What's Your Algo for Manager Selection ... and How Good Is It?

Making more systematic, data-driven decisions in private markets

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1. Welcome

In private markets, the dispersion of managerial performance is characteristically large: Choosing the right managers can materially boost an investor's overall performance, but picking the wrong managers carries a severe opportunity cost.[1,2,3] Hence, private-market manager selection is one of the most consequential decisions that investors face. An investor's **processes** for manager selection can materially impact their portfolio-level returns.[4] However, many investors struggle to think analytically about their selection processes and do not know *objectively* how good those processes are or how to improve them. One solution is to take an algorithmic perspective — that is, treating selection processes like algorithms — and in this Addepar Research Brief (ARB), we present a straightforward framework for doing just that.

Our goal is to help investors analyze and "debug" their selection processes and steer them closer to optimality, namely, by being more systematic and data driven. Below, we investigate common practices in private-market manager selection and how these often prevent investors from picking

[1] This ARB is complementary to recent work by O'Donnell [2024], which discussed dispersion dynamics in manager performance within private markets. That piece identified specific questions for investors to ask when judging manager performance. Here, we focus on presenting a general approach to systematically integrating such questions into manager-selection processes in order to help those processes become more performant (e.g., less biased, more efficient, more data-driven).
[2] To make discussion as general as possible, we use the term 'investor' to refer to an allocator of capital, and 'manager' to refer to a third-party recipient of that capital who is charged with deploying it to earn a return. In private markets, investors are often called 'limited partners', or LPs (and includes entities like family offices, pension funds and endowments), while managers are called 'general partners', or GPs.
[3] As we'll discuss, the right managers for a particular investor's portfolio may not be the managers who have been the top recent performers; there are many other factors to consider in judging which managers are the best fit for an investor's specific 'context' (see Monk and Rook [2023]).
[4] In this ARB, we concentrate on a selection of external managers in private markets (with an emphasis on private equity, such as venture capital, buyouts and private real estate). However, most of our discussion applies equally to manager selection in public markets.

the managers that best fit their specific contexts (see Monk and Rook [2024]). We then uncover emerging best practices and incorporate them into a framework — a kind of “proto-algorithm” that investors can use for modeling/ enhancing their own selection algos. This framework respects the fact that, to function properly, manager-selection algos depend on an investor’s hypotheses about what drives manager performance in private markets, along with what data are available on those drivers.

Our teams are uniquely positioned to present these insights for two reasons: 1) our deep experience and analytical abilities in private markets and 2) our world-leading dataset that covers private-market managers. This ARB is the first in a forthcoming series to explore how investors can improve their manager-selection decisions.

2. NTK

Here are the key takeaways you need to know (NTK) from this brief.

- **High-Stakes:** Picking the right private-market managers can lead to several hundred basis points of incremental return (or opportunity cost) per annum at the portfolio level. Picking the right private-market managers is thus one of the most consequential decisions that an investor can make.
- **Systematic:** Having properly designed processes rooted in well-founded hypotheses on the deep drivers of manager performance — is the single best way to increase the likelihood of selecting the right private-market managers.[5]
- **Data-Driven:** Unless an investor's selection processes are informed by high-quality data, they will be prone to failure.

3. Significance

Manager selection in private markets is a high-stakes exercise: Investors who choose well can earn substantial returns, and those who don’t can suffer significant losses. For example (see O'Donnell [2024]), from 2017–2021, top-quartile managers in private equity delivered returns of almost 40%, whereas bottom-quartile managers returned around 10%. (Median returns were 20%, and the top

[5] Relatedly - but no less crucially - having systematic processes is essential for investors to inspect their decision-making retrospectively, i.e., be able to identify what they did well when selecting managers and how they might improve.

5% of managers produced returns of about 75%. The bottom 5% had returns close to -10%).[6] Relative to public markets, where the top 5% of managers delivered only about 10% greater returns than the bottom 5%, this dispersion among PE managers is dramatic, even from a whole-portfolio standpoint.[7] To illustrate, assume that an investor allocates 10% of their portfolio to PE. Being able to pick top-quartile managers would deliver 200 extra basis points of return *at the portfolio level*, relative to choosing PE managers at random (this gap widens to >500 bps for investors who can select 95th-percentile managers).[8] Investors who lack good selection capabilities (but choose to invest in private markets) thus forego substantial amounts of incremental returns.[9]

What blocks many investors from capturing this sizable incremental return is the false temptation of past performance: Persistence in managerial performance is limited (see Golosovker et al. [2024]). In other words, past results aren't (by themselves) a reliable indicator of how well private-market managers are likely to perform in the future.[10] There are, however, deeper drivers of performance that can function as high-confidence signals of future results — and exposing those drivers is the entire point of this research series! Selecting managers based on these deeper drivers requires investors to be more systematic and data driven in their approaches, yet most investors aren't (we explain how and why in the next section). The cost of this is the forfeited returns we've described above.

A remedy is for investors to treat manager-selection processes as if they were algorithms that, by their nature, entail systematicity. They describe in a step-by-step manner what should be done to achieve an outcome. And they’re explicit in their interaction with data. In Section 6 of this brief, we cover how investors can make their manager-selection processes behave more like good algorithms. But first, it’s informative to look at some of the barriers to doing so.

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[6] Wide dispersion exists not only among managers, but also among investors' abilities to select managers who perform well. See Goyal et. al [2024].
[7] In general, the distribution of manager performance not only has high variance, but also has positive skew. That is, there is generally tighter clustering among performance in lower quartiles than in upper quartiles, and it is more typical that a manager underperforms the average return than exceeds it (although some do exceed it by enormous margins, but those managers are relatively rare). See Braun et. al [2020].
[8] These figures omit differences in managers' respective risk profiles (both inter- and intra-quartile). However, there is evidence that these profiles vary substantially and that investors often do not give them adequate consideration in their selection decisions (see, eg., Gompers et. al [2016]).
[9] These calculations likely understate the severity of having poor manager-selection capabilities, because the diversification potential (relative to public markets) of private assets is what attracts many investors to the asset class. Better private market managers generally tend to produce returns that are less correlated with public markets. By not selecting those managers, investors miss out on not only superior returns, but also the risk-reducing tendencies of their performance.
[10] As an example, consider the fact that first-time funds can often deliver top-quartile performance. Clearly, an investor that chooses managers only on the basis of past performance wouldn't select such funds, but would therefore reduce the likelihood of picking a top-performing manager.

4. Context

From studying hundreds of investors over decades, we've noticed that many investors' processes for selecting private-market managers don't qualify as *good* algorithms, since good algorithms are (per computer science):

- **Accurate:** They yield valid outputs, with minimal bias;
- **Consistent:** If repeatedly applied to the same set of inputs, they yield the same outputs;
- **Efficient:** They run in a reasonable amount of time (and tend to scale well as the volume of inputs increases) and respect available resources;
- **Measurable:** They are objectively testable for speed, efficiency, scalability, optimality etc. (both at the level of the entire algorithm as well as its component steps) and
- **Transparent:** Their inner workings are comprehensible and auditable, not "black boxes."

Commonly, investors' manager-selection algos are deficient in one or more of these dimensions. That is, they're overly subjective/biased, inconsistent, inefficient and/or opaque. This latter flaw (opacity) is perhaps the most problematic. By definition, an algorithm can be explicitly and precisely written. Yet, **many investors' selection algos aren't codified anywhere, which not only limits their consistency, accuracy and efficiency, but also reduces their amenability to "debugging.**"

However, investors aren't wholly to blame for these problems. Instead, the chief culprit is the nature of the private market ecosystem, itself. More specifically, the overall number of private-market managers of a given type is generally large — too large to perform deep diligence on every one of them (e.g., even for the best-resourced investors, it'd be infeasible to comprehensively analyze every mid-sized venture capital fund in the USA).[11] Therefore, investors necessarily face a **filtering problem** whereby they must efficiently pare the universe of private managers down to a select few who deserve extensive, intensive analysis. Such filtering is tricky because it should (ideally) identify not only which managers have the highest gross return prospects, but also those who have acceptable costs, risks and cash-flow profiles (along with any extra-financial considerations that an investor may have, such as socio-environmental impact).[12]

The enormity of this filtering problem tempts many investors to resort to heuristics, such as relying heavily on past performance (e.g., focusing exclusively on top-quartile managers) to select a set of

[11] Since 2010, on average over 3,000 new (investable, for the typical investor) private-capital funds have launched annually (with some 5,000 new funds launched in 2021 alone) [O'Donnell 2024].
[12] This problem is compounded by the fact that, ideally, risk should be appraised from the vantage of the entire portfolio (e.g., how much the manager contributes to diversification), rather than on a standalone basis.

managers for deeper analysis. Certainly, track records deserve some weight in a filtering process, but many investors overweight recent results, especially relative to more reliable drivers of future performance. This can be a source of inconsistency in selection algos. For example, many private-market performance benchmarks exist, and the managers who appear to be outperformers often vary according to which benchmarks are used — a problem worsened by the fact that many such benchmarks are flawed in their construction. For example, they are biased in which funds are included and can often be "gamed" by managers[13]; these flaws aren't always well publicized.[14,15] A related (but no less severe) problem concerns **attribution**. Over short horizons, it can be hard to distinguish managers who performed well because of skill (or other durable advantages) from those who were merely/mostly lucky (see O'Donnell [2023]). Accordingly, over-fixating on past results can cause investors to hire managers who are poorly equipped for sustained performance.[16]

Access to top managers is another ecosystemic factor that can frustrate investors' selection algos. Within private markets, many managers operate close-ended funds that accept a limited number of investors. When such managers outperform, it can attract investors to their chosen strategy or niche, which subsequently attracts additional managers to that strategy/niche to absorb investors who cannot access the top managers. When (as is often the case) a sufficient volume of such "copycat" managers emerges, the probability of some of them performing well due primarily to luck increases, which aggravates both attribution and filtering problems. For some (mostly larger) investors, this situation can pollute RFP processes (in the form of adverse selection), so many managers who respond to an RFP may be poorly situated for future performance, even if their recent returns have been favorable. (A similar situation exists for those investors who are contacted and "pitched" by managers.[17])

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[13] Benchmarks aside, many separate metrics can be used in gauging manager performance. Some managers may attempt to game these via market timing (although there is evidence that they vary in their ability to do so; see Jenkinson et. al [2022]).
[14] 'Benchmarks' are (mostly) pairings between metrics (e.g., IRR, TVPI, DPI) and sources for data on which those metrics are calculated (e.g., Preqin, Cambridge Associates, Burgiss, Pitchbook). Each metric-provider pairing has its own unique biases, and a manager might claim to be a "top-quartile" performer if they are in the upper 25% of performance on any one of such possible pairings.
[15] These benchmarks can unfairly omit first-time/emerging funds, even when their managers have sound track records from their prior organizations.
[16] Problems caused by attribution are often worse in private markets than in public markets, owing to the greater lag with which results are reported.
[17] "RFP" (request-for-proposal) processes are most common among institutional investors such as public pension funds, endowments and sovereign wealth funds. Typically, such processes invite managers who meet certain criteria to submit proposals that articulate why the investor should hire them. A very common view among institutional investors is that standard RFP approaches are "broken"; yet they still persist as a matter of convention.

Connected to all the foregoing difficulties is a stubborn reality: Deep diligence is both slow and expensive, making it a scarce resource for essentially all investors.[18] While some forms of artificial intelligence (AI) may alleviate the labor intensity and cost of deep diligence, it's unlikely that most investors will fully surrender their manager-selection processes to *computer* algorithms anytime soon — at least in private markets (where the unavailability of large amounts of reliable data prevents AI from giving fully trustworthy results).[19] There are two predominant reasons for the laboriousness of deep diligence: 1) many factors can drive a manager's outperformance in any particular set of market conditions (which themselves are never perfectly known ex ante), and 2) obtaining data on such factors is rarely easy (because it's not publicly available, or the manager doesn't have it readily prepared or is reluctant to disclose it).

Consequently, it's sensible for investors to organize deep diligence around exploring the most relevant, reliable drivers of manager performance — that is, those factors that they believe make the greatest contribution to manager performance. However, it's not always easy to know what these primary drivers are, partially because they vary across manager types (e.g., strategy, size, location) and market conditions.[20] This promotes an unfortunate satisficing tendency among investors: They often focus their deep diligence on what information is offered to them by prospective managers, rather than demanding the information that matters most. And a good amount of this information is often transmitted through conversations and interviews which — if the investor isn't careful — can differ significantly across managers and introduce unwanted, unwitting bias and inconsistency into the selection process.

All these difficulties conspire to push investors' manager-selection algos away from optimality by promoting inaccuracy, inconsistency, inefficiency and opacity. Is there an antidote to all this? Our long-running work with investors suggests that there is, by improving algorithm design, which we discuss below.

5. Approach

Our findings below represent what the social sciences call a *synoptic* output: a distillation of many interactions with hundreds of professional investors (namely, public pension funds, endowments, family offices and sovereign wealth funds) over more than a decade. Such interactions took many

[18] This costliness of deep diligence often prompts investors to outsource some (or all) of it to consultants. However, this outsourcing can create serious problems if incentives are not properly aligned; and it can still remain expensive in absolute cost.
[19] Likely, best-practice diligence will (in the near future) have a hybrid form and combine human and AI efforts.
[20] Our chief motivation in this research series is exposing those drivers!

forms — both academic and commercial — including structured and unstructured interviews, client conversations, consulting projects, research forums, conferences and more.[21] Given the sweeping scope of these inputs (many of which require confidentiality and anonymity), we avoid naming any particular entities and instead focus on identifying an overarching, general approach to manager selection that's constructed from observably good — and in many cases, *best* — practices among leading investors.

6. Findings

Here, we present a generalized framework for manager selection in private markets, which can be treated as a "proto-algorithm" — that is, one that investors can adapt to their specific contexts when selecting private-market managers. This framework unifies a diversity of best practices that we've observed to be consistently successful by leading investors. Crucially, this framework is designed to help investors identify managers with the highest prospects for future performance and discourage them from over-fixating on recent results.[22] Instead, it encourages them to be more systematic and data driven in manager selection.

A "rough sketch" of this framework is as follows (we elaborate on each of these elements and steps in greater detail throughout this section):

- Specific hypotheses about drivers of manager performance are articulated and then mapped onto objective, measurable scores.[23]
- Successive filters are then applied to these scores to select the most promising group for deep diligence (the number of managers who survive filtering should be dictated by the investor's resource capacity for deep diligence[24]).
- Deep diligence on the filtered list of prospective managers should be based on additional hypotheses about the drivers of manager performance and proceed according to a series of cleanly articulated steps (pre-established to mitigate bias and inefficiency).

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[21] This approach is well established in numerous social-science disciplines. See, e.g., Clark [1998] and Clark and Urwin [2008] and the references therein.

[22] Even when persistence exists, a manager's value proposition may change (e.g., from one fund to the next). This may occur due to so-called "style drift," a change in the availability of investment opportunities, the desire to attract a different set of investors or a rapid change in assets under management (among many other causes).

[23] Before the manager–selection stage of decision making, it is advisable that an investor have (testable) hypotheses on what strategies (e.g., venture capital, buyout, private real estate) they should be pursuing (and choosing managers for) in the first place.

[24] The capacity for deep diligence is both a relative and absolute resource. In an absolute sense, it entails both the person-hours available and expertise needed for extensive/intensive manager assessment. But it can be relative in that an investor can conduct deep diligence on some managers more readily than others. For example, it is often easier for an investor to perform deep diligence on managers in their "home" geography. While this proximity effect can induce so-called home bias, recent evidence suggests that some expected performance gains can arise from it (see Morkoetter and Schori [2021]).

- The entirety of this process should embed an openness to discovery: That is, it should admit a possibility of unexpected findings — and the response to such findings should be to return to an earlier stage of the process, with revised hypotheses, scores or filters.

At the core of this framework is the notion of articulation: An investor must “spell out” its processes for manager selection — that is, write down its selection algo — explicitly and in detail. Shockingly, many investors never do this, which makes it very hard to enforce or improve their selection algos. Articulation alleviates this problem by making selection processes transparent and, therefore, more enforceable (which enhances their consistency) and amenable to improvements.

However, articulation does not imply inflexibility. Writing down a selection algo, concretely and in detail, does not make it permanent. Indeed, such algos can (and should) change whenever the hypotheses that underpin them change. By "hypotheses," we mean the beliefs that an investor has about what factors drive manager performance, that is, what resources or processes lead a manager to meet or exceed their target results. (In cases of outperformance, a hypothesis would describe how a manager gets an edge over their competition.) We use the term “hypothesis” because it encourages investors to remember that their beliefs about what drives performance should be supported by — and changeable with — empirical evidence (i.e., hypotheses should be systematically constructed and tested using data). Therefore, investors’ selection algos ought to evolve in response to new findings about what drives their managers’ returns (e.g., better technology, richer networks, more inventive capitalizations).

Similar to the rest of the selection algo, hypotheses should be cleanly articulated, but they should also be particularized. By this, we mean that they should rarely (if ever) be generic statements about performance drivers. Instead, hypotheses should be constructed from the perspective of *how a manager (of a given type) creates value that significantly contributes to the investor’s particular strategy and objectives.*[25] One source of particularization could be from performance expectations, for example, what factors make it likely that a given type of investor will meet a fixed return target, versus what factors make it probable that that same manager type will earn best-in-class returns among peers. (These two sets of factors need not be identical, and investors should be clear about their needs. Are sufficient returns the aim, or is *outperformance* the goal?) Particularization should also be set within the context of the broader portfolio — for instance, by

[25] Alignment is a key factor for particularization. That is, how aligned is a prospective manager with your specific objectives and constraints as an investor?

hypothesizing how a manager is likely to contribute to diversification or overall risk (and how that contribution is achieved).[26]

Particularized hypotheses should be mapped to metrics; that is, the primary performance drivers identified by particularized hypotheses should be measurable through scored variables. These variables may be items such as the collective years of experience of senior personnel, the quality of data systems, the structure of a venture capitalist's professional network or any other property that a hypothesis identifies as being of primary significance for performance generation. These scores can have different formats (e.g., integers, letter grades, ratio values). However, what matters most is that: 1) scores for a particular variable are consistently derived across managers of the same type and 2) the score formats make them amenable to the chosen filtering approach (we'll be elaborating on what that means shortly).

Quality is imperative when it comes to these scores. They should be as objective and trustworthy as investors can reasonably make them (i.e., they should contain minimal bias and should be far better than mere "guesstimates." Otherwise, they likely shouldn't be used as selection criteria!). Of course, not all scores can be sourced from directly observable variables. For example, an investor might have a hypothesis that the structure of a venture capitalist's professional network is a key determinant of their performance. A reasonable metric for this variable then might come from some aggregate statistic that reflects the combined network structure of a venture fund's leading/most senior personnel.

However, the true structure of such a network is not directly visible and instead must be derived from proxy variables such as the connections captured through a LinkedIn profile. Proxied scores needn't be treated as lesser than those taken from directly visible values, but care must be taken to ensure the quality of proxies (e.g., an investor should spend time checking that a proxy is actually a robust indicator of what it's supposed to measure). A more general point here is that investors should pay just as much attention to (and time and effort thinking about) scores as they do hypotheses (said differently: A hypothesis isn't really valuable until it's measurable with a high degree of confidence). Furthermore, investors should make sure not to give undue (if any) priority to benchmarks as proxies: Scores should reflect *drivers* of performance, not merely performance outcomes.

[26] These hypotheses should generally become more refined (and revisited/updated periodically, in light of the accumulated evidence).

Now, readers might ask why all this fussing over hypotheses and scores is needed. The answer is that they address the filtering problem in manager selection. Once an investor has hypotheses and scores in place, they're ready to tackle the true mechanics of its selection algo by building and refining filtering rules.[27] Each rule should use scores (based on hypotheses) to rank prospective managers and restrict subsequent consideration/diligence to the subset of managers that exceed a threshold score (this threshold might be a preset value or a percentile cutoff, for example, the top 10% of managers for a particular score). When the pool of prospective managers is large and there are multiple primary determinants of performance (in most cases), multiple filters must be applied, successively or simultaneously (in the latter case, this may involve weighted combinations of scores).

Settling on the right combination of filters is integral to the proper functioning of a selection algo, especially when they're applied sequentially. Quite simply, given two filters (call them A and B), the resulting subset of managers that results from applying A then B can differ (vastly) from the subset that results from applying B then A. To some degree, the ordering of filters reflects the hierarchy of hypotheses relative to one another. However, it's not always obvious how to translate this hierarchy into a filter structure. Ultimately, a meaningful amount of engineering and experimentation will be needed. The essential point to consider is that the correct filter structure is needed to get the right subset of managers that warrants deeper diligence, which (after filters) is the next component of any good selection algo.[28]

As noted above, deep diligence is a scarce resource for all investors. It's expensive (both in time and dollar costs) and can be lengthy (which can hinder an investor's capacity to pursue emerging opportunities that have first-mover advantages, that is, wherein those who can act quickly get better outcomes). This is a crucial reason filter structure matters so much: It helps to use this scarce resource most efficiently and effectively. But there's also a need to ensure that processes for deep diligence are similarly well designed. Some vital considerations for such designs include the needs for the following:

- **Separative:** Processes for deep diligence should be designed so not all managers can "pass," and clear distinctions in manager suitability, quality etc. are apparent after diligence is complete.[29]

[27] Here, it's worth reiterating that any two investors are unlikely to have the same optimal selection algo, because their differing circumstances (resources, risk tolerances, asset allocations etc.) mean that the right set of managers for one investor may not be the right set for another investor—so their selection algos should differ.
[28] One important consideration in filter structure should be an investor's capacity for deep diligence. When such capacity is small, filtering should result (on average) in a relatively small pool of candidate managers after all filters have been applied. In this way, filter design should be mindful of an investor's resources for manager selection.
[29] Investors can have different objectives for deep diligence. In some cases, the aim is to pick one single manager for a mandate, or else some limited number of managers; in other cases (e.g., newly emerged opportunities), the aim may be to

- **Unbiased:** Diligence processes should be as identical as possible for all managers (at least managers of the same type for the same selection episode) and set up or implemented so all managers are given an equal chance (before the start of deep diligence) to earn a mandate (e.g., no manager should be treated as the "presumed favorite" ex ante).
- **Evidence-driven:** Deep diligence should be based on verifiable, objective criteria that are not (or minimally) based on subjective impressions (and it's usually best if these criteria are explicitly established before deep diligence begins).
- **Means-focused:** Although diligence should consider "what" a manager plans to do, it should be more attentive to "how" the manager intends to execute that plan (e.g., focus on what resources and competitive advantages the manager has).

Similar to filtering, deep diligence should also be hypothesis based in that it articulates the investor's beliefs about what factors underpin a manager's suitability, given the investor's particular needs and context. Some of these "diligence hypotheses" might be the same as those from the filtering stage of selection (and deep diligence serves to closely interrogate/verify the underlying performance factors for those managers who pass filtering). Nonetheless, diligence hypotheses can also be distinct from the hypotheses used for filtering, especially when they include hypotheses that are not mappable to metrics that can be easily measured for all managers at the onset of filtering. In any event, particularized hypotheses should be articulated before the start of deep diligence.

Frequently, deep diligence is both an intensive and extensive undertaking and tends to yield large amounts of data and information that can be difficult to gather, integrate and analyze. To alleviate this difficulty, investors should consider several tools to incorporate into their selection algos:

- **Checklists and scorecards:** The value of checklists in complex processes can be enormous (see Gawande [2009]), since they help ensure that critical steps aren't missed. Scorecards (which typically are like checklists that assign priorities to various steps and prompt users to enter a score for each step) are generally better than checklists and should be treated as a best practice in deep diligence.[30]
- **Investment memoranda:** These documents can be used with checklists and scorecards. As described in McEvilley et al. [2023], investment memos are detailed articulations of the "rationale" for making (or not making) a specific investment, whereby said rationale is

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determine whether any managers at all deserve a mandate. The design of deep diligence processes should reflect these goals.

[30] In some instances, it can be useful for scorecards to stipulate threshold scores that must be reached for diligence to continue (so that, at any step, if a manager's score isn't high enough, the next diligence step isn't executed and diligence is terminated for that manager).

decomposed into the key factors that are expected to drive outcomes for the investment. When structured properly, investment memos cleanly accommodate the hypothesis-driven approach to deep diligence.

Deep diligence is usually the final step in an investor's selection algo (as it should identify one or more — or perhaps no! — managers that most deserve a mandate). However, it's not always the final step. That's because investors should view diligence as a “discovery” exercise, wherein they enter with hypotheses but recognize that they might uncover information that causes them to return to an earlier stage of the selection algorithm. For example, during diligence, an investor might realize that some factor is significantly important for performance (for the type of manager being considered) but wasn't accounted for in the filtering process. That realization could prompt the investor to rerun the filtering process, this time considering the newly discovered factor. In this way, an investor’s selection algo should openly accept “loops” in that it’s possible to return to earlier stages when circumstances change.[31]

Likewise, it can often be helpful for investors to treat their selection algos as running persistently past the time at which diligence is completed and mandates are given (or not). The point of this persistence is to continue monitoring the performance of managers (both those who were given mandates and those who weren’t) to further validate hypotheses or even generate new ones. Of course, persistently tracking performance drivers for a large volume of managers can be onerous for many investors and may necessitate the assistance of third parties (namely, specialized data or software providers, or consultants).

7. The ARB-itrage

In the previous section, we sketched the basic components and functions that should be present in any manager-selection algo that respects best practices. The two most essential components are particularized hypotheses on what factors drive performance, and scores on those factors for all managers under consideration. Sharper, more accurate hypotheses and scores can improve the efficacy and efficiency of an investor's manager-selection algo.

The question then becomes: what can investors do to obtain such improved hypotheses and scores? The clearest answer is: get better data on manager performance - not merely data on

[31] As stated in a prior footnote, hypotheses should always be changeable in light of new evidence, even when such evidence is uncovered in the course of a selection process itself.

gross returns and fees, but deeper data on the myriad potential factors that can propel performance in various market/economic conditions. That is the purpose of this research series - to use our best-in-class dataset on manager performance (from the vantage point of actual investor portfolios) to identify better hypotheses and scores that investors can then particularize to their own contexts.

8. Coda

There are many prospective drivers of manager performance in private markets, and the relative importance of these drivers can vary according to market conditions. In future pieces, we will dive deep into these drivers for the primary asset classes in private markets (e.g., venture capital and buyout funds). We will also explore what foundational characteristics of private market funds cause them to be top performers across all macroeconomic and financial contexts, and separate those from characteristics that matter only in specific situations.

9. Compass questions

- What is your organization's 'algo' for manager selection in private markets? To what extent does it meet the criteria for a good algorithm (see Section 4)?
- What data sources do you use (or could you readily use) for deriving hypotheses about what drives performance among private market managers? What are the limitations of these sources?
- What is your capacity for deep diligence - i.e., what resources can you devote to it? Do you have any competitive 'edges' in deep diligence compared to your peers?

We regularly publish reports on investment trends we see across high-net-worth investors, including a companion piece to this brief, “Manager Selection and the Paradox of Skill”. Please reach out to us at research@addepar.com if you’re interested in discussing these topics.

References

Braun, R., T. Jenkinson, and C. Schemmerl [2020] "Adverse Selection and the Performance of Private Equity Co-Investments," *Journal of Financial Economics*, 136(1).

Clark, G. [1998] "Stylized Facts and Close Dialogue: Methodology in Economic Geography," *Annals of the Association of American Geographers*, 88(1).

Clark, G., and R. Urwin [2008] "Best-Practice Pension Fund Governance," *Journal of Asset Management*, 9(1).

Golosovker, D., D. O'Donnell, A. Patel, and D. Rook [2024] "Manager Selection Quant Screens: Case of Manager Track Record," *Addepar Research Note*.

Gompers, P., S. Kaplan, and V. Mukharlyamov [2016] "What Do Private Equity Firms Say They Do?" *Journal of FInancial Economics*, 121(3).

Goyal, A., S. Wahal, and M. Yavuz [2024] "Picking Partners: Manager Selection in Private Markets," *Swiss Finance Institute,* Research Paper Series: No. 21-86.

Jenkinson, T., S. Markoetter, T. Schori, and T. Wetzer [2022] "Buy Low, Sell High? Do Private Equity Fund Managers Have Market Timing Abilities?" *Journal of Banking & Finance*, 138.

Monk, A., and D. Rook [2023] "The 'Investor Identity': the Ultimate Driver of Returns," *Addepar Research Brief*.

Morkoetter, S., and T. Schori [2021] "Home Bias and Local Outperformance of Limited Partner Investments: Evidence from Private Equity Fund Manager Selection," *Social Science Research Network*, available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3810468.

O'Donnell, D. [2024] "Manager Selection & the Paradox of Skill", *Addepar Research Brief*.

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