

DOES PAST PERFORMANCE GUARANTEE FUTURE RETURNS?

**THE ROLE OF FUND GROWTH AND SECTOR IN PRIVATE
EQUITY PERFORMANCE PERSISTENCE**

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Does Past Performance Guarantee Future Returns? The Role of Fund Growth and Sector in Private Equity Performance Persistence

Abstract:

For investors in Private Equity (PE), the ability to identify persistent outperformers can significantly influence long term returns. In this paper we analyse performance persistence within PE using a comprehensive dataset containing both fund and deal level data; including 1004 funds managed by 419 general partners (GPs) and 36,292 deals across 755 GPs. We replicate the models in Harris et al. (2023) to measure persistence and extend them by looking at the role of sector and scaling. We find persistence over one and two fund cycles for both buyout and venture capital funds. Additionally, we find that excessive scaling negatively impacts the performance of buyout funds and that persistence diminishes when they scale above 200% over two fund cycles. Finally, we show that the existence of persistence varies depending on the sector or industry a GP invests in. These findings are useful to investors in deciding where to allocate their capital, showing that they should evaluate the past performance of PE firms as well as how they manage growth across fund vintages.

Keywords:

Private Equity, Performance Persistence, Fund Scaling, Investment Sector

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1. Introduction

If past performance is no guarantee of future results, why do we base so many investment decisions on it? Nowhere is this paradox more apparent than in private equity (PE), in which investors must commit capital long before final returns are known. Thus, the possibility of identifying repeatable outperformance over peers, so called performance persistence, would be of great value for limited partners (LPs) in deciding where to allocate their capital.

Since the first PE boom in the 1980s, the industry has seen extraordinary growth: global capital commitments surged from \$6.7 billion in the 1990s to \$7.6 trillion by 2022 (Sensoy, Wang and Weisbach, 2014; Ain Tommar, Darolles and Jurczenko, 2024). Findings from the early 2000s show that some PE firms consistently outperform their peers (Kaplan and Schoar, 2005; Kaplan and Strömberg, 2009). Such outperformance can be attributed to skill in deal sourcing, valuation, and execution (Kaplan and Schoar, 2005). Yet as the industry has become more mature and competitive, economic theory would suggest that opportunities to outperform net fees should become exhausted. Recent research shows the opposite to be true; top performing PE firms do not fully appropriate the returns to their skill through higher fees or aggressive scaling (Harris, Jenkinson, Kaplan and Stucke, 2023).

LPs typically agree to provide capital to a PE fund, which the general partner (GP) draws upon as investment opportunities arise and to cover management fees. When investments are exited, they are distributed back to the LPs, net of performance fees and carried interest. The PE industry encompasses both buyout and venture capital (VC) funds. Buyout funds tend to invest in mature companies, using control and leverage to drive performance, whereas VC funds generally invest in startups with large growth potential but higher risk. In this paper, we investigate performance persistence of both buyout and VC funds. We use the same definition for performance persistence as Kaplan and Strömberg (2009, p. 137), as when “performance by a private equity firm in one fund predicts performance by the firm in subsequent funds.”

While the existence of performance persistence among PE funds has been established by prior literature, a key challenge has been to find ways in which investors can identify and act on such in time to reap benefits from it. Moreover, limited research has been conducted on the effect of scaling on performance persistence, as well as on whether persistence is more prevalent in certain sectors GPs invest in. This paper extends Harris et al. (2023), by revisiting the question of whether performance persistence exists over one and two fund cycles for both buyout and VC funds. We are especially interested in understanding whether LPs, based on a GP’s prior performance, can predict future fund performance before allocating their capital. We also study whether persistence persists when GPs scale fund-to-fund and whether GPs have sector specific performance persistence. We use a novel dataset sourced from an LP and investment manager, updated as of 2025. This dataset includes performance data on 1004 funds and 36,292 holdings across four continents, spanning from 1981 to 2019.

Our primary findings can be summarised as follows. Firstly, we confirm prior literature by finding evidence of performance persistence over one fund cycle for buyout and VC funds, using a more recent and geographically diverse dataset than previously available. We contribute by showing that persistence is driven by consistent top performers for buyout funds and consistent

top and bottom performers for VCs. Secondly, we find evidence of persistence over two fund cycles for buyout and VC funds, a measure which is available to investors at the time of fundraising. Thirdly, we find that scaling above 200% over two fund cycles has a negative effect on performance for buyout funds. We show that performance persistence disappears when buyout funds scale more than 200% over two fund cycles, but find no evidence that scaling affects VC performance.

Lastly, we find that GPs have persistent performance in some sectors they invest in, while not in others. Our results show that a GP's past buyout performance in the Consumer, Industrials, and Information Technology (IT) sector predicts future performance in the same sector. However, past buyout performance in Health Care investments does not predict future performance in the Health Care sector. For VC funds, we find evidence of performance persistence in investments within Health Care Equipment & Services, Software Services, Technology Hardware & Equipment, and Telecommunication Services, but not in Media & Entertainment or Pharmaceuticals, Biotechnology & Life Sciences.

Early research into performance persistence finds strong evidence of its existence within PE. Kaplan and Schoar (2005) analyse US buyout and VC funds raised in the 1980s and 1990s and find that a GP's previous two funds are good predictors of current fund performance. The existence of persistence based on the most previous fund is reaffirmed in several studies, including Hochberg, Ljungqvist and Vissing-Jorgensen (2014), Robinson and Sensoy (2016), and Chung, Sensoy, Stern and Weisbach (2012). However, Harris, Jenkinson and Kaplan (2014) show that the Venture Economics data used to show evidence of persistence by Kaplan and Schoar (2005) and Hochberg et al. (2014) includes funds without recently updated figures. Harris et al. (2023) use a larger dataset than previously available and find evidence of performance persistence in U.S. buyout and VC funds raised between 1984 and 2015. Ain Tommar et al. (2024) are the first to examine persistence in PE beyond U.S. funds. They find evidence of persistence over one fund cycle in European buyout funds, but not in European VC or Asian funds. Using data from four continents, we reaffirm prior literature by showing evidence of persistence over one fund cycle. We also contribute by showing that persistence is driven by the top and bottom funds of the performance distribution.

Harris et al. (2023) note that investors usually commit to a GP's new fund while the previous fund is still active, meaning they can only assess its interim performance rather than its final returns when making a decision. Thus, even though persistence has been identified using ex-post values, this is not useful information to investors. Hochberg et al. (2014) therefore also examine persistence based on the interim performance of the previous fund at the time of new fundraising, and find evidence of weak persistence for VC funds. Similar results are found by Harris et al. (2023), who identify persistence based on interim performance for VC funds but not for buyout funds. The discrepancy in the predictive power of ex-post and interim performance stems from the low correlation between these metrics. Jenkinson, Sousa and Stucke (2013) find that the performance figures reported by funds during follow-on fund raising are poor predictors of their final returns due to temporarily inflated returns during fundraising. Brown, Gredil and Kaplan (2019) confirm that underperforming managers inflate reported returns during fundraising to attract investors; depleting the usefulness of interim performance as a reliable indicator of future results.

The ex-post performance of the second previous fund is also typically available to investors at the time of fundraising (Harris et al., 2023). However, past research on persistence over two fund cycles has yielded contradictory results. Chung et al. (2012) argue that persistence should weaken over subsequent fund cycles due to excessive fund growth following good performance, and find persistence over two fund cycles for buyout funds but not for VCs. To the contrary, Harris et al. (2023) find persistence for VCs but not for buyout funds when using second previous performance. Contradicting both Chung et al. (2012) and Harris et al. (2023), we find evidence of persistence over two fund cycles for both buyout and VC funds.

Kaplan and Schoar (2005) argue that heterogeneity in PE performance can exist because of an inefficient market. Having superior performance requires skills in management, access to deals, and the ability to secure good deal terms. If these skills and opportunities are scarce or proprietary, it will be difficult for new actors to compete efficiently, which could lead to persistence. Brown, Fei and Robinson (2023) find that 40% of persistent return variation across GPs is explained by skill, 48% by luck, and 12% by overlapping market conditions. Consistent outperformance in net returns can only persist if returns to skills are not appropriated by successful GPs. Hochberg et al. (2014) present a model for why returns to performance are not appropriated by raising fees: if current investors choose not to invest in subsequent funds, it signals that they possess private information suggesting the GP's skills are poor. As this would drive new investors away, GPs are reluctant to raise fees following good performance and persistence can survive. As an alternative way to earn a premium on their skill, GPs can scale their funds.

Our results on the negative effect of scaling on performance are consistent with foundational research within the field, such as Berk and Green (2004). Our analysis also strengthens the findings of Harris et al. (2023), who find weak evidence that scaling negatively affects the performance of buyout funds. They argue that buyout funds are less disciplined than VCs in avoiding scaling too rapidly to the detriment of their performance. Sensoy et al. (2014) reason that superior performance should decline when the PE industry grows in size and sophistication, with opportunities representing “low-hanging fruit” becoming exhausted. The higher up in the size pyramid of PE funds you look, the less scarce GP skills are and the more efficient the market for deals becomes, making it harder to consistently outperform. Kaplan and Schoar (2005) also highlight that inputs in PE like time, advice or human capital are scarce and not easily scalable. We extend prior research on the relationship between scaling and performance by showing that scaling excessively ultimately eliminates performance persistence for buyout funds.

Previous literature largely overlooks the question of whether performance persistence in PE varies by sector. Spaenjers and Steiner (2024) find that PEs specialised in a sector have higher performance in that sector. Hochberg, Mazzeo and McDevitt (2015) describe the tradeoff GPs face between reaping the benefits of building sector specialised skills and maintaining the flexibility to shift to other sectors if competition intensifies and valuations go up. They highlight the benefits of having specialised skills in sectors which are less crowded and require skills that are more scarce. Since Brown et al. (2023) attribute persistence to differences in GP skill, there is reason to believe that persistence could be stronger in such sectors. Our findings on sector specific persistence are a new addition to the field and show that the existence of persistence does indeed depend on the sector.

2. Data Description

We use data provided by HarbourVest Partners, a global PE fund of funds (a pooled investment fund that invests in other PE funds) and investment manager. The data is constructed by HarbourVest from an aggregation of investments made by HarbourVest funds and programs, data collected as part of due diligence, and investments of client portfolios monitored by HarbourVest. We use two datasets: one with fund level data and the other with deal level data. Our fund level data includes 1004 funds managed by 419 GPs and have vintage years between 1981 and 2019. Our deal level data includes 36,292 deals across 755 GPs, with investment years ranging from 1985 to 2019. Here, vintage year refers to when a fund first draws capital from its LPs and investment year to when a GP makes its first cash outlay to a deal. Following Harris et al. (2023), we exclude observations with vintages and investment years from the past five years to ensure that the investments are mature enough to provide meaningful performance measures. The fund level data covers 785 North American, 134 European, and 85 Asian funds. 684 of the funds are from the GPs' flagship family and 320 from adjacent fund families. The deal data covers 25,024 North American deals, 5703 European deals, 4408 Asian (non-emerging) deals, and 1157 deals from Emerging Markets (including South America, Eastern Europe, and parts of Southern Asia).

We winsorise the performance variables in our datasets at a 1% level on each tail and exclude unusually small investments to ensure the robustness of our results. We filter out buyout and VC funds with less than \$100 million in committed capital to minimise noise from very small or emerging funds. For the same reason, we exclude buyout deals with a total cost of less than \$1 million and VC deals with a total cost of less than \$100,000. The difference in threshold reflects the nature of the two strategies: buyout funds invest larger shares of their capital in mature companies, while VCs spread smaller investments across younger, riskier companies to diversify their exposure.

The data is likely to be accurate as it is used by HarbourVest for investment monitoring and due diligence on behalf of themselves as an LP and clients whose portfolio they manage. This reduces the risk of reporting bias or data manipulation, which can be a problem when data is sourced from GPs. The dataset is highly up to date, with performance measurements last updated as of April 2025, reducing the risk of timing bias. However, since the dataset is sourced from the investments of a single large LP and the portfolios of its clients, there is a possibility that the included funds and holdings are not representative of the broader PE market. While HarbourVest has a portfolio diversified across a wide range of strategies and geographies, they may for instance possess skills that lead them to make investments that outperform the average, potentially introducing an upward bias in the observed performance. The average IRR and capital committed in our fund data differ from those reported by Harris et al. (2023), who used Burgiss data sourced from over 1000 LPs. The differences could suggest limitations in the representativeness of our data, but could also be due to the fact that Harris et al. (2023) only include U.S. funds and cover fewer vintage years than we do.

Prior literature (Harris et al., 2023; Kaplan and Schoar, 2005) use public market equivalent return (PME) as their main performance metric when investigating persistence. This variable assumes that PE performance can be directly benchmarked against public market returns, which might not

be the case due to fundamental differences in liquidity, risk, and timing (Korteweg and Nagel, 2016). In our analysis, we instead use performance measurements that are standard industry practice: Net Internal Rate of Return (IRR) and Total Value to Total Cost (TVTC). We adjust these relative to the appropriate PE market.

Table 1 presents summary statistics on the 1004 funds in our sample, sorted by vintage year. Panel A includes 565 buyout funds with an overall average committed capital of approximately \$2.5 billion. For comparison, Harris et al. (2023) have a sample including 929 buyout funds, with an average capital committed of around \$1 billion. Panel B shows data on 439 VC funds, with an overall average committed capital of approximately \$580 million. Harris et al. (2023) analyse 408 VC funds, with total average committed capital of around \$250 million.

We also report average fund performance per vintage year using two metrics. Both are net of fees and carried interest, thereby measuring the returns appropriated by LPs. The IRR is based on the fund's cash flows and treats any unrealised value as a final cash flow. The Total Value to Paid-In capital (TVPI) measures the fund's total value, both realised and unrealised, relative to the capital paid-in by LPs. The unrealised value of a PE fund is its Net Asset Value (NAV) to this date, which Jenkinson, Landsman, Rountree and Soonawalla (2020) find to be close to its discounted future cash flows. The average Net IRR of buyout funds is 18% and the average Net TVPI is 2.02. For comparison, buyout funds in Harris et al. (2023) had an average IRR of 14% and an average TVPI of 1.81 (referred to as MOIC in their paper, although it is calculated in the same way as TVPI). The average IRR of VC funds is slightly below 16% and the average Net TVPI is 2.33, while the VC funds in Harris et al. (2023) had an average IRR of 19% and an average TVPI of 2.56.

Table 1: Summary statistics on funds
Panel A - Buyout funds

Vintage Year	Total Funds	Average Capital Committed	Average TVPI	Average IRR
1987	1	5,653,126,278	1.970	0.089
1993	2	432,121,205	2.762	0.346
1994	9	762,471,634	2.581	0.353
1995	1	1,100,989,941	2.290	0.345
1996	7	690,727,436	1.572	0.112
1997	9	1,248,123,640	1.616	0.100
1998	25	1,316,742,572	1.430	0.068
1999	15	1,282,886,419	1.798	0.107
2000	15	1,333,835,948	1.834	0.139
2001	13	1,250,535,403	1.810	0.258
2002	7	1,525,289,403	2.269	0.236
2003	7	2,000,834,186	1.699	0.195
2004	14	1,167,943,027	1.923	0.165
2005	18	2,364,372,571	1.810	0.116
2006	20	4,107,338,645	1.611	0.073
2007	34	2,654,129,579	1.776	0.112
2008	24	3,160,500,289	1.849	0.121
2009	12	1,709,184,306	2.296	0.229
2010	8	682,632,904	2.472	0.215
2011	20	2,456,519,519	2.278	0.171
2012	24	1,676,678,983	2.419	0.208
2013	25	2,684,027,295	2.280	0.193
2014	35	2,496,529,118	2.227	0.196
2015	23	2,094,159,934	2.097	0.195
2016	50	2,448,800,691	2.298	0.214
2017	39	2,629,772,840	2.523	0.259
2018	48	4,091,898,970	2.021	0.207
2019	60	3,175,387,268	1.662	0.198
Overall Average	20	2,443,769,080	2.018	0.180

Panel B - VC funds

Vintage Year	Total Funds	Average Capital Committed	Average TVPI	Average IRR
1981	1	45,313,000	2.010	0.152
1986	5	118,505,164	1.825	0.099
1987	3	166,358,750	3.493	0.228
1988	9	101,943,088	3.337	0.283
1989	5	53,266,381	3.442	0.243
1990	4	143,216,039	2.635	0.218
1991	1	20,000,000	6.114	1.064
1992	4	151,768,215	2.264	0.274
1993	7	190,617,857	5.920	0.590
1994	1	112,584,900	5.400	0.548
1995	7	499,845,612	2.856	0.325
1996	7	393,188,215	2.201	0.278
1997	13	208,091,027	3.294	0.437
1998	21	296,269,005	1.332	0.076
1999	19	317,460,772	0.887	-0.043
2000	39	583,555,964	1.138	0.003
2001	16	796,173,949	1.290	0.034
2002	4	651,474,748	1.078	0.009
2003	5	239,464,264	2.651	0.104
2004	10	323,479,125	1.875	0.138
2005	11	413,353,204	2.832	0.143
2006	11	636,293,437	1.388	0.019
2007	12	479,823,112	2.751	0.121
2008	12	734,318,487	2.820	0.143
2009	11	483,060,522	2.678	0.147
2010	7	997,429,036	2.518	0.178
2011	16	642,795,287	2.979	0.184
2012	11	429,244,775	3.925	0.178
2013	9	1,970,254,119	3.630	0.163
2014	22	843,004,626	3.303	0.202
2015	20	1,183,112,551	2.899	0.207
2016	19	335,851,135	2.443	0.137
2017	29	766,770,651	2.466	0.203
2018	36	526,095,597	2.096	0.210
2019	32	756,646,214	1.553	0.115
Overall Average	13	578,225,654	2.333	0.156

The table above replicates Table 1 in Harris et al. (2023) and shows summary statistics on the 565 buyout funds and 439 VC funds in our sample. 298 (189) of the buyout funds and 189 (133) of the VC funds can be used to measure persistence over one (two) fund cycles. The funds are sorted based on vintage year, which is defined as the year a fund first draws capital from its LPs. For each vintage year, the table reports the average capital committed by investors to the fund. The table also reports the average of two performance measures for each vintage year: 1) Internal Rate of Return (IRR) and 2) The ratio of the total value of the fund to the capital paid-in by investors (TVPI). Both variables include realised and unrealised values and are net of fees and carried interest. All data is sourced from HarbourVest Partners.

When possible, we link each fund to the previous and second previous fund by the same GP within the same fund family. We follow Harris et al. (2023) in studying fund sequences within the same fund family, as the nature and individual partners of funds often change when GPs deviate from their “flagship” strategies. Our data does not include side or annex funds, which typically replicate the performance of a previous fund. If a dataset includes fund 1, 3, 4, and 5, from a given fund sequence, this yields two pairings over two fund cycles (1-4, 3-5) and two pairings over one fund cycle (3-4, 4-5). Harris et al. (2023) note that such gaps in fund sequences are a natural consequence of using data from LPs, who may skip investing in certain funds offered by a GP. Our sample thus narrows when requiring linked performances.

We measure the degree of fund-to-fund scaling by GPs based on the percentage increase in total capital committed between subsequent funds. Since the scaling variable is right skewed, we remove single extreme upper outliers from the datasets of funds with prior performance data ahead of our regression analysis. Following the removal of outliers, buyout funds scaled on average 87% (with a median of 51%) over one fund cycle and 162% (with a median of 114%) over two fund cycles. VCs scaled on average 76% (with a median of 26%) over one fund cycle and 181% (with a median of 47%) over two fund cycles (see Appendix A).

After removing scaling outliers, 297 buyout funds in our dataset have previous performance and 188 have second previous performance. 182 VC funds have previous performance and 132 have second previous performance. Funds with prior performance data have performance averages close to the full dataset, with a slight upward trend. However, they have an overall higher average capital committed compared to the full sample (see Appendix B).

To identify sector performance, we use deal level data. Our dataset classifies each holding according to the 11 Global Industry Classification Standard (GICS) sectors and 25 GICS industry groups. We build “sector proxy funds” which include all deals from the same manager and within the same GICS classification during a 3 year interval. We build our proxy funds by grouping deals using sector classification for buyout funds and the narrower industry group classification for VC funds. This is since most VC funds in our dataset are concentrated in the Health Care, IT or Communication Services sector. To the contrary, buyout funds tend to be spread more evenly across sectors (Brown et al., 2023). Moreover, buyout funds generally invest in mature companies that tend to behave like their broader sector, while the dynamics of VC industries within the same sector vary significantly. Thus, looking at VC performance in terms of industry groups rather than broader sectors leads to a more meaningful and precise analysis. When possible, we link proxy funds to the previous proxy fund by the same GP in the same

sector or industry group. We also calculate the degree of scaling by a GP within a sector/industry group based on the percentage change in total cost between subsequent proxy funds.

Table 2 presents summary statistics on the 2608 proxy funds with prior performance data in our dataset, sorted by the investment year intervals of their deals. Panel A includes 1028 buyout sector proxy funds and Panel B 1580 VC industry proxy funds. We calculate the total cost of each proxy fund by summing the total cost of its deals. The overall average total cost is approximately \$155 million for buyout proxy funds and \$15 million for VC proxy funds. Since we do not have access to the IRRs of individual deals, the performance measurement we report is the capital weighted ratio of TVTC. The total value of a proxy fund is the sum of the realised and unrealised values of all its deals. We use a gross performance measure since fees and carried interest are charged at the fund level, which makes it difficult to allocate fees to individual deals. While this does not fully represent the returns investors experience, this is not a significant limitation as LPs do not invest in individual deals and incur fees solely at the fund level.

The overall average TVTC is 2.64 for buyout proxy funds and 2.66 for VC proxy funds. The full dataset of proxy funds, including those without previous performance, have capital committed and performance averages close to the proxy funds with previous performance presented in **Table 2** (see Appendix C). While **Table 2** includes observations from all GICS sectors and industry groups, we only perform analysis on sector and industry group subsets with more than 100 proxy funds.

Table 2: Summary statistics on proxy funds with previous performance
Panel A - Buyout sector proxy funds

Interval	Total Proxy Funds	Average Total Cost	Average TVTC
1991-1992	11	11,199,102	3.568
1994-1995	28	52,974,783	2.386
1997-1998	40	50,033,064	2.867
2000-2001	72	73,088,216	3.020
2003-2004	89	94,029,887	2.661
2006-2007	125	193,468,386	2.023
2009-2010	120	170,995,634	2.478
2012-2013	123	163,064,893	2.565
2015-2016	208	167,888,267	2.857
2018-2019	212	197,781,243	2.705
Overall Average	103	154,522,575	2.635

Panel B - VC industry proxy funds

Interval	Total Proxy Funds	Average Total Cost	Average TVTC
1985-1986	6	2,162,705	2.243
1988-1989	33	2,221,110	2.262
1991-1992	74	2,370,085	4.385
1994-1995	94	2,774,661	3.998
1997-1998	98	6,691,081	2.702
2000-2001	220	9,685,080	1.048
2003-2004	265	10,863,647	2.218
2006-2007	139	13,726,081	2.919
2009-2010	121	22,717,075	3.372
2012-2013	147	27,148,611	3.671
2015-2016	174	30,379,471	3.092
2018-2019	209	23,700,039	2.122
Overall Average	132	15,870,038	2.662

The table above replicates Table 1 in Harris et al. (2023) and shows summary statistics on the 1028 buyout sector proxy funds and 1580 VC industry proxy funds in our sample. A proxy fund includes all of the buyout (VC) deals from the same GP within the same sector (industry group) during a three year interval. The proxy funds are sorted based on the investment year intervals of their deals. Only proxy funds that can be used to measure persistence over one fund cycle are included. For each vintage year, the table reports the average total cost of the proxy funds. We calculate the total cost of each proxy fund by summing the total costs of its deals. The table also reports averages of the performance measure Total Value to Total Cost (TVTC). The TVTC of a proxy fund is defined as the sum of the realised and unrealised values of all its deals, divided by the sum of the total costs of those deals. All data is sourced from HarbourVest Partners.

To correct for cross-sectional correlation, and reduce skewness and spurious autocorrelation caused by macroeconomic cycles, we benchmark fund and proxy fund performance. To benchmark fund performance, we use data collected from MSCI's Burgiss Private Capital Indexes by HarbourVest. Burgiss has a global dataset of over 13,000 PE funds with return data sourced directly from LPs. They use this to calculate indices for different PE markets, as defined by stage (meaning VC or buyout) and geography. We benchmark performance by subtracting the Net IRR index of the corresponding market and vintage year from each fund's Net IRR (see Appendix E). Another way to benchmark performance is through performance quartiles. Burgiss provides quartiles based on the distribution of Net IRR for all funds within the same market and vintage year. To assess relative performance, we again use Burgiss data collected by HarbourVest to identify into which quartile each fund in our sample falls within its respective market.

To benchmark sector specific performance, we calculate the pooled, capital weighted TVTC for all buyout (VC) deals within the same sector (industry group) and investment year interval. Since

TVTC does not take on negative values, we also log it to reduce skewness. We adjust sector performance by subtracting the logged pooled TVTC of the corresponding sector and vintage year from each proxy fund’s logged TVTC (see Appendix F).

3. Empirical Results

3.1 Performance Quartile Persistence

We replicate prior studies (Kaplan and Schoar, 2005, Robinson and Sensoy, 2016, and Harris et al., 2023) in constructing a performance quartile transition matrix. We base our analysis on the Net IRR quartiles of funds in their respective market and vintage year, where quartile one represents top performers and quartile four bottom ones. We begin by dividing the funds into six groups: four quartiles based on performance of the previous fund of the same GP, first funds of a GP, and funds wherein data of a prior fund is missing but the fund is not first in its sequence. For each vintage year, the funds within one market have also been assigned into four quartiles based on their current performance. The proportion of funds within each of the six groups that end up in each quartile, as well as the average Net IRR for each group, is computed. In this way, we investigate whether the performance quartile of a previous fund predicts the performance quartile of the next.

Table 3: Buyout performance quartile transition matrix

Group	Q1 Count	Q2 Count	Q3 Count	Q4 Count	Total Count	Q1 Percentage	Q2 Percentage	Q3 Percentage	Q4 Percentage	Average Net IRR
Quartile 1	37	21	16	15	89	41.57%	23.6%	17.98%	16.85%	0.23
Quartile 2	24	20	14	11	69	34.78%	28.99%	20.29%	15.94%	0.20
Quartile 3	9	17	21	11	58	15.52%	29.31%	36.21%	18.97%	0.15
Quartile 4	4	12	6	6	28	14.29%	42.86%	21.43%	21.43%	0.16
First Time Funds	32	18	16	11	77	41.56%	23.38%	20.78%	14.29%	0.22
No Most Previous Fund	60	76	61	48	245	24.49%	31.02%	24.9%	19.59%	0.16

The table above replicates Table 2 in Harris et al. (2023) and shows a quartile transition matrix over one fund cycle for buyout funds. The column “Group” divides the funds as follows: funds with a prior fund are matched with the previous fund performance quartile, first funds of a GP in a fund family are sorted into the “First Time Funds” category, and funds with no prior fund data that are not first in their fund family are assigned to the “No Most Previous Fund” group. The distribution of each group’s fund performance across quartiles is calculated. Quartile one represents best performing funds and quartile four represents worst performing ones. The table also presents the average Net IRR of each group. Quartiles are pre-assigned to each fund using a Burgiss dataset, and represent their performance within the most appropriate PE market.

Table 3 shows that there is persistence based on previous fund performance among buyout funds, primarily driven by consistent top quartile performance. GPs whose previous fund had top quartile performance perform in the top quartile and above the median in 42% and 65% of cases, respectively. A top to bottom flip occurs 17% of the time and a bottom to top flip 14% of the

time. The average Net IRR is seven percentage points higher for GPs with a prior fund in the top quartile compared to GPs with one in the bottom quartile, and a t-test for equality of the means between these groups is rejected at the 5% significance level. Funds with previous performance in the first and second quartile outperform the overall buyout subsample average of 18% (see **Table 1**), while funds with previous performance in the third and fourth quartile underperform it. This means that if LPs had information about GPs' most previous fund performance before investing they could improve their performance significantly.

GPs with previous funds in the bottom quartile perform below the median only 42% of the time, primarily due to their high allocation to the second quartile. This could be due to a high attrition rate for bottom performing funds; only 11% of funds with a previous fund had prior bottom quartile performance, rather than the 25% you would expect at random. As noted by Harris et al. (2023), this could reflect the exit of GPs after poor performance and risks biasing the analysis. The average Net IRRs of GPs with prior performance in the intermediate quartiles are not significantly different from each other, nor from the average Net IRRs of GPs with prior performance in the other quartiles. It is notable that GPs with prior third quartile performance perform worse on average than those with fourth quartile previous performance, although this difference is not statistically significant.

First time funds rank between GPs with prior first quartile and second quartile results, yet the difference in average Net IRR is not statistically different compared to either group. First time funds also perform significantly better than funds with previous performance in the third quartile, but have no significant difference to funds with previous performance in the fourth quartile. They perform in the top quartile and above the median almost as frequently as funds with prior first quartile performance (42% and 65% of the time, respectively), and have an average Net IRR higher than the overall sample (see **Table 1**). This suggests that avoiding investments in funds managed by new GPs, or in new fund families launched by existing GPs, could mean forgoing above average returns. Non-first time funds with missing prior performance show a fairly even quartile distribution, suggesting the data may be missing at random, which makes it less likely to bias conclusions about persistence.

Table 4: VC performance quartile transition matrix

Group	Q1 Count	Q2 Count	Q3 Count	Q4 Count	Total Count	Q1 Percentage	Q2 Percentage	Q3 Percentage	Q4 Percentage	Average Net IRR
Quartile 1	23	11	13	5	52	44.23%	21.15%	25%	9.62%	0.21
Quartile 2	10	9	7	6	32	31.25%	28.12%	21.88%	18.75%	0.16
Quartile 3	7	11	6	1	25	28%	44%	24%	4%	0.13
Quartile 4	3	4	6	9	22	13.64%	18.18%	27.27%	40.91%	0.07
First Time Funds	24	8	16	12	60	40%	13.33%	26.67%	20%	0.18
No Most Previous Fund	84	68	57	40	249	33.73%	27.31%	22.89%	16.06%	0.15

The table above replicates Table 2 in Harris et al. (2023) and shows a quartile transition matrix over one fund cycle for VC funds. The column "Group" divides the funds as follows: funds with a

prior fund are matched with the previous fund performance quartile, first funds of a GP in a fund family are sorted into the “First Time Funds” category, and funds with no prior fund data that are not first in their fund family are assigned to the “No Most Previous Fund” group. The distribution of each group’s fund performance across quartiles is calculated. Quartile one represents best performing funds and quartile four represents worst performing ones. The table also presents the average Net IRR of each group. Quartiles are pre-assigned to each fund using a Burgiss dataset, and represent their performance within the most appropriate PE market.

Table 4 shows performance quartile persistence for VC funds based on their previous fund, driven by consistent top and bottom performance. GPs with previous top performance stay in the first quartile 44% of the time and above the median 65% of the time. GPs with previous funds in the bottom quartile stay in the bottom quartile and below the median 41% respectively 68% of the time. There is a semi high attrition rate for fourth quartile funds, as only 17% of funds with a previous fund had prior bottom quartile performance. A top to bottom flip only occurs 10% of the time and a bottom to top flip 14% of the time. GPs with prior top and bottom performance show an average Net IRR difference of a remarkable 14 percentage points, and a t-test for equality of their means is rejected at the 5% significance level. Funds with previous performance in the first or second quartile outperform the overall VC subsample average of slightly below 16%, while funds in the third or fourth quartile underperform it (see **Table 1**).

Similar to our findings for buyout funds, we find that the average Net IRRs of VC funds with prior quartile two and three performance are not significantly different from each other or from other groups. First time funds rank between funds with prior top and second quartile performance, with no significant difference in average Net IRR compared to either group. They perform in the top quartile 40% of the time and selectively not investing in first time funds would mean foregoing returns higher than the overall average of slightly less than 16% (see **Table 1**). The distribution of quartile performance for funds without a most previous fund is skewed toward high performance, which could suggest that there is some selection bias related to the missing data.

Given the limited value of ex-post persistence to investors and the poor predictive ability of interim results (Harris et al., 2023), we go on to examine persistence based on second previous fund performance. We present probability transition matrices looking at persistence over two fund cycles in Appendix G. These transition matrices show that information on buyout and VC performance quartiles from two fund cycles ago can give LPs insight on future top performance. However, due to high attrition rates and a resulting small sample of funds with second previous bottom performance, few conclusions can be drawn on persistent underperformance with this method.

3.2 Persistence Estimation Using Regressions

An alternative approach to measure persistence included in Harris et al. (2023), is to use linear regressions to relate current and previous performance to one another. We replicate this method using benchmarked Net IRR instead of PME as our performance metric. We use second previous performance as the independent variable since we aim to identify persistence based on a measure informative to LPs. In contrast to probability transition matrices, using linear regressions allows us to control for factors that may influence performance. Replicating Harris et al. (2023), we

introduce two non-cumulative dummy control variables for funds that scale by 50-200% and by more than 200% relative to their second previous fund. When time fixed effects are included in the regression, none of them are significant. We believe this is because the benchmarked Net IRR variable already captures the effects of cross-sectional correlation and spurious autocorrelation caused by macroeconomic effects. Therefore we omit time fixed effects from our regression analysis going forwards.

Table 5: Persistence regressions over two fund cycles

	<i>Dependent variable:</i>	
	Benchmarked Current Net IRR Buyout (1)	VC (2)
Benchmarked Second Previous Net IRR	0.175*** (0.063)	0.130*** (0.050)
Fund Size Increases (>200%)	-0.031** (0.016)	-0.043 (0.042)
Fund Size Increases (50% - 200%)	-0.024 (0.016)	-0.059 (0.038)
Constant	0.039*** (0.010)	0.010 (0.019)
Observations	182	132
R ²	0.047	0.042
Adjusted R ²	0.031	0.020
Residual Std. Error	0.089 (df = 178)	0.182 (df = 128)
F Statistic	2.923** (df = 3; 178)	1.871 (df = 3; 128)
Note:	* p<0.1; ** p<0.05; *** p<0.01 Standard errors (HC0) are reported in brackets.	

The table above replicates Table 8 in Harris et al. (2023) and shows an OLS regression in which benchmarked current Net IRR is regressed on benchmarked second previous Net IRR, with two scaling dummies. The regression is run separately for VC and buyout funds. One of the dummies is coded one when funds scale between 50-200% over two fund cycles, and the other when funds scale above 200%. Our samples consist of 182 (132) buyout (VC) funds, and only include funds with a corresponding second previous fund. Robust standard errors (HC0) are reported in parentheses. The number of observations, R², adjusted R², residual standard error, and F-statistics are provided as additional indicators of model fit and robustness. The regression is as follows:

$$\text{Current Benchmark Net IRR} = \beta_0 + \beta_1 \cdot \text{Second Previous Benchmark Net IRR} + D_1 \cdot \text{Scale Increase 50-200\%} + D_2 \cdot \text{Scale Increase >200\%} + \varepsilon$$

Table 5 reports performance persistence over two fund cycles at the 1% significance level for both buyout and VC funds. Contrary to Harris et al. (2023), we show that second previous fund performance can predict current fund performance not only for VC but also for buyout funds. We find no effect of scaling on the performance of VC funds. Scaling by more than 200% relative to the second previous fund has a negative effect on the performance of buyout funds at the 5% significance level. This negative effect of scaling on performance is consistent with Berk and Green (2004). It also confirms the findings of Harris et al. (2023), who find a negative effect of

scaling for buyout funds and argue that VC funds are more disciplined than buyouts in their approach to scaling.

3.3 Persistence When Scaling Fund-to-Fund

To examine whether persistence remains when GPs scale fund-to-fund, we create two subsets: one of funds that scale between 25-100% (50-200%) and one of funds that scale more than 100% (200%) over one (two) fund cycle. We run the regression with both previous and second previous fund performance as the independent variable to investigate if persistence persists over both one and two fund cycles when funds scale. We use different scaling cutoffs when looking over one and two fund cycles to reflect the difference in time periods when comparing funds with their most previous, and second most previous, predecessor. We regress the current benchmarked Net IRR on the (second) previous benchmarked Net IRR for these subsets separately.

Table 6: Buyout persistence regressions when scaling over one fund cycle

	<i>Dependent variable:</i>	
	Benchmarked Current Net IRR	
	Scaled between 25% - 100%	Scaled above 100%
	(1)	(2)
Benchmarked Previous Net IRR	0.377*** (0.072)	0.238* (0.128)
Constant	0.010 (0.008)	0.002 (0.015)
Observations	131	70
R ²	0.148	0.097
Adjusted R ²	0.141	0.084
Residual Std. Error	0.088 (df = 129)	0.133 (df = 68)
F Statistic	22.379*** (df = 1; 129)	7.324*** (df = 1; 68)
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01 Standard errors (HCO) are reported in brackets.	

The table above replicates Table 6 in Harris et al. (2023) and shows OLS regressions on our buyout scaling subsets, one for funds that scale between 25-100% and another for funds that scale above 100% over one fund cycle. We regress current benchmarked Net IRR on previous benchmarked Net IRR. Our sample consists of 131 funds that scale 25-100% and 70 that scale >100%. Robust standard errors (HCO) are reported in parentheses. The number of observations, R², adjusted R², residual standard error, and F-statistics are provided as additional indicators of model fit and robustness. The regression is run as follows for each subset:

$$\text{Current Benchmarked Net IRR} = \beta_0 + \beta_1 \cdot \text{Previous Benchmarked Net IRR} + \varepsilon$$

As shown in **Table 6**, there is performance persistence at the 1% significance level among buyout funds that scale between 25-100% over one fund cycle. There is also persistence at the 10% level for buyout funds that scale above 100% over one fund cycle. Scaling over one fund cycle thus does not eliminate persistence for buyout funds.

Table 7: Buyout persistence regressions when scaling over two fund cycles

	<i>Dependent variable:</i>	
	Benchmarked Current Net IRR Scaled between 50% - 200%	Scaled above 200%
	(1)	(2)
Benchmarked Second Previous Net IRR	0.257** (0.101)	0.064 (0.085)
Constant	0.011 (0.011)	0.018 (0.012)
Observations	64	59
R ²	0.068	0.010
Adjusted R ²	0.053	-0.008
Residual Std. Error	0.094 (df = 62)	0.090 (df = 57)
F Statistic	4.529** (df = 1; 62)	0.559 (df = 1; 57)
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01 Standard errors (HC0) are reported in brackets.		

The table above replicates Table 8 in Harris et al. (2023) and shows OLS regressions on our buyout scaling subsets; one for funds that scale between 50-200% and another for funds that scale above 200% over two fund cycles. We regress the benchmarked current Net IRR on the second previous benchmarked Net IRR. Our sample consists of 64 funds that scale 50-200% and 59 that scale >200%. Robust standard errors (HC0) are reported in parentheses. The number of observations, R², adjusted R², residual standard error, and F-statistics are provided as additional indicators of model fit and robustness. The regression is run as follows for each subset:

$$\text{Current Benchmarked Net IRR} = \beta_0 + \beta_1 \cdot \text{Second Previous Benchmarked Net IRR} + \varepsilon$$

Table 7 shows that performance persistence exists for buyout funds that scale between 50% and 200% over two fund cycles, but not for those that scale by more than 200%. As scaling above 200% over two funds has a negative effect on performance, this could potentially disrupt previous persistent outperformance (see **Table 5**), explaining why persistent differences in performance between GPs could diminish. Regressions on our VC scaling subsets over one and two fund cycles can be found in Appendix H, however, the conclusiveness of these results is limited due to small sample sizes.

3.4 Sector Specific Persistence

To investigate sector level persistence, we continue by creating sector and industry group subsets using our “sector proxy funds.” LPs cannot pick individual deals to invest in and therefore cannot selectively back investments in certain sectors. Thus, it is not interesting whether sector specific persistence is based on a measure available to LPs at the time of fundraising or not. We therefore only look at sector specific persistence over one fund cycle, i.e., using the most previous fund results. We repeat the methodology used in prior regressions (replicating Harris et al., 2023) by investigating if the performance of a GP’s previous proxy fund can predict the performance of their next proxy fund, within each sector/industry subset. Our performance metric in this case is benchmarked TVTC, since we do not have access to Net IRRs for our deal level data. We control for the effect of scaling by including two non-cumulative dummy variables: one for proxy funds that are 25-100% larger than their predecessor in the same sector/industry, and one for those that are more than 100% larger.

Table 8: Buyout persistence regressions by sector

	<i>Dependent variable:</i>			
	Consumer	Benchmarked Current TVTC Industrials	Health Care	Information Technology
	(1)	(2)	(3)	(4)
Benchmarked Previous TVTC	0.164*** (0.062)	0.205*** (0.079)	0.151 (0.097)	0.178** (0.070)
Capital Committed Increases (25% - 100%)	-0.123** (0.056)	-0.022 (0.067)	0.007 (0.100)	0.009 (0.073)
Capital Committed Increases (>100%)	-0.090 (0.064)	-0.110 (0.076)	-0.207** (0.097)	0.039 (0.078)
Constant	0.044 (0.033)	0.067 (0.043)	0.033 (0.069)	0.035 (0.039)
Observations	332	205	118	156
R ²	0.036	0.051	0.051	0.051
Adjusted R ²	0.028	0.037	0.026	0.033
Residual Std. Error	0.441 (df = 328)	0.419 (df = 201)	0.457 (df = 114)	0.375 (df = 152)
F Statistic	4.139*** (df = 3; 328)	3.615** (df = 3; 201)	2.024 (df = 3; 114)	2.738** (df = 3; 152)
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01 Standard errors (HC0) are reported in brackets.			

The table above replicates Table 6 in Harris et al. (2023) and reports the results from OLS regressions on our buyout sector subsets – consisting of sector proxy funds – including scaling dummies. One of the dummies is coded one when sector proxy funds scale between 25-100% over one fund cycle, and the other when they scale above 100%. Current performance is regressed on previous performance. Performance is measured using benchmarked (logged) TVTC. Our sample consists of 332 Consumer proxy funds, 205 Industrials proxy funds, 118 Health Care proxy funds, and 156 Information Technology ones. Robust standard errors (HC0) are reported in parentheses. The number of observations, R², adjusted R², residual standard error, and F-statistics are provided as additional indicators of model fit and robustness. The regressions are run as follows for each sector subset:

$$\text{Current Benchmarked TVTC} = \beta_0 + \beta_1 \cdot \text{Previous Benchmarked TVTC} + D_1 \cdot \text{Scale Increase 25-100\%} + D_2 \cdot \text{Scale Increase >100\%} + \varepsilon$$

Table 8 presents the results of our persistence regressions on sector specific subsets of buyout proxy funds. We identify performance persistence for buyout funds at the 10% significance level in the Consumer and Industrials sectors, and at the 5% level in the IT sector. Thus, prior buyout performance in these sectors can predict future performance in the same sector. However, we do not identify performance persistence for investments in the Health Care sector.

Table 9: VC persistence regressions by industry

	Dependent variable:					
	Healthcare (1)	Media (2)	Benchmarked Current TVTC Software (3)	Pharma (4)	Tech-Hardware (5)	Telecom (6)
Benchmarked Previous TVTC	0.169*** (0.065)	0.105 (0.081)	0.172*** (0.054)	-0.049 (0.083)	0.192** (0.077)	0.286*** (0.089)
Capital Committed Increases (25% - 100%)	0.155* (0.083)	0.047 (0.088)	0.012 (0.068)	0.239*** (0.092)	0.056 (0.145)	0.076 (0.149)
Capital Committed Increases (>100%)	0.152* (0.082)	0.293* (0.158)	0.037 (0.079)	0.051 (0.081)	-0.088 (0.131)	0.298* (0.163)
Constant	-0.065 (0.051)	-0.021 (0.062)	0.026 (0.045)	0.030 (0.051)	0.038 (0.071)	0.027 (0.080)
Observations	202	145	384	130	174	111
R ²	0.050	0.040	0.031	0.055	0.046	0.112
Adjusted R ²	0.035	0.020	0.023	0.032	0.029	0.087
Residual Std. Error	0.498 (df = 198)	0.617 (df = 141)	0.617 (df = 380)	0.421 (df = 126)	0.722 (df = 170)	0.660 (df = 107)
F Statistic	3.448** (df = 3; 198)	1.973 (df = 3; 141)	4.062*** (df = 3; 380)	2.444* (df = 3; 126)	2.741** (df = 3; 170)	4.479*** (df = 3; 107)
Note:	*p<0.1; **p<0.05; ***p<0.01 Standard errors (HCO) are reported in brackets.					

The table above replicates Table 6 in Harris et al. (2023). It reports the results from OLS regressions on our VC industry subsets – consisting of industry proxy funds – including scaling dummies. One of the dummies is coded one when industry proxy funds scale between 25-100% over one fund cycle, and the other when they scale above 100%. Current performance is regressed on previous performance. Performance is measured using benchmarked (logged) TVTC. Our sample includes 202 Healthcare, 145 Media, 384 Software, 130 Pharma, 174 Tech-Hardware, and 111 Telecom industry proxy funds. These are abbreviation of GICS industry groups: “Healthcare” denotes the “Healthcare Equipment & Services” industry; “Media” the Media & Entertainment industry; “Software” the Software & Services industry; “Pharma” the Pharmaceuticals, Biotechnology & Life Sciences industry; “Tech-Hardware” the Technology Hardware & Equipment industry; and finally “Telecom” the Telecommunications Services industry. Robust standard errors (HCO) are reported in parentheses. The number of observations, R², adjusted R², residual standard error, and F-statistics are provided as additional indicators of model fit and robustness. The regressions are run as follows for each industry subset:

$$\text{Current Benchmarked TVTC} = \beta_0 + \beta_1 \cdot \text{Previous Benchmarked TVTC} + D_1 \cdot \text{Scale Increase 25-100\%} + D_2 \cdot \text{Scale Increase >100\%} + \varepsilon$$

Table 9 presents the results of our persistence regressions on industry specific subsets of VC proxy funds. In the Healthcare Equipment & Services industry (denoted “Healthcare”), Telecommunications Services industry (denoted “Telecom”), and the Software & Services industry (denoted “Software”) we find performance persistence at the 1% level. We also find persistence at the 5% level within the Technology Hardware & Equipment industry (denoted “Tech-Hardware”). Thus, we conclude that prior VC investments within Healthcare, Software, Tech-Hardware, and Telecom can predict future performance in those industries. However, we find no performance persistence within the Media & Entertainment industry (denoted “Media”) or the Pharmaceuticals, Biotechnology & Life Sciences industry (denoted “Pharma”).

4. Discussion

Despite conflicting findings in past literature regarding the existence of performance persistence over two fund cycles, we find evidence of persistence using both previous and second previous performance for buyout and VC funds. Prior fund performance is especially informative if the previous fund was in the top quartile for buyout funds and top or bottom quartile for VCs. As earlier literature has suggested (Kaplan and Schoar, 2005; Brown et al., 2023), the existence of performance persistence can be explained by inefficiencies in the PE market; with the skills required to be successful scarce or proprietary. Performance persistence net of fees can exist since returns to high performance are not appropriated. This may be due to the negative signalling effect that would arise if current LPs chose not to invest in future funds, hindering GPs from raising fees following strong performance (Hochberg et al., 2014).

Our evidence of persistence over two fund cycles contradicts Chung et al. (2012), who argue that persistence should weaken over subsequent fund cycles due to excessive fund growth following strong performance. As argued by Kaplan and Schoar (2005), successful GPs face diseconomies of scale as the inputs they provide, like time or advice, are not easily scalable. This could disrupt prior consistent top performance. Our findings suggest that successful GPs exercise caution when scaling and avoid scaling excessively. Successful GPs who aim to scale may also face obstacles as there might only exist a limited number of opportunities present in the market at a given time, both in terms of investing and hiring (Kaplan and Schoar, 2005). Thus, persistence persists over both one and two fund cycles, and investors should be able to significantly improve their performance by basing investment decisions on the performance of a GP's second previous fund.

Another key finding of ours is the effect of scaling on persistence. According to Kaplan and Schoar (2005) and Sensoy et al. (2014), excessive scaling should diminish consistent outperformance since investment opportunities representing “low-hanging fruit” become exhausted in the higher end of the PE fund size distribution. We find that moderate scaling over two fund cycles (50-200%) has no significant effect on performance for either of our subsets, while more excessive scaling (>200%) has a significant negative effect on performance for buyout funds. We also find that persistence disappears when buyout funds scale more than 200% over two fund cycles. Harris et al. (2023) report similar findings, noting that scaling only negatively affects performance in their buyout sample. The authors argue that this is likely a consequence of buyout funds being less disciplined than VCs in avoiding scaling too rapidly to the detriment of their performance. An alternative explanation could be derived from the VC business model itself, as it might not be scalable by nature. For instance, the number of quality startups in a market might be limited and the value VCs add might stem from less scalable inputs such as mentorship and networks. This theory is consistent with the comparably smaller number of VC than buyout funds which scale in our data.

There are few precedent findings surrounding the impact of sector/industry on performance persistence in PE. However, Sensoy et al. (2014)'s conclusions surrounding the decline of superior performance as the PE industry grows in size and sophistication could be applicable to sectors/industries within PE too. As highlighted by Hochberg et al. (2015), having specialised skills in a sector is more valuable if competitors and skills within that sector are scarce. Since

Brown et al. (2023) attribute persistence to differences in GP skill, persistent outperformance could be stronger in such sectors. For buyout funds, we find performance persistence in every sector except for Health Care. Moreover, we find persistence in every VC industry except for Media and Pharma. This could be due to these sectors representing more crowded and efficient markets, with skills that are less scarce than in other sectors, making consistent outperformance more difficult.

An alternative explanation for the lack of persistence in some sectors could be a recent surge in sector concentrated GPs. Spaenjers and Steiner (2024) show that the proportion of GPs specialising in a sector has almost doubled during the last 20 years, mostly driven by new entrants. They also find that being specialised in a sector improves performance in that sector. It is thus possible that generalist GPs who were once top performers in a sector might no longer hold that position, due to specialised new entrants outperforming them. This shift could lead to a temporary transitional period during which performance persistence disappears in sectors where the number of specialised GPs have increased significantly. This could explain our inability to detect persistence in some sectors, should they have seen a recent increase in specialised actors. It would be interesting for future research to investigate if persistence in specific sectors varies across different points in time – and whether findings become more consistent across sectors once the surge in sector specialised GPs stabilises.

5. Concluding Remarks

Our findings confirm prior literature by showing that performance persistence over one fund cycle exists for buyout and VC funds, using a more recent and geographically diverse dataset. We contribute to the field by finding evidence of persistence based on a measure which is useful to investors when allocating their capital. Past performance is no guarantee of future results, however examining a GP's second previous fund results is informative for where to allocate capital next. By finding that scaling too aggressively destroys persistence for buyout funds, we show that LPs should not only evaluate past performance, but also how GPs manage growth across fund vintages. Our results on the variation of performance persistence across the different sectors are a new addition to the field, and future research on this topic would be particularly interesting.

PE is generally exempt from public disclosure requirements, making data hard to come by. Early research into persistence among PE funds therein relies on datasets voluntarily reported by GPs. While sourcing data from an LP and investment manager increases the reliability of our results, it also limits our sample size. Since analysing persistence requires data on prior fund performance, and given that we examine persistence separately for different subsets, our sample sizes become even more limited. We think that further research building on our contributions – especially looking at the effects of scaling on persistence as well as sector specific persistence – would benefit from larger datasets sourced from multiple LPs.

Most past research on persistence relies on North American funds due to limited international data. However, half of global PE investments are made in markets outside of North America (Ain Tommar et al., 2024). In this paper, we attempt to look at the aggregate PE market, and thus conduct our analysis on a geographically diverse sample. Recent studies by Ain Tommar et al.

(2024) find little evidence of persistence in Europe, Asia, and the rest of the world, compared to North America. This indicates that our results could be more driven by certain markets than others. If the prevalence or nature of persistence differs significantly across regions, our analysis would have benefitted from being completed on a geographical level. As more international PE data becomes available, a closer examination of regional differences in performance persistence would also be an interesting way of extending the field.

Finally, our analysis could also benefit from being conducted separately for different time periods, mitigating the risk that a few extreme vintages unproportionally influence the results. For instance, the negative effect on buyout performance we find from scaling excessively could be driven by the strong buyout growth seen leading up to the 2008 financial crisis (Kaplan and Strömberg, 2009). Therefore, it might be meaningful to conduct our scaling analysis separately for pre- and post- 2008 vintages.

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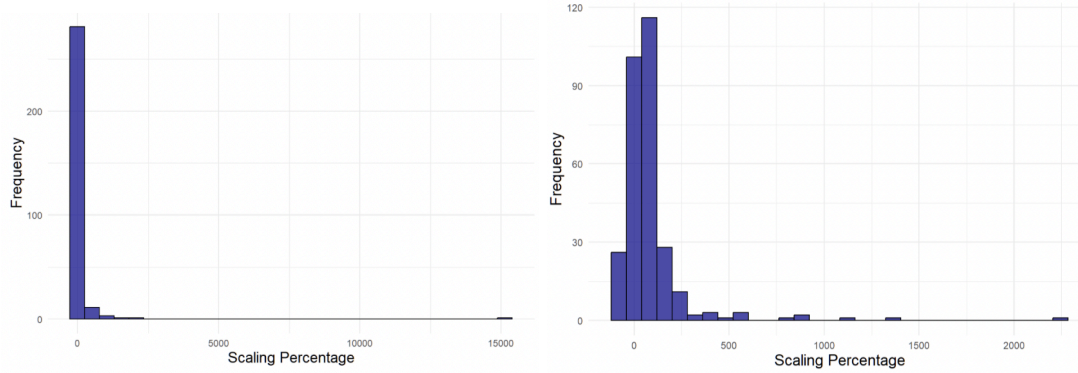
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7. Appendix

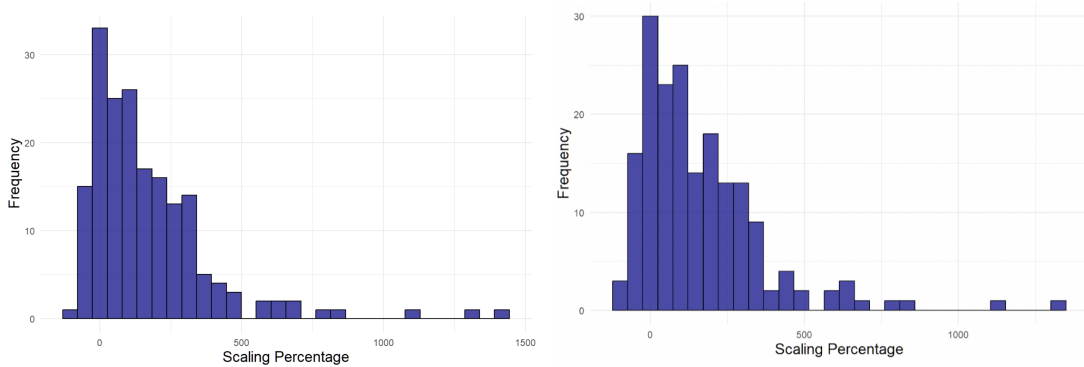
Appendix A

Figure A1: Distribution of buyout scaling over one fund cycle (pre- and post-outlier removal)



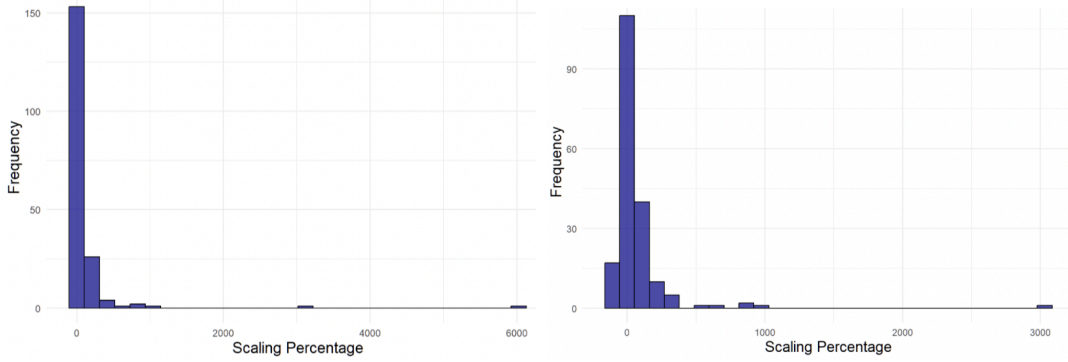
The left side of the table above shows the distribution of scaling over one fund cycle for buyout funds with previous performance data. Scaling is calculated as the percentage change in total capital committed by investors. The right side of the table shows the distribution after removing one extreme upper outlier.

Figure A2: Distribution of buyout scaling over two fund cycles (pre- and post-outlier removal)



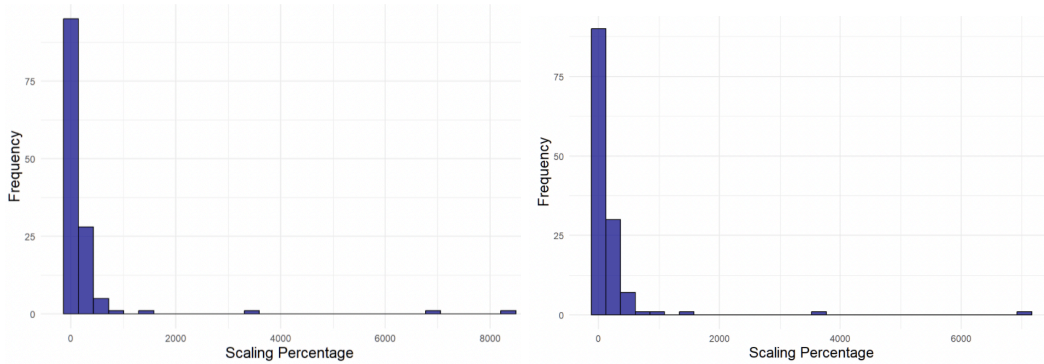
The left side of the table above shows the distribution of scaling over two fund cycles for buyout funds with second previous performance data. Scaling is calculated as the percentage change in total capital committed by investors. The right side of the table shows the distribution after removing one extreme upper outlier.

Figure A3: Distribution of VC scaling over one fund cycle (pre- and post-outlier removal)



The left side of the table above shows the distribution of scaling over one fund for VC funds with previous performance data. Scaling is calculated as the percentage change in total capital committed by investors. The right side of the table shows the distribution after removing one extreme upper outlier.

Figure A4: Distribution of VC scaling over two fund cycles (pre- and post-outlier removal)



The left side of the table above shows the distribution of scaling over two funds for VC funds with second previous performance data. Scaling is calculated as the percentage change in total capital committed by investors. The right side of the table shows the distribution after removing one extreme upper outlier.

Appendix B

Appendix B presents summary statistics on funds with prior performance information. The average Net IRRs of funds with available previous and second previous performance is within one percentage point of their respective overall sample Net IRRs (see **Table 1**). This is except for VC funds with second previous performance, which have a Net IRR that is 4.1 percentage points higher than the overall sample. Average TVPI for buyout funds with previous and second previous performance differs less than 4% from the overall sample, and VC funds differ less than 20% from the overall sample. Average capital committed differs less than 20% compared to the overall sample for buyout funds and less than 68% for VC funds.

Table B1: Summary statistics on funds with previous performance*Panel A - Buyout funds*

Vintage Year	Total Funds	Average Capital Committed	Average TVPI	Average IRR
1994	1	1,945,722,483	1.770	0.168
1996	1	2,458,754,795	0.970	-0.010
1997	1	6,011,622,000	1.790	0.132
1998	8	1,333,162,031	1.827	0.143
1999	2	1,886,925,000	1.880	0.149
2000	5	2,493,547,540	1.982	0.171
2001	6	2,249,960,866	2.115	0.396
2002	6	836,121,981	2.400	0.218
2003	3	4,541,800,000	2.091	0.190
2004	7	1,663,385,508	2.195	0.209
2005	10	3,233,597,623	1.940	0.117
2006	9	4,188,742,864	1.751	0.092
2007	16	5,364,474,020	1.829	0.121
2008	5	9,550,818,570	1.869	0.106
2009	6	3,410,758,633	2.192	0.199
2010	4	785,175,020	2.282	0.222
2011	10	3,112,601,225	1.965	0.130
2012	13	1,696,935,591	2.740	0.242
2013	20	3,459,938,062	2.226	0.179
2014	24	3,144,425,178	2.210	0.149
2015	16	1,671,048,081	2.171	0.195
2016	21	3,246,415,841	2.336	0.226
2017	20	3,068,044,988	2.890	0.296
2018	39	4,140,289,897	1.977	0.198
2019	44	3,508,425,899	1.579	0.165
Overall Average	12	3,293,938,578	2.084	0.186

Panel B - VC funds

Vintage Year	Total Funds	Average Capital Committed	Average TVPI	Average IRR
1988	1	60,600,000	2.762	0.213
1990	1	198,950,000	2.800	0.312
1992	4	235,900,902	2.952	0.462
1993	4	189,200,000	7.487	0.618
1994	1	112,584,900	5.400	0.548
1995	2	571,505,103	5.080	0.631
1997	7	383,383,588	3.890	0.576
1998	4	231,797,380	0.636	-0.050
1999	5	215,243,209	0.630	-0.094
2000	13	661,395,138	1.072	0.014
2001	8	508,579,318	1.312	0.050
2003	1	288,000,000	1.360	0.059
2004	3	565,559,374	1.589	0.055
2005	4	371,095,847	4.598	0.188
2006	6	455,040,067	2.072	0.093
2007	3	322,298,575	1.734	0.083
2008	2	515,173,500	3.941	0.185
2009	3	783,343,486	1.568	0.071
2010	9	893,146,668	2.931	0.184
2011	4	581,477,466	2.522	0.111
2012	4	501,851,103	3.976	0.215
2013	4	968,055,101	4.800	0.286
2014	13	1,077,499,058	3.403	0.205
2015	8	2,408,524,249	2.318	0.129
2016	11	505,174,929	2.320	0.148
2017	16	668,806,544	2.392	0.170
2018	20	604,485,922	1.899	0.153
2019	27	738,432,620	1.501	0.101
Overall Average	7	685,748,672	2.409	0.164

The table above replicates Table 1 in Harris et al. (2023) and shows summary statistics on the 298 buyout funds and 189 VC funds in our sample with previous performance data. The funds are sorted based on vintage year, which is defined as the year a fund first draws capital from its LPs. For each vintage year, the table reports the average capital committed by investors to the funds. The table also reports the average of two performance measures for each vintage year: 1) Internal Rate of Return (IRR); and 2) The ratio of the total value of the fund to the capital paid-in by investors (TVPI). Both variables include realised and unrealised values and are net of fees and carried interest. All data is sourced from Harbourvest Partners.

Table B2: Summary statistics on funds with second previous performance
Panel A - Buyout funds

Vintage Year	Total Funds	Average Capital Committed	Average TVPI	Average IRR
1997	2	3,407,311,000	1.465	0.079
1998	3	2,641,228,099	1.227	0.027
2000	3	3,042,588,768	2.274	0.200
2001	2	1,014,482,597	1.460	0.130
2002	3	2,033,845,886	2.564	0.268
2003	1	1,845,065,000	1.750	0.227
2004	3	1,954,772,522	2.167	0.182
2005	5	4,861,050,000	1.887	0.116
2006	4	16,212,536,500	1.679	0.079
2007	12	5,303,278,752	2.014	0.137
2008	5	9,597,998,247	2.085	0.140
2009	5	3,322,910,359	2.290	0.214
2010	3	1,029,908,347	2.091	0.178
2011	2	6,076,867,125	2.780	0.231
2012	6	1,235,660,840	2.857	0.219
2013	13	3,441,208,079	2.448	0.203
2014	10	6,363,018,179	2.725	0.125
2015	9	2,360,421,312	2.265	0.209
2016	22	3,378,241,895	2.318	0.232
2017	13	3,289,887,557	2.771	0.291
2018	26	5,414,815,758	1.647	0.153
2019	30	3,273,630,250	1.627	0.179
Overall Average	8	4,205,803,968	2.073	0.183

Panel B - VC funds

Vintage Year	Total Funds	Average Capital Committed	Average TVPI	Average IRR
1986	1	151,515,112	NaN	0.103
1988	1	41,677,240	4.120	0.358
1993	2	136,050,000	9.280	0.781
1995	3	610,000,000	7.570	1.010
1997	8	254,752,307	3.854	0.659
1998	4	393,787,500	0.522	-0.062
1999	3	235,747,451	0.720	-0.056
2000	11	743,358,179	1.010	-0.014
2001	3	617,164,428	1.230	0.030
2002	1	914,898,990	1.251	0.027
2004	4	243,158,505	1.453	0.018
2005	4	574,278,676	2.025	0.087
2006	3	1,501,380,135	1.471	0.075
2008	2	303,489,796	6.986	0.275
2009	3	655,478,333	1.976	0.112
2010	2	495,710,655	2.495	0.158
2011	4	770,877,731	3.930	0.248
2012	7	555,643,972	5.256	0.265
2013	4	493,427,702	6.403	0.312
2014	11	1,128,806,065	3.029	0.175
2015	6	945,720,231	4.059	0.231
2016	8	523,882,814	2.844	0.221
2017	10	1,083,383,125	1.993	0.153
2018	11	662,987,956	1.807	0.145
2019	16	794,664,403	1.698	0.124
Overall Average	5	689,152,044	2.788	0.197

The table above replicates Table 1 in Harris et al. (2023) and shows summary statistics on the 189 buyout funds and 133 VC funds in our sample with second previous performance data. The funds are sorted based on vintage year, which is defined as the year a fund first draws capital from its LPs. For each vintage year, the table reports the average capital committed by investors to the funds. The table also reports the average of two performance measures for each vintage year: 1) Internal Rate of Return (IRR); and 2) The ratio of the total value of the fund to the capital paid-in by investors (TVPI). Both variables include realised and unrealised values and are net of fees and carried interest. All data is sourced from Harbourvest Partners.

Appendix C

Appendix C presents summary statistics on all proxy funds in our sample. For both buyout and VC, average TVTC differs less than 7% from proxy funds with previous performance. Average total cost differs less than 13% from proxy funds with previous performance data (see **Table 2**).

Table C1: Summary statistics on proxy funds

Panel A - Buyout sector proxy funds

Interval	Total Proxy Funds	Average Total Cost	Average TVTC
1985-1986	2	2,546,057	1.341
1988-1989	21	83,525,021	1.605
1991-1992	46	24,130,772	2.765
1994-1995	73	43,690,510	2.950
1997-1998	152	43,064,867	2.717
2000-2001	178	62,699,965	2.537
2003-2004	247	90,130,506	2.634
2006-2007	346	158,566,768	1.928
2009-2010	253	172,459,989	2.548
2012-2013	367	137,392,544	2.630
2015-2016	443	155,533,628	2.798
2018-2019	376	193,963,968	2.760
Overall Average	209	134,496,254	2.575

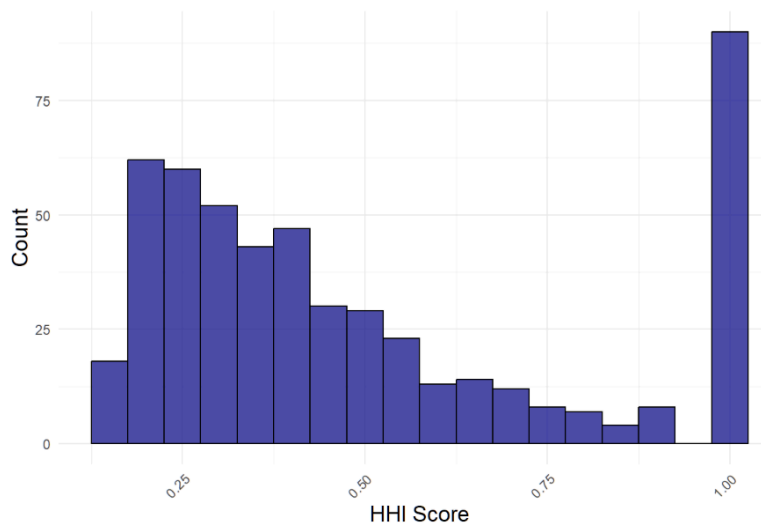
Panel B - VC industry proxy funds

Interval	Total Proxy Funds	Average Total Cost	Average TVTC
1982-1983	9	2,077,149	2.379
1985-1986	56	1,887,345	2.588
1988-1989	159	1,966,130	2.529
1991-1992	168	2,167,124	3.567
1994-1995	208	3,158,751	4.139
1997-1998	409	9,304,421	1.967
2000-2001	567	10,179,586	1.245
2003-2004	454	12,262,889	2.158
2006-2007	324	19,385,871	2.262
2009-2010	264	22,897,818	3.193
2012-2013	313	27,573,844	3.278
2015-2016	394	24,195,102	2.913
2018-2019	341	25,618,044	2.201
Overall Average	282	15,228,605	2.460

The table above replicates Table 1 in Harris et al. (2023) and shows summary statistics on the 2504 buyout sector proxy funds and 3656 industry proxy funds in our sample. A proxy fund includes all of the buyout (VC) deals from the same GP within the same sector (industry group) during a three year interval. The proxy funds are sorted based on the investment year intervals of their deals. For each vintage year, the table reports the average total cost of the proxy funds. We calculate the total cost of each proxy fund by summing the total costs of its deals. The table also reports averages of the performance measure Total Value to Total Cost (TVTC). The TVTC of a proxy fund is defined as the sum of the realised and unrealised values of all its deals, divided by the sum of the total costs of those deals. All data is sourced from HarbourVest Partners.

Appendix D

Figure D1: Distribution of HHI for buyout managers

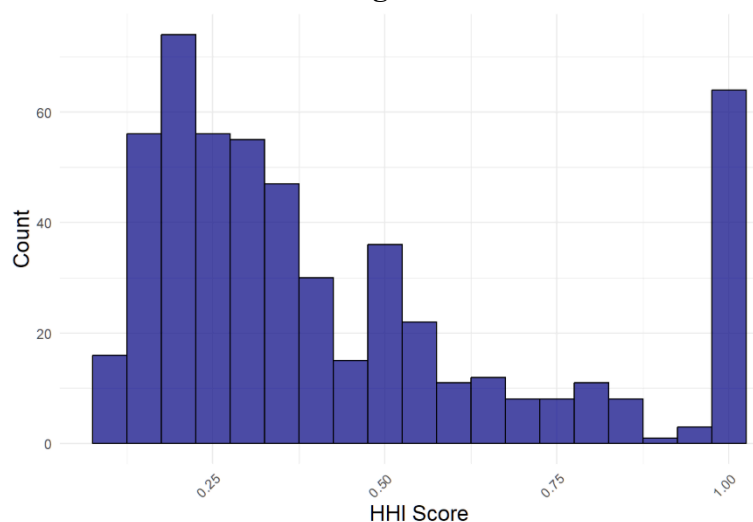


The table above shows the distribution of Herfindahl-Hirschman indices score (HHI) for all GPs with buyout deals in our deal data. HHI measures sector concentration. The score can range between $[0,1]$ and a higher value indicates a higher degree of concentration. A HHI score for GPj is calculated as follows:

$$HHI_j = \sum (w_i)^2$$

$$w_i = (\text{Lifetime total invested in sector } i) \div (\text{Lifetime total invested across all sectors})$$

Figure D2: Distribution of HHI for VC managers



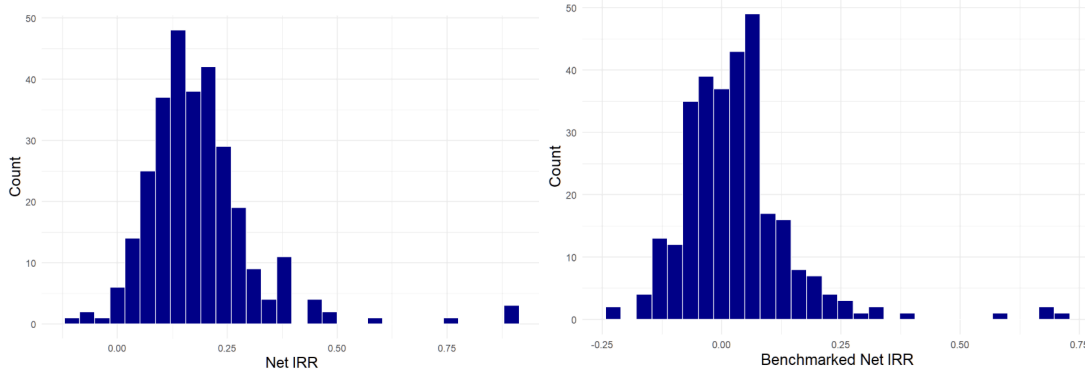
The table above shows the distribution of Herfindahl-Hirschman indices score (HHI) for all GPs with VC deals in our deal data. HHI measures industry concentration. The score can range between $[0,1]$ and a higher value indicates a higher degree of concentration. A HHI score for GPj is calculated as follows:

$$HHI_j = \sum (w_i)^2$$

$w_i = (\text{Lifetime total invested in industry group } i) \div (\text{Lifetime total invested across all industry groups})$

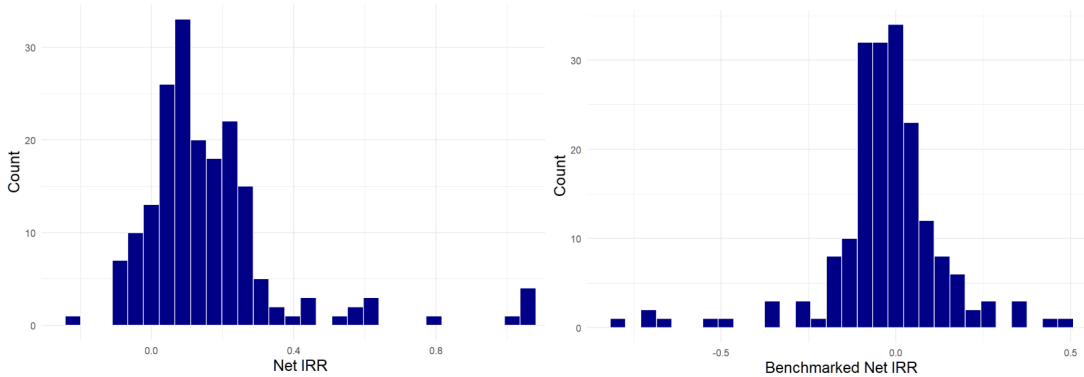
Appendix E

Figure E1: Distribution of buyout fund Net IRR (pre- and post-benchmarking)



The left side of the table above shows the distribution of Net IRR for buyout funds. Net IRR is based on the fund's cash flows, and treats any unrealised value as a final cash flow. The measure is net of fees and carried interest. The right side of the table shows the distribution of benchmarked Net IRR for buyout funds. The benchmarked metric is created by subtracting the Net IRR index of the corresponding buyout market and vintage year from each fund's Net IRR. We use MSCI's Burgiss Private Capital Indexes, and the market is defined by geography (North America, Asia or Europe).

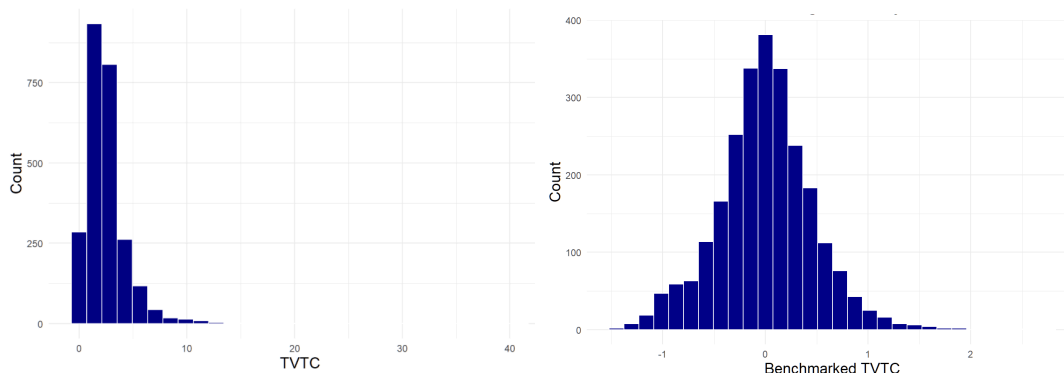
Figure E2: Distribution of VC fund Net IRR (pre- and post-benchmarking)



The left side of the table above shows the distribution of Net IRR for VC funds. Net IRR is based on the fund's cash flows, and treats any unrealised value as a final cash flow. The measure is net of fees and carried interest. The right side of the table shows the distribution of benchmarked Net IRR for VC funds. The benchmarked metric is created by subtracting the Net IRR index of the corresponding VC market and vintage year from each fund's Net IRR. We use MSCI's Burgiss Private Capital Indexes, and the market is defined by geography (North America, Asia or Europe).

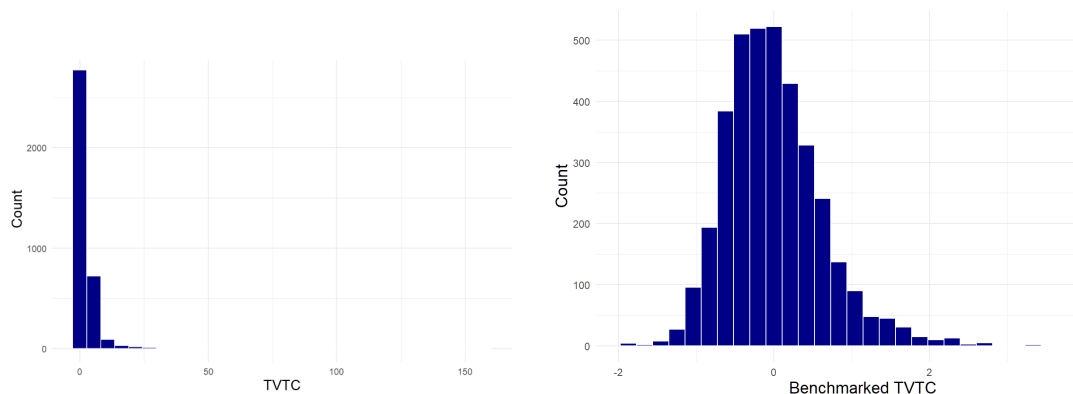
Appendix F

Figure F1: Distribution of buyout proxy fund TVTC (pre- and post-benchmarking)



The left side of the table above shows the distribution of the ratio Total Value to Total Cost (TVTC) for buyout sector proxy funds. A proxy fund includes all of the buyout deals from the same GP within the same sector during a three year interval. The TVTC of a proxy fund is defined as the sum of the realised and unrealised values of all its deals, divided by the sum of the total costs of those deals. The right side of the table shows the distribution of benchmarked TVTC for buyout sector proxy funds. We create the benchmarked measure by subtracting the logged pooled TVTC of the corresponding sector and vintage year from each proxy fund's logged TVTC. The pooled TVTC is the capital weighted TVTC of all buyout deals in our data within the same sector and investment year interval.

Figure F2: Distribution of VC proxy fund TVTC (pre- and post-benchmarking)



The left side of the table above shows the distribution of the ratio Total Value to Total Cost (TVTC) for VC industry proxy funds. A proxy fund includes all of the VC deals from the same GP within the same industry group during a three year interval. The TVTC of a proxy fund is defined as the sum of the realised and unrealised values of all its deals, divided by the sum of the total costs of those deals. The right side of the table shows the distribution of benchmarked TVTC for VC industry proxy funds. We create the benchmarked measure by subtracting the logged pooled TVTC of the corresponding sector and vintage year from each proxy fund's logged TVTC.

The pooled TVTC is the capital weighted TVTC of all VC deals in our data within the same industry group and investment year interval.

Appendix G

Table G1: Buyout performance quartile transition matrix over two fund cycles

Group	Q1 Count	Q2 Count	Q3 Count	Q4 Count	Total Count	Q1 Percentage	Q2 Percentage	Q3 Percentage	Q4 Percentage	Average Net IRR
Quartile 1	23	11	13	8	55	41.82%	20%	23.64%	14.55%	0.22
Quartile 2	17	9	7	7	40	42.5%	22.5%	17.5%	17.5%	0.20
Quartile 3	8	17	8	5	38	21.05%	44.74%	21.05%	13.16%	0.18
Quartile 4	3	1	3	3	10	30%	10%	30%	30%	0.15
First Time Funds	28	18	16	11	73	38.36%	24.66%	21.92%	15.07%	0.20
No Previous Fund	82	107	85	66	340	24.12%	31.47%	25%	19.41%	0.16

The table above replicates Table 2 in Harris et al. (2023) and shows a probability quartile transition matrix over two fund cycles for buyout funds. The column “Group” divides the funds as follows: funds with a second previous fund are matched with their second previous fund performance quartile, first funds of a GP in a fund family are sorted into the “First Time Funds” category, and funds with no prior fund data that are not first in their fund family are assigned to the “No Previous Fund” group. The distribution of each group’s fund performance across quartiles is calculated. The table also presents the average Net IRR of each group. Quartiles are pre-assigned to each fund using a Burgiss dataset, and represent their performance within the most appropriate PE market.

Table G1 shows that weaker quartile persistence can be established for buyout funds when we look at persistence over two fund cycles instead of one. GPs with second prior funds in the first quartile perform in the top quartile 42% of the time and above the median 62% of the time. Top to bottom flips occur only 15% of the time. Since the attrition rate is high, only 10 GPs have a second previous fund which performed in the bottom quartile. Thus, limited conclusions can be drawn on persistence in bottom quartile performance. While the average Net IRR decreases with the second previous fund quartile, the groups’ average Net IRRs are not significantly different from each other. First time funds have the same average performance as GPs with prior second quartile results, but there are no significant differences across first time funds and the other groups. The relatively even distribution of funds with missing second previous data suggests that the data is missing at random. Overall, few conclusions can be drawn on persistence over two fund cycles using this method due to the low sample sizes and high attrition rates.

Table G2: VC performance quartile transition matrix over two fund cycles

Group	Q1 Count	Q2 Count	Q3 Count	Q4 Count	Total Count	Q1 Percentage	Q2 Percentage	Q3 Percentage	Q4 Percentage	Average Net IRR
Quartile 1	13	9	11	4	37	35.14%	24.32%	29.73%	10.81%	0.20
Quartile 2	3	7	7	3	20	15%	35%	35%	15%	0.10
Quartile 3	2	4	2	3	11	18.18%	36.36%	18.18%	27.27%	0.05
Quartile 4	5	3	0	2	10	50%	30%	0%	20%	0.27
First Time Funds	24	8	16	12	60	40%	13.33%	26.67%	20%	0.18
No Previous Fund	103	80	69	49	301	34.22%	26.58%	22.92%	16.28%	0.15

The table above replicates Table 2 in Harris et al. (2023) and shows a probability quartile transition matrix over two fund cycles for VC funds. The column “Group” divides the funds as follows: funds with a second previous fund are matched with the second previous fund performance quartile, first funds of a GP in a fund family are sorted into the “First Time Funds” category, and funds with no prior fund data that are not first in their fund family are assigned to the “No Previous Fund” group. The distribution of each group’s fund performance across quartiles is calculated. The table also presents the average Net IRR of each group. Quartiles are pre-assigned to each fund using a Burgiss dataset, and represent their performance within the most appropriate PE market.

Table G2 shows that, similarly to buyout funds, VCs show weaker persistence when looking over two fund cycles than over one. GPs with second previous funds in the top quartile perform in the top quartile 35% of the time and above the median 59% of the time. A top to bottom flip only happens 11% of the time. However, due to high attrition rates, only 21 GPs performed below the median two fund cycles ago. This makes it hard to investigate persistence in poor performance. First time funds rank between funds with previous first and second quartile performance. None of the groups’ average Net IRRs are significantly different from each other. The performance of funds without a second previous fund is skewed towards higher performance, suggesting that data might not be missing at random. As for buyout funds, few conclusions can once again be drawn on persistence over two fund cycles using this method due to the low sample sizes and high attrition rates.

Appendix H

Table H1: VC persistence regressions when scaling fund-to-fund over one fund cycle

	<i>Dependent variable:</i>	
	Benchmarked Current Net IRR	
	Scaled between 25% - 100%	Scaled above 100%
	(1)	(2)
Benchmarked Previous Net IRR	0.176 (0.130)	0.109 (0.103)
Constant	-0.033* (0.020)	-0.068** (0.032)
Observations	57	40
R ²	0.074	0.016
Adjusted R ²	0.057	-0.010
Residual Std. Error	0.158 (df = 55)	0.205 (df = 38)
F Statistic	4.375** (df = 1; 55)	0.620 (df = 1; 38)
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01 Standard errors (HC0) are reported in brackets.	

The table above replicates Table 6 in Harris et al. (2023) and shows OLS regressions on our VC scaling subsets, one for funds that scale between 25-100% and another for funds that scale above 100%, over one fund cycle. We regress current benchmarked Net IRR on previous benchmarked Net IRR. Our sample consists of 57 funds that scale 25-100% and 40 that scale >100%. Robust standard errors (HC0) are reported in parentheses. The number of observations, R², adjusted R², residual standard error, and F-statistics are provided as additional indicators of model fit and robustness. The regression is run as follows for each subset:

$$\text{Current Benchmarked Net IRR} = \beta_0 + \beta_1 \cdot \text{Previous Benchmarked Net IRR} + \varepsilon$$

Table H2: VC persistence regressions when scaling fund-to-fund over two fund cycles

	<i>Dependent variable:</i>	
	Benchmarked Current Net IRR	
	Scaled between 50% - 200%	Scaled above 200%
	(1)	(2)
Benchmarked Second Previous Net IRR	0.031 (0.082)	0.157** (0.067)
Constant	-0.049 (0.033)	-0.031 (0.039)
Observations	40	24
R ²	0.001	0.054
Adjusted R ²	-0.025	0.011
Residual Std. Error	0.217 (df = 38)	0.189 (df = 22)
F Statistic	0.032 (df = 1; 38)	1.245 (df = 1; 22)
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01 Standard errors (HC0) are reported in brackets.	

The table above replicates Table 8 in Harris et al. (2023) and shows OLS regressions on our VC scaling subsets, one on funds that scale between 50-200% and another for funds that scale above 200%, over two fund cycles. We regress the current benchmarked Net IRR on the second previous benchmarked Net IRR. Our sample consists of 40 funds that scale 50-200% and 24 that scale >200%. Robust standard errors (HC0) are reported in parentheses. The number of observations, R^2 , adjusted R^2 , residual standard error, and F -statistics are provided as additional indicators of model fit and robustness. The regression is run as follows for each subset:

$$\text{Current Benchmarked Net IRR} = \beta_0 + \beta_1 \cdot \text{Second Previous Benchmarked Net IRR} + \varepsilon$$

Appendix I

To look at the effect of sector concentration on performance, we identify the degree of sector concentration of the GPs in our deal data. We classify each GP as belonging to one of three categories: specialist, focused, or generalist. To identify specialists we follow the method used by Brown et al. (2023) to calculate a Herfindahl-Hirschman indices score (HHI) for each GP. We calculate HHI by summing the squared lifetime portfolio weights in each sector for GPs with buyout funds, and in each industry group for GPs with VC funds (see Appendix D). While Brown et al. (2023) use fund level weights as they study fund level specialisation, we use lifetime portfolio weights since we are interested in consistent sector performance by GPs across funds. The score can range between $[0,1]$ and a higher value indicates a higher degree of specialisation. The distribution of HHI is skewed to the right with a median of 0.40 for buyout and 0.34 for VC (see Appendix D). We set a threshold of 0.35 to classify a GP as a specialist within the sector or industry in which they are overweight. In cases where a GP does not meet this threshold but has more than 35% of their lifetime deals and total investment cost concentrated in a single sector/industry, they are classified as focused within that sector/industry. GPs who do not meet the requirements to be classified as either specialists or focused are classified as generalists.

Table I1: Buyout persistence regressions by sector controlling for sector concentration

	Dependent variable:			
	Consumer	Industrials	Health Care	Information Technology
	(1)	(2)	(3)	(4)
Benchmarked Previous TVTC	0.159** (0.062)	0.191** (0.079)	0.151 (0.097)	0.179** (0.071)
Capital Committed Increases (25% - 100%)	-0.125** (0.056)	-0.017 (0.068)	0.009 (0.101)	0.008 (0.074)
Capital Committed Increases (>100%)	-0.088 (0.064)	-0.115 (0.075)	-0.208** (0.097)	0.037 (0.078)
Specialist	-0.018 (0.058)	-0.135 (0.107)		
Focused	-0.041 (0.075)	0.072 (0.079)	-0.023 (0.085)	-0.016 (0.081)
Constant	0.055 (0.035)	0.071 (0.049)	0.034 (0.069)	0.038 (0.042)
Observations	332	205	118	156
R ²	0.038	0.065	0.051	0.051
Adjusted R ²	0.023	0.041	0.017	0.026
Residual Std. Error	0.442 (df = 326)	0.418 (df = 199)	0.459 (df = 113)	0.377 (df = 151)
F Statistic	2.558** (df = 5; 326)	2.750** (df = 5; 199)	1.508 (df = 4; 113)	2.047* (df = 4; 151)
Note:	*p<0.1; **p<0.05; ***p<0.01 Standard errors (HC0) are reported in brackets.			

The table above replicates Table 6 in Harris et al. (2023) and reports the results from OLS regressions on our buyout sector subsets – consisting of our sector proxy funds – including scaling and sector concentration dummies. One of the scaling dummies is coded one when sector proxy funds scale between 25-100% over one fund cycle, and the other when they scale above 100%. The dummy variable “Specialist” is coded one if a fund’s GP is specialist in the same sector as the proxy fund. The dummy variable “Focused” is coded one if a fund’s GP is focused in the same sector as the proxy fund. If there are no specialist or focused GPs within the sector sample, the dummies are not included in the regression. We measure sector concentration by calculating the HHI scores for all GPs. These are calculated by taking the sum of the squared total deal portfolio sector weights of each GP in their lifetime. The score can range between [0,1] and a higher value indicates a higher degree of sector concentration. We set a threshold of 0.35 to classify a GP as a specialist within the sector in which they are overweight. A GP is classified as focused if more than 35% of their deals as well as more than 35% of their total costs are in the same sector, but their HHI score is below 0.35. Current performance is regressed on previous performance. Performance is measured using benchmarked (logged) TVTC. Our sample consists of 332 Consumer proxy funds, 205 Industrials proxy funds, 118 Health Care proxy funds, and 156 Information Technology ones. Robust standard errors (HC0) are reported in parentheses. The number of observations, R², adjusted R², residual standard error, and F-statistics are provided as additional indicators of model fit and robustness. The regressions are constructed as follows for each sector subset:

$$\text{Current Benchmarked TVTC} = \beta_0 + \beta_1 \cdot \text{Previous Benchmarked TVTC} + D_1 \cdot \text{Scale Increase } 25\text{-}100\% + D_2 \cdot \text{Scale Increase } >100\% + D_3 \cdot \text{Specialist} + D_4 \cdot \text{Focused} + \varepsilon$$

Table 11 repeats the regressions in **Table 8** on our buyout sector proxy funds while including dummies for sector specialisation and focus. We only identify matched specialists in the Consumer and Industrials subsets – in which being specialist has no significant effect on performance – limiting any conclusions on the effect of specialisation on performance. Moreover, we do not identify any significant effects of being focused within a sector. Thus, we do not find any conclusive evidence of sector concentration affecting performance.

Table 12: VC persistence regressions by industry controlling for industry concentration

	Dependent variable:					
	Healthcare (1)	Media (2)	Benchmarked Current TVTC Software (3)	Pharma (4)	Tech-Hardware (5)	Telecom (6)
Benchmarked Previous TVTC	0.169*** (0.065)	0.105 (0.081)	0.170*** (0.054)	-0.049 (0.083)	0.194** (0.076)	0.271*** (0.091)
Capital Committed Increases (25% - 100%)	0.156* (0.083)	0.046 (0.088)	0.013 (0.068)	0.239*** (0.092)	0.053 (0.147)	0.072 (0.147)
Capital Committed Increases (>100%)	0.153* (0.083)	0.293* (0.158)	0.042 (0.080)	0.051 (0.081)	-0.078 (0.127)	0.304* (0.165)
Specialist						
Focused	0.030 (0.175)	-0.022 (0.249)	0.037 (0.062)		0.249 (0.593)	0.327 (0.217)
Constant	-0.066 (0.052)	-0.020 (0.063)	0.012 (0.054)	0.030 (0.051)	0.028 (0.064)	-0.004 (0.080)
Observations	202	145	384	130	174	111
R ²	0.050	0.040	0.032	0.055	0.050	0.132
Adjusted R ²	0.030	0.013	0.022	0.032	0.027	0.099
Residual Std. Error	0.499 (df = 197)	0.619 (df = 140)	0.618 (df = 379)	0.421 (df = 126)	0.723 (df = 169)	0.656 (df = 106)
F Statistic	2.578** (df = 4; 197)	1.470 (df = 4; 140)	3.120** (df = 4; 379)	2.444* (df = 3; 126)	2.222* (df = 4; 169)	4.014*** (df = 4; 106)
Note:	*p<0.1; **p<0.05; ***p<0.01 Standard errors (HC0) are reported in brackets.					

The table above replicates Table 6 in Harris et al. (2023) and reports the results from OLS regressions on our VC industry subsets – consisting of our industry proxy funds – including scaling and industry concentration dummies. One of the scaling dummies is coded 1 when industry proxy funds scale between 25-100% over one fund cycle, and the other when they scale above 100%. The dummy variable “Specialist” is coded one if a fund’s GP is specialist in the same industry as the proxy fund. The dummy variable “Focused” is coded 1 if a fund’s GP is focused in the same industry as the proxy fund. If there are no specialist or focused GPs within the industry sample, the dummies are not included in the regression. We measure industry concentration by calculating the HHI scores for all GPs. These are calculated by taking the sum of the squared total deal portfolio industry weights of each GP in their lifetime. The score can range between [0,1] and a higher value indicates a higher degree of industry concentration. We set a threshold of 0.35 to classify a GP as a specialist within the industry in which they are overweight. A GP is classified as focused if more than 35% of their deals as well as more than 35% of their total costs are in the same sector, but their HHI score is below 0.35. Current performance is regressed on previous performance. Performance is measured using benchmarked (logged) TVTC. Our sample consists of 332 Consumer proxy funds, 205 Industrials proxy funds, 118 Health Care proxy funds, and 156 Information Technology ones. Robust

standard errors (HC0) are reported in parentheses. The number of observations, R^2 , adjusted R^2 , residual standard error, and F -statistics are provided as additional indicators of model fit and robustness. The regressions are constructed as follows for each industry subset:

$$\text{Current Benchmarked TVTC} = \beta_0 + \beta_1 \cdot \text{Previous Benchmarked TVTC} + D_1 \cdot \text{Scale Increase 25-100\%} + D_2 \cdot \text{Scale Increase >100\%} + D_3 \cdot \text{Specialist} + D_4 \cdot \text{Focused} + \varepsilon$$

Table 12 repeats the regressions in **Table 9** on our VC industry proxy funds while including dummies for industry specialisation and focus. We identify no matched specialists in our VC subsets and do not find any effect of being focused on performance. Thus, we once again make no conclusive findings on the effect of concentration on performance.

8. AI Disclosure

We have used the AI tool ChatGPT to check for grammar errors as well as to debug R code and format R tables/figures.