transactions effectuées par des sociétés et des fonds de capital-investissement «permanents» n'est pas significativement différente de la performance des transactions conclues par les GP traditionnels. En outre, les offres des GPs cotées en bourse surperforment considérablement les offres des GPs privés.

Pris ensemble, ces essais contribuent à divers flux de la littérature de gestion des investissements en jetant un regard neuf sur les compétences dans les classes d'actifs où il est difficile de mesurer (private equity), ou si le sujet n'a pas été étudié en profondeur.). Les résultats donnent des résultats contrastés, car il existe des preuves substantielles de compétences pour le capital-investissement, même après les frais, mais moins de preuves de compétences pour les familles de fonds communs de placement. Les raisons possibles de cette divergence peuvent inclure des incitations élevées des gestionnaires de fonds dans le secteur du capital-investissement, des rendements d'échelle décroissants dans le secteur des fonds communs de placement, des coûts de recherche pour les investisseurs, une inefficacité du marché ou une combinaison de ces facteurs.

Ces Essais contiennent également des informations utiles pour les praticiens et les investisseurs. En identifiant au moins quelques déterminants de compétence, les praticiens peuvent avoir une idée des comportements qui ajoutent (ou soustraient) à la valeur de leurs fonds. En quantifiant et en localisant les compétences dans différents types de fonds, les résultats des études peuvent également aider les investisseurs à concentrer leur recherche de compétences, et au moins augmenter la probabilité de trouver un gestionnaire de fonds qualifiés.

Une caractéristique de cette thèse est la variété des méthodologies empiriques qu'elle rassemble. Cela inclut les chevaux de labour classiques tels que OLS vanille, probabilités de transition de Markov, sélection de Heckman, analyse de score de propension, effets fixes OLS et variables instrumentales, mais j'applique aussi des approches récemment apparues dans la littérature financière comme bootstrap transversal, false taux de découverte, modèles à valeur ajoutée à valeur ajoutée et modèles à effets fixes récursifs. Nous introduisons également une nouvelle méthode d'estimation de l'impact des caractéristiques des gestionnaires de fonds.

Pour conclure cette introduction, le sujet de la compétence dans la gestion de fonds est extrêmement important pour beaucoup de gens, mais c'est un sujet complexe qui nécessite encore beaucoup de recherches sérieuses. Le mieux que je puisse espérer, c'est que ces Essais apportent un éclairage nouveau sur certains aspects du sujet qui n'ont pas encore été complètement explorés dans la littérature existante. Sur une note personnelle, j'ai trouvé que la recherche était une tâche très intéressante et stimulante qui fournissait un cadre riche pour faire progresser mes compétences en tant que chercheur financier empirique. J'espère que vous aimez lire ces Essais autant que j'ai aimé les assembler.

Essay 1

Estimating Skill in Private Equity Performance using Market Data

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 fund managers are skilled. The seminal study by Kaplan and Schoar (2005) was the first of a number[1] to show that the funds of some PE fund managers earn persistently higher (or persistently lower) returns than those of other fund managers. The question whether PE firms are skilled is important given 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 BNYMellon 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.

However, PE researchers face a number of challenges. Firstly, reliable,

The author would like to thank Sridhar Arcot and Sofia Ramos for their support and guidance. I am also grateful to Laurent Barras, Andras Fulop, Laurence Lescourret, Lorenzo Naranjo, Olivier Scaillet, and discussants and participants at the 2016 Paris Financial Management Conference (Yan Wang), the Eurofidai-AFFI 2016 Paris December Meeting (Florian Fuchs), the 2017 Hedge Fund and Private Equity Research Conference, the 2017 FMA European Conference (Alexander Groh), the 2017 Northern Finance Association conference (Murray Carlson), and the 2017 FMA Conference (Yong Chen). Project funding from the ESSEC-Amundi Chair is gratefully acknowledged.

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

unbiased data on traditional PE firm performance is difficult to obtain. As a result, estimates of PE performance (on which measures of PE persistence rely) vary widely[2], with some studies finding substantial outperformance and others finding substantial underperformance. Secondly, the nature of traditional PE funds and fundraising (funds of about 10 years duration, raised every 3 to 5 years) poses methodological challenges for researchers. Korteweg and Sorensen (2017) argue that methodologies commonly used to measure PE persistence have empirical limitations that could affect the interpretation of results derived using those methodologies.

While prior research has focused primarily on funds raised by traditional PE fund managers (known as General Partners or GPs), in this study I use a sample of publicly listed closed-end private equity (LPE) vehicles to analyze skill and luck in private equity performance. This LPE sample consist of firms and funds that are organized like closed-end funds[3], that is, they raise investment capital on public markets (typically via an initial public offering) which they then use to invest in a portfolio of 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).

This definition of LPE is more restrictive than that occasionally used in industry[4] and in the literature (cf Bergmann et al. (2009)). The broader listed private equity universe consists of both listed closed-end private equity and publicly listed GPs. Public GPs[5] allow shareholders (unitholders) gain expo-

[2] Driessen et al. (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.

[4] Most listed private equity indices and ETFs comprise listed closed-end funds/firms and public GPs.

[5] Examples of public GPs include KKR & Co LP, Blackstone Group LP, Partners Group Holding AG.

sure to fees and other income earned by these traditional PE fund managers, who raise and manage traditional 10-year PE funds. On the other hand, listed closed-end private equity[6] are permanent PE funds and fund-like firms that give shareholders direct exposure to the underlying private equity assets held by the firm or fund. This study focuses on the performance of closed-end private equity, and does not examine the performance of public GP fee vehicles[7,8]. For convenience I refer to listed closed-end private equity as LPE, and I use the term LPE-GP when referring to listed closed-end PE and public GPs together.

The LPE asset class has grown rapidly in recent years. In 1995 there were 52 LPE vehicles with combined assets under management (AUM) of around \$82.5 billion; in 2015 there were 154 LPEs with AUM of over \$926 billion. This compares with \$3.8 trillion AUM for the total PE universe reported by Preqin (2015). Furthermore, LPE and public GPs are increasingly seen by practitioners, academic researchers, and regulators as representative of the private equity asset class. In their analysis of PE risk and performance, Jegadeesh et al. (2015) argue that LPE firms follow the same investment strategies as traditional GPs, and they both face the same opportunity set. LPE-GP Net Asset Value (NAV) returns have been shown by Preqin and LPX Group (2012) to be highly correlated with those of traditional PE funds (Pearson coefficient: 0.94). Furthermore, after an extensive consultation process, regulators responsible for supervision of the \$10 trillion[9] insurance industry in Europe[10] adopted

[6]Examples of listed closed-end private equity vehicles include 3i Group plc, HgCapital Trust plc, Ares Capital Corp.

[7]Parallels can be drawn between publicly listed GPs and publicly listed mutual fund management companies. When considering mutual fund performance, the stock performance of public mutual fund management companies is of little interest; likewise the stock performance of publicly listed GPs is of little interest when considering PE fund performance.

[8]For an in-depth analysis and comparison of deal-level performance by LPE, public GPs and private GPs, see McCourt (2017).

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

[10]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.

an index of LPE-GPs as their private equity benchmark (EIOPA (2013)).

LPE has a number of attractive features for private equity researchers. Firstly, data is readily available. My LPE sample are constituents of publicly available indices of LPE-GP firms and funds whose stock prices and financial history are accessible via the standard databases used in financial research. Secondly, LPEs trade on regulated stock exchanges, and by law they must be transparent about their business activities and financial performance. Typically, LPEs must regularly publish audited financial reports following Generally Accepted Accounting Principles (GAAP); this level of public transparency would be unusual for traditional PE. Thirdly, LPE benefits from the assumption that markets are efficient. Private equity assets are illiquid and difficult to value, therefore estimates of the Net Asset Values (NAVs) provided by PE fund managers can be somewhat subjective, and there is evidence that some traditional PE firms may manipulate their NAVs[11], especially when trying to raise new funds (Brown et al. (2016)). LPE share prices, on the other hand, are an unbiased reflection of the market's best estimates of the true value of the LPEs' assets at any given time. Fourthly, LPE data is more timely than traditional PE data. NAV estimates provided by PE fund managers can be stale, in that they are issued on an infrequent basis, at best monthly. However the market prices of LPEs are updated continuously every trading day. Finally, 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, to separate skill from luck, and to identify the determinants of skill.

Firstly, I measure short-term persistence using the classic winner-minus-loser alpha test (Carhart (1997), Hendricks et al. (1993)). I find positive top-quartile minus bottom-quartile (4-1) portfolio alpha of 0.48% per month

[11] See the quotations at the beginning of this paper for examples.

(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 benchmark-adjusted NAV returns for Buyout and Mezzanine LPEs (about 8% and 9.5% per year, respectively).

There is also evidence that the NAV premium (the difference between the NAV per share and the share price) for Buyout, Venture and Mezzanine LPEs is a predictor of short-term changes in NAV; in other words, the NAV premium captures short-term market expectations of manager skill. I show that LPEs (except FoFs) with larger NAV premiums have larger NAV changes 12 months later. This result is consistent with the findings of Chay and Trzcinka (1999) for CEFs, and shows not only that certain LPEs have short-term skill, but also that investors can identify these skilled 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 et al. (2006)), and the the false discovery rate (Barras (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.

Thirdly, this study examines buyout transaction characteristics as a skill channel for Buyout and Mezzanine LPEs. PE firms that have the skills to identify good deals and make them work are more likely to prefer solo rather than syndicate buyout deals in order to maximize their returns. On the other hand, deal exits via secondary buyouts to other PE firms or via management buyouts are a signal that these deals have been not been successful as the PE firm was not able to bring the target firm to IPO or to find a trade buyer. In tests using buyout transaction data from CapitalIQ, I find that LPEs with higher proportions of recent solo acquisitions outperform LPEs with higher proportions of syndicate acquisitions. On the other hand, exits via secondary buyout and management buyout are negatively associated with skill measures.

A range of robustness checks is used to verify that the findings hold up under alternative specifications. These include using different benchmark models (CAPM, Dimson, Fama-French-Carhart 4-factors plus Pastor & Stambaugh Liquidity factor, Fama-French 5-factors, Fung-Hsieh 7-factors), short-term post-IPO LPE performance, applying the Fama and French (2010) specification for the cross-sectional bootstrap, tracking changes in short-term persistence over time, and implementing simple trading strategies.

The major contributions of this paper are as follows. Firstly, I use a novel dataset, listed closed-end private equity funds and firms. 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. Thirdly, this study shows that preferred transaction type is a channel through which skilled Buyout and Mezzanine LPEs differentiate themselves from unskilled ones.

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, whereas my paper uses LPE to examine persistence and skill in private equity returns. Also, Korteweg and Sorensen (2017) 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. As far as I am aware, no prior study has examined how transaction characteristics are associated with PE skill.

This paper is structured as follows: Section II summarises the relevant literature on private equity, mutual fund persistence and listed private equity; Section III describes 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, while in Section III analyzes the determinants of skill. Section IV describes a number of robustness checks. I discuss results and future research in Section VIII, and Section IX 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

A number of 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 et al. (2014b) find that PE persistence for Buyout and Venture funds was strong pre-2000, and post-2000 Venture persistence is unchanged, but for Buyouts it is weaker post-2000 especially at the upper end of the performance spectrum. Braun et al. (2017) 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 (2017) 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. Determinants of Skill in Private Equity

In mutual funds, fund-manager skill is typically attributed to stock-picking and market-timing (cf Kacperczyk et al. (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 et al. (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 et al. (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 (SBO) from other PE firms, and these deals are often expensive relative to comparable mergers and acquisitions (M&A) transactions. Likewise, PE firms may find themselves under pressure to sell portfolio firms at the end of their fund life and resort to suboptimal SBO exits. Lopez-de Silanes et al. (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 et al. (2015)) or making value-enhancing acquisitions.

Recent literature focuses on the educational and professional backgrounds of fund managers. Fuchs et al. (2018) find that fund-level performance is positively affected by the average position in academic rankings of the universities which the fund partners have attended, the academic variety of the fund managers, and prior experience in competitive environments such as investment banking. Educational ties between management teams of acquiring fund and target company increase the odds of winning a deal by 79% (Fuchs et al.

(2017)).

C. Skill in Open-end 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 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 (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 benchmark-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 et al. (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 et al. (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.

D. Skill in Closed-end Mutual Funds

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 VIII.

Cherkes et al. (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 the Berk 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.

E. 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 et al. (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. (2017) point out, will inevitably have gaps in the fund sequences, reflecting investorsâĂŹ 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 (2017) show that regressing fund n returns on fund $n-1$ returns is equivalent to an AR(1) timeseries[12] 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 (2017) 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

[12]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.

a Bayesian procedure.

F. Listed Private Equity

Bergmann et al. (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".

However, in his analysis of private equity deal-level performance, McCourt (2017) finds that there is little difference in deal-level performance for LPE compared to traditional GPs. 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. The evidence that the holding period for LPE is different from traditional PE is mixed - Strömberg (2007) finds that LPEs seem to hold their deals for longer than unlisted PE firms, while McCourt (2017) shows that the holding period is shorter.

LPE has also been the subject of numerous articles in the financial press[13], 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 listed private equity firms and funds, the LPE-GP universe for the 20-year period from 1995 to 2015. The LPE-GP universe includes Business Development Companies (closed-end funds of PE investments which are regulated by the Securities and Exchange Commission in the United States), private equity Investment Trusts (closed-end funds of PE investments run by members of the AIC in the United Kingdom), and the constituents of publicly available LPE-GP indices and ETFs. The main LPE-GP indices are the S&P Listed Private Equity index, the Société Générale Privex index, and the ALPS-RedRocks Global Listed Private Equity index. The constituents of the ProShares Global Listed Private Equity ETF which tracks the LPX Direct

[13] 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.

Listed Private Equity Index are also included.

Using equities that are constituents of LPE-GP 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). This study focuses on index-listed public financial investment firms and funds that most closely resemble traditional unlisted PE, including buyout, venture, and mezzanine, so public GPs, derivative entities, LPEs that are not LPE-GP index constituents, and non-financial LPEs are excluded from the final sample.

The LPE-GP indices came into existence in the mid-2000s, and as the time-period for this study starts in 1995, 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. I create the following screen in CapitalIQ: public investment companies and public funds that made buyout (turnaround, middle market or mature stage) or VC (mid venture, late venture, or later stage) deals (private placements or M&A) and that subsequently went out of business or were acquired. To minimize any potential survivorship bias, I include these firms in my final sample.

Summary statistics for the sample are provided in Table 3.2. While the LPE-GP universe comprises 202 firms and funds, the LPE sample used in this study (public financial entities, excluding GPs and infrastructure, that are included on LPE-GP indices) comprises 134 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 cate-

Table 1.1 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-GP 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-GP Universe that includes all index-listed stocks, excluding GPs, non-financials and infrastructure. LPEs in the final sample are classified by type: Buyout, Mezzanine, Venture, and Funds-of-Funds (FoF); and by region United States & Canada, Europe, Rest of World (RoW); and by structure: public limited companies (PLCs), closed-end funds (CEFs). The numbers of LPEs in the sample that were delisted before January 1st 2015 are given. Total (Net) Assets are the sum of the total (net) assets of all LPEs as of December 31st, 2015. The Net Assets of an LPE are estimated as its Total Assets minus its Total Liabilities (i.e. Total Shareholder Equity).

	LPE & GP Universe	Final LPE Sample	Buyout	Mezzanine	Venture	FoF	PLCs	CEFs
Total number of LPEs	202	134	50	26	34	24	75	59
US & Canada	78	32	6	22	4	0	9	23
Europe	104	88	39	4	24	21	56	36
RoW	20	14	5	0	6	3	10	0
PLCs	106	75	36	5	21	13		
CEFs	91	59	14	21	13	11		
Delisted before 2015	35	27	8	0	19	0		
Net Assets ($millions, 2015)	374,221	129,980	38,795	74,884	5,461	10,840	40,122	89,858
Total Assets ($millions, 2015)	980,599	234,826	102,540	114,664	6,265	11,357	103,071	131,756

gorization outlined by Bergmann et al. (2009): Buyout, Mezzanine, Venture, Funds-of-Funds (FoF). 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 retrieved from Datastream, and are winsorized at the 1% level. US dollar denominated currency values are used 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 where the monthly excess returns (R^e) of the LPE are regressed on market (MKT), size (SML), value (HML) and momentum (WML) factors is used to compute benchmark-adjusted excess returns (alpha).:

$$R^e_{it} = \alpha_i + \beta_i^{mkt} MKT_t + \beta_i^{sml} SML_t + \beta_i^{hml} HML_t + \beta_i^{wml} WML + \epsilon_{it} \quad (1.1)$$

Table 1.2 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 PastorâĂŹs 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)	

As the sample is an international one, I first evaluate the fit of 6 different sets of international factors. Four sets of factors (Global, Global ex-US, North American, European) are downloaded from Ken French's website, and also UK factors from Gregory et al. (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 1.2. The Global factors have the greatest explanatory power (largest R^2 value), and thus I use these for the tests which follow.

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 1.3. 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

Table 1.3 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. 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	252
	(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	252
	(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	252
	(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	252
	(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	252
	(2.14)	(13.64)	(5.82)	(1.81)	(-0.71)	(1.11)		

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[14]. The test is performed twice, for price returns and for NAV returns.

Using price returns, stocks are grouped by returns over a 12-month formation period (following the standard practice of skipping the most recent month to avoid short-term microstructure effects) to create 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.

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

Table 1.4 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 1.4 - 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)	

The excess price returns and factor coefficients for the quartile and winner-minus-loser (4-1) portfolios are provided in Table 1.4. Results are given 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 the benchmarks. For the full sample, the raw 4-1 return is positive and significant at the 10% level, but the benchmark-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 1.5. 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-

Table 1.5 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)	

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.

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 the average NAV premium and the average NAV return one year later are estimated. The results are presented in Table 1.6. 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 1.6 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

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 two tests are implemented that aim to separate luck from skill for LPEs to give a true measure of long-term persistence.

A. *Cross-Sectional Bootstrap*

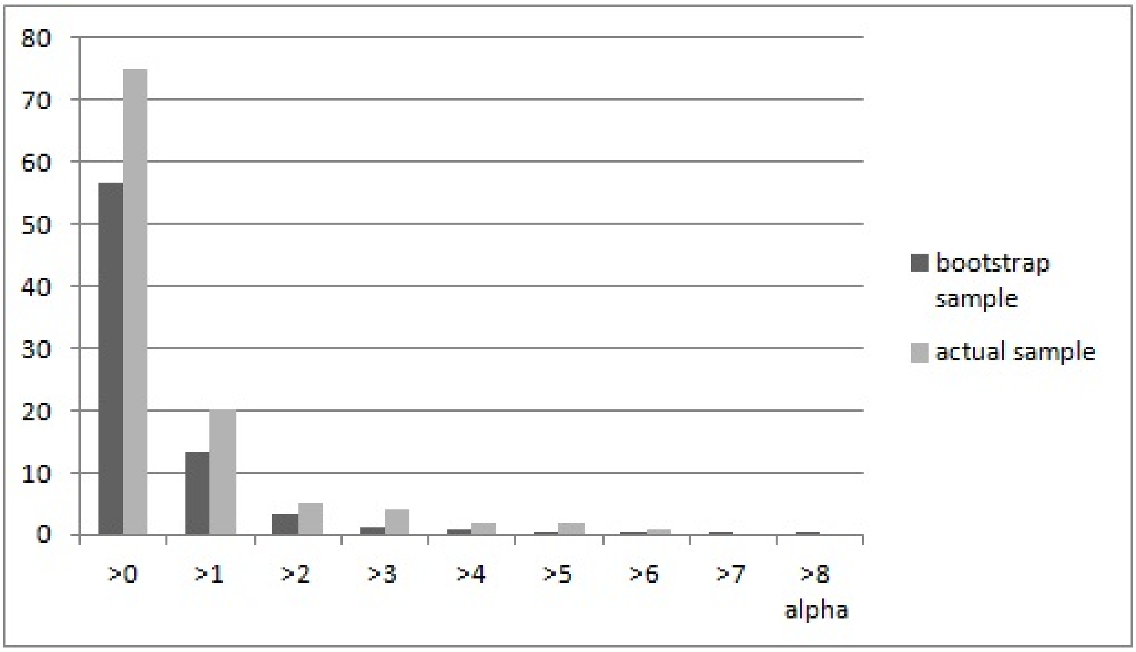
To separate skill from luck in mutual funds, Kosowski et al. (2006) use a bootstrapping approach that uses the existing sample of fund returns to generate 1000 new samples of pseudo-funds whose true alpha is zero by construction. This cross-sectional bootstrapped zero-alpha distribution captures the 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 in the real sample do not all have equal skill; some funds must be truly skilled and some must be truly unskilled.

Using the LPE sample, 1000 bootstrap samples of pseudo-LPEs are generated which have zero alpha by construction. 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 1.1 illustrates the results graphically.

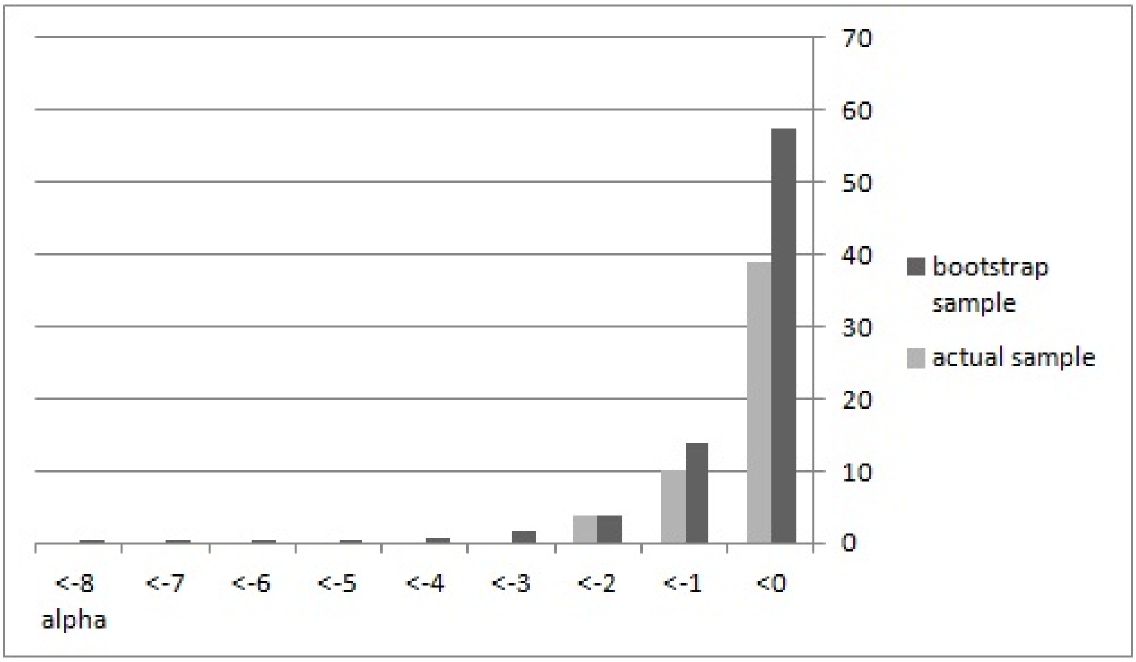
Furthermore, cross-sectional bootstrap p-values are estimated for individual LPEs at specific percentiles of the actual distribution. For example, a cross-sectional bootstrap p-value of 0.04 at the 80th alpha percentile means that the alpha of the pseudo-LPE at the 80th alpha percentile for 40 of the 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 1.7 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



(a) Positive alpha count



(b) Negative alpha count

Figure 1.1. 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.

Table 1.7 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

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 1.7) 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.

B. *False Discovery Rate*

Barras (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).

Figure 1.2 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

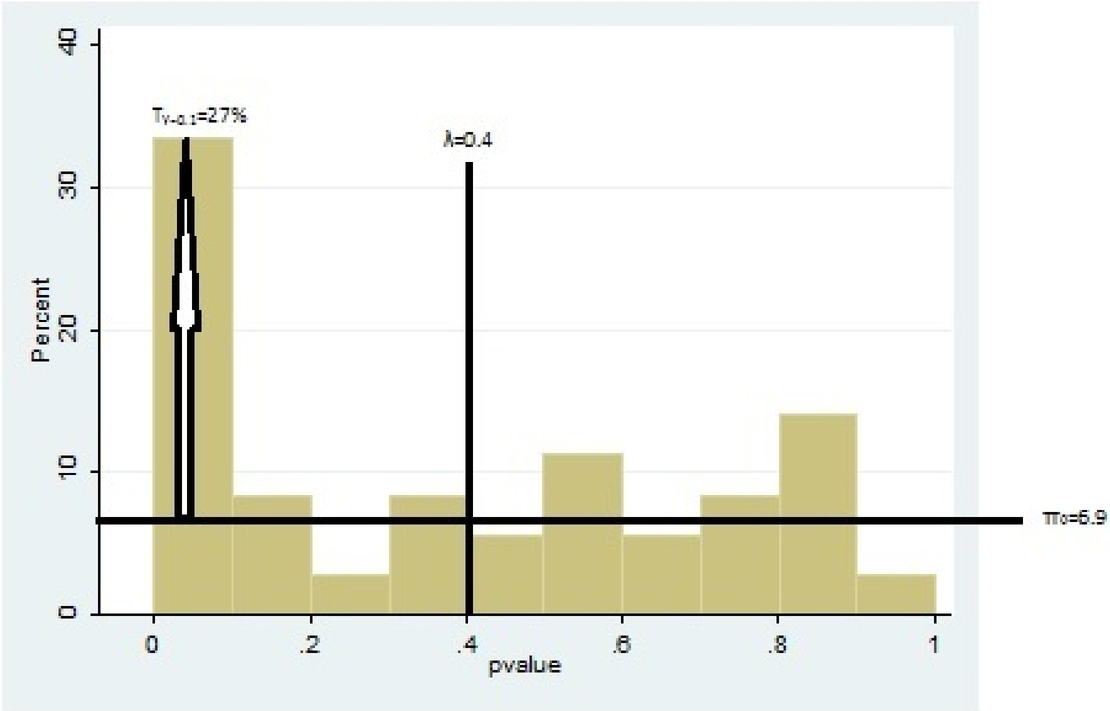


Figure 1.2. False Discovery Rate - Buyout LPEs

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.

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 (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 (2010) for further implementation details.

I implement the FDR for the LPE sample using p-values estimated with the cross-sectional bootstrap technique described before. Table 1.8 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

Table 1.8 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

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 (alpha) 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.

Dollar value-added is defined as the product of the fund's assets under management and its gross alpha. The alpha earned each year by each LPE is estimated 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:

$$R_{it}^{B} = \beta_i^{mkt} MKT_t + \beta_i^{sml} SML_t + \beta_i^{hml} HML_t + \beta_i^{wml} WML \tag{1.2}$$

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. The cross-sectional mean value-added is computed 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 1.9 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

Table 1.9 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

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).

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. Determinants of Skill

In this section, I analyze possible determinants of skill for Buyout and Mezzanine LPEs. As discussed in Section II, skilled PE firms identify good deals and make them work. I propose that characteristics of the transactions executed by a PE firm can proxy as measures of the ability of the firm to pick good deals and make them work.

PE firms can choose to invest in buyouts where they are the sole investor (solo deals), or they may invest in a buyout deal alongside other investors (syndicate deals). Solo buyouts by a PE firm suggest that the PE firm has has high confidence that the deal is a good one, while investing in a syndicate deal suggests either that the PE firm does not have the resources (such as capital, network or reputation) required to source its own solo deals, or it may be slightly less confident of deal outcomes and wishes to diversify potential risks. Therefore I propose that the proportion of solo transactions in the PE firm's transaction mix is a measure of the firm's deal selection ability. PE firms that make a high proportion of solo transactions are better at finding good deals and making them work than PE firms that make a high proportion of syndicate deals.

On the other hand, PE deals that are exited via a Secondary Buyout (SBO) or a Management Buyout (MBO) may be more likely to have been unsuccessful, as the PE firm was unable to bring the portfolio firm to IPO or to find a trade buyer. Thus I propose that the number of SBO and MBO exits is an inverse measure of how well the PE firm made their deals work. PE firms with large numbers of SBO or MBO exits are less skilled at deal execution.

A. Empirical Analysis

To test the measures of deal selection and execution ability discussed above, I link LPE performance to recent transactions performed by the LPE. For this analysis OLS regressions are used where the independent variables consist of lagged measures of transaction characteristics for each LPE. Buy and sell transaction data for all Buyout and Mezzanine LPEs are obtained from CapitalIQ (see Table 1.10 for a detailed breakdown of transaction characteristics). The variable *solobuysvalueratio3* is estimated as the value of solo buy transactions by the LPE in the previous 3 years as a proportion of the total value of buy transactions by the LPE over the same period. The variable *sbobuys3* is the

Table 1.10 Buyout and Mezzanine LPE Buy Transaction Characteristics

This table gives details of acquisition transaction characteristics for Buyout and Mezzanine LPEs. Transaction characteristics include the type of transaction, the period when the transaction occurred, the regional location of the target, and the industry classification of the target. Characteristics are given for all transactions, transactions where there is just one sponsor (solo transactions), and transactions where there are more than one sponsor (syndicate transactions). For each characteristic, the number of transactions (N), mean transaction value in millions of US dollars (Mean Value), and total value of all transactions in millions of US dollars (Total Value) are given. Where transaction values are missing in CapitalIQ, a Heckman procedure is used to impute transaction values (see Strömberg (2007) for details).

	All Transactions			Solo Transactions			Syndicate Transactions		
	N	Mean Value	Total Value	N	Mean Value	Total Value	N	Mean Value	Total Value
Total	875	106	92445	508	98	50034	367	116	42411
Public-to-private	25	218	5456	13	186	2417	12	253	3039
Divisional buyout	262	89	23235	164	78	12838	98	106	10397
Secondary buyout	118	248	29276	59	238	14056	59	258	15220
MBO	358	99	35532	181	105	19056	177	93	16476
Distressed	12	39	469	6	24	144	6	54	325
Cross-Border	334	147	49190	185	131	24233	149	167	24957
Unclassified	681	107	72651	388	101	39278	293	114	33373
Unique Targets	864			508			362		
Unique PE Firms	44			25			34		
1995-1999	142	63	8982	68	69	4662	74	58	4320
2000-2004	231	93	21376	133	76	10051	98	116	11325
2005-2009	292	128	37479	188	111	20779	104	161	16700
2010-2016	212	116	24609	121	120	14542	91	111	10067
US	242	91	22064	127	106	13419	115	75	8644
Canada	13	160	2085	8	158	1268	5	164	818
UK & Ireland	245	101	24811	109	108	11788	136	96	13023
France & BeNeLux	121	148	17960	72	108	7757	49	208	10203
Germanic De-Aus-CH	126	107	13528	108	84	9025	18	250	4503
Spain, Italy, Portugal	56	91	5095	31	89	2770	25	93	2325
Scandinavia	65	92	5999	51	73	3728	14	162	2271
Australia & NZ	3	62	187	2	30	60	1	127	127
Korea & Japan	5	131	654	2	110	221	3	144	433
RoW	1	63	63	0	.	.	1	63	63
Consumer Discretionary	229	116	26499	132	107	14135	97	127	12364
Consumer Staples	46	97	4456	33	91	3010	13	111	1445
Energy	15	62	930	7	54	376	8	69	554
Healthcare	65	121	7876	46	117	5393	19	131	2484
Industrials	266	104	27539	156	102	15970	110	105	11569
Information Technology	110	78	8533	64	60	3872	46	101	4662
Materials	68	82	5606	42	81	3411	26	84	2196
Telecommunication Services	8	107	859	4	73	293	4	142	566
Utilities	5	93	467	1	131	131	4	84	336
Other	65	149	9680	25	138	3445	40	156	6235

number of secondary buyout deals initiated by the LPE in the previous 3 years, and *sbosells3* is the number of deals exited via an SBO. Likewise, *mbobuys3* and *mbosells3* are the number of management buyout deals initiated by the LPE and the number of deals exited via MBO in the previous 3 years, respectively. I also include a number of lagged control variables for each LPE, including log total assets, log total liabilities, NAV, the NAV premium, log market capitalization, 4-factor alpha, LPE age, as well as region and year dummies.

The dependent variables are measures of short-term skill: the annual excess total return, the 4-factor alpha, and dollar value-added for each LPE. The alpha is estimated annually following Equation 3.1 where the betas are estimated using a minimum of 24 months data. Dollar value-added is also estimated annually as the alpha times lagged total assets.

Summary statistics are provided in Table 1.11.

The results for Buyout and Mezzanine LPEs are presented in Table 1.12. . The dependent variables are the annual excess returns, the annualized 4-factor alpha, and the annual dollar value-added for each sample. Regression coefficients for the control variables are presented, along with the results of three regression models for solo and syndicate buy transactions (Model I), for SBO buy and sell transactions (Model II), and MBO buy and sell transactions (Model III).

In Model I, the coefficient for the regressor representing the ratio of the value of solo buy transactions to the total value of transactions *solobuysvalueratio3* is positive and significant where alpha is the dependent variable. The coefficients are economically significant - for Buyout LPEs, a unit increase in the ratio leads to about a 11% increase in skill as measured by annual 4-factor alpha, while for Mezzanine LPEs the economic magnitude is even higher, with a unit increase in the ratio leading to an increase in alpha of 30%.

Table 1.11 Summary Statistics for Variables used in Skill Determinants Regressions

This table presents the annual mean, standard deviation, minimum and maximum values for variables used in the regressions to identify determinants of LPE skill. See Appendix AppendixA.A for a description of each variable.

Variable	Obs	Mean	Std.Dev	Min	Max
excess return	648	0.12	0.50	-0.87	2.91
alpha	572	0.04	0.35	-0.86	1.32
value-add	548	120.67	1289.57	-8152.54	9478
ta	682	2242.34	5108.66	8.63	42800
tl	682	1216.41	3594.98	-1.79	33300
gnav	682	1025.93	1783.72	-621.99	12100
mv	682	911.25	1600.24	0.07	11207
premium	678	-0.07	0.61	-0.86	9
age	718	8.63	7.26	0	38
expratio	589	0.0518	0.0964	0	1.0468
gwillratio	682	0.0010	0.0060	0	0.0603
randdratio	682	0.0003	0.0016	0	0.0210
voltoratio	593	1.08	3.75	0.00	51.64
buys3	632	3.41	7.92	0	58
buysvalue3	632	334.80	812.69	0	6592
sells3	632	5.50	20.59	0	248
sellsvalue3	632	567.82	1753.61	0	21532
solobuysvalueratio3	367	0.44	0.46	0	1
solobuysvalue3	632	200.43	607.63	0	5322
syndbuysvalue3	632	134.37	309.15	0	2241
sbobuys3	632	1.47	6.05	0	57
sbosells3	632	3.56	20.52	0	248
mbobuys3	632	2.51	7.70	0	58
mbosells3	632	3.81	20.60	0	248

In Model II, the coefficient for the independent variable *sbosells3* representing the number of SBO buy transactions for Buyout LPE firms is positive and significant, suggesting Buyout LPE firms are skilled at making SBO acquisitions. For SBO sell transactions, the coefficients for all LPE samples are negative, suggesting that LPEs that resort to an SBO to exit their deals are less skilled. Likewise in Model III we see that Buyout LPE firms are successful at making MBO acquisitions, but disposals via MBO are associated with negative performance for all LPE samples.

In summary, these results confirm the hypotheses outlined in the previous section that LPEs that make more solo deals as a proportion of all deals are more skilled, and that LPEs that make more SBO and MBO exits are less skilled. The MBO exits measure is the strongest predictor, while the solo deals ratio is the weakest.

B. *Trading Strategies*

To illustrate further the economic significance of the solo buy value ratio, the number of SBO sells, and the number of MBO sells as skill determinants for Buyout and Mezzanine LPEs, the results of simple trading strategies are plotted. The skill measures used are the annual excess return, the annual benchmark-adjusted return (alpha), and the annual dollar value-add. For each measure, each year, two portfolios are created, the first consisting of LPEs whose measure is above the median for the year, the second consisting of those LPEs with measures below the median. The portfolios are equal-weighted, and held for one year. The period for the tests is 2000-2015.

The cumulative performance of the portfolios are graphed in Figure 1.3. Using raw excess return as the performance measure, the High solo buy value ratio portfolio outperforms the Low solo ratio portfolio by about 114% over the sample period, while the Low SBO portfolio cumulative return is 54% higher

Table 1.12 Buyout Transaction Characteristics as Determinants of Skill

This table presents the results of OLS regressions to identify the determinants of Buyout and Mezzanine LPE skill. All variables are described in the Appendix. The dependent variables are the log of the annual excess return, the log of the annual 4-factor-alpha, and the annual dollar value-add. The independent variables are lagged 1 year. In Model I the regressors are measures of the number and proportion of solo buy transactions and syndicate buy transactions. In Model II, the regressors are measures of the number of Secondary Buyout buy and sell transactions. In Model III, the regressors are measures of the number of Management Buyout buy and sell transactions. Control variables and region and year dummies are included for all models. The last part of the table provides coefficients for control variables. Robust standard errors corrected for LPE level clustering are in parentheses.

	Buyout LPE			Mezzanine LPE		
	(1)	(2)	(3)	(4)	(5)	(6)
	(log) excess return	(log) alpha	value-add	(log) excess return	(log) alpha	value-add
			Model I			
tsolobuysvalueatio3 (lagged)	0.230***	0.115**	72.35	0.158	0.299**	246.5
	(0.0662)	(0.0545)	(325.5)	(0.115)	(0.0964)	(607.7)
tsolobuysvalue3 (lagged)	-0.0429	-0.0114	-28.14	-0.371***	-0.236***	-1,658***
	(0.0293)	(0.0286)	(270.4)	(0.0727)	(0.0740)	(442.0)
tsyndbuysvalue3 (lagged)	0.0586	0.0851**	21.50	0.650***	0.548*	594.2
	(0.0477)	(0.0365)	(309.8)	(0.198)	(0.292)	(1,021)
Observations	227	227	227	65	65	65
R-squared	0.675	0.198	0.253	0.771	0.512	0.490
			Model II			
tsbobuys3 (lagged)	0.00414	0.00579	76.42***	0.000498	-0.00132	-53.97***
	(0.00381)	(0.00481)	(7.206)	(0.00336)	(0.00216)	(13.23)
tsbosells3 (lagged)	-0.00186***	-0.00139**	-15.51***	-0.0124*	-0.0181***	-22.88
	(0.000561)	(0.000684)	(1.398)	(0.00664)	(0.00378)	(19.23)
Observations	363	363	363	135	135	135
R-squared	0.529	0.218	0.186	0.600	0.486	0.354
			Model III			
tmbobuys3 (lagged)	0.00295	0.00320	34.51***	0.00421	0.00223	-45.10***
	(0.00325)	(0.00372)	(4.270)	(0.00326)	(0.00243)	(11.95)
tmbosells3 (lagged)	-0.00177***	-0.00111	-10.15***	-0.0165*	-0.0227***	-39.50
	(0.000619)	(0.000702)	(0.965)	(0.00853)	(0.00573)	(26.88)
Observations	363	363	363	135	135	135
R-squared	0.529	0.218	0.174	0.602	0.489	0.356
			Control Variables			
lnta (lagged)	-0.0276	-0.0164	-15.10	0.240	0.0931	289.3
	(0.0615)	(0.0779)	(185.2)	(0.235)	(0.183)	(513.3)
lntl (lagged)	-0.00595	-0.0193	23.35	-0.0701	-0.0404	2.390
	(0.0175)	(0.0184)	(32.84)	(0.0538)	(0.0439)	(106.0)
lngnav (lagged)	0.0881	0.286	898.6**	0.552	0.432	-21.35
	(0.207)	(0.234)	(439.3)	(0.405)	(0.260)	(999.4)
lnmv (lagged)	-0.00550	-0.194	-779.2**	-0.694**	-0.426**	-253.0
	(0.198)	(0.208)	(372.4)	(0.259)	(0.175)	(719.8)
premium (lagged)	-0.194	0.0523	307.5	0.461	0.312	-248.7
	(0.195)	(0.182)	(268.6)	(0.276)	(0.195)	(913.4)
alpha (lagged)	0.0932	0.213**	263.1*	-0.0202	-0.0213	-150.5
	(0.0844)	(0.0809)	(142.7)	(0.0724)	(0.0604)	(315.5)
age	-0.000440	-0.00166	-5.454	-0.0146	-0.0249***	-2.141
	(0.00410)	(0.00406)	(6.896)	(0.00997)	(0.00724)	(21.51)
Year dummies	Y	Y	Y	Y	Y	Y
Region dummies	Y	Y	Y	Y	Y	Y
Observations	367	367	367	137	137	137
R-squared	0.523	0.215	0.151	0.575	0.420	0.194

than the High SBO portfolio, and the Low MBO portfolio return is 124% higher than the High MBO portfolio. Looking at the benchmark-adjusted return (alpha), the High solo ratio portfolio outperforms the Low solo ratio portfolio by about 25%. The High SBO sell portfolio underperforms the Low SBO sell portfolio by about 64%, while the High MBO sell portfolio underperforms the Low MBO sell portfolio by about 107%. For the dollar value-add, the Low MBO portfolio earns $1665 more than the High MBO portfolio; the Low SBO portfolio outperforms the High SBO portfolio by $897, while the High solo ratio portfolio outperforms the Low solo ratio portfolio by $223.

Overall, the MBO sell count seems to be the strongest determinant of the skill measures examined here. The SBO sell count also perform consistently. The solo buy value ratio does a reasonable job of predicting raw excess returns and benchmark-adjusted returns, while for dollar value-add the predictive power of the solo buy value ratio is less consistent, especially in recent years. This may be because LPEs with large total assets may find it hard to identify sufficient solo deals in which to invest, and resort to syndicate deals which may be easier to find.

Figure 1.3. Trading Strategies

This figure presents trading strategy results for portfolios of LPEs created using the determinants of Buyout and Mezzanine LPE skill. The determinants are: the proportion of solo buy transaction value to the total value of all transactions for each LPE (left column); the number of SBO sell transactions by each LPE (centre column); the number of MBO sell transactions (right column). Each year t, for each measure, two equal-weight portfolios are created, the Hi portfolio consists of LPEs whose measure is above the median for the year, the Lo portfolio consists of LPEs whose measure is below the median. The portfolios are held for 1 year. The skill measures are the year $t+1$ annual excess return (top row), the annual 4-factor alpha (middle row), and the annual dollar value-added (bottom row).

Finally, in Section IV it was shown that the NAV premium predicts short-term changes in Buyout and Mezzanine LPE NAV, suggesting that investors can identify skilled LPEs and set the NAV premium accordingly. Here I examine NAV premium as a predictor of skill as measured by NAV return, excess price returns, 4-factor alpha, and value-add. The NAV premium is used to create two annually rebalanced equal-weight portfolios as before, one consisting of LPEs whose NAV premium is above the median for the year, and the other consisting of LPEs whose NAV premium is below the median. The trading strategy results are presented in Figure 1.4. As in Section IV, it is clear that high premiums predict high NAV returns. However for the price-based skill measures, the result is the opposite: for example the benchmark-adjusted return for the low premium portfolio outperforms the high premium portfolio by about 210%.

Thus while high NAV premium is a predictor of skill as measured by NAV returns, low NAV premium is a very strong predictor of skill measured by price returns. A possible explanation for the success of low NAV premium as a predictor of price-based skill is that LPE managers are responding to pressure from the markets to improve performance.

VII. Robustness Checks

Sections IV and V present evidence for skill using 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 skill, and taken together they paint a consistent and complementary

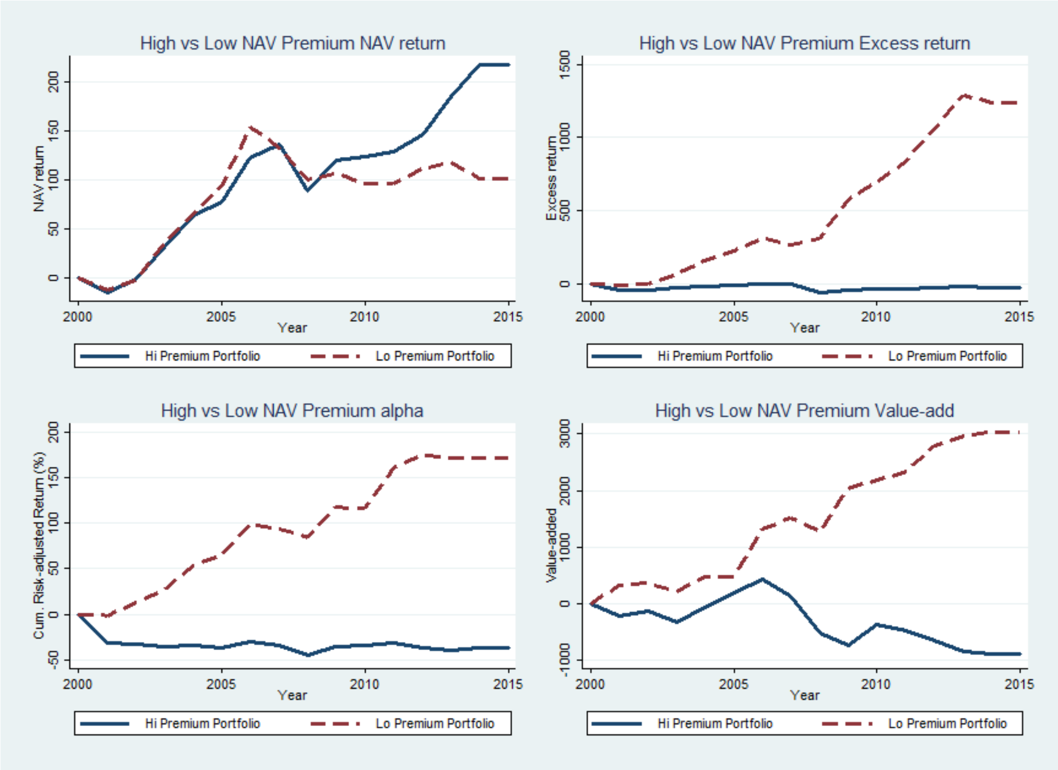


Figure 1.4. Trading Strategies using NAV Premium

This figure presents trading strategy results for portfolios of Buyout and Mezzanine LPEs created using the NAV premium as a determinant of skill. Two equal-weight portfolios are created, the Hi portfolio consists of LPEs whose NAV premium is above the median for year t, the Lo portfolio consists of LPEs whose NAV premium is below the median. The portfolios are rebalanced annually. The skill measures are the year $t+1$ annual NAV return (top right), annual excess return (top left), the annual 4-factor alpha (bottom right), and the annual dollar value-added (bottom left). NAV returns and NAV premiums are winsorised at the 1% and 99% levels.

picture. Nonetheless, I outline in this section a range of further checks to ensure that the test results are robust to a number of alternative specifications and interpretations.

A. *Jegadeesh et al. (2015) Sample*

My paper may be viewed as complementary 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 closed-end funds and fund-like firms that are included in major LPE-GP indices (and thus meet minimum stock liquidity requirements), whereas they focus just on LPE funds that are not necessarily listed on LPE-GP indices. As a robustness check, I repeat the 4-factor regression from Table 1.3 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*[15].

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 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 winner-minus-loser alpha test using NAV returns and for the NAV premium anticipates skill test do not change significantly, and the findings described in Section IV above are unaffected.

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

C. *Value-weighted Portfolios*

In Table 1.2 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 1.2 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 portfolios with the Global factors, using this combination for the persistence tests seems justified.

D. *Alternative Benchmark Models*

It may be that the significant alphas reported in Table 1.4 for winner-minus-loser (4-1) portfolios are due to some unique feature of the Fama-French-Carhart benchmarks used to estimate benchmark-adjusted returns.

In the Appendix, 4-1 portfolio factor loadings and alphas estimated using different benchmark models are presented. The benchmarks include CAPM, Dimson, Fama-French-Carhart 4-factors plus Pastor & Stambaugh Liquidity factor, Fama-French 5-factors, Fung-Hsieh 7-factors.

Under these alternative benchmarks, the main findings do not change. The alpha for the Buyout 4-1 portfolio remains significant, and insignificant for the other LPE types.

E. Cross-Sectional Bootstrap preserving Cross-Correlation

Fama and French (2010) implement a version of the cross-sectional bootstrap procedure that preserves cross-correlation between funds. For the standard cross-sectional bootstrap, zero-alpha pseudo-LPE returns are regressed on the same historical sequence of explanatory returns. In the approach that preserves cross-correlation, on the other hand, the sequence of months to use in a bootstrap sample is randomly selected (with replacement), and the same monthly sequence for all funds is used. Then the zero-alpha pseudo-LPE return for those months is regressed on the explanatory factor returns for those same months. The advantage of this approach 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 cross-correlation 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 standard methodology. If anything, the bootstrap p-values are marginally smaller using the cross-correlation approach; e.g. for Mezzanine LPEs, the 90% bootstrap p-value is 0.07 using the standard approach, and 0.06 using the cross-correlation approach.

F. Changes Over Time

Table 1.13 gives a picture of changes in short-term LPE skill during the sample period (1995-2015) using the winner-minus-loser portfolio 4-factor alpha as the skill measure. Overall, short-term LPE skill has been weakest in the period around 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 2010-2015 Venture skill is negative and not statistically significant while for Buyout LPEs it is positive

Table 1.13 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)
	{60}		{60}		{60}		{36}		{36}	
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)
	{60}		{60}		{60}		{36}		{36}	
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)
	{60}		{60}		{60}		{36}		{36}	
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)
	{-}		{60}		{60}		{36}		{36}	
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)
	{60}		{60}		{60}		{36}		{36}	

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.

VIII. Discussion

Overall, the skill tests detailed in this study paint a consistent picture (see Table 1.14 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 discov-

Table 1.14 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%	21%	24%	-	22%
False Discovery Rate (truly unskilled)	5%	10%	5%	-	5%
Dollar Value-add (USD millions)	16	11.6	34	2	21.7

ery 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 (2017). 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. (2017) 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 (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 a third 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 benchmark-adjusted returns of over 1.2% per month between the LPE at the 80th percentile and the LPE at the 20th percentile (see Table 1.7). 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. The tests for the determinants of skill for Buyout and Mezzanine LPEs show that the type of deals performed by an LPE are good predictors of short-term skill measures, and a very simple trading strategy can make substantial benchmark-adjusted returns.

IX. Conclusions

This study examines whether some listed closed-end private equity (LPE) funds and fund-like firms exhibit skill. LPE is increasingly seen by practitioners, academic researchers, and regulators as representative of the PE asset class. 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 fund nature of LPE means that robust measures for persistence and skill developed in the mutual fund literature can be estimated, including the winner-minus-loser 4-factor alpha, NAV changes predicted by NAV-premia, cross-sectional 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.

Over short horizons (12 months), 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 price and NAV returns. 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 (2017) 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.

The type of transactions favored by Buyout and Mezzanine LPEs is a good determinant of short-term skill. LPEs that make more solo acquisitions as a proportion of their transaction mix have significantly higher skill scores, while LPEs that make more exits via secondary buyouts and management buyouts have significantly weaker skill measures in the following years. Furthermore, while high NAV premiums predict higher NAV returns, the the opposite is true for NAV premiums and price returns - low NAV premiums are strong predictors of high price-based skill measures.

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 (cross-sectional bootstrap and false discovery rate) to my LPE sample confirms that there is large cross-sectional variation in LPE skill. By these measures, Buyout and Mezzanine LPEs again perform well, and significant proportions of these LPEs have alphas that are truly different from zero. Finally, Mezzanine and Buyout LPEs, along with FoFs, generate large dollar value-added.

While the dollar value-added measure may be a true measure of skill, it is based on gross alpha and thus 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 show that the net-of-fee outperformance by LPE is not competed away. Korteweg and Sorensen (2017) 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 why abnormal returns for PE are not competed away may lie in the nature of the managerial contracts used 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[16] concerns may limit PE fund managers' ability to adjust 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.

[16]In a similar vein, Huang et al. (2016) suggest that PE firmsâĂŹ 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.

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Appendix.

Table 1.A1 Description of Variables used in Skill Determinants Regressions

Variable	Meaning
excess-return	The annual total return, less the risk-free rate (previous twelve 1-month T-Bill rates compounded)
alpha	The annual excess return less the systematic return component estimated with a minumum of 24 months data using a Fama-French-Carhart 4-factor model
value-add	alpha times lagged total assets
ta	Total assets of the LPE (mm USD)
tl	Total liabilities of the LPE (mm USD)
gnav	Total assets minus total liabilities (mm USD)
mv	Market capitalization (mm USD)
premium	(Market cap - Net asset value)/Net asset value
age	LPE age (years)
expratio	The ratio of Sales&General Admin expenses to Total assets
gwillratio	The ratio of Goodwill impairment expenses to Total assets
randdratio	The ratio of Research & Development expenses to Total assets
voltoratio	The ratio of Share trading volume to Total assets
buys3	The total number of Buy transactions by the LPE in year t, t-1 and t-2
buysvalue3	The sum of the value of all Buy transactions by the LPE in year t, t-1 and t-2
sells3	The total number of Sell transactions by the LPE in year t, t-1 and t-2
sellsvalue3	The sum of the value of all Sell transactions by the LPE in year t, t-1 and t-2
solobuysvalue3	The total value of Buy transactions by the LPE in year t, t-1 and t-2 where the LPE is the sole sponsor
syndbuysvalue3	The total value of Buy transactions by the LPE in year t, t-1 and t-2 where the LPE is not the sole sponsor
solobuysvalueratio3	The ratio of the total value of solo Buy transactions by the LPE in year t, t-1 and t-2 to the total value of Buy transactions by the LPE in year t, t-1 and t-2
sbobuys3	The total number of Secondary Buyout acquisitions by the LPE in year t, t-1 and t-2
sbosells3	The total number of disposals via Secondary Buyout by the LPE in year t, t-1 and t-2
mbobuys3	The total number of Management Buyout acquisitions by the LPE in year t, t-1 and t-2
mbosells3	The total number of disposals via Management Buyout by the LPE in year t, t-1 and t-2

Table 1.A2 Factor Loadings for 4-1 Portfolios

This table gives the factor loadings for the 4-1 portfolios for CAPM, Fama-French 4-factor plus Pastor & Stambaugh liquidity factor, Dimson, Fama-French 5-factor, and Fung-Hsieh 7-factor models.

CAPM	MktRf							Constant	R2	Obs
Full	-0.14							0.39	0.04	241
	(-3.05)							(1.90)		
Direct	-0.08							0.54	0.01	241
	(-1.52)							(2.64)		
Venture	-0.24							0.76	0.01	224
	(-2.12)							(1.21)		
Mezzanine	-0.23							-0.14	0.06	147
	(-2.54)							(-0.46)		
FoF	-0.13							0.52	0.01	241
	(-1.78)							(1.49)		
DIMSON	MktRf	MktRf (Lagged)						Constant	R2	Obs
Full	-0.12	0.04						0.39	0.02	241
	(-1.84)	(0.70)						(1.71)		
Direct	-0.09	0.02						0.52	0.01	241
	(-1.33)	(0.36)						(2.38)		
Venture	-0.26	0.07						0.75	0.02	224
	(-2.06)	(0.51)						(1.18)		
Mezzanine	-0.18	-0.01						-0.05	0.04	147
	(-1.75)	(-0.09)						(-0.13)		
FoF	-0.12	0.07						0.52	0.01	241
	(-1.56)	(0.56)						(1.35)		
LIQUIDITY Factor	MktRf	SMB	HML	WML	LIQ			Constant	R2	Obs
Full	-0.02	-0.13	0.14	0.46	-0.03			-0.02	0.38	240
	-0.71	-1.5	1.94	9.06	(-0.73)			(-0.13)		
Direct	-0.04	0.01	-0.03	0.18	-0.08			0.44	0.09	240
	-0.8	0.08	-0.34	2.57	(-1.62)			(2.02)		
Venture	-0.01	0.12	0.85	0.77	0.11			-0.34	0.14	224
	-0.05	0.37	3.09	3.79	(0.66)			(-0.51)		
Mezzanine	-0.12	-0.31	0.14	0.38	0.05			-0.37	0.17	147
	-1.43	-1.29	0.61	2.47	(0.35)			(-1.07)		
FoF	-0.08	-0.02	0.16	0.22	0.21			0.14	0.06	240
	-0.99	-0.1	0.91	2.23	(2.17)			(0.37)		
FAMA-FRENCH 5-Factor	MktRf	SMB	HML	RMW	CMA			Constant	R2	Obs
Full	-0.04	0.13	-0.2	0.59	0.1			0.14	0.1	241
	-0.79	1.25	-1.66	3.39	0.52			(0.59)		
Direct	0	0.17	-0.23	0.48	0.08			0.36	0.06	241
	-0.07	1.75	-1.57	2.84	0.41			(1.67)		
DirectV	0.08	0.65	-0.05	1.11	0.64			-0.07	0.06	224
	0.56	1.98	-0.14	1.61	1.19			(-0.08)		
DirectM	-0.04	-0.07	-0.08	0.84	0.79			-0.55	0.13	147
	-0.52	-0.26	-0.3	2.31	1.65			(-1.39)		
FoF	-0.19	0.03	0.27	-0.08	-0.36			0.57	0.02	241
	-2.14	0.16	0.88	-0.28	-0.98			(1.36)		
FUNG-HSIEH 7-Factor	SNPMRF	SCMLC	BD10RET	BAAMTSY	PTFSFX	PTFSCOM	PTFSBD	Constant	R2	Obs
Full	-12.78	0.52	0.33	0.54	2.06	-0.59	-1.41	0.44	0.06	241
	(-3.09)	(0.08)	(0.37)	(0.40)	(1.35)	(-0.50)	(-1.02)	(2.10)		
Direct	-2.89	-4.52	0.6	1.37	0.01	1.11	-1.55	0.53	0.02	241
	(-0.67)	(-0.70)	(0.63)	(0.86)	(0.00)	(0.88)	(-1.08)	(2.50)		
Venture	-28.95	-2.4	1.24	-3.25	0.45	3.43	0.96	0.87	0.02	224
	(-2.10)	(-0.11)	(0.34)	(-0.95)	(0.08)	(0.80)	(0.24)	(1.28)		
Mezzanine	-17.75	-9.58	-0.03	2.92	4.78	-0.99	2.25	0.01	0.19	147
	(-1.41)	(-0.58)	(-0.02)	(1.39)	(2.14)	(-0.64)	(1.07)	(0.03)		
FoF	-6.76	0.18	1.71	3.65	1.86	-3.94	-1.94	0.55	0.04	241
	(-0.90)	(0.02)	(1.15)	(2.10)	(0.60)	(-1.84)	(-0.60)	(1.47)		

Essay 2

Do Publicly Listed Private Equity Firms make Bad Deals?

I. Introduction

Private equity is playing an increasingly significant role in the modern economic landscape. The sector is the largest private employer in the United States, employing 11 million people[1], has assets under management (AUM) valued at $4.3 trillion, and by some estimates, AUM will expand to $15 trillion in 10 years[2]. The rise of private equity has consequences for the wider economy and society. On the negative side, private equity has been linked with a reduction in the number of companies listed on public stock exchanges and reducing citizen-investors' exposure to corporate profits (Ljungqvist et al. (2016)), while on the positive side, industries where private equity funds invest grow more quickly in terms of total production and employment and appear less exposed to aggregate shocks (Bernstein et al. (2016)).

Given the rapid growth and the significant economic impact of the private equity model, understanding the organization and performance of private equity firms seems an important area of research. While a number of prior studies have examined private equity performance[3], there are few if any studies that empirically examine the link between performance and the organization forms of private equity firms. In this paper, we address this gap by measuring and comparing the deal-level performance of private equity firms that have adopted different organization structures. Furthermore, given that the business activity of all private equity firms is fundamentally the same - acquiring, adding value to, and exiting leveraged buyout deals - private equity provides a unique setting for examining more generally the interaction between the organization

The author would like to thank Sridhar Arcot and Sofia Ramos for their support and guidance. Thanks also to José-Miguel Gaspar, Laurence Lescourret, and Per Strömberg for useful comments, and also to the discussants and participants at ESSEC Student Research Seminar (2017), AFFI International Conference (2017), Paris Financial Management Conference (2017). Project funding from Inquire Europe is gratefully acknowledged.

[1]See "Private equity and Donald Trump's quest for jobs", Financial Times, 4.May.2017.

[2]See "Ten Predictions For Private Equity In 2017", Forbes, 25.Jan, 2017.

[3]Some recent studies include Jegadeesh et al. (2015), Harris et al. (2014), Ang et al. (2014).

form chosen by a firm and firm performance.

The traditional private equity buyout fund (Kaplan and Strömberg (2009)) is structured as a private partnership that has a limited life (10 to 13 years) and is managed by a General Partner (GP), usually a private equity partnership firm. Investors participate in the fund by becoming Limited Partners (LPs). These investors must be large and patient, as the minimum fund investment is typically several millions of dollars, which is committed to the fund for the duration of the fund life.

However market-based alternatives to the traditional PE partnership fund exist. Investors of all sizes and investment horizons may gain exposure to the PE asset class by purchasing the stocks of PE firms that are listed on international stock markets. Investors can choose between the shares of publicly listed GP firms, which raise and manage traditional PE partnership funds, or of publicly listed permanent capital PE funds (or fund-like firms) which invest their IPO capital in private companies. Public GPs[4] give shareholders access to the fees earned by these traditional PE fund managers, while public permanent PE[5] gives shareholders direct exposure to the gains earned on the PE deals made by the firm or fund (see Table 2.1 for an overview of the terminology used in this paper to identify different PE organization forms and fundraising models).

[4]Examples of public GPs include KKR & Co LP, Blackstone Group LP, Partners Group Holding AG. Private GPs include Bain Capital LLC, Clayton Dublilier & Rice LLC, Ardian SA.

[5]Examples of public permanent capital firms include Wendel SA, Deutsche Beteiligungs AG, Onex Corp; examples of public permanent capital funds include 3i Group plc, HgCapital Trust plc, Ares Capital Corp.

Table 2.1 Private Equity Organization Structures and Fundraising Styles

This table presents an overview of private equity organization structures and fundraising styles.

Type	**Investment capital**	**Subtype**	**Organization form**	**Shareholder Entitlements**	**Ownership**
Traditional GP	Sequence of fixed-life partnership funds	Private GP	Private company or partnership	N/A	Private PE
		Public GP	Publicly listed company or partnership	Share of fees earned managing PE funds	Public PE
Permanent PE	Investment funds raised on public markets	Permanent PE fund	Publicly listed closed-end fund	Share of profits on deals	
		Permanent PE firm	Publicly listed limited company		

Permanent capital has attracted interest[6] 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. Traditional GPs have also continued to seek listings on public stock markets, either to provide liquidity to the stakes built up by senior managers, or to raise funds to develop new product lines, or both[7].

However concerns have been raised about giving PE firms permanent public capital to invest (Jensen (2007)). As traditional GPs 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" (p.25). These incentives would be weakened or lost if PE firms were given permanent public capital. Furthermore, taking traditional GPs public raises the risk of misalignment between the interests of public shareholders of the firm and the interests of the limited partners investing in the firm's funds. In a similar vein, public PE firms (that is, public GPs and permanent PE) may have a short investment horizon (Lopez-de Silanes et al. (2015)), and thus may opt for large fund size at the cost of poorer future performance, as being large increases fees in the short term but lowers returns in the long term.

A further motivation for this study is that, after an extensive consultation process, the regulator of the $10 trillion[8] European insurance industry recently adopted an index of listed PE firms as the private equity benchmark for its Solvency II framework. This move has stimulated vigorous debate in the PE industry (EIOPA (2013)). Opponents to using listed PE as a PE benchmark argue, among other things[9], that the performance of funds managed by listed

[6]See, for example, "Long-term private equity funds: The Omaha play", The Economist, 10.September 2016; "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.

[7]See, for example, "K.K.R. Going Public Next Week", New York Times DealBook, 7.July, 2010.

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

[9]Other arguments against using an index as the PE benchmark are that an index of

PE firms may be different from the performance of the PE asset class as a whole.

One of the main aims of our study is to examine the empirical evidence for the concerns that deals by public PE firms underperform those by private GPs. To do this, we build a comprehensive dataset of transactions and realized deals by permanent PE firms and public and private GPs, for the period from January 1990 to June 2016, using transaction data from CapitalIQ[10]. Our sample consists of 33,471 solo buy and sell transactions for non-financial targets, with an imputed[11] value of almost $3 trillion (in 2007 US dollars), and 4,624 realized solo deals (5,581 if club deals are included). Our dataset is among the largest and most complete used in private equity research, and is free of selection and survivorship bias.

To ensure that deal characteristics are identified as precisely as possible, we focus on deals where there is a single PE sponsor (solo deals), and where there is a change in control of the target company. Focusing on solo deals means that measures of deal performance[12] reflects the maximum individual contribution a PE firm makes to the value of the target firm. In deals where a PE firm invests alongside other PE firms (syndicate or club deals), it is not possible to precisely identify the value added by each individual PE firm. Similarly, for deals which do not involve a change in control, the PE sponsor may not have

companies may carry too much idiosyncratic risk to be considered a good measure for all private equity; some buyout firms in the index are more leveraged (and therefore riskier) than the average private equity firm; part of the return for firms in the index is due to management fees and other non-investment driven returns, not only the performance of any underlying investments.

[10] CapitalIQ data has been used in a number of significant studies of private equity, including Strömberg (2007), Kaplan and Strömberg (2009), Lerner et al. (2011), Axelson et al. (2013), Arcot et al. (2015), and Bernstein et al. (2016).

[11] As total transaction values for some transactions are missing or incomplete, we follow standard practice in the literature that uses CapitalIQ data and estimate imputed transaction values using a Heckman procedure (see Appendix).

[12] We define deal multiple as the total sell transaction value divided by the total buy transaction value. As transaction values are not available for all transactions, we estimate imputed deal multiples using a Heckman procedure (see Appendix). Deal-level Public Market Equivalent (which I refer to as dPME) is the multiple for the deal divided by the return on the S&P500 over the life of the deal.

full control of the target firm, and thus the deal performance may reflect value added to the target firm from sources other than the PE sponsor.

We start in the spirit of Kaplan (1991) and Strömberg (2007) by providing a demography of deals by public PE (public GPs and permanent PE firms) and private GPs that includes statistics on deal quantity, size and performance by deal initiation year, deal target region and deal target industry sector. Deals by public PE firms[13] represent about 7%, by number, and 12% by value, of those by private GPs. Public PE make, on average, much larger deals than private GPs ($114m average buy transaction value for public PE versus $62m on average for private GPs), achieve higher imputed deal multiples (2.43 on average for public PE vs 2.36 for private GPs), and have higher imputed dPME values (2 on average for public PE versus 1.79 for private GPs). Looking more closely at the subcomponents of public PE, that is public GPs and permanent PE, the deal profile of permanent PE closely resembles that of private GPs, while public GPs' deal profile is markedly different from either private GPs or permanent PE - the average public GP imputed deal price is $206m, over 3 times that of private GPs or permanent PE ($62m and $66m, respectively), and despite the large deal size, the average public GP imputed deal multiple of 3 and dPME of 2.4 are much greater those for the other categories.

In the second part of this study, we compare more formally the performance of realized deals by public PE and private GPs[14]. Specifically, we test four pairs of hypotheses comparing performance of public PE and private GPs; traditional GPs and permanent PE; private GPs and public GPs; and permanent PE closed-end funds and permanent PE public limited companies.

We first compare the deal-level performance of private GPs and public PE (that is, public GPs and permanent PE firms), and find that deals by public

[13] We count deals by public GPs before their IPO as public deals.

[14] We do not examine fund-level performance. As Braun et al. (2017) point out, funds are merely legal wrappers for deals by the same PE firm.

PE firms outperform deals by private GPs. The mean imputed multiples and dPME values are both higher for public PE by about 8% (t-statistic: 2.7). Public PE firms hold their deals for a slightly shorter period, on average, and their capital gains are larger, on average.

Comparing performance of permanent PE and traditional GPs (that is, public and private GPs), we find that the evidence is not strong enough to reject the null hypothesis that deal performance for traditional GPs is the same as that for permanent PE. The mean imputed deal multiple for permanent PE is marginally smaller (-0.75%) than that of traditional PE firms, but the mean imputed dPME value for permanent PE is marginally larger (0.25%) than that for traditional PE; the differences are not statistically significant by either measure. Thus we find no evidence that traditional PE firms make better deals than permanent PE firms.

Looking at deals by private GPs and deals by public GPs, we find that the mean imputed multiple and dPME for public GPs are larger than those for private GPs, and the difference is statistically and economically significant. The imputed multiple and imputed dPME for deals by public GPs are both 22% (t-statistic: 4.9) higher than for private GPs. Given that public GPs regularly feature among the top performers in the private equity rankings[15] it is perhaps not too surprising that public GPs outperform; what is surprising however is the magnitude of this outperformance, especially in the light of the large size of the public GP deals; diseconomies of scale found elsewhere for private equity (Lopez-de Silanes et al. (2015)) do not seem to apply, at the deal level, to public GPs. Furthermore, we find that public GP deal performance actually improves after the GP goes public, by about 8% by both the imputed multiple measure (t-statistic: 1.9) and imputed dPME (t-statistic: 1.7).

Our final set of hypotheses exploit one of the unusual aspects of permanent

[15]See, for example, Private Equity International's Top 300 list, published annually.

PE capital, which is that two public organizational forms are possible - limited companies and closed-end funds. This unique setting gives an opportunity to make a direct comparison of the characteristics and performance of these two public organization structures. Given that managers of public limited companies are perceived to be myopic (Stein (1988)) in that they sacrifice long-term projects to boost short-term profits, and face serious agency problems (Jensen (1989)), we expect deals of public limited companies to be shorter and to underperform those of closed-end funds. We find that permanent PE firms do in fact tend to make shorter deals than permanent PE funds, and have lower multiples, but their annualized multiple (that is, the geometric average annual multiple) is slightly greater. Permanent PE funds, on the other hand, hold their deals for longer and achieve higher overall deal multiples.

The contribution of this paper is threefold. First, we develop a novel and comprehensive dataset of private equity deal performance metrics. In particular, we extend the use of CapitalIQ data to estimate deal multiples and dPMEs for public and private GPs and for permanent capital PE firms. Second, we contribute to the debate on the effectiveness of the private equity model by exploring the performance of different flavors of the model (traditional partnerships and permanent capital). Third, we compare the performance of different organization forms (public and private companies), and of different public organization structures (limited companies and closed-end funds).

Our analysis adds to a number of strands in the asset management literature. Some prior studies argue that mutual funds and hedge funds managed by publicly listed asset management companies underperform those of private asset management companies (Ferris and Yan (2009), Sun and Teo (2018)). This underperformance is typically attributed to public companies raising larger funds (and thus achieving decreasing returns to scale) and/or charging higher fees. Our study shows that gross (pre-fee) deal-level performance for public

PE is better than that of private GPs. Furthermore we find little evidence of diseconomies of scale at the individual deal level - public GPs make larger acquisitions than either private GPs or permanent capital PE firms, yet they also make larger deal multiples and dPMEs.

Consistent with Braun et al. (2017) and Kartashova (2014), we find that buyout deal performance declined during the 2000-2009 period. This decline has been interpreted to be a sign of the increasing competition for deals among PE firms (Braun et al. (2017)). However in the period 2010-2016, buyout deal performance has rebounded significantly. Thus competition for deals may have declined since the 2007-2008 financial crisis, allowing skilled PE fund managers to differentiate themselves from unskilled ones, and to deliver strong deal-level returns in the years following the crisis.

In the next section, Section II, we start by outlining the evolution of the private equity model, reviewing relevant literature and developing our hypotheses; in Section III we describe how we construct our dataset and present detailed deal demographics; in Section IV we test hypotheses about the characteristics and performance of deals by public PE and private GPs. Sections V and III round out our analysis with propensity score matching analysis and a deeper look at deal performance by holding period. Section VII discusses the findings and concludes.

II. Background and Hypotheses

A. Fundraising Models

There are three ways that private equity firms raise funds. The first, and the most common, approach is for the PE firm to raise funds that are legally organized as limited partnerships in which the general partners (GPs) manage the fund and the limited partners (LPs) provide most of the capital. The LPs typically include institutional investors, such as corporate and public pension funds, endowments, and insurance companies, as well as wealthy individuals. The private equity firm serves as the fund's GP. It is customary for the GP to provide at least 1 percent of the total capital.

The partnership fund typically has a fixed life, usually ten years, but can be extended for up to three additional years. The GP normally has up to five years to invest the fund's capital committed into companies, and then has an additional five to eight years to return the capital to its investors. After committing their capital, the LPs have little say in how the GP deploys the investment funds, as long as the basic covenants of the fund agreement are followed. Common covenants include restrictions on how much fund capital can be invested in one company, the types of securities a fund can invest in, and the amount of debt at the fund level (as opposed to debt at the portfolio company level, which is unrestricted).

Some PE firms (GPs) list on public stock exchanges, not to raise private equity investment capital, but rather to realize some firm value on behalf of the PE firm's partners or to raise funds for developing new product lines (eg hedge-funds, REITs). These PE firms continue to raise their PE investment capital from private investors following the partnership fund model. Shareholders are thus not directly exposed to the inherent risk of the underlying PE investments. They are entitled instead to a share of the fee income earned by the PE firm (and income from the firm's other product lines).

The second way private equity firms raise investment capital is to create a closed-end fund and list it on public stock-markets (we refer to these funds as permanent PE funds). Public closed-end funds exist for a variety of illiquid assets (real estate, municipal bonds etc), and are subject to regulation in the jurisdiction where the fund is listed (such as the Securities and Exchange

Commission (SEC) in the United States[16]).

Permanent PE funds enjoy tax benefits (such as corporation tax exemption on gains made on disposals of investments), however they face restrictions on investment activities which are similar to the covenants imposed by LPs in partnership PE funds - caps on leverage, fees, the amount investable in a single firm, etc. Permanent PE funds are usually “evergreen”, in that the fund has indefinite life, although a fund’s shareholders may move a resolution to wind up the fund at the fund’s general meetings.

Some closed-end PE funds invest as LPs in partnership funds raised by other PE firms rather than investing directly in private companies[17]. Such funds are known as indirect PE funds, or funds-of-funds.

The third way PE firms may raise investment capital is to seek a listing on the stock market as a public limited company, and use the IPO proceeds to invest in private companies (we refer to theses as permanent PE firms). Permanent PE firms do not enjoy the tax benefits that regulated closed-end PE funds do, but face fewer restrictions in their investment activities. In the United States, unfettered access to PE investments is perceived by regulators as too risky for smaller and possibly less informed investors, therefore raising PE investment capital this way is not permitted.

Permanent PE firms and permanent PE funds are closely related, in that they both raise their investment capital from public investors, and for most of this study we do not distinguish between these two forms of permanent PE except where explicitly noted.

[16]In the United States, listed closed-end PE funds are known as Business Development Companies (BDCs).

[17]Funds-of-funds, like LPs in general, occasionally take direct positions in private companies as co-investors with their GPs.

B. Arguments for the partnership model

Thus leveraged buyouts may be performed by private equity firms that raise their investment capital in different ways and that adopt different structural forms. The way investment capital is raised and the structural form of the PE firm does not change the inherent benefits of the LBO model as identified by Jensen (1989). However in his later remarks, Jensen (2007) identifies what he sees as the strengths of the fixed-life partnership funding model, and the weaknesses of the permanent public capital funding model. He argues that the reputation of partnerships' GPs is very important - the necessity to pay back investors (LPs) funds at the end of the contract period, and raise new funds, mean that mediocre returns are a disaster for GPs - two low-return funds and they are "out". GPs have big incentives to do good deals and make them work. On the other hand, PE firms that raise investment capital by listing a closed-end fund or a private limited company, do not have the same reputational concerns faced by GPs. They do not have to return funds to their investors, nor do they have to go back to investors to raise new funds on a regular basis. The implication therefore is that permanent PE firms do not have the same incentives to make successful deals that traditional GPs have.

These arguments have not gone unexamined however, and there is a growing body of literature highlighting incentive problems and agency costs in partnership funds. Axelson et al. (2009) develop an optimal contracting model in which the financial structure of partnership funds is designed to minimize agency conflicts between GPs and investors. However, even optimally designed PE contracts do not completely eliminate incentive problems and agency costs embedded in the GP-LP relationship. Arcot et al. (2015) show how GPs that 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) can feel pressure to make quick acquisitions, typically secondary buyouts from other PE firms, and these deals are often expensive relative to comparable mergers and acquisitions (M&A) transactions. Likewise GPs holding unsold investments at the end of their fund's life feel pressure to make secondary deals, and these deals sell at relatively low transaction multiples. Robinson and Sensoy (2013) report that GP behavior in booms and around certain contractual triggers seems consistent with the existence of agency conflicts. In particular they find evidence that suggests GPs hold on to underperforming investments instead of selling them and returning the cash to investors. Robinson and Sensoy (2013) suggest that, as GPs receive fee income from their LPs for managing active investments, and these fees are discontinued when the investment is sold, so GPs may delay selling in order to prolong their fee income. Other studies have highlighted window-dressing behavior by GPs. Brown et al. (2016) and Jenkinson et al. (2013) find that around the time the GP needs to raise a new fund, the valuations of their current fund tend to be inflated.

C. Arguments about GPs going public

Jensen (2007) also expresses concern about traditional PE firms going public, suggesting that the interests of the holders of a public PE firm's stock may not be aligned with the interests of the investors (LPs) in the partnership funds managed by the public PE firm. This tension between public shareholder and LP interests is unique to publicly listed GPs; in permanent PE vehicles there are no LPs, and in private GPs there are no public shareholders.

Chemmanur and Jiao (2012) develop a model of the choice of security-voting structure, in which market-driven short-termism plays a key role. In their model, entrepreneurs may prefer to go public with a dual-class share structure to commit to pursuing long-term strategies. By selling equity without votes, the entrepreneur can insulate himself from short-term market pressure. This form of managerial entrenchment can be beneficial in situations in which agency costs are low.

Publicly listed GPs may organize their share structure to minimize pressures from public shareholders. The shareholders (common unitholders) of most public GPs[18] have virtually no say in the governance of the enterprise - they have limited voting rights and no right to elect or remove the general partner or directors.

D. *Permanent Closed-End Funds versus Permanent Limited Companies*

One of the unusual aspects of permanent PE capital is that two organizational forms are possible - public limited companies and publicly listed closed-end funds. The underlying activities for both are fundamentally the same - leveraged buyouts. The incentives and agency costs for fund managers and firm managers however are different. Fund managers take fees from their investors which are similar to those of private GPs, including fixed investment management fees and variable performance fees. Firm managers, on the other hand, earn a compensation package that includes a salary, and usually a performance related bonus, and a stock or stock options component. As a result, the transaction characteristics and deal performance may be different for firms versus funds. Permanent PE provides a unique setting to make a direct comparison of the characteristics and performance of these two structural forms.

E. *Hypotheses*

We conclude by outlining 4 sets of hypotheses that arise from the previous discussion. Refer to Table 2.2 to see more clearly which hypotheses apply to

[18] See for example Jensen (2007), or "Here's The Real Problem With Investing In The Carlyle IPO", Business Insider, 4.February, 2012.

which PE models.

1. Private GP versus Public PE
    - Assuming public companies are myopic (Stein (1988)), and suffer from agency problems (Jensen (1989)), we expect to find that deal performance is better for private GPs than for public PE.
    - We further infer that public PE make shorter deals than private GPs.
2. Traditional GP versus Permanent PE
    - Assuming traditional GPs are incentivized to make good deals and make them work (Jensen (2007)), we expect to find that deals by traditional GPs (public and private together) outperform those by public permanent PE firms.
    - Assuming their permanent capital gives permanent PE firms more flexibility to time deal entry and exit (Strömberg (2007)), we expect to find that the deal holding period for public permanent PE firms is longer than that of traditional GPs (public and private together).
3. Private GP versus Public GP
    - Assuming shareholder and LP interests are misaligned for public GPs (Lopez-de Silanes et al. (2015), Jensen (2007)), we expect to find that deals by private GPs outperform those by public GPs.
    - We also expect to find that deal performance declines after a GP goes public.
4. Permanent Closed-End Funds versus Permanent Limited Companies
    - Assuming public limited companies are myopic (Stein (1988)), and suffer from agency problems (Jensen (1989)), we expect to find that deal performance is better for permanent PE organized as closed-end funds than for permanent PE organized as limited companies.

Table 2.2 Linking hypotheses to PE models

Hypotheses 1: the light shaded areas represent private GPs, the dark shaded areas represent public PE

Type	Investment capital	Subtype	Organization form	Shareholder Entitlements	Ownership
Traditional GP	Sequence of fixed-life partnership funds	Private GP	Private company or partnership	N/A	Private PE
		Public GP	Public company or partnership	Share of fees earned managing funds	Public PE
Permanent PE	Investment funds raised on public markets	Permanent PE fund	Public closed-end fund	Share of profits on deals	
		Permanent PE firm	Public limited company		

Hypotheses 2: the light shaded areas represent traditional GPs, the dark shaded areas represent permanent PE

Type	Investment capital	Subtype	Organization form	Shareholder Entitlements	Ownership
Traditional GP	Sequence of fixed-life partnership funds	Private GP	Private company or partnership	N/A	Private PE
		Public GP	Public company or partnership	Share of fees earned managing funds	Public PE
Permanent PE	Investment funds raised on public markets	Permanent PE fund	Public closed-end fund	Share of profits on deals	
		Permanent PE firm	Public limited company		

Hypotheses 3: the light shaded areas represent private GPs, the dark shaded areas represent public GPs

Type	Investment capital	Subtype	Organization form	Shareholder Entitlements	Ownership
Traditional GP	Sequence of fixed-life partnership funds	Private GP	Private company or partnership	N/A	Private PE
		Public GP	Public company or partnership	Share of fees earned managing funds	Public PE
Permanent PE	Investment funds raised on public markets	Permanent PE fund	Public closed-end fund	Share of profits on deals	
		Permanent PE firm	Public limited company		

Hypotheses 4: the light shaded areas represent permanent PE funds, the dark shaded areas represent permanent PE firms

Type	Investment capital	Subtype	Organization form	Shareholder Entitlements	Ownership
Traditional GP	Sequence of fixed-life partnership funds	Private GP	Private company or partnership	N/A	Private PE
		Public GP	Public company or partnership	Share of fees earned managing funds	Public PE
Permanent PE	Investment funds raised on public markets	Permanent PE fund	Public closed-end fund	Share of profits on deals	
		Permanent PE firm	Public limited company		

- We also expect that deal holding times for permanent PE closed-end funds are longer than for permanent PE limited companies

III. Data

The S&P CapitalIQ database contains comprehensive data on buy and sell transactions for public and private targets by public and private companies. CapitalIQ data has been used in a number of significant studies of private equity, including Strömberg (2007), Kaplan and Strömberg (2009), Axelson et al. (2013), Arcot et al. (2015) and Bernstein et al. (2016). Strömberg (2007) provides a very detailed analysis of CapitalIQ data from a private equity perspective.

We define a deal using CapitalIQ data as two transactions involving a target firm, a buy transaction where there is a change of control for the target firm, followed by a sell transaction where the sellers are the same as the buyers from the buy transaction, or a bankruptcy, for the same target firm, whichever comes first. In the small number of cases where there is more than one buy transaction for a target involving the same buyers, we keep the one where the largest stake is acquired, usually the first transaction. We treat multiple sell transactions involving the same targets and sellers in a similar way. Using the target name and the list of buyers as keys, we match buy transactions with sell transactions and with bankruptcies.

To ensure that deal characteristics are identified as precisely as possible, we focus on deals where there is a single PE sponsor (solo deals), and where there is a change in control of the target company. Focusing on solo deals means that the deal multiple reflects the maximum individual contribution a PE firm makes to the value of the target firm. In deals where a PE firm invests alongside other PE firms (syndicate or club deals), it is not possible to precisely identify the value added by each individual PE firm. Similarly, for deals which do not involve a change in control, the PE sponsor may not have full control of the target firm, and thus the multiple may reflect value added to the target firm from sources other than the PE sponsor.

The buy date for the deal is the closing date of the buy transaction and the sell date is the closing date of the nearest matching sell transaction (or the announcement date in the case of bankruptcy) to the buy date. We exclude deals of less than 30 days duration.

Thus our data provide accurate estimates of the size and timing of the largest deal-level cashflows, that is, of the deal buy and sell transactions. However other types of intermediate deal-level cashflow are possible, for example dividend recapitalizations where target firms take on additional debt in order to pay a dividend to PE owners. Our data do not directly capture the timing of such dividend recaps, but the buy and sell transaction values, which include net assumed liabilities, capture the magnitude of changes in target firms' debt position brought about by such intermediate cashflows.

We estimate the multiple of invested capital for a deal as the deal's sell value divided by its buy value. We use actual (not imputed), unwinsorised, values to estimate actual multiples, but to control for outliers and potential data errors, multiples are winsorized at the 1% and 99% levels. As actual value information is not available for all deals, we use a Heckman procedure to impute the multiple for deals where the value information is incomplete. Details of the procedure are given in the Appendix.

The Public Market Equivalent (PME)[19] measure has been shown by Sorensen and Jagannathan (2015) to control for market risk and other risks which vary with the credit cycle, such as leverage. Our deal-level dPME measure consists of the return achieved by investing \$1 in the deal (the deal's multiple) divided by the return that could have been achieved by investing \$1 in the S&P500 at the deal buy date and selling at the deal sell date. A dPME value less than one means that the deal earned less than could have been achieved by investing in the S&P500 over the lifetime of the deal, and a dPME value greater than one means that the deal earned more than the market. To estimate the market return, we use daily total return data for the value-weighted S&P500 index downloaded from the Center for Research in Securities Prices (CRSP).

We identify public PE firms and funds as Business Development Companies (closed-end funds of PE investments which are regulated by the Securities and Exchange Commission in the United States), private equity Investment Trusts (closed-end funds of PE investments run by members of the AIC in the United Kingdom), and the constituents of publicly available LPE indices

[19] Korteweg and Sorensen (2017) propose a generalized PME measure (GPME) that adapts stochastic discount factor (SDF) valuation methods and is estimated using using GMM. While this measure yields different performance estimates for venture capital funds, the largest differences are prior to 1998, and post-1998 the PME and GPME estimates are fairly close. Most of the deals in our sample are post-1998, so for convenience we follow the traditional approach to derive our dPME measure.

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. The constituents of the ProShares Global Listed Private Equity ETF which tracks the LPX Direct Listed Private Equity Index are also included. We identify permanent PE firms as PE firms which pursue a private equity investment strategy where their proprietary (balance sheet) capital is the dominant source of funds (that is, proprietary capital represents more than 50% of the firm's investment capital, or the firm is the largest LP in its own funds).

Table 2.A4 presents data on the number, value, and performance of deals. Our final sample consists of 5,581 deals, of which 4,640 are solo deals. 4,242 deals are by private GPs, and 398 (9.5% of the private GP total) are by public PE firms and funds.

A. *Comparison with Other Studies*

A small number of other studies use deal-level data (eg Braun et al. (2017), Lopez-de Silanes et al. (2015)), and these source deal-level data from LPs. However, only GPs who sought capital from these LPs are included in their sample, thus selection bias is a possibility. Survivorship bias may be a concern too - GPs who had raised funds in the past (from other investors) but subsequently quit the sector will be excluded. Also LPs do not invest in deals by public permanent capital firms, so these deals are completely excluded. Our sample avoids all of these problems - it includes deals by all GPs, even if they did not seek investment from certain investors, or if the GP exited the sector. Of course, we also include all deals by permanent capital PE firms.

Nonetheless, our measures of deal-level performance are consistent with results from other recent studies. Comparing deal performance characteristics with those found by Braun et al. (2017) in their study of PE persistence, their average multiple for 6,048 realized deals for the period 1990-2013, ranges from 1.5 to 2.2, while our average imputed multiples for non-financial targets located in OECD countries in the 1990-2016 period, are 2.3 for 4,640 solo deals, and 2.0 for 941 syndicate deals. In their study of economies of scale in PE, Lopez-de Silanes et al. (2015) report a median multiple of 2.1 for their sample of 5,106 deals realized between 1973-2005, which is also in line our finding.

B. Demography

We finish this section by giving a demographic picture of private and public PE deals in Table 2.3. We break down deal volumes, values, and performance, by time period (from the 1990s through to the 2010s), by the geographic location of target firms, and by the industry classification of target firms.

The quantity of deals made by public PE firms in proportion to those made by private GPs has varied slightly over time, from about 5% in the 2010s to 9% in the early 2000s; the overall proportion is about 7%. The number of deals per private GP has remained close to 2 despite a large increase (250%) in the number of deals between the 1990s and the late 2000s. For public PE on the other hand, the number of deals grew even more (over 300%) over the same period, and the average number of deals per public PE firm was almost 16. The figures suggest that there were a relatively large number new entrants among the private GP ranks. Average deal Buy prices for public PE were nearly double those for private GPs (\$114m vs \$62m), multiples and dPME values for public PE (2.43 and 2) were slightly higher than for private GPs (2.36 and 1.8), and holding periods were shorter, on average, for public PE (4.38 years) vs private GPs (4.55 years). While deals by private GPs were focused on US and UK&Ireland targets (50% and 15% respectively), deal targets for public PE were distributed more globally, with 34% of targets based in the US, 17% in Germany/Austria/Switzerland, and 16% in the UK&Ireland. The distribution by industry sector for both public and private PE targets is remarkably similar: 29% industrials, 27% consumer discretionary, and 15% information technology.

Looking more closely at the subcomponents of public PE, that is public GPs and permanent PE, we see that the deal profile of public GPs differs markedly from that of both private GPs and permanent PE. Public GPs make deals with much higher buy prices ($206m on average) and earn higher multiples (3.0 on average) and higher dPMEs (2.39 on average). The deal profile for permanent PE ($66m buy price, 2.13 multiple, 1.82 dPME), on the other hand, is similar to that of private GPs ($62m buy price, 2.36 multiple, 1.82 dPME). Public GPs make the most deals (19.8 on average per firm), compared to 14.5 deals per firm for permanent PE and 2.84 for private GPs. Permanent PE have the shortest average deal holding period (4.24 years, versus 4.66 years for public GPs and 4.55 years for private GPs. Public GPs invest mainly in US (45%) and Scandinavian (17%) targets focusing on industrials (32%), consumer discretionary (25%) and information technology (18%). Permanent PE invest in targets located in the US (28%), Germany/Austria/Switzerland (22%) and UK&Ireland (18.6%), and which are active in industrials (28%), consumer discretionary (28%) and information technology (16%) sectors.

Table 2.3 Deal Demography

This table presents demographic statistics for deals by public PE and private GPs for the period 1.January, 1990 to 30.June, 2016. The variables of interest are: the number (N firms) of firms that realized at least one deal; the number (N deals) of realized deals; the mean number of realized deals per firm (Deals/Firm); the mean holding period (Years), imputed buy price (iBuyprice), imputed multiple (iMultiple) and imputed dPME (idPME) for realized deals. The demographic categories are the yearly interval when the deal was initiated; the headquarter country of the deal target firm; and the GICS industry sector classification of the deal target firm. See Appendix 2.A1 for variable definitions.

	Private GP									Public PE								
	N (firms)		N (deals)		Deals/ firm	Years	iBuyprice	iMultiple	idPME	N (firms)		N (deals)		Deals/ firm	Years	iBuyprice	iMultiple	idPME
1990-2016	1482	100%	4212	100%	2.84	4.55	61.99	2.36	1.79	18	100%	287	100%	15.94	4.38	114.56	2.43	2.02
1990-1999	325	13.5%	716	17.0%	2.20	5.45	58.27	2.75	1.87	9	17.0%	40	13.9%	4.44	6.01	85.03	2.99	2.37
2000-2004	604	25.1%	1039	24.7%	1.72	4.6	54.87	2.24	1.79	14	26.4%	95	33.1%	6.79	4.45	80.96	2.31	1.95
2005-2009	967	40.2%	1795	42.6%	1.86	4.66	64.3	2.05	1.7	17	32.1%	123	42.9%	7.24	4.12	135.05	2.02	1.75
2010-2016	511	21.2%	662	15.7%	1.30	3.09	70.9	2.97	1.93	13	24.5%	29	10.1%	2.23	3.01	178.46	4.23	2.92
US	810	45.1%	2104	50.0%	2.60	4.68	63.71	2.24	1.68	9	20.5%	98	34.1%	10.89	4.81	129.61	2.69	2.1
Canada	80	4.4%	85	2.0%	1.06	4.68	39.34	2.06	1.38	1	2.3%	3	1.0%	3.00	7.25	37.6	1.19	1.11
UK & Ireland	202	11.2%	647	15.4%	3.20	4.44	59.21	2.07	1.57	7	15.9%	46	16.0%	6.57	4.13	123.82	2.15	1.89
France & BeNeLux	218	12.1%	441	10.5%	2.02	4.6	68.73	2.36	1.76	7	15.9%	30	10.5%	4.29	4.04	96.04	2.18	1.82
Germanic De-Aus-CH	156	8.7%	314	7.5%	2.01	4.24	76.91	1.66	1.3	7	15.9%	50	17.4%	7.14	3.38	90.13	2.02	1.7
Spain, Italy, Portugal	109	6.1%	173	4.1%	1.59	4.16	55.77	2.3	1.77	3	6.8%	15	5.2%	5.00	3.95	108.2	2.62	2.58
Scandinavia	98	5.5%	233	5.5%	2.38	4.38	50.9	2.31	1.75	4	9.1%	34	11.8%	8.50	5.35	75.8	3.21	2.48
Australia & NZ	49	2.7%	94	2.2%	1.92	4.44	45	2.97	2.3	1	2.3%	2	0.7%	2.00	2.57	222.27	1.83	1.6
Korea & Japan	24	1.3%	35	0.8%	1.46	3.87	64.92	0.98	0.76	3	6.8%	7	2.4%	2.33	3.4	291.82	3.02	2.09
RoW	52	2.9%	86	2.0%	1.65	4.04	33.99	10.46	8.29	2	4.5%	2	0.7%	1.00	4.81	146.62	4.88	3.33
Consumer Discretionary	679	37.8%	1160	27.5%	1.71	4.62	66.09	1.9	1.43	17	22.1%	78	27.2%	4.59	4.13	121.08	2.57	2.1
Consumer Staples	277	15.4%	321	7.6%	1.16	4.56	64.92	4.46	3.36	8	10.4%	19	6.6%	2.38	5.41	147.9	2.36	1.72
Energy	59	3.3%	58	1.4%	0.98	3.67	97.86	2.79	2.06	4	5.2%	5	1.7%	1.25	3.3	119.11	1.95	1.8
Healthcare	278	15.5%	371	8.8%	1.33	4.34	60.18	2.44	1.86	8	10.4%	22	7.7%	2.75	4.4	104.88	2.66	2.11
Industrials	721	40.1%	1231	29.2%	1.71	4.66	58.81	2.07	1.6	14	18.2%	85	29.6%	6.07	4.22	118.31	2.49	2.1
Information Technology	427	23.7%	594	14.1%	1.39	4.34	45.31	2.56	1.96	12	15.6%	48	16.7%	4.00	4.58	72.04	2.35	1.9
Materials	300	16.7%	397	9.4%	1.32	4.68	69.45	2.36	1.73	8	10.4%	24	8.4%	3.00	5.11	99.65	2.52	1.97
Telecommunication Services	40	2.2%	33	0.8%	0.83	3.52	95.85	3.66	2.86	4	5.2%	4	1.4%	1.00	2.43	368.06	3.39	2.74
Utilities	38	2.1%	32	0.8%	0.84	3.28	158.71	2.25	1.7	1	1.3%	1	0.3%	1.00	4.06	233	1.03	0.58
Other	13	0.7%	15	0.4%	1.15	4.59	30.76	2.32	1.54	1	1.3%	1	0.3%	1.00	3.41	111.01	1.18	1.3

Table 2.3, continued

	Public GP									Public Permanent PE									
	N (firms)		N (deals)		Deals/ firm	Years	iBuyprice	iMultiple	idPME	N (firms)		N (deals)		Deals/ firm	Years	iBuyprice	iMultiple	idPME
1990-2016	5	100.0%	99	100.0%	19.80	4.66	206.39	3	2.39	13	100.0%	188	100.0%	14.46	4.24	66.2	2.13	1.82
1990-1999	4	21.1%	18	18.2%	4.50	6.29	131.26	3.85	3.32	5	14.7%	22	11.7%	4.40	5.76	47.21	2.25	1.54
2000-2004	5	26.3%	24	24.2%	4.80	5.11	154.34	2.59	1.94	9	26.5%	71	37.8%	7.89	4.22	56.15	2.22	1.96
2005-2009	5	26.3%	38	38.4%	7.60	4.59	261.8	2.75	2.16	12	35.3%	85	45.2%	7.08	3.92	78.39	1.7	1.58
2010-2016	5	26.3%	19	19.2%	3.80	2.92	232.51	3.72	2.51	8	23.5%	10	5.3%	1.25	3.16	75.76	5.21	3.72
US	4	22.2%	45	45.5%	11.25	5.08	193.45	3.11	2.43	5	19.2%	53	28.2%	10.60	4.58	75.41	2.32	1.8
Canada	0	0.0%	0	-	-	-	-	-	-	1	3.8%	3	1.6%	3.00	7.25	37.6	1.19	1.11
UK & Ireland	3	16.7%	11	11.1%	3.67	3.89	345.44	2.3	1.83	4	15.4%	35	18.6%	8.75	4.21	54.17	2.1	1.91
France & BeNeLux	2	11.1%	4	4.0%	2.00	3.67	153.5	2.53	1.77	5	19.2%	26	13.8%	5.20	4.09	87.2	2.13	1.83
Germanic De-Aus-CH	2	11.1%	9	9.1%	4.50	4.89	267.6	2.61	1.81	5	19.2%	41	21.8%	8.20	3.05	51.17	1.89	1.68
Spain, Italy, Portugal	1	5.6%	3	3.0%	3.00	2.19	176.73	1.71	1.86	2	7.7%	12	6.4%	6.00	4.39	91.07	2.85	2.77
Scandinavia	1	5.6%	17	17.2%	17.00	5.38	99.3	4.29	3.31	3	11.5%	17	9.0%	5.67	5.31	52.29	2.12	1.64
Australia & NZ	1	5.6%	2	2.0%	2.00	2.57	222.27	1.83	1.6	0	0.0%	0	-	-	-	-	-	-
Korea & Japan	2	11.1%	6	6.1%	3.00	3.56	324.84	3.01	2.02	1	3.8%	1	0.5%	1.00	2.45	93.69	3.1	2.57
RoW	2	11.1%	2	2.0%	1.00	4.81	146.62	4.88	3.33	0	0.0%	0	-	-	-	-	-	-
Consumer Discretionary	5	16.7%	25	25.3%	5.00	4.92	220.6	2.97	2.22	12	25.5%	53	28.2%	4.42	3.77	74.14	2.39	2.05
Consumer Staples	4	13.3%	6	6.1%	1.50	5.45	296.65	2.94	2.09	4	8.5%	13	6.9%	3.25	5.38	79.25	2.05	1.51
Energy	1	3.3%	1	1.0%	1.00	2.1	339.3	1.54	1.3	3	6.4%	4	2.1%	1.33	3.6	64.06	2.05	1.93
Healthcare	4	13.3%	6	6.1%	1.50	4.3	185.8	4.02	2.86	4	8.5%	16	8.5%	4.00	4.44	74.54	2.14	1.83
Industrials	5	16.7%	32	32.3%	6.40	4.24	199.28	3.06	2.55	9	19.1%	53	28.2%	5.89	4.21	69.42	2.15	1.83
Information Technology	3	10.0%	18	18.2%	6.00	5.01	133.15	2.79	2.11	9	19.1%	30	16.0%	3.33	4.32	35.37	2.07	1.78
Materials	3	10.0%	6	6.1%	2.00	7.2	204.03	4.82	3.26	5	10.6%	18	9.6%	3.60	4.42	64.85	1.75	1.54
Telecommunication Services	3	10.0%	3	3.0%	1.00	2.31	447.38	3.58	2.83	1	2.1%	1	0.5%	1.00	2.92	130.08	2.63	2.41
Utilities	1	3.3%	1	1.0%	1.00	4.06	233	1.03	0.58	0	0.0%	0	0.0%	-	-	-	-	-
Other	1	3.3%	1	1.0%	1.00	3.41	111.01	1.18	1.3	0	0.0%	0	0.0%	-	-	-	-	-

Table 2.3, continued

	Permanent Firm									Permanent Fund								
	N (firms)		N (deals)		Deals/ firm	Years	iBuyprice	iMultiple	idPME	N (firms)		N (deals)		Deals/ firm	Years	iBuyprice	iMultiple	idPME
1990-2016	11	100.0%	129	100.0%	11.73	4.02	63.52	2.15	1.75	3	100.0%	63	100.0%	21.00	4.62	69.18	2.31	2.09
1990-1999	4	13.8%	9	7.0%	2.25	5.46	51.44	2.51	1.45	1	14.3%	13	20.6%	13.00	5.97	44.29	2.07	1.6
2000-2004	8	27.6%	38	29.5%	4.75	4.33	51.83	1.98	1.59	1	14.3%	33	52.4%	33.00	4.07	61.12	2.51	2.4
2005-2009	10	34.5%	72	55.8%	7.20	3.77	70.82	1.75	1.56	3	42.9%	15	23.8%	5.00	4.83	107.58	2.05	1.84
2010-2016	7	24.1%	10	7.8%	1.43	2.77	66.22	5.69	4.18	2	28.6%	2	3.2%	1.00	3.21	76.03	2.49	1.9
US	3	13.6%	50	38.8%	16.67	4.42	78.6	2.41	1.89	2	28.6%	3	4.8%	1.50	7.27	22.18	0.76	0.4
Canada	1	4.5%	3	2.3%	3.00	7.25	37.6	1.19	1.11	0	0.0%	0	0.0%	-	-	-	-	-
UK & Ireland	4	18.2%	8	6.2%	2.00	3.82	76.4	1.17	0.94	1	14.3%	29	46.0%	29.00	4.22	45.92	2.31	2.14
France & BeNeLux	5	22.7%	16	12.4%	3.20	3.71	70.33	2.41	2.02	1	14.3%	11	17.5%	11.00	4.5	108.1	2.19	1.96
Germanic De-Aus-CH	5	22.7%	39	30.2%	7.80	3.11	46.38	2.13	1.77	1	14.3%	3	4.8%	3.00	3.17	100.69	2	1.81
Spain, Italy, Portugal	1	4.5%	1	0.8%	1.00	1.05	39.96	2.59	2.63	1	14.3%	11	17.5%	11.00	4.7	95.72	2.87	2.78
Scandinavia	2	9.1%	11	8.5%	5.50	4.93	42.96	1.98	1.56	1	14.3%	6	9.5%	6.00	6.01	69.4	2.38	1.78
Australia & NZ	0	0.0%	0	0.0%	-	-	-	-	-	0	0.0%	0	0.0%	-	-	-	-	-
Korea & Japan	1	4.5%	1	0.8%	1.00	2.45	93.69	3.1	2.57	0	0.0%	0	0.0%	-	-	-	-	-
RoW	0	0.0%	0	0.0%	-	-	-	-	-	0	0.0%	0	0.0%	-	-	-	-	-
Consumer Discretionary	11	28.2%	38	29.5%	3.45	3.3	66.04	2.46	1.98	2	20.0%	17	27.0%	8.50	4.85	88.48	2.45	2.39
Consumer Staples	3	7.7%	10	7.8%	3.33	5.24	83.6	1.99	1.57	1	10.0%	3	4.8%	3.00	5.87	64.76	2.27	1.31
Energy	2	5.1%	2	1.6%	1.00	5.52	82.2	1.61	0.52	1	10.0%	2	3.2%	2.00	1.68	45.92	2.5	3.34
Healthcare	3	7.7%	7	5.4%	2.33	4.92	102.26	1.18	1.05	1	10.0%	9	14.3%	9.00	4.06	52.97	2.89	2.44
Industrials	8	20.5%	40	31.0%	5.00	4.12	66.02	2.1	1.77	1	10.0%	13	20.6%	13.00	4.5	79.88	2.29	2
Information Technology	8	20.5%	21	16.3%	2.63	3.98	36.87	2.52	1.96	2	20.0%	11	17.5%	5.50	4.71	28.09	2.1	1.8
Materials	4	10.3%	11	8.5%	2.75	3.8	50.3	1.93	1.61	1	10.0%	7	11.1%	7.00	5.38	87.72	1.47	1.44
Telecommunication Services	0	0.0%	0	0.0%	-	-	-	-	-	1	10.0%	1	1.6%	1.00	2.92	130.08	2.63	2.41
Utilities	0	0.0%	0	0.0%	-	-	-	-	-	0	0.0%	0	0.0%	-	-	-	-	-
Other	0	0.0%	0	0.0%	-	-	-	-	-	0	0.0%	0	0.0%	-	-	-	-	-

IV. Deal Performance Comparison

In the previous section we estimated and presented two core measures of deal performance, the imputed multiple of invested capital and the imputed Public Market Equivalent (dPME). In this section we do a formal comparison of deal performance for different PE types. Specifically, we test the 4 sets of hypotheses outlined in Section II.

A. Overview

Table 2.4 presents the results of regressions of dummy variables for deals by public PE (public and permanent PE together), permanent PE, public GPs (pre- and post-IPO), and public GPs post-IPO only, on log deal multiple (Panel A) and log dPME (Panel B). Public PE deals significantly outperform private GP deals in all models, especially where dPME is the performance measure. The results show that there is very little difference in deal performance between permanent PE and other types of PE (that is, traditional GPs). The coefficient for permanent PE is slightly negative where the deal multiple is the performance measure, but it is slightly positive where dPME is the performance measure. Deals by public GPs clearly outperform deals by private GPs and permanent PE. The coefficients for the public GP dummy are large and highly significant. Post-IPO deals by public GPs have even larger and more significant coefficients, suggesting that not only do deals by public GPs outperfom, this outperformance actually improves after the public GP's IPO (we will provide more formal evidence of this result later in this Section).

Table 2.5 presents the results of t-tests comparing other deal performance characteristics for different types of PE firm including the imputed buy price for the deal, the annualized imputed deal multiple (i.e. the annual return which when compounded over the period of the deal yields the deal multiple),

Table 2.4 Deal Performance Regressions

*This table presents the results of regressions of dummy variables for different PE types on measures of deal performance. The performance measures (dependent variables) are the log imputed deal multiple (Panel A) and the log imputed deal dPME (Panel B). The independent variables are indicator variables that are equal to 1 for deals by Public PE (public GPs and permanent PE firms together), Permanent PE, Public GPs (pre- and post-IPO), and Public GPs (post-IPO only). Models 1-4 exclude control variables, models 5-8 include them. Control variables include dummies for deal target country, industry, buy and sell year, holding period (Hold-year), and buy and sell transaction characteristics (Tx-characteristics) such as LBO, MBO etc. Standard errors are clustered by the deal buy year. t-statistics are given in parentheses. ***,**, and * denote significance at the 1%, 5% and 10% level, respectively.*

Panel A - Performance regression results using deal multiples

VARIABLES	(1) ln_multiple	(2) ln_multiple	(3) ln_multiple	(4) ln_multiple	(5) ln_multiple	(6) ln_multiple	(7) ln_multiple	(8) ln_multiple
Public PE (d)	0.0795*				0.0809**			
	(1.646)				(2.721)			
Permanent PE (d)		-0.0973				-0.00751		
		(-1.642)				(-0.153)		
Public GP (d)			0.393***				0.224***	
			(4.935)				(6.096)	
Public GP (Post-IPO) (d)				0.608***				0.270***
				(3.922)				(7.725)
Industry dummies	No	No	No	No	Yes	Yes	Yes	Yes
Country dummies	No	No	No	No	Yes	Yes	Yes	Yes
Year dummies	No	No	No	No	Yes	Yes	Yes	Yes
Hold-year dummies	No	No	No	No	Yes	Yes	Yes	Yes
Tx-characteristic dummies	No	No	No	No	Yes	Yes	Yes	Yes
Observations	4,538	4,538	4,538	4,538	4,538	4,538	4,538	4,538
R-squared	0.001	0.001	0.005	0.003	0.814	0.814	0.815	0.815

Panel B - Performance regression results using deal dPME

VARIABLES	(1) ln_dPME	(2) ln_dPME	(3) ln_dPME	(4) ln_dPME	(5) ln_dPME	(6) ln_dPME	(7) ln_dPME	(8) ln_dPME
Public PE (d)	0.150***				0.0890***			
	(3.067)				(3.056)			
Permanent PE (d)		0.00788				0.00257		
		(0.131)				(0.0513)		
Public GP (d)			0.395***				0.227***	
			(4.893)				(6.167)	
Public GP (Post-IPO) (d)				0.510***				0.266***
				(3.242)				(7.558)
Industry dummies	No	No	No	No	Yes	Yes	Yes	Yes
Country dummies	No	No	No	No	Yes	Yes	Yes	Yes
Year dummies	No	No	No	No	Yes	Yes	Yes	Yes
Hold-year dummies	No	No	No	No	Yes	Yes	Yes	Yes
Tx-characteristic dummies	No	No	No	No	Yes	Yes	Yes	Yes
Observations	4,538	4,538	4,538	4,538	4,538	4,538	4,538	4,538
R-squared	0.002	0.000	0.005	0.002	0.808	0.807	0.809	0.808

the capital gain for the deal (i.e. the difference between the buy transaction value and the sell transaction value).

Table 2.5 Other Deal Performance Characteristics Comparison for Public and Private PE

*This table presents the results of unpaired t-tests comparing deal performance statistics for private GPs and public PE (public GPs and permanent PE together), permanent PE and traditional GPs, and private GPs and public GPs. The performance measures are the average imputed buy price (iBuyprice), the average annualized imputed deal multiple (iMultiple per Year), and the average capital gain per deal. The results of an unpaired t-test comparing the holding period (years) is also presented. t-statistics are given in parentheses. ***,**, and * denote significance at the 1%, 5% and 10% level, respectively.*

	iBuyprice	iMultiple per Year	Capital Gain	Hold Years	Deal Count
Public PE vs Private GP:					
Public PE	143.98	1.45	140.75	4.37	296
Private GP	81.38	1.37	103.89	4.53	4242
Difference	62.60	0.08	36.86	-0.16	
	(8.49)	(0.33)	(1.69)	(-1.05)	
Traditional GP vs Permanent PE:					
Traditional GP	85.06	1.38	108.48	4.54	4346
Permanent PE	92.81	1.25	91.24	4.20	192
Difference	-7.75	0.14	17.24	0.34	
	(-0.85)	(0.45)	(0.64)	(1.83)	
Public GP vs Private GP:					
Public GP	241.68	1.84	237.78	4.70	104
Private GP	81.38	1.37	103.89	4.54	4242
Difference	160.30	0.47	133.89	0.16	
	(13.26)	(1.13)	(3.62)	(0.62)	

B. *Hypotheses Test Results*

Private GP versus Public PE

The hypothesis that deals by private GPs perform better than public PE is not supported. The imputed multiples and imputed dPMEs for private GPs are significantly smaller than those for public PE. The coefficients for the public PE dummy suggest that public PE multiples are about 8% larger on average than for private GPs, both with and without controls, although the t-statistic with controls is higher (t-statistic: 2.72) than without (t-statistic

1.65). Using the dPME measure, public GP dPMEs are about 9% larger on average when controls are included, or 15% larger without controls; statistical significance for the dPME results is statistically strong (t-statistic: 3.1).

The hypothesis that the deal holding period for public PE firms is shorter than for private GPs is also not supported. While the holding period for public PE is shorter than for private GPs (4.37 years versus 4.53 years), the difference is not significant.

Traditional GP versus Permanent PE

We find that for the hypothesis that deals by traditional GPs outperform those of permanent PE, the evidence is not strong enough to reject the null that there is no difference in performance. While the coefficient for the permanent PE dummy suggests that permanent PE multiples are about 10% smaller than for traditional GPs, the coefficient is not statistically significant. Looking at the dPME measure, the permanent PE dummy coefficient is positive but not significant. Thus we cannot conclude that traditional PE firms make better deals than permanent PE firms.

There is weak evidence to reject the second hypothesis that the holding period for deals by permanent PE firms is the same as for traditional PE firms. However, the result is the opposite to what was hypothesized - the holding period for deals by traditional PE firms is longer, on average, than for permanent PE firms, and this result is statistically significant at the 10% level. For deals by permanent PEs, the mean holding period is 4.2 years, while for traditional GPs, the mean holding period is over 4.5 years.

Private GP versus Public GP

Contrary to the hypothesis that private GPs make better deals than public ones, we find that in fact private GPs make significantly worse deals than public

Table 2.6 Private GP vs Public GP Deal Performance

*This table presents the results of regressions of deal performance measures where the sample is restricted to deals by private GPs and public GPs. The performance measures (dependent variables) are the log imputed deal multiple (ln_multiple) and the log imputed dPME (ln_dPME). The independent variables are indicator variables that are equal to 1 for deals by Public GPs (pre- and post-IPO), and Public GPs (post-IPO only). Models 3-4 and 7-8 include dummy control variables for deal target country, industry, buy and sell year, holding period (Hold-year), and buy and sell transaction characteristics such as LBO, MBO etc. Standard errors are clustered by the deal buy year. t-statistics are given in parentheses. ***,**, and * denote significance at the 1%, 5% and 10% level, respectively.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	ln_multiple	ln_multiple	ln_multiple	ln_multiple	ln_dPME	ln_dPME	ln_dPME	ln_dPME
Public GP (d)	0.389***		0.222***		0.396***		0.227***	
	(4.897)		(6.730)		(4.912)		(6.940)	
Public GP (Post-IPO) (d)		0.604***		0.260***		0.510***		0.258***
		(3.905)		(6.966)		(3.252)		(6.802)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Observations	4,346	4,346	4,346	4,346	4,346	4,346	4,346	4,346
R-squared	0.005	0.003	0.823	0.822	0.006	0.002	0.816	0.815

GP firms. Table 2.6 gives the results of regressions of deal performance where the sample is restricted to deals by public and private GPs. The coefficient for the public GP dummy suggests that public GP deals outperform private GP deals by about 39% without controls (t-statistic: 4.9) or 22% with controls (t-statistic: greater than 6.7), and this result is statistically significant. The outperformance of post-IPO deals by public GPs is even stronger.

For the purposes of the study up until now, we classified all transactions by public GPs as public GP transactions, even if the transactions were completed before the GP went public. We take a closer look here at the characteristics of transactions and deals by public GPs before and after their IPO. In particular, going back to Jensen's prediction in 2007, we are looking to see if going public had a negative impact on deal performance (this is our second hypothesis in this section).

First we examine deal size. A t-test (unreported) of imputed buy values for deals initiated before and after GPs go public shows that post-IPO, public

GPs make significantly larger deals (t-stat=2.48).

The post-IPO performance identified in the univariate regressions in Tables 2.4 and 2.6 may be due to a variety of factors, not just the GP's IPO, so we also run the following multivariate model to examine the effect of going public on public GPs:

$$Y = \alpha + \beta_1 PublicGP + \beta_2 PostIPO + \gamma Controls \tag{2.1}$$

The dependent variable (Y) is the log deal multiple or log dPME. Post-IPO is an indicator variable which is set to 1 for deals by public GPs initiated after the GP goes public, and 0 otherwise, and Public-GP is an indicator variable set to 1 for all deals by public GPs, irrespective of initiation date. The coefficient β_2 can be interpreted as the effect of going public on public GP deal performance.

The results are presented in Table 2.7. The loading on the public GP dummy is positive and significant, confirming our earlier finding that deals by public GPs have significantly larger multiples than the rest of the deal population over the entire sample period; the coefficient on the post-IPO dummy is positive, and (weakly) statistically significant. Thus the performance of deals made after a public GP goes public is about 8% (t-statistic:1.9) higher (with controls) than those made before going public. We repeat the test using the log of the dPME for each deal as the dependent variable, but the conclusions are unchanged.

Permanent Closed-End Funds versus Permanent Limited Companies

Table 2.8 gives the results of regressions of deal performance where the sample is restricted to deals by permanent closed-end funds and permanent limited companies. The results show that permanent PE funds make better deals, on average, than permanent PE firms. The coefficient for the permanent

Table 2.7 Public GP deal Performance Pre- and Post-IPO

*This table presents the results of a regression of the log of imputed deal multiples on an indicator variable (Public GP) which is 1 for all deals by public GPs both before and after their IPO, and an indicator variable (Post-IPO) which is 1 for deals by public GPs initiated after the GP's IPO date. Dummy variables for other deal characteristics are also included as controls, as are dummies for deal buy and sell year, industry, country, and holding period (in years). The test is repeated using the log of the imputed dPME. Standard errors are clustered by the deal buy year. t-statistics are given in parentheses. ***,**, and * denote significance at the 1%, 5% and 10% level, respectively.*

	imputed ln_multiple	imputed ln_multiple	imputed ln_dPME	imputed ln_dPME
Public GP (d)	0.315***	0.203***	0.352***	0.208***
	(3.421)	(4.924)	(3.769)	(5.004)
Public GP (post-IPO) (d)	0.298*	0.0825*	0.163	0.0735*
	(1.661)	(1.930)	(0.898)	(1.745)
Controls	No	Yes	No	Yes
Observations	4,538	4,538	4,538	4,538
Adj R-square	0.006	0.816	0.005	0.809

fund dummy is positive for both performance measures (imputed multiple and imputed dPME), and is statistically significant if controls are omitted.

In Table 2.9 we give the results of unpaired t-tests comparing other deal characteristics including annualized average deal multiple, average capital gain, and average holding period for permanent PE funds and permanent PE firms. We find that the average annualized multiple for funds is smaller than for firms, implying that funds add less value to their target firms each year than permanent PE firms. On average, permanent PE firms tend to make shorter, higher impact deals that have higher annualized returns, while funds make deals that take longer to mature but in the end, deliver higher deal-level returns. These results also suggests that permanent PE funds do not game their fee structure to prolong fee income from their investors - funds do actually add value to their targets during the longer holding period.

Table 2.8 Performance Regression for Closed-end Funds and Companies

This table gives the results of regressions of deal performance where the sample is restricted to deals by permanent closed-end funds and permanent limited companies.

	(1)	(2)	(3)	(4)
VARIABLES	ln_multiple	ln_multiple	ln_dPME	ln_dPME
Permanent Fund (d)	0.246*	0.147	0.270**	0.261
	(1.911)	(0.694)	(2.066)	(0.973)
Controls	No	Yes	No	Yes
Observations	192	192	192	192
R-squared	0.019	0.949	0.022	0.947

Table 2.9 t-test of Other Characteristics for Deals by Permanent PE Funds and Firms

This table presents the results of unpaired t-tests comparing deal characteristics of permanent PE firms and funds, including the geometric average annual imputed multiple (iMultiple per Year), the capital gain on the deal, and the average deal holding period (Hold Years).

	iMultiple per Year	Capital Gain	Hold Years	Deal Count
PermanentFund vs PermanentFirm				
PermanentFund	1.22	119.66	4.62	63
PermanentFirm	1.26	53.36	3.99	129
Difference	-0.03	66.29	0.62	
	(-0.34)	(1.25)	(1.63)	

V. Propensity Score Analysis

A. Public GPs vs Private GPs

Whereas the documented difference in deal multiples between public GP firms and private GPs appears to be due to the public GPs' ability to better make good deals and make them work, our baseline results could also be attributed to other potential interpretations. One possible interpretation is that public GPs are much more experienced (complete more deals) than private GPs, and if we control for experience then there may be no difference in deal-level performance between public and private GPs. Another interpretation is that larger deals may be more profitable, and public GPs simply make more large deals than private GPs. Similarly, some types of deals - public-to-private, secondary buyout, management buyout etc - may be more profitable than others, and public GPs make more of these deal types than private GPs. We consider the possibility that public and private GPs might invest in firms in radically different industries or regions. In other words, public GPs may have superior selection abilities to identify industries and regions with high growth potential to begin with. Finally, public GPs may be able to time their deals better - they may make more deals in years when good target firms are available at attractive valuations.

To gauge how public and private GP backed deals differ in their observable characteristics, we start by reporting in Table 2.10 the univariate comparisons of measures of deal size (imputed buy transaction values) and of the GPs' experience at the time of each deal (the number of deals completed by the GP prior to the deal) between these two groups. For deals completed after the public GPs' IPO, Panel A columns (1)-(3) show that deals by public GPs are slightly larger on average that those by private GPs, while public GPs have significantly more experience prior to the deal compared to private GPs. For deals completed prior to the GPs' IPO (Panel B), both buy prices and the prior experience are highly significantly larger for public GPs.

The propensity score matching approach allows us to disentangle the treatment and the selection effect of public GP sponsorship on the performance of buyout deals based on observable deal characteristics. The results of our baseline analysis are consistent with both selection and treatment: the superior ability of public GPs to create value and the superior skill of public GPs to select firms with higher value-creation potential. To disentangle these two effects, an ideal experiment would be to evaluate value-creation where deals are randomly assigned to public and private GPs. Although such an experiment is not feasible to implement, the propensity score matching analysis allows us to minimize the effect of selection bias on observables and is therefore the second-best approach.

We use a nearest-neighbor matching implementation of the propensity score matching approach originally developed by Rosenbaum and Rubin (1983). The propensity scores are estimated based on probit regressions at the deal level. In order to be able to compare deal performance for public GPs before and after their IPOs, we estimate propensity scores twice: once using a probit regression where the dependent variable is a binary variable equal to one for deals sponsored by public GPs after their IPO (and zero for private GP-backed deals); and once where the dependent variable is a binary variable equal to one for deals sponsored by public GPs before their IPO (and zero for private GP-backed deals).

We use two control variables as matching dimensions - the deal transaction value (the natural logarithm of the imputed buy price) and GP experience prior to the deal (measured as the number of prior deals completed by the GP ranked on a scale of 1 to 5 where 1 indicates five prior deals or less, 2 indicates six to ten prior deals, 3 denotes eleven to fifteen deals, 4 indicates sixteen to twenty deals, and 5 indicates more than twenty deals). The probit models are estimated across 4,303 solo deals containing non-missing data for all of the matching dimension variables. We present the estimation results in the "Prematch" section of Table 2.10, Column (4). We observe the same significant differences between public and private deal characteristics as with those reported in Column (3). The results also show that the specification captures a significant amount of variation in the choice variable, as indicated by a pseudo-R^2 of 11.2% for post-IPO deals and 22.2% for pre-IPO deals.

We then use the propensity score (i.e., the predicted probability) from the prematch probit regression and perform a propensity score matching with replacement. We conduct diagnostic tests to assess the accuracy of the matching procedure. First, we report the univariate comparison between public and private GP deals for the matched pairs and report the results in Columns (5) and (6). We observe statistically insignificant differences between public GP deals (both pre- and post-IPO) and private GP deals across all characteristics. Next, we rerun the probit model restricted to the matched sample and reported the results in Column (7). The magnitude of the probit regression coefficient for deal transaction value declines substantially. In addition, the pseudo-R^2 drops dramatically, from 11.2% prior to the matching to 1.5% post matching for post-IPO deals, and from 22.4% prior to the matching to 0.4% post matching for pre-IPO deals. Thus the matching process removes meaningful differences along observable dimensions between these two groups of deals.

Table 2.11 reports the deal multiples analysis using the propensity score matched pairs of deals. We report results for single nearest neighbor matches, with different limitations on the pool of control firms (year, industry, or region). We find that even after we non-parametrically control for deal characteristics (using propensity score matching), deals by public GPs still have much higher deal multiples, both before and after the GP's IPO. From Panel A it can be

Table 2.10 Public and Private GP deal Propensity Score Matching: Diagnostic tests

*This table presents the diagnostic tests of the propensity score matching. Panel A gives the results where the treatment group comprises deals completed by public GPs after their IPO, while Panel B gives the results where the treatment group comprises deals completed by public GPs before their IPO. Columns 1-3 give the results of univariate comparisons for deal size (natural logarithm of imputed buy transaction values) and GP experience at the time of each deal (the number of deals completed by the GP prior to the deal, on a scale of 1 to 5, where 1 indicates 5 deals or less, 2 indicates 6 to 10 deals, 3 denotes 11 to 15 deals, 4 indicates 16 to 20 deals, and 5 indicates more than 20 deals) for public and private GPs. The dependent variable in columns 4 and 7 equals one if the GP is public (treatment firm) and zero if it is private (control firm). The probit is run at the deal level; the covariates are the natural logarithm of the imputed buy transaction value, and the experience of the GP (measured as the number of deals completed by the GP prior to each deal). The Prematch column contains the parameter estimates of the probit estimated on the entire sample, prior to matching. This model is used to generate the propensity scores for matching. The Postmatch column contains the parameter estimates of the probit estimated on the subsample of matched treatment and control observations, after matching. The t -statistics for comparison of means tests are reported in parenthesis. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.*

	Panel A - post-IPO						
		Prematch			Postmatch		
	Public GP (1)	Private GP (2)	Difference (3)	Probit (4)	Private GP (5)	Difference (6)	Probit (7)
Deal Size	4.700	3.903	0.797	0.193	4.981	-0.281	-0.131
			(3.97)	(2.59)		(-0.89)	(-0.78)
GP Experience	3	1.585	1.415	0.225	2.760	0.66	0.073
			(6.25)	(4.61)		(0.07)	(0.50)
Pseudo R-square				0.112			0.015
Number of obs				4,303			50
	Panel B - pre-IPO						
Deal size	5.203	3.885	1.318	0.503	5.287	-0.084	-0.054
			(11.38)	(8.78)		(-0.54)	(-0.49)
GP Experience	3.041	1.568	1.472	0.228	2.851	0.189	0.040
			(11.24)	(6.71)		(0.68)	(0.64)
Pseudo R-square				0.222			0.004
Number of obs				4,303			148

seen that after their IPO, public GPs achieve deal multiples that are about twice those of private GPs, while before their IPO, public GP deals were about 50% higher than those of private GPs.

In summary, the results from our propensity score matching analysis confirm our earlier finding that deals by public GPs earn much higher multiples than those of private GPs, and that after the public GPs' IPO, the difference gets larger. One caution is that, because of the lack of target firm characteristics on which to base our matching, we cannot fully eliminate superior selection ability by public GPs as an alternative explanation for our results.

B. Permanent PE vs Private GPs

Here we perform a similar propensity matching exercise to match deals by permanent PE firms and funds with deals by private GPs. We want to compare deal multiples for permanent PE firms with private GPs while controlling for potential selection effects. We use the same deal characteristic variables as before (deal value, prior PE experience). Table 2.12 presents the results of diagnostic tests for the matching, while Table 2.13 reports the deal multiples analysis using the propensity score matched pairs of deals. We report results for single nearest neighbor matches, with different limitations on the pool of control firms (year, industry, or region).

Overall the multiples for permanent PE firms are not significantly different from those of matched deals by private GPs, and these results are consistent with those reported earlier in Section IV.B.

VI. Performance and Holding Period

In this section we illustrate the relationship between performance and holding period in more detail. The length of time a private equity firm holds a

Table 2.11 Public and Private GP deal Propensity Score Matching: Results

*This table reports the differences in imputed multiples based on a sample in which public GP deals are matched to private GP deals using the propensity score matching algorithm with various restrictions. We consider various restrictions: matching deals based solely on the propensity score value (No Restriction), and forcing the matching deals to be from the same year, industry, region or transaction type (Tx Type); see Appendix 2.A1 for the list of industries, regions and transaction types. The treatment group in the post-IPO column is defined as all deals by public GPs completed after the GP's IPO; the treatment group in the pre-IPO column is defined as all deals by public GPs completed before the GP's IPO. The control group is defined as a set of private GP deals. Columns 1 & 4 report the differences in mean natural logarithm of imputed deal multiples between treated and matched control firms. Columns 2 & 5 give the number of deals on support in the treatment group, and columns 3 & 6 give the number of deals on support in the control group. t-statistics estimated using clustered standard errors are given in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.*

	Post-IPO			Pre-IPO		
	Difference (1)	Treated Obs on Support (2)	Control Obs on Support (3)	Difference (4)	Treated Obs on Support (5)	Control Obs on Support (6)
No restriction	1.003 (3.59)	24	4,260	0.498 (4.83)	74	4,229
Year	0.531 (2.57)	24	2,554	0.504 (5.45)	73	3,109
Industry	0.561 (1.89)	24	4,137	0.380 (6.45)	72	4,138
Region	0.814 (2.34)	24	4,260	0.421 (5.75)	73	4,211
Tx Type	1.130 (9.10)	24	4,278	0.421 (3.88)	74	4,147

Table 2.12 Permanent PE and Private GP deal Propensity Score Matching: Diagnostic tests

*This table presents the diagnostic tests of the propensity score matching. The treatment group comprises deals completed by permanent PE firms and the control group comprises deals by private GP firms. Columns (1)-(3) and (5)-(6) give the results of univariate comparisons for deal size (natural logarithm of imputed buy transaction values) and firm experience at the time of each deal (the number of deals completed by the firm prior to the deal, on a scale of 1 to 5, where 1 indicates 5 deals or less, 2 indicates 6 to 10 deals, 3 denotes 11 to 15 deals, 4 indicates 16 to 20 deals, and 5 indicates more than 20 deals). The dependent variable in columns (4) and (7) equals one if the firm is a permanent PE firm (treatment firm) and zero if it is a private GP (control firm). The probit is run at the deal level. The Prematch column contains the parameter estimates of the probit estimated on the entire sample, prior to matching. This model is used to generate the propensity scores for matching. The Postmatch column contains the parameter estimates of the probit estimated on the subsample of matched treatment and control observations, after matching. The t -statistics for comparison of means tests are reported in parenthesis. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.*

		Prematch			Postmatch		
	Permanent PE	Private GP	Difference	Probit	Private GP	Difference	Probit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Deal Size	3.979	3.880	0.099	-0.074	3.956	0.023	0.015
			(1.34)	(-1.96)			(0.23)
PE Experience	3.085	1.560	1.525	0.345	3.079	0.005	0.000
			(18.18)	(14.60)		(0.03)	(0.00)
Pseudo R-square				0.137			0.000
Number of obs				4,393			378

Table 2.13 Permanent PE and Private GP deal Propensity Score Matching: Results

*This table reports the differences in imputed multiples based on a sample in which permanent PE deals are matched to private GP deals using the propensity score matching algorithm with various restrictions. We consider various restrictions: matching deals based solely on the propensity score value (No Restriction), and forcing the matching deals to be from the same year, industry, region or transaction type (Tx Type); see Appendix 2.A1 for the list of industries, regions and transaction types. The treatment group defined as all deals by permanent PEs. The control group is defined as a set of private GP deals. Columns (1) & (4) report the differences in mean natural logarithm of imputed deal multiples between treated and matched control firms. Columns (2) & (5) give the number of deals on support in the treatment group, and columns (3) & (6) give the number of deals on support in the control group. t-statistics estimated using clustered standard errors are given in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.*

	Difference	Treated Obs Support	Control Obs Support
No restriction	0.054 (0.66)	189	4,204
Year	0.050 (0.35)	188	4,071
Industry	-0.044 (-1.27)	189	4,129
Region	-0.024 (-0.96)	189	4,172
Tx Type	-0.058 (-0.27)	189	4,010

position in a target firm is an area where differences between public PE and private GPs may arise. For example, Ferreira et al. (2014) suggest that private firms may prefer to take on risky projects and terminate them early if they go bad, while public firms prefer to take on less risky projects and to cash in early if they go well (to give their share price a boost). The results we have already presented show that permanent PE firms hold their deals for a shorter time than traditional GPs. Also, we have already seen that private GPs hold their deals for longer than permanent PE firms, yet there is no difference in average deal performance.

Looking first at Figure 2.1, Panel A, we see that a higher proportion of deals by permanent PE have shorter holding periods than either public or private GPs, but the difference is not huge. For example, about 75% of deals by permanent PE firms have holding period of 5 years or less, while for the other PE types the proportion is about 65%.

Figure 2.1, Panel B and Panel C, provide graphs of the fitted multiples and dPMEs from a linear regression of deal multiples on the holding period, and the square of the holding period. Using the square of holding period captures possible non-linearity (convexity) of multiples over holding periods. In general, multiples decline for deals with longer holding periods. While the outperformance of public GPs across all holding periods is clearly visible, performance declines almost linearly with holding period. For private GPs, there is little change in performance for deals up to about year 5, and then a decline in performance after year 5. The curvature for permanent PE is quite pronounced, with performance rising slightly up to year 5, and then declining rapidly.

Figure 2.1 also illustrates how multiples for private GPs are higher, on average, across all holding periods than for permanent PE. Using the dPME measure, however, permanent PE firms clearly outperform private GPs for all deals with a holding period of less than ten years. dPME may be vewed as a risk-adjusted return measure for private equity as it controls for market risk and other risks that vary with the credit cycle. In this sense, permanent PE deals earn higher risk-adjusted returns than private GPs.

VII. Discussion and Conclusions

Based on our analysis, publicly traded PE firms make deals which perform at least as well as those made by private GPs, and in the case of publicly traded GPs, significantly outperform those of private GPs. So a number of questions arise: Why do deals by publicly listed GPs perform the best? Why do so few private GPs go public? Why do investors place their funds with PE firms that are not public GPs? While we cannot hope to fully answer these questions, we try to shed some new light using the results of our analysis.

One explanation why deals by public GPs outperform could be that there is a matching phenomenon going on that allows public GPs choose the best deals, leaving the leftovers for other PE firms. Sørensen (2007) finds that experienced Venture Capital (VC) firms choose to invest in better targets, and better targets choose investments from more influential VCs. Likewise, the buyout fund GPs that choose to go public do so clearly because they were already successful, and therefore better able to find, or match with, good deals. It could be that going public has a quality signaling effect - high quality targets observe that a GP has successfully gone public, and respond to that signal. The increase in deal size and performance for GPs after they go public appears to support this hypothesis

Another possible explanation for their superior deal-level performance is that public GPs take on riskier deals and are rewarded by higher returns. Bebchuk and Fershtman (1994) propose that managers of public firms take on

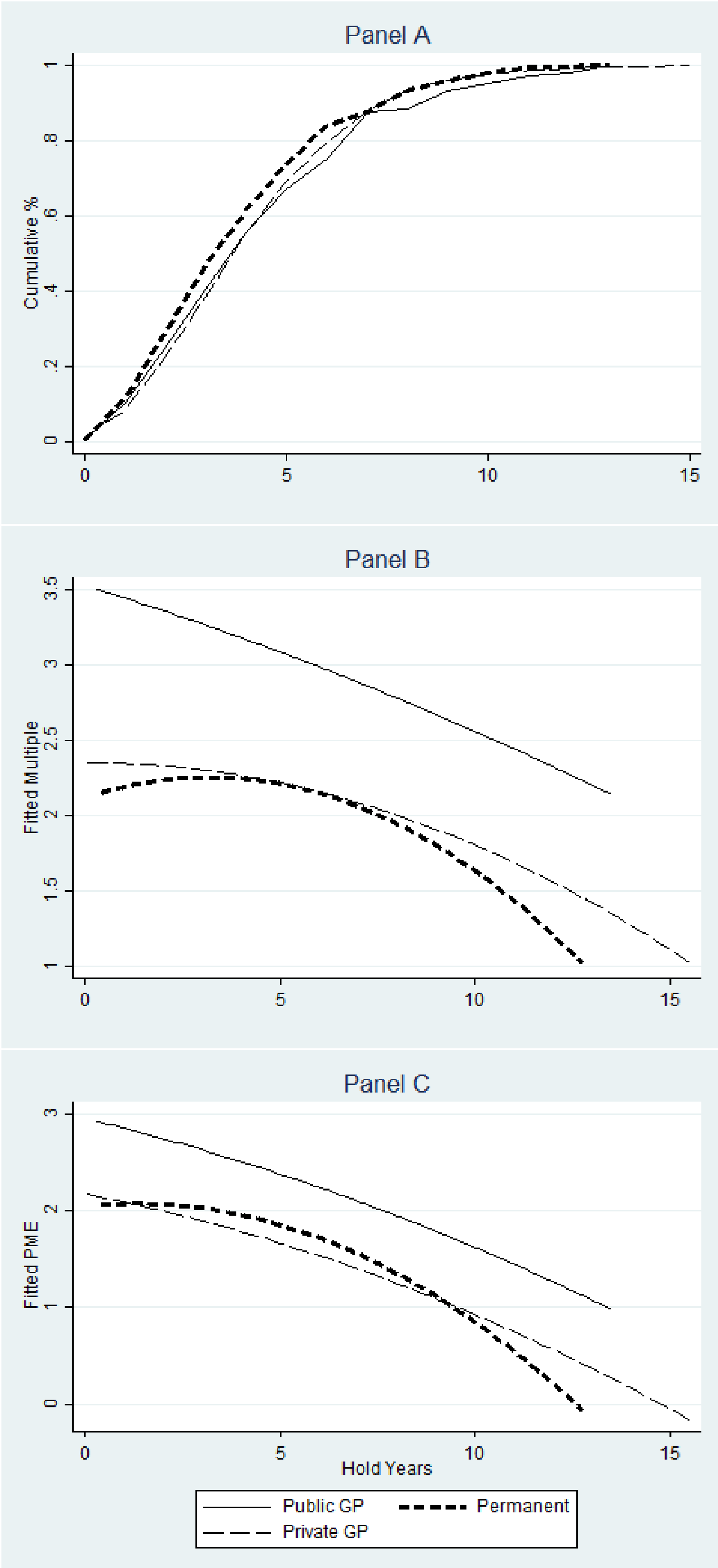

Figure 2.1. Holding Period Effect on Performance

Panel A (top) graphs the cumulative proportion of deals, as a percentage of all deals for a PE type, by deal holding period. Panel B (middle) graphs a quadratic fit of deal multiples against deal holding periods, and Panel C (bottom) plots fitted dPME values.

risky projects as they can use their inside information to sell the firms stock if the projects go wrong. Certainly deals by public GPs are larger than those by other PE firms, however there is little evidence that they take on riskier deals - fewer deals by public GPs go bankrupt compared to private GPs.

So why do most GPs choose not to go public? First, the stock performance of the public GPs has been somewhat disappointing. Both KKR and Blackstone stocks traded below their IPO price for many years after their IPO. Private GPs may now feel that investors will adjust downwards the price they are willing to pay for future GP IPOs. Second, the process of going public forces the PE firm to expose many details about their business that they may prefer not to reveal[20]. Third, some GPs that went public did so to raise investment capital for new business lines, such as hedge funds, real estate investment trusts etc. It may be that GPs that choose not to go public are making a strategic decision to focus on LBOs[21], and thus do not see the need for any extra investment capital to fund new product lines.

It is a well-known investors rule of thumb to invest with "top quartile" funds, so the question arises why some investors place money with mediocre funds instead of with public GPs. It may be that search costs for investors are high - Korteweg and Sorensen (2017) note that skilled GPs are difficult to identify, therefore investors with the skills required to identify them are also rare. However Korteweg&Sorensen did not separate deals by public and private GPs, and therefore may not have observed the important distinction in performance between these two different organization forms.

Another possible explanation is that our performance measure, the multiple of invested capital, is a measure of gross performance, not the net performance to the investor. For closed-end funds, Berk and Stanton (2007) argue that

[20]For example, the KKR IPO prospectus showed that the cost of Henry Kravis' use of company limousines in 2009 came to $98,771.

[21]An example is Clayton Dubilier Rice - see "Engineers of a different kind", The Economist, 22.June, 2013.

skilled managers raise their fees to absorb the rents they generate, leaving investors with no abnormal return. This may also be the case with private equity, although Korteweg and Sorensen (2017) find evidence of significant abnormal net returns for skilled traditional PE buyout funds, and McCourt (2016) finds similar results for permanent PE buyout firms.

A number of other important insights emerge from our results. Consistent with Braun et al. (2017) and Kartashova (2014), we find that buyout deal performance declined during the 2000-2009 period. This decline has been interpreted to be a sign of the increasing competition for deals among PE firms (Braun et al. (2017)). However in the period 2010-2015, buyout deal performance has rebounded significantly. Thus competition for deals may have declined since the 2007-2008 financial crisis, allowing skilled GPs to differentiate themselves from unskilled ones, and to deliver strong deal-level returns in the years following the crisis. Also, we find little evidence of diseconomies of scale at the deal level. Public GPs make larger acquisitions than either private GPs or permanent capital PE firms, yet they also make larger multiples and dPMEs.

We are aware that there are limitations to our approach. In order to focus our study, we have purposely chosen to examine a precise question - pre-fee deal performance for public PE and private GPs. In doing so we have imposed a narrow definition of performance, that is multiples and dPMEs for solo deals where there is a change in control, and thereby we have excluded a number of possible scenarios where the overall fund performance of some types of PE firms could be different from what we identify here. For example, some PE firms could focus on making syndicate deals, or on taking minority positions in their portfolio firms. Furthermore our measures of deal performance are gross measures, the net return to investors may be different due the fees applied by the PE fund manager.

Our results point to a segmentation of PE firms in terms of deals, skills and organization forms. One segment consists of a very small number of GPs that can find or attract the very largest and most profitable deals and that have the skills to make these deals work. They have the ability to raise the large amounts of debt needed to complete these deals, and to tap into the complex operational expertise required to add significant value to the targets. These GPs seem to choose to list on public markets. The second, much larger, segment is shared by private GPs and by public permanent PE firms. These PE firms seem to make similar-size deals and achieve similar returns. Further research could examine if similar segmentation occurs based on a PE investor catering hypothesis - public GPs cater to the largest and most skilled investors, while private GPs may cater to medium-sized institutional investors with average skills and lower liquidity needs, and public permanent PE caters to smaller institutional or retail investors with average skills and higher liquidity needs.

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AppendixA.

Table 2.A1 Variable Definitions

This table describes variables used in this study.

LBO	is a dummy variable equal to one if the buy or sell transaction	is a Leveraged Buyout
Going-private	is a dummy variable equal to one if the buy transaction	is a public to private buyout
Divisional	is a dummy variable equal to one if the buy transaction	is a buyout of a company division
SBO	is a dummy variable equal to one if the buy or sell transaction	is a Secondary Buyout
Distressed	is a dummy variable equal to one if the buy transaction	is a buyout of a company in financial distress
MBO	is a dummy variable equal to one if the buy or sell transaction	is a Management Buyout
Sponsor>20 deals	is a dummy variable equal to one if the buy or sell transaction	is sponsored by an investment firm with more than 20 deals in the sample
Solo	is a dummy variable equal to one if the buy or sell transaction	is sponsored by just one investment firm
Cross-border	is a dummy variable equal to one if the buy or sell transaction	involves a sponsor and a target in different countries
Bankrupt	is a dummy variable equal to one if the sell transaction	is a bankruptcy
IPO	is a dummy variable equal to one if the sell transaction	is an Initial Public Offering
Cash Merger	is a dummy variable equal to one if the sell transaction	is a cash merger exit
Stock Merger	is a dummy variable equal to one if the sell transaction	is a stock merger exit
Buyer=Seller	is a dummy variable equal to one if the buy or sell transaction	is a syndicate transaction involving the same buyers and seller
Public Inv Firm	is a dummy variable equal to one if the buy or sell transaction	is sponsored by a public investment firm
LPE GP	is a dummy variable equal to one if the buy or sell transaction	is sponsored by a public GP
LPE Permanent	is a dummy variable equal to one if the buy or sell transaction	is sponsored by a public permanent PE firm
France-Benelux	is a dummy variable equal to one if the buy or sell transaction	target is located in France, Belgium, Luxembourg or Holland
Germany-Austria-Switz	is a dummy variable equal to one if the buy or sell transaction	target is located in Germany, Austria, or Switzerland
Scandinavia	is a dummy variable equal to one if the buy or sell transaction	target is located in Sweden, Norway, Finland or Denmark
Southern Europe	is a dummy variable equal to one if the buy or sell transaction	target is located in Spain, Italy, Porugal or Greece
Eastern Europe	is a dummy variable equal to one if the buy or sell transaction	target is located in Czech Republic, Slovakia, Slovenia, Poland, Hungary or Estonia
Korea-Japan	is a dummy variable equal to one if the buy or sell transaction	target is located in Japan or South Korea
Australia-New Zealand	is a dummy variable equal to one if the buy or sell transaction	target is located in Australia or New Zealand
Canada	is a dummy variable equal to one if the buy or sell transaction	target is located in Canada
RoW	is a dummy variable equal to one if the buy or sell transaction	target is located in any other OECD country

Table 2.A1 , contd

1990-1999	is a dummy variable equal to one if the transaction or deal was initiated	between 1990 and 199
2000-2004	is a dummy variable equal to one if the transaction or deal was initiated	between 2000 and 2004
2005-2009	is a dummy variable equal to one if the transaction or deal was initiated	between 2005 and 2009
2010-2012	is a dummy variable equal to one if the transaction or deal was initiated	between 2010 and 2012
Hold years $<$2	is a dummy variable equal to one if the deal was held for	less than 2 years
Hold years $>=$2 $<$4	is a dummy variable equal to one if the deal was held for	2 to 3 years
Hold years $>=$4 $<$6	is a dummy variable equal to one if the deal was held for	4 to 5 years
Hold years $>=$6 $<$8	is a dummy variable equal to one if the deal was held for	6 to 7 years
Consumer staples	is a dummy variable equal to one if the transaction or deal target GICS industry sector is	Consumer staples
Consumer discretionary	is a dummy variable equal to one if the transaction or deal target GICS industry sector is	Consumer discretionary
Energy	is a dummy variable equal to one if the transaction or deal target GICS industry sector is	Energy
Health	is a dummy variable equal to one if the transaction or deal target GICS industry sector is	Health
Industrials	is a dummy variable equal to one if the transaction or deal target GICS industry sector is	Industrials
IT	is a dummy variable equal to one if the transaction or deal target GICS industry sector is	IT
Materials	is a dummy variable equal to one if the transaction or deal target GICS industry sector is	Materials
Telecoms	is a dummy variable equal to one if the transaction or deal target GICS industry sector is	Telecoms
Utilities	is a dummy variable equal to one if the transaction or deal target GICS industry sector is	Utilities

A. *Transactions*

We start by creating three subsets of CapitalIQ data - buy transactions, sell transactions, and bankruptcies - for targets located in the 35 member countries of the OECD. We identify all buy and sell transactions by private GP/VC investment firms, public investment firms, and public funds in CapitalIQ which closed between January 1st, 1990 and June 30th, 2016. To identify buy transactions where there is a change of control, we exclude transactions which are not going private transactions, leveraged buyouts (LBOs), secondary LBOs, management buyouts (MBOs), or cash mergers. We also exclude transactions by non-investment firms and funds, investment arms of corporations or financial service firms, transactions involving financial targets or targets located outside the 35 OECD countries, and sell transactions involving public companies or stock mergers. For bankruptcies we identify all private company bankruptcies in CapitalIQ.

We classify buy transactions as "public" where at least one of the buyers is a public investment company or a public fund; the remainder are classified as private. CapitalIQ returns all transactions by public firms, including those completed before the firm's IPO. Thus we also label transactions completed before a firm's IPO as public. In Section IV we explore transaction characteristics before and after IPO. To identify public GPs and permanent PE firms, we follow the approach described in McCourt (2016). Using information hand-collected from PE firm indices and ETFs, public PE firms are categorized as public GPs, public permanent PE firms and funds, and others (PE firms that are not included in PE firm indices or ETFs, or funds-of-funds, or venture capital firms).

We identify and correct a small number of misclassifications in CapitalIQ data where some public PE firms are misclassified as private GPs, or as hedge funds. Also, to control for outliers and potential data errors, the values of buy and sell transactions are winsorized at the 1% and 99% levels. All transaction values[22] are converted to 2007 US dollars. The value of IPO sell transactions are adjusted to reflect the percentage of equity offered in the IPO. Price information is not available in CapitalIQ for all transactions, so we use a Heckman procedure introduced by Strömberg (2007), and also used in Arcot et al. (2015) and Bernstein et al. (2016), to estimate imputed values for the transactions where values are missing. Details of the procedure are given in the Appendix.

Table 2.A2 and Table 2.A3 present summary statistics on the number and value of buy and sell transactions in our final sample. We identify 23,651 buy transactions, 5,646 of which are club deals. Of the 18,005 solo buy transactions, 16,666 are by private GPs and 1,339 (8% of the private GP total) are by public PE firms.

Our database of sell transactions consists of 30,477 observations[23]. 15,446 of these are solo transactions, 14,333 of which are by private GPs and 1,133 (7.9% of the private GP total) are by public PE firms.

Our raw bankruptcy database consists of 22,669 private company bankruptcy observations. As bankruptcies in CapitalIQ do not include ownership information, it is impossible to determine how many of these are linked to private equity deals until they are matched to buy transactions.

[22] For transaction values we use Total Transaction Value in Capital IQ. Total Transaction Value is the same as the Total Gross Transaction Value when the latter is available in CapitalIQ, which is the consideration paid, plus net assumed liabilities and adjustment size, plus total cash and short-term investments.

[23] Terms are not disclosed in CapitalIQ for a subset of sell transactions, thus some of these may involve sales of minority stakes rather than full changes of control.

Table 2.A2 Summary of Transaction Counts

This table presents summary statistics for the numbers of transactions by public (listed) and private (unlisted) PE firms between January 1st, 1990 and June 30th, 2016. Transactions are grouped into acquisitions (Buys) and disposals (Sells) and by transaction features. Transaction turnover counts (ie the sum of buy and sell transaction counts) are provided in the last section. The first column gives data for all solo transactions. Columns 2 and 3 present data for solo transactions by private GPs and public PE firms respectively. Columns 4-6 give a more detailed breakdown of solo public PE transactions for public GPs, permanent PE firms, and other public PE firms. Column 7 summarizes data for syndicate transactions. See Appendix 2.A1 for variable definitions.

	Transaction Count													
	1		2		3		4		5		6		7	
Buys	Solo		Private GP		Public PE		Public GP		Permanent		Public Other		Syndicate	
	N		N		N		N		N		N		N	
Total number of transactions	18,005		16666		1339		371		492		476		5646	
Mean	4.76		4.60		8.42		61.83		20.50		3.69			
Median	2		2		2		52		8		1			
Std Deviation	9.80		9.02		20.43		48.26		33.10		6.41			
Unique Targets	17,296		15257		1330		369		492		469		5,367	
Unique PE firms	3784		3625		159		6		24		129			
Percentage of Private GP			100.0%		8.0%		2.2%		3.0%		2.9%			
Percentage of Public PE					100.0%		27.7%		36.7%		35.5%			
	N	%	N	%	N	%	N	%	N	%	N	%	N	%
Public-to-private	683	3.8%	614	3.7%	69	5.2%	40	10.8%	12	2.4%	17	3.6%	295	5.2%
Divisional buyout	3,897	21.6%	3531	21.2%	366	27.3%	85	22.9%	160	32.5%	121	25.4%	1235	21.9%
Secondary buyout	2,055	11.4%	1922	11.5%	133	9.9%	53	14.3%	57	11.6%	23	4.8%	627	11.1%
MBO	3,702	20.6%	3439	20.6%	263	19.6%	57	15.4%	178	36.2%	28	5.9%	1601	28.4%
Distressed	582	3.2%	557	3.3%	25	1.9%	4	1.1%	6	1.2%	15	3.2%	175	3.1%
Cross-Border	3,577	19.9%	3064	18.4%	513	38.3%	154	41.5%	180	36.6%	179	37.6%	1813	32.1%
Unclassified	7	0.0%	0	0.0%	7	0.5%	1	0.3%	1	0.2%	5	1.1%	3	0.1%

Table 2.A2 , continued

Transaction Count														
	1		2		3		4		5		6		7	
Sells/Exits (All)	Solo		Private GP		Public PE		Public GP		Public Permanent		Public Other		Syndicate	
	N		N		N		N		N		N		N	
Total number of transactions	15445		14295		1150		288		715		147		14977	
Mean	3.70		3.47		20.54		48.00		26.48		6.39			
Median	2		2		6		45		5		6			
Std Deviation	8.8		5.96		54.11		33.19		74.65		5.03			
Unique Targets	14630		13606		1140		283		713		144		14309	
Unique PE Firms	4170		4114		56		6		27		23			
Percentage of Private GP			100.0%		8.0%		2.0%		5.0%		1.0%			
Percentage of Public PE					100.0%		25.0%		62.2%		12.8%			
	N	%	N	%	N	%	N	%	N	%	N	%	N	%
IPO	237	1.5%	161	1.1%	76	6.6%	44	15.3%	18	2.5%	14	9.5%	615	4.1%
LBO	3614	23.4%	3353	23.5%	261	22.7%	59	20.5%	185	25.9%	17	11.6%	2078	13.9%
Secondary buyout	1859	12.0%	1747	12.2%	112	9.7%	25	8.7%	84	11.7%	3	2.0%	849	5.7%
MBO	1055	6.8%	942	6.6%	113	9.8%	13	4.5%	94	13.1%	6	4.1%	520	3.5%
Bankrupt	385	2.5%	365	2.6%	20	1.7%	6	2.1%	14	2.0%	0	0.0%	319	2.1%
Cross-Border	4018	26.0%	3688	25.8%	330	28.7%	76	26.4%	228	31.9%	26	17.7%	4050	27.0%
Cash merger	6360	41.2%	5873	41.1%	487	42.3%	121	42.0%	322	45.0%	44	29.9%	6398	42.7%
Stock merger	525	3.4%	499	3.5%	26	2.3%	12	4.2%	6	0.8%	8	5.4%	1254	8.4%
Unclassified	4314	27.9%	4045	28.3%	269	23.4%	56	19.4%	165	23.1%	48	32.7%	3919	26.2%
Turnover (Buys & Sells)	Solo		Private GP		Public PE		Public GP		Public Permanent		Public Other		Syndicate	
	N		N		N		N		N		N		N	
Total number of transactions	33,450		30,961		2,489		659		1,207		623		20,623	
Percentage of Private GP			100.0%		8.0%		2.1%		3.9%		2.0%			
Percentage of Public PE					100.00%		26.5%		48.5%		25.0%			

Table 2.A3 Summary of Transaction Values

This table presents summary statistics for the imputed total transaction values (iValue) of transactions by public (listed) and private (unlisted) PE firms between January 1st, 1990 and June 30th, 2016. All values are converted to millions of 2007 US dollars, and are winsorized at the 1% and 99% levels. Transactions are grouped into acquisitions (Buys) and disposals (Sells), and by transaction features. Transaction turnover values (ie the sum of buy and sell transaction values) is provided in the last section. The first column summarizes data for all solo transactions. Columns 2 and 3 present data for solo transactions by private GPs and public PE firms respectively. Columns 4-6 give a more detailed breakdown of solo public PE transactions for public GPs, permanent PE firms, and other public PE firms. Column 7 summarizes data for syndicate transactions. See Appendix 2.A1 for variable definitions.

Transaction Values							
	1	2	3	4	5	6	7
Buys	Solo	Private GP	Public PE	Public GP	Public Permanent	Public Other	Syndicate
	iValue	iValue	iValue	iValue	iValue	iValue	iValue
Total value of transactions	1,566,828	1,386,759	180,069	97,872	49,681	32,516	695,656
Mean	87	83	134	264	101	68	123
Median	44	43	58	183	53	48	63
Std Deviation	129	122	185	218	140	138	163
Percentage of Private GP		100.00%	12.98%	7.06%	3.58%	2.34%	
Percentage of Public PE			100.00%	54.35%	27.59%	18.06%	

	1		2		3		4		5		6		7	
	iValue	%	iValue	%	iValue	%	iValue	%	iValue	%	iValue	%	iValue	%
Public-to-private	158,094	10.1%	135,203	9.7%	22,891	12.7%	17,869	18.3%	2,307	4.6%	2,715	8.3%	90,658	13.0%
Divisional buyout	333,056	21.3%	291,324	21.0%	41,732	23.2%	20,644	21.1%	12,477	25.1%	8,611	26.5%	153,785	22.1%
Secondary buyout	397,122	25.3%	356,328	25.7%	40,794	22.7%	21,509	22.0%	14,300	28.8%	4,985	15.3%	132,190	19.0%
MBO	280,701	17.9%	248,800	17.9%	31,901	17.7%	9,738	9.9%	19,480	39.2%	2,683	8.3%	163,584	23.5%
Distressed	22,598	1.4%	21,821	1.6%	777	0.4%	312	0.3%	149	0.3%	316	1.0%	16,748	2.4%
Cross-Border	515,204	32.9%	424,091	30.6%	91,113	50.6%	45,950	46.9%	24,831	50.0%	20,332	62.5%	348,091	50.0%
Unclassified	313	0.0%	0	0.0%	313	0.2%	87	0.1%	91	0.2%	135	0.4%	57	0.0%

Table 2.A3 , continued

Transaction Values

	1	2	3	4	5	6	7
Sells/Exits	Solo	Private GP	Public PE	Public GP	Public Permanent	Public Other	Syndicate
	iValue	iValue	iValue	iValue	iValue	iValue	iValue
Total value of transactions	1,430,750	1,284,796	145,954	73,286	60,975	11,693	1,720,142
Mean	93	90	127	254	85	80	115
Median	41	40	51	148	42	23	50
Std Deviation	146	139	210	297	134	204	170
Percentage of Private GP		100.0%	11.4%	5.7%	4.7%	0.9%	
Percentage of Public PE			100.00%	50.21%	41.78%	8.0%	

	iValue	%	iValue	%	iValue	%	iValue	%	iValue	%	iValue	%	iValue	%
IPO	59,955	5.6%	37,243	2.9%	22,711	15.6%	15,015	20.5%	3,373	5.5%	4,323	37.0%	103,562	7.9%
LBO	537,610	50.4%	488,281	38.0%	49,329	33.8%	26,348	36.0%	21,015	34.5%	1,966	16.8%	400,255	30.4%
Secondary buyout	356,242	33.4%	324,621	25.3%	31,621	21.7%	17,347	23.7%	13,749	22.5%	525	4.5%	220,689	16.8%
MBO	108,462	10.2%	96,784	7.5%	11,678	8.0%	3,088	4.2%	8,069	13.2%	521	4.5%	75,243	5.7%
Bankrupt	6,923	0.6%	6,420	0.5%	503	0.3%	241	0.3%	262	0.4%	0	0.0%	8,545	0.6%
Cross-Border	472,880	44.3%	421,717	32.8%	51,163	35.1%	24,807	33.8%	24,739	40.6%	1,617	13.8%	559,935	42.6%
Cash merger	877,273	82.2%	797,486	62.1%	79,786	54.7%	36,629	50.0%	39,715	65.1%	3,442	29.4%	1,007,870	76.6%
Stock merger	51,954	4.9%	48,269	3.8%	3,685	2.5%	1,799	2.5%	1,307	2.1%	579	5.0%	130,780	9.9%
Unclassified	167,366	11.7%	151,645	11.8%	15,722	10.8%	8,641	11.8%	5,616	9.2%	1,465	12.5%	227,743	13.2%

Turnover (Buys & Sells)	Solo	Private GP	Public PE	Public GP	Public Permanent	Public Other	Syndicate
	iValue	iValue	iValue	iValue	iValue	iValue	iValue
Total value of transactions	2,997,578	2,671,555	326,023	171,158	110,656	44,209	2,415,798
Percentage of Private GP		100.0%	12.2%	6.4%	4.1%	1.7%	
Percentage of Public PE			100.00%	52.5%	33.9%	13.6%	

Table 2.A4 Deals by Public and Private PE Firms

This table presents the number, average holding period (Hold Years), buy value, sell value, capital gain, imputed multiple (iMultiple), and imputed dPME (idPME), for deals by public (listed) and private (unlisted) PE firms, between January 1st, 1990 and June 30th, 2016. Data are presented for solo and syndicate deals, deals by private and public GPs (traditional GPs), deals by public permanent PE firms and public GPs (public PE), and deals by other public investment firms (typically funds-of-funds or venture firms). Deals for each PE firm type are further grouped by the characteristics of their buy and sell (exit) transactions. The number of unique PE firms and targets are also given. See Appendix 2.A1 for variable definitions.

	Solo							Syndicate						
	N	Hold Years	Buy Value	Sell Value	Capital Gain	iMultiple	idPME	N	Hold Years	Buy Value	Sell Value	Capital Gain	iMultiple	idPME
All deals	4640	4.51	125.91	231.49	105.58	2.35	1.79	941	4.28	151.32	259.43	108.12	2.02	1.58
Public-to-private	168	4.5	218.03	341.59	123.56	1.92	1.47	54	3.85	350.89	366.4	15.51	1.51	1.27
Secondary buyout	491	4.41	200.52	326.66	126.13	2	1.49	87	4.32	214.15	343.03	128.88	1.4	1.09
MBO	1381	4.72	100.97	184.04	83.07	2.17	1.64	351	4.64	135.45	217.73	82.27	2.02	1.57
Distressed	105	3.72	152.13	313.15	161.02	2.48	1.87	24	3.72	359.74	351.76	-7.97	1.47	0.99
Cross-border	842	4.23	177.73	320.49	142.77	2.65	2.05	303	3.98	207.9	297.18	89.29	1.91	1.48
LBO exit	1626	4.68	139.84	257.01	117.17	2.47	1.85	313	4.47	178.33	300.15	121.82	2.13	1.63
SBO exit	1236	4.68	138.96	263.89	124.93	2.51	1.88	237	4.5	186.38	317.47	131.09	2.19	1.68
MBO exit	223	4.56	113.48	223.12	109.64	2.23	1.75	96	4.2	167.88	272.79	104.92	2.23	1.82
IPO exit	60	4.52	319.39	852.68	533.28	3.66	2.51	15	3.32	322.57	3045.12	2722.55	4.75	4.4
Bankruptcy exit	167	3.78	117.92	40.25	-77.67	0.23	0.22	21	3.45	177.42	92.13	-85.28	0.27	0.28
Cross-border exit	1312	4.44	139.85	256.79	116.94	2.78	2.11	275	4	161.58	248.77	87.19	2.08	1.56
Unique targets	4386							932						
Unique PE firms	1402													

	Private GP							Traditional GP						
	N	Hold Years	Buy Value	Sell Value	Capital Gain	iMultiple	idPME	N	Hold Years	Buy Value	Sell Value	Capital Gain	iMultiple	idPME
All deals	4242	4.54	122.6	226.49	103.89	2.36	1.79	4346	4.54	125.24	233.72	108.48	2.38	1.8
Public-to-private	149	4.45	209.8	316.93	107.13	1.88	1.44	162	4.51	211.15	338.38	127.23	1.95	1.48
Secondary buyout	450	4.43	184.98	311.86	126.88	1.99	1.47	462	4.42	183.97	312.02	128.05	2.03	1.5
MBO	1262	4.7	96.29	179.11	82.82	2.17	1.62	1286	4.71	96.2	179.44	83.24	2.19	1.64
Distressed	103	3.76	157.89	329.47	171.58	2.49	1.88	103	3.76	157.89	329.47	171.58	2.49	1.88
Cross-border	689	4.23	167.18	308.15	140.97	2.76	2.13	735	4.22	168.9	321.51	152.61	2.77	2.12
LBO exit	1508	4.72	132.4	247.69	115.3	2.5	1.86	1536	4.72	137.22	256.87	119.64	2.5	1.86
SBO exit	1152	4.74	130.38	250.22	119.84	2.52	1.88	1172	4.73	134.03	259.19	125.16	2.53	1.88
MBO exit	402	4.58	107.03	218.93	111.91	2.29	1.78	406	4.59	111.24	227.66	116.41	2.29	1.78
IPO exit	37	4.42	273.02	963.15	690.13	3.71	2.42	52	4.46	261.31	928.27	666.96	3.83	2.59
Bankruptcy exit	152	3.83	117.92	40.25	-77.67	0.24	0.22	153	3.85	117.92	40.25	-77.67	0.24	0.22
Cross-border exit	1183	4.48	139.58	252.65	113.07	2.82	2.12	1215	4.49	141.94	257.19	115.26	2.82	2.12
Unique targets	4026							4119						
Unique PE firms	1340							1345						

Table 2.A4 , continued

	Public GP							Public Permanent						
	N	Hold Years	Buy Value	Sell Value	Capital Gain	iMultiple	idPME	N	Hold Years	Buy Value	Sell Value	Capital Gain	iMultiple	idPME
All deals	104	4.7	199.35	437.12	237.78	3.11	2.39	192	4.2	132.09	223.33	91.24	2.16	1.84
Public-to-private	13	5.14	231.86	665.55	433.69	2.74	1.99	3	4.52	.	.	.	1.3	1.31
Secondary buyout	12	3.8	135.39	319.93	184.53	3.58	2.91	21	4.24	413.88	553.93	140.05	1.6	1.36
MBO	24	5.19	90.44	199.57	109.13	3.36	2.66	80	4.82	139.14	236.52	97.37	2.04	1.78
Distressed	0	.	.	.	.	.	.	0	.	.	.	.	.	.
Cross-border	46	4.13	189.5	481.75	292.25	2.79	2.07	65	4.15	180.72	297.87	117.15	2.03	1.8
LBO exit	28	4.39	266.97	503.37	236.4	2.81	2.1	63	3.75	107.05	175.72	68.67	2.01	1.82
SBO exit	20	3.82	242.16	525.26	283.1	3.01	2.23	45	3.63	114.51	220.99	106.48	2.17	1.9
MBO exit	4	5.93	290.4	598.35	307.95	1.85	1.29	30	4.43	80.89	85.26	4.37	1.82	1.64
IPO exit	15	4.55	237.88	858.51	620.63	4.12	3.01	6	5.57	493.65	625.89	132.25	2.69	2.02
Bankruptcy exit	1	7.1	.	.	.	0.14	0.14	8	2.7	.	.	.	0.16	0.17
Cross-border exit	32	4.96	217.94	403.66	185.72	2.88	2.11	68	3.74	108.52	225.22	116.7	2.57	2.25
Unique targets	104							192						
Unique PE firms	5							14						

	Public PE							Public Other						
	N	Hold Years	Buy Value	Sell Value	Capital Gain	iMultiple	idPME	N	Hold Years	Buy Value	Sell Value	Capital Gain	iMultiple	idPME
All deals	398	4.22	147.64	264.36	116.72	2.25	1.81	102	3.79	131.56	194.41	62.85	1.55	1.16
Public-to-private	19	4.89	318.51	642.44	323.93	2.24	1.71	3	4.17	665.12	550	-115.12	1.05	0.92
Secondary buyout	41	4.17	337.64	457.18	119.54	2.06	1.73	8	4.56	319.98	355.18	35.2	1.01	0.93
MBO	119	4.92	139.49	224.68	85.19	2.25	1.88	15	5.03	181.89	194.34	12.45	1.56	1.11
Distressed	2	1.55	60	52	-8	1.56	1.48	2	1.55	60	52	-8	1.56	1.48
Cross-border	153	4.21	208.72	356.76	148.04	2.14	1.69	42	4.38	271.2	346.37	75.17	1.61	1.1
LBO exit	118	4.1	195.03	326.09	131.05	2.17	1.78	27	4.61	266.07	393.15	127.08	1.89	1.33
Secondary buyout exit	84	3.89	211.67	379.76	168.09	2.38	1.9	19	4.6	296.56	436.48	139.92	2.19	1.56
MBO exit	45	4.43	159.18	252.79	93.61	1.69	1.46	11	3.88	254.36	413.31	158.94	1.27	1.03
IPO exit	23	4.68	365.77	742.2	376.44	3.58	2.64	2	3.02	.	.	.	2.21	1.7
Bankruptcy exit	15	3.23	.	.	.	0.17	0.16	6	3.29	.	.	.	0.18	0.14
Cross-border exit	129	4.09	141.4	281.04	139.64	2.47	2	29	3.95	160.46	318.72	158.26	1.77	1.32
Unique targets	398							102						
Unique PE firms	62							44						

Table 2.A5 Deal Characteristics of Permanent PE Funds and Firms

This table presents the number (N), and averages for the following variables: : holding period (Hold Years), total transaction values (Buy Value, Sell Value) in millions of 2007 US dollars, capital gain, imputed multiple (iMultiple), and imputed dPME (idPME), for deals by permanent PE funds and firms, between January 1st, 1990 and June 30th, 2016. Deals for each PE firm type are further grouped by the characteristics of their buy and sell (exit) transactions (see Appendix 2.A1 for variable definitions). The number of unique PE firms and targets are also given. †denotes mean, median and standard deviations of the number of deals per firm.

	Permanent Firm							Permanent Fund						
	N	Hold Years	Buy Value	Sell Value	Capital Gain	iMultiple	idPME	N	Hold Years	Buy Value	Sell Value	Capital Gain	iMultiple	idPME
Deals	133							63						
Unique targets	133							63						
Unique PE firms	12							3						
Mean	11.08†	3.97	139.65	205.08	65.43	2.2	1.78	21†	4.62	117.92	237.58	119.66	2.31	2.09
Median	8†	3.18	60.15	131	21.68	1.6	1.39	2†	4.5	53.94	94.44	43.6	1.64	1.46
Std Deviation	12.46†	2.62	194.04	249.83	189.92	3.34	2.42	33.78†	2.18	148.97	286.32	177.29	2.11	2.24
Going-private	1	2.06	.	.	.	1.13	1.41	2	5.75	.	.	.	1.38	1.26
Secondary buyout	17	4.55	470.55	569.38	98.83	1.64	1.3	4	2.91	300.54	523.05	222.51	1.4	1.63
MBO	32	4.95	255.04	360.13	105.09	1.7	1.29	48	4.74	111.55	207.09	95.54	2.27	2.11
Distressed	1	0.21	.	.	.	2.26	2.14	0	.	.	.	.	.	.
Cross-border	37	3.62	182.62	223.08	40.46	2.09	1.68	32	4.64	151.98	364.71	212.73	2.42	2.17
LBO exit	41	3.19	87.49	141.49	54	2.31	1.96	24	4.7	100.89	206.78	105.89	2.17	1.94
Secondary buyout exit	31	3.16	49.49	124.55	75.06	2.58	2.17	16	4.55	126.58	282.55	155.97	2.33	1.9
MBO exit	14	3.55	163.01	171.53	8.52	1.63	1.56	16	5.2	48.04	50.75	2.71	1.98	1.71
IPO exit	5	6.18	666.16	660.41	-5.75	2.48	1.79	1	2.47	148.62	556.86	408.24	3.75	3.18
Bankruptcy exit	7	2.8	.	.	.	0.14	0.14	1	2.01	.	.	.	0.3	0.35
Cross-border exit	42	3.58	83.2	150.41	67.21	2.72	2.3	27	4.05	128.41	284	155.58	2.26	2.1

Table 2.A6 Heckman Selection Model to Estimate Buy Values

*This table shows the results of a Heckman selection model used to create the imputed buy values (total transaction values) for buy transactions without complete value information. The dependent variable is the log of the transaction buy value. See Table 2.A1 for independent variable definitions. The outcome equation includes transaction buy year dummies, country dummies, and industry dummies, where industries are defined using the 10 Global Industry Classification Standard (GICS) sectors (for the selection regression) and 157 GICS sub-industries (for the outcome regression). Standard errors are reported in parentheses and the symbols ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.*

	(1)	(2)	(3)
VARIABLES	ln_buyvalue	select	mills
Going-private (Buy)	1.116***	1.133***	
	(0.144)	(0.0442)	
Divisional (Buy)	0.153**	0.468***	
	(0.0626)	(0.0203)	
SBO (Buy)	1.077***	0.101***	
	(0.0542)	(0.0288)	
MBO (Buy)	-0.0669	0.0719***	
	(0.0407)	(0.0227)	
Distressed (Buy)	-0.839***	0.571***	
	(0.0981)	(0.0478)	
Sponsor>20 deals	0.620***	0.241***	
	(0.0440)	(0.0209)	
Solo	-0.464***	-0.223***	
	(0.0415)	(0.0211)	
Cross-border	0.721***	0.139***	
	(0.0396)	(0.0218)	
Public Inv Firm	-0.587***	1.438***	
	(0.165)	(0.0284)	
LPE GP	1.195***	-1.402***	
	(0.183)	(0.0624)	
LPE Permanent	0.443***	-1.186***	
	(0.151)	(0.0537)	

	(1)	(2)	(3)
VARIABLES	ln_buyvalue	select	mills
1990-1999		0.145***	
		(0.0300)	
2000-2004		-0.197***	
		(0.0267)	
2005-2009		-0.218***	
		(0.0300)	
2010-2012		-0.370***	
		(0.0302)	
UK & Ireland		0.143***	
		(0.0416)	
US		-0.364***	
		(0.0373)	
France-Benelux		-0.635***	
		(0.0424)	
Germany-Austria-Switz		-0.883***	
		(0.0487)	
Scandinavia		-0.545***	
		(0.0503)	
Southern Europe		-0.00818	
		(0.0486)	
Eastern Europe		-0.332***	
		(0.0787)	
Korea-Japan		0.262***	
		(0.0781)	
Australia-New Zealand		0.0919	
		(0.0640)	
Canada		-0.318***	
		(0.0578)	

	(1)	(2)	(3)
VARIABLES	ln_buyvalue	select	mills
Consumer staples		0.0490	
		(0.0492)	
Consumer discretionary		-0.0652	
		(0.0569)	
Energy		0.181**	
		(0.0742)	
Health		0.0468	
		(0.0541)	
Industrials		-0.0339	
		(0.0497)	
IT		-0.0727	
		(0.0527)	
Materials		-0.0384	
		(0.0553)	
Telecoms		0.0800	
		(0.0907)	
Utilities		-0.162**	
		(0.0733)	
lambda			0.0661
			(0.206)
Constant	1.145	-0.0834	
	(0.907)	(0.0634)	
Industry Dummies	Yes		
Year Dummies	Yes		
Country Dummes	Yes		
Observations	27630		
Censored obs	16310		
Uncensored obs	11320		

Table 2.A7 Heckman Selection Model to Estimate Sell Values

*This table shows the results of a Heckman selection model used to create the imputed sell values (total transaction values) for sell transactions without complete value information. The dependent variable is the log of the transaction sell value. See Table 2.A1 for independent variable definitions. The outcome equation includes transaction sell year dummies, country dummies, and industry dummies, where industries are defined using the 10 Global Industry Classification Standard (GICS) sectors (for the selection regression) and 157 GICS sub-industries (for the outcome regression). Standard errors are reported in parentheses and the symbols ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.*

	(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
VARIABLES	ln_sellvalue	select	mills	VARIABLES	ln_sellvalue	select	mills	VARIABLES	ln_sellvalue	select	mills
IPO	1.054***	1.338***		1990-1999		0.0849***		Consumer staples		-0.0163	
	(0.174)	(0.0377)				(0.0305)				(0.0549)	
LBO (Sell)	0.221*	-0.818***		2000-2004		-0.0790***		Consumer discretionary		-0.0919	
	(0.121)	(0.0283)				(0.0277)				(0.0614)	
SBO (Sell)	0.607***	-0.0274		2005-2009		-0.190***		Energy		0.342***	
	(0.0791)	(0.0354)				(0.0290)				(0.0680)	
MBO (Buy)	-0.202***	-0.180***		2010-2012		-0.334***		Health		0.180***	
	(0.0714)	(0.0309)				(0.0286)				(0.0567)	
Bankrupt	-1.988***	-0.0173		UK & Ireland		-0.201***		Industrials		-0.0628	
	(0.0919)	(0.0522)				(0.0331)				(0.0553)	
Stock Merger	0.375***	0.952***		US		-0.496***		IT		-0.0339	
	(0.141)	(0.0307)				(0.0269)				(0.0545)	
Cash Merger	0.910***	1.390***		France-Benelux		-0.648***		Materials		-0.0589	
	(0.181)	(0.0170)				(0.0346)				(0.0603)	
Cross-border	0.633***	0.113***		Germany-Austria-Switz		-0.789***		Telecoms		0.00322	
	(0.0345)	(0.0176)				(0.0407)				(0.0734)	
Solo	0.553***	0.127***		Scandinavia		-0.639***		Utilities		0.0368	
	(0.0511)	(0.0267)				(0.0402)				(0.0847)	
Sponsor>20 deals	-0.510***	-0.177***		Southern Europe		-0.263***		lambda			0.592***
	(0.0354)	(0.0160)				(0.0435)					(0.213)
Public Inv Firm	-0.163***	0.399***		Eastern Europe		-0.507***		Constant	1.193	-0.0593	
	(0.0565)	(0.0230)				(0.0700)			(1.068)	(0.0623)	
LPE GP	0.711***	-0.799***		Korea-Japan		0.105*					
	(0.150)	(0.0593)				(0.0635)		Industry Dummies	Yes		
LPE Permanent	0.139*	-0.281***		Australia-New Zealand		-0.123**		Year Dummies	Yes		
	(0.0812)	(0.0435)				(0.0563)		Country Dummes	Yes		
				Canada		-0.249***					
						(0.0417)		Observations	37591		
								Censored obs	19774		
								Uncensored obs	17817		

Table 2.A8 Heckman Selection Model to Estimate Multiples

*This table shows the results of a Heckman selection model used to create the imputed multiples for deals without complete transaction value information. The dependent variable is the log of the deal sell value divided by its buy value. See Table 2.A1 for independent variable definitions. The outcome equation includes deal buy and sell year dummies, hold year dummies, where hold year is the number of years the deal is held, and industry dummies, where industries are defined using the 10 Global Industry Classification Standard (GICS) sectors (for the selection regression) and 157 GICS sub-industries (for the outcome regression). Standard errors are reported in parentheses and the symbols ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.*

	(1)	(2)	(3)		(1)	(2)	(3)		(1)	(2)	(3)
VARIABLES	ln_multiple	select	mills	VARIABLES	ln_multiple	select	mills	VARIABLES	ln_multiple	select	mills
LBO (Buy)	-0.183	-0.180		Public Inv Firm	-0.301**			Consumer staples		-0.206	
	(0.170)	(0.112)			(0.137)					(0.311)	
Going-private (Buy)	-0.511	0.753***		LPE GP	0.535**			Consumer discretionary		-0.326	
	(0.331)	(0.0841)			(0.214)					(0.317)	
Divisional (Buy)	-0.0706	0.282***		LPE Permanent	0.318*			Energy		0.331	
	(0.134)	(0.0452)			(0.181)					(0.338)	
SBO (Buy)	-0.276*	0.336***		UK-Ireland		0.338***		Health		-0.133	
	(0.164)	(0.0624)				(0.116)				(0.315)	
Distressed (Buy)	-0.0274	-0.0176		US		-0.382***		Industrials		-0.175	
	(0.194)	(0.138)				(0.111)				(0.311)	
MBO (Buy)	-0.0156	0.101**		France-Benelux		-0.420***		IT		-0.170	
	(0.0763)	(0.0442)				(0.120)				(0.313)	
Sponsor>20 deals (Buy)	-0.0889	0.142*		Germany-Austria-Switz		-0.630***		Materials		-0.155	
	(0.121)	(0.0800)				(0.132)				(0.315)	
Solo	0.396	-0.109**		Scandinavia		-0.439***		Telecoms		-0.281	
	(0.549)	(0.0524)				(0.136)				(0.351)	
Cross-border(Buy)	-0.0844	0.120***		Southern Europe		0.116		Utilities		-0.0755	
	(0.0885)	(0.0451)				(0.130)				(0.369)	
Bankrupt (Sell)	-2.191***	0.0429		Eastern Europe		0.0750		lambda			-0.361
	(0.145)	(0.105)				(0.197)					(0.595)
SBO (Sell)	0.114	0.176**		Korea-Japan		0.249		Constant	-1.864	-0.768**	
	(0.140)	(0.0786)				(0.196)			(2.055)	(0.349)	
MBO (Sell)	-0.0241	0.0286		Australia-New Zealand		0.212					
	(0.103)	(0.0731)				(0.161)		Industry Dummies	Yes		
Sponsor>20 deals (Sell)	0.000689	-0.0882		Canada		-0.306*		Buy Year Dummies	Yes		
	(0.127)	(0.0916)				(0.165)		Sell Year Dummies	Yes		
IPO (Sell)	0.512*	0.326**		Hold years <2		0.299***		Hold Year Dummies	Yes		
	(0.278)	(0.146)				(0.0933)					
Cross-border(Sell)	-0.0348	0.134***		Hold years >=2 <4		0.321***		Observations	7030		
	(0.0822)	(0.0454)				(0.0809)		Censored obs	5686		
LBO (Sell)	0.173	-0.515***		Hold years >=4 <6		0.231***		Uncensored obs	1344		
	(0.252)	(0.0766)				(0.0793)		Standard errors in parentheses			
Cash Merger (Sell)	-0.0151	0.873***		Hold years >=6 <8		0.154*		*** p<0.01, ** p<0.05, * p<0.1			
	(0.394)	(0.0444)				(0.0808)					
Stock Merger (Sell)	-0.0907	0.539***									
	(0.316)	(0.149)									
Buyer=Seller	-0.233***										

Table 2.A9 Alternative Approaches to Estimating Imputed Multiple

This table presents a comparison of 2 ways of estimating the imputed multiple. In Panel A, the imputed multiple is estimated by first estimating the imputed buy and sell values - the Heckman procedure is applied to the values, not to the multiple. In Panel B, the imputed multiple is estimated by first estimating the actual multiple (actual buy value divided by actual sell value), and then applying the Heckman procedure to the multiple. Each row in the table represents a regression of a dependent variable (first column) on an independent variable (second column) which is usually the predicted value of the dependent variable, and the alpha, the coeffcient on the independent variable, the adjusted R^2, and the number of observations for the regression. As can be seen from the table, the imputed multiples using the second approach have much better explanatory power when the actual multiples are regressed on them (adjusted R^2 of 0.2) than those estimated using the first approach (adjusted R^2 of 0.02). Throughout this study we use imputed multiples estimated using the second approach.

dependent variable (actual values)	**independent variable (p(x) = predicted value of x)**	**alpha**	**beta**	**Adj R-Square**	**N**
	Panel A - multiple estimated using imputed buy and sell values				
ln(buyValue)	p(ln(buyValue))	0.00	1.00	0.26	11322
		(0.00)	(62.70)		
buyValue	exp(p(ln(buyValue)))	60.17	1.04	0.16	11322
		(27.45)	(47.27)		
ln(sellValue)	p(ln(sellValue))	0.00	1.00	0.22	16207
		(0.00)	(69.34)		
sellValue	exp(p(ln(sellValue)))	78.86	0.95	0.12	16207
		(39.99)	(47.70)		
sellValue/buyValue	exp(p(ln(sellValue)))/exp(p(ln(buyValue)))	2.34	0.51	0.02	1209
		(9.96)	(4.98)		
	Panel B - multiple imputed using actual buy and sell values				
ln(sellValue/buyValue)	p(ln(sellValue/buyValue))	0	1	0.38	1366
		(0.00)	(29.09)		
sellValue/buyValue	exp(p(ln(sellValue/buyValue)))	-0.08	1.40	0.20	1366
		(-0.43)	(18.49)		

Essay 3

Persistence and Skill in the Performance of Mutual Fund Families

I. Introduction

We examine persistence and skill in the performance of mutual fund families. While the performance of individual mutual fund managers is one of the most researched topics in finance, and the influence of fund family on fund manager performance has also received considerable attention (see below), few studies have analyzed the average performance of all funds belonging to a family.

Understanding fund family performance is important for a number of reasons. Firstly, from an investor perspective, the choice of fund family is significant. Many investors consider family performance when choosing funds (Elton et al. (2007), Brown and Wu (2016)). Fund families reduce investors' cost of switching between funds (Massa (2003)). Affiliated funds of mutual funds (AFoMFs) have been adopted by many fund families and have become popular with investors (Bhattacharya et al. (2013)).

Secondly, the most crucial factor affecting fund performance is the skill of the fund manager, and the decision to hire or fire an individual fund manager is made at the fund family level. Some families may have better talent selection and allocation skills than others. The family may appoint a team rather than an individual to manage a fund. Berk et al. (2014) estimate that at least 30% of the value mutual fund managers add can be attributed to the family's role in efficiently allocating capital amongst its mutual fund managers. Fang et al. (2014) show that a firm allocates its skilled managers to funds targeting inefficient markets.

Other family-level behaviour affects fund performance. Gaspar et al. (2006) and Bhattacharya et al. (2013) find evidence that mutual fund families transfer performance from one group of funds to another group of funds through coordinated trades. Kempf and Ruenzi (2008) show that intra-firm competition has important effects on managers' appetite for risk. Chen et al. (2013)

find that funds outsourced to advisory firms underperform funds managed in-house. In their study of stock lending to short-sellers by mutual funds, Evans et al. (2017) argue that although equity lending is associated with negative fund performance, the decision to lend is made out of strategic family-wide considerations.

Knowledge-sharing and economies of scale within fund families affect individual fund performance. Brown and Wu (2016) find evidence of cross-fund learning within families that may positively or negatively influence performance. Cici et al. (2016) show that the speed of information dissemination within fund families positively affects fund performance. Cici et al. (2015) and Latzko (1999) find differences in efficiency in administration and trading costs at family level that reduce costs to the funds in the family.

Given the weight of this evidence, it seems reasonable to assume that there is heterogeneity in the average fund performance of fund families, and that a substantial portion of this heterogeneity is due to decisions, policies and processes adopted at the family level. The question then arises whether some fund families are more skilled than others. Skilled fund families may be able to create an environment where the average returns of funds in the family are persistently higher (or persistently lower) than the average returns of funds in other fund families.

Specifically, in this paper, we set out to address two key questions: we first ask is the performance of some families more persistent than others, and how much of that persistence is due to skill rather than luck? Secondly, we want to know what are the determinants of family skill - what is it that skilled families are doing that unskilled ones are not doing, and vice-versa?

We estimate measures of performance persistence and skill for actively managed equity fund families, and for comparison we estimate the equivalent measures for individual funds. We focus on the gross benchmark-adjusted returns of US-domiciled US-equity funds drawn from the CRSP survivorship-bias free funds database for the period 1999-2017. We perform an extensive exercise to validate that the fund family associated with a fund is correct, and to take into account mergers in the fund industry over the period. Our final sample consists of 4946 funds belonging to 1084 families.

We first test for fund performance persistence. The probability that a top decile fund family in one 5-year period will remain a top-decile family in the subsequent 5-year period is 0.14, which is larger than the equivalent measure for individual funds (0.10). Over shorter periods (1 to 4 years), the pattern remains the same, family performance is generally more persistent than fund performance. The persistence gap peaks for the 3-year period where top-decile fund persistence is 0.11 and family persistence is 0.19. This suggests that some families may create the conditions required to sustain outperformance over the long term.

Then we examine the distribution of skill in funds and families using a cross-sectional bootstrap approach where we use t-statistic of benchmark-adjusted gross returns, t(alpha), as the performance measure. The cross-sectional bootstrap allows us to estimate how many funds or families in the sample that we could expect to observe at different t(alpha) threshold values under the null hypothesis that all funds in the sample have a true alpha of zero (that is, they are neither skilled nor unskilled), but some funds or families may have significant observed t(alpha) through sampling error or luck.

For funds, these tests suggest that about 2% more funds have positive observed t(alpha) than would be expected if all managers had true t(alpha)=0, that is, were neither skilled nor unskilled. However, of the funds with positive t(alpha) in our sample, a strikingly large number perform better than expected at higher performance thresholds - for example, there are 293 more funds (6.4% of our sample) with t(alpha)>2 than would be expected under the null hypothesis that all fund managers are neither skilled nor unskilled. To put this another way, the higher the fund's observed t(alpha), the chances that the fund is truly skilled increase dramatically.

For fund families, the picture is not dramatically different. Overall, just 3% more families have t(alpha)>0 than would be expected under the null. However, at higher performance thresholds, the number of skilled families is much higher than expected - about 51 families (6% of our sample) with t(alpha)>2 are truly skilled. On the other hand we also find that 70 families (8% of our sample) are truly unskilled at the t(alpha)<-2 threshold. Thus some families seem to be able to group together highly skilled fund managers, while a slightly larger number seem to be able to group together highly unskilled ones.

In the second part of the study, we examine a range of family characteristics that may plausibly contribute to (or subtract from) family skill. These characteristics include the size of the family (that is, the aggregate TNA of all funds in the family), the average fund size, the number of funds in the family. The amount of team-managed or outsourced funds in the family may affect performance, and we consider the mix of index funds, retail funds, institutional funds, and international funds in the family. We also examine the number of funds recently launched or recently closed by the family, and whether the family is a publicly listed firm.

First we examine specifically the impact of family size on individual fund performance. In fund fixed effects regressions which control for endogeneity between fund size and fund performance[1], we show that family size has a negative impact on fund performance, but this is not statistically significant. Fund size has a slight positive but insignificant impact, and industry size (that is, the total TNA of all actively managed funds in the CRSP mutual fund database) has a positive impact on benchmark-adjusted fund returns.

[1]We use forward recursive demeaning to control for fixed effects and an instrumental variable to control for endogeneity.

To estimate the impact of family characteristics on family skill, we use a novel approach that is a logical extension of the average fund fixed effects measure used by Pástor et al. (2015) to estimate changes in mutual fund manager skill over time. The advantage of the approach is that it allows skill to be estimated in a way that is decoupled from returns - skill levels may change even though returns may not have changed. For example, Pástor et al. (2015) argue that average fund skill (fund fixed effects) may have increased over time, but returns may not have increased due to growth and increased competition in the fund industry.

We estimate the family fixed effects in a panel regression of the value-weighted average gross benchmark-adjusted returns of funds in a family on lagged family size and lagged industry size and use this as a baseline. We then estimate the change in family fixed effects that occurs when we include the characteristics, one at a time, as lagged regressors in the baseline model. In this way we estimate what happens when each characteristic is fixed (that is, set to 0) across all families (baseline plus characteristic) versus when it is allowed to vary across families (baseline only).

For example, in our baseline model, the family fixed effects are 9.9 basis points. If we add the lagged value-weighted average expense ratio of funds in a family as a regressor to the baseline model, the family fixed effects fall to 4 basis points, a decrease of 5.9 basis points. This suggests that expense ratio is an important determinant of family skill. Letting expense ratios vary across families causes family fixed effects to rise, thus expense ratio has a positive effect on average family skill.

The family characteristics that have the most positive effect on skill are weighted-average fund expense ratios (5.9 basis points), proportion by number of retail funds (4.4 basis points) and proportion by TNA of team-managed funds (1.8 basis points). The characteristics with the largest negative skill impact include the proportion by TNA of retail funds in the family's fund mix (-3.5 basis points) and the number of international funds (-1.9 basis points).

We also observe that the majority of families (800) in our sample have just one actively-managed US equity fund. Therefore we divide our sample into single-fund families and multi-fund families, and when we examine persistence, skill and the determinants of skill for these subsamples, we find a divergence in results. While the 1-year top-decile performance persistence of single- and multi-fund families are about the same (0.18), the 3-year top-decile persistence measure for multi-fund families (0.24) is about one third higher than for single-fund families (0.18). After controlling for noise in the performance measure, we find that overall (that is, at the t(alpha)=0 threshold) there are about 4% more skilled single-fund families than unskilled ones, while there are about 4% fewer truly skilled multi-fund families than there are truly unskilled ones. However at higher t(alpha) thresholds, the proportion of truly skilled single-fund families is slightly lower than for multi-fund families; for example, 5.5% of the single fund family sample have true t(alpha)>2, while over 6% of multi-fund families are truly skilled at this threshold.

Finally we examine skill and skill determinants using net-of-fee benchmark-adjusted returns. Not surprisingly, the evidence for skill is much weaker than when using gross benchmark-adjusted returns. Using net returns we find that over 19% of our sample have true t(alpha)<0. At the t(alpha)>2 threshold however there is a tiny glimmer of hope - 3 families with t(alpha)>2 (0.3% of our sample) are truly skilled when net alpha is the skill measure. The determinants of skill measured using net returns are more or less the same as the determinants of skill measured using gross returns, with one notable exception. Average expense ratio is strongly positively associated with skill measured using gross returns, but is strongly negatively associated with skill measured using net returns.

Given the volume of research focused on fund performance, there is surprisingly little literature that focuses directly on fund family performance. In their working paper, Guedj and Papastaikoudi (2003) report that performance persistence is more prevalent within big fund families, suggesting that families purposefully allocate resources across funds in an unequal way. The closest study to ours is that by Berk et al. (2014) who examine capital reallocation decisions of mutual fund firms. They find evidence that the aggregate dollar value-added of mutual fund firms is persistent, that is, firms that added value in the past keep adding value in the future. While Berk et al focus on the narrow (but important) topic of capital allocation within fund families, we take a broader approach, applying a range of tests for skill, comparing the distribution of fund family skill with the distribution of fund skill, and analyzing a broader set of potential determinants of fund family skill.

II. Persistence and Skill

A. Background

The analysis of skill in the mutual fund industry has been focused at the fund level. The evidence for skill at the fund level (Fama and French (2010), Barras et al. (2010)) suggests that most mutual fund managers exhibit little true skill, and if skill does exist, it is concentrated in the right tail of the cross-sectional distribution of fund alphas.

At the family level, there is no such analysis. However, the pieces of evidence suggest that asset management firms seem to know what enhances performance. Empirical evidence shows that firms coordinate actions across funds in the complex in order to enhance the performance of funds that are the most valuable to the family, even if this comes at the expense of the performance of other member funds (Gaspar et al., 2006) or that firms allocate skilled managers to funds targeting inefficient markets (Fang et al., 2014). Berk et al. (2014) hypothesise that the family has informational advantages and show evidence that the decision of adding a manager or removing a fund from a manager add value to investors.

As investors show sensitiveness to past performance, firms have incentives to create "star funds". Nanda et al. (2004) show that star funds have positive spillover effects on flows into other funds in the family. In addition, asset management firms have incentives to generate assets under management (AUM) because revenues are proportional to AUM, which might lead them to disregard performance. Family skill might be "diluted" by incentives to create AUM revenue. For instance, firms might be tempted to launch new trendy styles funds that increase overall AUM but hardly create value for investors. For example, Cheng et al. (2018) find evidence that globalization allows low skilled families to adopt a strategy of launching cross-border funds that deliver lower performance and offer lower diversification benefits.

This leads to two opposing hypotheses for the distribution of skill in fund families. First, it may be that small number of truly skilled funds are dispersed among a number of different firms. In this case, we could see little skill in the cross-sectional distribution of skill in fund families, even in the right tail. This is because the one or two skilled funds in a family could be dominated by unskilled ones, and thus have little effect on fund family performance. The alternative hypothesis is that most skilled funds are concentrated in just a small number of fund families. In this case we could see evidence of skill just in the individual families located at the extreme right tail.

B. Data

Our mutual fund data are drawn from the CRSP survivorship-bias-free US Mutual Fund database[2]. We restrict the sample to actively managed US-focused equity funds, and exclude funds-of-funds, closed-end, index tracking, international and offshore funds[3]. We eliminate multiple share classes to avoid double-counting funds. Although multiple share classes are listed as separate funds in CRSP, they have the same holdings, the same manager, and the same returns before expenses and loads. We sum the total net assets (TNA) of the share classes to estimate the total TNA for the fund. We follow Pástor et al. (2015) and adjust fund TNA to 2017 US dollars by dividing the TNA at the end of each year by the total market value of all stocks in CRSP at the end of the same year, and multiplying by the total market value of all stocks in CRSP at the end of 2017. We exclude fund-months where the expense ratio is missing, and fund-months before the fund reaches $15 million (in 2017 US dollars) in TNA.

To identify fund families, we use the management company code field that is available for each fund in CRSP since 1999, and we use the management company name to complement the management company code where necessary. The relationship between management company codes and management company names is 1:n, where n can be greater than or equal to 1. We take steps to clean this data. We standardize management company names; for example some names are identical except for the use of abbreviations, so we expand abbreviations such as "mgmt" to "management". Then for funds with the same management company name but where the management company code is present for some funds while it is missing for the others, we fill in the

[2]We are grateful to Doshi et al. (2015) for sharing their SAS scripts for accessing the CRSP Mutual Fund database.

[3]Although we exclude the returns of index funds and international funds as dependent variables, we keep a monthly count and sum of monthly TNA for use as explanatory variables.

management company codes for the funds where it is missing. There are a number of cases where two or more unrelated management companies are allocated the same management company code. Using data manually collected from management company websites, we identify these cases and we create new management company codes for each distinct family. For a small number of management company names, the management company code is missing, but in most of these cases it is clear from the management company name which management company code is applicable; for example, the management company code is missing for eight funds where "PIMCO" is the first word in the management company name, so we use the PIMCO management company code for these funds. Finally, for some management company names the management company code is missing and the management company does not appear to belong to any existing family; in these cases we create a new management company code. Where a fund changed family during the sample period, we use the management company code and name for the family that the fund belonged to the longest, and drop the fund-months when the fund did not belong to that family. Our final sample consists of 4,946 funds, belonging to 1,084 fund families, for the period January 1, 1999 to December 31, 2017.

Table 3.1 gives annualized statistics for funds and families for each year in the sample period (Figure 3.1 gives a graphical overview). In our sample, the number of active fund families each year has stayed in the 430-540 range since 2000, likewise the number of active funds each year has been fairly stable (1970-2200). The total unadjusted TNA of all funds in the sample (dashed line in Panel B of Figure 3.1) has risen significantly from about \$1.5 trillion in 2000 to about \$3 trillion in 2017. The unadjusted TNA value has also fluctuated over the period, especially around the financial crisis period of 2007-2008 which saw total TNA drop by about 40% from \$2.5 trillion in 2007 to just over \$1.5 trillion in 2009. When TNA values are adjusted to 2017 dollars however, the total TNA (solid line in Figure 3.1 Panel B) rose from \$3.3 trillion in 1999 to \$4.2 trillion in 2007, but by 2017 total TNA fell back to 1999 levels. The graph of adjusted TNA is relatively flat compared to unadjusted TNA, and while 2007 marked a turning point in adjusted TNA, the 2007-2009 drop was not as marked as for unadjusted TNA. Note that if we did not drop fund-months where a fund changed family, the total TNA values would be substantially higher. For comparison, Panel C of Figure 3.1 gives the total TNA of all actively-managed US equity funds in the CRSP mutual fund database.

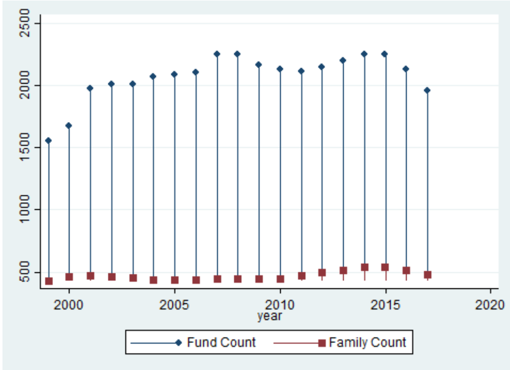
Table 3.1 Annualized Fund and Family Total Net Assets

This table presents annualized summary statistics for the Total Net Assets (TNA) of the funds and fund families in our sample. TNA values are in thousands of 2017 US dollars.

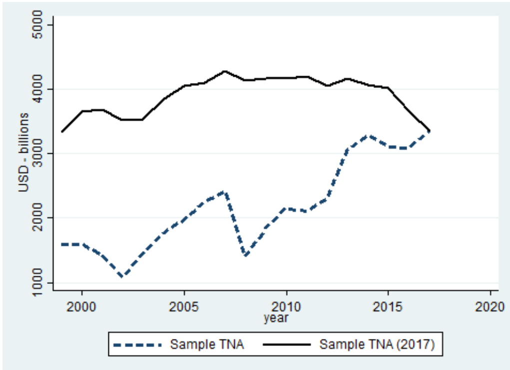
		Funds				Fund Families			
Year	Total TNA	Count	Mean TNA	Median TNA	TNA Std Dev	Count	Mean TNA	Median TNA	TNA Std Dev
1999	3,340,343	1549	2,156	334	7,209	430	7,768	388	38,136
2000	3,658,754	1676	2,183	375	6,821	461	7,937	403	38,898
2001	3,685,729	1971	1,870	346	5,781	473	7,792	470	36,622
2002	3,511,759	2011	1,746	341	5,388	459	7,651	604	35,742
2003	3,535,887	2005	1,764	358	5,580	453	7,805	598	37,100
2004	3,858,192	2065	1,868	385	5,950	433	8,910	728	39,310
2005	4,057,624	2089	1,942	408	6,260	440	9,222	755	39,679
2006	4,102,536	2100	1,954	408	6,549	435	9,431	708	39,419
2007	4,276,382	2250	1,901	385	6,762	442	9,675	519	40,003
2008	4,129,587	2250	1,835	371	6,829	443	9,322	492	37,951
2009	4,161,925	2162	1,925	395	6,540	443	9,395	531	38,004
2010	4,167,006	2127	1,959	416	6,151	443	9,406	504	38,302
2011	4,197,374	2115	1,985	420	6,001	471	8,912	447	37,544
2012	4,054,159	2146	1,889	406	5,725	496	8,174	409	35,769
2013	4,169,968	2197	1,898	414	5,635	517	8,066	352	35,672
2014	4,062,406	2245	1,810	371	5,461	542	7,495	267	34,522
2015	4,009,062	2246	1,785	341	5,573	542	7,397	276	35,713
2016	3,658,477	2129	1,718	337	5,314	516	7,090	264	33,416
2017	3,355,818	1960	1,712	309	5,310	483	6,948	251	33,151

Table 3.2 gives monthly summary statistics for fund and family variables used in this study.

Panel A - Sample Fund and Family Count



Panel B - Sample TNA



Panel C - Industry TNA

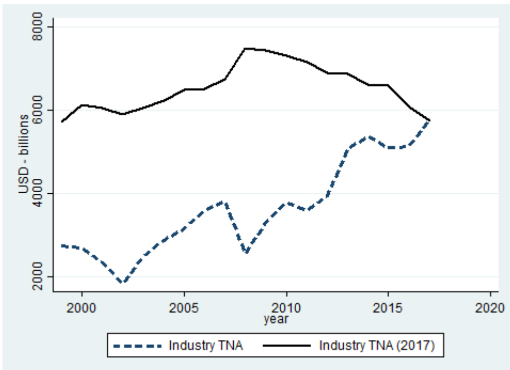


Figure 3.1. Fund and Family Count and TNA

These graphs give annualized counts and Total Net Assets (TNA) for funds and families in our sample, and the total mutual fund industry TNA. The sample consists of actively managed US equity funds in the CRSP Survivorship-bias-free US mutual fund database. Where a fund changed family during the sample period, we keep the fund-months for the family that the fund belonged to the longest, and drop the fund-months when the fund did not belong to that family. Panel A gives the number of funds and fund families in our sample that are active in December of each year of the sample period (1999-2017). Panel B gives the sum of TNA of all active funds at the end of each year. The dashed line gives the total unadjusted TNA, the solid line gives total TNA adjusted to 2017 US dollars by dividing the TNA at the end of each year by the total market value of all stocks in CRSP at the end of the same year, multiplied by the total market value of all stocks in CRSP at the end of 2017. Panel C gives the total TNA of all actively-managed US equity funds in the CRSP Survivorship-bias-free US mutual fund database.

Table 3.2 Summary Statistics

This table presents summary statistics for variables used in this study. The variables are described in detail in the Appendix. Panel A presents fund-level variables, Panel B presents family level variables. Fund data (Panel A) are by fund-month, family data (Panel B) are by family-month.

	Panel A - Fund-level Variables							
	n	mean	sd	p1	p25	p50	p75	p99
gret	378,433	0.0075	0.0505	-0.1404	-0.0167	0.0106	0.0355	0.1306
galpha	378,433	0.0001	0.0231	-0.0658	-0.0091	0.0001	0.0093	0.0654
exp_ratio_m	378,433	0.001	0.001	0.0002	0.0008	0.001	0.0012	0.0022
fund_size	378,433	1,938	4,237	7	127	483	1,681	28,162
ind_size	378,433	0.1851	0.0148	0.1594	0.1719	0.1851	0.194	0.2142
	Panel B - Family-level Variables							
	n	mean	sd	p1	p25	p50	p75	p99
vwfgret	89,800	0.0065	0.0469	-0.1297	-0.0153	0.0086	0.0318	0.122
vwfgalpha	89,800	0	0.0215	-0.0611	-0.0076	0	0.0076	0.0597
fly_exp_ratio_vwa	89,800	0	0.0016	0	0.0008	0.001	0.0012	0.0029
fly_ptna_av	89,778	1,424	5,598	4	86	320	1,175	14,105
fly_size	89,778	9,813	40,637	16	131	670	5,269	150,774
fly_total_fund_n	89,800	4.8705	8.156	1	1	2	5	33
fly_idx_fund_n	89,800	1.9819	10.4424	0	0	0	0	38
fly_retail_fund_n	89,800	3	6.0677	0	1	2	4	23
fly_inst_fund_n	89,800	1.4125	3.2566	0	0	0	1	15
fly_intl_fund_n	89,800	1.9646	4.6157	0	0	0	2	22
fly_team_fund_n	89,800	3.2387	4.8443	0	1	1	4	23
fly_n_osource	89,800	0.4472	1.6371	0	0	0	0	9
fly_ppn_n_idx	96,700	0.5236	7.2676	0	0	0	0	4.5
fly_ppn_n_retail	96,700	0.7671	0.3587	0	0.5882	1	1	1
fly_ppn_n_inst	96,700	0.2098	0.3439	0	0	0	0.3333	1
fly_ppn_n_intl	96,700	0.3002	0.5944	0	0	0	0.4	3
fly_ppn_n_team	96,700	0.6293	0.411	0	0.2	0.8	1	1
fly_ppn_n_osource	96,700	0	0	0	0	0	0	1
fly_ppn_tna_idx	89,800	0.059	0.1794	0	0	0	0	0.9569
fly_ppn_tna_retail	89,800	0.7671	0.3796	0	0.6158	1	1	1
fly_ppn_n_inst	89,800	0.2151	0.3465	0	0	0	0.3333	1
fly_ppn_tna_intl	89,800	0.6961	6.2451	0	0	0	0.1869	13.3223
fly_ppn_tna_team	89,800	0.6509	0.4235	0	0.081	0.9337	1	1
fly_ppn_tna_osource	89,800	0	0	0	0	0	0	1
public_flag	89,800	0	0	0	0	0	0	1
n_launched	89,800	0.4	1.3127	0	0	0	0	6
n_closed	89,800	0.8866	4.8337	0	0	0	0	13
fly_age	89,528	223	190	36	96	173	271	946
fly_fund_age_av	89,528	143	96	33	75	120	185	515

C. Markov transition probabilities

We estimate the persistence of fund and family benchmark-adjusted gross returns using a Markov transition probability model. Each year, benchmark-adjusted gross returns of each fund (or of each family) are calculated (by monthly compounding). The returns for each year are grouped into 10 performance deciles, numbered from 1 to 10, 1 being the bottom decile, 10 being the top decile. The decile of each fund (or family) in one year is checked against its decile in the next year to compute the Markov probability of a fund (or family) changing decile between years.

Family benchmark-adjusted returns are estimated as the value-weighted average benchmark-adjusted returns of the funds in the family. We estimate benchmark-adjusted fund returns (alpha) using a Fama-French-Carhart model:

$$R^e_{it} = \alpha_i + \beta_i^{mkt} MKT_t + \beta_i^{sml} SML_t + \beta_i^{hml} HML_t + \beta_i^{wml} WML_t + \epsilon_{it} \quad (3.1)$$

where R^e_{it} is the gross fund return in excess of the risk-free rate for fund i in month t, MKT_t, SML_t, HML_t, and WML_t are the realizations of the four benchmark portfolios (excess return on the market, small minus big, high minus low, and winners minus losers) and β_i are benchmark sensitivities of the ith fund, which can be estimated by regressing the fund return on to the benchmarks, and α_i is the return in excess of the benchmarks, that is, the benchmark-adjusted return. We interpret the regressors MKT_t, SML_t, HML_t, and WML_t as diversified passive benchmark returns that capture patterns in average returns during our sample period. The benchmark data we use are the four North American Fama-French-Carhart factors downloaded from Kenneth French's website.

Table 3.3 presents the transition probabilities within the top 2 deciles and the bottom 2 deciles (the other decile transition probabilities are omitted to save space) for periods of 1, 3 and 5 years. For each period, top decile return persistence is stronger for families than for funds. For example, for the 5 year period, the probability of a top decile family in one period being a top decile fund in the following period is 0.14, while the same measure for families is 0.10. The pattern holds for the shorter periods also. Thus we conclude that funds with higher than average performance persistence are concentrated in some fund families.

Table 3.3 Markov Transition Probabilities

This table presents the probability of the decile performance ranking of a fund or family changing from one period to the next. Each period, benchmark-adjusted gross returns of each fund (or family) are calculated (by monthly compounding). The returns for each period are grouped into 10 performance deciles, numbered from 1 to 10, 1 being the bottom decile, 10 being the top decile. The decile of each fund (or family) in one period is checked against its decile in the next period to compute the Markov probability of a fund (or family) changing decile between periods. The probabilities are estimated for periods of 1, 3, and 5 years. The results for the two bottom deciles (1, 2) and the two top deciles (9, 10) are given.

	Families 1-year				Funds 1-year			
	1	2	9	10	1	2	9	10
1	0.21	0.10	0.10	0.19	0.20	0.10	0.10	0.18
2	0.09	0.12	0.14	0.10	0.10	0.11	0.10	0.11
9	0.10	0.10	0.09	0.08	0.11	0.10	0.10	0.11
10	0.18	0.12	0.09	0.18	0.17	0.12	0.10	0.16
Obs	6806				28785			
	Families 3-year				Funds 3-year			
1	0.17	0.13	0.10	0.16	0.26	0.09	0.11	0.22
2	0.08	0.11	0.13	0.12	0.09	0.09	0.14	0.11
9	0.08	0.15	0.06	0.14	0.07	0.14	0.08	0.10
10	0.22	0.10	0.10	0.19	0.20	0.10	0.09	0.11
Obs	1691				6885			
	Families 5-year				Funds 5-year			
1	0.17	0.10	0.10	0.13	0.13	0.07	0.10	0.21
2	0.15	0.09	0.03	0.15	0.12	0.14	0.14	0.10
9	0.09	0.06	0.18	0.03	0.05	0.15	0.12	0.10
10	0.24	0.11	0.11	0.14	0.34	0.07	0.06	0.10
Obs	583				3054			

D. Cross-sectional Bootstrap

The cross-sectional bootstrap controls for the fact that some fund families may have positive and significant observed alpha due to luck, or sampling error, even if their true alpha is zero. Furthermore the test allows the data-driven estimation of p-values for the null that alpha is zero based on the actual distribution of skill in the sample rather than assuming that skill follows a parametric normal distribution. These bootstrap p-values allow us to determine the location of skill in the distribution rather than assuming it is located just in the tails. The cross-sectional bootstrap was first applied to mutual funds by Kosowski et al. (2006), and was refined further by Fama and French (2010).

We start by estimating family benchmark-adjusted gross returns using Equation 3.1 where the dependent variable is value-weighted average gross returns of the funds in the family, less the risk-free rate. We then create a zero-alpha pseudo timeseries of monthly excess returns where, for each family, the alpha is subtracted from the excess return. Then we generate 1000 bootstrap samples where 228 months of data (there are 228 months in our sample period) are randomly selected (with replacement) from the zero-alpha pseudo timeseries[4]. For each bootstrap sample, we regress each family's zero-alpha returns on the benchmarks (we require each family to have at least 8 monthly observations). Thus we have 1000 distributions where each family's true alpha is set to zero by construction, but due to sampling error or luck, some families may have observed alphas that are significantly different from zero. If the number of families in the real sample with significantly positive observed alpha is greater than the average number of lucky families in the 1000 bootstrap samples, then it can be inferred that some families in the real sample must be truly skilled rather than just lucky.

[4]This cross-sectional bootstrap approach is close to that used by Fama and French (2010), and allows for cross-correlation between excess returns and the benchmarks.

We use t-statistic of alpha, t(alpha), as the main measure of performance, as the t-statistic has superior statistical properties relative to alpha because alpha estimates have differing precision across fund families with varying lives and portfolio volatilities (Kosowski et al. (2006)). In the tables we follow Fama and French (2010) and report the cumulative proportion of bootstrap samples where the percentile t(alpha) is less than the percentile t(alpha) in the actual sample ("%<Actual").

The results are presented in Table 3.4. For the funds in our sample, the percentage of the bootstrap samples that produce lower values of t(alpha) than the actual t(alpha) at the same percentile (bootstrap %<Actual) are close to zero up until about the 40th percentile, where the bootstrap percentage is 25% (this is equivalent to a bootstrap p-value of 0.75). From the 50th percentile the t(alpha)'s bootstrap p-values exceed the parametric p-values. We find evidence of statistically significant fund-level skill above the 70th percentile (bootstrap p-value < 0.05), suggesting that more funds are truly skilled than would be expected if we assumed the distribution of fund skill followed a parametric normal distribution.

For families, there is also evidence of skill , although it is slightly weaker than for funds. Bootstrap p-values fall below 0.05 from about the 70th percentile, and are below 0.01 from the 90th percentile. Thus we find more evidence that fund families are truly skilled than if we assumed a parametric normal distribution.

Figure 3.2 provides a graphical view of the results. For different t(alpha) threshold values, the cross-sectional bootstrap allows us to estimate the number of funds/families with t(alpha)'s above this threshold that we would expect to observe due to sampling error. We compare this with the number of actual funds/families in our sample whose actual observed t(alpha) is greater than the threshold.

Table 3.4 Cross-sectional Bootstrap - Percentiles of t(alpha) for Funds and Families

This table presents the cross-sectional bootstrap results for funds and fund families at specific percentiles of the t-statistic of alpha t(alpha). Panel A gives the results for funds, and Panel B gives results for families. t(alphas) are estimated using gross returns in a Fama-French-Carhart model. Column (1) gives the t(alpha) percentile (%-ile), the remaining columns give statistics for the fund or family located at that percentile: column (2) is the alpha, column (3) is the t-statistic of alpha t(alpha), column (4) gives the expected proportion (percentage divided by 100) of funds or families whose t(alpha) is less than the actual if normality is assumed (parametric %<Actual), column (5) is the proportion of the bootstrap samples that produce lower values of t(alpha) than the actual t(alpha) at the same percentile (bootstrap %<Actual), and column (6) is the ranking by t(alpha) of the fund or family in the sample (1 is lowest rank).

Panel A - Funds

%-ile (1)	alpha (2)	Actual t(alpha) (3)	parametric %<Actual (4)	bootstrap %<Actual (5)	rank (6)
min	-0.124	-23.223	0	0	1
1	-0.433	-4.501	0	0	46
5	-0.2	-2.872	0.002	0	229
10	-0.449	-2.104	0.019	0	457
20	-0.087	-1.301	0.098	0.001	914
30	-0.161	-0.801	0.213	0.024	1370
40	-0.033	-0.353	0.362	0.249	1827
50	0.016	0.025	0.51	0.592	2283
60	0.029	0.402	0.656	0.9	2740
70	0.148	0.818	0.792	0.985	3196
80	0.151	1.281	0.898	0.997	3653
90	0.193	1.954	0.973	1	4109
95	0.083	2.665	0.996	1	4337
99	0.709	4.171	1	1	4520
max	0.604	10.07	1	0.984	4565

Panel B - Families

%-ile (1)	alpha (2)	Actual t(alpha) (3)	parametric %<Actual (4)	bootstrap %<Actual (5)	rank (6)
min	-0.182	-8.433	0	0.001	1
1	-0.35	-4.074	0	0.001	9
5	-0.168	-2.756	0.003	0	45
10	-0.384	-2.08	0.02	0	89
20	-0.197	-1.361	0.088	0.004	177
30	-0.284	-0.841	0.201	0.034	265
40	-0.051	-0.412	0.341	0.151	353
50	0.007	0.068	0.527	0.663	441
60	0.1	0.425	0.664	0.857	529
70	0.165	0.804	0.788	0.948	617
80	0.101	1.221	0.888	0.971	705
90	0.314	1.915	0.971	0.997	793
95	0.484	2.541	0.994	1	837
99	0.314	3.876	1	0.998	872
max	0.262	9.509	1	0.612	880

At the t(alpha)>0 threshold, we see that about 50 more funds (or about 2% of our sample) have actual observed t(alpha)>0 than would be expected if all funds were neither skilled nor unskilled (true t(alpha)=0). This outpeformance gets even stronger as the threshold is raised. At t(alpha)=2, 437 funds have actual t(alpha) that is greater than 2, while the number we would expect to see is 144. In other words, 293 funds with actual t(alpha)>2 are truly skilled.

For families, the number of families with actual t(alpha)>0 is marginally (3%) higher than would be expected due to sampling error alone. However for higher t(alpha) thresholds, the number of families with actual t(alpha) greater than the threshold is much higher than the number predicted by the cross-sectional bootstrap. At the t(alpha)>2 threshold, 79 families have actual t(alpha)>2 which is 51 more than expected, implying that about 28 families in our sample are truly skilled. Another way of interpreting this result is that there is a 51/79 = 0.65 probability that a family with t(alpha)>2 is truly skilled.

Comparing right tail results with left tail results however, it is clear that more funds and families are truly unskilled at higher absolute t(alpha) thresholds than are truly skilled. 293 more funds than expected have t(alpha)>2 (about 6.5% of our fund sample), while 362 more funds than expected have t(alpha)<-2 (about 8% of our fund sample). For families, the situation is similar; 51 more families than expected have t(alpha)>2 (6% of our sample) while 70 more families than expected have t(alpha)<-2 (almost 8% of our family sample).

Thus the cross-sectional bootstrap shows that substantial numbers of truly skilled funds and families do exist, however these are outnumbered by the truly unskilled funds and families.

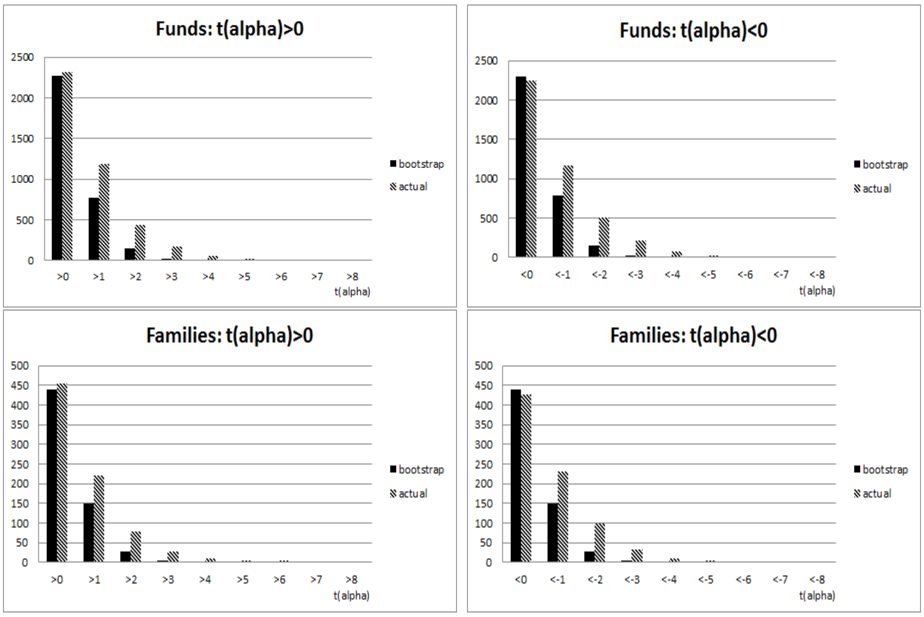


Figure 3.2. Actual and Bootstrap t(alpha) Counts for Funds and Families
These graphs compare the number of funds (on the top) or fund families (on the bottom) that have actual t(alpha)'s above (on the left) or below (on the right) certain threshold values compared with the number predicted by the cross-sectional bootstrap where the true fund and family alpha's are set to zero by construction.

E. *False Discovery Rate*

The second technique we use to separate luck from skill is the false discovery rate, which allows us to estimate the proportions of truly skilled fund families and truly unskilled fund families while controlling for noise (false positives) in the distribution of skill. The general statistical technique was developed by Storey (2002), and applied to mutual funds by Barras et al. (2010). The technique works by first estimating the proportion of true zero-alpha fund families in the sample, and then extrapolating to estimate the proportions of truly positive alpha (skilled) and truly negative alpha (unskilled) fund families.

The false discovery rate allows the estimation of the proportions of funds and families that are truly skilled (t(alpha) $>$0), truly unskilled (t(alpha) $<$0), or neither skilled nor unskilled (t(alpha)=0). As in the previous section, we apply the test to funds and families. The t(alpha) p-values used in the test are the bootstrap p-values estimated in the previous section.

Table 3.5 presents the results. The proportion of neither skilled nor unskilled funds and families is slightly higher for funds (68%) than for families (67%). However the proportion of truly skilled funds (16%) is higher than the proportion of truly skilled families (14%). Also, the proportion of truly unskilled funds (16%) is lower than the proportion of truly unskilled families (19%).

Table 3.5 False Discovery Rate for Funds and Families

This table presents the False Discovery Rate (FDR) results for funds and families. FDR allows estimation of the proportion of funds and families that are truly skilled (that is, the true alpha of these funds and families is positive and significant), truly unskilled (the true alpha of these funds and families is negative and significant), or that are neither skilled nor unskilled (the true alpha is not significantly different from zero). The parameters used for the estimation are threshold p-value $\lambda = 0.6$ *and significance level* $\gamma = 0.4$.

	Funds	Families
skilled	0.16	0.14
unskilled	0.16	0.19
neither	0.68	0.67

III. Skill Determinants

In the previous section we showed that a proportion of fund families are truly skilled, and a slightly highly proportion are truly unskilled. In this section we identify some characteristics of families that are skill enhancing, or skill destroying.

A. Size and fund performance:

We first examine the effects of family size on fund performance as a special case. To properly understand the effect of family size on fund performance, we must first control for the effect of fund size on fund performance after addressing the potential endogeneity between fund size and fund performance.

Standard OLS regressions of fund performance on lagged fund size suffer from endogeneity in that funds that have a high return automatically increase in size in the following period due to the increase in value of the assets held by the fund. Furthermore successful funds attract inflows, further increasing the fund size.

To overcome the endogeneity problem, Pástor et al. (2015) propose using a fixed effects regression where all variables, except fund size, are forward recursively demeaned. Reverse recursively demeaned fund size is used as an instrument for forward recursively demeaned fund size. Using reverse recursively demeaned fund size as an instrument overcomes the endogeneity problem as reverse demeaning fund size breaks the spurious negative relation between changes in fund size and future fund performance.

Following Carhart (1997) and Ferreira et al. (2012), we estimate fund performance as the benchmark-adjusted gross fund returns ($galpha$):

$$galpha_{i,t} = R^e_{i,t} - (\beta^{mkt}_{i,t-1}MKT_t + \beta^{sml}_{i,t-1}SML_t + \beta^{hml}_{i,t-1}HML_t + \beta^{wml}_{i,t-1}WML_t) \tag{3.2}$$

where R^e_{it} is the fund i's gross excess return (that is, the net return plus one twelfth of the fund's annual expense ratio, less the risk-free rate). The other variables are as in Equation 3.1. We use rolling 24-month windows to create a monthly time series of fund $galpha$s.

The results of regressions showing the effects on gross benchmark-adjusted fund performance ($galpha$) of lagged fund size, family size and industry size are given in Table 3.6. To allow for differences in fund manager skill, three fixed effects models are estimated: an OLS fixed effects model, a plain recursive-demeaned (RD) fixed effects model, and an instrumented RD model where recursive forward-demeaned fund size is instrumented by recursive reverse-demeaned fund size. The OLS FE and plain RD FE models suffer from endogeneity between the dependent variable (fund performance) and fund size. The instrumented RD model overcomes the endogeneity by instrumenting for forward recursive demeaned fund-size using reverse recursive demeaned fund-size. Instruments are not required for family size or industry size as there is no reason to believe that innovations in family size or industry size are correlated with the benchmark-adjusted returns of any given fund.

The results for the full sample are presented in Table 3.6 Panel A, where we do not include family size as a regressor because many families are single-fund families. The OLS FE and plain RD FE coefficients are negative and significant at the 1% level for fund size, positive and significant for industry size. The results for the instrumented RD FE regression (columns 7 and 8) show that when we control for the endogeneity between fund size and fund returns, neither the size of the fund nor the industry size have a significant effect of fund returns. The large Kleibergen-Paap rk Wald F statistic mean that the null hypothesis that reverse recursive demeaned fund size is a weak instrument is strongly rejected.

In Table 3.6 Panel B we give the results for the subset of families which have more than one fund. Here it is clear that fund size and family size do not have a significant effect on fund performance after controlling for fund size/fund performance endogeneity (columns 15 and 16). Industry size however does seem to have a positive and weakly significant effect.

These results differ somewhat from those reported by Pástor et al. (2015) (PST). In their main findings, they show that after controlling for endogeneity using the instrumented RD FE approach, the coefficient for fund size is negative and insignificant, and the coefficient for industry size is negative and significant. In their online Appendix, they report that family size has a positive but insignificant coefficient. Our results may be different from theirs for a number of reasons. PST estimate benchmark-adjusted fund returns as the difference between the fund return and the fund's Morningstar benchmark return, whereas we use the alpha from a regression of fund returns on a four-factor Fama-French-Carhart model. PST use the subset of funds from CRSP that overlaps with Morningstar; we find that this reduces the sample size substantially; for example, of the 1084 fund families we identify in our CRSP sample, only 600 or so exist in Morningstar. Also, we find that a substantial effort is required to cleanly identify the family associated with each fund, but it is not clear how PST identify the families associated with their funds. Finally, we use a different time frame, 1999-2017, while they focus on the 1979-2011 period. Industry size did not change much during our timeframe, while in the PST timeframe, industry size grew significantly.

B. Family characteristics as skill determinants

The family characteristics that could affect family skill include general family characteristics, and characteristics of the funds managed by the family. General family characteristics include family size, age, number of funds managed, average size of funds managed, average fund expense ratio. Families with large numbers of funds or higher average fund size may have lower skill measures due to diseconomies of scale in the mutual fund industry. However, large families can also have more resources that help enhance performance. Older families may have more experience, and thus their performance may be better due to learning. A family with a large number of funds might mean that the family has been successful in innovating and launching new products, but could also mean that the firm is marketing oriented, and has a wide range of products that are focused on catering to particular investor tastes rather on generating performance. Families with higher average expense ratios may have higher skill measures due to their greater ability to compensate skilled

Table 3.6 Relation between size and fund performance

*This table presents the results of fixed effect regressions of fund returns on fund size, family size and industry size, estimated using an OLS fixed effects model, a recursive demeaned fixed effects model, and a recursive demeaned fixed effects model that uses an instrument for fund size. Panel A gives the results for all families for fund and industry size, but excluding family size. Panel B gives the fund, industry and family size effects for families that have more than one fund. The dependent variable is gross benchmark-adjusted fund returns (galpha) from a 4-factor Fama-French-Carhart model. Fund size is estimated for each fund as the fund TNA each month divided by the total value of all stocks in CRSP that month, multiplied by the total value of all stocks in CRSP at the end of December 2017. Family size is the sum of the fund size of all funds in the family. Industry size is the sum total TNA of all actively managed US equity funds in CRSP each month, divided by the total value of all stocks in CRSP for that month. Columns 1-3 and 9-11 give the results for OLS fixed effects regressions. Columns 4-6 and 12-14 give the results for plain recursive forward demeaned fixed effects regressions. Columns 7-8 and 15-16 give the results for instrumented recursive demeaned fixed effects regressions where forward recursive demeaned fund size is instrumented by reverse recursive demeaned fund size. The Kleibergen Paap rk Wald F statistic for underidentification is also reported. t-statistics using robust standard errors are in parentheses, and the symbols ***, **, * denote statistical significance at the 1%, 5%, and 10% levels, respectively.*

Panel A - Fund and Industry Size Effects - All Families

VARIABLES	(1) galpha	(2) galpha	(3) galpha	(4) rfm_galpha	(5) rfm_galpha	(6) rfm_galpha	(7) rfm_galpha	(8) rfm_galpha
L.fund_size	-3.05e-05***		-3.07e-05***					
	(-11.04)		(-11.06)					
L.ind_size		0.0100***	0.0109***					
		(3.187)	(3.485)					
L.rfm_fund_size				-3.03e-05***		-3.06e-05***		
				(-14.90)		(-15.11)		
L.rrm_fund_size (IV)							5.42e-06	-1.56e-07
							(0.0545)	(-0.00150)
L.rfm_ind_size					0.00826***	0.0101***		0.00827
					(2.698)	(3.310)		(1.175)
Observations	377,288	377,288	377,288	377,288	377,288	377,288	377,288	377,288
Kleibergen-Paap							15.43	14.24

Panel B - Fund, Family and Industry Size Effects - Families with more than 1 Fund

VARIABLES	(9) galpha	(10) galpha	(11) galpha	(12) rfm_galpha	(13) rfm_galpha	(14) rfm_galpha	(15) rfm_galpha	(16) rfm_galpha
L.fly_size	-6.03e-07***	2.21e-07	1.49e-07					
	(-2.606)	(0.840)	(0.564)					
L.fund_size		-3.02e-05***	-3.01e-05***					
		(-10.20)	(-10.12)					
L.ind_size			0.0151***					
			(4.726)					
L.rfm_fly_size				-6.58e-07***	1.54e-07	8.12e-08	-1.74e-06	-1.43e-06
				(-3.180)	(0.705)	(0.371)	(-0.274)	(-0.221)
L.rfm_fund_size					-2.96e-05***	-2.99e-05***		
					(-13.62)	(-13.73)		
L.rrm_fund_size (IV)							3.94e-05	2.56e-05
							(0.171)	(0.108)
L.rfm_ind_size						0.0138***		0.0124*
						(4.390)		(1.885)
Observations	344,318	344,318	344,318	344,318	344,318	344,318	344,318	344,318
Kleibergen-Paap							3.44	3.25

managers and to invest in good research.

Families that manage more index funds (in absolute terms, or as a proportion of all funds managed) may be less skilled on average (as index replication is more straightforward, and therefore these families may care less about acquiring or training skilled managers). Retail funds may also be associated with reduced family skill as retail investors may be less able to discern or demand skilled fund management. On the contrary, institutional funds may be associated with higher family skill levels as institutional investors could be more demanding. Team-managed funds may be associated with higher skill due to better decision-making and knowledge-sharing within the family; alternatively team-managed funds may introduce a negative correlated noise effect which leads to lower average family skill (Brown and Wu (2016)). We also analyse the number of recent fund launches and closures by the family. A large number of fund launches by a family may be a sign of commitment to innovation and trying to get early-mover advantage, or it can also be a sign that the firm might be too sales oriented. A large number of closed funds might be a sign that the firm has launched too many funds or that the firm is quite proactive in eliminating inefficient funds. A description of the variables used in this part of the study is given in the Appendix; Table 3.2 gives summary statistics.

C. Methodology

We first establish a baseline measure of average family skill using a panel regression with family fixed effects. We then make the family and fund characteristics observable by adding them, one at a time, to the baseline model, and examine the impact on family fixed effects. Adding a characteristic to the baseline model is akin to setting the value of the characteristic to zero for all families, so if adding the characteristic to the baseline generates a smaller average family fixed effects than for the pure baseline model, then we can conclude that heterogeneity in this characteristic contributes positively to family skill.

Our approach is a logical extension of the average fund fixed effects measure used by Pástor et al. (2015) to estimate changes in mutual fund manager skill over time. The advantage of the approach is that it allows skill to be estimated in a way that is decoupled from fund returns - for example average fund manager skill may have increased over time, but fund returns may not have increased due to increased competition in the fund industry.

We estimate family gross performance as the weighted average gross performance of all funds in the family:

$$vwfgalpha_{i,t} = \sum_{j=1}^{N_i} (galpha_{i,j,t} * TNA_{i,j,t}) / \sum_{j=1}^{N_i} TNA_{i,j,t} \tag{3.3}$$

where $vwfgalpha$ is the gross performance of family i in month t, $galpha_{i,j,t}$ is the $galpha$ of fund j of family i in month t estimated using Equation 3.2, N_i is the number of funds belonging to family i, and $TNA_{i,j,t}$ is the TNA of fund j of family i in month t in 2017 US dollars.

We then establish a baseline measure of average family skill using a family fixed effects panel regression. To control for possible decreasing returns to scale at the family and industry level, we regress $vwfgalpha$ on lagged family size and lagged mutual fund industry size, and estimate the average family fixed effects:

$$vwfgalpha_{i,t} = a_{i,bl} + \beta_i^{ft} fly\_size_{i,t-1} + \beta_i^{is} ind\_size_{t-1} \tag{3.4}$$

where $vwfgalpha_{i,t}$ is the benchmark-adjusted return of family i in month t (Equation 3.3), $a_{i,bl}$ is the baseline fixed effect for family i, $fly\_size_{i,t-1}$ is the size of family i in month $t-1$ and ind_size_{t-1} is the mutual fund industry size in month $t-1$.

Then we estimate the average fixed effect for each family characteristic, that is, when it is added to the baseline model:

$$vwfgalpha_{i,t} = a_{i,k} + \beta_{i,k}^{ft} fly\_ptna_{i,t-1} + \beta_{i,k}^{is} ind\_size_{t-1} + \beta_{i,k}^{fc} family\_characteristic \tag{3.5}$$

where $a_{i,k}$ is the fixed effects for family i when characteristic k is included in the model.

Finally, we measure the impact of the characteristic on family skill as the change in the fixed effects when the characteristic is included versus the baseline fixed effect:

$$Impact_k = a_{bl} - a_k \tag{3.6}$$

A positive impact value means that innovations in value of the characteristic are associated with increased family skill. Adding the characteristic to the baseline model has the effect of setting the value of the characteristic to zero for all families. Thus if adding the characteristic to the model (that is, fixing the characteristic value for all families) results in a fixed effects that is greater than for the baseline (where the characteristic value may very across families), then we infer that variations in characteristic value must be driving the fixed effects down, that is, reducing our measure of family skill.

D. Results

Table 3.7 presents the impact measures for the family characteristics. Looking at general family characteristics (family age, number of funds per family, average fund size, average fund age, average fund expense ratio) we see that varying average expense ratio and average fund size have positive effects on our skill measure. The average expense ratio of funds in the family has the largest positive impact of any of the characteristics that we identify, accounting for a 5.9 basis point increase in skill. Average fund size also has a relatively large positive effect on skill (0.9 basis points). The total number of funds in the family has no effect on skill, while family age and average fund age have small negative effects.

The absolute number and proportion by number of retail funds in the family have positive effects on skill; for example, an increase in the proportion by number of retail funds in the family fund mix increases skill by 4.4 basis points. However, the proportion by TNA of retail funds reduces skill by 3.5 basis points, the largest negative effect of any of the characteristics that we study. The proportion of the number institutional funds has a negative effect of skill of 1.4 basis points, and the proportion of institutional funds by TNA also has a small negative effect. Measures of international funds in the fund mix have negative effects; an increase in the proportion by number of international funds leads to a decrease of 1.9 basis points in our skill measure. Index funds also have slight negative effects; an increase in the absolute number of index funds reduces family skill by 1.3 basis points.

The proportion by TNA of team managed funds is associated with a relatively large positive skill outcome of 1.8 basis points. Our measures for outsourced funds on the other hand have small skill effects both in positive and negative directions. The skill of publicly listed fund families may differ from private fund families due to differing incentive structures, agency costs etc. In our data we see a small reduction in skill for publicly listed families (1.1 basis points).

Finally we examine effects of recent fund launches and closures by the family. Families may launch new funds that target novel or inefficient sectors, thereby capturing early-mover gains. Alternatively, some families may be more proactive in closing underperforming funds, thus increasing the overall family performance. Our tests show that increases in the number of fund launched in the previous 12 months are associated with slightly higher skill outcomes (0.8 basis points), while increases in the number of fund closures in the previous 12 months leads to an increase in skill of 0.4 basis points.

IV. Other Tests

A. *Single-fund versus Multi-fund Families*

A growing number of fund families consist of just one actively managed fund focused on US equities. Panel A of Figure 3.3 shows that the number of single-fund families in our sample has risen from 165 in 2004, to a peak of 249 in 2014, before dropping back to 222 in 2017. The amount of capital managed by these single-fund families has also increased, growing from $93 billion (adjusted to 2017 USD) in 2000 to $211 billion in 2010, before falling back in 2017 to $144 billion. The number and TNA of multi-fund families in our sample, on the other hand, has been relatively stable since about 2000 (Panel B of Figure 3.3); around 270 multi-fund families manage around $3.9 trillion.

We divide our sample into single-fund families and multi-fund families and estimate the Markov transition probabilities. Table 3.8 presents the results. The probability of top-decile persistence between one 1-year period and the next is quite similar for funds, single-fund families and multi-fund families, between 0.16 and 0.18. Looking at the 3-year period, however, marked differences emerge. For funds, top-decile persistence is just 0.11, while for single-fund families, it is 0.16. For multi-fund families, top-decile persistence is highest at 0.24.

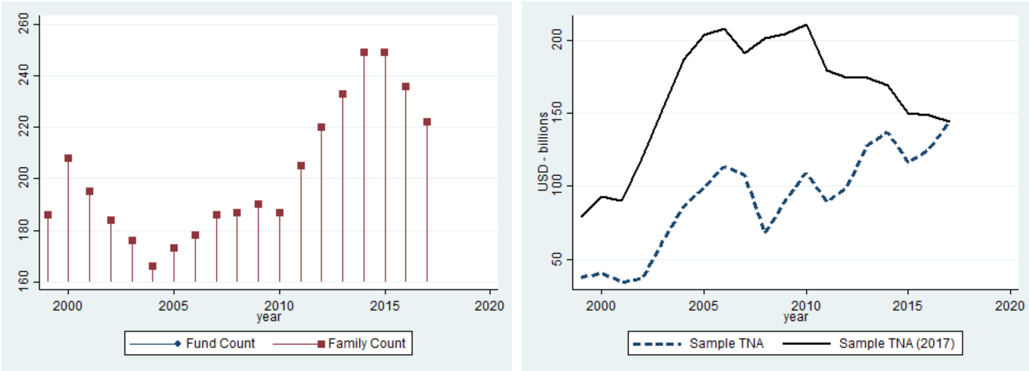
We then apply the cross-sectional bootstrap test to estimate how many of each type of family are truly skilled or truly unskilled. Figure 3.4 gives the

Table 3.7 Impact of family characteristics on family skill

This table presents impact of family characteristics on average family skill. First, a baseline value for family skill is estimated as the fixed effects in a family fixed effects regression of benchmark-adjusted family returns (vwfgalpha) on lagged family size (fly_size) and lagged industry size (ind_size). Then, for each characteristic, the fixed effects are re-estimated by adding the lagged family characteristic to the baseline regression. The impact factor is then estimated as the baseline fixed effects minus the characteristic fixed effects. The family characteristics are described in the Appendix. The regression coefficient for the characteristic and its (heteroscedasticity robust) t-statistic is given in columns (1) and (2), the family fixed effects (multiplied by 100 for ease of visualization) are in column (3), and the impact factors for the characteristics are given in column (4).

	(1)	t-stat (2)	Family Fixed Effects (3)	delta from baseline (4)
L.fly_size	-2.02e-08***	(-3.476)		
L.ind_size	-0.00431	(-0.683)	.099	baseline
L.fly_ptna_av	-1.43e-07***	(-2.826)	.09	0.009
L.fly_exp_ratio_vwa	0.657**	(2.439)	.04	0.059
L.fly_age	-2.08e-06	(-1.303)	.1	-0.001
L.fly_fund_age_av	-2.89e-06	(-1.425)	.102	-0.003
L.fly_total_fund_n	1.73e-06	(0.0621)	.099	0
L.fly_idx_fund_n	3.20e-05***	(2.795)	.112	-0.013
L.fly_ppn_n_idx	4.86e-05	(1.402)	.101	-0.002
L.fly_ppn_tna_idx	0.00227**	(2.154)	.101	-0.002
L.fly_n_osource	0.000137*	(1.916)	.101	-0.002
L.fly_ppn_n_osource	-0.000275	(-0.183)	.1	-0.001
L.fly_ppn_tna_osource	-0.000192	(-0.192)	.1	-0.001
L.fly_retail_fund_n	2.74e-05	(0.675)	.096	0.003
L.fly_ppn_n_retail	0.000515	(0.703)	.055	0.044
L.fly_ppn_tna_retail	-0.000403	(-0.534)	.134	-0.035
L.fly_inst_fund_n	-3.92e-05	(-0.791)	.095	0.004
L.fly_ppn_n_inst	-0.00102	(-1.572)	.113	-0.014
L.fly_ppn_tna_inst	-0.000238	(-0.437)	.102	-0.003
L.fly_team_fund_n	3.12e-06	(0.0753)	.099	0
L.fly_ppn_n_team	-2.59e-05	(-0.0290)	.1	-0.001
L.fly_ppn_tna_team	0.000340	(0.429)	.081	0.018
L.fly_intl_fund_n	8.96e-05**	(2.488)	.118	-0.019
L.fly_ppn_n_intl	0.000132	(0.482)	.102	-0.003
L.fly_ppn_tna_intl	1.31e-05	(1.264)	.102	-0.003
L.fly_public	-0.000907***	(-5.567)	.11	-0.011
L.n_launched	0.000100*	(1.890)	.091	0.008
L.n_closed	4.82e-06	(0.711)	.095	0.004
Obs			88,742	

Panel A - Single-Fund Families



Panel B - Multi-Fund Families

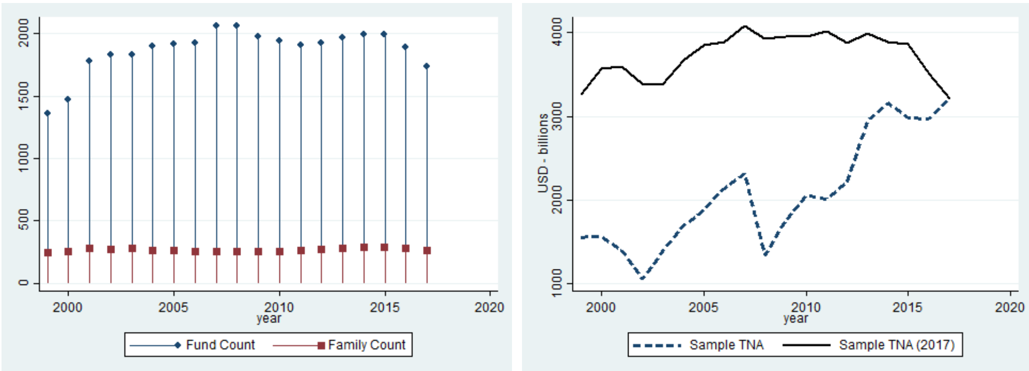


Figure 3.3. Single-Fund and Multi-Fund Count and TNA

These graphs give the number and TNA of single-fund (Panel A) and multi-fund (Panel B) families that are active in December of each year of the sample period. The solid line gives TNA values are adjusted to 2017 US dollars, the dashed line gives unadjusted TNA values.

Table 3.8 Markov transition probabilities for single- and multi-fund families

This table presents the probability of the decile performance ranking of a fund, a single-fund family, or a multi-fund family changing from one period to the next. Each period, benchmark-adjusted gross returns of each fund (or family) are calculated (by monthly compounding). The returns for each period are grouped into 10 performance deciles, numbered from 1 to 10, 1 being the bottom decile, 10 being the top decile. The decile of each fund (or family) in one period is checked against its decile in the next period to compute the Markov probability of a fund (or family) changing decile between periods. The probabilities are estimated for periods of 1, 3, and 5 years. The results for the two bottom deciles (1, 2) and the two top deciles (9, 10) are given.

	Funds 1-year				Funds 3-year			
	1	2	9	10	1	2	9	10
1	0.20	0.10	0.10	0.18	0.26	0.09	0.11	0.22
2	0.10	0.11	0.10	0.11	0.09	0.09	0.14	0.11
9	0.11	0.10	0.10	0.11	0.07	0.14	0.08	0.10
10	0.17	0.12	0.10	0.16	0.20	0.10	0.09	0.11
Obs	28785				6885			
	Single-fund Families 1-year				Single-fund Families 3-year			
1	0.20	0.11	0.07	0.18	0.28	0.10	0.03	0.17
2	0.09	0.09	0.11	0.08	0.10	0.06	0.13	0.06
9	0.10	0.07	0.11	0.11	0.10	0.13	0.07	0.13
10	0.15	0.10	0.07	0.19	0.15	0.09	0.03	0.18
Obs	2230				440			
	Multi-fund Families 1-year				Multi-fund Families 3-year			
1	0.20	0.09	0.11	0.20	0.13	0.18	0.09	0.15
2	0.09	0.12	0.11	0.15	0.11	0.10	0.17	0.11
9	0.10	0.12	0.10	0.09	0.12	0.10	0.13	0.08
10	0.17	0.13	0.08	0.18	0.19	0.11	0.11	0.24
Obs	4341				1112			

results. The number of single-fund families with t(alpha)>0 is slightly higher than what would be expected if all families in the sample had the same level of skill. 323 single-fund families have actual t(alpha)>0, which is 25 more than would be expected under the null; thus about 4% of our sample are truly skilled at this threshold.

At higher t(alpha) thresholds we see that single-fund families are more likely to be truly skilled. For example, under the null hypothesis, we would expect to see 19 single-fund families with t(alpha)>2, but we actually observe 53, suggesting that 34 families (about 5.5% of the single-fund family sample) are truly skilled.

For multi-fund families, however, there is evidence of skill, but it is more skewed towards the right-tail than for single-fund families. Under the null hypothesis, we would expect to see 142 families with t(alpha)>0, instead we observe just 130. However we observe 26 fund families with actual t(alpha)>2, 17 more than the number predicted by the cross-sectional bootstrap, implying that 6% of the multi-fund family sample are truly skilled at this threshold.

Looking at the left tail, there is evidence that some families are truly unskilled. Families with smaller t(alpha)'s are increasingly likely to be truly unskilled. At the t(alpha)<-2 threshold, 42 families, or almost 7% of the single-fund family sample, are truly unskilled, while for multi-fund families the picture is even more negative: 36 families of the multi-fund family sample have observed t(alpha)<-2 compared to 8 expected under the null. In other words, 28 families, about 10% of the multi-fund family sample, are truly unskilled. If a multi-fund family has observed t(alpha)<-2, there is 28/36 = 0.78 probability that it is truly unskilled.

The cross-sectional test results suggest that single-fund families are generally more skilled than multi-fund families. Now we examine the determinants of skill for the single-fund family and multi-fund family samples. Table 3.9

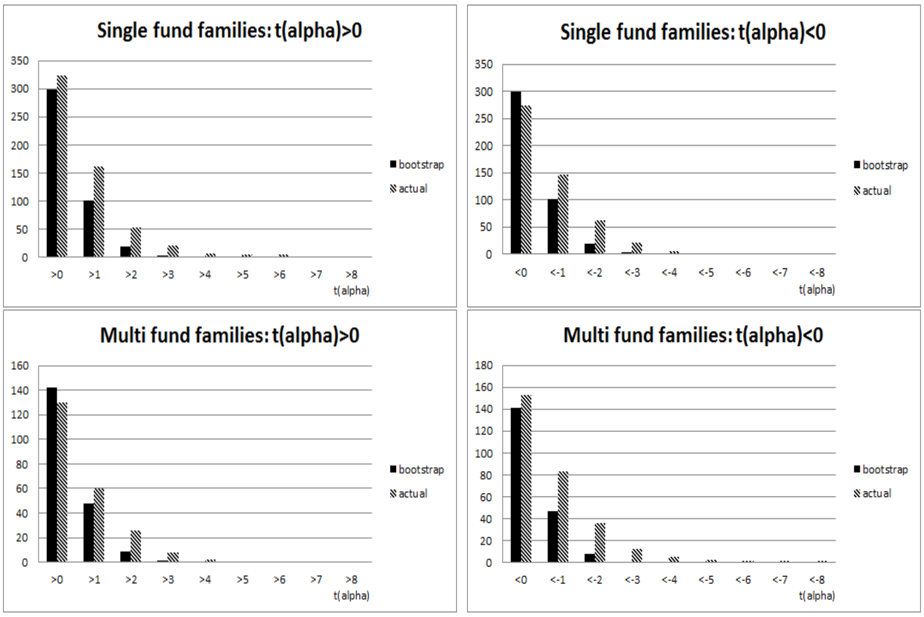


Figure 3.4. Actual and Bootstrap t(alpha) Counts for Single-fund and Multi-fund Families

These graphs compare the number of single-fund families (top graphs) or multi-fund families (bottom graphs) that have actual t(alpha)'s above (left graphs) or below (right graphs) certain threshold values compared with the number predicted by the cross-sectional bootstrap where the true family alpha's are set to zero by construction.

presents skill impact factors estimated using family fixed effects regressions for each sample. The baseline skill measure for single-fund families is 63 basis points larger than the baseline for multi-fund families, which is consistent with the previous finding that single-fund families are more skilled than multi-fund families.

Single-fund family skill is positively impacted by team fund management (28.7 basis points), expense ratio (15.3 basis points) and institutional funds (3.5 basis points). Retail funds have a negative effect on single-fund family skill (17.6 basis points) as does fund age (4.1 basis points) and family age (2.2 basis points). The number of closed funds in the prior 12 months also has a strong negative impact (20.5 basis points).

Multi-fund family skill on the other hand is positively impacted by retail funds and the number of funds closed or launched in the previous 12 months. The proportion by number of retail funds increases skill by 8.7 basis points, while the number of recently closed funds is associated with a 1.9 basis point skill increase. Expense ratio has a large negative impact for multi-fund manager skill (10.3 basis points). The other family characteristics tend to have small negative skill impact.

The skill gap between single-fund families and multi-fund families is largest for team management - an increase in our team management measures increases single-fund family skill by 29.5 basis points more than it does for multi-fund families. Similarly, an increase in expense ratio increases single-fund family skill by 25.6 basis points more than for multi-fund families. On the other hand, retail funds increase multi-fund family skill, but decreases single-fund family skill. The skill gap on this measure is more than 26.3 basis points. Fund and family age also have a positive effect on multi-fund families while they have a negative effect on single-fund families - the gap for average fund age, for example, is 4.1 basis points.

B. *Gross vs net returns*

In general in this paper we use benchmark-adjusted gross-of-fee returns to estimate family performance. In this section we will examine skill, and the determinants of skill, using benchmark-adjusted net-of-fee returns to estimate family performance.

Figure 3.5 gives the cross-sectional bootstrap results. The evidence is that extremely few families are truly skilled when net-of-fee benchmark-adjusted returns is the performance measure. Only at thresholds of t(alpha)>2 is the number of families with actual t(alpha) greater than the number expected if all families were neither skilled nor unskilled, and even then they are very few. At the t(alpha)>2 threshold, only 3 families are truly skilled. On the other hand there is substantial evidence that many families are truly unskilled. At the t(alpha)<0 threshold, 611 families have actual t(alpha)<0 versus an expected

Table 3.9 Impact of family characteristics on single-fund and multi-fund family skill

This table presents impact of family characteristics on average family skill for single-fund families and multi-fund families. For comparison the impact measures estimated for all families are also given. Δ stands for the variation from the baseline model. The family characteristics are described in the Appendix. The family fixed effects are multiplied by 100 for ease of visualization.

	Single Fund Families		Multi Fund Families		All Families	
	Fixed Effects	Δ	Fixed Effects	Δ	Fixed Effects	Δ
L.fly_size L.ind_size	.432	baseline	-.204	baseline	.099	baseline
L.fly_ptna_av	.417	0.015	-.201	-0.003	.09	0.009
L.fly_exp_ratio_vwa	.279	0.153	-.101	-0.103	.04	0.059
L.fly_age	.454	-0.022	-.205	0.001	.1	-0.001
L.fly_fund_age_av	.473	-0.041	-.204	0	.102	-0.003
L.fly_total_fund_n	.432	0	-.204	0	.099	0
L.fly_idx_fund_n	.433	-0.001	-.189	-0.015	.112	-0.013
L.fly_ppn_n_idx	.433	-0.001	-.202	-0.002	.101	-0.002
L.fly_ppn_tna_idx	.43	0.002	-.205	0.001	.101	-0.002
L.fly_n_osource	.453	-0.021	-.201	-0.003	.101	-0.002
L.fly_ppn_n_osource	.453	-0.021	-.209	0.005	.1	-0.001
L.fly_ppn_tna_osource	.453	-0.021	-.205	0.001	.1	-0.001
L.fly_retail_fund_n	.608	-0.176	-.208	0.004	.096	0.003
L.fly_ppn_n_retail	.608	-0.176	-.291	0.087	.055	0.044
L.fly_ppn_tna_retail	.608	-0.176	-.223	0.019	.134	-0.035
L.fly_inst_fund_n	.397	0.035	-.213	0.009	.095	0.004
L.fly_ppn_n_inst	.397	0.035	-.189	-0.015	.113	-0.014
L.fly_ppn_tna_inst	.397	0.035	-.201	-0.003	.102	-0.003
L.fly_team_fund_n	.145	0.287	-.205	0.001	.099	0
L.fly_ppn_n_team	.145	0.287	-.196	-0.008	.1	-0.001
L.fly_ppn_tna_team	.145	0.287	-.196	-0.008	.081	0.018
L.fly_intl_fund_n	.438	-0.006	-.183	-0.021	.118	-0.019
L.fly_ppn_n_intl	.438	-0.006	-.201	-0.003	.102	-0.003
L.fly_ppn_tna_intl	.441	-0.009	-.201	-0.003	.102	-0.003
L.fly_public	.434	-0.002	-.187	-0.017	.11	-0.011
L.n_launched	.432	0	-.216	0.012	.091	0.008
L.n_closed	.637	-0.205	-.219	0.015	.095	0.004
Obs	32,499		55,772		88,742	

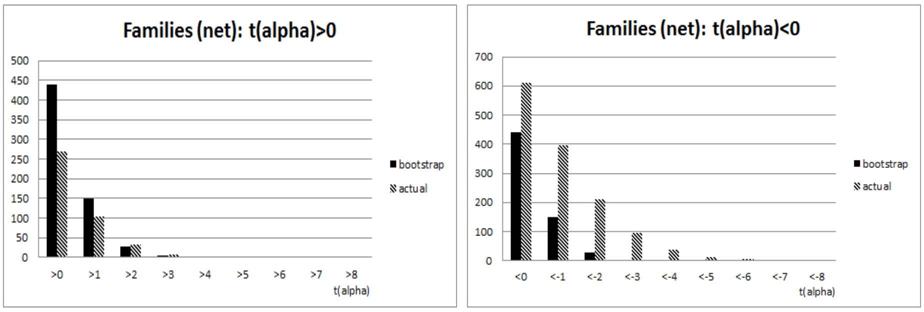


Figure 3.5. Actual and Bootstrap t(alpha) Counts for Using Net Returns
These graphs give the number of families that have actual t(alpha)'s estimated using net-of-fee above or below certain threshold values compared with the number predicted by the cross-sectional bootstrap where the true family net-of-fee alpha's are set to zero by construction.

value of 440. In other words 171 families, or 19% of the sample, are truly unskilled.

Table 3.10 gives the family fixed-effects where the value-weighted benchmark adjusted net returns of funds in a family is used as the dependent variable. The characteristics with the largest positive impact on net skill are similar to those for gross returns - number (but not TNA) of index funds in family fund mix, average fund size, number of recently launched or closed funds. The notable exception is expense ratio, which has the strongest positive impact on the gross skill measure (5.9 basis points), but which has the second-strongest negative impact on the net skill measure (2.4 basis points). The proportion by TNA of retail funds has a negative impact on net skill (6.5 basis points), as does the amount of international funds in the family fund mix.

V. Conclusions

The debate on skill in the mutual fund industry has focused on the fund manager. This paper presents an analysis of the existence of skill at the family level. Using a sample of actively managed US equity funds and families domiciled in the US, the results presented in this paper show that some fund families exist whose funds have persistent long term performance, on average.

Table 3.10 Impact of family characteristics on family skill - using net returns

This table presents impact of family characteristics on family skill, where the dependent variable in the family fixed-effect panel regressions to estimate skill is the value-weighted average net returns of the funds in the family. For comparison the impact measures estimated using gross returns are also given. The family characteristics are described in the Appendix. The family fixed effects are multiplied by 100 for ease of visualization.

	NET		GROSS	
	Family Fixed Effects	Δ baseline	Family Fixed Effects	Δ baseline
L.fly_size				
L.ind_size	.009	baseline	.099	baseline
L.fly_ptna_av	0	0.009	.09	0.009
L.fly_exp_ratio_vwa	.033	-0.024	.04	0.059
L.fly_age	.01	-0.001	.1	-0.001
L.fly_fund_age_av	.012	-0.003	.102	-0.003
L.fly_total_fund_n	.009	0.000	.099	0
L.fly_idx_fund_n	.022	-0.013	.112	-0.013
L.fly_ppn_n_idx	.011	-0.002	.101	-0.002
L.fly_ppn_tna_idx	.011	-0.002	.101	-0.002
L.fly_n_osource	.011	-0.002	.101	-0.002
L.fly_ppn_n_osource	.012	-0.003	.1	-0.001
L.fly_ppn_tna_osource	.01	-0.001	.1	-0.001
L.fly_retail_fund_n	.005	0.004	.096	0.003
L.fly_ppn_n_retail	-.015	0.024	.055	0.044
L.fly_ppn_tna_retail	.074	-0.065	.134	-0.035
L.fly_inst_fund_n	.005	0.004	.095	0.004
L.fly_ppn_n_inst	.022	-0.013	.113	-0.014
L.fly_ppn_tna_inst	.01	-0.001	.102	-0.003
L.fly_team_fund_n	.01	-0.001	.099	0
L.fly_ppn_n_team	.008	0.001	.1	-0.001
L.fly_ppn_tna_team	-.011	0.020	.081	0.018
L.fly_intl_fund_n	.03	-0.021	.118	-0.019
L.fly_ppn_n_intl	.012	-0.003	.102	-0.003
L.fly_ppn_tna_intl	.012	-0.003	.102	-0.003
L.fly_public	.017	-0.008	.11	-0.011
L.n_launched	0	0.009	.091	0.008
L.n_closed	.004	0.005	.095	0.004
Obs	88,742		88,742	

A larger proportion of fund families perform persistently well over the long term than individual funds, which suggests that some families have a higher concentration of skilled funds. These skilled families may be better at creating conditions where fund managers outperform.

However the performance measure used to measure persistence - benchmark-adjusted returns - is quite noisy, due to luck or sampling error. After separating skill from luck, we find there are many families with positive benchmark-adjusted returns who are not truly skilled. The truly skilled families that do exist tend to cluster to the right of the performance distribution and have a t-statistic of alpha that is greater than 1. On the other hand, many truly unskilled fund families also exist - families with a t-statistic of alpha less than -2 have at least a 70% chance of being truly unskilled rather than just unlucky.

We find that family size does not convey much information about the performance of funds belonging to the family, once the endogenous relationship between fund size and fund performance is controlled for. The average expense ratio on the other hand is positively associated with family skill when skill is measured using as a fixed effects regression on gross benchmark adjusted returns. This suggests that acquiring and retaining skill in a family is costly. Also, families that have higher turnover in their portfolio of funds have higher skill measures - skilled families close more existing funds and launch more new funds, on average. Team management is also positively associated with skill.

Families that manage just one fund have slightly higher skill levels, and are less likely to be truly unskilled. There may be a self-selection explanation for this. As they are dependent on a unique source of revenues, these firms might engage in more effort to perform well. Many single-fund families are likely to be start-ups as they are smaller and younger than multi-fund families. Fund managers that select to start or join a single-fund family are likely to be confident that they have the skills to make it a success, otherwise they would be unlikely take this highly risky career step. Furthermore, team management has a highly positive impact on single-fund family skill, much more so than for multi-fund families. Thus it is possible that entire fund management teams may make the leap to start a new fund family and make it a success.

From an investor perspective however, the picture is bleak. Extremely few fund families are truly skilled when benchmark-adjusted net returns is the skill measure, and a high proportion of fund families are truly unskilled. While families with higher average family expense ratios have higher skill measured using gross returns, the opposite is true when skill is measured using net returns. One possible interpretation is that skilled fund families completely capture the gains from their skills.

While we go to some lengths to ensure that our results paint as precise a picture as possible of family skill, some caveats are required. To associate fund performance as closely as possible to family performance, we link each fund to the one family that it belonged to the longest during the sample period, and drop fund-months where the fund belonged to other families. This means that the sample size, in terms to total TNA of all funds in the sample, is much smaller than the total TNA of the mutual fund industry. Also, an extensive exercise was required to ensure funds were linked to the correct family, and while we believe most fund-family relationships in our sample are correct, there is still a small risk that some are misidentified either due to errors in the CRSP mutual fund database or in our own cleaning exercise.

We also ignore, for now, the effects of family flows. It would be reasonable to expect that more skilled fund families attract higher inflows into the funds that belong to the family. It would be interesting to explore how family flows and family skill interact. We leave this question to future research.

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AppendixA.

A. Variable Definitions

Table A1 Fund and Family Variable Defnitions

This table presents definitions of fund and family level variables used in this study. All variables are estimated monthly, except where specified otherwise.

gret	Fund gross return, that is, the fund's net return plus one twelfth of the fund's annual expense ratio
galpha	Fund gross alpha, estimated using Equation 3.2
exp_ratio_m	Fund expense ratio, that is, one twelfth of the fund's annual expense ratio
vwfgret	Family gross return, estimated as the average gross return (gret) of all funds in the family weighted by their TNA
vwfgalpha	Family gross alpha estimated as the average gross alpha (galpha) of all funds in the family weighted by their TNA, estimated using Equation 3.3
fly_ptna	Family TNA (in 2017 USD), estimated as the sum of the TNA (in 2017 USD) of each fund in the family. The adjustment to 2017 USD is done as follows: the fund's (unadjusted) TNA is first divided by the total value of all stocks in CRSP for that month, and then multiplied by the total value of all stocks in CRSP at the end of December 2017.
ind_size	Industry size, estimated as the sum of the unadjusted TNA of all active funds, divided by the total value of all stocks in CRSP
fly_ptna_av	Average monthly TNA (in 2017 USD) of all funds in the family
fly_exp_ratio_vwa	Average expense ratio for the family, estimated as the average monthly fund expense ratio weighted by fund TNA
fly_age	Family age in months, estimated as the age of the oldest fund in the family
fly_fund_age_av	Average age in months of all funds in the family
fly_total_fund_n	The number of actively managed US-focused equity funds, excluding funds-of-funds, closed-end, index tracking, international and offshore funds, and funds with less than than $15 million in TNA (in 2017 USD)
fly_idx_fund_n	The number of index funds in the family
fly_ppn_n_idx	The number of index funds in the family, expressed as a proportion of the the number of actively managed funds in the family (fly_total_fund_n)
fly_ppn_tna_idx	The TNA of index funds in the family, expressed as a proportion of the the TNA of actively managed funds in the family (fly_ptna)
fly_n_osource	The number of outsourced funds in the family. Outsourced funds are funds whose fund name is different from their advisor name.
fly_ppn_n_osource	The number of outsourced funds in the family, expressed as a proportion of the the number of actively managed funds in the family (fly_total_fund_n)
fly_ppn_tna_osource	The TNA of outsourced funds in the family, expressed as a proportion of the the TNA of actively managed funds in the family (fly_ptna)
fly_retail_fund_n	The number of retail funds in the family.
fly_ppn_n_retail	The number of retail funds in the family, expressed as a proportion of the the number of actively managed funds in the family (fly_total_fund_n)
fly_ppn_tna_retail	The TNA of retail funds in the family, expressed as a proportion of the the TNA of actively managed funds in the family (fly_ptna)
fly_inst_fund_n	The number of institutional funds in the family.
fly_ppn_n_inst	The number of institutional funds in the family, expressed as a proportion of the the number of actively managed funds in the family (fly_total_fund_n)
fly_ppn_tna_inst	The TNA of institutional funds in the family, expressed as a proportion of the the TNA of actively managed funds in the family (fly_ptna)
fly_team_fund_n	The number of team-managed funds in the family.
fly_ppn_n_team	The number of team-managed funds in the family, expressed as a proportion of the the number of actively managed funds in the family (fly_total_fund_n)
fly_ppn_tna_team	The TNA of team-managed funds in the family, expressed as a proportion of the the TNA of actively managed funds in the family (fly_ptna)
fly_intl_fund_n	The number of funds in the family that focus on international (non-US) stocks.
fly_ppn_n_intl	The number of international funds in the family, expressed as a proportion of the the number of actively managed funds in the family (fly_total_fund_n)
fly_ppn_tna_intl	The TNA of international funds in the family, expressed as a proportion of the the TNA of actively managed funds in the family (fly_ptna)
fly_public	Dummy variable equal to 1 if the family is publicly listed
n_launched	Number of new funds launched by the family in a year
n_closed	Number of funds terminated by the family in a year