WHITE PAPER

Benchmarking Private Market Performance

From Alpha to Market Beta in Private Market Funds

March 2025

Executive Summary

Investors in private asset funds, such as private equity and private infrastructure funds, aim to select top-performing fund managers. However, by definition, only 25% of funds can be in the top quartile, leaving most investors (Limited Partners, or LPs) with lower-performing funds. Measuring outperformance is crucial for LPs when selecting new managers or deciding whether to reinvest with existing ones. This paper explores different benchmarking methods to assess private asset fund performance using a large dataset of fund cash flow and NAV data.

1. **Most fund returns come from market performance, not manager skill.**

• Private equity fund managers function like active equity managers, with returns largely driven by market exposure (**beta**) rather than true outperformance (**alpha**).

• Private funds outperform public markets on average, but this does not help investors select the best managers.

2. **Traditional benchmarking methods are flawed.**

• **Peer Group Comparisons** fail to separate market-driven returns from manager skill, making manager selection unreliable.

• **Public Market Equivalents (PME)** use public indices, which do not reflect private market risks and returns, as benchmarks.

3. **Private Market Equivalents (PtME) provide the best benchmarking approach.**

• Uses private market indices to distinguish **allocation alpha** (sector selection) from **pure alpha** (manager skill).

• Findings show that most private funds generate **zero net alpha after fees**, confirming that **manager skill is not consistently rewarded**.

• Successful funds tend to outperform by **choosing high-performing sectors rather than superior investment selection**.

Investors cannot reliably pick top-performing managers using traditional benchmarks. **PtME is the most effective method for assessing manager skill**, revealing that **true alpha is rare and primarily driven by sector allocation rather than investment selection**.

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Introduction

Investors in private asset funds, like private equity or private infrastructure funds, all want to select top quartile fund managers. Yet, by definition, only 25% of funds and their managers can be in the top performance quartile in any given fund vintage. This leaves most of the limited partners (LPs) of private funds invested in lower-, if not badly, performing funds, three quarters of the time (again, by definition).

Measuring private asset fund outperformance is an important part of a complex investment decision for LPs, who need to select new managers and decide whether or not to "re-up" with existing managers on a regular basis.

This paper examines how investors may assess the outperformance of private asset funds using different types of benchmarks. We use a large sample of fund cash flow and NAV data covering both buyout and private infrastructure equity funds, and test different approaches available to LPs to benchmark private funds. Of course, benchmarks can also be important to fund managers (or General Partners, GPs) who often need to showcase their historical performance as fairly as possible to raise capital for new funds.

Our most important premise is that private asset investing does not happen in a vacuum, but in a *market* for private assets i.e. the market for the equity stakes of private companies. This market is *very* large: we estimate the Broad Market Universe (BMU) for private equities and infrastructure companies combined, in 160 countries, to represent c.USD65T of market capitalisation as of YE2024 or approximately USD120T of Enterprise Value.[1] We further estimate the size of the Private Equities Universe (PEU), a subset of the BMU meeting certain criteria of size, profitability and activity that reflects the characteristics of the transactions made by private equity fund managers,[2] to represent 192k companies or c.USD20T of market capitalisation and c.USD39T of enterprise value. In comparison, with approximately USD5T of AuM according to Preqin, buyout or infrastructure fund managers only hold a minority of existing private companies.

This is a key point when it comes to benchmarking: while LPs mostly access private assets through funds, *private asset funds are not the private asset market*, but only a slice of it. The private market into which GPs invest on their behalf is much larger and the adequate benchmark for this market is very unlikely to be limited to what private fund managers do.

As in any market, the market price of private equities is driven by supply and demand: if more investors want to buy stakes in AI companies in 2025, the market price of the average AI

[1] We use the following criteria to select companies that enter the Broad Market Universe. 1/ The company should not be dissolved, liquidated, or declared bankrupt at the time of consideration. 2/ Is a for-profit private company with a capital structure that does not have any security (equity or bond) traded publicly at the time of consideration. 3/ If it is a subsidiary of another private company, only the parent company is eligible for inclusion, provided its financial information is available. 4/ Is not entirely government-owned or controlled. 5/ Has non-negative sales, with the average sales in the past being over USD 1 million, and preferably has two fiscal years of financial accounting data that is accessible. 6/ Has a business and industrial activity description. 7/ Excludes infrastructure companies that are specifically available to be included in the infrastructure indices of infraMetrics®, 8/ Information on the key factors that are used to price the private company using our factor model approach is available. Missing information is imputed provided there is sufficient information in the sector, year, and country available and the factor being imputed is not one of the primary factors affecting its valuation. See https://docs.sipametrics.com/docs/1-4-1-universe-determination for more information.

[2] PEU size filter: https://docs.sipametrics.com/docs/size-filters. PEU profit filter: https://docs.sipametrics.com/docs/profitability-filters. PEU activity filter: https://docs.sipametrics.com/docs/activity-filters.

company must go up, and vice versa. As a result of private market price dynamics, any investor in a private equity fund is exposed to **private equities market risk**, just like any investor in a public equity or mutual fund is exposed to public equities market risk.

In effect, in the market for private equities, private fund managers are the equivalent of *long-only active equity managers*. As such, their performance should be described with the familiar combination of their market **beta** i.e., how exposed their portfolio is to private asset market risk, and their **alpha** i.e., performance achieved over (or below) that of the market.

While this framework is very familiar to any investor in public equity funds, estimating the market beta and alpha of private funds has long been challenging due to a lack of robust and representative market data and benchmarks. In this paper, we consider three approaches to benchmarking the performance of private asset funds and their managers:

1/ **Peer-grouping** using reported fund returns and multiple quartiles or indices of fund manager returns. This approach amounts to using an *active* fund manager benchmark, thereby conflating the market beta and alpha of each fund. In other words, a fund that performs well because it is exposed to a rising market is indistinguishable from one that performs equally well because it selected and managed specific investments skilfully. We find that most buyout funds beat their hurdle rate, indicating that selecting funds on the basis of an absolute return benchmark is no guarantee of selecting the best funds. We also show that the endemic paucity of reported data must lead to *very low confidence* in selecting the right manager on the basis of manager peer groups.

2/ **Public Market Equivalents** (PME) using a listed equity index as the market proxy. Conceptually, the Direct Alpha version of the PME represents significant progress on peer group data: it aims to separate a fund's beta from its alpha and addresses the robustness issue of peer group data, as a market index can achieve robustness through diversification. However, PMEs use a public equity reference, which is not representative of the risk of private equities. Indeed, the private equites universe is different from public equities, where companies tend to be larger and buyers and sellers have different investment preferences. At best, PMEs provide information about the relative benefit of investing in a given private fund instead of a cheaper listed alternative. While the average private manager outperforms the public equities market, this does not help in choosing better fund managers since they are not being compared to the relevant benchmark. As a result, investors in private asset funds cannot confidently pick a top performing manager using a PME.

3/ **Private Market Equivalents** (PtME), conceptually similar to PMEs but using a newly available, asset-level private market index as the benchmark. The PtME approach allows fund alpha and beta to be measured against a private market index, as well as the fund alpha to be split between two sources: "allocation alpha" obtained by selecting sector tilts different from the broad market, and "pure alpha" generated by selecting, structuring and timing investments.

Results are very similar to the well-established academic literature on active equity managers: *on average*, private asset funds produce zero alpha net of fees. A famous 2010 paper by Eugene Fama and Kenneth French, entitled "Luck versus Skill in the Cross-Section of Mutual

Fund Returns”,[3] analyses the performance of actively managed U.S. equity mutual funds relative to the market benchmark. Their key conclusion was that mutual fund performance is distributed *around* the market benchmark, with little evidence that active managers, on average, can consistently outperform after accounting for costs. A similar result with the PtME confirms that Scientific Infra & Private Assets (SIPA) private market indices represent the relevant market i.e., if the market index represents the average market performance, then it is normal that about half of the investors in this market perform better than the average, while the other half does not.

We also show that most of the returns of private equities funds come from market returns, while alpha is very variable, with some funds generating high positive alpha while others underperform the market. Moreover, most of the positive alpha of private asset funds comes from making informed allocation tilts i.e., picking sectors that perform better than the broad private equities market, while *net* pure alpha is negative *on average* and close to zero before fees, but can be very positive or negative at the individual fund level.

Finally, we look at alpha persistence in private funds and find that the average manager does not generate alpha consistently. In other words, the average manager has a 50% chance of generating alpha with their next fund. However, we show that some managers are much more likely to do so than others, with a few generating alpha with 90% probability time after time.

We discuss the implications for fund benchmarking and selection in the conclusion.

[3] Fama, E. F., & French, K. R. (2010). Luck versus Skill in the Cross-Section of Mutual Fund Returns. The Journal of Finance, 65(5), 1915–1947.

Approach

Review of Benchmarking Methods in Private Markets

In this paper, we use a database of 1,000+ private funds that is representative of the private equity (buyout) and private infrastructure fund universe through which LPs have been investing over the past decades (see next section and Appendix A).

We use cash flow and fund NAV data to review different benchmarking approaches available to fund investors in private asset markets and consider to what extent LPs are *more or less likely to select the best buyout or infrastructure fund managers* using each approach and available data.

We first consider the **Peer Grouping** of fund returns and multiples quartiles, as well as indices using pooled fund manager returns. Such indices represent an average of 'long-only' private funds and not the assets that make up the market but rather a combination of market risk, cash flow risk and liquidity risk to which investors are exposed within each fund.

We then consider using listed equity market proxies in the form of **Public Market Equivalents (PME)**, using the Direct Alpha methodology[4] a well-established metric of private fund outperformance relative to a market index.

Finally, we look at **Private Market Equivalents (PtME)**, using private market indices created by SIPA for the private equities and private infrastructure markets with the Direct Alpha methodology.

These indices use asset-level prices to reflect the dynamics of the market for private equit*ies* i.e., the market risk to which private asset funds are exposed. They are built to be representative of the private equities universe (PEU) in which private fund managers invest and can also be adjusted or customised to reflect the choice of sector or geography exposures made by fund managers. These indices are registered with ESMA and as a result comply with IOSCO benchmark guidelines, which is not the case for peer group benchmarks.

The impact of the fund lifecycle

Because private market funds take several years to be fully invested, in the early years, fund investors continue to pay fees on their total commitment, while receiving return only on a part of their portfolio. This creates what is known as a "J-curve effect": the typical pattern of a fund's net cash flow or net asset value (NAV) over its lifecycle resembles the shape of the letter "J". Therefore, in this paper we divide our data into three subsets:

- **All Funds** analysed together to describe alpha patterns over the fund lifecycle.

[4] Gredil, O. R., Griffiths, B., & Stucke, R. (2023). Benchmarking Private Equity: The Direct Alpha Method. Journal of Corporate Finance, 81, 102360.

- **Fully-Invested funds** until the 2018 vintage to examine long-term alpha generation.
- **Still-Investing funds** of more recent vintages (from 2019) and likely still investing.

The impact of appraisals

As mentioned in the introduction, our approach consists of estimating fund alpha using reported cash flows and NAV. This begs the question of the impact of appraisals on the estimation of fund alpha since private asset funds have been shown not to update the NAV of their investments to reflect the latest state of market prices (see for example Cummings & Walz 2010, Jenkinson *et al.*, 2013 and Brown *et al.*, 2019)[5].

We show in Appendix B that this effect is likely to be significant in younger funds for which the use of under- or over-valued NAVs likely distorts reported IRRs and the implied Alpha estimate. Conversely, the more mature the fund becomes, the less stale appraisals distort the IRR computation and the relevant Alpha calculation.

For this reason, we present our results first for fully invested funds and then for all funds.

The impact of fees

Fees play an important role in private markets and can be much higher than in public equity markets. The cash flow data described above is sourced net of fees and the IRR and TVPI are also computed net of fees using these cash flows and the reported NAV.

To better understand how fees impact returns and the difference between Alpha and net Alpha, we built an estimate of the average impact of management fees and carry in infrastructure and buyout funds.

We approximate this impact using the fee terms for the funds in a large sample of funds (see next section) and the average IRR of private equity and infrastructure funds, as shown in Table 1.

Note that we only consider management fee and carry as the main components of expenses in private market funds, when in practice, there can be other expenses as well that can impact the final net of fees return. Still, management fees and carry can be considered to be the primary drivers of investment costs in private funds (see Phalippou, 2020)[6].

[5] Cumming, D., & Walz, U. (2010). Private Equity Returns and Disclosure around the World. Journal of International Business Studies, 41, 727-754
Jenkinson, T., Sousa, M., & Stucke, R. (2013). How Fair are the Valuations of Private Equity Funds?. Available at SSRN 2229547.
Brown, G. W., Gredil, O. R., & Kaplan, S. N. (2019). Do Private Equity Funds Manipulate Reported Returns?. Journal of Financial Economics, 132(2), 267-297. https://doi.org/10.1016/j.jfineco.2018.10.011
[6] Phalippou, An Inconvenient Fact: Private Equity Returns and the Billionaire Factory. Journal of Investing, 11-39.

TABLE 1: AVERAGE FEE TERMS IN PRIVATE EQUITY AND INFRASTRUCTURE FUNDS

Metric	Private Equity Funds	Private Infrastructure Funds
Number of Obs.	559	100
Vintage Years	2013-2024	2011-2024
Average Management Fee	1.9%	1.6%
Average Carry	20%	18.5%
Average Hurdle	8%	7.6%
Average Impact on Net Return	**3.34%**	**1.50%**

Assuming the average IRR across funds represents the annualised return of a typical fund, we define the following relationship:

$$\text{Net IRR} = \text{Gross IRR} - \text{Mgmt Fee} - \text{Carry} * \max\left(0, \text{Gross IRR} - \text{Mgmt Fee} - \text{Hurdle Rate}\right)$$

Using this relationship and the data in our sample, we estimate the **average impact of fees on returns to be 1.50% in infrastructure funds and 3.34% in private equity buyout funds**. The large difference between the two asset classes springs from the level of hurdle rates, which is almost similar in infrastructure and buyout funds when average realised returns are much lower in infrastructure investment as shown above.

In what follows, we compute estimates of net fund Alpha and use the average fee impact reported above to further discuss the findings.

Private Asset Fund Dataset

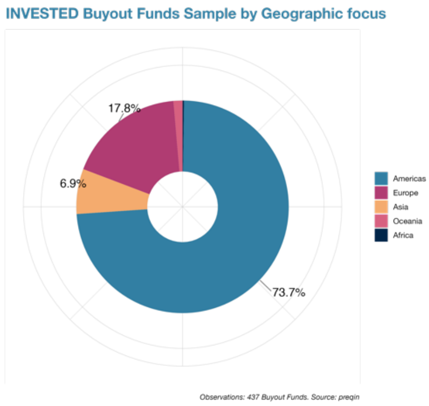
This paper uses a large and representative sample of private equity and private infrastructure funds for vintages 2013 to 2024. The data is sourced and processed from a combination of sources including Pitchbook, Preqin and hundreds of Fund Annual Reports.[7]

Buyout fund sample

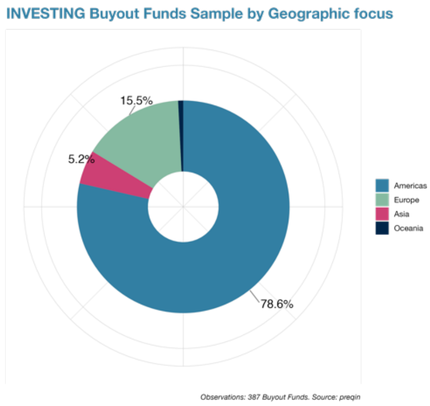
The private equity fund sample include 824 buyout funds from the 2013 to 2024 vintages with a combined Assets under Management (AuM) of $2tn. Our sample includes funds for which a complete set of historical cash flow data could be obtained. This is approximately half the MSCI/Burgiss fund manager universe for the same vintage years (1,529 funds, $2.7tn AuM). As shown in Appendix A, our sample of buyout funds is aligned with the MSCI universe and can be considered representative of the buyout opportunity set for LPs in the relevant period. Figure 1 shows the sample of buyout funds by investment region and sector focus for either invested (pre-2019 vintages - 1A and 1C) or still investing funds (1B and 1D).

FIGURE 1: BUYOUT FUND SAMPLE BY REGION AND SECTOR FOCUS

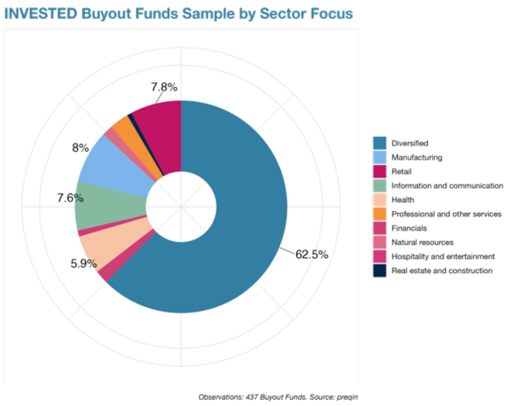
(1A)



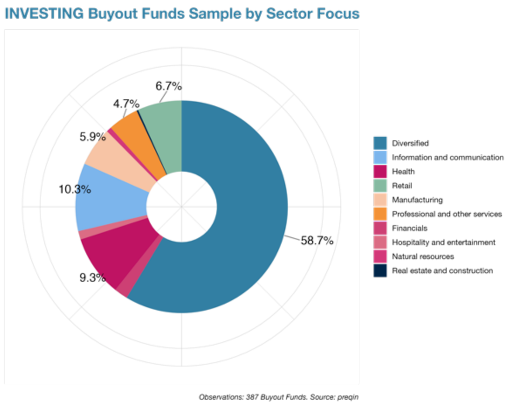
(1B)



(1C)



(1D)



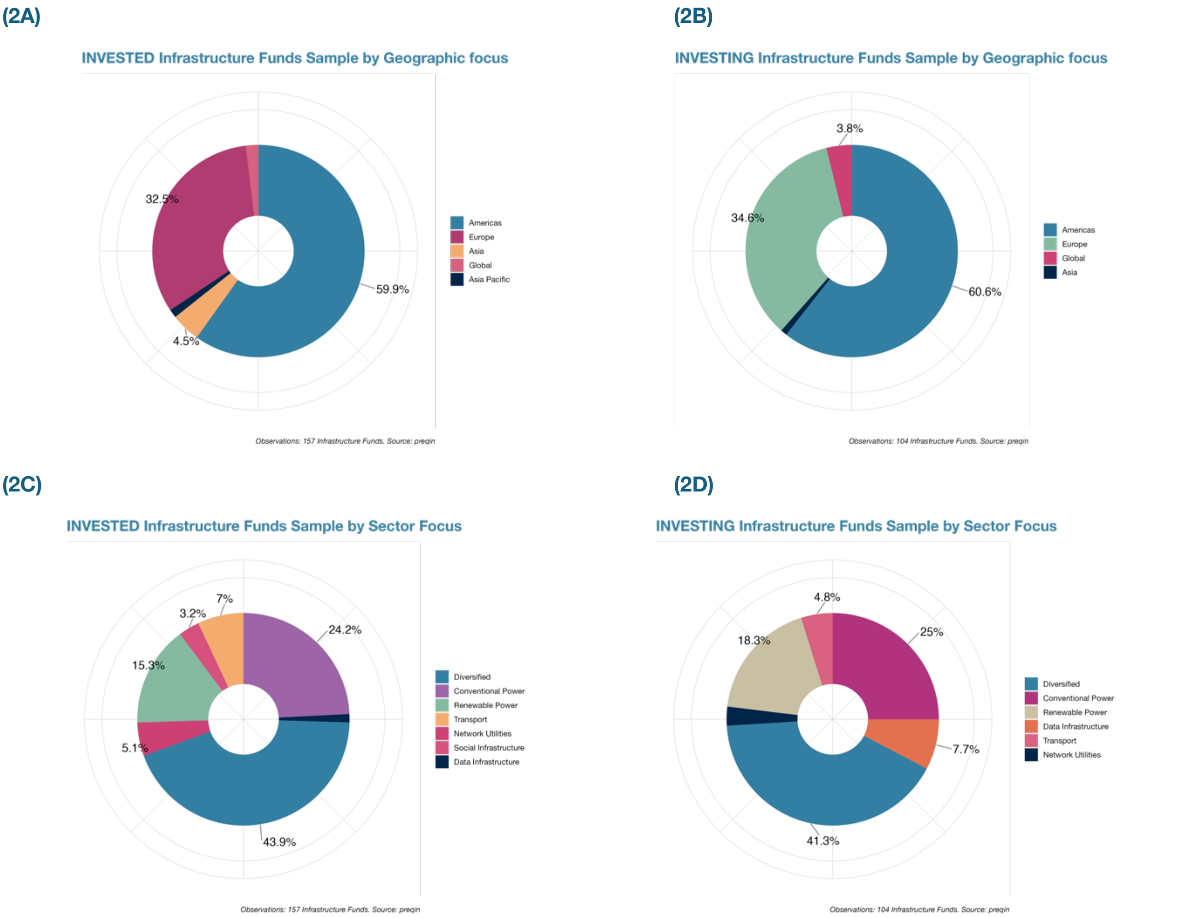
[7] SIPA has developed a proprietary application of natural language processing algorithms that can read and process data from company and fund annual report documents. This technology is instrumental in the development of the privateMetrics database. All data is validated by a team of human analysts.

Private infrastructure fund sample

There are 263 infrastructure funds in our sample with vintages ranging from 2011 to 2023 and total AuM of $650bn. For comparison, the MSCI Burgiss database has 297 infrastructure funds with a total size of $696bn. We also show in Appendix A how this sample is consistent with the MSCI/Burgiss manager universe, confirming its representativity of the infrastructure fund opportunity set available to investors.

Figure 2 shows the proportion of funds by investment region and sector focus for fully invested (2A, 2C) and still investing funds (2B, 2D).

FIGURE 2: PRIVATE INFRASTRUCTURE FUNDS SAMPLE BY REGION AND SECTOR



With both types of funds, we see that the fully-invested and still-investing funds (post 2019 vintage) represent fairly similar exposures to different markets and sectors or combination of sectors.

The two samples include a majority of funds focused on North America, as well as a majority of "diversified" strategies i.e., investing across multiple sectors. The proportion of other sector-specific strategies, while different in the two cohorts of funds, remains comparable.

Thus, any large difference between the two generations of funds is *unlikely* to be driven by shifts in the sector or geographic focus on the funds.

Fund Performance

We use the funds' reported cash flows and NAV to compute an IRR and TVPI, thus ensuring consistent comparisons between funds. As shown in Tables 2 and 3 (also Figure 3), buyout funds have a mean (median) net IRR of 14.4% (13.7%) and a mean and median net TVPI of 1.3x, while infrastructure funds have a mean (median) net IRR of 6.3% (6.9%) and mean (median) TVPI of 1.2x (1.1x).

The net IRR IQR or inter-quartile range[8] is 2,728 basis points for buyout funds (1,782bps for infrastructure). The IQR of the net TVPI is 0.6x (0.4x for infrastructure). Clearly, the dispersion of returns is very large, albeit less so for infrastructure funds. This is likely with private asset funds that are mostly concentrated in a few assets.

The buyout fund sample contains 437 fully-invested funds (2013-2019 vintages) and 387 still-investing funds from vintages younger than 2019 (Table 2). As expected, older vintages achieve higher IRRs on average but also include a wide range of values from very negative to very high returns, on par with the range of values found in still-investing funds.

The infrastructure fund sample contains 157 fully-invested funds (2011-2019 vintages) and 104 still-investing funds (Table 3). Here, the median IRR of younger funds is higher than that of older vintages, suggesting that the market in which younger infrastructure funds invest has changed over time. We know that the sectors and geographies of the two fund cohorts are not very different (see above). This is because expected returns have increased in infrastructure markets since 2019 (see infraMetrics[9]). Clearly, this makes comparisons between cohorts difficult without taking into account the impact of the market on returns.

TABLE 2: PRIVATE EQUITY FUND IRR STATISTICS

Metric	All Vintages	Fully Invested Funds	Still Investing Funds
Number of Obs.	824	437	387
Min Net IRR	-60.3%	-52.5%	-60.3%
Mean Net IRR (median)	14.4% (13.7%)	16% (14.7%)	12.6% (11.7%)
Max Net IRR	169%	144%	169%
Min Net TVPI	0.08x	0.09x	0.08x
Mean net TVPI (Median)	1.34x (1.25x)	1.52x (1.44x)	1.14x (1.11x)
Max Net TVPI	5.08x	5.08x	3.59x
Proportion of Positive Net IRR	73.7%	81.5%	64.9%
Proportion of Net IRR > 8%	61.2%	66.4%	55.3%
Proportion of Net IRR > 6%	65.1%	70.9%	58.7%

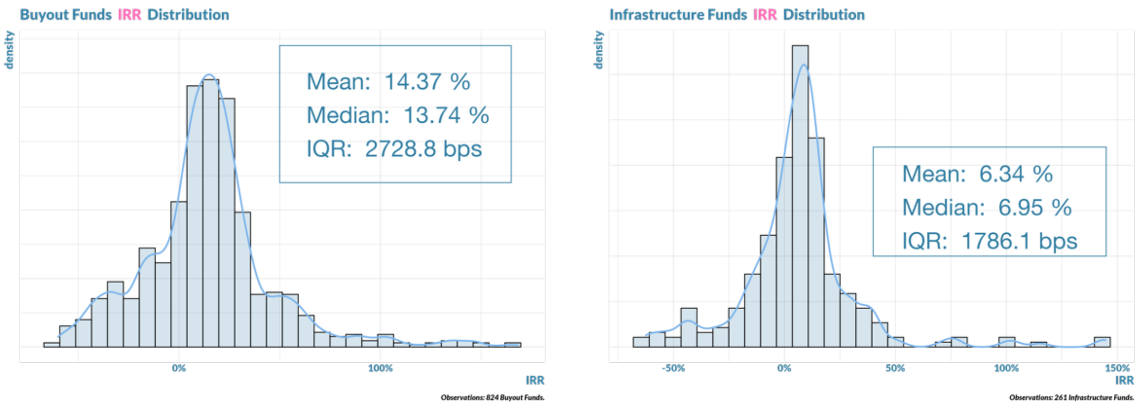
TABLE 3: PRIVATE INFRASTRUCTURE FUND IRR STATISTICS

Metric	All Vintages	Fully Invested Funds	Still Investing Funds
Number of Obs.	261	157	104
Min Net IRR	-62.7%	-61.7%	-62.7%
Mean Net IRR (median)	6.34% (6.9%)	6.81% (6.1%)	5.63% (8.8%)
Max Net IRR	144%	144%	115%
Min Net TVPI	0.04x	0.3x	0.04x
Mean net TVPI (Median)	1.17x (1.13x)	1.23x (1.19x)	1.06x (1.09x)
Max Net TVPI	2.83x	2.83x	2.49x
Proportion of Positive Net IRR	68.4%	72.0%	63.2%
Proportion of Net IRR > 8%	48.3%	44.6%	53.8%
Proportion of Net IRR > 6%	52.5%	50.3%	55.7%

[8] The difference between the 25th and 75th percentile values
[9] indices.inframetrics.com

Table 2 and 3 also show that 81.5% fully-invested funds in the buyout sample have a positive net IRR (72% for infrastructure), 66.4% have an IRR higher than 8% (44.6% for infrastructure), and 71% higher than 6% (50.5% for infrastructure). Thus, the majority of fully-invested and even of still-investing funds show positive performance in absolute terms and half or more have achieved returns higher than their hurdle rate.

FIGURE 3: BUYOUT AND INFRASTRUCTURE FUND IRR DISTRIBUTION (ALL VINTAGES)



At this stage, we can make the following remarks when it comes to benchmarking the performance of private asset funds:

- Usefulness of absolute return benchmarks: The ability of funds to beat their hurdle rate or a typical absolute return benchmark is not very useful to select the best managers: half or more of the funds achieve this level of return even after being fully-invested but investors cannot know how much risk was taken to clear this hurdle.
- Comparing recent fund performance to historical data without taking into account the state of the market at the time of older vintages could lead to misleading comparisons. For instance, more recent and still-investing infrastructure funds exhibit higher returns than older, fully invested vintages. Is it because expected broad market infrastructure returns have increased or because infrastructure fund managers have moved up the risk spectrum? If both, in which proportion does it impact reported performance?
- Robustness: The very wide dispersion of performance metrics suggests that a lot of data is needed to estimate quartile rankings in a robust manner (we return to this below).

Next, we consider how investors can use different benchmarks to try and answer such questions. In particular, we consider *how likely they are to pick the best funds* when using each benchmarking approach.

Peer Group Benchmarking

Peer-grouping consists of comparing the performance of an individual fund or manager with a sample of fund data grouped by asset class (e.g., buyout or infrastructure), geographic focus, vintage year or sector specialisation. This approach raises two key questions:

- **Conceptually**: By aggregating fund-level data, peer grouping conflates the impact of market risk on performance (the *beta* of the fund) with the added value of the manager (the *alpha* they create through their investment choices). Peer grouping makes it difficult to know if a fund performs well because it is exposed to a rising market or because its manager made the right investment decisions at the right time, structured transactions and improved portfolio companies in such a way that they created value over and above the market return. A fund peer group is a *long-only, active* (*private) equities manager* benchmark, but not a market benchmark.

- **Empirically**: In principle, the absence of distinct measures of fund beta and manager alpha in such datasets could be addressed though the construction of *representative and robust* peer groups that account for the impact of the market on all funds within each peer group. Unfortunately, as we demonstrate below, this is virtually impossible to achieve in private markets due to an endemic lack of data. Indeed, even if all private transaction price data was available to market participants, there would still not be enough data to build robust and representative peer-group benchmarks.

Next, we consider the different ways in which peer-grouping is likely to lead to misleading conclusions when it comes to selecting the best funds.

Peer group data is biased

Peer-grouping is so common in private fund investing that it is often referred to as "benchmarking" by data vendors, despite the fact that such approaches have little to do with a market benchmark.

Indeed, a good market benchmark should be relevant, unambiguous, specified in advance[10] and include a curated list of constituents determined by an index administrator to ensure that the index is representative of the price dynamics of the market of interest at all times.

Instead, pooling fund manager data creates numerous biases:

1. Selection Biases: Fund managers exercise discretion over whether, when, and how they report performance to industry databases. They may report only after achieving favourable returns, creating a dataset skewed toward successful outcomes (see Agarwal *et al.*, 2010).[11] Research also shows that underperforming or liquidated funds

[10] See conclusion for a discussion of the key characteristics of private market benchmarks, including whether or not they should be investible.
[11] Agarwal, V., Fos, V., & Jiang, W. (2013). Inferring Reporting-Related Biases in Hedge Fund Databases from Hedge Fund Equity Holdings. Management Science, 59(6), 1271-1289.

are also less likely to report. This results in incomplete datasets with a continuously changing cast of constituents, making serious, i.e., prudent, period-on-period, comparisons impossible.

2. Survivorship Biases: manager datasets typically include only "surviving" funds that remain active or have successfully exited, while failed funds are excluded, inflating performance metrics.
3. Valuation Biases: Reported fund NAVs are often stale and backward-looking, resulting in NAV undervaluation in rising markets and vice-versa. Research has shown that fund managers also overstate valuations to attract additional capital for follow-on funds. Research by Cummings & Walz (2010), Jenkinson *et al.* (2013), and Brown *et al.* (2019) highlights this issue, particularly among less experienced managers, who are more prone to overvaluing portfolios to appeal to new investors (Gompers & Lerner, 1999).[12] Such under- or over-estimation of asset values “pollutes” peer grouping data, making it unusable for benchmarking purposes.

As a result, peer group “benchmarks” are more than likely to be very noisy and potentially misleading for fund selection purposes.

Quartile rankings are not robust

The most common peer grouping approach is “quartile ranking”, which aims to identify top-performing funds based on their reported Internal Rate of Return (IRR) or Total Value to Paid-In (TVPI) compared to a sample of historical fund data. The top 25% of funds or managers are then typically considered to be outperformers relative to their peers.

Beyond the biases in the data described above, there is a more fundamental problem of robustness when peer grouping private market funds: there is not enough data to begin with to build robust quartile ranks.

For example, if we try to rank the performance of GI Partners Fund IV: a US Tech Buyout fund of 2013 vintage with a size of $2 billion and an IRR of 15.57%. An accurate ranking of its performance should rest on peer group data that takes into account the fund’s characteristics, such as vintage year, strategy, geography, and size. Table 4 shows a peer group strictly matching these criteria—US-based buyout funds from the 2013 vintage, larger than $1 billion, and focused on the technology sector—but comprises only 6 datapoints. In this narrowly defined peer group, GI Partners Fund IV ranks in the top quartile.

[12] Gompers, P., & Lerner, J. (1999). What Drives Venture Capital Fundraising?

TABLE 4: QUARTILE RANKINGS FOR GI PARTNERS FUND IV.

Peer Group	Q1	Q2	Q3	Number of Funds	Quartile Ranking
US PE Funds, vintage 2013	23.5%	15.1%	10.1%	89	2
Global PE Tech Funds, vintage 2013	29.5%	15.6%	10.7%	36	3
US PE Buyout Tech Funds, vintage 2013 > $1bn	15.3%	14.1%	10.1%	6	1

Six data points, however, are too small a sample when estimating a mean value, let alone quartiles. To achieve some robustness, the peer group definition must be relaxed to include a broader set of funds. Removing the size constraint or including global buyout funds increases the sample size but does so at the expense of relevance: the sample becomes less representative of the fund's unique strategy and characteristics. Under broader definitions of the peer group, yielding 36 and 89 observations respectively, the quartile rank of GI Partners Fund IV is 3rd against "US PE Funds 2013" and 2nd against "Global PE Tech funds 2013."

In these conditions, what are investors to do? Can they consider this fund to be top quartile using six datapoints or not against a more robust but less representative peer group?

Using quartile rankings is not that different from gambling

The lack of raw market data is an endemic issue for investors in private markets: at the global level; there are millions of private companies they could invest in (1.2M+ in the privateMetrics universe) but c.5,000 buyout funds are invested in a much smaller subset of c.50,000 portfolio companies. Globally, the number of buyout transactions is c.4,000 to c.6,000 annually. At the fund or deal level, taking strategy, geography, size and other factors into account, the likelihood of creating a representative peer group benchmark that also includes enough data to be robust is very low.

Thus, because of an endemic lack of transaction data, *peer group benchmarks almost never provide investors with a good representation of fund performance*. As a result, most uses of quartile ranks are highly uncertain and can be compared to gambling with aggressive odds.

Indeed, investors can take one of two alternative approaches when building quartile benchmarks: either maximise the sample size at the expense of relevance or try to build a representative peer group at the expense of robustness. Let's consider both approaches using the data described above.

First, we consider all buyout funds of all types and geographies for the 2011-2016 vintages i.e. funds that are either completed or winding down and have by now returned their investment to LPs. This yields a broad sample of 280 buyout funds, which can be considered robust. Table 5 shows the IRR boundaries of the sample and the corresponding 95% confidence intervals.

TABLE 5: IRR QUARTILE BOUNDARIES AND CONFIDENCE INTERVALS, 2011-2016 VINTAGES, 280 BUYOUT FUNDS

	IRR	95% Confidence Interval
Top quartile boundary	24.9%	[21.9%, 27.7%]
Q3/Q2 quartile boundary	14.7%	[12.0%,16.7%]
Bottom quartile boundary	3.4%	[1.8%,5.9%]

The confidence intervals are *very* important because investors observe only a sample of fund data; they cannot be certain of the exact value of the quartile boundary, but they can have statistical confidence that the true 25th, 50th and 75th percentiles of the population from which the sample was drawn are within the confidence interval range.

Consider the top quartile: any fund with an IRR above 24.9%. By definition, 25% of the data in the sample is above this top quartile boundary. However, some of these observations fall within the confidence interval i.e., we cannot be sure that they are above or below the quartile limit. This is illustrated in Figure 5. Even with a large sample of 280 fund IRRs over multiple vintages, about 20% of the data cannot be classified as belonging to a specific quartile with certainty, as the quartile boundaries themselves are not known with enough precision.

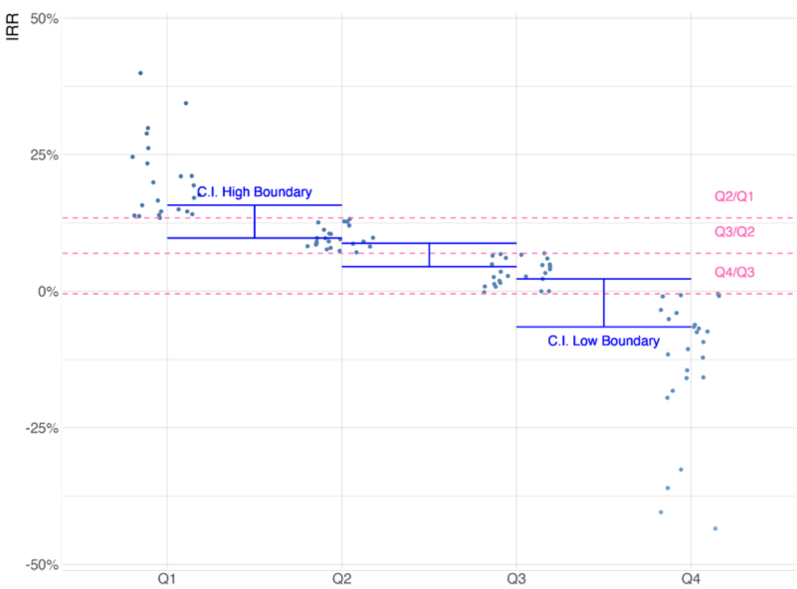
Table 6 shows the proportion of observations that are classified in each quartile but also fall within the range of the quartile boundary confidence interval and could be misclassified depending on the true (and unknown) value of the quartile boundary. With such a large sample the betting odds (to get the fund quartile rank right) remain excellent. Still, it is a gamble to consider 20% of the best ranked funds as top quartile when they may not be.

The main problem in this case is that such a broad peer group is not very useful: it includes all buyout funds in all sectors and geographies across multiple vintages. This is not relevant enough and, while statistically robust, unlikely to yield predictive information about the performance of the single US Tech fund.

TABLE 6: IRR QUARTILE CONFIDENCE INTERVAL – 2011-2016 VINTAGES, 280 BUYOUTS FUNDS

	Observations within the boundary confidence interval	Observations outside of the boundary confidence interval	Betting odds of getting the quartile right
Top quartile data	20%	80%	1:4
Second quartile data	25.7%	74.3%	1:3
Third quartile data	20%	80%	1:4
Fourth quartile data	20%	80%	1:4

FIGURE 5: IRR DISTRIBUTION BY QUARTILE AND QUARTILE CONFIDENCE INTERVALS – 2011-2016 VINTAGES, 280 GLOBAL BUYOUTS FUNDS



Next, we consider a narrower and much more relevant set of peers for the same 2013 US Buyout Tech Fund and restrict the sample to the relevant sector (Tech) and vintages (2012-2016). This yields a peer group of 19 funds. This much smaller sample should feel much more familiar to investors trying to use peer groups to benchmark their fund investments.

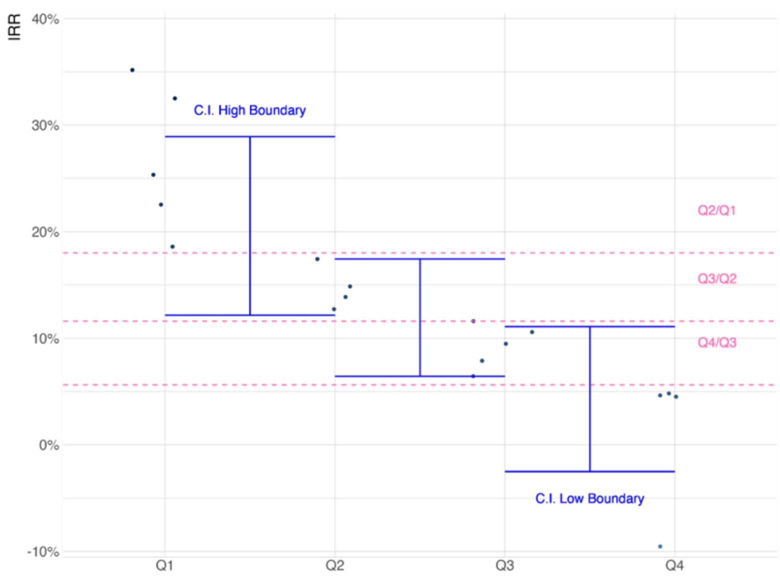
The gain in relevance of the peer group is so costly in terms of robustness that it turns the entire benchmarking exercise into **a very aggressive gamble**. Table 7 shows the proportion of the data that is found to be within the quartile boundary confidence interval, and that which can be safely considered outside of these limits. At 3:2 chances of picking a true top quartile fund, this is not how a 'prudent person' should run institutional money.

Figure 6 confirms how unlikely investors are to get it right with 19 datapoints: the confidence intervals of the quartile boundaries are now so large that almost all the data sits within them. The quartiles have become completely meaningless.

TABLE 7: IRR QUARTILE CONFIDENCE INTERVAL – 2012-2016 VINTAGES, 19 TECH BUYOUTS FUNDS

	Observations within the boundary confidence interval	Observations outside of the boundary confidence interval	Betting odds of getting the quartile right
Top quartile data	60%	40%	3:2
Second quartile data	100%	0%	N/A
Third quartile data	80%	20%	4:1
Fourth quartile data	60%	40%	3:2

FIGURE 6: IRR DISTRIBUTION BY QUARTILE AND QUARTILE CONFIDENCE INTERVALS – 2012-2015 VINTAGES, 19 TECH BUYOUTS FUNDS



Because the relevant peer group data is rarely robust, investors take significant risk of misclassifying funds as top quartile: the more specific the peer group, the less data, the larger the chance of making the wrong call. Conversely, much larger datasets allow less reckless – but still uncertain – decisions to be made when it comes to fund manager ranking. However, such decisions remain ill-informed because a very large peer group is… not a peer group anymore!

It should be noted that weak or irrelevant peer group benchmarks are also unfair to many managers who either get compared to a handful of other funds without any robustness when it comes to style or geography, or against a larger sample of funds that includes very different investment strategies, thus misrepresenting their market risk.

Fund Manager Indices

Beyond quartiles, another example of peer group benchmarks are fund manager indices: combining fund data to calculate a performance index. Again, such benchmarks have both conceptual and empirical issues.

Conceptually, they are still long-only active manager benchmarks instead of market benchmarks and thus continue to conflate a fund's market *beta* and its manager's *alpha*. It is not possible to use them to distinguish between managers unless a very specific yet robust sub-index can be produced that precisely captures the dynamics of the market segment in which the fund of interest is active.

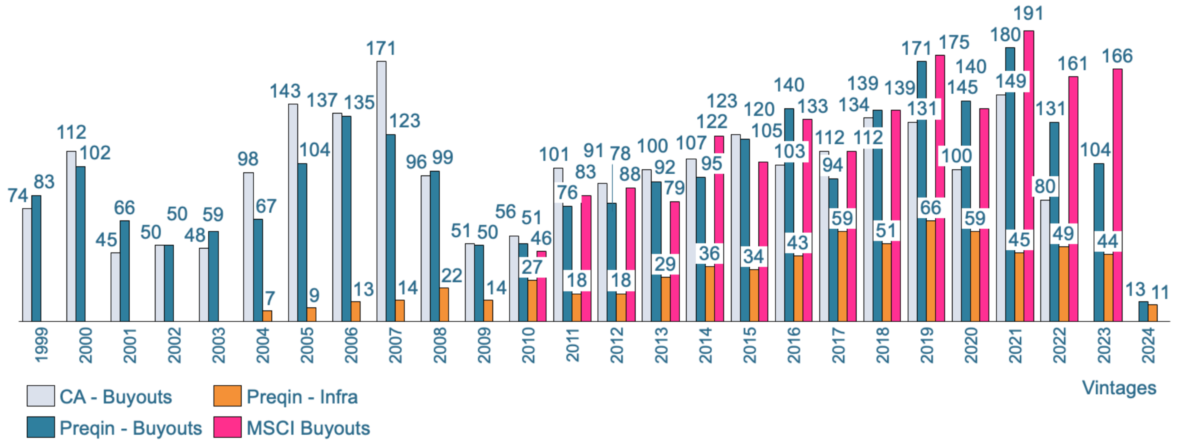
Unfortunately, as is the case with performance quartiles, empirical limitations make these manager indices useless in practice. With too few data points, they capture a limited set of market segments and present significant performance and risk biases.

Too few and changing observations

Fund manager benchmarks fail to meet the standards of a market index: their composition is neither fixed nor transparent. As illustrated in Figure 7, the number of fund observations used in benchmarking is both limited and highly variable over time.

The sharp fluctuations in observations between years and across periods confirms that funds are constantly added or omitted in any given year, raising concerns about the representativeness of the dataset. Of course, the limited number of observations in some periods exacerbates selection bias, as it likely excludes a significant portion of the fund universe.

FIGURE 7: Number of Individual Buyout Funds in Fund Manager Benchmarks (latest available in JAN 2025)



Sources: MSCI Private i, Preqin Pro, Cambridge Associates

Too few strategies

As a result of observing a fluctuating cast of funds, it is not possible to create indices for specific strategies, which is what would be needed for benchmarks to be relevant and representative. Table 8 shows the number of off-the-shelf private manager indices available from different vendors and compares them with the number of market benchmarks created within the SIPA privateMetrics platform using individually priced constituents from a much larger dataset.

Clearly the number of indices that are published using fund manager data is too low to capture specific strategies other than a broad fund manager index. As a result, they cannot be used to capture the market dynamics of a specific fund.

TABLE 8: NUMBER OF OFF-THE-SHELF PRIVATE MARKET INDICES AVAILABLE

		MSCI/Burgiss	CA	Preqin	privateMetrics
Unique Geographies	Buyouts	6	2	4	100+
	Infrastructure	3	N/A	4	25
Unique Strategies	Buyouts	N/A	N/A	5	200+
	Infrastructure	N/A	N/A	1	30+

Sources: MSCI Private i, Preqin Pro, Cambridge Associates, privateMetrics

Biased metrics

Private fund manager benchmarks report either Pooled IRRs or Modified Dietz returns, neither of which is likely to represent performance fairly.

Pooled IRR indices (Cambridge Associates) present numerous issues:

- Due to the inherent **non-additivity of IRRs**, pooled IRRs do not accurately reflect the average performance of the underlying funds (CFA Institute, 2022).[13]

[13] Saccone, M. (2022). Drowning in the Private Equity Pool. CFA Institute.

- Pooled IRRs are highly **sensitive to the timing of cash flows**. Early distributions, particularly large ones, can disproportionately inflate IRRs. IRR aggregation also distorts the timing of investments and exits, potentially inflating performance.
- Additionally, pooled IRRs often represent "since inception" returns, which **disproportionately emphasise initial successes** while overlooking later, less exceptional performance. For example, pooling KKR's funds from 1976-1998 yields an IRR of 26.1%, while including funds from 1999-2024 reduces the IRR to 16.1%. When pooling all funds from 1976-2023, the IRR rises again to 25.5% (KKR, 2025)[14].

The Modified Dietz method (MSCI, Preqin) is an improvement: it provides a time-weighted return adjusting for the timing and magnitude of cash flows during the period.

Nevertheless, all these indices face a fundamental issue : the reliance on appraisals.

In the return calculation, beginning and end-of-period NAVs are the result appraisals that lag real market performance by several months or quarters and tend to be “smooth” i.e., change very slowly and not reflect actual market prices at the time of reporting.

Table 9 and Figure 8 show the return, risk and performance of three fund manager indices and provide a comparison with the privateMetrics market indices (last two columns, see section on private market equivalent for details on these indices).

The three fund manager indices are remarkably similar, which suggests not only that they use similar sources but also that the main driving force behind these indices is the appraisal NAVs.

Table 9 and Figure 8 show that:

- The returns of the fund manager benchmarks are very high when compared to the market returns (private2000 and infra300), suggesting reporting and survivorship bias.
- The risk of the fund manager benchmarks is very low and implies very high Sharpe Ratios that are not realistic. In comparison, private market indices have attractive but realistic Sharpe ratios.
- Appraisals lead to NAVs being typically under-estimated in periods of market growth (here, 2013 to 2019) and over-estimated following periods of market contraction or shock, such as the 2020-22 period.

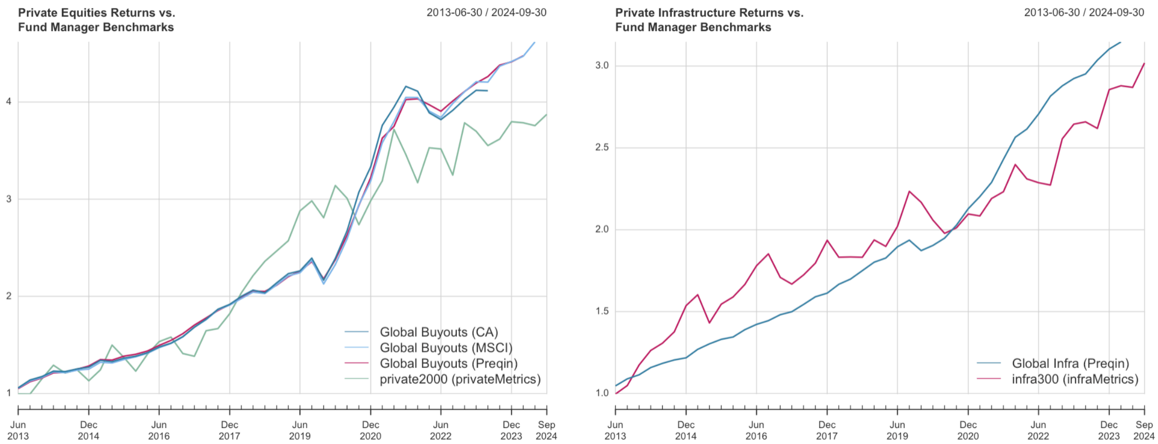
TABLE 9: NET 10Y RETURNS AND RISK OF MANAGER INDICES AND PRIVATEMETRICS MARKET INDICES

	CA: Buyouts[1]	MSCI Buyouts[2]	Preqin Buyouts[2]	Preqin Infra[2]	private2000[3]	infra300[4]
Annualised Return	14.80%	14.60%	14.60%	11%	11.90%	10.1%
Annualised Std Dev	9%	8.10%	7.20%	3.10%	17.20%	10.4%
Annualised Sharpe (Rf=1%)	1.526	1.654	1.871	3.215	0.631	0.866

[1] Pooled net IRR [2] net Pooled Dietz [3] privateMetrics, net total returns [4] infraMetrics, net total returns – see fee assumptions in paper

[14] KKR 10K Annual Report (2025). Retrieved from https://ir.kkr.com/sec-filings-annual-letters/sec-filings

FIGURE 8: NET PERFORMANCE OF MANAGER INDICES AND PRIVATE2000 MARKET INDEX



What about unsmoothing fund manager indices?

Investors sometimes choose to unsmooth the returns of the fund manager benchmarks using approaches such as autoregressive filtering (Geltner, 1993), the equity volatility method (Fisher, Geltner & Webb, 1994) or the market states method (Chaplin, 1997).[15]

However, unsmoothing can lead to completely different results depending on the choice of technique as illustrated in Table 10. For example, the level of risk almost doubles when Geltner 1-lag is used and quadruples with Geltner 2-lags.

If the risk calculations depend on the choice of unsmoothing method rather than the actual risk of the asset class, investors might as well pick any number they prefer… In other words, fund manager indices are unusable to measure risk in private markets.

As a result of these limitations, any attempt at decomposing the sources of performance in private funds with such indices is also doomed. For example, MSCI applies a factor model to the returns of private infrastructure funds and uses a Bayesian unsmoothing technique to estimate the "true" returns of private infrastructure assets by adjusting for smoothed and lagged appraisal values and decomposing returns into beta-adjusted public, pure private, and specific risk components.

TABLE 10: COMPARISON OF RISK-RETURN PROFILES FOR SMOOTH AND GELTNER 1 LAG AND GELTNER 2 LAGS UNSMOOTHED INDICES.

Index	10-Year Total Return	10-Year Volatility	10-Year Sharpe Ratio (RF=1%)
Smoothed Preqin PE Index	14.08%	7.39%	1.77
Unsmoothed PE (Geltner 1-Lag)	13.07%	14.23%	0.84
Unsmoothed PE (Geltner 2-Lags)	7.17%	31.94%	0.18

Unfortunately, given the biased nature of the data and the uselessness of unsmoothing when it comes to genuinely measuring risk, this can only lead to the wrong results.

[15] Geltner, D. (1993). Estimating Market Values from Appraised Values without Assuming an Efficient Market. Journal of Real Estate Research 8(3): 325–345
Fisher, J. D., Geltner, D. M., & Webb, R. B. (1994). Value Indices of Commercial Real Estate: A Comparison of Index Construction Methods. The Journal of Real Estate Finance and Economics, 9, 137-164.
Chaplin, R. (1997). Unsmoothing Valuation-Based Indices Using Multiple Regimes. Journal of Property Research, 14(3): 189-210.

Who uses fund manager indices anyway?

With quartile rankings, investor have to make an impossible choice between robustness and representativity; given the nature of private market data, they cannot have both.

With fund manager indices they have neither: these indices are both empirically weak and not representative of the state of the market. Since the private asset market is much larger than the private assets controlled by asset managers, such an index cannot represent the private asset opportunity set. Moreover, aggregating biased, backward-looking and stale appraisals leads to a misleading representation of both performance and risk.

In effect, and unlike quartile rankings which are common, we are not aware of many uses of such fund manager indices amongst investors in private equities and private infrastructure.

Using Market Proxies

The idea of using a *market* benchmark to assess the performance of funds is a powerful improvement on the peer grouping of fund managers, which is almost always statistically weak and rarely representative. A market index is a *portfolio*. As such, it should remove the two sources of bias investors suffer from when looking at peer groups:

- **A market index shows the risk and performance of the market** for underlying assets and can therefore be used to distinguish the impact of the market on fund performance (which sectors or factors performed well to begin with) from that of managers and their own choices and value-add.
- A market index relies on a construction methodology to create a weighted average of a representative set of assets trading in the market of interest. Such a portfolio of assets is **almost always more robust than a peer group dataset** built from *ad hoc* data contributed to a database by a changing cast of managers.

From Ranking Quartiles to Ranking Alpha

A simple way to use a market benchmark to decompose the performance of private funds is the Direct Alpha approach of Gredil *et al.* (2023) by which a fund IRR can be written as:

$$Fund\ IRR = Market\ Return + Total\ Fund\ Alpha$$

The Direct Alpha calculations are described in Appendix C.

Next, the alpha of each manager can be broken down into multiple sources. Fund managers generate alpha through a combination of strategic decision-making and execution capabilities. Broadly, these efforts fall into three categories: asset allocation, asset selection, and structuration. Asset allocation involves making strategic bets on different market segments, such as sector and geographic focus. Asset selection involves choosing specific investments and determining the optimal timing for distributions, aiming to maximise returns. Lastly, structuration includes adjusting leverage or reducing market risk through mechanisms such as preferential exit strategies, which can enhance returns while managing exposure.

We extend this approach to distinguish between sources of alpha. Using a broad market benchmark to measure Total Fund Alpha in combination with a strategy-specific benchmark e.g. mid-market US Tech, to control for the impact of asset allocation decisions, it is straightforward to split Total Fund Alpha into two components: Asset Allocation Alpha and Pure Alpha.

The difference between Total Fund Alpha and Pure Alpha is the Allocation Alpha,

$$Allocation\ Alpha = \text{Total Fund Alpha} - \text{Pure Alpha}$$

The total fund net IRR is written:

$$Fund\ net\ IRR = Market\ Return + Asset\ Allocation\ Alpha + Pure\ Alpha - Fees$$

$$Fund\ net\ IRR = Market\ Return + Asset\ Allocation\ Alpha + Net\ Pure\ Alpha$$

Asset Allocation Alpha represents the portion of returns attributable to the fund manager's choice of market segment or style exposures (sectoral, geographic or factor tilts).

Net Pure Alpha isolates the value added by the manager's investment selection and structuring skills, which includes timing of distributions, leverage decisions, and exit strategies, after fees.

Net Pure Alpha shows how fund managers create value and enables investors to assess which proportion of market outperformance stems from specific strategic decisions or operational and investment expertise.

How Equivalent is the Public Market?

Market equivalents are not new and since Kaplan and Schoar's 2005 paper,[16] Public Market Equivalents or PMEs have become a frequent alternative to peer groups and are reported by most data providers.

Unfortunately, a public market equivalent does not answer the question of what drives private fund managers' performance. A public equity index may be unambiguous, measurable, reflective of current investment options and specified in advance, but it is **not** the relevant benchmark.

The choice of public market index used for PME benchmarking also introduces another level of noise and may be considered opportunistic. Phalippou (2024)[17] discusses the fact that the S&P 500 was a common benchmark of private equity performance in the pre-2008 period, when its low returns favoured PME results. In more recent periods, indices such as MSCI, Russell 2000, and Russell 3000 have been employed instead.

Crucially, none of these indices can convincingly be linked to the investment universe available to private market investors. Figure 10 shows the GICS sector comparison between the Russell 2000 Index and the fund universe tracked by Cambridge Associates (CA). The Information Technology sector holds the highest weight in the CA Universe, accounting for

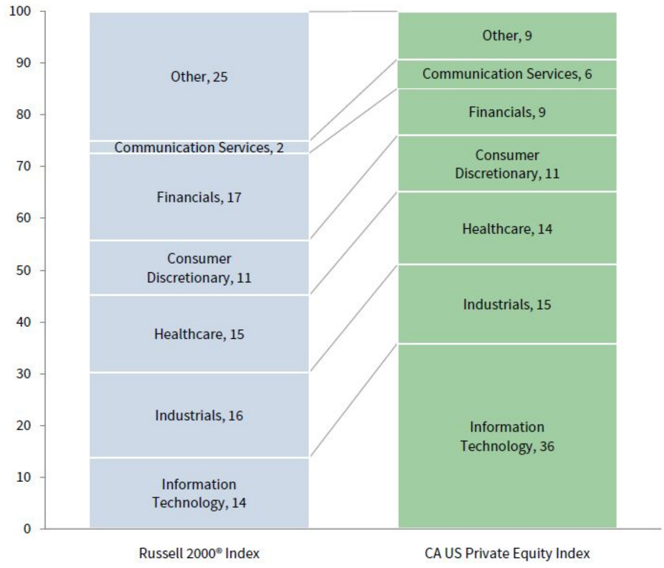
[16] Kaplan, S. N., & Schoar, A. (2005). Private Equity Performance: Returns, Persistence, and Capital Flows. The Journal of Finance, 60(5), 1791-1823. https://doi.org/10.1111/j.1540-6261.2005.00780.x
[17] Phalippou, L. (2024). The Trillion Dollar Bonus of Private Capital Fund Managers. Available at SSRN.

36%, while in the Russell 2000, it ranks fifth, with a weight of 14%. This discrepancy in sector allocations leads to differing risk-return exposures.

Consequently, selecting private funds based on their alpha but using (for example) the Russell 2000 as the market benchmark does not make sense since it does not take into account the risk profile of the private equities market.

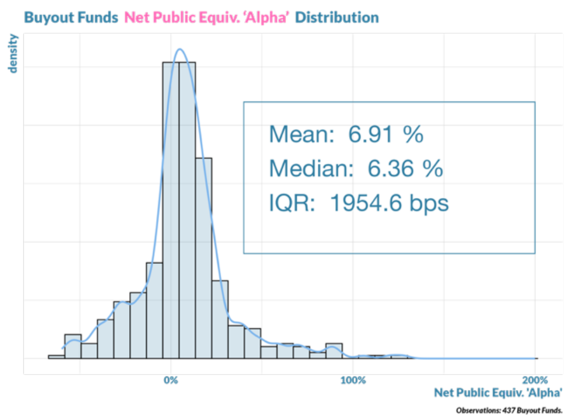
Figure 11 shows the distribution of net Total Fund Alpha of our fully invested buyout fund sample when benchmarked against the Russell 2000 index using the Direct Alpha method. On average, 68% of fully invested buyout funds exhibit a positive net "alpha", with a median of 6.9%. Adding our average fee estimate, that is an average gross alpha of c.10.5%!

FIGURE 10: COMPARISON BETWEEN RUSSELL2000 AND CAMBRIDGE ASSOCIATES BY SECTOR



Sources: Cambridge Associates LLC, Frank Russell Company, and FTSE International Limited.

FIGURE 11: PUBLIC MARKET EQUIVALENT DIRECT ALPHA WITH RUSSELL (2000) INDEX AS A BENCHMARK – FULLY INVESTED FUNDS



A comparison with public markets can be useful to understand the potential upside of investing in private market funds over a passive public market strategy. But this is an average: 32% of fully invested buyout funds exhibit *negative* net Total Fund Alpha against the Russell

2000. If anything, the PME confirms that it remains essential to pick the better fund managers since picking the less good ones could mean underperforming listed equities! But it does not provide a basis for selecting them.

The PME does not provide information about the risks taken by the fund manager and whether returns come from the fund's exposure to the private assets market (beta) or the manager's alpha. With this PME, if investors select a manager randomly in our buyout fund sample, they face approximately 1:2 odds of underperforming a Russell2000 ETF...

A Private Market Equivalent (PtME)

A private market equivalent is built using the same approach as a Direct Alpha PME but switching the public market index for a more relevant private market index.

Indices of choice

We use the privateMetrics indices and benchmarks because they are specifically designed to capture changes in market conditions. privateMetrics indices are calculated benchmarks and focus solely on the aggregate price movements of private assets, with this not reflecting the performance of individual managers at all.

The two market indices we use are the private2000® and infra300® indices. Both are registered with the European Securities and Market Authority (ESMA) as market benchmarks, indicating that they follow rigorous index construction standards and governance and comply with IOSCO guidelines. Updated monthly and using a fixed list of constituents which is managed by a dedicated Index Committee, these indices reflect market dynamics accurately and consistently (see Table 11 for details).

The privateMetrics market indices and benchmarks are specifically designed to capture the price movements of individual private assets (companies), as opposed to investments made by funds, the value of which is determined by a combination of market risk and manager skills.

infraMetrics also allows custom benchmarks reflecting the strategy of a fund to be built e.g., combining two sectors with specific weights across a specific region. Such benchmarks will be used to capture the strategy of the funds and distinguish between asset allocation and pure alpha.

To find out more about privateMetrics indices, download our factsheet here.

TABLE 11: SUMMARY DESCRIPTION OF THE PRIVATE2000 AND INFRA300 MARKET INDICES

	Constituents	privateMetrics Universe	Market Cap	10-y Return	Sharpe
private2000®	2,000 in 30 countries	Private Equities (1M, in 150 countries)	USD2.1T	15%	0.70
infra300®	300 in 20 countries	Private Infrastructure (9,000 in 25 countries)	USD323bn	8.6%	0.72

Fully-invested funds: Long-term alpha

Next, we use these two market indices to measure the alpha of the *fully-invested* funds in our sample. We limit the analysis to fully invested funds for which the performance is mostly realised and the impact of appraisals NAVs on performance is very limited (see Appendix B for a demonstration).

Figure 12a shows that when using the private2000 index to compute the PtME of buyout funds, the median net alpha is 0.05% (mean: 1.58%). In other words, the median net alpha is not different from zero. Note that while the mean value is positive, as shown in Figure 12a, the distribution of Fund Alpha is very skewed to the right, with a few very high performers. The median is more representative of the average of the market.

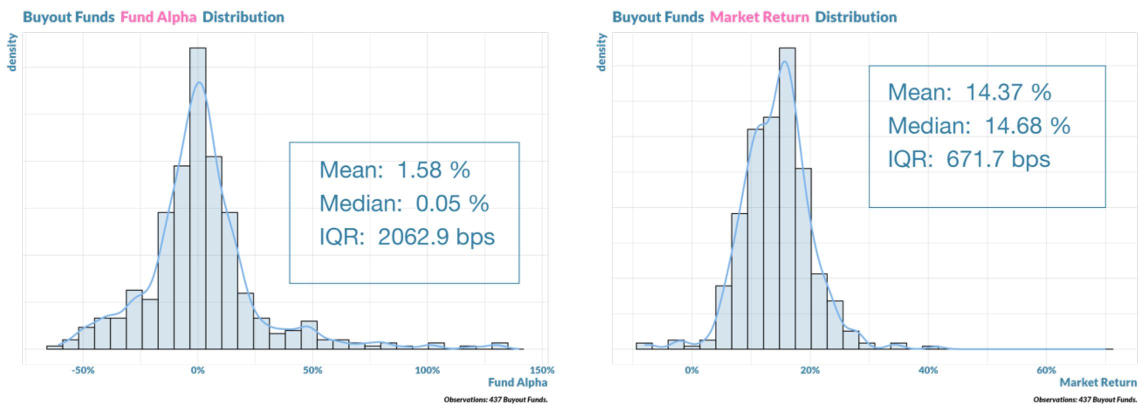
As shown in Figure 12b, the contribution of the market return to average fund returns is 14.4%, which is not different from the aggregate IRR of the same sample of buyout funds.

Thus:

- On average, we find close to zero net alpha in private asset funds when benchmarked against the relevant private market index. Approximately half the funds exhibit positive net alpha. This is normal since the market index represents the *average performance of the market* and half of the population of active managers is below/above the average.
- This result also implies that the private2000 index is indeed the relevant market benchmark for private equities: it accurately represents the average market performance.
- Market performance (market risk) is the main driver of fund performance. This is also to be expected. If a market exists, then investing in and out of this market should be the primary explanatory factor of the performance of any individual investment strategy.
- Gross of fees, using the average fee estimate described earlier, the average fund alpha is about 3.5%. Buyout funds thus tend to generate positive gross alpha, but in line with other findings in the finance literature (see for example Fama & French, 2010, on mutual funds) the average outperformance of fund managers is consumed by the average level of management fees.

FIGURE 12: PRIVATE EQUITY FUNDS DIRECT ALPHA PRIVATE MARKET EQUIVALENT AND MARKET RETURN USING PRIVATE2000 INDEX – FULLY-INVESTED FUNDS

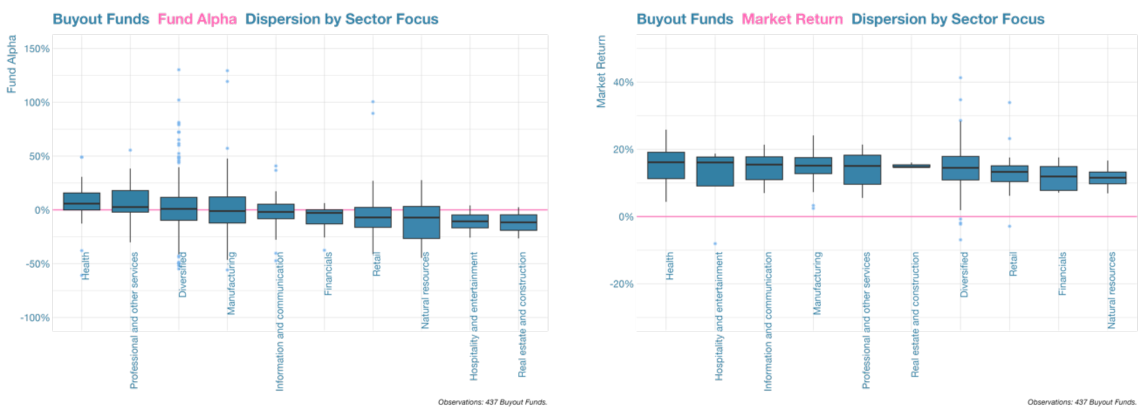
(12a) **(12b)**



Looking at the alpha of buyout funds by strategy, Figure 13a shows that only a few sector-focused strategies such as Health and Professional Services achieve positive alpha *on average* once the private2000 is the market benchmark. Again, the market return is the main driver of returns on average for all sector-focused strategies (Figure 13b). Nevertheless, the dispersion of fund alpha is significant and some sector-focused funds achieve high positive alpha, especially in the manufacturing and retail strategies.

FIGURE 13: PRIVATE EQUITY FUNDS DIRECT ALPHA PRIVATE MARKET EQUIVALENT AND MARKET RETURN BY SECTOR FOCUS – INVESTED FUNDS

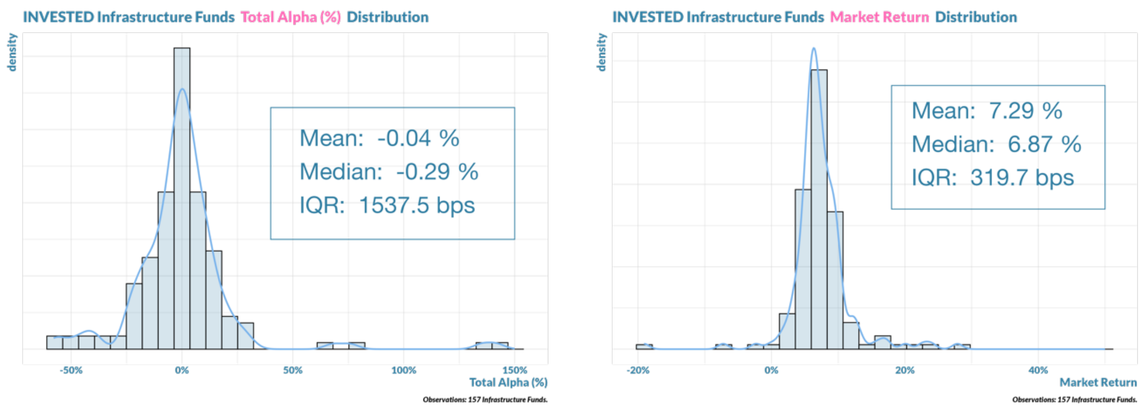
(13a) **(13b)**



Turning to infrastructure funds we find similar results: using the infra300 index as the market benchmark, Figure 14a shows that the median net alpha is -0.29% (mean: -0.04%), which corresponds to circa 1.2% gross alpha, on average. Figure 14b shows that most of the average return of infrastructure funds comes from market risk, at c.7%.

FIGURE 14: INFRASTRUCTURE FUNDS DIRECT ALPHA PRIVATE MARKET EQUIVALENT AND MARKET RETURN USING INFRA300 INDEX – FULLY INVESTED FUNDS ONLY

(14a) **(14b)**

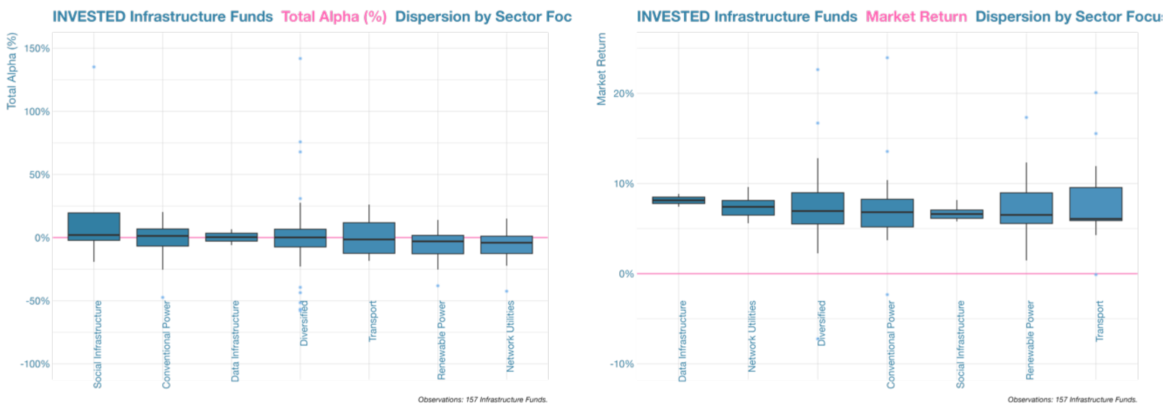


At the fund strategy level, Figure 15a shows that only funds focused on Social Infrastructure achieved positive alpha on average, while other sectors have a zero median or negative net alpha and almost all average returns by strategy can be explained by exposure to market risk. We note that Alpha dispersion is lower than with buyout funds.

To summarise, for both private equity and private infrastructure funds, we find approximately zero net alpha on average when benchmarked against a representative private market index. Note that this is consistent with previous findings in the academic literature about mutual funds and active equity funds; see for example Jensen (1968) and Fama & French (2010).[18]

FIGURE 15: INFRASTRUCTURE FUNDS DIRECT ALPHA PRIVATE MARKET EQUIVALENT AND MARKET RETURN BY SECTOR FOCUS.

(15a) **(15b)**



Breaking down fund alpha

As described above, investors can also use a benchmark that reflects the fund's strategy to derive the fund's alpha "controlling for strategy" i.e. what we have called "Pure Alpha."

[18] Jensen (1968) The Performance of Mutual Funds in the Period 1945–1964." Journal of Finance, 23(2), 389–416
Fama, E. F., & French, K. R. (2010). Luck versus Skill in the Cross-Section of Mutual Fund Returns. The Journal of Finance, 65(5), 1915-1947.

For each fund in the sample, we use the privateMetrics custom benchmark tool to build a benchmark reflecting the geography and sector focus of the fund. As described above, the Asset Allocation alpha is then the difference between the Total Fund Alpha derived against the broad market index, and the Pure Alpha derived against the strategy-adjusted benchmark.

TABLE 12: SOURCES OF ALPHA IN BUYOUT AND INFRASTRUCTURE FUNDS – FULLY INVESTED FUNDS

	Alpha Source	**Mean**	**Median**	**IQR**
Buyouts	Asset Allocation Alpha	3.82%	3.92%	639bps
	Net Pure Alpha	-2.54%	-4.04%	2069bps
	Pure Alpha (assuming fees of 3.4%pa)	0.86%	-0.64%	N/A
Infrastructure	Asset Allocation Alpha	6.22%	6.7%	902bps
	Net Pure Alpha	-6.26%	-5.97%	1333bps
	Pure Alpha (assuming fees of 1.5%pa)	-4.76%	-4.47%	N/A

For buyout funds the median Asset Allocation Alpha is 3.92%, indicating that fund managers generate value over and above the market by making sector specific bets. This value add is however, completely offset on average by a median Net Pure Alpha of -4.04%.

Hence, while buyout fund managers generate most of their performance through their exposure to market risk, they also create alpha by making long-term sector and geography bets. Since we estimated average fees in buyout funds to be c3.4%, adding this back to net Pure Alpha suggests an average gross pure Alpha of -0.64%.

Thus, in this sample of 800+ buyout funds, the average manager does not produce any Alpha. However, the interquartile range (IQR) of net Pure Alpha is 2,069bps, indicating a very wide dispersion. This implies that while on aggregate pure alpha is close to zero, many fund managers are still able to pick and structure superior investments and generate high Alpha.

Like buyout funds, infrastructure funds in our sample exhibit a median Asset Allocation Alpha of 6.3%, indicating that infrastructure fund managers also primarily generate value by choosing sector tilts. The median net Pure Alpha stands at -6.26% and at -4.76% before fees (see Table 12).

Again, the average infrastructure fund manager generates returns primarily through broad market exposure and selecting sectors that they expect to outperform the broad market e.g. Data infrastructure and Renewables. But this only partly offsets a large and negative average Pure Alpha both before and after fees.

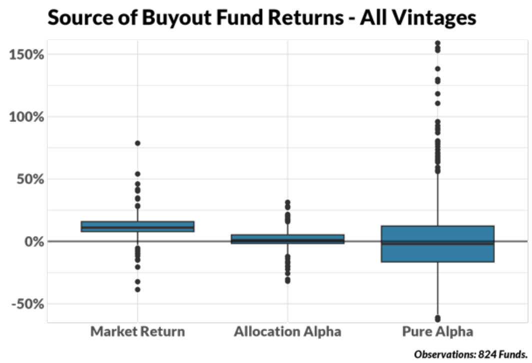
In the end the average infrastructure fund manager does not deliver positive Pure Alpha. This can be interpreted as partly driven by the nature of infrastructure companies, many of which are akin to a fully amortising bond with risky cash flows. With immobile assets, high fixed costs and high operating leverage, operational improvements are necessarily limited (you do not “turn around” a toll road. It has either been built in the right place and attracts traffic, or not). Perhaps picking infrastructure companies is more unforgiving than in the more diverse private equities market (see for example on the Thames Water debacle, Blanc-Brude, Gupta & Whittaker, 2024[19])

[19] Blanc-Brude, F., Gupta, A. & Whittaker, T. (2024). Low Tide: Benchmarking Risks in Infrastructure Investments: What the data showed about Thames Water. EDHEC Infrastructure & Private Assets - link

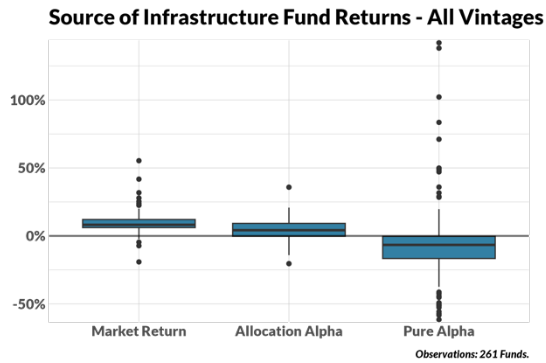
Figure 16 shows the same results in aggregate by sources of return in buyout (16a) and infrastructure (16b). Again, the returns of both types of fund are on average driven by positive market returns, slightly positive average Allocation Alpha and negative average net Pure Alpha. As before, the dispersion around the average is significant, with some funds generating above average returns including very positive Pure Alpha.

FIGURE 16: Sources of Returns in Buyout and Infrastructure Funds

(16a)



(16b)

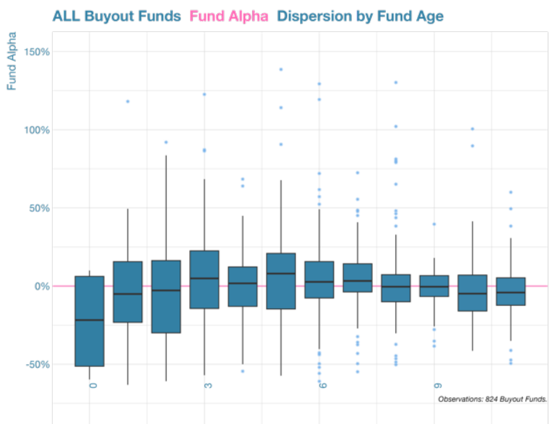


Full sample: Alpha through the fund lifecycle

In this section, we include more recent (still-investing) vintages in the alpha analysis to better understand the role of the fund lifecycle. Figure 17 shows the dispersion of buyout fund performance by age, focusing on fund alpha (17a) and market returns (17b). The impact of the fund lifecycle is clearly visible, with early vintages (before year 5) starting in negative alpha territory and improving over time, albeit not delivering above zero alpha in the long run, on average. Meanwhile, the market return that accrues to the same buyout funds compounds over time and, as we know from the previous results, corresponds to the majority of fund returns.

FIGURE 17: ALPHA AND MARKET RETURN IN BUYOUT FUNDS BY FUND AGE – ALL VINTAGES

(17a)



(17b)

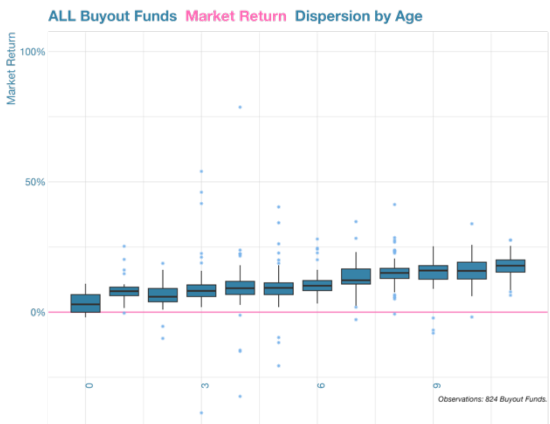


FIGURE 18: SOURCE OF ALPHA IN BUYOUT FUNDS BY FUND AGE – ALL VINTAGES

(18a) (18b)

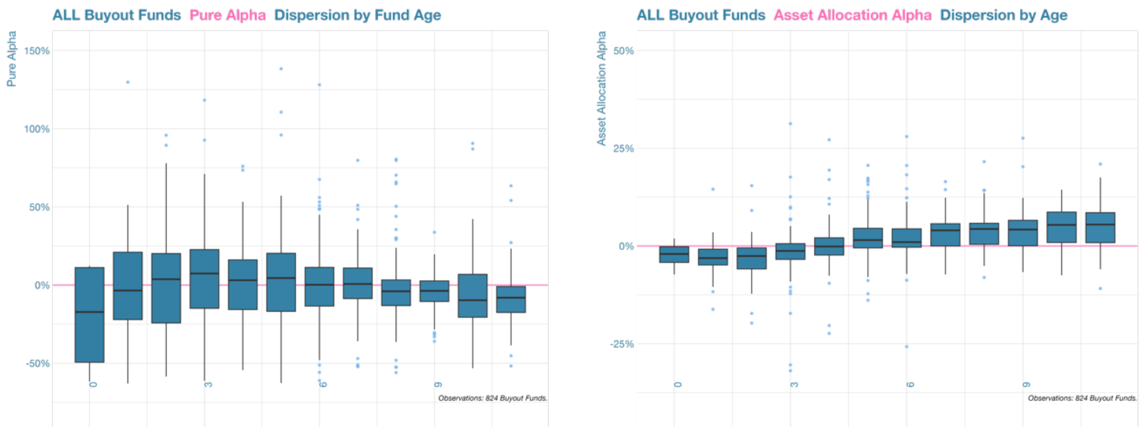


Figure 18 shows the sources of alpha in buyout funds by vintage year, differentiating between Pure Alpha (18a) and Asset Allocation Alpha (18b). Again the impact of the j-curve is clearly visible but does not change the bigger picture: average Pure Alpha trends towards zero on the long run but with huge dispersion between funds, while Asset Allocation Alpha increases over time and increasingly offsets the lack of Pure Alpha in the average fund.

Figures 19 and 20 make the same point about infrastructure funds. Unlike buyout funds which exhibit a positive long term trend in expected returns, infrastructure funds have been active in a market that has radically changed over the past decade.

The alpha of infrastructure exhibits the same lifecycle patterns as buyout funds, with a zero long-term trend but the market returns of younger funds in the sample are higher because infrastructure equity expected returns, having reached a nadir in the 2017-19 period, have since increased due to higher interest rates and the evolution of the risk profile of infrastructure assets, especially in the energy and utilities sectors.

As a result, the split between Pure and Allocation Alpha of infrastructure funds by age is less clear cut than that of buyout funds, but the same pattern of increasing Allocation Alpha and consistently negative average net Pure Alpha is visible as well.

FIGURE 19: ALPHA AND MARKET RETURN IN INFRASTRUCTURE FUNDS BY VINTAGE

(19a) (19b)

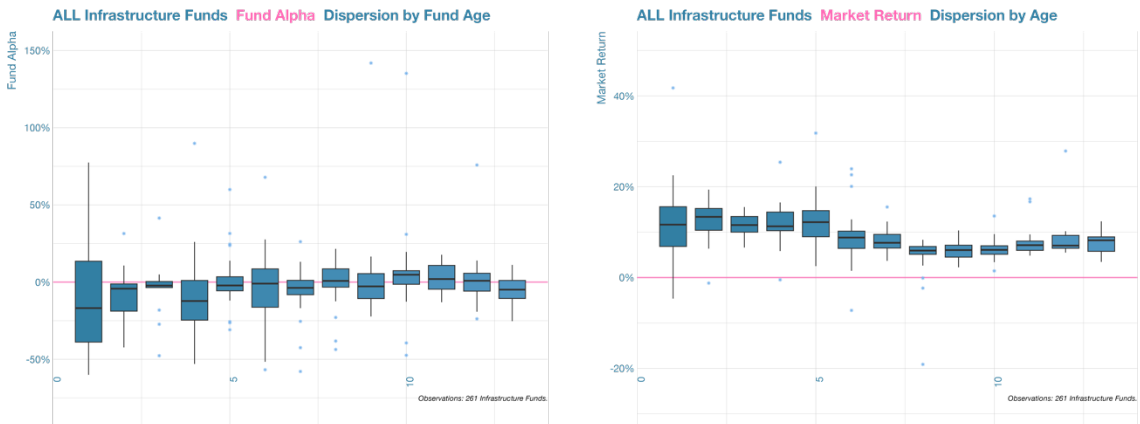
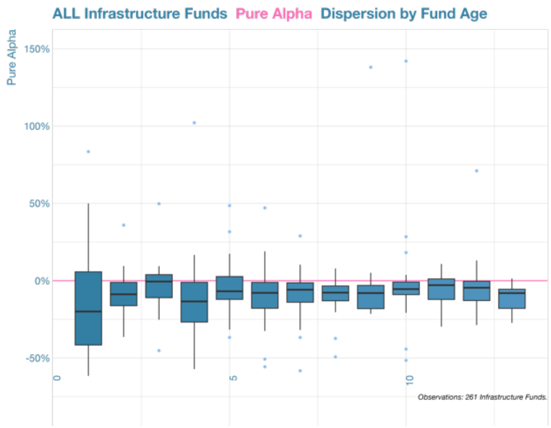
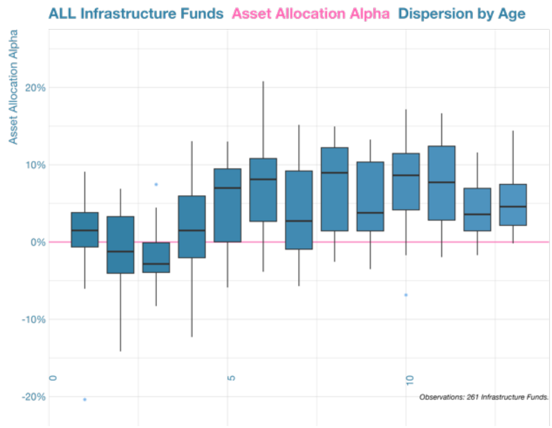


FIGURE 20: SOURCE OF ALPHA IN INFRASTRUCTURE FUNDS BY VINTAGE

(20a)



(20b)



Fund Alpha, Market Return and Fund IRR

Finally, we examine the link between fund manager alpha, fund market returns and Fund IRR.

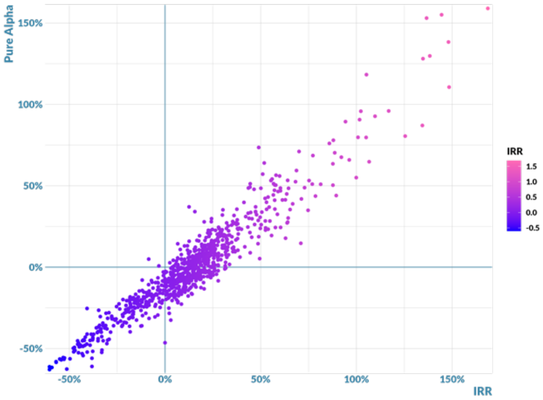
Figure 21 illustrates these relationships for buyout funds. 21a shows that Pure Alpha is highly predictive of the fund IRR but also that a number of funds have positive IRR but negative alpha (the bottom right quadrant of figure 21a). Asset Allocation Alpha on the other hand (21b) is not related to IRR, further demonstrating that fund managers may or may not generate alpha by beating a broad market index irrespective of their IRR.

Figure 21c further illustrates the relationship between fund Pure Alpha and the market return component of the fund IRR. It shows that higher Pure Alpha tends to come with higher market exposure to market risk. In other words, those managers that are creating high positive Pure Alpha also have to take market risk to access such opportunities, which are likely to be in the sectors or geographies with the highest expected returns. Of course, some managers can still generate alpha in a low or even negative market return environment, but this is very rare and unlikely to be repeatable (see next section on alpha persistence).

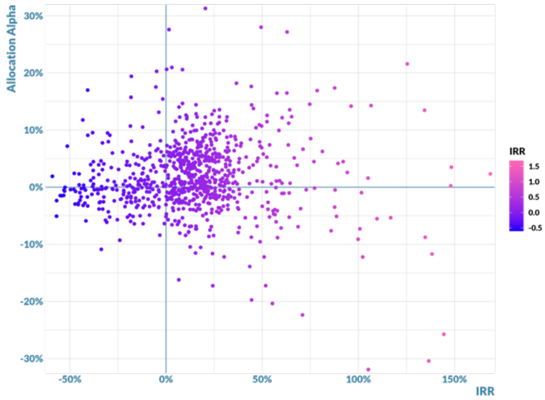
Figure 21d shows that Allocation Alpha and the market return component of the IRR are not related. Since generating Allocation Alpha consists of making bets based on the expectation that certain segments will outperform the broad market, the lack of direct relationship between the two is normal. We do not reproduce these charts for infrastructure funds as they exhibit very similar patterns.

FIGURE 21: PURE ALPHA AND ALLOCATION ALPHA – BUYOUT FUNDS, ALL VINTAGES

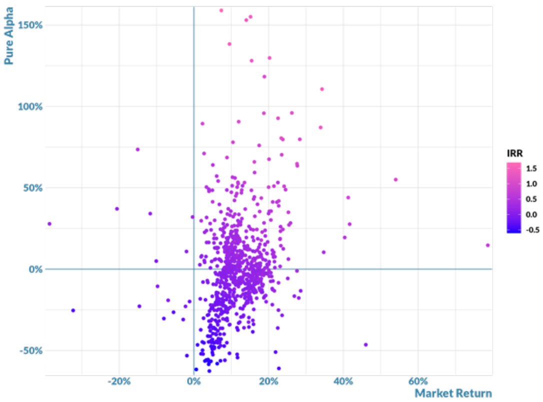
(21a) Pure Alpha vs Fund IRR



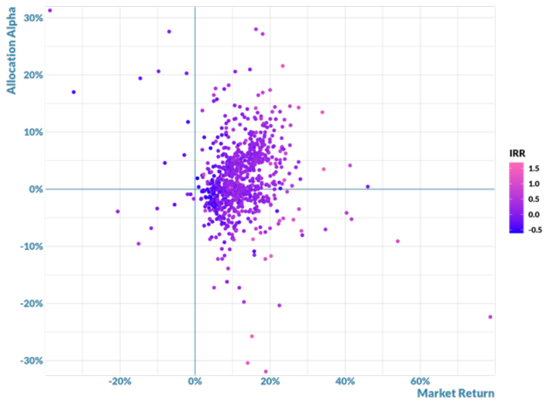
(21b) Allocation Alpha vs Fund IRR



(21c) Pure Alpha vs Fund Market Return



(21d) Allocation Alpha vs Fund Market Return



Using a Private Market Equivalent works!

We have seen that peer grouping lacks robustness, that PMEs lack representativity and therefore that using them to select funds is akin to making investment decisions with a blindfold on, selecting managers more or less at random. In contrast, the private market equivalent (PtME) provides a robust and granular understanding of the performance of private asset funds *relative to the market*. We return to this in the conclusion. Next, we look at the persistence of fund alpha on average across all funds and at the manager level.

Alpha persistence

A key question for investors in private funds is to know whether past performance (which is what they can observe) is likely or not to be repeated. In the end, even if the selection of a fund and manager can be made in a robust and representative manner using a PtME, it remains based on backward-looking data. A manager that exhibits high positive alpha in the past may be highly skilled but she may also have just been lucky.

The notion of persistence in investment funds implies that top-performing managers are more likely to generate strong returns in subsequent funds, while underperforming managers are more likely to continue underperforming. A number of studies have assessed the relationship between past and future fund performance in private equity funds across fund vintages. A common approach is to rank funds by quartile performance based on the fund IRR and examine whether top-quartile funds are more likely to produce strong returns in subsequent vintages. Academic research also includes econometric techniques, such as autoregressive models and rank correlation analysis, to quantify the degree of persistence and test whether it is statistically significant over time (Kaplan & Schoar, 2005; Harris, Jenkinson, & Kaplan, 2014)[20]. Some studies further control for factors such as fund size, investment strategy, and macroeconomic conditions to isolate the persistence effect from broader market trends.

The evidence is mixed, with some studies finding persistence in the tendency for managers to be a top quartile fund, and some not. Given the data robustness issues highlighted earlier when it comes to ranking funds by IRR using contributed fund data, the lack of conclusive research results may not be a surprise.

In this section, we use the PtME total alpha to estimate the "alpha persistence" of buyout funds for a sample of 80+ managers for which we have evidence for multiple funds.

Average manager alpha persistence

We examine average alpha persistence using two different approaches:

- Building the transition matrices of Alpha using the historical funds of a manager.
- Regression analysis to determine which factors are influential in explaining Alpha.

Transition Matrices

We first compute the positive alpha transition probability of each manager with one lag (Table 13) and two lags (Table 14).

Table 13 suggests that there is limited performance persistence in buyout funds. While there is a slightly higher probability for positive alpha funds to remain successful, the fact that nearly half (46%) transition to negative alpha in the next period highlights a lack of persistence on average. Similarly, managers with negative alpha funds are almost equally likely to have a

[20] Harris, R. S., Jenkinson, T., & Kaplan, S. N. (2014). Private Equity Performance: What Do We Know? The Journal of Finance, 69(5), 1851-1882.

positive alpha fund the next round or to continue underperforming, reinforcing the idea that past performance does not strongly dictate future results.

Table 14 suggests asymmetrical performance persistence, where underperformance is more likely to persist than outperformance. The 63% probability of continued negative alpha implies that poorly performing fund managers are significantly less likely to reverse trajectory. Moreover, even with two positive alpha funds under their belt, the average manager is not more likely (51% vs. 49%) to deliver a third one.

TABLE 13: ALPHA PERSISTENCE OF MANAGERS WITH AT LEAST ONE PRIOR FUND.

	Fund (t)	
Fund (t-1)	Positive Alpha	Negative Alpha
Positive Alpha	54%	46%
Negative Alpha	53%	47%

TABLE 14: ALPHA PERSISTENCE OF MANAGERS WITH AT LEAST TWO PRIOR FUNDS.

		Fund (t)	
Fund (t-2)	**Fund (t-1)**	Positive Alpha	Negative Alpha
Positive Alpha	Positive Alpha	51%	49%
Negative Alpha	Negative Alpha	37%	63%

Regression Analysis

Next, we use regression analysis on a sample of 259 buyout fund managers with two funds in their track record. The dependent variable is alpha of the fund at time t, and the explanatory variables include market return at time t, the alpha of the previous fund (t-1) and fund size at time t (log scale).

$$Alpha_t \sim Market\ Return_t + \ Alpha_{t-1} + \log(Size_t)$$

TABLE 15: REGRESSION RESULTS OF ALPHA AGAINST MARKET RETURN, PRIOR ALPHA AND FUND SIZE.

	Estimate	**Std. Error**	**t-value**	**Pr(>|t|)**	**Significance**
Alpha (t-1)	0.112472	0.060782	1.85	0.06540	.
Market Return	1.928218	0.251259	7.674	0.00000	***
Size_log	-0.022918	0.003787	-6.052	0.00000	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 | R^2: 0.198

Table 15 summarises the results of the regression:

- The previous fund alpha is barely significant, with a t-value of less than 2. It cannot be considered highly statistically significant above the 10% confidence level (there is a 10% probability that the value of the coefficient is not different from zero). This is consistent with the average probabilities obtained above.
- Market returns are a large and very significant driver of positive fund alpha.
- Fund size has a large negative impact, indicating diminishing returns to scale in private equity.

Next, we can also conduct a similar analysis on the two individual components of alpha, i.e., Pure Alpha and Allocation Alpha. These results are presented in Tables 16 and 17. We now find some evidence of *conditional* persistence: when a manager generates positive Pure Alpha or positive Allocation Alpha with their previous fund, they do tend to generate positive Pure or Allocation Alpha with their next fund. We also note that like total fund alpha, Pure

Alpha is positively related to market returns and negative to fund size, whereas Allocation Alpha is independent of market trends or fund size.

This last result suggests that while the average manager may not exhibit persistent alpha, which is consistent with the earlier finding that alpha is not different from zero on average, some managers do exhibit such persistence.

TABLE 16: REGRESSION RESULTS OF PURE ALPHA AGAINST MARKET RETURN, PRIOR PURE ALPHA AND SIZE.

	Estimate	Std. Error	t value	Pr(>|t|)	Significance
Pure Alpha (t-1)	0.169292	0.060396	2.803	0.00545	**
Market Return	1.843381	0.262038	7.035	0.00000	***
Size_log	-0.022135	0.003951	-5.603	0.00000	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 | R^2: 0.184

TABLE 17: REGRESSION RESULTS OF ALLOCATION ALPHA AGAINST MARKET RETURN, PRIOR ALLOCATION ALPHA AND SIZE.

	Estimate	Std. Error	t value	Pr(>|t|)	Significance
Allocation Alpha (t-1)	0.3006542	0.0553624	5.431	0.00000	***
Market Return	0.0640209	0.0523062	1.224	0.22200	
Size_log	-0.0010479	0.0007899	-1.327	0.18600	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1 | R^2: 0.115

Next, we use a manager-specific approach to try to detect the prevalence of alpha persistence amongst some fund managers.

Individual manager alpha persistence

Since there is evidence that some managers do deliver positive alpha persistently but that on average it is not the case, we apply the following approach to estimating the probability of alpha persistence of each manager.

There are too few observations of individual funds for each manager to compute the odds of delivering alpha for a given manager. Instead, we apply a simple Bayesian approach: the probability for a given fund manager of delivering positive alpha with any given fund is modelled as a beta distribution (a two-parameter distribution that can take any value between 0 and 1). The informed *prior* for this value is 0.5 i.e., using the results above we assume that, with any other information, a manager has a 50% chance of delivering positive alpha with their next fund, which is the equivalent of a Beta(2,2) distribution which has a mean of 0.5.

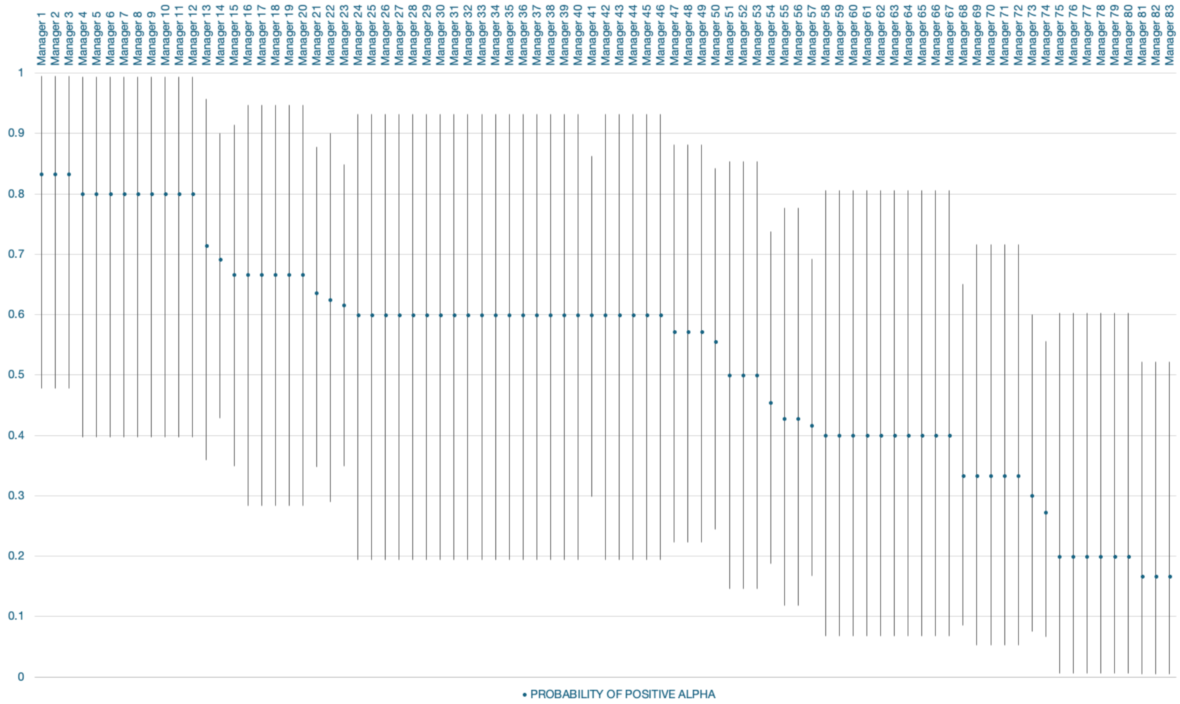
Next, we observe realisation of alpha in each manager's funds, and *update* the parameters of the distribution accordingly (see Appendix D for technical details).

The more funds we observe, the more precise our estimate of the probability of generating positive alpha with the next fund becomes. Thus, we also compute a confidence interval of the probability of outperformance.

Figure 22 shows the manager level probability of delivering positive alpha and its confidence interval. Clearly some managers are very likely to deliver positive alpha, with close to 90% probability of doing so, while other have lower and some very low probability of delivering a positive alpha buyout fund.

These results confirm that while the average manager is not an alpha manager, some managers are and are very likely to deliver alpha fund after fund.

FIGURE 22: ALPHA PERSISTENCE OF BUYOUT FUND MANAGERS – PROBABILITY OF GENERATING ALPHA AND 95% CONFIDENCE INTERVAL.



Source: privateMetrics

Conclusions

The pitfalls of benchmarking private asset funds

In this paper, we have reviewed four ways to benchmark private asset funds: peer grouping performance metrics, fund manager indices, public market equivalents (PMEs) and private market equivalent (PtME).

We have shown that peer grouping is flawed for a fundamental reason: the amount of raw data available in private markets is such that peer groups are either not robust, to the point that using them to select managers is equivalent to a very aggressive gamble, or not informative because they must combine many different styles, risk profiles and vintages to become robust.

We have also shown that fund manager benchmarks are even worse: achieving neither robustness nor granularity and displaying very biased results that are not representative of current market conditions.

We have argued that such benchmarks also conflate a fund's exposure to market risk (its beta) and the added-value of the fund manager (alpha), making manager selection on the basis of performance more dependent on market trends than on individual manager skills. With such data, investors are more likely to select managers that benefitted from supportive market conditions than ones that can still beat the market when the going gets tough.

We have also argued that the serious and prudent way to address these issues is to rely on a market index that can be used to separate the impact of market risk on fund returns from that of the manager, thus distinguishing between fund beta and manager alpha.

This "market equivalent" approach relies on the simple and widely used Direct Alpha methodology. It solves the data paucity issues of private market benchmarking since all an investor needs is the index and the cash flows of the one fund that needs to be benchmarked.

However, we also showed that using the market equivalent approach with the wrong index, such as a public equity index, is not conducive to more informed manager selection. Instead, when private equities have historically outperformed the stock market, most fund managers would seemingly qualify as outperforming the market, which makes little sense.

A better way: PtME and alpha persistence

Finally, we showed that using a private market index solves the question of how funds and fund managers should be selected:

- When used to compute the alpha of private funds, the privateMetrics market indices give an average net alpha of zero, which is not only aligned with all previous academic research on active fund managers but also makes the most sense as a genuine market benchmark: only half of market participants can beat the market average, by definition. Hence the privateMetrics indices, which are computed independently of any fund reporting data, are the correct benchmarks for private equities and infrastructure markets.

- The PtME approach provides investors with a clear understanding of the sources of fund return: which part is attributable to market risk and which to manager skills (or luck). This allows investors to differentiate between managers that deliver positive IRR because they invest in a favourable market from those who do so because they create value over and above the market in which they invest.
- Measuring manager alpha on an ongoing basis allows alpha persistence and whether a manager really is skilled or just lucky to be estimated. We show that some managers clearly are more skilled than others and that their probability of delivering positive alpha funds after fund can be very high, and for others very low.

Characteristics of a good private market benchmark

Finance 101 defines a good benchmark as being unambiguous, *investable*, measurable, appropriate, reflective of current investment options and specified in advance. But unlike for public market indices, whose constituents represent securities that can be traded in real time, the investability criterion is not straightforward when it comes to private markets.

By definition, private assets such as private equity and infrastructure are not continuously available for purchase or sale. A private market benchmark *must* be based on assets that are inherently illiquid and not for sale at any given point in time. Consequently, private market benchmarks cannot be expected to represent a directly tradable basket of assets, but instead, must serve as a reference portfolio, reflecting the characteristics, risk exposures, and performance trends of the investable universe.

Thus, a private market benchmark should be unambiguous, *measurable, relevant, reflective of current investment options and specified in advance*. However, whether or not the benchmark is *investable* is not that relevant. In principle any asset in the benchmark *could be* purchased by an investor in order to qualify as a private asset. But the logic of market equivalent is not to be a cheap alternative to active management. It is to provide a counterfactual to individual funds: how would a typical investor in the average fund have performed under current market conditions? Only then can LPs determine how *their* fund investments have performed.

Investors can then rely on such benchmarks as a starting or anchoring point to make a comparison with their own portfolio's performance, assess market conditions, and set realistic expectations, even if the constituents of the benchmark are not immediately accessible for investment.

This disqualifies peer group benchmarks, which do not meet any of these criteria. It also disqualified PMEs which are not *reflective of current investment options* in private markets.

The infra300 and private2000 indices and other benchmarks available via the privateMetrics platform do, however, meet all the relevant criteria.

These indices are calculated by calibrating an asset pricing model with the latest market transactions each month. This model has been shown to predict the average exit price in each segment with great precision and thus the index of the price (and change in price) of these assets, which is an average, can be considered reflective of current market conditions. They are also measurable, relevant and specified in advance, as required by the EU benchmark regulation (BMR) under which they are registered.

Lessons learned

Private assets trade in a market like any other financial security, and private asset funds trade in and out of this market, like any other active equity manager. In other words, private assets do not begin or end with private fund managers, nor are private asset fund benchmarks an accurate representation of a much larger and active market for private assets. In fact, private fund managers only hold a fraction of the market for private assets.

Private markets are risky. As in any other market for financial assets, market prices change continuously as a result of supply and demand, macro-economic conditions and investor preferences. High returns are available, especially when trades are executed by the most skilled managers but typically involve a significant amount of market and idiosyncratic risk. Private companies are exposed to economic risks, they can default or go bankrupt and, as with any equity investments, equity owners can lose everything.

Private asset beta matters. Private investment performance results from: A/ exposure to private market risk (beta) and B/ investment selection, management and timing (alpha). This is the unescapable reality of any financial market. Fund managers can generate alpha in numerous ways by selecting, improving and structuring specific investments, but it remains that alpha typically comes with taking significant market risk.

Only some private fund managers outperform the market (about half the time). It is difficult to beat any market. We find strong evidence that some private fund managers generate high alpha, but only half of them generate positive alpha and on average (across all managers) private fund alpha is close to zero. Also, **(average) fees offset most of the (average) alpha**. Any alpha that managers can generate on average is offset by the fees they charge for their service.

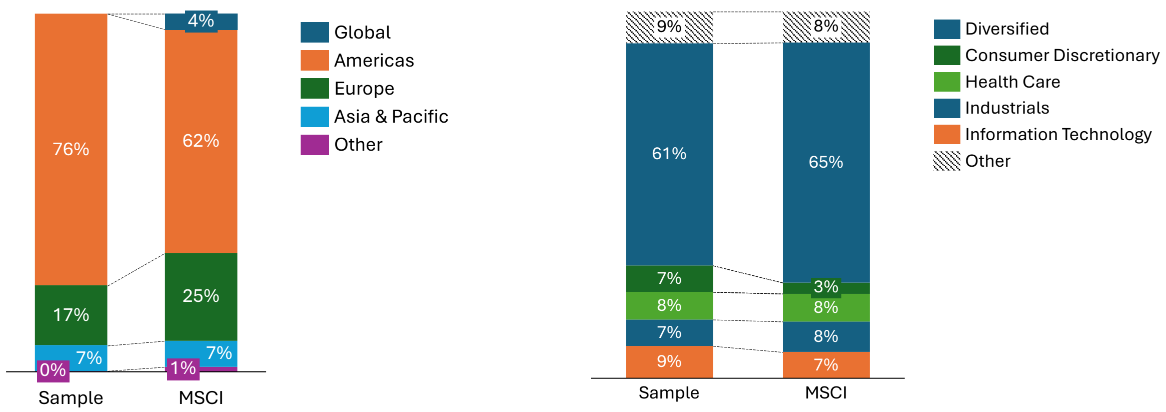
These last two points are very close to well-established research results about active equity managers in public markets. This is normal. Private equities are also a market, albeit with different dynamics, buyers and sellers than public equities. Recognising this does not mean giving up on investing in private markets, on the contrary. It means investing with eyes open and therefore in line with an investor's fiduciary responsibility. Using a private market benchmark, investors can select the best managers, managers can truly showcase their skills, and plan members can fully receive the benefits of investing in private markets.

Benchmarking private funds against a robust and representative private market index allows investors to determine what proportion of the fund returns comes from market returns, what is the alpha of the funds and what drives this alpha. Measuring alpha, in turn, allows investors to pick managers that have genuinely created value over the market and observing manager alpha over time allows managers that are the most likely to consistently create value with their next fund to be picked.

Appendix A: Buyout and Infrastructure Fund Sample vs. Burgiss Manager Universe

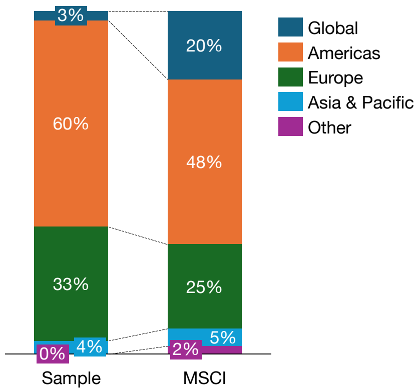
To assess the representativeness of our results, we compare the data used in this paper with the MSCI/Burgiss manager universe, which is typically considered to represent the universe of funds available to most LPs. The buyout fund sample includes 824 buyout funds from the 2013 to 2024 vintages with a combined Assets under Management (AuM) of $2tn. This sample includes funds for which a complete set of historical cash flow data could be obtained. This is about half of the MSCI/Burgiss fund manager universe for the same vintage years (1,529 funds, $2.7tn AuM). Figure 23 shows that both datasets are aligned, with the majority of funds concentrated in the Americas. Likewise, in terms of industry focus, over 60% of funds in our datasets and the Burgiss universe follow a diversified multi-industry strategy.

FIGURE 23: BUYOUT FUNDS SAMPLE VS MSCI FUND UNIVERSE BY GEOGRAPHY AND INDUSTRY FOCUS.



The 263 infrastructure funds from 2011 to 2024 in our sample represent a total AuM of $650bn and are in line with the MSCI fund universe, which includes 297 infrastructure funds with a total size of $696bn. Figure 24 shows that both datasets include Europe- and Asia-focused funds. The Americas region, while the largest in both datasets, is partially offset by a higher representation of global funds in the MSCI dataset.

FIGURE 24: INFRASTRUCTURE FUNDS SAMPLE VS MSCI MANAGER UNIVERSE



Appendix B: Impact of Stale Appraisals on Fund IRRs

In this example, we show the impact of stale appraisals on reported Fund IRR at different moments in the fund lifecycle. We assume a simple fund with ten years of cash flows including an initial $100 capital call. Say we know the full fund life data, we get an IRR of 14,8% (see Table A1). This is the benchmark we use to illustrate the impact of stale NAVs.

Next, we consider the case when the IRR is reported in year 4 based on existing cashflows and the reported NAV. In hindsight, the discount rate of future cash flows should be the IRR of the fund's full life. If we use this value (14.8%) to discount the future cash flows (assuming they are known but uncertain), we get a NAV of $151 and fund IRR in year 4 of 14.8%, which is correct. However, if we assume that the fund manager is overestimating the NAV of its assets which is not uncommon (see main text for references), and uses the equivalent of a lower discount rate of 12.8%. we compute a fund NAV of $161 and a fund IRR of 17.1% or 238 basis points higher than then true IRR.

However, the mechanical effect of stale NAVs on reported IRR dissipates over time: in the final example, we compute the fund NAV in year 8. If we use the original discount rate, we still find the original IRR of 14.8%. But when using a lower discount rate (because the assets are still over-valued), the difference with the correct IRR is now very small (16bps).

It follows that estimating alpha based on the cash flows and NAVs of mature funds should be seldom impacted by stale NAVs. However, in younger funds, this effect can be significant and an adjustment of the NAV to reflect current market prices may be needed to derive the correct IRR and Alpha metrics.

TABLE A1: ILLUSTRATIVE CASH FLOW AND APPRAISALS IMPACT ON REPORTED FUND IRR

FULL FUND LIFE											
Disc Rate	IRR	Year 1 CF	Year 2 CF	Year 3 CF	Year 4 CF	Year 5 CF	Year 6 CF	Year 7 CF	Year 8 CF	Year 9 CF	Year 10 CF
	14.8%	-100	0	0	0	20	20	100	30	0	80
EARLY FUND LIFE: NAV COMPUTED IN YEAR 4											
Disc Rate	IRR	Year 1 CF	Year 2 CF	Year 3 CF	Year 4 CF+NAV						
14.8%	14.8%	-100	0	0	151						
12.8%	17.1%	-100	0	0	161						
IRR Diff	238 bps										
LATE FUND LIFE: NAV COMPUTED IN YEAR 8											
Disc Rate	IRR	Year 1 CF	Year 2 CF	Year 3 CF	Year 4 CF	Year 5 CF	Year 6 CF	Year 7 CF	Year 8 CF+NAV		
14.8%	14.8%	-100	0	0	0	20	20	100	91		
12.8%	14.9%	-100	0	0	0	20	20	100	93		
IRR Diff	16 bps										

Appendix C: Direct Alpha Methodology

Compound the fund cash flows by the return of the private market index from the date of the cash flow to the calculation date. Then calculate the internal rate of return of the adjusted cash flows, which is the *Private Market Equivalent*

Inputs required: Fund's historical cash flows and NAV, Private Market Index

Step 1: Adjust the cash flows

$$\tilde{C}_t = C_t . \frac{V_b(T)}{V_b(t)}$$

C_t: Cash flow at time t (positive for distributions, negative for contributions)

$V_b(T)$: Value of the private market index on the calculation date T

$V_b(t)$: Value of the private market index at the initial time t

$\tilde{C}_t$: represents the adjusted fund cash flow

Step 2: Solve for the rate α equation linking the adjusted cash flows and the residual value:

$$\sum_{t=0}^{T} \frac{\tilde{C}_t}{(1+\alpha)^t} + \frac{NAV}{(1+\alpha)^T} = 0$$

α is the Direct Alpha rate (analogous to IRR)

A *Private Market Equivalent* greater/lower than 0 indicates that the fund has outperformed or underperformed the private market index.

We have made it easy to calculate alpha of a private equity or Infrastructure fund using the privateMetrics API and a pre-defined excel template. It involves three simple steps:

1. **Select the relevant broad market and strategy benchmarks**

Given a private fund, select a corresponding privateMetrics broad market index, for example the private2000 index for global private equities and a strategy index corresponding to the fund's style e.g., US Tech Mid-Cap.

2. **Get the fund data needed to compute Direct Alpha**

For the same fund, all historical cash flow and NAV data are required to apply the Direct Alpha methodology.

3. **Find Total Alpha, Style Alpha and Pure Alpha for the fund**

Using the two privateMetrics benchmarks selected above and the fund cash flow and NAV data, it is possible to compute Total Fund Alpha (relative to the Broad Market, Pure Alpha (relative to the Style Benchmark) and Style or Asset Allocation Alpha (the difference between Total and Pure Alpha) Refer to this use case for more details.

Appendix D: Fund Manager Alpha Persistence Probability

We model the probability of delivering alpha in a given fund for a given manager as a probability of success given a certain number of observable funds and alpha realisations. To model this phenomenon we use a Beta-Binomial model to update the belief about the probability of success (θ) as new data is observed.

Step 1: Define the Prior
Since you initially assume a 50/50 chance for success and failure, a reasonable choice for the prior distribution is a Beta distribution:

$$\theta \sim Beta(\alpha, \beta)$$

Beta(2,2) has a mean of 0.5 and gives slightly more weight to values near 0.5. Given the results obtained for all managers, a 50% chance of delivering a positive alpha fund is good informed prior.

Step 2: Likelihood Function
The process being modelled is a Bernoulli or Binomial (multiple independent trials). That is, if we observe S successes and F failures, the likelihood is:

$$P(S, F|\theta) = \theta^S (1-\theta)^F$$

Step 3: Compute the Posterior
Using Bayes' theorem, the posterior distribution is:

$$P(\theta|S, F) \propto P(S, F|\theta)P(\theta)$$

We know that the Beta distribution is conjugate to the Binomial likelihood, thus the posterior remains a Beta distribution:

$$\theta|\, S, F \sim Beta(\alpha + S, \beta + F)$$

Step 4: Estimating the Probability of Success
The mean (expected value) of the posterior Beta distribution is:

$$E[\theta|S, F] = (\alpha + S)/(\alpha + S + \beta + F)$$

Step 5: Credible Intervals (Uncertainty Estimation)
Since the posterior is also Beta-distributed, we compute a confidence intervals for θ. A 95% confidence interval is given by:

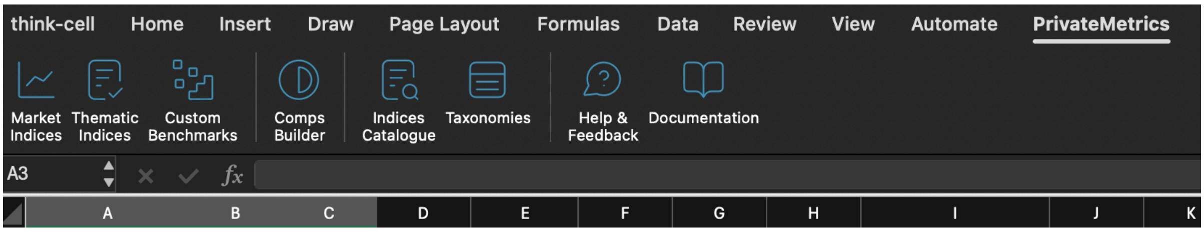
$$[Beta^{-1}(0.025, \alpha + S, \beta + F), Beta^{-1}(0.975, \alpha + S, \beta + F)]$$

where $Beta^{-1}$ is the inverse cumulative distribution function of the Beta distribution.

Thus, starting from a prior of 50% probability, and the meta parameters (2,2) for the Beta distribution describing the probability of delivering positive alpha, the meta-parameters are updated with each observation of a fund’s positive alpha (positive = success) and the probability of delivering alpha is recomputed.

The more a manager delivers positive alpha funds, the higher the probability of delivering another success with the follow up fund.

Appendix E: Private Fund Alpha with the privateMetrics® API



Excel Add-in provides access to the privateMetrics API

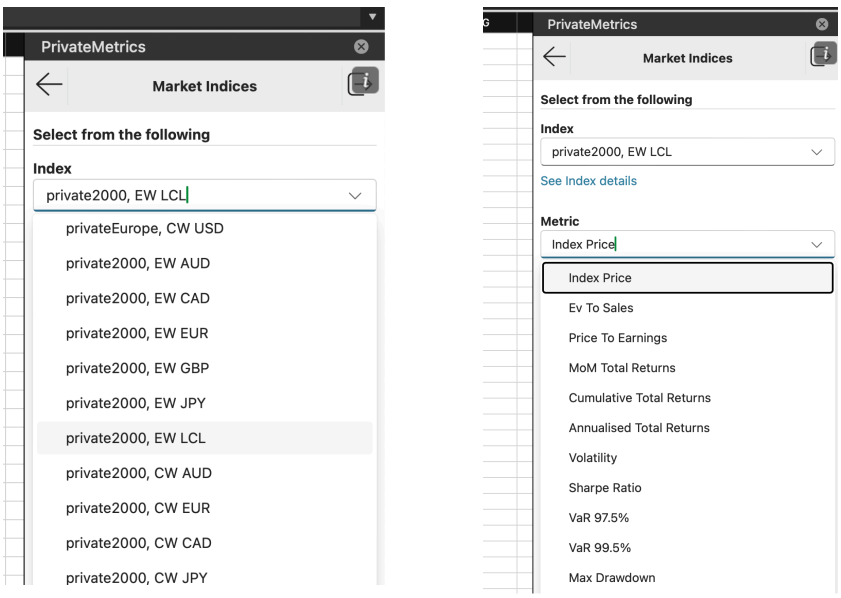
The privateMetrics API (Application Programming Interface) is accessible via a range of software and enables a seamless and customised implementation of the Direct Alpha approach to make a quantitative assessment of a fund's performance.

Our detailed use case provides an excel template with calculations.

For example, say a fund investor need to decide between two funds and has access to their track record, including fund-level historical cash flows and fund NAVs.

Selecting a Market Index

Next, the investor needs to define a market index benchmark that represents the broad market in which the fund is active. A typical choice of broad market index is the private2000: representing the largest 2,000 private companies in the 30 most active markets for PE investors. Subsets of the private2000 Market Index Universe (or MIU) include the privateUS index, privateEurope index and the privateAPAC index. The DA calculated against this index would result in the estimation of the market return of each and the total alpha that each fund generated above that market return.

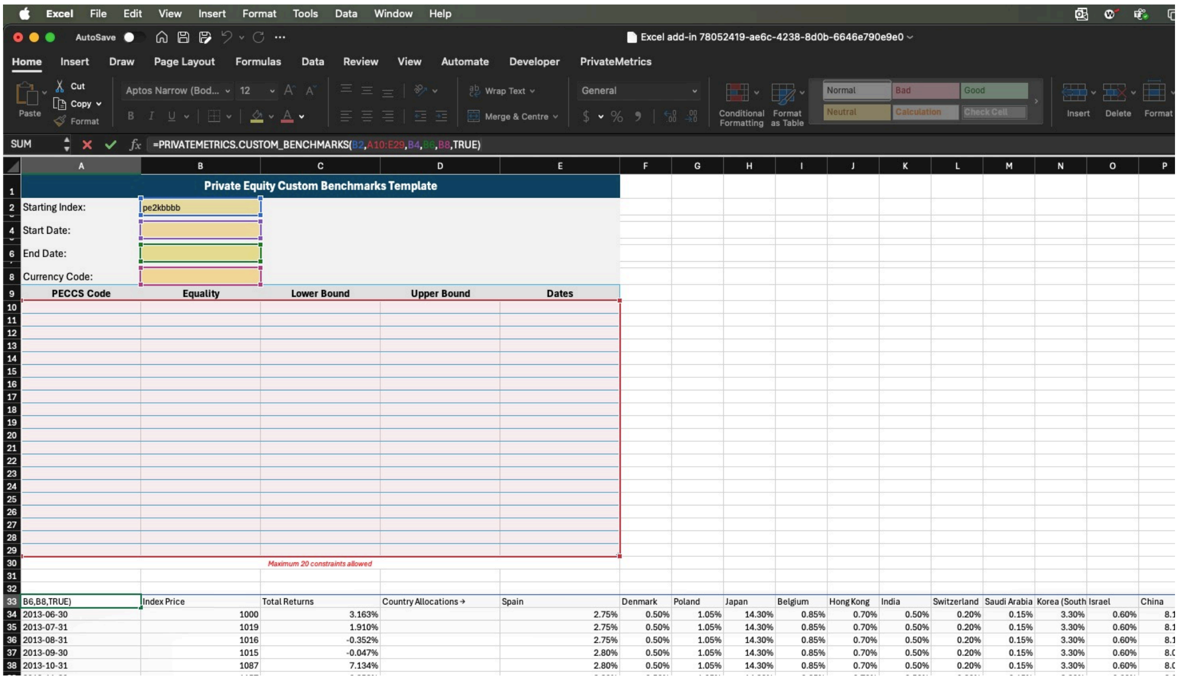


Excel Add-in task pane used to select and download privateMetrics market index data

Select a representative fund benchmark

To isolate the drivers of alpha (Allocation vs Pure Alpha) a customised strategy benchmark can be created that represents the choice of market segments (such as sectors and geographies) of the investments made by each fund. LPs can easily obtain this information from their manager or fund prospectus.

The custom benchmark is built from a base index universe, like the private2000, and specifying allocations by PECCS pillars and geography such as Activity, Revenue Model, Country, etc. With the flexibility of either specifying a range of allocation to a particular sector, or a fixed allocation to any segment, and with up to 20 such constraints possible, users can easily mirror the allocations of the fund under consideration and build a representative benchmark.



Excel Add-in functions to create a custom benchmark from the privateMetrics database

USER INPUTS

Period	Manager	Fund	Contribution	Distribution	NAV
30/09/2023	Manager 1	Fund 1	4,673.38	5,427.29	1,079.96
30/06/2023	Manager 1	Fund 1	4,683.84	5,381.77	1,062.11
31/03/2023	Manager 1	Fund 1	4,714.87	5,877.62	1,098.40
31/12/2022	Manager 1	Fund 1	4,714.87	5,852.39	1,127.31
30/09/2022	Manager 1	Fund 1	4,703.59	5,681.32	1,217.09
30/06/2022	Manager 1	Fund 1	4,699.38	5,676.63	1,240.59
31/03/2022	Manager 2	Fund 2	4,699.38	4,240.84	2,709.93
31/12/2021	Manager 2	Fund 2	4,692.54	3,529.04	3,325.56
30/09/2021	Manager 2	Fund 2	4,665.34	3,274.43	3,369.62
30/06/2021	Manager 2	Fund 2	4,659.73	3,089.35	3,578.39
31/03/2021	Manager 2	Fund 2	4,634.51	2,106.08	4,090.16
31/12/2020	Manager 2	Fund 2	4,645.71	2,502.33	3,870.38
30/09/2020	Manager 2	Fund 2	4,618.60	2,500.46	3,410.38

Fund cash flow and NAV data used to calculate the Alpha of individual funds

Alpha calculations

Using the market index, custom fund benchmark, and the fund cash flows data, the privateMetrics Alpha Tracking template performs all the calculations and produces the results for the fund: Total Alpha, Market Return, Allocation Alpha and Pure Alpha.

In the template, the “TOTAL ALPHA” sheet performs the calculations to compute Direct Alpha of each fund against the market index specified in Index 1 and Index 2 tabs.

The “ALPHA – SELECTION” sheet calculates the Pure Alpha of each fund against its representative bespoke benchmark.

The “RESULTS” tab shows the total alpha of each fund and manager against the specified market index. It also breaks down the return into market return (beta) and sources of alpha: allocation and pure components.

		Fund 1	Fund 2
Fund IRR		17.64%	21.37%
Fund TVPI		1.39	1.46
Public Equity Benchmark			
	Beta	11.63%	10.64%
	Alpha	6.01%	10.72%
Private Market Benchmark			
	Beta	18.25%	16.55%
	Alpha	-0.61%	4.81%
	Alpha - Allocation Tilt	0.12%	1.20%
	Alpha - Investment Selection	-0.73%	3.61%

Appendix F: the privateMetrics® Market Indices

The **private2000** index comprises the top 2,000 companies by size representing the largest investable universe across 30 key countries attractive to private equity investors. → privateMetrics® product factsheet

The **Infra300** index comprises 300 infrastructure companies worldwide and is designed to track the different TICCS® segments of the unlisted infrastructure reference universe. → infraMetrics® product factsheet

Figure 29 and Table 18 show the historical performance and risk-return summary of these market indices (private2000 in value-weighted and local currency, infra300 in equal-weighted and local currency) as of 31st December 2024. Both Private2000 and Infra300 indices demonstrate a strong risk-return profile, with Private2000 delivering higher long-term returns (14.98% over 10 years) alongside greater volatility, while Infra300 offers stable returns (8.65% over 10 years) with lower risk.

FIGURE 29: PRIVATEMETRICS MARKET INDICES HISTORICAL PERFORMANCE.

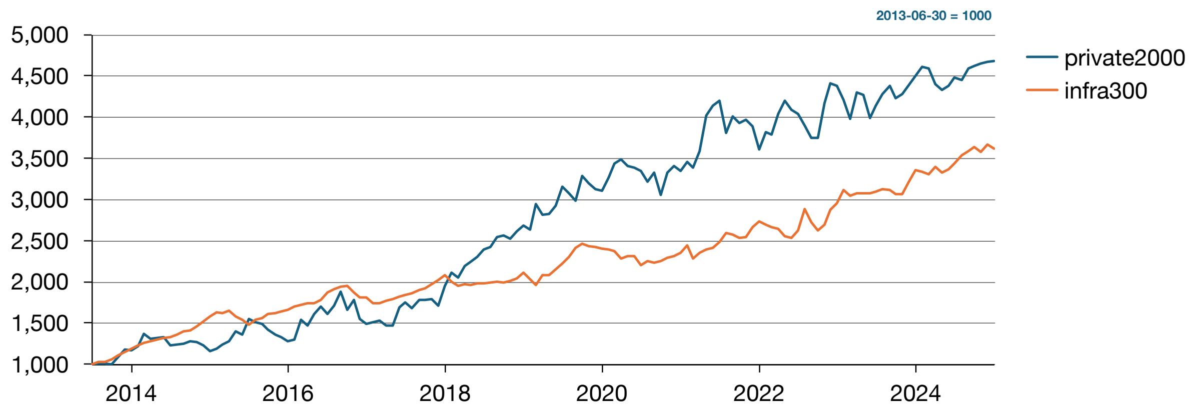


TABLE 18: PERFORMANCE SUMMARY OF PRIVATEMETRICS MARKET INDICES.

Index	3M Return	2024 Return	5Y Ann. Return	10Y Ann. Return	5Y Ann. Volatility	10Y Ann. Volatility
private2000	1.38%	4.13%	8.58%	14.98%	15.15%	18.77%
infra300	-0.53%	7.85%	8.57%	8.65%	10.23%	10.24%

Appendix G: The privateMetrics® Valuation Model

Our approach to the valuation of private companies is designed to maximise the available transaction and financial data in private markets and provide a standardised and systematic manner to update prices with every observed transaction.

First, we construct a multi-factor model of prices using a sample of observed transactions over time which can infer the unbiased and precise factor prices that investors pay for different characteristics of a private asset. Although every transaction is idiosyncratic or unique, in a large sample of transactions, the individual errors in each transaction price can be diversified away to discern the price attributable to each factor. Factor prices refer to the premium (or discount) that an investor is willing to pay to seek exposure to a specific factor of return in private companies. For example, observing the relationship between size and valuation among reported transactions, it can be inferred how much premium or discount an investor is willing to pay for purchasing a larger private company.

Second, an important and key application of this approach is that, with the estimated factor prices, say for size, it would then be possible to price unlisted private companies whose size information is available, irrespective of whether they are traded or not. This approach provides a more robust estimate for FV and enables the creation of representative indices of private companies.

Our approach's novelty is calibrating the model to newly observed transactions obtaining the factor price evolution over time, which allows us to update the valuation for all tracked unlisted private companies.

Common risk factors

If investors trade unlisted private companies from each other in mutually negotiated transactions, there must be some common characteristics that at least partially explain prices. For example, private companies that have higher profits or growth opportunities may be more valuable to investors than those that are not.

To arrive at a potential list of factors, we follow simple criteria that there needs to be an economic rationale for the factor to affect valuation. The factor should also be statistically related to the valuation. Moreover, the factor should also be objectively observable or measurable. With a potential list of factors, our factor selection is the result of a statistical approach, where the factors that can satisfactorily explain the variation in observed transaction valuations are included in the final model while trading off being parsimonious with being able to explain a higher variance in valuation. The privateMetrics asset pricing model uses five key risk factors as below:

- **Size**: Larger companies may be more complex, have higher transaction costs, and be less liquid, all of which can make them trade at a lower valuation per $ of revenue.
- **Growth**: As traditional PE strategies rely on growing the entry multiple, that may involve both increasing its top and bottom lines, i.e., revenue and profits. Thus,

companies that can grow faster can be more sought after, making them more valuable.

- **Leverage**: Leverage can make a company riskier as it increases the risk of default. However, there is also a signalling effect of leverage, as companies with stable consistent cash flows can support a higher leverage, and vice versa. Thus, leverage is expected to influence the valuation of a company.
- **Profits**: More profitable companies have more predictable (less risky) future payouts and hence attract a lower risk premium, making them more valuable.
- **Maturity**: Younger companies have fewer track records and face higher information uncertainty. Studies have shown that firms with high uncertainty tend to be overvalued and earn lower future returns. Thus, the maturity negatively affects valuation.
- **Country risk**: Investors may require a high return when investing in a high-risk country, thus depressing the current valuation. In other words, in countries with lower risk, investors may be willing to purchase assets at a higher valuation as government policies may be more predictable with lower macroeconomic risks.

TABLE 1: KEY FACTORS, THEIR EFFECT ON VALUATION, & THE ECONOMIC RATIONALE FOR INCLUDING THEM IN THE MODEL

Factor	Definition (Proxy)	Effect on price	Economic Rationale	References
Size	Revenues	Negative	Larger firms are more illiquid and trade a lower price	Fama & French (1993)
Growth	Change in Revenues	Positive	Companies with higher revenue growth trade at a higher price	Fama & French (1992), Petkova & Zhang (2005)
Leverage	Total debt / Revenues	Positive	Companies that can borrow more have a lower cost of capital and a higher value	Gomes & Schmid (2010), George & Hwang (2010)
Profits	Ebitda Margin	Positive	Companies that have higher profits have a higher value	Novy-Marx (2013), Hou et al. (2015)
Maturity	Years since incorporation	Negative	Companies that are mature exhibit less growth potential and trade a at a lower price	Jiang et al. (2005)
Country Risk	Term Spread	Negative	Companies in high-risk countries face more uncertain prospects	Chen & Tsang (2013)

SOURCE: CALCULATED USING OVER 10K DEALS FROM PITCHBOOK, CAPITALIQ, FACTSET, AND OTHER PRIMARY SOURCES BETWEEN 1999-2022

Our factors have been documented in prior academic studies to be associated with valuation. We also include factors that have been identified as key determinants of valuation from a survey of private equity practitioners that we conducted in 2023. Table 1 summarises the key factors that we use in the model, how they are measured, each factor's effect we document in the data on average, the economic rationale for their inclusion, and citations for the work that underpins their inclusion.

Model set up

The privateMetrics asset pricing model uses the Price-to-Sales ratio of observable transactions (the entry price multiple) as the modelled variable. The model is estimated as the linear sum of the product of factor exposures and factor prices. The estimation can then separate the systematic part of the valuation while leaving out "noise" in each valuation.

$$\frac{P}{S} = a + \sum_{k=2}^{K} b_k l_k + e$$

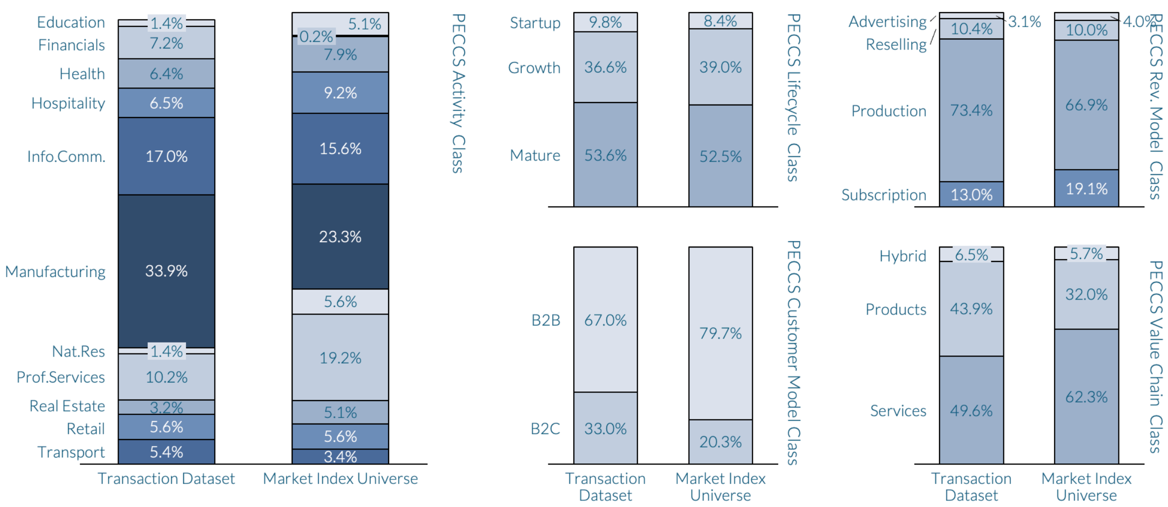
Following standard asset pricing notation, the factor exposure or factor loading is called a beta (β), and the factor premium is called a lambda (l) for the k factors in the model. a is the intercept and e is the noise or idiosyncratic part of the valuation.

Model calibration

The privateMetrics model uses a carefully curated dataset of more than 10k+ unlisted private company investments going back two decades sourced from a wide variety of datasets including PitchBook, Factset, Capital IQ, fund manager reports, and other publicly available data sources. We calibrate this model using new observations monthly to update its estimation of the price of risk of each factor. In other words, each transaction observed is then used to 'update' this model (i.e., obtain new ls) through a dynamic estimation (using a Kalman filter), which retains the memory of past ls while also allowing the new transaction to influence the relationship while keeping the average e close to zero. More details on the implementation of the model are available in our online documentation and Selvam and Whittaker (2024). The dataset covers all key segments of the market as shown in Figure 1.

A good application of using the model to value unlisted private companies is to create a representative marked-to-market index of private companies that are regularly valued. The privateMetrics index universe in Figure 1 includes the constituents of the private2000® index constructed by Scientific Infra and Private Assets, which is developed on this shadow pricing idea and captures the performance of private companies in 30 countries globally that are important for private equity investors (read more about the index here).

Figure 1: privateMetrics Transaction Dataset Compared to the privateMetrics Index Universe by PECCS Pillar & Class



How precise are the predictions across PECCS® pillars?

To examine how closely the predicted valuations track the raw modelled valuations in transactions, we compute the average estimation errors of the full sample, and also by classes within each PECCS® pillar. What stands out is that although the model by design is expected to have lower estimation errors in the full sample, the within PECCS® class estimation errors are also very small. All the errors are within ±10%, reassuring that the model predictions on average even within each segment of PECCS® are reasonable. The errors are summarised in Table 5.

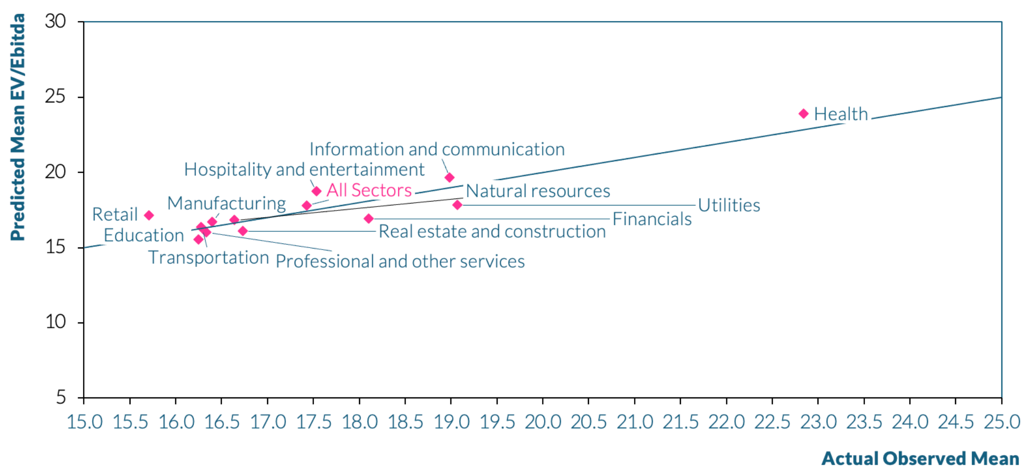
The most commonly used metric of valuation in private markets is EV/EBITDA as PE owners have the flexibility to alter the capital structure of their holding company and hence are more interested in operational profitability without factoring interest costs. However, our model is based on P/S because P/S is statistically better, stable, and not affected by loss-making companies. Thus, one may be concerned whether our predictions for EV/EBITDA might be biased. To ensure that is not the case, we compute the EV based on the book value of debt and predicted equity valuation and divide the sum by the EBITDA to get a predicted EV/EBITDA and compare it to transaction implied ratios. Figure 3 presents the average predicted and observed EV/EBITDA by PECCS® activity classes. We find that the predictions are very close to the observed values, thus mitigating this concern.

Table 5: Average estimation errors across PECCS® classes, based on the difference between transacted valuations and factor model predictions

PECCS Pillar	**PECCS Class**	**Mean Estimation Error**	**PECCS Class**	**Mean Estimation Error**	**PECCS Pillar**
PECCS Activity	Education and public	0.9%	Startup	0.1%	PECCS Lifecycle Phase
	Financials	1.8%	Growth	-1.7%	
	Health	2.6%	Mature	2.8%	
	Hospitality and entertainment	-1.1%	Advertising	1.2%	PECCS Revenue Model
	Information and communication	-4.4%	Reselling	4.6%	
	Manufacturing	2.5%	Production	2.9%	
	Natural resources	9.4%	Subscription	-6.9%	
	Professional and other services	3.3%	B2B	1.5%	PECCS Customer Model
	Real estate and construction	1.9%	B2C	0.9%	
	Retail	0.5%	Hybrid	0.6%	PECCS Value Chain
	Transportation	7.2%	Products	1.1%	
Full Sample		**1.1%**	Services	3.4%	

Source: Calculated using over 10k deals from PitchBook, CapitalIQ, FactSet, and other sources between 1999-2022

Figure 3: Predicted versus actual EV/EBITDA ratios by PECCS® activity classes - Source: PitchBook, CapitalIQ, FactSet etc



About Scientific Infra & Private Assets

Our products come from the cutting-edge R&D of the EDHEC Infrastructure & Private Assets Research Institute, established in 2016 by EDHEC Business School. In 2019, we transformed this academic research into a commercial enterprise, providing services like private market indices, benchmarks, valuation analytics, and climate risk metrics. We take pride in our unique dual identity, bridging scientific research and market applications.

The EDHEC Infrastructure & Private Assets Research Institute (EIPA) continues to advance academic research and innovate with technologies in risk measurement and valuation in private markets, especially utilising artificial intelligence and language processing. Our company, Scientific Infra & Private Assets (SIPA), supplies specialised data to investors in infrastructure and private equity.

Merging academic rigor with practical business applications, our dedicated team excels in integrating quantitative research into private asset investing. Our products, infraMetrics® and privateMetrics®, are unique in the market, stemming from thorough research rather than being ancillary services of larger data providers. We are the Quants of Private Markets, leading with innovation and precision.

About the Authors

Frederic Blanc-Brude, Ph.D. is the CEO of Scientific Infra & Private Assets. He is based in Singapore. Contact: frederic.blanc-brude@sipametrics.com

Abhishek Gupta, CAIA, is a Director of Scientific Infra & Private Assets and the head of Product Development. He is based in London

Moataz Farid, Ph.D. is a Senior Research Engineer at Scientific Infra & Private Assets in the London team.

Contact Information

London Office
10 Fleet Place
London EC4M 7RB
United Kingdom
+44 (0)20 7332 5600

Singapore Office
One George Street
#15-02
Singapore 049145
+65 66538575

email: sales@scientificinfra.com

web: www.scientificinfra.com

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