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Is private equity performance persistence related to the skill of fund managers and which other factors may explain it?

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Abstract

Whether fund managers have skill in managing their portfolios, and whether this skill allows them to persistently generate superior returns for investors are crucial questions for investors' capital allocation decisions. In this thesis, we study performance persistence in private equity and investigate the relationship between skill and persistence, as well as look into other factors that may affect this relationship. We find that that there is persistence for the first follow-on fund, but it decreases drastically already from the second follow-on fund. When tested for the similarity of market conditions, it does not help to explain persistence. Therefore, short-term persistence may be attributed to the skill of general partners. The lack of long-term persistence may be explained by the decreasing returns to scale. This factor is especially strong in eroding performance persistence in venture capital funds, while the managers of buyout funds seem to have more scalable skills. Finally, persistence is stronger for worse performing funds. This, however, does not necessarily mean the lack of skill of good-performing managers. It can also mean that they are backed by sophisticated investors who make more informed capital allocation decisions and cause the flow of funds to decrease performance persistence due to the diseconomies of scale. Overall, the findings are not conclusive about the skill of fund managers due to the limitations of this work. However, they shed light on some important considerations for investors and provide grounds for further research.

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1. Introduction

The question of whether active management can outperform a passive benchmark has long been a key question in financial theory. Studies of a wide range of asset classes, including individual stocks, mutual funds, and hedge funds, generally find that returns are unpredictable and that investors cannot consistently outperform the market (Korteweg & Sorensen, 2014).

Private equity is a special asset class in the sense that active ownership of portfolio companies comes in a form of operational and capital improvements and turnarounds, and investments are illiquid and with a long horizon.

The private equity industry experienced tremendous growth over the last decades. Some reports and market studies show that PE has outperformed the public market. Looking at the 10-year period ending in June 2017, US buyout funds in aggregate returned 9.7% vs. a 7.9% return for the S&P 500 indexed using PME. Funds in developed Europe returned 8.7% vs. 3.6% for the MSCI Europe, and Asia-Pacific buyout and growth funds posted 10.5% vs. 4.5% for the MSCI AC Asia Pacific (Global Private Equity Report 2018, Bain & Company). Research also supports the idea that PE generates higher excess returns (Ljungqvist & Richardson, 2003; Kaplan and Schoar, 2005; Phalippou and Gottschalg, 2008; Lopez de Silanes, Phalippou & Gottschalg, 2011; Harris, Jenkinson & Kaplan, 2014).

Thus, PE has been of interest to institutional investors (henceforth also limited partners or LPs) and now it is not just a niche investment opportunity, but a common strategy. PE committed capital has been continuing to grow since 2012, and its CAGR is high relative to other market components, especially in buyout capital sector, with the 23%-CAGR over 2016-17 (Global Private Equity Report 2018, Bain & Company).

Nevertheless, there is evidence of a maturing industry and the decreasing ability of institutional investors to extract superior returns (Sensoy, Wang and Weisbach, 2014). Hence, questions of interest are why investors still see PE investments as an attractive opportunity, even despite these facts. Among the main reasons comes the fact that investors aim for the portfolio diversification and constantly try to improve the risk-reward characteristics of their investment portfolio. Another reason under consideration is that PE investments are an active investment strategy, which calls for a specialized skill set that is a key due diligence area for investors' assessment of a fund manager (henceforth also a general partner or GP).

The attractiveness of PE investments is due to the fact that general partners can beat the passive market benchmarks, and even generate these superior returns over certain periods. Identifying the feasible link between GPs' actions and the returns they generate, as well as the persistence of those returns, might offer a better understanding of the benefits of active investment strategy. With this in mind, we propose the following research question:

Is private equity performance persistence related to the skill of fund managers and which other factors may explain it?

To answer this question, we use fund-level data such as vintage year, funds' internal rates of return (henceforth IRRs) and multiples, funds' sizes and fund's number in the sequence provided by Preqin database (performance is reported net-of-fees). We deploy multivariate regression models to test for the persistence of returns by regressing the current fund's performance measure on the previous funds' performance controlling for the relevant factors. We also look at other factors, such as the flow of funds, the similarity of market conditions and the difference in persistence between good- and bad-performing funds, to interpret the results and link persistence to the skill of GPs.

Overall, our findings show that first, there is persistence for the first previous fund, and no persistence lasts for the second previous fund. Second, this persistence is potentially explained by the skill of GPs since the similarity of market conditions does not affect performance. We also find that persistence is partially deteriorated by the flow of funds. This effect is particularly strong for the venture capital funds, while the managers of the buyout funds seem to have a more scalable skill. Finally, the performance persistence is stronger for the bad-performing funds.

Our research makes the following main contributions: First, while previous research has focused on the funds raised before 2000 (Chung, 2012, Kaplan, Schoar, 2005), our study examines funds raised up to 2010. Since PE investments have been growing over the last decades, we investigate whether the additional capital inflows affected the performance of funds and its persistence. This is also interesting to look at since the amount of dry powder (committed capital) in the buyout funds drastically increased during the examined period and exceeded the dry powder in VC funds. Second, we improve the previous research by analyzing the performance persistence of PE teams, rather than PE firms, since some global PE firms raise funds with different geographical focus. Therefore, we analyze the performance of the PE firm within a particular country or part of the world, which helps us to better observe performance persistence. Third, while the previous studies mainly focused on either VC or Buyout funds, and just one of the performance measures, our research extensively covers both Buyout and VC funds, as well as IRRs and Multiples both taken as the performance measures to be able to obtain better results and analyze the differences of performance of different categories of funds. Fourth, unlike the previous researches based only on the latest fund and the several previous funds, we use all combinations of successive funds allowing us to increase the sample size. Finally, we combine different approaches for analyzing determinants of performance persistence to obtain a comprehensive picture and draw the links between them.

The paper is organized as follows.

In Section 2 we review the existing literature and theory connected to the research topic.

In Section 3 we describe the data we are using.

In Section 4 we develop the hypotheses to investigate.

In Section 5 we discuss the empirical methodology, describe the main analysis and report the results.

In Section 6 we discuss our main results and make conclusions and potential recommendations based on those.

2. Literature review and theory

This section is structured as follows: We first review the literature, where we will begin with the performance of portfolio managers in general and how they can outperform the market, proceeding with the persistence of their performance. Next, we will move on to discussing the major economic and financial theories, which explain the market and investors' behavior concerning investments in private equity.

2.1 Literature review

In a broad context, the analysis of the performance of portfolio managers started in 1986 with Jensen, who studied excess performance and persistence of mutual funds and found little evidence that active management can beat the passive benchmark. Since then, a lot of studies focused on the analysis of the extent to which the public market can be beaten and how long does the persistence of the excess returns last.

Grinblatt, Titman (1992) analyzed mutual funds and found evidence that differences in performance between funds persist over time and that this persistence is consistent with the ability of fund managers to earn abnormal returns. On the contrary, Elton, Gruber & Blake (1996) proved that if the risk is taken into account, then post expenses, mutual fund managers on average underperform a combination of passive portfolios of similar risk. They also proved that for all the studies having found that managers or a subset of managers with a common objective (such as growth) outperform passive portfolios, most, if not all, would reach opposite conclusions when survivorship bias and/or correct adjustment for risk are taken into account. Malkiel (1995) also finds that mutual fund managers tend to underperform the public market, even though the persistence of returns is found for some of the time periods.

As far as private equity is concerned, there are the same two major underlying issues of investing in it. Can active management outperform the public benchmark? Is there persistence in the PE returns? Academics have been looking for proof if the public benchmark can be beaten and whether this can be done consistently. As discussed in the introduction, the fact of PE outperformance is rather controversial; some studies suggest that many private equity investments do not outperform public market benchmarks (Kaplan, Schoar, 2005; Phalippou, Gottshalg, 2008), while some others prove that on a net basis PE beats the public market (Harris, Jenkinson & Kaplan, 2014; Robinson, Sensoy, 2016; Axelson, Sorensen & Strömberg 2013). The fact that the results are mixed is also due to the fact of existing higher leverage and illiquidity in PE transactions (Fang, Ivashina & Lerner, 2015). Another reason concerns the quality and the coverage of different private equity databases. Academics and investors are also interested in the fact of the persistence of performance, either good or bad, as still PE investments are seen as one of the good ways to diversify their investment portfolios.

Kaplan and Schoar (2005) were the first to use persistence tests to identify skill of GPs. They find persistence for up to two funds due to the skill of GPs. They ascribe this persistence to the differential and proprietary skills of funds' general partners. Phalippou (2010) finds that there is ex-ante performance persistence for below-median funds but not for above-median funds. Whether or not an ex-ante measure is used, the persistence is largely due to unsophisticated investors. When investors are sophisticated, the performance of earlier funds, sequence and fund size do not help predict the performance of the focal fund.

Chung (2012) shows that there is persistence for the 1st previous fund, and no persistence for 2nd and 3rd fund. Moreover, this study shows that this persistence is explained by the common market conditions for the two consecutive funds and length of the overlapping investment period, while GP proprietary skills do not matter. Braun, Jenkinson & Stoff (2017) claim that the persistence of fund managers has substantially declined as the private equity sector has matured and become more competitive. Private equity has, therefore, confirmed to the pattern found in most other asset classes in which past performance is a poor predictor of the future. They found proof in the data of no persistence of PE performance after 1999. Hochberg, Ljungqvist & Vissing-Jørgensen (2014) find that persistence in PE performance is due to the high bargaining power of LPs in negotiating the terms of follow-up fund investments with GPs, whenever GP has the skill, net of GP fee high LP returns in a first fund predict high LP returns in a follow-on fund. Harris, Jenkinson & Kaplan (2014) show that for the VC funds, performance is persistent in both pre- and post-

2000, while for buyout funds, there is no persistence in post-2000. Korteweg and Sorensen (2017) suggest that there is long-term persistence of GPs' returns and LPs can earn superior returns by investing in these managers. They use variance decomposition model, which allows distinguishing between skill and luck and study long-term persistence. Taking the LP's perspective, performance persistence has three components. First, long-term persistence refers to the possibility that some PE firms generate consistently higher (or lower) expected returns (net of fees). LPs can outperform by investing in these skilled PE firms with high expected returns. Second, investable persistence reflects the difficulty of identifying the PE firms with higher expected returns. When performance is noisy, top quartile past performance could be due to luck and does not necessarily predict future top quartile performance. This noise makes it difficult for LPs to identify skilled PE firms, implying low investable persistence. The third component, spurious persistence, arises from the partial overlap of consecutive funds that are managed by the same PE firm. Partially overlapping funds are exposed to the same market conditions during the overlap period. They find that past performance is a noisy measure of GP skill and LPs would need to obtain comprehensive data to spot skilled GPs.

Another part of research relates to studying flow-performance relationship, starting by Berk and Green (2004) who explained the anomalies observed in investors' behavior and derived a model for mutual funds. They found that fund flows rationally respond to past performance even though performance is not persistent and active managers do not outperform passive benchmark on average. Fund managers are skilled but face decreasing returns to scale, and due to the competitive provision of capital from investors, the ability of managers to generate abnormal returns is competed away. As a result, mutual fund managers capture the return from their skill in the form of increased fees. For PE, Kaplan and Schoar (2005) concluded that fund managers voluntarily restrict the size of the fund.

Further research attempted to rationalize this behavior. Marquez, Nanda and Yavuz (2010) showed that managers leave some money on the table and decide not to increase the fund size to the extent that Berk and Green (2004) equilibrium would predict due to the special nature of PE investments, in particular, the need to match skilled fund managers and quality targets. Therefore, GPs need to manipulate entrepreneurs' beliefs about their ability to create value by not increasing fees/limiting the fund size. However, it should be noted that this holds true only for VC funds, whereas managers of LBO funds do prefer to increase fund size.

Axelson, Strömberg, and Weisbach (2009) suggest that due to the fee structure, in particular, carried interest component that is based on performance, managers are penalized for scarifying returns for size. Also, Hochberg, Ljungqvist, and Vissing-Jørgensen (2014) present a model and evidence suggesting that LP rents stem in part from incumbent LPs' ability to hold up the GP given their superior soft information during fundraising periods.

2.2 Theories applied

In order to generate sharp, empirically testable implications, we assume that markets are highly competitive and arbitrage-free. We also employ other theories on the mechanism and the relationships in private equity, such as active management, delegated asset management, agency theory, and the theory of contracts.

A *competitive market* is a market where no systematic arbitrage opportunities exist. The *no-arbitrage condition* implies that it is impossible to consistently outperform the market without taking on more risk. PE as an asset class challenges this theory since it attracts investors exactly with its ability to beat the market and generate better returns. However, due to the competitiveness of the market, it is impossible for PE to outperform the market consistently.

Here comes also the theory of *active management*, as the GPs are the ones that manage the PE funds that beat the passive benchmarks. The evidence is rather contradictory. On one hand, some studies prove that due to the active management, mutual funds and private equity funds are able to beat the public market benchmarks (Grinblatt, Titman, 1992; Harris, Jenkinson & Kaplan, 2014; Robinson, Sensoy, 2016; Axelson, Sorensen & Strömberg, 2013). On the other hand, there also exists evidence that if one accounts for the risk, then active management consistently underperforms (Elton, Gruber & Blake, 1996; Malkiel, 1995; Kaplan, Schoar, 2005; Phalippou, Gottshalg, 2008). Even in case of outperformance, the concern comes in the persistence of these high returns, as it has been shown by Berk and Green (2004), the performance of funds is not persistent and investments with active managers do not outperform passive benchmarks on average.

Delegated asset management theory is related to the fact that LPs make investments in GPs, and GPs are the ones that manage the funds. Thus, the LPs are not the ones to manage their investments, but they invest in the funds that need to meet the objective and risk level set by the institutional investors. Along with the delegated asset management comes the principal-agent problem of the *agency theory*. Fund managers (“agents”) are able to make decisions and take actions on behalf of the institutional investors (“principals”). Higher fees earned by GPs lead to lower returns earned by LPs, there is a conflict of interests, as the two parties have the main objective of maximizing their return, but the maximized return (fee) of one party does not mean the maximized return of another. GPs are motivated to act in their own interests, which are contrary to those of their principles, which causes a *moral hazard*. On the one hand, the research by Robinson and Sensoy (2016) argues that there is no conflicting relationship between the returns of LPs and GPs, thus it might prove that there is no principal-agent problem in that sense, though there is still a potential conflict of interest originating from the *information asymmetry*. On the other hand, some findings suggest that with the increase of the fund size, which is in the best interests of the GPs, the returns of LPs are deteriorated, which indicates the presence of the moral hazard.

3. Description of the data

We are using performance data obtained from Preqin database, comprising of venture capital and buyout funds raised between the years 1990 and 2010. The data includes firms' and funds' ID, vintage year, fund size, primary geographic focus and performance measures IRRs and multiples (performance reported net-of-fees). To make our research more extensive, we further divide private equity firms into private equity teams, as some firms have subsequent funds in different parts of the world. In such case, analysis of persistence between two funds, one, for instance, in Japan, and the next one in the US does not make much sense due to the different markets and the different teams within the PE firm working for those funds.

The initial sample consists of 2584 funds, including 1262 venture capital and 1322 buyout funds. We chose to include both liquidated and closed funds based on the industry expert's opinion for the following reasons. Firstly, valuation reported by fund managers in Preqin prior to liquidation date is conservative. Secondly, the fraction of the remaining non-liquidated value close to the liquidation date is insignificant. Therefore, our sample includes 1314 liquidated and 1270 closed funds.

For the purpose of analyzing persistence, we restrict the funds to have at least one (two) subsequent fund(s), depending on the specification of the regression used. Among those, there are 1155 funds that have IRR measure for the first previous fund (641 buyout, 514 VC) and 609 funds with an IRR for the second previous fund (336 buyout, 273 VC). 1345 among all funds have multiple measures for one subsequent fund (723 buyout, 622 VC) and 751 funds with multiple measures for the two subsequent funds (400 buyout, 351 VC).

Descriptive statistics is reported in Tables 1-3. Looking at the funds by the vintage year (see Table 1), there are 1300 Buyout funds that report the final close size, with the average of 790m USD, and 1218 VC funds with the average size of 173.5m USD. 1199 and 1062 Buyout and VC funds respectively report their IRR figures, with the time series averages of 18.5% and 17.4% respectively. The IRR averages for the Buyout funds are not varying a lot, with the lowest being 8% and the highest one 28.8%, while for the VC funds the lowest yearly average is -2.5%

and the highest one is 54.25%. Multiples, on the contrary, have higher time series averages for VC funds – 2.258x, while for Buyout funds the figure is 1.941x.

Table 1. Summary statistics by vintage year

This table presents summary statistics of the funds by vintage year. The sample consists of Buyout and Venture Capital funds in Preqin database from 1990 to 2010. Columns 1 to 3 report the number of funds in the corresponding year. Columns 4 to 6 report the mean sizes (in million USD), IRRs and multiples in the given year. Panel A reports Buyout funds, Panel B reports VC funds

Panel A

	Buyout funds					
	# of funds			Mean		
Vintage	Size	IRR	Multiple	Size	IRR	Multiple
	(1)	(2)	(3)	(4)	(5)	(6)
1990	21	21	23	304.287	25.548	2.654
1991	10	10	10	209.090	28.830	2.491
1992	20	24	21	471.436	23.179	2.117
1993	15	16	16	293.101	28.130	2.464
1994	40	41	42	612.865	28.440	2.186
1995	36	35	37	474.545	18.194	1.807
1996	36	34	35	332.305	15.790	1.803
1997	55	53	57	693.441	10.725	1.542
1998	77	72	75	804.557	8.020	1.563
1999	82	75	77	701.616	12.710	1.705
2000	96	91	97	867.930	17.952	2.021
2001	55	54	56	766.045	26.340	2.097
2002	48	46	45	692.296	21.020	1.922
2003	56	49	54	903.752	23.463	1.882
2004	64	59	62	797.111	17.522	2.077
2005	116	102	116	1075.091	12.914	1.657
2006	133	119	128	1821.205	9.965	1.648
2007	131	114	129	1417.372	12.545	1.724
2008	99	91	97	1825.725	15.849	1.812
2009	55	42	54	863.666	16.886	1.790
2010	55	51	54	661.907	14.735	1.796
Total	1300	1199	1285	789.969	18.512	1.941

Panel B

Vintage	# of funds			Mean		
	Venture capital funds					
	Size	IRR	Multiple	Size	IRR	Multiple
	(1)	(2)	(3)	(4)	(5)	(6)
1990	25	22	27	78.140	18.554	2.266
1991	13	14	14	75.767	47.999	4.200
1992	25	26	30	94.422	21.818	2.717
1993	33	31	35	66.436	32.391	3.549
1994	32	31	36	78.753	30.609	4.043
1995	34	31	34	86.113	54.258	4.688
1996	39	35	42	129.013	34.539	3.025
1997	73	60	74	115.076	51.213	2.599
1998	71	61	70	141.198	17.272	1.499
1999	79	72	81	288.052	-0.691	1.076
2000	140	108	135	305.169	-0.374	1.085
2001	90	76	87	272.540	2.757	1.289
2002	52	43	52	144.198	4.985	1.266
2003	43	40	44	165.539	-2.527	1.224
2004	55	47	51	187.555	2.282	1.611
2005	75	63	74	177.432	4.066	1.515
2006	87	79	89	304.511	4.616	1.448
2007	95	82	93	215.544	8.505	1.664
2008	80	75	81	249.267	8.360	1.945
2009	33	31	36	297.638	10.916	1.524
2010	44	35	40	172.727	15.664	3.183
Total	1218	1062	1225	173.576	17.486	2.258

Industry-wise (see Table 2), the highest average IRR for the Buyout funds goes for Energy and Utilities – 37.6%, and the lowest one for the Materials – only 6.9%. The highest average multiple figure stands for the Information Technology industry – 2.502x, and the lowest one for the Materials, as well as IRR, – 1.510x. For the Venture Capital funds, Information technology industry has the highest IRR and multiple – 17.7% and 2.573 respectively. The lowest IRR of -14.4% corresponds to the Clean Technology industry, while the lowest multiple of 0.821x goes for the Industrials.

Table 2. Summary statistics by core industry

This table presents summary statistics of the funds by industry. The sample consists of Buyout and Venture Capital funds in Preqin database from 1990 to 2010. Columns 1 and 2 report the number of funds in the corresponding industry Columns 3 and 4 report the mean sizes, IRRs and multiples in the given industry Panel A reports Buyout funds, Panel B reports VC funds.

Panel A

	Buyout funds			
	# of funds		Mean	
Industry	IRR	Multiple	IRR	Multiple
	(1)	(2)	(3)	(4)
Business Services	31	33	12.679	1.705
Business Services, Diversified	-	-	-	-
Clean Technology	-	-	-	-
Consumer Discretionary	73	79	14.290	1.696
Diversified	866	939	15.787	1.821
Energy and Utilities	8	10	37.608	2.084
Energy and Utilities, Clean Technology	-	-	-	-
Food and Agriculture	2	2	27.895	1.830
Healthcare	21	23	12.869	1.710
Healthcare, Information Technology	19	19	16.562	1.977
Industrials	83	83	15.699	1.935
Information Technology	26	27	35.397	2.502
Information Technology, Clean Technology	-	-	-	-
Information Technology, Telecoms, Media and Communications	24	24	16.935	1.704
Materials	3	3	6.980	1.510
Real Estate	4	4	15.633	1.613
Telecoms, Media and Communications	39	39	14.108	1.847

Panel B

	Venture capital funds			
	# of funds		Mean	
Industry	IRR	Multiple	IRR	Multiple
	(1)	(2)	(3)	(4)
Business Services	12	13	6.529	1.720
Business Services, Diversified	1	1	-2.600	0.880
Clean Technology	17	23	-14.412	0.879
Consumer Discretionary	13	13	13.050	2.076
Diversified	271	345	14.454	1.807

Energy and Utilities	14	15	-0.141	1.062
Energy and Utilities, Clean Technology	3	3	-0.467	0.963
Food and Agriculture	-	-	-	-
Healthcare	202	210	7.145	1.527
Healthcare, Information Technology	141	155	15.520	1.905
Industrials	7	9	-7.249	0.821
Information Technology	194	224	17.753	2.573
Information Technology, Clean Technology	2	2	9.810	2.000
Information Technology, Telecoms, Media and Communications	160	183	17.227	2.110
Materials	3	3	13.500	2.057
Real Estate	-	-	-	
Telecoms, Media and Communications	22	26	1.547	1.134

Overall, higher IRRs and Multiples correspond to the industry-focused funds, and only the average IRR of the VC funds is higher for the diversified funds than for the industry-focused (see Table 3).

Table 3. Summary statistics by core industry (focused vs diversified)

This table presents summary statistics of the funds by industry. The sample consists of Buyout and Venture Capital funds in Preqin database from 1990 to 2010. Columns 1 and 2 report the number of funds in the corresponding industry Columns 3 and 4 report the mean sizes, IRRs and multiples in the given industry Panel A reports Buyout funds, Panel B reports VC funds.

	Buyout funds			
	# of funds		Mean	
Industry	IRR	Multiple	IRR	Multiple
	(1)	(2)	(3)	(4)
Focused	333	347	16.941	15.375
Diversified	866	939	15.787	1.821
Total	1199	1286	16.364	8.598
	Venture capital funds			
	# of funds		Mean	
Industry	IRR	Multiple	IRR	Multiple
	(1)	(2)	(3)	(4)
Focused	791	881	12.481	7.271
Diversified	271	345	14.454	1.807
Total	1062	1226	13.467	4.539

4. Hypothesis development

We start the hypothesis development by repeating here our research question:

Is private equity performance persistence related to the skill of fund managers and which other factors may explain it?

To investigate this question, we draw on two primary streams of research: (1) persistence of GPs' performance, and (2) additional analysis determining the drivers of persistence if there is any.

The motivation for investigating these issues is as follows: our primary interest is to see whether GPs have the skill in managing funds. As discussed in Sections 1 and 2, private equity as an asset class has some unique features that attract LPs to invest in it. Even though active management is reported to beat the market benchmarks and generate superior returns on average, the question of primary attention for investors is whether GPs have differentiating skill that allows some of them to generate higher returns compared to other GPs. Since there is no direct indication of skill, a proxy or a factor model should be used to test it statistically. We use persistence as such proxy since it shows whether GPs are able to consistently generate higher returns. That, however, requires additional analysis to accurately interpret the results, which we will get back to later in this section.

Therefore, our first hypothesis is formulated as follows:

Hypothesis 1: GPs performance is persistent.

To build on this, we incorporate some of the ex-post performance measures (IRRs and multiples) and develop multivariate regression models, regressing these current fund's measures on the values for one and two preceding funds, including some control variables. More specifically, the methodology will be discussed further in the next section.

Next, as mentioned above, we need additional analysis to validate the results we get when testing Hypothesis 1. If the answer to the question "Is PE performance persistent?" is "Yes", the next question is "Does it indicate that GPs have the skill in managing investments?". We are attempting to answer this question by investigating some other factors, which may cause persistence but do not indicate skill. The similarity of market conditions and time overlap between two subsequent funds is such a factor. Thus, we are testing whether performance persists after controlling for these factors.

This way, our next hypotheses are formulated as follows:

Hypothesis 2.1: Similarity of market conditions explains performance persistence.

Hypothesis 2.2: Time overlap between subsequent funds explains performance persistence.

Regarding the first hypothesis, we are using committed capital to PE (dry powder) as a proxy for the measure of similarity of market conditions. We then use multivariate regressions to test whether performance persists after controlling for the similarity of market conditions. If the similarity of market conditions explains persistence, we expect persistence to decrease as the market conditions become dissimilar.

Regarding the second hypothesis, we divide the funds into subsamples based on the length of the spread between two subsequent funds. If the time overlap does explain persistence, we expect persistence to decrease or disappear with higher spreads (smaller overlap). On the contrary, if the performance persistence is explained by the proprietary skills of the fund managers, we expect persistence not to depend on the size of the spread.

On the other hand, if the answer to the question "Is PE performance persistent?" is "No", the next question is "Does it indicate that GPs do not have the skill in managing investments?". We are now looking into the factors that may deteriorate persistence but do not mean lack of skill. Following Berk and Green (2004) and Chung (2012), we investigate the effect of the flow of funds on performance and performance persistence. Decreasing returns to scale, if found, might explain why skilled GPs fail to generate consistent returns with increasing fund size.

Therefore, our next hypothesis is formulated as follows:

Hypothesis 3: Flow of funds deteriorates performance persistence.

We test hypothesis 3 by, firstly, including fund growth as a factor into the model for testing performance persistence. Secondly, we divide the teams into subsamples depending on how drastically they increased fund size and compare performance persistence.

Finally, we investigate whether it is good- or bad-performing funds that drive persistence. For this, we formulate the hypothesis:

Hypothesis 4: Good-performing funds drive performance persistence.

To validate the hypothesis, we use conditional probabilities and the multivariate regression analysis to scrutinize the magnitude of performance persistence in the subsamples of funds based on their quartile.

5. Empirical methodology, analysis, and results

5.1 PE performance persistence

In this section, we attempt to investigate whether there exists GPs performance persistence. First, to test for the performance persistence in PE, we are using (1) multivariate regressions, as in Kaplan and Schoar (2005), when an ex-post performance measure (IRR or multiple) of the current fund is regressed on the performance measures of the previous fund and the fund before the last.

Literature findings show that there is performance persistence for one previous fund for the VC funds and a little more than one for the buyout funds (Chung, 2012; Kaplan, Schoar, 2005). The other research also finds persistence of at least one previous fund, ascribing it to the different factors when aiming to give explanation to it (Phalippou, 2010; Braun, Jenkinson & Stoff, 2017; Hochberg, Ljungqvist & Vissing-Jørgensen, 2014; Harris, Jenkinson & Kaplan, 2014; Korteweg and Sorensen, 2017).

We estimate the following regression model, further applying it to the different samples and specifications:

$$Performance_{i,t} = \alpha + \beta Performance_{i,t-1} + \gamma Performance_{i,t-2} + \varphi'^{Z_{i,t}} + \varepsilon_{i,t} \quad (1)$$

where Z includes a list of control variables: the logarithm of the current fund size, sequence number of the current fund, dummy variables for each vintage year. If the coefficients β and γ are positive and significant, this would mean that the past performance is somewhat determining the future performance and thus it might mean that there is persistence in performance.

Results for the sample that includes all funds are reported in Table 4. Panel A includes the coefficient estimates based on IRRs and Panel B based on multiples.

Table 4. Cross-sectional regression of current fund performance on preceding fund performance for all funds

This table presents the coefficient estimates of the regression:

$Performance_{i,t} = \alpha + \beta Performance_{i,t-1} + \gamma Performance_{i,t-2} + \varphi' Z_{i,t} + \varepsilon_{i,t}$

Panel A reports performance measured by IRR and Panel B reports performance measured by multiple. Performance is measured either for 1 previous fund (columns 1-3) or 2 previous funds (columns 4-6). Z includes control variables: logarithm of the preceding fund's size, sequence number and dummy variables for each vintage year. In regressions 2, 3, 5 and 6 buyout dummy (equal to 1 if a fund is buyout and 0 if venture capital) is included and in the regression 3 and 6 the interaction of it with the performance variable is also included. Standard errors are reported in parentheses. Statistical significance at the 1%, 5% and 10% levels is denoted by ***, **, and *, respectively.

Panel A

Dependent variable:	IRR (t)					
Performance:	IRR (t-1)			IRR (t-2)		
	(1)	(2)	(3)	(4)	(5)	(6)
Performance (t-1)	0.139***	0.138***	0.151**	0.212***	0.208***	0.232***
	(0.049)	(0.049)	(0.062)	(0.063)	(0.063)	(0.078)
Performance (t-2)				-0.017	-0.015	-0.018
				(0.017)	(0.017)	(0.019)
log(Fund size) (t)	-0.166	-0.792	-0.832	1.312***	0.587	0.496
	(0.545)	(0.690)	(0.684)	(0.440)	(0.581)	(0.594)
Sequence (t)	-0.405	-0.230	-0.242	-0.439	-0.241	-0.268
	(0.314)	(0.329)	(0.331)	(0.428)	(0.460)	(0.474)
Buyout		3.558*	4.912**		4.109	5.932**
		(1.977)	(2.037)		(2.596)	(2.898)
Buyout* Performance (t-1)			-0.069			-0.135
			(0.078)			(0.112)
Buyout* Performance (t-2)						0.026
						(0.046)
Constant	26.549***	28.794***	28.661***	17.628	2.083	20.171
	(2.679)	(3.249)	(3.330)	(16.047)	(2.707)	(16.572)
Vintage F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1143	1143	1143	605	605	605
Adjusted R2	0.0923	0.0943	0.0945	0.124	0.126	0.127

Panel B						
Dependent variable:	Multiple (t)					
Performance:	Multiple (t-1)			Multiple (t-2)		
	(1)	(2)	(3)	(4)	(5)	(6)
Performance (t-1)	0.159***	0.160***	0.167***	0.129	0.130	0.131
	(0.042)	(0.041)	(0.048)	(0.090)	(0.089)	(0.097)
Performance (t-2)				0.011	0.014	0.010
				(0.025)	(0.025)	(0.025)
log(Fund size) (t)	-0.004	-0.018	-0.021	0.019	-0.016	-0.013
	(0.026)	(0.030)	(0.029)	(0.038)	(0.041)	(0.042)
Sequence (t)	-0.021*	-0.018	-0.020	-0.031**	-0.024*	-0.023*
	(0.011)	(0.013)	(0.013)	(0.012)	(0.013)	(0.013)
Buyout		0.081	0.286**		0.207***	0.047
		(0.105)	(0.126)		(0.080)	(0.214)
Buyout*			-0.102			0.005
Performance (t-1)			(0.077)			(0.113)
Buyout*						0.068
Performance (t-2)						(0.061)
Constant	1.641***	1.696***	1.696***	1.125***	1.250***	2.018**
	(0.559)	(0.564)	(0.560)	(0.204)	(0.218)	(0.793)
Vintage F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1329	1329	1329	743	743	743
Adjusted R2	0.074	0.143	0.143	0.132	0.135	0.134

According to the results determined by the basic specification of the regression, a one percent increase in the first previous fund's IRR (Multiple) is associated with a 13.9 (15.9) basis point increase in the IRR (Multiple) of the current fund for the whole sample of funds.

Columns (2) and (5) include the buyout dummy variable (1 if a fund is a buyout fund and 0 if it is a venture capital fund), and columns (3) and (6) include the interaction term between the buyout dummy variable and performance. This lets us see whether the effect of the past on the current performance is different between the buyout and venture capital funds. The regressions become as follows:

$$Performance_{i,t} = \alpha + \beta Performance_{i,t-1} + \gamma Buyout\ Dummy + \varphi'^{Z_{i,t}} + \varepsilon_{i,t} \quad (2)$$

$$Performance_{i,t} = \alpha + \beta Performance_{i,t-1} + \gamma Performance_{i,t-1} * Buyout\ Dummy + \delta Buyout\ Dummy + \varphi'^{Z_{i,t}} + \varepsilon_{i,t} \quad (3)$$

In the given regression specification, coefficient β is the estimate for the VC funds and γ is the incremental performance persistence for the Buyout funds compared with the VC funds. The coefficient for the IRR of the VC funds is 0.151 and the estimate is 0.082 (0.151-0.069) for the buyout funds, which shows that the persistence is driven mainly by the VC funds. If we analyze the results in Panel B, with the multiple being performance variable, we get an even better proof that the persistence is driven by the VC funds, as the coefficients for VC and buyout funds are respectively 0.167 and 0.065.

Columns (4) to (6) report the performance of the two preceding funds together. When IRR is taken for measurement, we observe strong and significant persistence of the first previous fund, with the coefficient estimate of 0.212 for all sample of funds. For the VC and buyout funds, the coefficients are respectively 0.232 and 0.097. However, when multiples are taken for the two previous funds, the performance persistence fades away as the coefficients lose their significance.

Next, we analyze the subsamples of VC and buyout funds separately (see Table 5). Columns (1) to (4) report the performance based on IRR, and columns (5) to (8) based on multiple.

Table 5. Regression of current fund performance on preceding fund performance for VC and Buyout funds separately

This table presents the coefficient estimates of the regression:

$Performance_{i,t} = \alpha + \beta Performance_{i,t-1} + \gamma Performance_{i,t-2} + \varphi' Z_{i,t} + \varepsilon_{i,t}$

Panel A reports performance measured by IRR and Panel B reports performance measured by multiple. Performance is measured either for 1 previous fund (columns 1-2) or 2 previous funds (columns 3-4). Z includes control variables: logarithm of the preceding fund’s size, sequence number and dummy variables for each vintage year. Columns 1 and 3 report estimates for VC funds, columns 2 and 4 for the buyout funds. Standard errors are reported in parentheses. Statistical significance at the 1%, 5% and 10% levels is denoted by ***, **, and *, respectively.

Panel A

Dependent variable:	IRR (t)			
Performance:	IRR (t-1)		IRR (t-2)	
	Venture	Buyout	Venture	Buyout
	(1)	(2)	(3)	(4)
Performance (t-1)	0.104	0.159***	0.206***	0.177***
	(0.065)	(0.059)	(0.075)	(0.061)
Performance (t-2)			-0.030	0.015
			(0.026)	(0.043)
log(Fund size) (t)	0.433	-1.156**	1.898**	-0.216
	(1.249)	(0.553)	(0.910)	(0.577)
Sequence (t)	-0.833	0.665	-1.041	0.931
	(0.545)	(0.516)	(0.710)	(0.673)
Constant	25.823***	50.175***	1.359	48.998***
	(5.793)	(4.086)	(4.527)	(3.385)
Vintage F.E.	Yes	Yes	Yes	Yes
Observations	505	638	268	337
Adjusted R2	0.171	0.165	0.181	0.152

Panel B

Dependent variable:	Multiple (t)			
Performance:	Multiple (t-1)		Multiple (t-2)	
	Venture	Buyout	Venture	Buyout
	(5)	(6)	(7)	(8)
Performance (t-1)	0.140***	0.195***	0.122	0.214***
	(0.026)	(0.039)	(0.092)	(0.043)
Performance (t-2)			0.019	0.076**
			(0.027)	(0.037)
log(Fund size) (t)	0.021	-0.043	-0.048	0.024***
	(0.056)	(0.026)	(0.073)	(0.026)
Sequence (t)	-0.029	0.003	-0.031*	0.002
	(0.022)	(0.016)	(0.017)	(0.021)
Constant	1.579***	1.735***	1.422***	1.486***
	(0.601)	(0.243)	(0.338)	(0.515)
Vintage F.E.	Yes	Yes	Yes	Yes
Observations	609	720	343	400
Adjusted R2	0.220	0.122	0.186	0.144

With this analysis, we also find proof that there is performance persistence for one previous fund and no performance persistence for the two previous funds.

These results are consistent with the results of Chung (2012), as well as Phalippou (2010) and Kaplan, Schoar (2005) in spite of the fact that we analyzed performance persistence taking the different variables measuring it.

The difference in results obtained when using IRRs and multiples potentially lies within the nature of these measures themselves. IRR reflects the compounded annual percentage every dollar earns during the period it is invested. Multiple is the amount of money an investor will actually receive by the end of the deal. The issue and difference in results occur because of the IRR measurement and its potential to be manipulated. With the use of leverage, and in particular, credit lines (also subscription line loans), fund managers are able to attract more money in the short run than through the capital calls. The use of credit facilities is completely legal for the fund managers, but the problem is being created, as the short-term cash-flows used for calculating IRR during the fund's life are inflated and the IRR figures are biased (Sherer, 2018; Puca, 2019).

5.2 Similarity of market conditions and time overlap

Since we found proof that performance persists for one previous fund, in this section, we analyze whether performance persistence could be explained by other factors than the skill of GPs. Some funds were raised within several years one after another when the same economic conditions were prevalent on the market. Therefore, it might be the case that performance persistence is not due to the talented managers, but simply due to the favorable conditions. In this section, we will follow approaches suggested by Chung (2012) and Phalippou (2010) to determine whether the market conditions and the good timing have anything to do with performance persistence.

5.2.1 Similarity of market conditions

Chung (2012) develops several non-exhaustive market condition variables that could affect funds' performance and performance persistence. These variables are chosen as proxies for the general condition of the economy.

1) The sum of all committed capital during three years surrounding the vintage year of a fund,

2) The GDP growth during a fund's life,

3) The S&P 500 stock returns over a fund's life,

4) The average default spreads, which is the difference in spread between triple-A and Baa-rated corporate bond yields.

The data we obtained from Preqin itself imposes some limitations on the research we can conduct. First, Preqin does not report the funds' liquidation dates, which is why it is impossible to use the measures of market conditions for the whole funds' lives. Therefore, the only measure possible to use is the sum of the committed capital (dry powder) during three years surrounding the vintage year of the fund. The second limitation of Preqin is that the amounts of dry powder are only reported starting from the year 2000. Thus, we are taking the subsample of our whole sample, including the funds with the vintages from 2000 to 2010 only to be able to test for the similarity of market conditions.

Chung (2012) finds that the overall evidence suggests that as the common economic conditions under which the successive funds are managed become more similar, there is more performance persistence in private equity funds.

Based on the market conditions measure (sum of dry powder for each of the 10 vintages), we construct the Market Similarity Measure, following Chung (2012):

$$MSM_{i,t} = abs\left[Market\ Condition_{i,t+1} - Market\ Condition_{i,t}\right] \qquad (4)$$

which is the absolute value of the difference in market conditions during a follow-on fund's life compared to what it is during a current fund's life. Regression is estimated:

$$Performance_{i,t} = \alpha + \beta Performance_{i,t-1} + \gamma MSM_{i,t} + \delta MSM_{i,t} * Performance_{i,t} + \varphi'^{Z_{i,t}} + \varepsilon_{i,t} \quad (5)$$

If the coefficient δ is negative, this would mean that with the increase of the dissimilarity of market conditions the performance persistence fades away and thus the persistence is actually explained mainly by the similarity of market conditions. Results are reported in Table 6.

Table 6. The effects of the similar market condition on the performance persistence

This table presents the coefficient estimates of the regression:

$Performance_{i,t} = \alpha + \beta\ Performance_{i,t-1} + \gamma MSM_{i,t} + \delta MSM_{i,t} * Performance_{i,t} + \varphi' Z_{i,t} + \varepsilon_{i,t}$

In columns 1 and 2 performance is measured by IRR and for columns 3 and 4 by multiple. Columns 1 and 3 report estimates for the VC funds and columns 2 and 4 for the buyout. MSM is the market similarity measure, calculated as the absolute difference of the sums of committed capital during the 3 years surrounding the fund's vintage year. Standard errors are reported in parentheses. Statistical significance at the 1%, 5% and 10% levels is denoted by ***, **, and *, respectively.

Dependent variable:	Performance (t)			
Performance:	IRR (t-1)		Multiple (t-1)	
	Venture	Buyout	Venture	Buyout
	(1)	(2)	(3)	(4)
Performance (t-1)	0.260**	0.005	0.052	0.050
	(0.112)	(0.012)	(0.067)	(0.044)
log(Fund size) (t)	0.161	-0.149	-0.042	-0.007
	(0.471)	(0.296)	(0.073)	(0.014)
Sequence (t)	0.006	0.171	-0.011	0.004
	(0.153)	(0.257)	(0.010)	(0.008)
MSM	-0.044***	-0.063***	-0.010***	-0.010***
	(0.014)	(0.007)	(0.001)	(0.0005)
MSM*Performance (t)	0.006***	0.004***	0.006***	0.006***
	(0.0004)	(0.0003)	(0.0008)	(0.0003)
Constant	6.847*	13.654***	1.972***	1.695***
	(3.710)	(2.810)	(0.568)	(0.132)
Observations	186	275	222	320
Adjusted R2	0.639	0.770	0.369	0.756

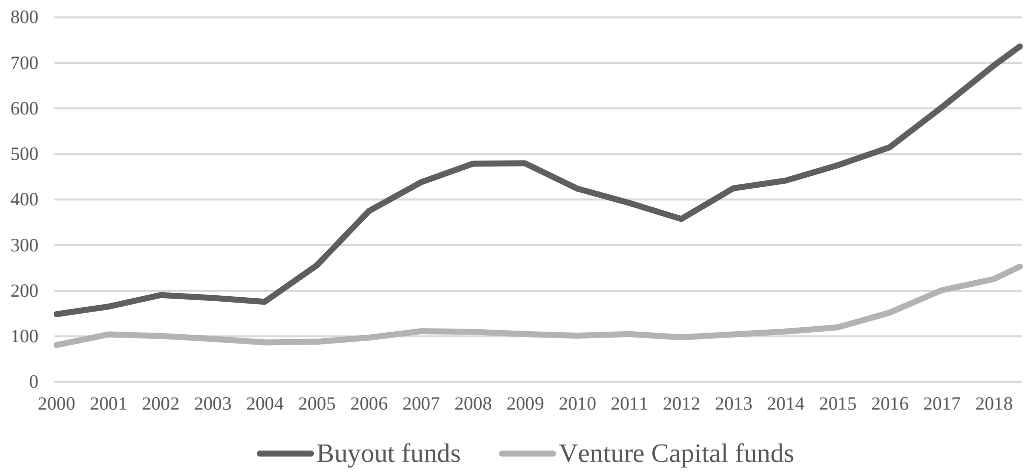
The estimates we get for the δ coefficient are very low, positive and significant, which means that with the increase of the dissimilarity of market conditions, the performance persistence increases and thus the persistence is not explained by the similarity of the market conditions, but by the other factors. Another fact that we find, is that the coefficient γ is negative and significant, which means that with the growth of the PE industry the performance persistence diminishes.

These findings are contradicting the results of Chung (2012), who found that the performance persistence was explained by the similarity of market conditions to a high extent. This might be so because of the sample we took, as Chung did not analyze the funds raised after the year 2000. In the period 2000 – 2010 the PE industry experienced very rapid growth, with the large amounts of committed capital coming in every year.

Another reason is that committed capital amount may not be the optimal measure to account for the similarity of market conditions. Instead of reflecting the changes in the state of the economy, it reflects the expectations of the investors regarding the future market conditions. Looking at Figure 1, we can clearly track the boom in the buyout industry with the huge inflows of capital. But these inflows continue up to the year 2008 and stay at the maximum value until 2011, instead of dropping immediately after to show the effect of the crisis. It may be explained by the fact of commitment, which implies that LPs' capital is tied up and they are obliged to provide it upon the capital call. It may also reflect the expectations of investors, who were betting on the buyout industry, and not the real economy growth. The expectations of investors could be different for the buyout industry and the real economy due to the two-fold nature of private equity investments, when GPs invest in portfolio companies and LPs invest in GP, hoping for abnormal returns generated by the utilization of the PE toolbox.

We applied several other regression specifications, including the dummy variables for the crisis years in an attempt to control for the effect of it, but it did not have an impact on the results we obtained. With all this in mind, the growth of real investments in the economy or the growth of GDP could be the better measures that would contain more real-time information about the state of the market.

Figure 1. Amounts of committed capital in the PE industry



Source: Preqin database

This also corresponds to the findings of Pastor, Stambaugh & Taylor (2014), who found similar results for the mutual funds' industry. According to them, as the size of the active mutual fund industry increases, a fund's ability to outperform public benchmarks declines and the fund's performance persistence deteriorates.

What is also important to notice is that the results are similar for the buyout and for the venture capital funds, even though the capital inflows (dry powder amounts) for the two industries have been different during the period under investigation, with the boom in the buyout and the stability in the VC industry. Further explanation of the reasons why this is the case can be found in Section 5.3.3.

5.2.2 Time overlap

Phalippou (2010) also looks into the similarity of market conditions, which might explain the performance persistence.

Unlike Chung (2012), Phalippou (2010) record the spread between the vintage years of each preceding fund and those of the focal fund and form groups (terciles) based on these spreads (overlaps). Following this approach, we construct 3 subsamples of funds:

- low spread: from 0 to 2 years between the two consecutive funds (high overlap),

- medium spread: from 3 to 5 years (intermediate overlap),

- high spread of more than 6 years (low overlap).

Phalippou (2010) shows that the highest performance persistence is found for the funds with the highest time overlap (lowest spread) and fades away for the funds with the lower overlap, which proves that it is the similarity of market conditions that determines performance, not the proprietary skill of the fund managers.

We then estimate the following regression for each of these subsamples separately:

$$Performance_{i,t} = \alpha + \beta Performance_{i,t-1} + \varphi'^{Z_{i,t}} + \varepsilon_{i,t} \quad (6)$$

Results are reported in Table 7. Panel A reports results based on the IRR as the dependent variable, and Panel B – based on multiple.

Table 7. Performance persistence for the funds with the low, medium and high spreads between the vintage years

This table presents the coefficient estimates of the regression:

$Performance_{i,t} = \alpha + \beta Performance_{i,t-1} + \varphi' Z_{i,t} + \varepsilon_{i,t}$

Panel A reports performance measured by IRR and Panel B reports performance measured by multiple. Performance is measured either for the funds with low spread (0-2 years, columns 7-9), medium (3-5 years, columns 4-6) and high (6 and more, columns 1-3). Z includes control variables: logarithm of the current fund's size, the sequence number of the fund and the dummy variables for each vintage year. Columns 2, 3, 5, 6, 8 and 9 include Buyout Dummy, which is equal to 1 for the buyout funds and 0 for Venture Capital. Columns 3, 6, 9 include an interaction term between the Buyout Dummy and past performance. Standard errors are reported in parentheses. Statistical significance at the 1%, 5% and 10% levels is denoted by ***, **, and *, respectively.

Panel A

Dependent variable:	IRR (t)								
	High spread			Medium spread			Low spread		
Performance:	(Low overlap)			(Intermediate overlap)			(High overlap)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Performance (t-1)	0.021	0.024	0.035	0.228	0.218	0.241	0.033	0.033	0.023
	(0.070)	(0.071)	(0.085)	(0.188)	(0.186)	(0.217)	(0.026)	(0.026)	(0.020)
log(Fund size) (t)	-2.815	-3.342	-3.353	1.108	-0.163	-0.377	0.739	0.731	0.504
	(2.317)	(2.451)	(2.439)	(1.008)	(1.219)	(1.207)	(1.234)	(1.353)	(1.336)
Sequence (t)	-1.136	-0.984	-0.983	-0.738	-0.329	-0.327	-0.519	-0.519	-0.058
	(0.798)	(0.891)	(0.890)	(0.538)	(0.451)	(0.449)	(1.177)	(1.169)	(1.178)
Buyout		3.114	4.306		7.865**	11.601***		0.048	-5.917
		(4.602)	(4.471)		(3.449)	(3.905)		(5.350)	(7.309)
Buyout* Performance (t-1)			-0.047			-0.186			0.312
			(0.099)			(0.220)			(0.209)
Constant	57.180***	56.888***	46.001**	78.257	84.468	83.278	2.951	11.427***	3.214
	(20.405)	(20.154)	(19.342)	(58.837)	(58.980)	(58.666)	(9.397)	(3.216)	(9.609)
Vintage F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	315	315	315	213	213	213	88	88	88
Adjusted R2	0.106	0.105	0.102	0.116	0.117	0.116	0.068	0.055	0.063

Panel B

Dependent variable:	Multiple (t)								
	High spread			Medium spread			Low spread		
Performance:	(Low overlap)			(Intermediate overlap)			(High overlap)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Performance (t-1)	0.276***	0.277***	0.401***	0.402***	0.400***	0.444***	0.024	0.024	0.012
	(0.088)	(0.084)	(0.106)	(0.111)	(0.111)	(0.117)	(0.026)	(0.026)	(0.021)
log(Fund size) (t)	-0.014	-0.019	-0.050	0.040	0.021	-0.003	0.072	0.048	0.043
	(0.057)	(0.077)	(0.073)	(0.044)	(0.050)	(0.048)	(0.057)	(0.070)	(0.068)
Sequence (t)	-0.047	-0.045	-0.061	-0.016	-0.010	-0.011	-0.097*	-0.095*	-0.085
	(0.050)	(0.056)	(0.061)	(0.018)	(0.018)	(0.017)	(0.053)	(0.053)	(0.052)
Buyout		0.030	1.269***		0.116	0.846***		0.152	-0.288
		(0.275)	(0.319)		(0.156)	(0.270)		(0.282)	(0.497)
Buyout* Performance (t-1)			-0.537			-0.361***			0.218
			(0.178)			(0.127)			(0.201)
Constant	2.226***	2.086***	2.626***	0.960	0.104	1.595**	1.572***	2.118***	2.122***
	(0.642)	(0.588)	(0.692)	(0.602)	(0.856)	(0.693)	(0.405)	(0.149)	(0.148)
Vintage F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	315	315	315	213	213	213	88	88	88
Adjusted R2	0.170	0.167	0.184	0.227	0.224	0.232	0.120	0.112	0.114

The results we get show that there is only some performance persistence for the funds with the intermediate overlap when IRR is taken as the performance variable, even though the coefficient estimates are not significant. When multiple is taken, the coefficients are significant for the funds with low and intermediate overlap, with the intermediate overlap showing better performance persistence.

The results we obtain do not confirm the results of Phalippou (2010). The possible explanations for this are:

- different samples, as Phalippou (2010) used funds raised from 1983 to 2003, while we took funds raised from 1990 to 2010

- different performance measures – we took IRRs and multiples, while Phalippou (2010) took PME (Public market equivalent)

- different databases – we used Preqin, not Venture economics. This might have had a big impact, as Harris, Jenkinson & Kaplan (2014), Stucke (2011), Chung (2012) found a systematic downward bias in the Venture economics data.

5.3 The flow of funds and performance persistence

In this section, we investigate whether the lack of persistence, in the long run, could be explained by the funds' inflow and diminishing returns to scale. We follow Chung (2012) and study the following three relationships: 1) the reaction of capital inflow to past performance; 2) effect of the flow of funds on the following fund's performance; 3) effect of the flow of funds on performance persistence.

These questions are of continuing interest both for academics and industry. Most investors see past performance as a useful (though not the only) criteria in making investment decisions. At the same time, LPs are worried that a drastic increase in a fund size erodes performance since the number of GPs managing the fund almost never grows proportionally. Therefore, many investors impose a cap on the fund size.

Literature documents capital chasing returns (Ippolito, 1992; Sirri and Tufano. 1998) and decreasing returns to scale (Chen, Hong, Huang, and Kubik, 2004) in mutual funds. Same trends are reported for PE. Chung, Sensoy, Stern, and Weisbach (2012) find a positive effect of past performance on the flow of funds in PE. Inspired by the model for mutual funds by Berk and Green (2004), they explain it by the rational learning model rather than behavioral alternatives of “naive reinvestment” or “return chasing”, when investors react to the past performance regardless of its informativeness. Kaplan and Schoar (2005) and Lopez de Silanes, Phalippou, and Gottschalg (2008) document diseconomies of scale in PE.

5.3.1 Capital chasing returns

We first study the effect of past performance on future fund growth. For that, we regress fund growth between two subsequent funds (between t-1 and t) on the performance of the previous fund (t-1). Control variables (Z) include the logarithm of the fund size and sequence number of the preceding fund (t-1).

$$Fund\ Growth_{i,t-1,t} = \alpha + \beta Performance_{i,t-1} + \varphi'^{Z_{i,t}} + \varepsilon_{i,t} \qquad (7)$$

Results are reported in Table 8. Columns (3) and (6) include the interaction term between the buyout dummy variable (1 if a fund is a buyout fund and 0 if it is a venture capital fund) and performance to see whether the effect of past performance on the fund growth is different between the buyout and venture capital funds.

Table 8. The effect of past performance on future fund growth

This table presents the coefficient estimates of the regression:

$Fund\ Growth_{i;t-1,t} = \alpha + \beta Performance_{i,t-1} + \varphi' Z_{i,t} + \varepsilon_{i,t}$

Performance is measured either by IRR (columns 1-3) or multiples (columns 4-6). *Fund growth (t-1,t)* denotes the fund growth between the first preceding to the current fund. *Z* includes control variables: logarithm of the preceding fund's size and the preceding fund's sequence number. In regressions 3 and 6 buyout dummy (equal to 1 if a fund is buyout and 0 if venture capital) is included and interacted with the performance variable. Standard errors are reported in parentheses. Statistical significance at the 1%, 5% and 10% levels is denoted by ***, **, and *, respectively.

Dependent variable:	Fund growth (t-1:t)					
Performance:	IRR (t-1)			Multiple (t-1)		
	Buyout	Venture	All	Buyout	Venture	All
	(1)	(2)	(3)	(4)	(5)	(6)
Performance (t-1)	0.006	0.004	0.004	0.232*	0.036	0.038
	(0.007)	(0.003)	(0.003)	(0.136)	(0.032)	(0.026)
Performance*						
Buyout			0.004			0.119
			(0.008)			(0.141)
Buyout			1.263***			1.149***
			(0.291)			(0.347)
log(Fund size) (t-1)	-0.866***	-0.895***	-0.872***	-0.850***	-0.910***	-0.839***
	(0.208)	(0.176)	(0.132)	(0.174)	(0.165)	(0.120)
Sequence (t-1)	0.506**	0.097	0.230*	0.418**	0.079	0.197*
	(0.247)	(0.089)	(0.136)	(0.192)	(0.077)	(0.115)
Constant	5.319***	5.031***	4.654***	5.071***	5.117***	4.487***
	(0.888)	(0.841)	(0.524)	(0.797)	(0.810)	(0.500)
Observations	630	498	1219	716	594	1328
Adjusted R2	0.15	0.196	0.155	0.159	0.172	0.152

The coefficient estimates for past performance are statistically insignificant, with an exception for buyout funds when using multiples as a performance measure. In this case, multiple of the previous fund has a significant and positive effect on follow-on fundraising. These results are consistent with Chung, Sensoy, Stern, and Weisbach (2012).

Another observation is that coefficients for buyout dummy variables are positive and statistically significant in both specifications, which is explained by a boom in buyout fundraising during years 2004-2010, while the committed capital for venture funds remained flat and much lower than for buyout, as seen in Figure 1.

5.3.2 Diminishing returns to scale

We next study the effect of fund growth on follow-on performance. For that, we regress current performance (t) on the fund growth between the current and preceding fund (between t-1 and t) and the performance of the previous fund (t-1). Control variables (Z) include the logarithm of the current fund size and sequence number (t).

$$Performance_{i,t} = \alpha + \beta Fund\ Growth_{i,t-1,t} + \gamma Performance_{i,t-1} + \varphi'^{Z_{i,t}} + \varepsilon_{i,t} \quad (8)$$

Results are shown in Table 9. Columns (3) and (6) include the interaction term between the buyout dummy variable (1 if a fund is a buyout fund and 0 if it is a venture capital fund) and fund growth to see if the effect of past fund growth on the current performance is different between buyout and venture capital funds.

Table 9. The effect of past fund growth on future performance

This table presents the coefficient estimates of the regression:

$Performance_{i,t} = \alpha + \beta Fund\ Growth_{i;t-1,t} + \gamma Performance_{i,t-1} + \varphi' Z_{i,t} + \varepsilon_{i,t}$

Performance is measured either by IRR (columns 1-3) or multiples (columns 4-6). *Fund growth (t-1,t)* denotes the fund growth between the first preceding to the current fund. *Z* includes control variables: logarithm of the current fund's size and the current fund's sequence number. In regressions 3 and 6 buyout dummy (equal to 1 if a fund is buyout and 0 if venture capital) is included and interacted with the performance variable. Standard errors are reported in parentheses. Statistical significance at the 1%, 5% and 10% levels is denoted by ***, **, and *, respectively.

Dependent variable:	IRR (t)			Multiple (t)		
	Buyout	Venture	All	Buyout	Venture	All
	(1)	(2)	(3)	(4)	(5)	(6)
Fund growth (t-1:t)	0.022	-1.439***	-1.393***	-0.001	-0.073***	-0.073***
	(0.262)	(0.519)	(0.486)	0.013	(0.023)	(0.023)
Fund growth*Buyout			1.445***			0.074***
			(0.533)			(0.025)
Buyout			2.965			0.061
			(2.628)			(0.116)
Performance (t-1)	0.174***	0.164**	0.167***	0.216***	0.169***	0.173***
	(0.052)	(0.078)	(0.066)	(0.048)	(0.063)	(0.058)
log(Fund size) (t)	-2.047***	-1.110	-1.489***	-0.061**	-0.042	-0.047*
	(0.656)	(1.174)	(0.604)	(0.030)	(0.057)	(0.029)
Sequence (t)	0.832	-1.216*	-0.455	0.010	-0.058**	-0.034*
	(0.610)	(0.673)	(0.424)	(0.019)	(0.029)	-0.020
Constant	22.141***	20.399***	19.672***	1.737***	1.867***	1.800***
	(4.109)	(7.696)	(4.307)	(0.240)	(0.357)	(0.225)
Observations	628	496	1124	716	601	1317
Adjusted R2	0.061	0.044	0.049	0.061	0.051	0.053

Overall, fund growth has a negative effect on follow-on performance, though it is statistically significant only for venture capital funds. The difference in this effect between the buyout and venture capital funds is statistically significant, indicating that the performance of venture capital funds suffers more from the inflow of capital. The results can be interpreted in a way that managers of buyout funds have a more scalable skill compared to the mangers of venture funds and that the buyout industry is more capital-intensive (Chung, 2012).

5.3.3 The effect of the flow of funds on performance persistence

Finally, we study the effect of fund growth on performance persistence. For that, we regress current performance (t) on the fund growth between the current and preceding fund (between t-1 and t), the performance of the previous fund (t-1) and the interaction term between these two variables. Control variables (Z) include the logarithm of the current fund size and sequence number (t), as well as dummy variables for the vintage year.

$$Performance_{i,t} = \alpha + \beta Fund\ Growth_{i,t-1,t} + \gamma Performance_{i,t-1} + \delta Fund\ Growth_{i,t-1,t} * Performance_{i,t-1} + \varphi' Z_{i,t} + \varepsilon_{i,t} \quad (9)$$

Results are shown in Table 10. Columns (3) and (6) include the interaction term between the buyout dummy (1 if a fund is a buyout fund and 0 if it is a venture capital fund) and fund growth, between the buyout dummy and fund growth, and a triple interaction between buyout dummy, performance and fund growth.

Table 10. The effects of fund growth on performance persistence

This table presents the coefficient estimates of the regression: $Performance_{i,t} = \alpha + \beta Fund\ Growth_{i;t-1,t} + \gamma Performance_{i,t-1} + \delta Fund\ Growth_{i,t-1,t} * Performance_{i,t-1} + \varphi' Z_{i,t} + \varepsilon_{i,t}$. Performance is measured either by IRR (columns 1-3) or multiples (columns 4-6). *Fund growth (t-1,t)* denotes the fund growth between the first preceding to the current fund. *Z* includes control variables: logarithm of the current fund's size and the current fund's sequence number, as well as dummy variables for vintage years. In regressions 3 and 6 buyout dummy (equal to 1 if a fund is buyout and 0 if venture capital) is included and interacted with the performance variable. The triple interactions of *Performance, Fund Growth,* and *Buyout dummy* variables are included in regressions (3) and (6). Standard errors are reported in parentheses. Statistical significance at the 1%, 5% and 10% levels is denoted by ***, **, and *, respectively.

	IRR (t)			Multiple (t)		
	Buyout	Venture	All	Buyout	Venture	All
	(1)	(2)	(3)	(4)	(5)	(6)
Performance (t-1)	3.182***	9.107*	8.356**	0.157***	0.542**	0.462***
	(1.002)	(4.792)	(3.396)	(0.043)	(0.226)	(0.168)
Fund growth (t-1:t)	-0.037	-1.955*	-2.295**	-0.075*	-0.047	-0.032
	(0.730)	(1.092)	(1.116)	(0.045)	(0.059)	(0.059)
Performance* Fund growth	0.709	-6.123**	-4.859**	0.091	-0.242*	-0.263*
	(0.987)	(3.035)	(2.172)	(0.058)	(0.151)	(0.140)
Buyout			4.179*			0.269
			(2.226)			(0.175)
Performance*Buyout			-2.367			-0.168
			(1.889)			(0.116)
Fund growth*Buyout			1.666*			-0.042
			(1.030)			(0.059)
Performance* Fund growth*Buyout			2.490**			0.242***
			(1.166)			(0.094)
log(Fund size) (t)	-1.260**	0.96477	-0.626	-0.039	0.046	-0.007
	(0.587)	(1.167)	(0.589)	(0.028)	(0.057)	(0.030)
Sequence (t)	0.780	-1.062***	-0.327	0.005	-0.038**	-0.026**
	(0.610)	(0.401)	(0.335)	(0.018)	(0.017)	(0.013)
Constant	52.688***	22.479***	26.685***	3.495***	1.688***	1.765***
	(3.015)	(5.699)	(3.940)	(0.170)	(0.570)	(0.499)
Vintage F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	628	496	1124	716	601	1317
Adjusted R2	0.182	0.187	0.115	0.138	0.226	0.154

The results show that the coefficient estimate of the interaction term between performance and fund growth is negative and statistically significant for venture capital funds, while it is not significant for buyout funds. It means that the performance persistence of venture capital decreases with the flow of funds. The coefficient estimate for the triple interaction term is positive and statistically significant, meaning that the effect of fund flows on performance persistence is stronger for venture capital funds. These results are consistent with the ones from Table 9, where performance is negatively related to fund growth for venture capital funds and is not affected by it for buyout funds.

These findings help to explain the results obtained in Section 5.2.1, where we found similar results for the effect of similarity of market conditions (using committed capital as a proxy) on venture capital and buyout funds. Despite the boom in the buyout industry during 2000-2010, performance persistence of the buyout industry did not deteriorate as expected.

Overall, the findings from this section suggest that there is a capital chasing returns pattern for buyout funds. Performance deteriorates with the flows of funds in venture capital, while this is not true for buyout funds. Performance persistence also decreases with capital inflows for venture capital. These results indicate that diminishing returns to scale could be a reason for lack of long-term persistence, especially for VC. In addition, the skill of venture capital managers is not as scalable as one of the buyout managers.

We further study the effect of fund growth on performance persistence by measuring performance persistence for three groups of funds: 1) funds that did not increase the fund size (fund growth is less than 0%), 2) funds that increased the fund size relatively moderately (fund growth is between 0% and 100%) and 3) funds that drastically increased the fund size (fund growth is more ta 100%). The three groups were chosen based on the distribution of fund growth level (Figures A and B in Appendix), so that the sample sizes are approximately equal for (2) and (3).

For each group, we regress current performance (t) on the performance of the previous fund (t-1). Control variables (Z) include the logarithm of the current fund size and sequence number (t), as well as dummy variables for the vintage year.

$$Performance_{i,t} = \alpha + \beta Performance_{i,t-1} + \varphi'^{Z_{i,t}} + \varepsilon_{i,t} \qquad (10)$$

Results are reported in Table 11.

Table 11. Performance persistence of subsamples of funds based on fund growth
This table presents the coefficient estimates of the regression:
$Performance_{i,t} = \alpha + \beta Performance_{i,t-1} + \varphi' Z_{i,t} + \varepsilon_{i,t}$
Panel A reports performance measured by IRR and Panel B reports performance measured by multiple. Performance is measured either for the funds that decreased the fund size (fund growth from t-1 to t is less than 0%, columns 1-2), increased relatively moderately (fund growth from t-1 to t is between 0% and 100%, columns 3-4) or increased drastically (fund growth from t-1 to t is more than 100%, columns 5-6). Z includes control variables: logarithm of the current fund's size, the sequence number of the fund and the dummy variables for each vintage year. Standard errors are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A

Dependent variable:	IRR (t)					
	Fund growth <0%		Fund growth 0-100%		Fund growth >100%	
	Venture	Buyout	Venture	Buyout	Venture	Buyout
	(1)	(2)	(3)	(4)	(5)	(6)
Performance (t-1)	-0.270*	0.345**	0.284***	0.202***	0.014	0.146**
	(0.151)	(0.157)	(0.105)	(0.070)	(0.031)	(0.062)
log(Fund size) (t)	-2.969	-0.223	3.215**	-1.744*	0.961	-0.695
	(2.417)	(1.247)	(1.634)	(0.961)	(1.893)	(0.911)
Sequence (t)	-0.228	0.212	-0.685	1.325	-1.652	0.677
	(0.768)	(1.232)	(0.477)	(0.969)	(1.439)	(0.843)
Constant	47.954***	-1.512	-7.861	76.962***	12.814	48.725***
	(12.559)	(16.282)	(7.353)	(5.380)	(20.965)	(4.809)
Vintage F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	126	102	217	264	150	259
Adjusted R2	0.145	0.253	0.258	0.260	0.180	0.169

Panel B

Dependent variable:	Multiple (t)					
Performance:	Fund growth <0%		Fund growth 0-100%		Fund growth >100%	
	Venture	Buyout	Venture	Buyout	Venture	Buyout
	(1)	(2)	(3)	(4)	(5)	(6)
Performance (t-1)	-0.077	0.183	0.197**	0.213***	0.015	0.230***
	(0.112)	(0.130)	(0.087)	(0.049)	(0.016)	(0.047)
log(Fund size) (t)	0.001	-0.137*	0.046	0.006	0.091	-0.015
	(0.081)	(0.071)	(0.123)	(0.034)	(0.078)	(0.044)
Sequence (t)	-0.021	-0.013	-0.029	-0.018	-0.068	0.013
	(0.041)	(0.054)	(0.027)	(0.026)	(0.053)	(0.022)
Constant	3.045**	5.161***	0.624	3.719***	1.013**	2.881***
	(1.424)	(0.526)	(0.580)	(0.679)	(0.409)	(0.218)
Vintage F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	164	124	256	295	181	293
Adjusted R2	0.016	0.136	0.256	0.154	0.164	0.174

The results confirm the findings from the first part of this section that performance persistence of venture capital funds deteriorates due to the flow of funds, while for buyout it does not. Both using IRR (Panel A) and multiple

(Panel B), the coefficient estimates for the performance of the previous fund (t-1) are positive and statistically significant for the buyout and venture teams that increased fund size by less than 100% (columns 3-4). For the teams that more than doubled the fund size, performance persistence remains only for buyout funds (column 6), while for venture capital funds it does not (the coefficient estimates for the performance of the previous fund becomes insignificant) (column 5). It can also be seen from the descriptive statistics (Table 12) – while there is no big difference in the means and medians of performance measures between the 3 groups for buyout funds, for venture capital mean (median) IRR drops from 18.9% (6.6%) to 3.4% (1.1%) and mean (median) multiple drops from 2.6 (1.4) to 1.2 (1.0) when the fund growth exceeds 100%. For the teams that decreased fund size the results are not conclusive.

Table 12. Summary statistics by fund growth
This table presents summary statistics of the funds by fund growth. The sample consists of Buyout and Venture Capital funds in Preqin database from 1990 to 2010. Columns 1 and 2 report the number of funds in the corresponding group based on fund growth between t-1 and t. Columns 3 and 4 report the means of IRRs and multiples in the given group, and columns 5 and 6 - medians. Panel A reports Buyout funds, Panel B reports VC funds.

Panel A

	Buyout					
	# of funds		Mean		Median	
Fund growth	IRR	Multiple	IRR	Multiple	IRR	Multiple
	(1)	(2)	(3)	(4)	(5)	(6)
<0%	102	124	15.415	1.866	13.070	1.720
0-100%	264	295	15.301	1.795	12.850	1.730
>100%	259	293	14.424	1.768	13.030	1.690
Total	625	712				

Panel B

	Venture capital					
	# of funds		Mean		Median	
Fund growth	IRR	Multiple	IRR	Multiple	IRR	Multiple
	(1)	(2)	(3)	(4)	(5)	(6)
<0%	126	164	10.798	1.520	6.560	1.335
0-100%	217	256	18.941	2.257	6.610	1.385
>100%	150	181	3.377	1.193	1.125	1.010
Total	493	601				

5.4 Performance persistence of good- and bad-performing funds

This section aims to further understand the question explored in Section 5.1 – whether past performance is an indication of future performance (performance persistence), as well as investigate whether it is good or bad performing funds that drive performance persistence.

5.4.1 Transitional probabilities

Table 13 reports transitional probabilities, meaning conditional probabilities that a team's follow-on fund will either stay in the same quartile as the current fund or that it will move into one of the other three quartiles. Performance quartiles are reported by Preqin. Each fund is put into a benchmark group based on vintage year, fund strategy and region focus. Quartile rankings are then assigned within these benchmark groups based on net multiples and net IRRs. The sum of probabilities is 100% across each row of the table. Transitional probabilities are calculated both for the first and second follow-on funds to examine whether persistence remains and to what extent it shrinks after the first follow-on fund.

Table 13. Transitional (conditional) probabilities from current performance quartiles to follow-on performance quartiles

Current funds are divided into four quartiles based on performance (1 denoting the top quartile and 4 denoting the bottom quartile). Conditional probabilities that a team's first and second follow-on funds will either stay in the same quartile or move in one of the other three quartiles are calculated. Expected probabilities (as if the transition is independent) are also calculated based on the current distribution of funds. Panel A reports results for buyout funds, Panel B for venture capital. Rows 1 to 4 are the quartile portfolios formed on the basis of current performance. Columns 1 to 4 are the quartile portfolios of the follow-on funds. *# funds* denotes the number of funds in each portfolio. $\chi 2$ reports Chi-square statistics of testing the hypothesis of independence of the transition (no relationship between the current and follow-on performance). Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Panel A. Buyout funds

		Conditional probabilities					
		Quartile of the first follow-up fund					
		1	2	3	4	# funds	χ2
	# funds	193	207	177	172	749	56.23***
Quartile of the current fund	1	36.7%	29.7%	18.3%	15.3%	229	
	2	27.7%	31.4%	21.8%	19.1%	220	
	3	16.9%	26.6%	29.9%	26.6%	177	
	4	14.6%	18.7%	27.6%	39.0%	123	
		Expected probabilities					
		Quartile of the first follow-up fund					
		1	2	3	4	# funds	
	# funds	193	207	177	172	749	
Quartile of the current fund	1	25.8%	27.6%	23.6%	23.0%	229	
	2	25.8%	27.6%	23.6%	23.0%	220	
	3	25.8%	27.6%	23.6%	23.0%	177	
	4	25.8%	27.6%	23.6%	23.0%	123	
		Conditional probabilities					
		Quartile of the second follow-up fund					
		1	2	3	4	# funds	χ2
	# funds	100	120	86	109	415	6.42
Quartile of the current fund	1	28.4%	30.5%	19.9%	21.3%	141	
	2	20.5%	31.5%	21.3%	26.8%	127	
	3	23.7%	26.9%	21.5%	28.0%	93	
	4	22.2%	22.2%	20.4%	35.2%	54	
		Expected probabilities					
		Quartile of the second follow-up fund					
		1	2	3	4	# funds	
	# funds	100	120	86	109	415	
Quartile of the current fund	1	24.1%	28.9%	20.7%	26.3%	141	
	2	24.1%	28.9%	20.7%	26.3%	127	
	3	24.1%	28.9%	20.7%	26.3%	93	
	4	24.1%	28.9%	20.7%	26.3%	54	

Panel B. Venture capital funds

		Conditional probabilities					
		Quartile of the first follow-up fund					
		1	2	3	4	# funds	χ2
	# funds	170	181	158	140	649	51.32***
Quartile of the current fund	1	34.8%	29.3%	20.4%	15.5%	181	
	2	28.6%	32.4%	23.6%	15.4%	182	
	3	24.5%	28.2%	27.0%	20.2%	163	
	4	12.2%	18.7%	27.6%	41.5%	123	
		Expected probabilities					
		Quartile of the first follow-up fund					
		1	2	3	4	# funds	
	# funds	170	181	158	140	649	
Quartile of the current fund	1	26.2%	27.9%	24.3%	21.6%	181	
	2	26.2%	27.9%	24.3%	21.6%	182	
	3	26.2%	27.9%	24.3%	21.6%	163	
	4	26.2%	27.9%	24.3%	21.6%	123	

		Conditional probabilities					
		Quartile of the second follow-up fund					
		1	2	3	4	# funds	χ2
	# funds	91	108	88	83	370	25.74**
Quartile of the current fund	1	21.4%	41.1%	17.0%	20.5%	112	
	2	28.4%	23.9%	32.1%	15.6%	109	
	3	25.3%	26.4%	26.4%	21.8%	87	
	4	22.6%	21.0%	17.7%	38.7%	62	
		Expected probabilities					
		Quartile of the second follow-up fund					
		1	2	3	4	# funds	
	# funds	91	108	88	83	370	
Quartile of the current fund	1	24.6%	29.2%	23.8%	22.4%	112	
	2	24.6%	29.2%	23.8%	22.4%	109	
	3	24.6%	29.2%	23.8%	22.4%	87	
	4	24.6%	29.2%	23.8%	22.4%	62	

On the right side of the table expected probabilities are calculated (as if the performance of subsequent funds is independent). If the observed and expected probabilities are close, then it can be concluded that the performance of the current and follow-on funds is independent. On the other hand, if there is a significant difference, it can be interpreted as there is performance persistence between the current and follow-on fund.

The conditional probability that the first follow-on fund will stay in the top-quartile portfolio is 36.7% for buyout and 34.8% for venture capital funds. In both cases, it is greater than the expected probabilities (25.8% and 26.2% respectively). The conditional probability that the first follow-on fund will stay in the bottom-quartile portfolio is 39% for buyout and 41.5% for venture capital funds. In both cases, it is greater than the expected probabilities (23% and 21.6% respectively). The Chi-square tests reject the null hypothesis of performance independence for both buyout and venture capital funds at 1% significance level. Therefore, it can be concluded that there is strong performance persistence between the current and the first follow-on fund. These findings are in line with the results from Section 5.1. In addition, both good- and bad-performing funds exhibit persistence, though the magnitude of persistence is slightly higher for bad-performing funds.

When the transitional probabilities are examined with regards to the second follow-on fund, persistence decreases. The Chi-square test rejects the null hypothesis of independence at a 5% significance level only for venture capital funds, while for buyout fund the difference is insignificant. The conditional probability that the second follow-on fund will stay in the top-quartile portfolio is 28.4% for buyout and 21.4% for venture capital funds (compared to expected probabilities of 24.1% and 24.6% respectively). Interestingly, while top-performing buyout funds show a bit higher persistence than expected, it is the opposite for venture capital funds. Regarding the bottom quartile, the conditional probability that the second follow-on fund will stay in the bottom-quartile portfolio is 35.2% for buyout and 38.7% for venture capital funds. In both cases, it is greater than the expected probabilities (26.3% and 22.4% respectively). Therefore, there is stronger long-term persistence for worse performing funds.

Overall, this section concludes that while there is strong performance persistence for the first follow-on funds, it decreases for the second-follow up fund. For buyout funds, persistence becomes insignificant from the second follow-up fund, while it remains significant for venture capital funds. The magnitude of performance persistence is greater for bottom-quartile funds, especially in the long run. Persistence from the current to the second follow-on fund is driven mostly by worse performing funds for both venture and buyout.

5.4.2 Tracking performance of initial quartiles

This section studies the performance of the portfolios of funds formed on the basis of current performance (quartiles). Quartiles reported by Preqin are used to divide the funds into 4 groups based on current performance. Performance of these portfolios is then tracked for up to three follow-on funds.

Table 14 reports mean and median IRRs and multiples for the quartile portfolios. Column t denotes current portfolios, columns t+1, t+2, and t+3 – first, second and third follow-on funds, respectively. The difference between the top and the bottom quartile is reported in the line headed 1-4. Panel A reports means and medians of IRRs and Panel B – of multiples. Columns under the headline N report the sample size for each corresponding portfolio. T-tests are used to report p-values for the difference in means.

Table 14. Subsequent performance of quartile portfolios formed on the basis of current performance

Current funds are divided into four quartiles based on performance (1 denoting the top quartile and 4 denoting the bottom quartile). Rows from 1 to 4 stand for current quartile portfolios. Columns t to t+3 report mean and median performance of the portfolios of current, first follow-on, second follow-on and fourth follow-on funds, respectively. Row *1-4* reports the difference between top- and bottom-quartile portfolios. *p-value* reports the p-values of difference tests in means (Student t-test) between quartiles 1 and 4. The columns under N report the sample size of each corresponding portfolio. Panel A reports means and medians based on IRRs, and Panel B reports means and medians based on multiples.

Panel A. IRR, %

Fund type	Quartile	Mean				Median				N			
		t	t+1	t+2	t+3	t	t+1	t+2	t+3	t	t+1	t+2	t+3
Venture	1	40.53	19.10	11.22	8.25	19.60	8.02	4.34	7.70	295	158	97	62
	2	14.52	12.78	8.65	5.40	8.90	6.90	5.35	5.38	295	149	86	57
	3	1.94	10.28	8.73	4.89	1.35	4.00	6.25	4.00	245	123	72	41
	4	-13.06	3.27	2.53	3.67	-10.35	-0.85	0.99	1.78	224	94	51	24
	1-4	53.59	15.83	8.70	4.58	29.95	8.87	3.35	5.92				
	p-value	0.00	0.00	0.05	0.22								
Buyout	1	32.18	19.59	16.70	16.13	26.13	16.57	14.94	13.74	330	198	116	72
	2	18.09	15.39	15.39	15.66	15.95	13.14	12.30	12.55	336	190	109	48
	3	10.28	11.68	13.56	12.95	9.80	10.50	12.90	13.77	287	146	78	40
	4	-1.37	9.37	12.60	12.12	1.53	8.06	10.70	9.89	244	94	39	19
	1-4	33.55	10.22	4.10	4.01	24.60	8.51	4.23	3.85				
	p-value	0.00	0.00	0.12	0.19								

Panel B. Multiple

Fund type	Quartile	Mean				Median				N			
		t	t+1	t+2	t+3	t	t+1	t+2	t+3	t	t+1	t+2	t+3
Venture	1	4.03	2.33	1.73	1.48	2.46	1.43	1.30	1.32	316	179	111	75
	2	1.75	1.59	1.42	1.38	1.46	1.38	1.30	1.29	330	181	112	66
	3	1.13	1.67	1.46	1.27	1.08	1.20	1.25	1.18	298	160	89	50
	4	0.54	1.22	1.35	1.53	0.48	0.94	1.08	1.09	280	109	54	26
	1-4	3.49	1.10	0.38	-0.05	1.98	0.49	0.22	0.23				
	p-value	0.00	0.00	0.09	0.44								
Buyout	1	2.73	1.95	1.88	1.83	2.47	1.91	1.76	1.79	334	220	134	86
	2	1.95	1.84	1.72	1.73	1.89	1.76	1.72	1.68	348	211	121	55
	3	1.53	1.64	1.75	1.81	1.54	1.62	1.69	1.90	309	167	83	41
	4	1.00	1.65	1.63	1.45	1.02	1.49	1.60	1.40	290	118	53	26
	1-4	1.73	0.30	0.25	0.38	1.45	0.42	0.15	0.39				
	p-value	0.00	0.00	0.02	0.01								

If we look first at Panel A, the mean (median) IRR for the currently best-performing venture capital portfolio is 40.53% (19.6%), for the worst performing it is -13.06% (-10.35%). The difference between the means (medians) of these two portfolios is large and significant: 53.59% (29.95%). For the first follow-on funds, the mean (median) IRR for the top quartile portfolio decreases to 19.10% (8.02%), and for the bottom quartile portfolio it increases to 3.27% (-0.85%) The difference between the top and the bottom portfolios is still significant and equal 15.38% (8.87%). However, it is more than 3 times lower than in the current funds, meaning that the difference shrinks drastically already from the first follow-on fund. Starting from the second follow-on funds, the difference decreases even more and becomes insignificant (with the exception for the second follow-on venture capital funds), meaning that the initial top performers become indistinguishable from bottom performers. The big difference between the mean and the median of the top performing portfolio points out that there are several venture capital funds reporting exceptionally high performance (for one such fund IRR is equal 218% for the current fund and 514% for the first follow-on fund). The fact that difference in means is still significant for the second follow-on fund for venture capital funds can, therefore, be explained by these top-performing outliers.

For buyout funds, the pattern is similar. The mean (median) IRR for the current top quartile portfolio is 32.18% (26.13%), for the bottom quartile it is -1.37% (1.53%). The difference between the means (medians) of these two portfolios is large and significant: 33.55% (24.6%). For the first follow-on funds, the mean (median) IRR for the top quartile portfolio decreases to 19.59% (16.57%), and for the bottom quartile portfolio it increases to 9.37% (8.06%) The difference between the top and the bottom portfolios is still significant and equal 10.22% (8.51%). Like for venture capital funds, it is more than 3 times lower than in the current funds, and the same trend of drastically shrinking difference is observed. Starting from the second follow-on funds, the difference decreases even more and becomes insignificant, meaning that the initial top performers become indistinguishable from bottom performers.

If we now look at Panel B, the means and medians of multiples follow the same pattern as those of IRRs. The difference between top-and bottom-quartile performance shrinks quickly from the first follow-on fund, and this effect is especially strong for buyout funds (the difference between the first and the fourth quartiles in the first follow-on funds is almost 6 times smaller compared to that difference within the current funds). When using multiples, there is a smaller relative gap between top and bottom performing funds in general. This observation is in line with the discussion in Section 5.1 about the use of leverage by fund managers which allows them to manipulate IRRs. Therefore, multiples exhibit less variation between extreme portfolios.

Overall, this section concludes that the difference in performance between top- and bottom-quartile portfolios shrinks drastically already from the first follow-on fund, and it becomes small from the second follow-on fund.

5.4.3 Multivariate regression framework to track performance of initial quartiles

Another approach we use to analyze whether the good- or bad-performing funds drive performance is similar to the one used by Chung (2012). Chung (2012) was separating funds according to the performance of the initial terciles and tracking their performance. The findings are that the majority of the positive performance persistence is driven by funds in the bottom or medium tercile portfolios, while the funds in the upper tercile portfolio consistently have weaker persistence.

In this study, we are tracking the performance of the initial quartiles, based on the quartiles reported by Preqin.

The regression is estimated as follows:

$$Performance_{i,t} = \alpha + \beta Performance_{i,t-1} + \gamma Performance_{i,t-1} * Quartile\ 1_{i,t-1} + \delta Performance_{i,t-1} * Quartile\ 2_{i,t-1} + \theta Performance_{i,t-1} * Quartile\ 3_{i,t-1} + \rho Quartile\ 1_{i,t-1} + \omega Quartile\ 2_{i,t-1} + \sigma Quartile\ 3_{i,t-1} + \varphi'^{Z_{i,t-1}} + \varepsilon_{i,t-1} \quad (11)$$

$Quartile1_{i,t-1}$, $Quartile2_{i,t-1}$, $Quartile3_{i,t-1}$ are dummy variables, which are equal to 1 if the 1st previous fund is ranked in the 1st, 2nd or 3rd quartile portfolios among the funds raised in the same year and 0 otherwise. The coefficient estimate β is measuring the association between the performance of the first previous and the current fund for the fourth quartile funds. The coefficient estimates γ, δ and θ show the incremental strength of persistence for funds that belong to the 1st, 2nd and 3rd quartiles compared to the fourth quartile.

Results are reported in Table 15. Columns (1) and (2) include the results obtained when IRR is used as the performance measure and columns (3) and (4) include multiple.

Table 15. Performance of initial quartiles

This table presents the coefficient estimates of the regression:

$$Performance_{i,t}=\alpha+\beta Performance_{i,t-1}+\gamma Performance_{i,t-1}*Quartile\ 1_{i,t-1} + \delta Performance_{i,t-1}* Quartile\ 2_{i,t-1} + \theta Performance_{i,t-1} * Quartile\ 3_{i,t-1} + \rho Quartile\ 1_{i,t-1} + \omega Quartile\ 2_{i,t-1} + \sigma Quartile\ 3_{i,t-1} + \varphi' Z_{i,t-1} + \varepsilon_{i,t-1}$$

Columns 1 and 2 report performance measured by IRR and Columns 3 and 4 report performance measured by multiple. Quartile 1, Quartile 2 and Quartile 3 are dummy variables, equal to 1 if the fund belongs to one of the first three quartiles and 0 otherwise. Z includes control variables: logarithm of the current fund's size, the sequence number of the fund and the dummy variables for each vintage year. Standard errors are reported in parentheses. Statistical significance at the 1%, 5% and 10% levels is denoted by ***, **, and *, respectively.

Dependent variable:	Performance (t)			
Performance:	IRR (t-1)		Multiple (t-1)	
	Venture	Buyout	Venture	Buyout
	(1)	(2)	(3)	(4)
Performance (t-1)	0.491*	0.510*	-0.992	0.327
	(0.264)	(0.246)	(0.866)	(0.246)
log(Fund size) (t)	1.922***	-1.308***	0.064	-0.045
	(0.722)	(0.466)	(0.050)	(0.023)
Sequence (t)	-0.617	0.558	-0.021	-3.4832e-05
	(0.507)	(0.562)	(0.024)	(0.017)
Quartile 1	6.849	7.212***	-0.212	0.347
	(4.156)	(2.682)	(0.513)	(0.277)
Quartile 1 * Performance(t-1)	-0.409	-0.456*	1.120	-0.217
	(0.316)	(0.240)	(0.864)	(0.233)
Quartile 2	2.763	4.385	-0.181	0.515*
	(3.970)	(2.716)	(0.512)	(0.309)
Quartile 2 * Performance (t-1)	-0.438	-0.463*	0.936	-0.312
	(0.284)	(0.280)	(0.795)	(0.251)

Quartile 3	2.226	0.060	-1.679	-0.142
	(3.645)	(2.601)	(1.021)	(0.364)
Quartile 3 * Performance(t-1)	-0.563*	-0.338	2.323	-0.012
	(0.319)	(0.275)	(1.068)	(0.293)
Constant	6.831	49.581***	2.034***	3.135***
	(6.568)	(3.145)	(0.755)	(0.363)
Vintage F.E.	Yes	Yes	Yes	Yes
Observations	501	636	610	718
Adjusted R2	0.211	0.172	0.246	0.109

The only significant results are obtained for the IRRs. The β coefficient is high, significant and positive, while all the interaction terms have negative coefficient estimates, which gives the proof that the performance persistence is mainly driven by the fourth-quartile funds – the worst-performing ones. For all the funds in the top three quartiles, the performance persistence is weaker than for the fourth quartile.

6. Conclusions and discussion

The main aim of our thesis was to answer whether there is persistence in private equity performance. If there were persistence, we intended to analyze the topic further and find out whether good or bad performing funds are the ones that drive performance persistence. We also wanted to figure out which factors might possibly explain this persistence, whether it is the skill of the fund managers, or potentially some other factors, such as the similar market conditions that could drive persistence. Finally, we aimed to analyze which factors may deteriorate performance persistence, even if there is no lack of skill of the fund managers. In particular, we conducted an analysis on the effect of fund flows on performance persistence.

Our main findings are that there is performance persistence for one previous fund and no persistence for the second previous fund, both for buyout and venture capital funds, whether analyzed in the whole sample framework or separately. We next found that for the period under investigation, the similar market conditions do not explain persistence, which lets us assume that the persistent returns were generated due to the skill of fund managers. We also found that persistence is partially deteriorated by the flow of funds. This effect is particularly strong for the venture capital funds, while the managers of the buyout funds seem to have a more scalable skill. We finally found that the performance persistence is stronger for the bad-performing funds, and in particular, those are the funds in the fourth (worst-performing) quartile.

Our analysis was done in the following way: First, we developed the multivariate regression framework to analyze the whole sample of funds we obtained, as well as look at the subsamples of Buyout and Venture Capital funds separately. Second, we were looking into possible explanations for performance persistence by analyzing whether similar market conditions had anything to do with it. We found that for the time period we analyzed, similarity of market conditions does not determine performance persistence, both taken as the market similarity measure with the sum of committed capital as a proxy, and the spread in the vintage years of the funds. These findings mean that persistence is potentially accounted for by the skill of GPs. Third, we were analyzing whether the lack of persistence, in the long run, could be explained by the funds' inflow and diminishing returns to scale. We studied the following three relationships: 1) the reaction of capital inflow to past performance; 2) effect of the flow of funds on the following fund’s performance; 3) effect of the flow of funds on performance persistence. Finally, we tracked the performance of the funds in the different performance quartiles to find out whether the good or the bad funds drive performance persistence.

The performance of buyouts possibly does not deteriorate because of the size of the investment. Buyout funds are in general larger than the VC funds, due to their size and power they are able to choose fewer better and bigger investment targets. With this, the investors’ attention does not get diluted and can stay focused on the targets. On the contrary, according to Kaplan, Schoar (2005), the number of good startups is limited at each point of time, which determines the strategy of VC investors, who need to invest in the bigger number of targets, some of which appear to be not as good as the others. Thus, the VC investments are not as scalable as the buyout and the investor attention is diluted between a bigger number of companies.

Our results do not necessarily imply the lack of skill of the good managers (compared to the bad managers). It may mean that better performing funds are backed up by the more sophisticated (skilled) investors (Phalippou, 2010), who use the information about past performance and update their capital allocation decisions according to it. As a result of this, better performing funds have weaker performance persistence as a consequence of stronger flow-performance relationship (Berk & Green, 2004).

There are several limitations of our analysis, which are at the same time opportunities for further research on the topic:

First, there is still no clear conclusion about the skill of the fund managers. To answer this question explicitly, we need a broader set of data, with a more qualitative approach including the interviews with GPs to determine their strategies and approach in managing the funds, which is not fully reflected in the available quantitative data. With the more extensive data, the model should include more factors so that the other potential determinants of performance persistence are also examined.

Second, we only had access to fund-level data, with all the performance indicators reported net-of-fees. Due to this, we were not able to track the absolute amount of fees earned by GPs. With the absolute amounts of fees, the skill of fund managers would be more easily trackable. Moreover, since the GP fees are a fraction of the committed capital, these fees can potentially dilute the returns of investors. Therefore, with access to LP-level data, we could get more insights in the GP performance, their skill in managing funds and generating returns, and potentially, even the skills of the limited partners in choosing fund managers to invest in.

Third, the issue comes in the performance measures we use. As discussed in Section 5.1, fund managers can manipulate IRRs with the use of leverage – credit lines, which allows them legally boost IRR figures not impacting the multiples. This leads to the fact that the results we get from estimating the models with IRRs and multiples are different from each other. Thus the best way out could be to get the data on IRRs without the use of credit lines, which would already give better estimates. Moreover, if we had the data on the PMEs, the comparison of the results of the models based on the 3 kinds of data would give us even better insights.

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Appendix

Figure A. Histogram of fund growth levels for Venture Capital funds

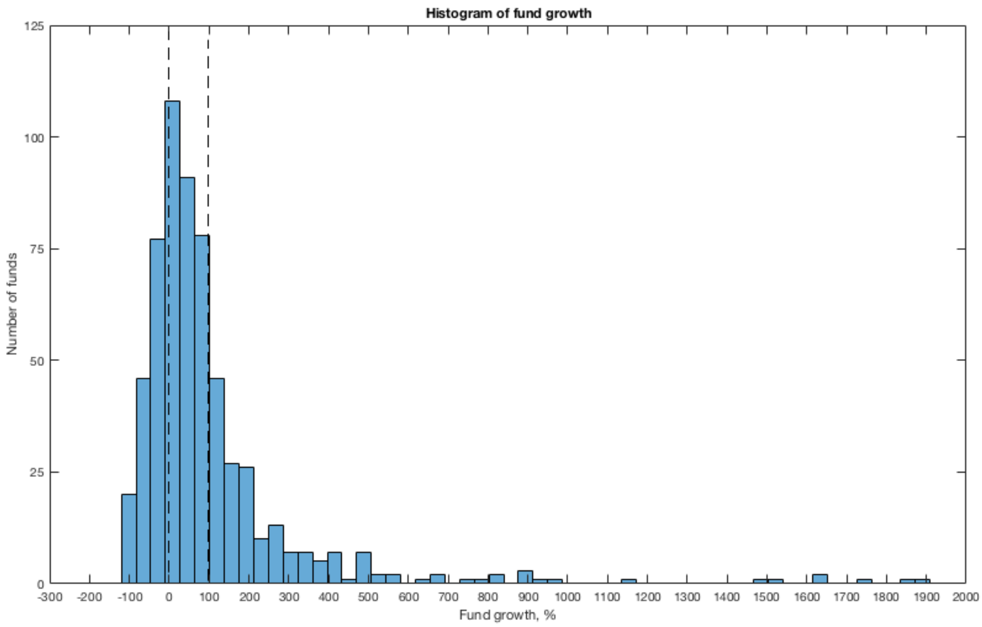

Figure B. Histogram of fund growth levels for Buyout funds