The 'Algorithmic' Mindset for Selecting Best-Fit Managers in Private Markets

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1. Systematic, Data-Driven Selection Matters

In private markets, performance differentials are typically vast: top-quartile performers routinely deliver returns that are thousands of basis points better than their median-level peers. Therefore, at *portfolio scale*, an ability to pick the right private-market managers can generate hundreds of basis points in incremental return - making manager selection one of the most consequential decisions an investor faces.[1] Yet, many investors forgo this performance gain by hewing to unsystematic, heuristic-driven processes for picking private-market managers, which lowers their chances of selecting **best-fit** managers.[2,3]

Helpfully, investors can make their selection processes more systematic and data-driven by treating those processes as algorithms. This algorithmic mindset forces investors to pay more attention to the **design elements** of each step of their process, in terms of its efficiency, objectivity, informativeness, and the degree to which it is backed by empirical evidence. This fourth property - **empirical validity** - is vital, as many false conceptions exist about the drivers of manager performance, and how to measure those drivers. For example, many investors believe in the validity of 'persistence', i.e., that past results are a strong indicator of future returns and

[1] By private-market managers, we mean general partners of funds within non-public asset classes such as venture capital, buyout, real estate, etc.
[2] We emphasize "best-fit" managers, because the managers that deliver the best returns might not be the managers who are the most appropriate investor: there is also a need to factor in alignment, contribution to portfolio-level diversification and risk management, and various other relevant properties.
[3] To worsen matters, having an unsystematic selection process also weakens an investor's capacity to improve that process, because it becomes harder (relative to systematic processes) to diagnose what is not working well and how to best fix it.

"winners keep winning". However, our analysis elsewhere confirms that persistence is a very weak indicator (and much more complex than one might expect).[4] An algorithmic approach to selection can help investors identify and deploy selection criteria that have high empirical validity, and boost their expected returns in doing so. We summarize the essentials of such an approach below.

2. Pay Attention to Design Elements

In the case of computer algorithms, there is no one algorithm that is universally perfect. The same is true of manager-selection approaches: what works well for one investor will fail for another, so each investor should tailor its selection processes to its own unique context, i.e., specific resources, strategy, portfolio, risk preferences, and objectives. Yet, despite the fact that no two investors' ideal selection processes are likely to be identical, there are five properties that all good selection processes share - and these happen to be the same properties shared by all good algorithms in general: *accuracy*, *consistency*, *efficiency*, *measurability* and *transparency*.[5] The easiest way for an investor to achieve these properties is by paying scrutinous attention to the design elements of its selection processes - namely its:

- Hypotheses: are the investor's beliefs about what drives the (out-)performance of private-market managers. Good hypotheses should be systematically derived from data. They should also be *particularized* to an investor's context - i.e., they should be tuned to how a manager will drive specific value for the investor (e.g., in terms of offering well-calibrated diversification, or enforceable alignment). Most investors should have multiple formally-articulated hypotheses that they use in their selection processes (but not too many - the number of hypotheses must be manageable!)
- Scores: are quantifications of a manager's capabilities in light of the investor's hypotheses.[6] Scores should be as objective and data-driven as possible. For example, if an investor has a hypothesis that the returns from a venture capital fund are significantly driven by the quality of its general partners' professional networks, then numerical scores for those networks should be assigned to all candidate funds in the selection process.
- Filters: are cutoff rules that use scores to reduce the number of managers that remain under consideration. Typically, an investor will apply multiple filters in succession (and, as

[4] See Golosovker et al. [2024].
[5] See Rook et al. [2024] for detailed explanations.
[6] These quantifications need not be numerical. For instance, in some cases, they might be letter scores (A, B, C,..) that are earned by an investor having specific attributes that are very finely articulated (that is, the difference between a B and C is cleanly-defined and largely objective).

we discuss in our companion piece, order matters!). Each filter may incorporate several hypotheses, and use a relevant formula to combine a manager's scores on those hypotheses. Just like hypotheses, filters - and the overall procedure for applying them - should be empirically validated. The point of filters is to reduce the universe of candidate managers down to a number that can be subjected to deep diligence.

- Deep Diligence: is a scarce resource, and few investors have ample resources to deeply examine more than a handful of managers before making a final selection (thereby necessitating the use of filters). Like filters, specific procedures for deep diligence should be based on data-derived hypotheses on what drives manager performance, as well as objective scores based on those hypotheses. The result of a good deep-diligence process is clear distinction of which manager is the best fit (or whether there is any such manager at all!).

When assembled well, these design elements work together programmatically, like any good algorithm, so that a selection process has a systematic, efficient, and transparent flow to it - one that will maximize the likelihood of choosing the best-fit managers in an evidence-based way.

Of course, the algorithmic approach we advocate is underpinned by having appropriate data on manager attributes, which makes working with best-in-class data partners vital to investors' success in selecting private-market managers.

References

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