Introducing Objective Benchmark-Based Attribution in Private Equity

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In this article, we propose that in private equity, measurement of asset manager (general partner [GP]) skill should begin with a repeatable benchmark-based performance attribution, which is then extended to explicitly quantify sources of alpha. Furthermore, in this article, we lay out a framework for repeatable measurement of performance attribution. Modern proxy benchmarks form a key component of this framework by enabling public market information to systematically inform private equity performance.

For manager evaluation, benchmarks serve as a standard against which past performance is measured and compared. In private equity, creating such a standard is confounded by the absence of price for extended periods and by the vicissitude of exposures and cash flows a private equity fund will experience over its lifetime. Recent advances in data science technology now support a host of indexing capabilities that work within these constraints, allowing fully modernized benchmarking and performance evaluation.

Modern indexes, as described by Lo (2016), are similar in concept to the modern proxy benchmark by their systematic construction and ability to highlight systemic behavior of a set of stocks against a given factor(s). Such indexes are diverse, at the forefront of financial innovation, and—notable to this article—include non-market-cap-weighted (fundamental value) varieties.

Technology can now systematically and objectively determine a suitably stable set of stocks based on their similarity to a target asset, providing the basis for quantifying *systemic* elements of performance. The custom index, thus composed, closely resembles the size and sector style returns described by Sharpe (1992) and can be used to define the highly prized excess returns produced by the manager relative to that of a passive mix with the same style (see Exhibit 1).

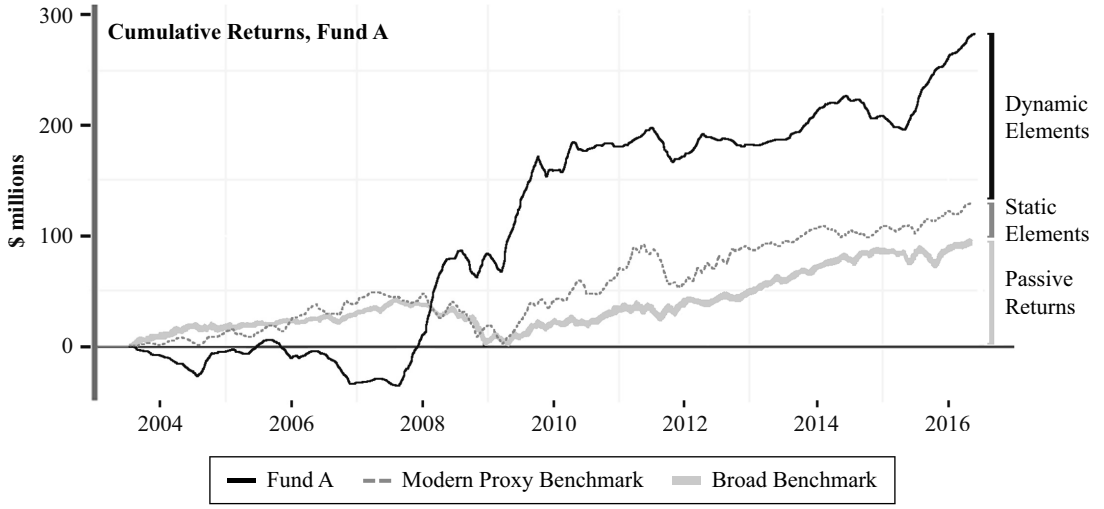
PROPERTIES OF MODERN PROXY BENCHMARKS

Modern proxy benchmarks are constructed as custom modern indexes but with two distinct (additional) properties: They satisfy fully the CFA Institute's criteria for a valid benchmark ("SAMURAI"),[1] and they are functionally ideal for performance comparison because they are objective, actually investable, and transparent. These properties are nontrivial to achieve and introduce two requisite quantities to the construction process: technical similarity and stability.

[1] "SAMURAI" stands for Specified in advance; Appropriate; Measurable; Unambiguous; Reflective of manager's universe; Accountable; Investable.

EXHIBIT 1

The Role of Modern Proxy Benchmarks in the Decomposition of Fund Performance



Notes: The modern proxy benchmark is a public peer set, adjusted for liquidity and control, reflective of the target entity's industry, economic size (not market cap), and interplay of financial ratios. It has 50–150 companies, objectively composed by technology for optimal specificity and stability.

Technical Similarity

Within the attribution taxonomy described by Sharpe (1992), and within our own related approach, *similarity* between the target asset and the benchmark is germane to its economic meaning. But what is similarity? Arguably, the most enduring markers of similarity are also the most fundamental: financial quantities and business descriptors of the companies within the funds (Arnott, Hsu, and Moore 2005).

The second question then becomes how it is measured. In this work, we develop a similarity measurement based on a combination of a company's fundamental components: its economic size[2] (as opposed to market cap or price), industry, and interplay of financial ratios. Similarity can then be implemented as a distance function, in which components are mapped along these three axes, with closer companies being more similar to the target company. This approach, which measures at the underlying company level as opposed to the fund level, is made possible by data science technology.

Technical similarity radically transforms similarity from a subjective notion (inevitably biased toward familiar companies[3]) into an objective empirical quantity.

Stability

The purpose of the benchmark is to capture systemic behavior against which idiosyncratic behavior (i.e., excess returns) may be measured. It is critical then that its constituents be sufficiently numerous to aggregate to a systemic representation and attenuate idiosyncratic behavior. A benchmark's ability to reliably capture systemic behavior describes the property of *stability*.

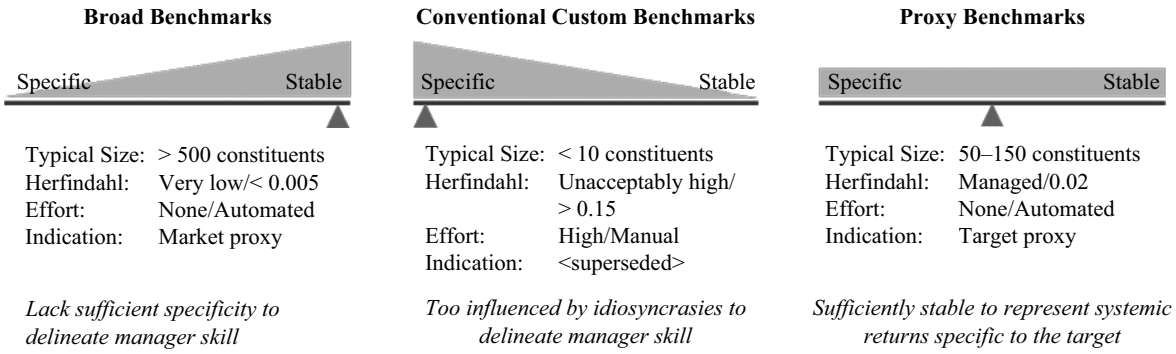
We propose that stability is an essential property of a benchmark, central to the integrity of an excess returns measure. An unstable benchmark can be unduly influenced by a subset (or one) of its constituents, misrepresenting systemic returns and causing unavoidable confusion of constituent and target idiosyncrasies. An unstable benchmark therefore makes a repeatable definition of manager alpha unattainable.

[2] Economic size—what we call *fundamental economic value*—is itself a mathematically valid indexation of a company's intrinsic value as measured by statistical models. The predictive accuracy (to market value) of these statistical models is 0.813 (the R^2 statistic) and is equally accurate across the public–private divide.

[3] For further reading on familiarity bias, see Heath and Tversky (1991).

EXHIBIT 2

Benchmarking Private Equity—Balancing a Fundamental Trade-Off between Specificity and Stability (and effort)



Appropriating the Herfindahl Index to Measure Stability

The Herfindahl (also called the Herfindahl–Hirschman Index, or HHI) is a commonly accepted device to measure market concentration.[4] However, the Herfindahl can be appropriated to calibrate stock exposures in benchmark construction and determine the number of constituents needed to control for benchmark stability. Higher concentrations are represented by a larger Herfindahl. For example, a benchmark containing fewer than 10 constituents—not uncommon for custom benchmarks in private equity—approximates to a Herfindahl between 0.10 and 0.25, sometimes even larger. At a Herfindahl of 0.05—far more stable than 0.15—a benchmark produces unacceptable variances and is at high risk of being materially skewed by idiosyncratic behavior of its constituents.

Our research finds evidence of concentration thresholds in a benchmark that provide guidance for a stability range. The upper threshold corresponds to a Herfindahl of 0.05, as previously stated; however, the lower threshold should be considered in the context of what the benchmark is trying to capture: systemic behavior specific to the target entity.

[4] For example, the United States Department of Justice and the Federal Trade Commission consider the Herfindahl a measure of market concentration: https://www.justice.gov/atr/herfindahl-hirschman-index.

The Specificity–Stability Spectrum

In general, by making the benchmark more stable, we are trading off specificity to the target asset(s). Conventional practice in private equity bunches benchmarks at either end of this spectrum, in which a custom benchmark with (typically) fewer than 10 constituents is at one end, and a broad benchmark like the Russell 3000 is at the other (see Exhibit 2). Although practitioners may be aware that neither case is suitable for performance evaluation, gaining consensus on a larger set of subjectively chosen stocks and weighting them in an index is an extremely difficult and universally tiresome process with little clarity in the end.

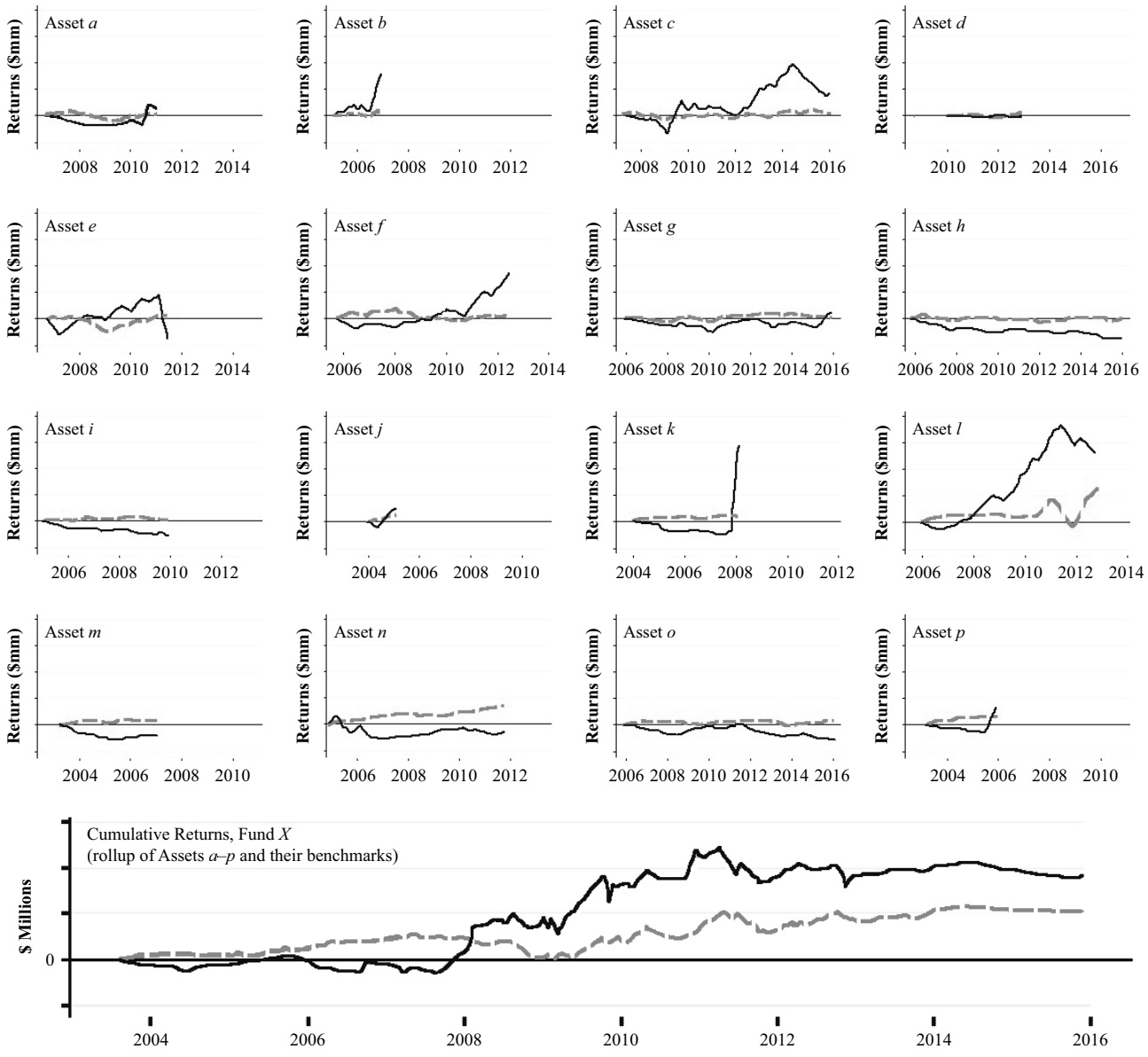
The compelling "middle ground" of this spectrum, in which a benchmark is stable *and* specific to its target, typically requires between 50 and 150 constituents that are each monitored to continuously satisfy the requirement of technical similarity.

BENCHMARKING TECHNOLOGY

Practitioners will recognize that, in the absence of benchmarking technology, benchmark construction is an intensely subjective stock-picking process. Because of this difficulty, a (conventionally constructed) custom benchmark is typically aimed at the fund or manager level and composed of far fewer than the 50 constituents per target company needed for benchmark stability; however, this crude approach is a practical workaround rather than a theoretical consideration—a

EXHIBIT 3

Cumulative Returns of Assets (dark line) and Their Modern Proxy Benchmarks (dashed), Rolled Up to Their Fund



constraint readily removed by automated benchmarking technology.

The efficiency of technology makes robust benchmarking at the company level feasible and excess returns calculable on a per company basis (see Exhibit 3). Alpha can be "rolled up" outside of the fund wrapper and examined in compelling ways (i.e., by industry, company size, and even deal team). As represented by Korteweg and Sørensen (2014), this intelligence—afforded by technology—may unlock greater predictive power in the manager evaluation process.

Data science technology is already behind remarkable innovation in finance and investing, so it is perhaps unsurprising that it also has the power to unlock new capabilities in private equity. Modern proxy benchmarks and benchmark-based attribution are one such example,

with precision and objectivity offering new capabilities, such as

- Quantification and indexation (i.e., direct comparison) of manager skill
- Consistent delineation of systemic returns (i.e., company size, industry, region)
- Emergence of risk metrics and portfolio construction
- Consideration of dynamic and static elements of active returns in fee structures.

Maintenance of the Modernized Benchmark

The changing composition of a private equity fund as assets enter and exit is further complicated (in terms of performance attribution) by asset bolt-ons, divestments, and restructuring during the holding period. The changing nature of a fund's exposures and the economic size of its assets is the result of GP operational control and is constitutive to private equity investing; however, despite these changes being implicit to GP skill, the fixed benchmark typical in private equity is indifferent to it.

Through its efficiency, benchmarking technology makes it possible to preserve specificity and stability over time in a systematic manner. In so doing, the GP's skill is more accurately captured because it is always being gauged appropriately. To illustrate, imagine a merger of two similar assets. The strategy is to drive operating efficiency, strengthen exit multiples, and generate higher total returns. If the benchmark did not change to reflect the merged entity, then the GP would be gauged against companies that had lower operating efficiencies, with no understanding of the potential returns or the opportunity as indicated by its similarly sized peers. If the benchmark is adjusted to reflect the larger entity, then the opportunity (and by extension the opportunity cost) is made measurable.

To capture the more predictive components of performance (i.e., GP skill), the benchmark must be meticulously maintained to reflect the actions of the GP as it changes the composition and nature of the fund.

APPROACH

The exactitude of the approach enabled by technology starts with measuring at the holdings or asset level. For every company inside the fund, a proxy benchmark consisting of between 50 and 150 technically similar companies (peers) is systematically constructed. With today's computing power, technology can evaluate the similarity of 6,000 companies in less than six seconds, making a scan of all public exchanges (including over-the-counter stocks) for fundamentally similar constituents a rapid process.

Constituents with greater similarity to the target company are weighted accordingly by the number of their shares held in the benchmark. Therefore, for each private company in a fund, benchmark technology creates a mathematically precise cloud of public peers. The company-level public benchmarks are then rolled up to the fund level to create the equivalent of a virtual synthetic investment.

A private equity fund can be thought of as a series of stakes in various companies over time. Change in fund composition or the nature of any one component company is generally accompanied by a cash flow event; a stake is the period between cash flow events (see Exhibit 4). Each stake is treated as its own virtual synthetic investment that is completely cashed out and immediately reinvested as a new stake at cash flow events. The synthetic fund is actively managed by the technology to mirror the changed nature of every stake for the life of the fund.

In this way, the GP's actions are precisely replicated in the benchmark. Furthermore, implied returns may be captured without forcing the benchmark to engineer its way around going short—a nontrivial issue that various public market equivalent (PME[5]) methods handle differently.

Much like the S&P 500 is not a fixed basket of stocks, technically similar companies are actively moved in and out of the benchmark based on a consistent methodology that is specified in advance. Although computationally intensive, rigorous ex post analysis of a private equity fund for the purpose of manager evaluation can be completed in seconds.

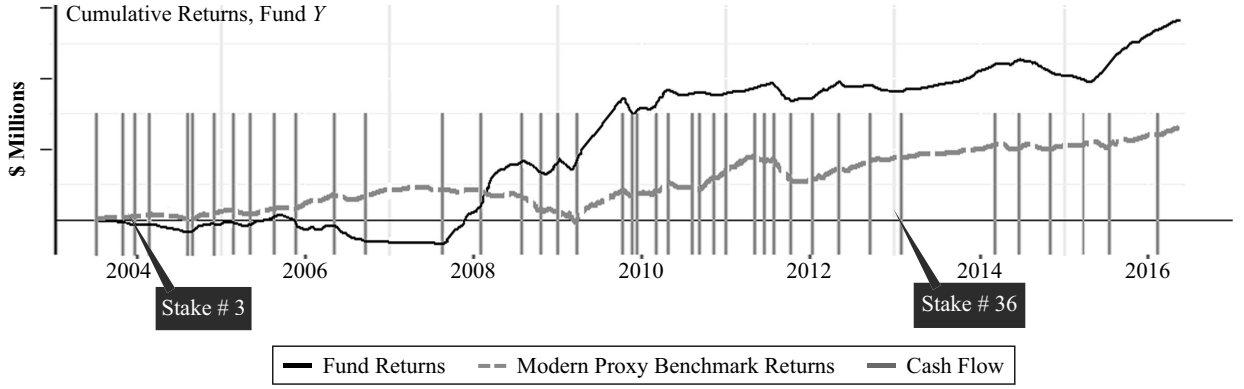
FRAMEWORK FOR DECOMPOSITION OF RETURNS

An asset's cumulative returns are modeled from unsmoothed cash flows and explicitly account for

[5] PME—also known as the Index Comparison Method, or ICM—analysis was first proposed by Long and Nickels (1996); subsequent flavors have worked toward minimizing technical issues, including the public index going short.

EXHIBIT 4

The Benchmark Is Adjusted Synchronous with Every Cash Flow to Reflect the Actions of the GP



Note: Each vertical line represents a cash flow event, indicative of a change in the fund's exposures or component company size.

economic value growth and market fluctuations with an objective and measurably accurate continuous pricing mechanism. Data science technology provides such a mechanism.[6]

Active/Passive Decomposition

Market returns are indicated by a broad index such as the ACWI or Russell 3000 or by returns of the investor's own public equities portfolio. The market, so defined, marks the active/passive decomposition of the private asset's returns (see Exhibit 5).

Limitations of the PME in Performance Attribution

Broad benchmarks differ substantially in similarity to a given fund and do not offer a meaningful marker of manager skill. For example, consider the Russell 3000 gaining 20% while the technology sector goes down 15%. A fund (or GP) weighted in technology assets would appear unskilled but when the technology sector recovers it would look highly skilled.

This simple example illustrates the major limitation of the PME approach to performance attribution: It is simultaneously driven and limited by its benchmark. It is the benchmark that drives the legitimacy of performance attribution (Cumming, Hass, and Schweizer 2013) in the dimension of time and in the dimension of similarity/stability. As previously discussed, a meaningful measure of alpha is dependent on a systematic and robust quantification of systemic performance that is *always* technically similar to the target asset.

Decomposition of Active Returns

From the active/passive decomposition, active returns are further decomposed into static and dynamic elements by the modern proxy benchmark.

Static Elements of Active Returns

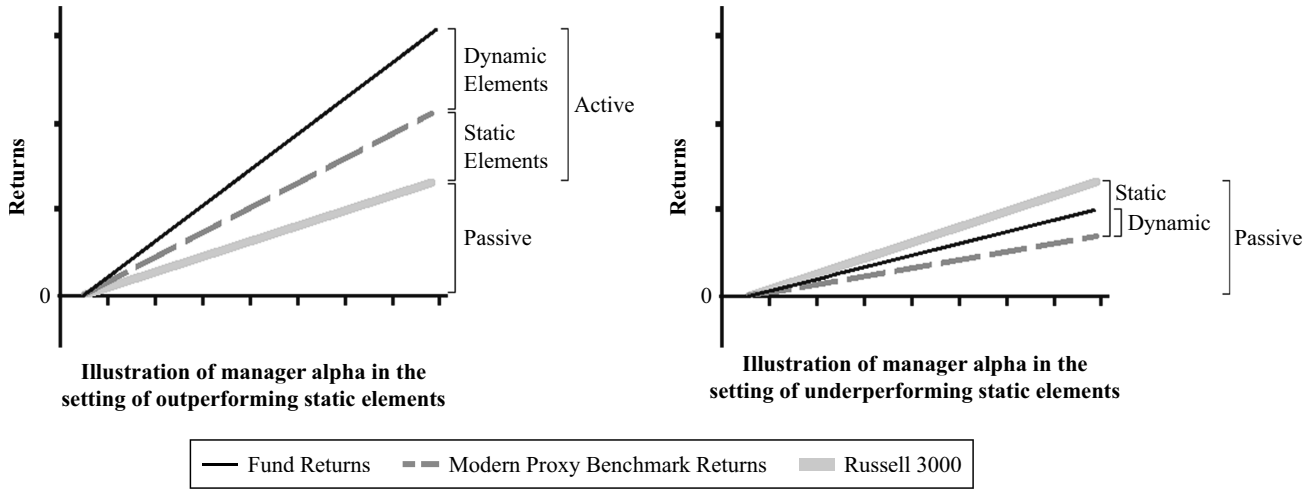
Modern proxy benchmarks capture the systemic portion of active returns, namely the contribution of industry, asset size range, and region. Therefore, cumulative returns of the proxy benchmark in excess of passive returns approximate the economic value of a GP's exposure to these systemic factors.

For most GPs, the systemic factors to which their funds provide limited partners (LPs) access are relatively static over time. It could be argued then that the value added by static elements reflects a strategic bet on beta made *explicitly by the LP*. Certainly, an objective segmentation of systemic returns gives perspective to the concern of many LPs that they may be paying high fees for beta.

Nevertheless, as framed by Lo (2007), there exists a potential economic value in a GP's weighting of certain

[6] See the section "Objective Measurement of Interim Valuations" later in this article for elaboration on the continuous pricing mechanism.

EXHIBIT 5
Framework for Decomposition of Returns



Notes: Advanced applications of data science technology allow modeling of private equity performance in time series and the componentization of returns. The structure of these components, shown in the exhibit, allows independent consideration and comparison of market returns, the investor's choice of systemic exposures, and the GP's skill in producing excess returns. Within this framework, manager alpha is excess return from the proxy benchmark, provided the proxy benchmark exhibits the properties of stability and technical similarity and is actively maintained to continuously mirror the fund.

exposures within a given fund. In other words, the degree to which a GP uses prior information to "launch boats onto rising tides" may be considered the private equity equivalent of timing. Strategic weighting of static elements by the GP is an interesting source of potential value, further examination of which is supported by our attribution framework.

Dynamic Elements of Active Returns: Manager Skill

If the modern proxy benchmark represents systemic returns, then excess returns are idiosyncratic in origin. The GP's operational control of the asset makes these idiosyncrasies a genuine approximation of GP skill. Therefore, within an attribution framework, excess returns to the proxy benchmark equals manager alpha, which equals manager skill.

The control levers available to a GP—namely asset growth, financial engineering, and transaction premiums[7]—are applied dynamically in the marketplace by the GP to maximize yield given contemporaneous market conditions and opportunities. The GP's ability to forecast and execute winning strategies underwrites how it works the control levers, and alpha is its measure.

Because of their predictive nature, dynamic elements are worthy of greater examination. Modern proxy benchmarks support an attribution framework capable of extending to a novel quantification of contributions to alpha by source. These sources are described fully in a forthcoming paper by Porter and Porter on performance attribution measurement in private equity.

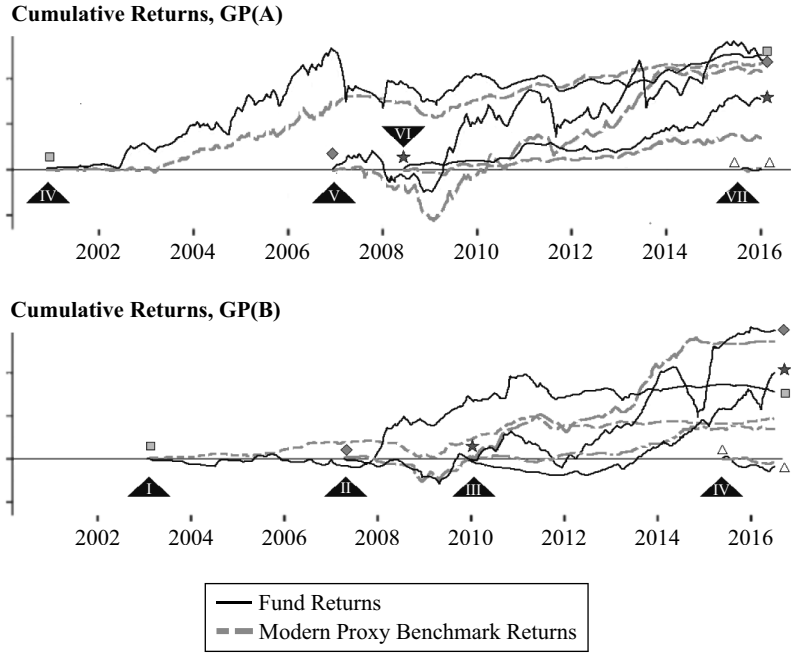
APPLICATION OF MODERN BENCHMARK-BASED ATTRIBUTION TO MANAGER EVALUATION

Benchmark-based attribution using technology provides an objective, consistent decomposition of performance ex post that allows simultaneous comparison between GPs and to the market (see Exhibit 6). This allows the LP to index investment proposals by the

[7] We measure the premium paid on the asset (company) at entry and exit as per $Market\ premium = \frac{(Price - FEV)}{FEV}$.

The asset's premium is mapped to a distribution of the modern proxy benchmark's component firm premiums at the exact corresponding times. This determines whether the GP paid a higher or lower premium relative to the market at each transaction (i.e., buy low and sell high) and whether the premium percentile moved favorably between transactions.

EXHIBIT 6
Comparing Alpha across Funds and Between GPs



Fund	Vintage	% Realized	Fund Alpha	Overall Alpha
IV	2001	93%	1.3%	
V	2006	71%	0.8%	**1.8 %**
VI	2008	47%	11.6%	
VII	2015	0%	21.9%	

Fund	Vintage	% Realized	Fund Alpha	Overall Alpha
I	2003	68%	5.5%	
II	2007	60%	1.8%	**4.4 %**
III	2009	26%	10.1%	
IV	2015	0%	–12.1%	

factor that is widely accepted as most predictive of future performance: GP skill.

Reducing the Influence of Gameable Metrics

The cash flow–weighted metrics that dominate the industry impose severe limitations on GP evaluation because, fundamentally, they do not offer predictive intelligence (Porter and Porter 2018). In the absence of viable alternative performance metrics, the industry has nonetheless drawn conclusions from, and made inferences based on, internal rates of return (IRRs) to inform investment decision-making.

Unfortunately, the gameable nature of IRR inputs has opened the door to it being used for the purpose of *mis*information. For instance, peer ranking is most commonly based on fund-level IRR as compiled by numerous third parties. A "top quartile" fund has an IRR in the top 25% of its vintage year cohort.[8] Aside from issues pertaining to data completeness and selection bias of the proprietary database, the IRR cannot determine manager skill or rank performance. Research by Gottschalg and Phalippou (2007) illustrated this. They found that the IRR materially misstated returns, even on fully realized funds, and that rankings were not preserved when reinvestment rates were adjusted using the modified IRR function (MIRR).[9] For example, the top two ranked funds by the MIRR did not make an appearance in the top 10 funds ranked by the IRR.

The potential for distortion, even misrepresentation, is increased when either IRR or MIRR analysis involves current assets (i.e., interim funds) because of the subjectivity of underlying asset valuations. Discussed widely in the literature and echoed by the Securities and Exchange Commission repeatedly from 2013 (Karpati 2013; Bowden 2014), GPs generally inflate valuations to peak IRR at the time of fundraising (Barber and Yasuda 2016). Subjectivity means that valuations can be (and generally are) manipulated for the express purpose of influencing the investor

[8] The definition of *vintage year* varies among researchers. It may mean the date of fund closing, the date of first capital call, or the fund's date of first entry. This wiggle room can potentially be used to identify a fund with a cohort in which it ranks more favorably.

[9] $$MIRR = \sqrt[n]{\frac{FV\ (Positive\ cashflows,\ Reinvestment\ rate)}{-PV\ (Negative\ cashflows,\ Finance\ rate)}} - 1.$$

(Barber and Yasuda 2016)—despite the fact that interim valuations are typically produced by independent valuation experts.[10]

Against a backdrop of at-times flagrant gaming of the IRR,[11] the industry has nonetheless been driven to infer that successive top-quartile funds indicate GP skill (Sensoy, Wang, and Weisbach 2014). As an illustration of the degree to which this persistence is prized: A GP with an existing top-quartile buyout fund can raise a follow-on fund 5.7 times faster than a bottom-quartile counterpart (Barber and Yasuda 2016). However, the IRR cannot discern between skill and luck. It *is* possible to be lucky on multiple occasions, especially if the market is generally rising and competition does not increase. These conditions unfortunately do not describe the current or likely future scenario of private equity, and at least for buyouts, persistence as an indicator of future performance has already evaporated (Braun, Jenkinson, and Stoff [2015]).

BENCHMARK-BASED ATTRIBUTION WITHIN AN OBJECTIVE MEASUREMENT FRAMEWORK

The decomposition of returns discussed in this article provides a clarity of analysis because it is created by repeatable measurement. Creation of an objective measurement framework necessarily begins with high-accuracy valuation technology.

Objective Measurement of Interim Valuations

The approach to interim valuation underpinning the framework described herein involves the capture of three sets of information: the economic size of the target company, company idiosyncratic factors, and market movements.

1. The *economic size* of the target company is measured by its fundamental economic value (FEV). The FEV is a unique size measure produced by data science technology, with certain properties:
   i. High predictive accuracy of market price (R^2 = 0.813)
   ii. Objective and systematic, requiring no forward-looking or subjective quantities
   iii. Simultaneously measures public and private companies with equal accuracy on a standardized basis
   iv. Fundamentals-driven
   v. Automated
2. *Company idiosyncratic factors* are estimated by computing the premium of each company from its entry price. By also computing the premium distribution of the proxy benchmark at that date, the distance of the company's premium from the median premium can be attributed to company idiosyncratic factors, which might include brand power, customer base, assets, growth potential, and so on. The premium percentile of the company purchase price represents the overall impact of idiosyncratic factors at entry. Under the assumption that these idiosyncratic sources of value vary slowly, the premium percentile can be used as a proxy for them.
3. *Market movements* are captured by the modern proxy benchmark. Together with the FEV, it is possible to simultaneously measure pricing changes and growth in the economic ecosystem of each company and roll these up to the fund and GP levels.

Interim valuations are calculated by computing the FEV of each company's most recently available financial information, calculating the premium distribution of the proxy benchmark on the valuation date, using the

[10] According to the (formerly named) Financial Services Authority (2006) (FSA Discussion Paper 06/06), private equity firms number among the largest clients for most big financial intermediaries—banks, lawyers, accountants, management consultants—creating the potential for moral hazard. In particular, the revenue stream a service provider receives from a private equity firm "may cause them to consider actions that they would normally discount." For example, one (unnamed) bank earned almost €900 million from its private equity–related activities in a year, whereas another bank was shown to generate over 50% of its income from private equity.

[11] In addition to manipulating valuations, the IRR can be gamed by delaying capital calls. GPs can finance acquisitions using short-term debt, delaying capital calls by months or potentially years; however, if the debt is secured against LP commitments, the LP bears default risk (off balance sheet). Although this is not an illegal practice, it nonetheless has the effect of juicing the IRR, which is then used to substantiate the skill and fees of the GPs in their marketing process.

distribution and the premium percentile to estimate the market premium of the company, and then deriving *Fair value* = *FEV* × (1 + *Estimated market premium*).

This interim valuation method is wholly objective and has been tested on more than 100,000 public company quarterly valuation estimates. The tests show that the method is unbiased, with a median absolute percent error of less than 0.05.

Outputs of the Objective Modern Framework Beneficial to GP Performance Attribution Analysis

- An objectively constructed and investable benchmark (full SAMURAI compliance)
- A high-integrity benchmark in terms of specificity and robustness—that is, a robust public proxy
- An efficient and exacting mechanism for maintaining benchmark integrity over time
- An elegant method for calculating implied returns from the benchmark
- Rigorous delineation of dynamic and static elements of active returns
- The means to align performce compensation with the investment decision-making process

In addition, the objective basis of this framework permits an approach of continuous improvement and accountability to the manager evaluation process itself. Whether corroborating or challenging an investment narrative, objectivity enhances the overall probity of the process.

CONCLUSION

Benchmark-based attribution as described throughout this article disambiguates the quantification and comparison of manager skill.

Technology efficiencies radically change our understanding of what is practical; LPs can measure and index manager skill on a far broader scale than what has been previously possible. For instance, early-stage rigorous analysis that incurs less cost, time, and effort may be implemented by LPs as a screening mechanism. Collectively, these analyses can inform an LP's understanding of the changing fund-raising climate over time, which in turn informs investment discipline and tactical excellence alongside pacing plans or other forms of investment pressure. The evaluation process can take on more of a funnel shape with a significantly wider catchment than is currently normal and eliminate the LP's equivalent of potentially harmful sample selection bias.

Finally, the systematic separation of active returns into static and dynamic elements by the modern proxy benchmark allows LPs to actively seek improved performance from both.

Although the performance metrics of public equities have surged in dimensionality and predictive power, a similar scientific quest has not flourished in private equity. The reason might have cultural underpinnings, but the absence of a continuous price mechanism has historically posed an intractable technical barrier. Advances in data science—a combination of computational power, statistical programming language, and the development of advanced mathematical models—have now allowed that barrier to be broken, engendering exciting opportunities for private equity, risk management, and portfolio management.

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