

# Value Creation in the Hedge Fund Industry

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## Abstract

We measure the value-added in the hedge fund industry—an ideal setting to study how manager and investor sophistication shape value creation. Our fund-level approach jointly examines the magnitude, sharing, dynamics, and optimality of value-added. Most hedge funds add value by forming levered strategies that are highly profitable but hard to scale, which prevents them from consistently outperforming mutual funds. Investors allocate capital far more efficiently than in the mutual fund sector, yet they capture only a small share of value. Although these patterns are broadly aligned with a rational model, the hedge fund industry nonetheless operates at excess capacity.

*Keywords:* Hedge funds, Value Creation, Investor Behavior, Capital Allocation, Optimality

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## I. Introduction

Value creation in the active fund industry is an important theme in financial economics. The ability of funds to generate value from their investment skills is a necessary condition for improving price informativeness—a mechanism through which they contribute to the efficient allocation of resources in the economy (*e.g.*, Bond, Edmans, and Goldstein, 2012). Understanding how investors allocate capital across funds is equally important for assessing whether they capture part of the value created. This question provides a natural setting for analyzing how economic agents make high-stakes financial decisions (*e.g.*, Campbell and Ramadorai, 2025; Shiller, 2005). Finally, the analysis of value creation informs whether the multi-trillion-dollar size of the fund industry is consistent with equilibrium models, thereby contributing to the broader debate on the optimal size of the financial sector (*e.g.*, Cochrane, 2013; Greenwood and Scharfstein, 2013).

The study of value creation is pioneered by Berk and van Binsbergen (2015) who measure it using the value-added  $va_i = E[\alpha_{i,t}w_{i,t}]$ , where  $\alpha_{i,t}$  denotes the fund gross alpha relative to the benchmark assets available to investors, and  $w_{i,t}$  is the fund capital. Intuitively,  $va_i$  parallels the concept of net present value (NPV)—a fund with a positive value-added creates value for investors, just as an investment project with a positive NPV creates value for shareholders. Whereas an emerging literature focuses on mutual funds, much less is known about how hedge funds create value—and how that value is shared with investors.<sup>1</sup>

The sophistication of the hedge fund industry offers unique insights into value creation. Hedge fund managers take long and short positions, use leverage, and deploy complex trading algorithms to exploit information and provide liquidity—features that set them apart from mutual fund managers. Ex ante, these capabilities suggest that hedge funds create more value, both by identifying more profitable opportunities and by scaling them more effectively. Likewise, the institutional clients of hedge funds are widely regarded as more sophisticated than the retail investors who populate the mutual fund industry. They therefore plausibly possess both the bargaining power to capture part of the value created and the learning ability to reallocate capital efficiently over time. Ultimately, the sophistication of the hedge fund industry makes it an ideal laboratory for testing rational models of active management (*e.g.*, Berk and Green, 2004; Pástor and Stambaugh, 2012).

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<sup>1</sup>Studies on mutual fund value-added include Barras, Gagliardini, and Scaillet (2022), Berk and van Binsbergen (2015), and Zhu (2018). A notable exception in the hedge fund literature is Ling, Satchell, and Yao (2023), who focus on the persistence of value-added and do not explore the broader dimensions analyzed in this paper.

To address these issues, we develop a novel methodology with two key ingredients. First, we specify the value-added as  $va_i = a_i E[w_{i,t}] - b_i E[w_{i,t}^2]$  with  $\alpha_{i,t} = a_i - b_i w_{i,t}$ . This expression formalizes the intuition that the value created by a fund depends on (i) its skill at identifying profitable strategies—captured by the first-dollar alpha  $a_i$ —and (ii) its scalability constraints—captured by the scale coefficient  $b_i$ . Although our expression is always numerically equivalent to the non-parametric estimator of Berk and van Binsbergen (2015), it offers sharper insight into multiple dimensions of value creation. In particular, it allows us to decompose the value-added into its skill and scale components and derive its optimal level for the normative analysis. Second, we take a fund-level approach and examine the entire distribution of value-added across funds. Hedge funds differ widely in their skill and scalability reflected in the fund-specific coefficients  $a_i$  and  $b_i$ . Because of this heterogeneity, simple averages provide limited information about hedge fund value creation. For example, it is silent on the unique characteristics of the most valuable funds or the proportion of funds that charge excessive fees to investors.

Our approach is specifically tailored to hedge funds and therefore departs from that of Barras, Gagliardini, and Scaillet (2022, BGS) for mutual funds. A key distinction is that we address the benchmarking challenge posed by hedge funds as they pursue alternative strategies that investors cannot easily replicate (*e.g.*, Cochrane, 2013). We show theoretically that these non-replicable strategies not only contribute to the value-added but also generate cross-fund dependencies that amplify estimation noise. Our approach also allows for hedge fund leverage—a variable typically unreported in standard databases. Introducing fund-specific coefficients  $a_i$  and  $b_i$  allows us to capture the unobserved heterogeneity in leverage across funds.

We measure value creation across 2,517 hedge funds in three categories (equity, macro, arbitrage). We merge four major databases and correct for backfill, selection, and survivorship biases. The main inputs for our analysis are the fund-specific coefficients  $a_i$  and  $b_i$  obtained from time-series regressions of monthly gross returns on lagged capital and factor returns. In our main specification, we benchmark funds against five factors—market, size, value, carry, and time-series (TS) momentum.<sup>2</sup> This choice reflects both relevance and replicability—these factors capture common hedge fund strategies that can be implemented by investors (Ardia et al., 2024; Jorion, 2021).

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<sup>2</sup>The market, size, and value factors are constructed by Cremers, Petajisto, and Zitzewitz (2012) using the S&P 500 and Russell indices. The carry and TS momentum factors follow Koijen et al. (2018) and Moskowitz et al. (2012) for four asset classes (equities, bonds, commodities, and currencies).

Our analysis over the period 1994–2020 shows that hedge funds create substantial economic value. Close to 70% of funds exhibit positive value-added, with an average of \$5.7 million per year. This evidence aligns with the view that hedge fund trading contributes to price efficiency, as recently suggested by Ha, Hu, and Tang (2024). Consistent with intuition, hedge funds create value because they are skilled at forming profitable strategies. The first-dollar alpha is positive for more than 86.4% of funds and is economically large, averaging 12.5% per year. At the same time, they struggle to scale up these strategies—on average, the gross alpha declines by 1.5% per year for every additional \$10 million of capital. These scalability constraints are somewhat less severe among arbitrage funds, which helps explain why roughly 80% of them generate positive value-added, compared with 67% for equity funds and 51.6% for macro funds.

Our comparison with mutual funds reveals striking differences in skill and scalability. On average, the first-dollar alpha of mutual funds is only equal to 2.6% per year and their gross alpha declines by just 0.2% per year for every additional \$10 million of capital. These differences do not stem from hedge funds having fundamentally better ideas or trading technologies. Rather, they are largely explained by the leverage employed by hedge funds—a conclusion supported by proprietary leverage data from Barth, Hammond, and Monin (2020). Because of their greater scalability, some mutual fund groups—such as small-cap, low-turnover funds—rival or even surpass segments of the hedge fund industry in value creation. These findings challenge the notion that hedge fund managers systematically outperform due to superior sophistication.

There is substantial heterogeneity in value creation across hedge funds. The top 10% of funds account for at least 40% of the total value generated across the industry. This pronounced concentration implies that some managers possess distinctive capabilities relative to the rest of the industry. Examining this issue, we find that the most valuable funds do not deliver the highest first-dollar alphas. Instead, they pursue strategies that strike a balance between skill and scalability. These balanced strategies maximize value because both dimensions are strongly correlated across funds, indicating that great ideas are inherently difficult to scale. Moreover, the top funds tend to exploit informational advantages rather than rely on mechanical, hard-to-replicate strategies. Controlling for more complex factors linked to illiquidity, betting-against-beta, and variance, we find that the value-added remains largely unchanged.

An important question is whether hedge fund investors benefit from the value created by the industry. On average, the net-of-fee value-added amounts to \$0.5 million per year, representing only 8.8% of the total value created. This finding has two implications. First, it departs from the strong net alphas documented in prior studies.<sup>3</sup> The discrepancy arises because periods of poor performance carry greater weight in the value-added calculation as they coincide with higher levels of capital. Therefore, the net alpha fails to measure the value actually received by investors as it ignores both the level and time-variation of capital allocations. Second, the positive net value-added does not support the view that hedge fund investors suffer from agency problems that lead them to overpay for active management (*e.g.*, Greenwood and Scharfstein, 2013). This stands in sharp contrast with mutual fund investors who, on average, pay nearly \$8 million per year in excessive fees—a pattern widely attributed to their lower financial literacy (*e.g.*, French, 2008).

The modest average value for hedge investors might suggest that funds extract all rents, consistent with the prediction of Berk and Green (2004). However, this interpretation is misleading as it conceals substantial heterogeneity across funds. Half of all funds generate a positive net value-added for investors, largely driven by arbitrage funds. The complexity of arbitrage strategies likely enhances the bargaining power of the limited pool of investors willing to allocate capital. Conversely, the other half of the population destroys investor wealth—mainly in the macro category. Among these funds, 62.2% appear skilled but operate at an inefficiently large scale. Therefore, excessive capital rather than lack of skill is the primary source of negative value-added.

The next step is to examine whether investors improve their capital allocation over time. We find that they are able to discriminate between unskilled and skilled funds. To show this, we track the evolution of capital over each fund’s lifecycle, dividing its full history into five subperiods. Whereas capital in unskilled funds declines steadily over time, skilled funds attract increasing allocations. Focusing on the latter, we show that investors progressively identify the most valuable funds—the value created in the top decile rises from \$18.5 to \$24.0 million per year between the first and last subperiods. However, they fail to address excessive capacity as nearly one third of the funds still destroy value as they reach the last stage of their lifecycle. This mixed evidence suggests that, despite their sophistication, hedge fund investors adjust capital only partially.

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<sup>3</sup> A non-exhaustive list includes Ackermann, McEnally, and Ravenscraft (1999), Capocci and Hübner (2004), Chen, Cliff, and Zhao (2017), Diez de los Rios and Garcia (2010), Kosowski, Naik, and Teo (2007), and Liang (1999).

We conclude with a normative analysis of the hedge fund industry. As noted by Barth et al. (2023), hedge funds today collectively manage more than \$6 trillion, prompting the question of whether an industry of this size is consistent with economic logic. We consider an extended version of the rational model of Berk and Green (2004), in which investors can retain part of the value created by funds. We show that the model matches the data reasonably well. The actual and optimal value-added are closely aligned, with a pairwise correlation of 0.81. It also reproduces the strong correlation between total and net value-added—a feature absent from the original Berk and Green (2004) model in which funds extract all rents from their skill. Finally, the model implies that investors capture only about 10% of the total value created, consistent with the positive, but limited bargaining power observed in the data.

Quantitatively, the actual value-added amounts to roughly 40% of its optimal level. This gap arises because hedge funds operate at excessive scale—consistent with the sizable proportion of value-destroying funds. While the optimal fund size averages \$164 million, the estimated value-added implies an actual size of \$316 million. Using the model, we quantify the two forces behind this excess capacity. First, funds set fees too low, inducing investors to increase their capital allocation. Second, even at prevailing fees, investors allocate too much capital relative to the level implied by the model. Each force contributes roughly half of the total value gap.

The remainder of the paper is as follows. Section II presents our baseline specification of the value-added. Section III describes the methodology for measuring the value-added across funds. Section IV presents the hedge fund dataset and the benchmark model. Section V contains the empirical analysis, and Section VI concludes. The appendix provides additional information on the methodology, the data, and the empirical results.

## II. Hedge Fund Value Creation

### II.A. Definition of the Value-Added

We consider a population of  $n$  hedge funds over  $T$  periods, where we denote each fund by the subscript  $i$  ( $i = 1, \dots, n$ ) and each period by the subscript  $t$  ( $t = 1, \dots, T$ ). The variable  $w_{i,t}$  denotes the capital (in real terms) endowed by investors to the fund,  $r_{i,t+1}$  denotes the gross excess return of the fund, and  $r_{b,i,t+1}$  denotes the excess return of the corresponding benchmark, which represents the best alternative investment available to investors. The benchmark return is

defined as  $r_{b,i,t+1} = \beta'_{i,R} f_{R,t+1}$ , where  $f_{R,t+1}$  is the excess return vector of the trading strategies that investors are able to replicate ( $R$  stands for replicable).<sup>4</sup>

We define the value created by each fund using the value-added proposed by Berk and van Binsbergen (2015):

$$va_i = E[\alpha_{i,t} w_{i,t}], \quad (1)$$

where the gross alpha  $\alpha_{i,t} = E[r_{i,t+1} - r_{b,i,t+1} | I_t]$  is the expectation of the difference between  $r_{i,t+1}$  and  $r_{b,i,t+1}$  conditional on the publicly available information set  $I_t$  which includes the fund capital  $w_{i,t}$ . Because the value-added is a dollar value that depends on the entire (benchmark-adjusted) fund payoff  $\alpha_{i,t} w_{i,t}$ , the gross alpha alone is not sufficient to infer fund value—a point forcefully made by Berk and van Binsbergen (2015).

Equation (1) measures value creation from the viewpoint of investors. It determines whether the fund creates value relative to their best alternative opportunity (captured by  $f_{R,t+1}$ ). Building on this insight, we can also express the value-added within the stochastic discount factor (SDF) valuation framework (see Cochrane, 2005). We consider hedge fund investors whose marginal utility of consumption  $m_{t+1}$  is independent of  $w_{i,t}$  and linear in their wealth, which itself depends on the available factors  $f_{R,t+1}$  (e.g., Chen and Knez, 1996; Ferson, 2013). Because  $m_{t+1}$  prices the factors  $f_{R,t+1}$  by construction, we have  $E[m_{t+1} r_{b,i,t+1}] = 0$ . The value investors attach to the fund can therefore be written as  $va_i^{sdf} = R_f E[m_{t+1} r_{i,t+1} w_{i,t}] = R_f E[m_{t+1} ((r_{i,t+1} - r_{b,i,t+1}) w_{i,t})]$ , where  $R_f$  is one plus the riskfree rate (assumed constant for simplicity). Expanding the above expression yields  $va_i^{sdf} = E[(r_{i,t+1} - r_{b,i,t+1}) w_{i,t}] + R_f cov[m_{t+1}, (r_{i,t+1} - r_{b,i,t+1}) w_{i,t}]$ . Since  $r_{i,t+1} - r_{b,i,t+1}$  is orthogonal to  $m_{t+1}$ , the covariance term vanishes and the SDF-based and traditional value-added measures coincide:  $va_i^{sdf} = E[(r_{i,t+1} - r_{b,i,t+1}) w_{i,t}] = E[\alpha_{i,t} w_{i,t}] = va_i$ .

## II.B. Framework for Measuring Value-Added

### II.B.1. Specification of the Gross Alpha

To derive the expressions for the value-added presented in Section II.C, we impose additional structure on Equation (1). For each fund, we write the expected (benchmark-adjusted) revenue as

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<sup>4</sup>The use of constant betas is not restrictive because  $f_{R,t+1}$  can include factor-timing strategies (managed portfolios) based on public information. To elaborate, suppose that investors can replicate a hedge fund strategy that consists of changing the market beta after observing a public signal  $z_t$  that predicts the equity market return  $r_{m,t+1}$ . We can absorb the time-variation in betas by including the scaled factor  $z_t r_{m,t+1}$  in the vector  $f_{R,t+1}$  (e.g., Cochrane, 2005).

$TR_{i,t} = a_i w_{i,t}$  and total cost as  $TC_{i,t} = b_i w_{i,t}^2$ . This convex cost function reflects the idea that the active strategy cannot be scaled without eroding returns. Taking the difference between  $TR_{i,t}$  and  $TC_{i,t}$  and dividing by  $w_{i,t}$  yields a linear specification for the gross alpha:

$$\alpha_{i,t} = a_i - b_i w_{i,t}, \quad (2)$$

where the skill and scale coefficients  $a_i$  and  $b_i$  are fund-specific, in contrast to the standard panel specification that imposes constant scalability across funds ( $b_i = b$ ).<sup>5</sup> To do so, we interpret Equation (2) as a random coefficient model (*e.g.*, Hsiao, 2003), in which  $a_i$  and  $b_i$  are not fixed parameters but random realizations from their cross-sectional distributions  $\phi(a)$  and  $\phi(b)$ . This flexibility allows us to absorb the potentially large and unobservable set of fund characteristics that drive the cross-sectional differences in skill and scalability.

The skill coefficient  $a_i$  corresponds to the alpha on the first dollar of capital (*i.e.*, when  $w_{i,t} = 0$ ). It therefore measures the profitability of the fund strategy before accounting for the frictions of real-world implementation (Perold and Salomon, 1991). Hedge funds can generate a positive  $a_i$  in two ways. They can exploit superior information to pursue stock-picking or factor-timing strategies, or rely on public information to implement alternative strategies that investors cannot replicate.<sup>6</sup> The scale coefficient  $b_i$  measures the sensitivity of the gross alpha to changes in fund capital. Its magnitude captures various aspects of diseconomies of scale. As the fund grows, it may become more difficult to execute trades at low cost, while organizational growth may dilute talent and increase delegation costs.

### *II.B.2. Interpretation of the Coefficients*

The notions of skill and scalability captured by  $a_i$  and  $b_i$  should be interpreted broadly. A high  $a_i$  may reflect unique investment abilities and a low  $b_i$  may result from a unique trading infrastructure. Yet both coefficients can absorb other sources of variation across funds. For instance, some funds may exhibit higher  $a_i$  because they operate in less efficient markets (*e.g.*, Fang, Kempf, and Trapp, 2014), whereas others may display higher  $b_i$  because they invest in illiquid assets and trade

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<sup>5</sup>A non-exhaustive list includes Chen et al. (2004), Fung et al. (2008), Naik, Ramadorai, and Stromqvist (2007), Pástor, Stambaugh, and Taylor (2015), and Zhu (2018).

<sup>6</sup>This point is well summarized by Cochrane (2011): "I tried telling a hedge fund manager, 'You don't have alpha. Your returns can be replicated with a value-growth, momentum, currency and term carry, and short-vol strategy.' He said, 'Exotic beta is my alpha. I understand those systematic factors and know how to trade them. My clients don't.'"



more often (van Binsbergen et al., 2024; Busse et al., 2021).

A particularly relevant determinant for hedge funds is leverage, which mechanically increases both coefficients. To see this, we denote by  $a_i^{as}$  and  $b_i^{as}$  the skill and scale coefficients of an unlevered (fully collateralized) active strategy, for which the gross asset exposure equals the fund capital.<sup>7</sup> If the fund applies constant leverage to this strategy, its gross asset exposure becomes  $q_{i,t} = \pi_i w_{i,t}$ , where the leverage ratio  $\pi_i = \frac{q_{i,t}}{w_{i,t}} > 1$ . Rewriting total revenue and cost as  $TR_{i,t} = a_i^{as} q_{i,t}$  and  $TC_{i,t} = b_i^{as} q_{i,t}^2$  and substituting  $q_{i,t} = \pi_i w_{i,t}$ , it follows that leverage scales the coefficients as  $a_i = a_i^{as} \pi_i$  and  $b_i = b_i^{as} \pi_i^2$ .

As discussed in Section III.A, we can estimate  $a_i$  and  $b_i$  without modeling the underlying sources of their cross-sectional variation. This flexibility is especially valuable for hedge funds for two reasons. First, it is practically impossible to specify all the characteristics that shape the complex strategies these funds pursue. Second, the set of observable hedge fund characteristics is limited. For example, leverage—a key determinant of returns—is typically unreported in hedge fund databases.<sup>8</sup> In our specification in Equation (2), we sidestep this issue by modeling alpha solely as a function of equity capital (rather than debt), which implicitly absorbs unobserved leverage into the estimated coefficients.

## II.C. The Four Measures of Value-Added

### II.C.1. The Value-Added

We now use our framework to derive several expressions for the value-added. Substituting  $\alpha_{i,t}$  with  $a_i - b_i w_{i,t}$  in Equation (1) yields the following expression for the value created by the fund:

$$va_i = a_i E[w_{i,t}] - b_i E[w_{i,t}^2]. \quad (3)$$

<sup>7</sup>To illustrate, consider a fund that invests its capital in the riskfree asset and takes two self-financing long and short positions in undervalued and overvalued securities. Denoting by  $a_{i,l}$  and  $a_{i,s}$  the average returns of these positions, we obtain  $a_i^{as} = x_{i,l} a_{i,l} + x_{i,s} a_{i,s}$ , where  $x_{i,l} + x_{i,s} = 1$  such that the gross asset exposure  $x_{i,l} w_{i,t} + x_{i,s} w_{i,t} = w_{i,t}$ .

<sup>8</sup>Some databases, such as TASS, provide cross-sectional data on the average fund leverage. However, data is self-reported on a voluntary basis, which implies that coverage is limited and calculation methods are not consistent across funds (see Liang and Qiu, 2019). Accounting for time variation in leverage is even more challenging, as databases typically do not record historical leverage ratios. To our knowledge, only two papers have reliable but proprietary access to such data. Ang, Gorovyy, and van Inwegen (2011) study leverage data obtained from one fund-of-funds, while Barth, Hammond, and Monin (2020) work with data from the SEC on large hedge fund advisors having at least \$1.5 billion under management.

Equation (3) formalizes the intuition that the fund value-added ultimately depends on (i) its skill at identifying profitable investment opportunities and (ii) its constraints on scaling these opportunities efficiently as capital increases. Similar to the other expressions derived below, the value-added in Equation (3) is fund-specific. Since  $va_i$  inherits the randomness of  $a_i$  and  $b_i$ , we treat it as a random realization from the cross-sectional distribution  $\phi(va)$ , which we infer from the data. The only required inputs are the estimated coefficients  $a_i$  and  $b_i$  for all funds, which also enable us to quantify the relative contributions of skill and scalability to hedge fund value creation.

### II.C.2. The Net Value-Added

Next, we determine how the value created by hedge funds is shared with investors. Previous research show that investors extract none of the value created by mutual funds (*e.g.*, BGS; Cooper, Halling, and Yang 2021). By contrast, hedge fund investors may possess a comparative advantage in understanding the complexity of hedge fund strategies and supplying scarce capital. For instance, they may leverage soft information that is difficult for funds to communicate to outsiders (Hochberg, Ljungqvist, and Vissing-Jørgensen, 2014), or threaten to appropriate the fund's investment ideas (Glode and Green, 2011). For these reasons, hedge fund investors may be able to capture a portion of the value created by the fund.

To examine this issue, we denote by  $fee_{i,t+1}$  the fee rate defined as the sum of management and performance fees divided by capital. The net value-added received by investors is then given by  $va_i^{\text{net}} = E[\alpha_{i,t}^{\text{net}} w_{i,t}]$ , where  $\alpha_{i,t}^{\text{net}} = E[r_{i,t+1}^{\text{net}} - r_{b,i,t+1} | I_t]$  and  $r_{i,t+1}^{\text{net}} = r_{i,t+1} - fee_{i,t+1}$ . Analogous to Equation (3), we specify  $\alpha_{i,t}^{\text{net}} = a_i^{\text{net}} - b_i^{\text{net}} w_{i,t}$ , which yields

$$va_i^{\text{net}} = a_i^{\text{net}} E[w_{i,t}] - b_i^{\text{net}} E[w_{i,t}^2]. \quad (4)$$

The gap between  $a_i$  and  $a_i^{\text{net}}$  ( $b_i$  and  $b_i^{\text{net}}$ ) captures the impact on fees on skill and scalability. To illustrate, consider a simple case in which the fund charges investors a fraction  $f_i$  of capital (management fees) and a fraction  $p_i$  of the benchmark-adjusted return  $r_{i,t+1} - r_{b,i,t+1}$  (performance fees).<sup>9</sup> In this setup,  $a_i^{\text{net}} = (1 - p_i)a_i - f_i$  and  $b_i^{\text{net}} = (1 - p_i)b_i$ , implying that performance fees proportionally scale both  $a_i$  and  $b_i$ , while management fees uniquely reduce the skill coefficient.

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<sup>9</sup>In practice, the computation of performance fees is more complex because they are asymmetric and depend on the high-water mark provision and the payment frequency. We discuss these implementation details in the Section IV.

### II.C.3. The Subperiod Value-Added

Equations (3)-(4) capture the average levels of value-added, but provide no insight into how the value-added evolves over the fund's lifecycle. This evolution is potentially important, as investors require time to learn about a fund skill and scale coefficients (Berk and Green, 2004; Pástor and Stambaugh, 2012). As they update their beliefs based on return information, they reallocate capital, thereby altering the value created by the funds.<sup>10</sup>

To extend Equation (3) to a dynamic setting, we follow BGS and split the observations on each fund into  $S$  subperiods of equal length. For each subperiod  $s$  ( $s = 1, \dots, S$ ), we then define the subperiod value-added as

$$va_i(s) = a_i \bar{w}_i(s) - b_i \bar{w}_{i,2}(s) \quad (5)$$

where  $\bar{w}_i(s)$  and  $\bar{w}_{i,2}(s)$  denote the realized averages of capital and its squared value in subperiod  $s$ . Importantly,  $va_i(s)$  is computed using the coefficients  $a_i$  and  $b_i$  estimated over the full sample. This specification allows us to analyze the dynamics of value creation over shorter horizons without introducing additional estimation noise. Applying this approach to the net value-added, we obtain

$$va_i^{\text{net}}(s) = a_i^{\text{net}} \bar{w}_i(s) - b_i^{\text{net}} \bar{w}_{i,2}(s). \quad (6)$$

### II.C.4. The Optimal Value-Added

Finally, we can determine whether the value created by the hedge fund industry is consistent with economic rationale. To conduct this normative analysis, we start with a static version of the Berk and Green (2004) model in which funds with heterogeneous skill and scalability maximize their total fee revenue  $fee_i w_i$ . Funds may employ leverage up to a maximum ratio  $\pi_i$  reflecting regulatory and margin constraints (Ang, Gorovyy, and van Inwegen, 2011; Lhabitant, 2007; Pedersen, 2015). We then allow hedge fund investors to hold some bargaining power in the fee negotiation by requiring a minimum benchmark-adjusted return  $\kappa$  per unit of capital as compensation for due diligence and monitoring costs (Stein, 2009). Under this assumption, funds optimally operate at the maximum leverage ratio  $\pi_i$ , which is consistent with our baseline specification  $\alpha_{i,t} = a_i - b_i w_{i,t}$ .<sup>11</sup>

<sup>10</sup>As emphasized by Pástor, Stambaugh, and Taylor (2015), investors' learning also provides an identification mechanism for  $a_i$  and  $b_i$ , since it induces time variation in fund capital. In the limiting case where investors perfectly know these parameters (and face no liquidity shocks), capital remains constant, preventing the estimation of  $a_i$  and  $b_i$ .

<sup>11</sup>Fixing the gross asset exposure at  $\bar{q}_i$ , we can express total value-added as  $\bar{va}_i(\bar{q}_i) = a_i^{as} \bar{q}_i - b_i^{as} \bar{q}_i^2$ . Since equity financing entails an additional cost  $\kappa$ , it is optimal for the fund to minimize the amount of equity required to support

The fund maximizes the value-added net of the amount transferred to investors:  $\max_{w_i} a_i w_i - b_i w_i^2 - \kappa w_i$ . The optimal level of capital is  $w_i^o = \frac{a_i - \kappa}{2b_i}$ , which is achieved when the fee rate equals  $fee_i^o = \frac{a_i - \kappa}{2}$ .<sup>12</sup> The corresponding optimal value-added measures are given by

$$va_i^o = \alpha_i(w_i^o)w_i^o = \frac{a_i^2 - \kappa^2}{4b_i}, \quad (7)$$

$$va_i^{\text{net},o} = \kappa w_i^o = \frac{\kappa(a_i - \kappa)}{2b_i}. \quad (8)$$

If investors have no bargaining power ( $\kappa = 0$ ), our framework collapses to the benchmark case of Berk and van Binsbergen (2015). In this setting, investors extract no value and the optimal value-added simplifies to  $va_i^o = \frac{a_i^2}{4b_i} = \frac{(a_i^{as})^2}{4b_i^{as}}$ , which can be interpreted as the profit of a monopolist—namely, the markup price of its product (alpha) multiplied by the total quantity sold (capital).

Equations (7)-(8) show that the optimal value-added measures depend only on the coefficients  $a_i$  and  $b_i$  as primary inputs. This tractability makes our framework a natural starting point for a normative analysis comparing the actual and optimal values  $va_i$  and  $va_i^o$  ( $va_i^{\text{net}}$  and  $va_i^{\text{net},o}$ ). At the same time, the static model abstracts from learning dynamics. In practice, the optimal quantities may evolve as funds revise their fees in response to changes in investors' perceptions of skill (Berk and Green, 2004).<sup>13</sup> Equation (7) should therefore be interpreted as the long-run optimal value-added once learning has occurred.

## II.D. Remarks about the Specification

Our baseline framework imposes that the skill and scale coefficients are constant over time. In particular, it assumes a constant leverage ratio, which is broadly consistent with empirical evidence from proprietary hedge fund data.<sup>14</sup> Nonetheless, some hedge funds may adjust their leverage over time to protect the present value of future fees (Lan, Wang, and Yang, 2013; Stein, 2009),

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$\bar{q}_i$ —or, equivalently, to maximize the leverage ratio.

<sup>12</sup>The model is silent on the types of fees that the fund should charge. Any combination of management and performance fees that yields the same expected dollar revenue is feasible, as discussed in a more general context by Goetzmann, Ingersoll, and Ross (2003).

<sup>13</sup>In the short run, hedge funds may also modify the risk profile of their strategies to affect how investors learn about their skill (Makarov and Plantin, 2015).

<sup>14</sup>Ang, Gorovyy, and van Inwegen (2011) document that gross leverage is highly persistent, with an autocorrelation of 0.97. Similarly, Barth, Hammond, and Monin (2020) find that 89% of the variation in fund leverage in a panel regression is explained by fund fixed effects, indicating that leverage is largely a cross-sectional, rather than time-varying, characteristic.

or in response to constraints imposed by their prime brokers. More generally, Equation (2) becomes misspecified if the gross alpha depends on additional state variables, such as business cycle conditions or industry competition (Avramov, Barras, and Kosowski, 2013; Hoberg, Kumar, and Prabhala, 2018; Pástor, Stambaugh, and Taylor, 2015). To elaborate, suppose that the regression coefficients depend on a demeaned vector of state variables  $z_t$ . In this case, the true alpha is given by  $\alpha_{i,t} = a_{i,t} - b_{i,t}w_{i,t} = a_i + a'_{i,z}z_{i,t} - (b_i + b'_{i,z}z_{i,t})w_{i,t}$ , implying that Equation (2) omits the relevant terms  $z_{i,t}$  and  $z_{i,t}w_{i,t}$ .

Overall, misspecification has limited impact on our analysis of value creation. In particular, Equations (3)-(4) remain valid measures of the true value-added even if the specification of the gross alpha is incorrect. To see this, start from the definition of true value-added  $va_i = E[\alpha_{i,t}w_{i,t}]$  (the same analysis applies to  $va_i^{\text{net}} = E[\alpha_{i,t}^{\text{net}}w_{i,t}]$ ). For any time-series variable  $\alpha_{i,t}$ , we can always take its linear projection on  $w_{i,t}$ :  $\alpha_{i,t} = \text{proj}(\alpha_{i,t}|w_{i,t}) + \epsilon_{\alpha,t}$ , where  $\text{proj}(\alpha_{i,t}|w_{i,t}) = a_i - b_iw_{i,t}$ . By construction, the projection error satisfies  $E[\epsilon_{\alpha,t}w_{i,t}] = 0$ , which implies that  $va_i = E[\alpha_{i,t}w_{i,t}] = a_iE[w_{i,t}] - b_iE[w_{i,t}^2]$  as per Equation (3).

Whereas the value-added itself remains unaffected, model misspecification does alter the normative analysis of value creation. In particular, the coefficients  $a_i$  and  $b_i$  lose their structural interpretation because they become biased when  $z_{i,t}$  or  $z_{i,t}w_{i,t}$  are omitted. Consequently, Equations (7)–(8) need not represent the true optimal values in a time-varying environment. To gauge the empirical importance of this concern, we follow BGS and conduct formal specification tests for all funds in the sample. The results, summarized in Section V.A, indicate that the linear specification  $\alpha_{i,t} = a_i - b_iw_{i,t}$  provides a reasonable approximation to the gross alpha.

### III. Methodology

#### III.A. Estimation of the Value-Added Distribution

##### III.A.1. Motivation for a Fund-Level Approach

We now describe the methodology used to estimate the value created by hedge funds. We adopt a fund-level approach that allows us to infer the entire value-added distribution across funds. Focusing on the entire distribution is important because hedge funds pursue a wide range of strategies with distinct levels of skill and scalability (captured by  $a_i$  and  $b_i$ ). We therefore expect substantial dispersion in value creation that cannot be summarized by a simple average. For instance, the av-

erage conceals important distributional features, such as the value created by top-performing funds or the share of funds that charge excessive fees to investors.

Our econometric approach builds on recent studies on estimation and inference in large cross-sectional datasets (*e.g.*, Gagliardini, Ossola, and Scaillet, 2016). This framework is particularly well suited for measuring the value-added across hedge funds. Contrary to standard parametric or Bayesian approaches (*e.g.*, Harvey and Liu, 2018; Jones and Shanken, 2005), it does not require specifying the shape of the true value-added distribution for which theory offers little guidance. Our approach is also simple and fast even with thousands of hedge funds—intuitively, it boils down to computing an histogram. It therefore departs from sophisticated and computer-intensive Gibbs sampling and expectation maximization methods. Last but not least, it comes with a full-fledged theory to conduct statistical inference on the estimated value-added distribution.

To save space, we focus on the estimation and inference procedure for the distribution of value-added  $\phi(va)$ . The appendix provides the corresponding analysis for the other distributions examined in the empirical section, which share the same statistical properties described below.

### III.A.2. Benchmarking and Non-Replicable Factors

The key inputs for constructing the value-added distribution are the estimated skill and scale coefficients  $a_i$  and  $b_i$  obtained from the time-series regression

$$r_{i,t+1} = \alpha_{i,t} + r_{b,i,t+1} + \varepsilon_{i,t+1} = a_i - b_i w_{i,t} + \beta'_{i,R} f_{R,t+1} + \varepsilon_{i,t+1}. \quad (9)$$

To run this regression, we must specify the appropriate benchmark portfolio  $r_{b,i,t+1} = \beta'_{i,R} f_{R,t+1}$ . Hedge funds employ a wide range of complex alternative strategies. They invest across multiple countries and asset classes, and often implement sophisticated option-based and factor-timing strategies using public information (*e.g.*, Avramov, Barras, and Kosowski, 2013; Ferson and Schadt, 1996; Karehnke and de Roan, 2020). It is therefore highly unlikely that investors are sufficiently sophisticated to replicate all of these mechanical strategies. To formalize this point, we write the excess return vector of all hedge fund strategies as  $f_{t+1} = (f'_{R,t+1}, f'_{NR,t+1})'$ , where  $f_{R,t+1}$  denotes the subset of replicable strategies, and  $f_{NR,t+1}$  the subset of strategies that investors cannot replicate (with *NR* standing for non-replicable).

The non-replicable factors  $f_{NR,t+1}$  are absorbed by the various elements of Equation (9). To

see this point, we write the fund return as a function of the full set of factors:  $r_{i,t+1} = \alpha_{i,t}^* + \beta_{i,R}^{*'} f_{R,t+1} + \beta_{i,NR}^{*'} f_{NR,t+1} + \varepsilon_{i,t+1}^*$ . We then regress  $f_{NR,t+1}$  on  $f_{R,t+1}$  to break the non-replicable factors into three components:  $f_{NR,t+1} = \alpha_{NR} + \Psi_{NR,R} f_{R,t+1} + u_{NR,t+1}$ , where  $\alpha_{NR}$  is the vector of factor alphas,  $\Psi_{NR,R}$  is the matrix of slope coefficients, and  $u_{NR,t+1}$  is the vector of errors.

The first component  $\alpha_{NR}$  is absorbed into the skill coefficient:  $a_i = a_i^* + \beta_{i,NR}^{*'} \alpha_{NR}$ . This expression formalizes the intuition that hedge funds generate profitable ideas in two ways: (i) by exploiting private information signals (captured by  $a_i^*$ ), and (ii) by earning the premia associated with non-replicable strategies (captured by  $\beta_{i,NR}^{*'} \alpha_{NR}$ ). The second component  $\Psi_{NR,R} f_{R,t+1}$  is absorbed by the replicable factors  $f_{R,t+1}$ , which yields  $\beta_{i,R}^{*'} f_{R,t+1} = (\beta_{i,R}^{*'} + \beta_{i,NR}^{*'} \Psi_{NR,R}) f_{R,t+1}$ . Its magnitude depends on the ability of the replicable factors to span the non-replicable factors (captured by  $\Psi_{NR,R}$ ). Finally, the third component  $u_{NR,t+1}$  is absorbed into the error term:

$$\varepsilon_{i,t+1} = \varepsilon_{i,t+1}^* + \beta_{i,NR}^{*'} u_{NR,t+1}. \quad (10)$$

Equation (10) has important implications for the statistical properties of the estimated value-added distribution. It reveals that the error terms are strongly correlated across funds because they all depend on the error term of the non-replicable factors  $u_{NR,t+1}$ . As shown in Proposition 1 below, this correlation implies that the cross-sectional distribution of value-added is estimated with substantial uncertainty. The intuition is straightforward—even though we observe value-added estimates for a large number of funds ( $n$  is large), these estimates are noisy because they are driven primarily by the common component  $u_{NR,t+1}$ .

### III.A.3. Estimation of the Distribution Characteristics

The first step of the estimation procedure is to compute the least-square the coefficient vector in Equation (9) for each fund as  $\hat{\gamma}_i = (\hat{a}_i, \hat{b}_i, \hat{\beta}_{i,R}')' = (\hat{Q}_{x,i})^{-1} \frac{1}{T_i} \sum_t I_{i,t} x_{i,t} r_{i,t+1}$ , where  $I_{i,t}$  is an indicator variable equal to one if  $r_{i,t+1}$  is observable,  $T_i = \sum_t I_{i,t}$ ,  $x_{i,t} = (1, -w_{i,t}, f_{R,t+1}')'$  is a  $(K+2)$ -vector, and  $\hat{Q}_{x,i} = \frac{1}{T_i} \sum_t I_{i,t} x_{i,t} x_{i,t}'$ . Replacing the estimated skill and scale coefficients  $\hat{a}_i$  and  $\hat{b}_i$  in Equation (3), we compute the fund value-added as

$$\hat{v}a_i = \hat{a}_i \bar{w}_i - \hat{b}_i \bar{w}_{i,2}, \quad (11)$$

where  $\bar{w}_i = \frac{1}{T_i} \sum_t I_{i,t} w_{i,t}$ ,  $\bar{w}_{i,2} = \frac{1}{T_i} \sum_t I_{i,t} w_{i,t}^2$ .

We then account for the unbalanced nature of the hedge fund sample. Following Gagliardini, Ossola, and Scaillet (2016), we introduce a formal selection rule  $\mathbf{1}_i^x$  equal to one if the following conditions are met:  $\mathbf{1}_i^x = \mathbf{1} \{ \tau_{i,T} \leq \chi_{1,T}, CN_i \leq \chi_{2,T} \}$ , where  $\tau_{i,T} = T/T_i$ ,  $CN_i = \sqrt{\text{eig}_{\max}(\hat{Q}_{x,i}) / \text{eig}_{\min}(\hat{Q}_{x,i})}$  is the condition number of  $\hat{Q}_{x,i}$ , and  $\chi_{1,T}$ ,  $\chi_{2,T}$  denote the two threshold values. The first condition  $\tau_{i,T} \leq \chi_{1,T}$  excludes funds for which the sample size is too small. The second condition  $CN_i \leq \chi_{2,T}$  excludes funds for which the time-series regression is subject to multicollinearity problems (e.g., Belsley, Kuh, and Welsch, 2004). Both thresholds  $\chi_{1,T}$  and  $\chi_{2,T}$  increase with the sample size  $T$ —with more return observations, we estimate the fund coefficients with greater accuracy, which allows for a less stringent selection rule. Applying this selection rule, we work with a population size equal to  $n_\chi = \sum_{i=1}^n \mathbf{1}_i^x$ .

Finally, we summarize the shape of the value-added distribution using the following characteristics: (i) the cross-sectional mean  $M$ , (ii) the proportion of funds with a value-added below a given value  $a$ , denoted by  $P(a)$ , and (iii) the quantile at a given percentile level  $u$ , denoted by  $Q(u) = (P)^{-1}(u)$ . We estimate these characteristics using as only inputs the estimated vector  $(\hat{v}a_1, \dots, \hat{v}a_{n_\chi})'$  obtained from Equation (11). The estimated mean, proportion, and quantile are given by

$$\hat{M} = \frac{1}{n_\chi} \sum_i \mathbf{1}_i^x \hat{v}a_i, \quad (12)$$

$$\hat{P}(a) = \frac{1}{n_\chi} \sum_i \mathbf{1}_i^x \mathbf{1}\{\hat{v}a_i \leq a\}, \quad (13)$$

$$\hat{Q}(u) = (\hat{P})^{-1}(u). \quad (14)$$

### III.B. Properties of the Estimated Value-Added Distribution

#### III.B.1. Asymptotic Distribution of the Estimated Characteristics

We now examine the statistical properties of the value-added distribution. In the following proposition, we derive the asymptotic distributions of the estimated characteristics  $\hat{M}$ ,  $\hat{P}(a)$ , and  $\hat{Q}(u)$  as the numbers of funds  $n$  and observations  $T$  grow large (simultaneous double asymptotics with  $n, T \rightarrow \infty$ ). To capture the large cross-sectional dimension of the hedge fund population observed in the data, we require that  $n$  is larger than  $T$ .



**Proposition 1.** As  $n, T \rightarrow \infty$ , such that  $T/n \rightarrow 0$ , we obtain the following properties for the estimated characteristics of the cross-sectional distribution of the value-added  $va_i$ :

$$\sqrt{T} (\hat{M} - M) \rightarrow_d N(0, V[M]), \quad (15)$$

$$\sqrt{T} (\hat{P}(a) - P(a)) \rightarrow_d N(0, V[P(a)]), \quad (16)$$

$$\sqrt{T} (\hat{Q}(u) - Q(u)) \rightarrow_d N(0, V[Q(u)]), \quad (17)$$

where  $\rightarrow_d$  denotes convergence in distribution. The variance terms are given by

$$V[M] = E [\eta'_{M_1}] \Omega_{ux} E [\eta_{M_1}] + E [\eta'_{M_2}] \Omega_w E [\eta_{M_2}], \quad (18)$$

$$V[P(a)] = E [\eta'_{P_1}] \Omega_{ux} E [\eta_{P_1}] + E [\eta'_{P_2}] \Omega_w E [\eta_{P_2}], \quad (19)$$

$$V[Q(u)] = V[P(Q(u))]/\phi_{va}(Q(u))^2, \quad (20)$$

where  $\eta_{M_1} = (\beta_{i, NR}^{*'} \otimes \zeta_i' Q_{x,i}^{-1} B_i)'$ ,  $\eta_{M_2} = (a_i b_{i,w}, -b_i b_{i,w})'$ ,  $\eta_{P_1} = E[\eta_{M_1} | va_i = a] \phi_{va}(a)$ ,  $\eta_{P_2} = E[\eta_{M_2} | va_i = a] \phi_{va}(a)$ ,  $\zeta_i = E_1 E[w_{i,t}] - E_2 E[w_{i,t}^2]$ ,  $E_1$  and  $E_2$  are  $(K+2)$  vectors with zeros everywhere except on the first and second positions,  $Q_{x,i} = E[x_{i,t} x_{i,t}']$ ,  $B_i$  is the  $(K+2) \times (K+2)$  matrix of coefficients of the regression of the  $(K+2)$  vector  $x_{i,t}$  on the  $(K+2)$  vector  $x_{t+1} = [1, w_t, f_{R,t+1}]'$  whose second row is given by  $(b_{i,0}, b_{i,w}, 0, \dots, 0)$ ,  $w_t = \sum_i I_{i,t} w_{i,t}$ ,  $\Omega_{ux} = \lim_{T \rightarrow \infty} V \left[ \frac{1}{\sqrt{T}} \sum_t u_{NR,t} \otimes x_t \right]$ ,  $\Omega_w = \lim_{T \rightarrow \infty} V \left[ \frac{1}{\sqrt{T}} \sum_t e_{w,t} \right]$ ,  $e_{w,t} = [u_{w,t}, u_{w,2,t}]'$ ,  $u_{w,t} = (w_t - E[w_t])$ ,  $u_{w,2,t} = (w_t^2 - E[w_t^2])$ ,  $\beta_{i, NR}^*$  and  $u_{NR,t+1}$  denote the vectors of betas and residuals associated with the non-replicable factors  $f_{NR,t+1}$ , and  $\phi_{va}(a)$  is the value-added density evaluated at  $a$ .

**Proof.** See the appendix.

Proposition 1 establishes two key properties of the estimated distribution characteristics. First, they converge to their true values. Hence, we can estimate them without applying any error-in-variables (EIV) bias adjustment, even though the inputs are noisy measures of value-added (i.e., we use  $\hat{va}_i$  instead of  $va_i$ ). Second, the estimates are noisy since the rate of convergence is only  $1/\sqrt{T}$ . This result may appear counterintuitive as these characteristics are computed by averaging across funds rather than across time.

Both properties arise from the influence of the non-replicable hedge fund factors  $f_{NR,t+1}$ . From Equation (10), the estimated fund value-added  $\hat{va}_i$  depends on  $\bar{\varepsilon}_i = \bar{\varepsilon}_i^* + \beta_{i, NR}^{*'} \bar{u}_{NR}$ , where  $\bar{\varepsilon}_i$ ,  $\bar{\varepsilon}_i^*$ , and  $\bar{u}_{NR}$  denote the time-series averages of the residuals. The key driver is the common error term  $\bar{u}_{NR}$ , which affects all funds and converges to zero only at the rate  $1/\sqrt{T}$ . This slow convergence (i) reduces the overall convergence rate of the estimated characteristics to  $1/\sqrt{T}$ , and (ii) dominates the error-in-variables (EIV) bias, making any explicit bias correction unnecessary.<sup>15</sup>

<sup>15</sup> As shown by BGS, the EIV bias is of order  $1/T$ , which is asymptotically negligible relative to the variance term

To apply Proposition 1 and conduct statistical inference, we need a consistent estimator of each variance term  $V$ . This term depends on the error term  $u_{NR,t+1}$  and betas  $\beta_{i,NR}^*$  associated with all non-replicable factors, which are unknown to the econometrician. However, we can still derive a consistent variance estimator  $\hat{V}[\hat{C}]$  for each estimated characteristic  $\hat{C} \in \{\hat{M}, \hat{P}(a), \hat{Q}(u)\}$  based on the observed fund residuals of each model  $\hat{\varepsilon}_{i,t+1} = r_{i,t+1} - x'_{i,t+1}\hat{\gamma}_i$  (see the appendix for details). The following proposition shows that  $\hat{V}[\hat{C}]$  is a consistent variance estimator as the numbers of funds  $n$  and observations  $T$  grow large.

**Proposition 2.** *As  $n, T \rightarrow \infty$  such that  $T/n \rightarrow 0$ , we have*

$$\hat{V}[\hat{C}] \rightarrow_p V[\hat{C}], \quad (21)$$

where  $\rightarrow_p$  denotes convergence in probability.

**Proof.** *See the appendix.*

### III.B.2. Formal Comparisons With Mutual Funds

We can extend Proposition 1 to enable comparison tests with mutual funds. Unlike hedge funds, mutual funds typically do not rely on complex strategies as they load on standard factors such as market, size, and value. Building on this observation, BGS assume that the mechanical strategies followed by mutual funds are fully replicable ( $f_{t+1} = f_{R,t+1}$ ). In this case, the common term  $\hat{u}_{NR,t+1}$  vanishes and the error term  $\bar{\varepsilon}_i = \bar{\varepsilon}_i^*$  becomes weakly correlated across funds. As the characteristics of the mutual fund value-added converge at the faster rate of  $1/\sqrt{n}$  (rather than  $1/\sqrt{T}$ ), we can treat them as known in the comparison tests.

We compute the differences in distribution characteristics between the populations of hedge funds and mutual funds as  $\Delta\hat{M} = \hat{M} - \hat{M}_{mf}$ ,  $\Delta\hat{P}(a) = \hat{P}(a) - \hat{P}_{mf}(a)$ , and  $\Delta\hat{Q}(u) = \hat{Q}(u) - \hat{Q}_{mf}(u)$ , where  $\hat{M}_{mf}$ ,  $\hat{P}_{mf}(a)$ , and  $\hat{Q}_{mf}(u)$  denote the estimated mean, proportion, and quantile across mutual funds. The next proposition derives the asymptotic distributions of  $\Delta\hat{M}$ ,  $\Delta\hat{P}(a)$ , and  $\Delta\hat{Q}(u)$  as the numbers of funds  $n$  and observations  $T$  grow large.

**Proposition 3.** *As  $n, T \rightarrow \infty$ , such that  $T/n \rightarrow 0$ , we obtain the following properties for the differences between the estimated characteristics of the distributions of the value-added  $va_i$  across*

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of order  $1/\sqrt{T}$  in Proposition 1.

*hedge funds and mutual funds:*

$$\sqrt{T} \left( \Delta \hat{M} - \Delta M \right) \rightarrow_d N(0, V[M]), \quad (22)$$

$$\sqrt{T} \left( \Delta \hat{P}(a) - \Delta P(a) \right) \rightarrow_d N(0, V[P(a)]), \quad (23)$$

$$\sqrt{T} \left( \Delta \hat{Q}(u) - \Delta Q(u) \right) \rightarrow_d N(0, V[Q(u)]), \quad (24)$$

where  $\rightarrow_d$  denotes convergence in distribution, and the variance terms are given in Proposition 1.

**Proof.** See the appendix.

## IV. Data Description

### IV.A. Construction of the Hedge Fund Dataset

Our empirical analysis covers the period from January 1994 to December 2020. We collect monthly data on net-of-fee returns and capital, along with cross-sectional information on investment objectives, fees, and other fund characteristics from standard hedge fund databases. In the baseline analysis, we exclude funds-of-funds and multi-strategy funds, and take several steps to mitigate well-known data biases. To reduce selection bias, we merge four major databases (BarclayHedge, HFR, Morningstar, and TASS). To address survivorship bias, we retain both live and dead funds. Finally, we remove the first 12 months of reported data for each fund to correct for backfill bias. Additional details on dataset construction are provided in the appendix.

A key input for measuring the value-added is the unreported monthly gross return of each fund. We construct this variable manually by estimating monthly management and performance fees and adding them back to the reported net return. Unlike mutual funds, reconstructing the gross return series for hedge funds is not trivial because it requires accounting for accrued performance fees. To do so, we track the evolution of the high-water mark provision, which depends on the frequency with which performance fees are paid. Since this information is typically undisclosed, we follow Jorion and Schwarz (2014) and assume an annual payment frequency (see the appendix for computational details). Another key variable in our analysis is the monthly fund capital. Following Berk and van Binsbergen (2015), we express all reported capital values in real terms in million of January 1, 2000 dollars.

To address the unbalanced nature of the hedge fund sample, we apply the fund selection rules described in Section III.A. Following the thresholds used by BGS, we require a minimum of 60 return observations and a minimum condition number of 15. We also exclude micro funds whose

capital falls below \$10 million for at least one-third of the sample period. To further mitigate the influence of outliers, we drop the 1% of funds with extreme values of  $\hat{a}_i$ ,  $\hat{b}_i$ , or  $\hat{v}a_i$ . After applying these filters, our final sample consists of 2,517 funds over the full period ( $n\chi = 2,517$ ).

While the original sample includes all dead funds, the selection rules described above may introduce survivorship bias. If value-destroying funds disappear early, the value-added distribution will be biased upward. However, two offsetting effects may mitigate this concern. First, value-creating funds may also disappear early following unexpectedly poor realized returns—a phenomenon known as reverse-survivorship bias (Linnainmaa, 2013). Second, many top funds stop reporting to commercial databases once their client base is sufficiently established. Taken together, these forces suggest that the overall magnitude of the bias is a priori unclear. Our analysis in the appendix reveals that our conclusions remain largely unchanged when using a minimum number of observations of 36 and 84.

#### *IV.B. Construction of the Benchmark Model*

To estimate the value-added, we must specify the investment opportunities available to investors as captured by  $f_{R,t+1}$  in Equation (9). In our baseline analysis, we extend the three-factor model of Cremers, Petajisto, and Zitzewitz (2013) by augmenting the standard market, size, and value factors with global carry and time-series (TS) momentum. These strategies, constructed by Kojien et al. (2018) and Moskowitz, Ooi, and Pedersen (2012), invest in assets with high carry and positive 12-month returns across four asset classes (equities, bonds, currencies, and commodities).

The rationale for selecting these five factors is twofold. First, they capture mechanical strategies that hedge funds plausibly follow. As noted by Ardia et al. (2024), Carhart et al. (2014), and Pedersen (2015), these factors are grounded in economic intuition and explain a sizable share of hedge fund average returns. Second, it is reasonable to assume that hedge fund investors can take positions in these factors. The market, size, and value factors from Cremers, Petajisto, and Zitzewitz (2013) track the S&P 500 and Russell indices and can be replicated using passive products. By construction, they assign zero alpha to the S&P 500 and Russell 2000—two widely used benchmarks in the fund industry. The carry and TS momentum factors can also be traded through liquid futures markets or alternative premia funds increasingly offered by financial institutions (Jorion, 2021). Consistent with this rationale, Ardia et al. (2024) show that hedge fund investors chase funds with high past alphas, but do not chase funds whose past returns primarily reflect exposures

to these five factors. This evidence suggests that investors are sufficiently sophisticated to replicate these factor exposures on their own.<sup>16,17</sup>

In our computations of the value-added, we use the gross-of-fee returns of the five factors in  $f_{R,t+1}$ . Consequently, we exclude the replication services that hedge funds provide to investors since these services can also be obtained through passive products (Berk and van Binsbergen, 2015). As shown in the appendix, all but one factor (value) earn positive premia over the sample period. Moreover, the factors are exposed to distinct sources of risk as none of the pairwise correlations exceeds 0.5 in absolute value.

#### IV.C. Summary Statistics

Table I reports summary statistics for an equal-weighted portfolio of all existing funds at the start of each month. The full hedge fund sample consists of (i) 974 equity funds (long–short and market neutral), which rely on discretionary or quantitative analysis to detect mispriced stocks; (ii) 631 macro funds (global macro and managed futures), which take directional positions across asset classes using broad economic and financial indicators; and (iii) 912 arbitrage funds (relative value and event-driven), which primarily exploit mispricings in debt markets. For comparison, we also compute the same statistics for a sample of 2,238 U.S. equity mutual funds constructed following the procedure of BGS.

Panel A shows that the portfolio of all hedge funds delivers an average gross return of 9.9% per year. After accounting for management fees (1.4% per year) and performance fees (1.7% per year), the average net return declines to 6.7% per year. These results are consistent with prior evidence on gross and net hedge fund performance (*e.g.*, Elaut, Frömmel, and Sjödin, 2015; Jorion and Schwarz, 2014). In terms of size, hedge funds are substantially smaller than mutual funds—the time-series average of cross-sectional average (median) capital is \$226 million (\$74 million) for hedge funds, compared with \$908 million (\$245 million) for mutual funds.

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<sup>16</sup>We also consider alternative benchmark models in which investors have access to (i) only the market factor (CAPM), (ii) the equity market, size, and value factors, and (iii) the equity market, size, and value factors together with two bond factors (default and term). The last specification is particularly relevant for pension funds—major hedge fund investors which typically hold balanced portfolios of stocks and bonds. Results for these alternative benchmarks are reported in the online appendix.

<sup>17</sup>Our benchmark choice for measuring value creation is oriented toward factor replication and differs from that of Ling, Satchell, and Yao (2023) who form for each fund a benchmark portfolio of six HFR-style indices. Since each index aggregates about 500 hedge funds, this benchmark portfolio is difficult for investors to replicate.

Panel B reports the estimated portfolio betas with respect to the five factors (market, size, value, carry, and TS momentum). All betas of the aggregate hedge fund portfolio are positive, consistent with the view that hedge funds take on market risk, tilt toward small-cap and value stocks, buy high-carry assets, and exploit return trends to enhance performance (Pedersen, 2015). Among styles, equity funds exhibit the strongest exposure to the equity market (0.46), whereas macro funds load most heavily on TS momentum (0.34) as they rely on past returns to exploit trends driven by behavioral biases, frictions, or slow-moving capital. Turning to model fit, the factors explain only 42.3% of the average portfolio return and 68.8% of its time-series variation (compared with 94.4% and 98.6% for mutual funds). Contrary to mutual funds, hedge funds pursue strategies that are not spanned by the five factors—a result that underscores the importance of our methodology which explicitly controls for the impact of non-replicable factors  $f_{NR,t+1}$ .

Please insert Table I here

## V. Main Empirical Results

### V.A. Magnitude of the Value-Added

#### V.A.1. The Value-Added across Funds

We begin our empirical analysis by measuring the value created by the hedge fund industry. Specifically, we infer the entire cross-sectional distribution of value-added using as inputs the estimated value-added  $\hat{v}a_i = \hat{a}_i \bar{w}_i - \hat{b}_i \bar{w}_{i,2}$ . We summarize the shape of the distribution using the mean and median, the proportions of funds with positive and negative value-added, and the 10th and 90th quantiles. To compute the standard errors of these characteristics, we set  $T$  equal to the average number of fund return observations (134) to account for the additional estimation noise arising from the unbalanced structure of the hedge fund panel.

Panel A of Table II provides robust evidence of hedge fund value creation. Across the full sample, nearly 70% of funds generate positive value-added, with an average of \$5.7 million per year. This average is statistically highly significant, despite the substantial estimation noise inherent in hedge fund return data. The ability of hedge funds to create value suggests that their trading activity enhances asset price efficiency—a channel often invoked to justify their economic importance. Improvements in price informativeness are socially valuable because they facilitate

better decisions by capital providers, managers, employees, and regulators (Bond, Edmans, and Goldstein, 2012). Although this mechanism is difficult to verify directly, Ha, Hu, and Tang (2024) study the daily trades of institutional investors and provide evidence that only hedge fund trading enhances the informational efficiency of capital markets.

Another insight from Panel A is the large heterogeneity across hedge funds. Value creation varies markedly across investment styles. More than 80% of arbitrage funds create value, compared with 67% of equity funds and 51.7% of macro funds. In addition, heterogeneity remains large even within style groups—funds in the top decile generate a value-added more than three times higher than the average. Motivated by these findings, we next focus on the drivers of value creation, focusing on whether hedge funds add value by identifying profitable strategies or by scaling them efficiently.

Please insert Table II here

#### V.A.2. *Fund Skill and Scalability*

Given the prevalence of value creation among hedge funds, we expect most of them to be skilled at designing profitable investment strategies. To test this idea, we infer the cross-sectional distribution of the skill coefficient  $a_i$ . Panel B of Table II confirms that 86.4% of funds exhibit a positive alpha on their first dollar of capital. More surprising is the magnitude of the skill coefficient—on average, it is above 11% per year in all three investment categories. These high first-dollar returns are therefore the primary engine of hedge fund value creation.

On the downside, Panel C shows that hedge funds suffer from severe scalability constraints. A \$10 million increase in capital reduces the gross alpha by 1.5% per year on average. Although hedge funds can spread capital across multiple ideas by taking long and short positions, this flexibility does not translate into high scalability. Our fund-level estimates contribute to the literature by showing that the scale coefficient is positive not only on average (*e.g.*, Fung et al., 2008; Naik, Ramadorai, and Stromqvist, 2007), but for the vast majority of funds. This evidence provides strong support for equilibrium models of active management with diseconomies of scale (*e.g.*, Berk and Green, 2004; Glode and Green, 2011).

For a minority of funds, Panel C yields the counterintuitive result that scale improves returns ( $b_i < 0$ ). One plausible explanation is estimation noise—the lower bound of the 95% confidence

interval barely exceeds 7.3%. Alternatively, these cases may reflect model misspecification due to omitted nonlinearities or relevant predictors of alpha. To assess this possibility, we follow BGS and conduct a specification test of the null hypothesis  $H_{0,i}$  that  $\alpha_{i,t} = a_i - b_i w_{i,t}$  is correctly specified (see the appendix for details).

### V.A.3. *Impact of Leverage*

Hedge fund strategies are both highly profitable and highly unscalable. In the context of hedge funds, Equation (2) highlights a key mechanism—leverage mechanically raises both  $a_i$  and  $b_i$  by simultaneously increasing the gross alpha and the trading costs associated with each dollar of equity capital.<sup>18</sup> Given the lack of data on hedge fund leverage, we rely on Barth, Hammond, and Monin (2020), who report leverage statistics for their proprietary hedge fund dataset. Using their estimates, we set the average leverage ratio  $\hat{\pi}$  equal to 2.1, 5.9, and 2.7 for equity, macro, and arbitrage funds, and 3.3 for the entire population (see the appendix for details). We then recover the unlevered coefficients by dividing the average skill coefficient by  $\hat{\pi}$  and the average scale coefficient by  $\hat{\pi}^2$ .

Figure 1 shows that leverage is the primary driver of the high skill and scale coefficients observed for hedge fund strategies. Once we remove the effect of leverage, the average skill and scale coefficients fall to 3.8% and 0.2% per year—only 30.4% and 13.3% of their levered counterparts reported in Table II (3.8/12.5 and 0.2/1.5, respectively). Examining the unlevered coefficients also helps explain why arbitrage funds create more value. These funds trade remarkably efficiently. An unlevered \$10 million increase in capital reduces the gross alpha by only 0.1% per year—nearly identical to macro funds, which operate in more liquid markets. When this low unlevered scale coefficient is combined with a moderate leverage ratio of 2.7, the resulting scale coefficient is only 1.0% per year, roughly half the value observed for equity funds and macro funds (1.9% and 1.4%). As emphasized by Duarte, Longstaff, and Yu (2006), arbitrage strategies rely heavily on intellectual capital and sophisticated implementation techniques—inputs that appear crucial for achieving such efficient trading at scale.

Please insert Figure 1 here

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<sup>18</sup>Competitive forces also help generate a positive correlation between  $a_i$  and  $b_i$ . Costly strategies must deliver sufficiently high expected returns to justify their implementation. For example, van Binsbergen et al. (2024) show that high-turnover strategies entail substantial trading costs (high  $b_i$ ) and are adopted only when their profitability is high enough to compensate for those costs (high  $a_i$ ).



#### V.A.4. *Characteristics of the Most Valuable Funds*

Table II reveals that value creation in the hedge fund industry is highly concentrated. A conservative estimate based on the 90th-quantile indicates that the top 10% of funds account for at least 40% of the total value created by the industry ( $\frac{21.7 \cdot 10\%}{5.7}$ ). This result implies that some hedge funds possess special abilities that are hard to replicate. In Table III, we examine what distinguishes the top decile of value-creating funds.

We find that these funds do not simply generate the most profitable ideas. Instead, they pursue distinctive strategies that balance skill and scalability. To illustrate this point, we sort each fund estimated  $\hat{\alpha}_i$  and  $\hat{\beta}_i$  into deciles, creating a scoring system from 1 (worst) to 10 (best). The top funds score, on average, 7 on both dimensions. Moreover, only 10% of them reach the maximum score of 10 for skill or scalability. These balanced strategies deliver the highest value-added because they navigate the inherent trade-off between skill and scalability highlighted earlier.

The top funds create value by exploiting superior information or by following strategies that investors cannot replicate. To distinguish between these two channels, we augment the benchmark model with three hard-to-replicate strategies commonly used by hedge funds: illiquidity, betting-against-beta (BAB), and variance.<sup>19</sup> Controlling for these factors leaves both the mean and median value-added essentially unchanged. Panel B shows that the largest average contribution of these strategies is 23.8% for arbitrage funds (14.0/58.7), reflecting their exposure to variance risk (see Ardia et al., 2024). Overall, these results indicate that distinctive informational advantages—rather than reliance on hard-to-replicate strategies—are the primary source of skill among top funds.

Please insert Table III here

#### V.A.5. *Comparison with Mutual Funds*

It is instructive to compare the drivers of value creation between hedge funds and mutual funds. We find that the gap in skill coefficient is substantial—the first-dollar alpha of mutual funds averages only 2.6% per year. At the same time, mutual fund strategies are far more scalable—a \$10 million increase in capital reduces the annual alpha by only 0.2% on average. As a result,

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<sup>19</sup> Ardia et al. (2024), Carhart et al. (2014), and Pedersen (2015) provide evidence that hedge funds pursue these strategies. The illiquidity factor of Pástor and Stambaugh (2003) captures marketwide liquidity shocks, the BAB strategy of Frazzini and Pedersen (2014) exploits mispricing created by leverage-constrained investors, and the variance strategy tracks realized S&P 500 variance.

the implications for value creation are ambiguous. In Figure 2, we compare the average value-added of hedge funds and mutual funds. For mutual funds, we examine the full population as well as subgroups sorted by stock size (small- and large-cap), turnover (low- and high-turnover), and distribution channel (direct- and broker-sold).

On average, hedge funds generate about \$5.3 million more in value-added per year—a difference that is economically large and statistically significant with a  $p$ -value below 1%.<sup>20</sup> However, this advantage is almost entirely driven by arbitrage funds. The other two hedge fund categories—equity and macro—produce a value-added that is comparable to, or even lower than, that of several mutual fund groups (notably small-cap, low-turnover, and direct-sold funds). Overall, these findings challenge the view that the greater sophistication of hedge fund managers allows them to systematically outperform their mutual fund counterparts.

Please insert Figure 2 here

## *V.B. Sharing of the Value-Added with Investors*

### *V.B.1. The Net Value-Added across Funds*

Our earlier results show that hedge funds create substantial value. The next step is to ask how this value is shared between funds and their investors. To address this question, we compute the net value-added received by investors as  $\hat{v}a_i^{\text{net}} = \hat{a}_i^{\text{net}}\bar{w}_i - \hat{b}_i^{\text{net}}\bar{w}_{i,2}$ , where  $\hat{a}_i^{\text{net}}$  and  $\hat{b}_i^{\text{net}}$  are obtained from the time-series regression of the fund net return:  $r_{i,t+1}^{\text{net}} = r_{i,t+1} - fee_{i,t+1} = a_i^{\text{net}} - b_i^{\text{net}}w_{i,t} + \beta'_{i,R}f_{R,t+1} + \varepsilon_{i,t+1}$ . We then apply our methodology to infer the distribution of the net value-added across all funds.

On average, hedge fund investors capture only a small fraction of the value-added. Panel A of Table IV shows that the average net value-added amounts to \$0.5 million per year, representing only 8.8% of the \$5.7 million in value created by hedge funds. Based on this result, it is tempting to conclude that hedge fund investors have little bargaining power—consistent with the prediction of the Berk and Green (2004) model that funds extract all rents from their skill.

This interpretation is misleading because the average masks substantial heterogeneity across funds. We find that investors extract positive value-added from roughly half of the funds in the

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<sup>20</sup>The value added by mutual funds is positive at \$0.3 million but smaller than the estimates reported by BGS and Berk and van Binsbergen (2015) because we use a different benchmark model and a shorter period (1994–2020).

population. When positive, these amounts are economically meaningful—in the top decile, investors receive more than \$10 million per year. These patterns are particularly pronounced among arbitrage funds, where 66.2% deliver positive net value-added to investors. As noted by Duarte, Longstaff, and Yu (2006) and Pedersen (2015), arbitrage strategies are complex, which likely increases the bargaining power of the limited pool of investors willing to allocate capital.

At the same time, we find that half of the funds deliver a negative value-added net of fees. A common explanation for such wealth destruction is the presence of unskilled funds—those whose first-dollar alpha is too low to cover fees ( $a_i^{\text{net}} < 0$ ). As shown in Panel B, hedge fund fees have a pronounced effect on net profitability—on average, the difference between  $a_i$  and  $a_i^{\text{net}}$  amounts to 3.3% per year (12.5% versus 9.2%). However, only 18.2% of funds exhibit a negative  $a_i^{\text{net}}$ , implying that merely 37.8% of the wealth-destroying funds are unskilled (18.2/48.1). The remaining 62.2% destroy wealth by operating at an excessive scale. Put differently, capital misallocation rather than lack of skill appears to be the primary driver of negative net value-added.

Please insert Table IV here

#### V.B.2. *Limitations of the Net Alpha*

The sizable proportion of value-destroying funds in Table IV appears at odds with the strong hedge fund performance documented in previous studies (*e.g.*, Ackermann, McEnally, and Ravenscraft, 1999; Chen, Cliff, and Zhao, 2017; Liang, 1999; Kosowski, Naik, and Teo, 2007). Consistent with this literature, we also find evidence of positive performance, as measured by the net alpha  $\alpha_i^{\text{net}} = E[\alpha_{i,t}^{\text{net}}] = a_i^{\text{net}} - b_i^{\text{net}} E[w_{i,t}]$ . Applying our methodology to the estimated values  $\hat{\alpha}_i^{\text{net}} = \hat{a}_i^{\text{net}} - \hat{b}_i^{\text{net}} \bar{w}_i$ , we find that 66.4% of funds exhibit positive alpha, with an average of 1.8% per year (see the appendix).

To reconcile both findings, consider a simple two-period example. In the first period, investors allocate a small amount of capital such that the net alpha is positive ( $\alpha_{i,1}^{\text{net}} = a_i^{\text{net}} - b_i^{\text{net}} w_{i,1} > 0$ ). In the second period, they invest a much larger amount of capital, driving the net alpha negative ( $\alpha_{i,2}^{\text{net}} = a_i^{\text{net}} - b_i^{\text{net}} w_{i,2} < 0$ ). Because this period of poor performance coincides with greater capital allocation ( $w_{i,2} > w_{i,1}$ ), it receives more weight in the computation of the value-added. As a result, the fund can display a positive net alpha over the entire sample ( $\alpha_i^{\text{net}} = (\alpha_{i,1}^{\text{net}} + \alpha_{i,2}^{\text{net}})/2 > 0$ ), but a

negative net value-added ( $va_i^{\text{net}} = (\alpha_{i,1}^{\text{net}}w_{i,1} + \alpha_{i,2}^{\text{net}}w_{i,2})/2 < 0$ ).<sup>21</sup>

A key takeaway from our analysis is that the net alpha is a poor proxy for the value that funds deliver to investors for two reasons. First, it ignores the average scale  $E[w_{i,t}]$  at which the fund operates—a limitation similar to that highlighted by Berk and van Binsbergen (2015) in the context of the gross alpha. Second, even if we control for  $E[w_{i,t}]$ , the resulting measure  $\alpha_i^{\text{net}}E[w_{i,t}]$  does not reflect the actual value captured by investors because it neglects their time-varying capital allocation decisions.

### V.B.3. Comparison with Mutual Funds

Previous studies suggest that hedge fund investors may suffer from agency problems that cause them to overpay for active management. For instance, Lakonishok, Shleifer, and Vishny (1992) argues that pension fund officers might favor hedge funds—even when fees are excessive—because such relationships help justify their own positions. The modest yet positive average net value-added reported in Table IV does not support this interpretation. Instead, it indicates that hedge fund investors fare substantially better than mutual fund investors.

Figure 3 reports the average net value-added in the mutual fund industry. The value-added is negative across all fund categories, consistent with BGS and Cooper, Halling, and Yang (2021), who show that mutual funds systematically charge excessive fees to their clients. The gap of \$7.9 million per year relative to hedge funds is both economically large and highly significant with a  $p$ -value below 1%. This difference is consistent with the view that mutual funds primarily cater to less sophisticated retail investors who are more likely to be unaware of underperformance (Gruber, 1996), constrained by high search costs (Roussanov, Ruan, and Wei, 2021), and willing to pay higher fees for financial advice (Del Guercio and Reuter, 2014).

Please insert Figure 3 here

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<sup>21</sup>This result is an application of Jensen's inequality. With scalability constraints, the net value-added function  $va_i^{\text{net}}(w_{i,t}) = (a_i^{\text{net}} - b_i^{\text{net}}w_{i,t})w_{i,t}$  is concave in  $w_{i,t}$ , which implies that  $va_i^{\text{net}} = E[va_i^{\text{net}}(w_{i,t})] < va_i^{\text{net}}(E[w_{i,t}]) = \alpha_i^{\text{net}}E[w_{i,t}]$ . We further have  $E[va_i^{\text{net}}(w_{i,t})] - va_i^{\text{net}}(E[w_{i,t}]) = -b_i^{\text{net}}V[w_{i,t}]$ , where  $V[w_{i,t}]$  denotes the variance of capital. Hence, greater variation in capital over time increases the likelihood that the net value-added and the net alpha differ in sign.

## V.C. The Value-Added over the Fund's Lifecycle

### V.C.1. Dynamics of Fund Capital

Our earlier findings provide evidence of capital misallocation, as half of all funds destroy value due to either insufficient skill or excessive scale. A natural question is whether this misallocation dissipates over time. When investors face excessive fees, they have strong incentives to withdraw capital and reallocate it toward more profitable opportunities. Consistent with this mechanism, prior studies show that hedge fund flows respond positively to past performance (*e.g.*, Fung et al., 2008; Baquero and Verbeek, 2021). More recent evidence from Agarwal, Green, and Ren (2018) and Ardia et al. (2024) further suggests that hedge fund investors adjust for factor exposures—such as market, carry, and time-series momentum—when evaluating performance. Motivated by this evidence, we examine how fund capital and value-added evolve over the fund's lifecycle.

We begin by examining how investors allocate capital between unskilled and skilled funds. For each fund, we track the evolution of invested capital using the ratio  $\Delta \bar{w}_i(s) = \bar{w}_i(s)/\bar{w}_i$ , where  $\bar{w}_i(s)$  denotes the average capital in subperiod  $s$  and  $\bar{w}_i$  the average capital over the full sample. The sample is divided into five subperiods ( $S = 5$ ) to capture the capital adjustment as investors learn about fund skill and scalability (Pástor and Stambaugh, 2012).<sup>22</sup> To distinguish skilled from unskilled funds, we group funds based on the sign of their estimated net skill coefficient  $\hat{a}_i^{\text{net}}$  and compute the cross-sectional average of  $\Delta \bar{w}_i(s)$  for each group.

Figure 4 shows that investors are able to distinguish between unskilled and skilled funds. Capital invested in unskilled funds declines steadily over time, falling to about 65% of its average level by the final subperiod. In contrast, investors gradually increase their allocations to skilled funds. The capital ratio starts around 0.7 in the first subperiod and rises slightly above one by the last subperiod. These patterns are not driven by specific investment styles, as we observe similar trends for equity, macro, and arbitrage funds.

Another notable finding is that capital invested in skilled funds overshoots midway through their lifecycle. In subperiods 3 and 4, it rises to more than 110% of the full-sample average. This pattern may suggest that investors temporarily allocate more capital than is justified by the fund skill and scalability. Such excess capacity may help explain the evidence in Table IV showing that a substantial fraction of funds eventually deliver negative a net value-added. To further explore

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<sup>22</sup>In the appendix, we also partition the sample into ten subperiods and find qualitatively similar results.

this mechanism, we next analyze the evolution of the value-added among skilled funds.

Please insert Figure 4 here

### *V.C.2. Dynamics of the Value-Added*

We compute the subperiod value-added measures of the skilled funds as  $\hat{v}a_i(s) = \hat{a}_i\bar{w}_i(s) - \hat{b}_i\bar{w}_{i,2}(s)$  and  $\hat{v}a_i^{\text{net}}(s) = \hat{a}_i^{\text{net}}\bar{w}_i(s) - \hat{b}_i^{\text{net}}\bar{w}_{i,2}(s)$ . Applying our methodology, we then estimate the cross-sectional distribution of each subperiod measure. The results are reported in Figures 5 and 6, where we plot the evolution of the proportions of funds with negative and positive value-added, as well as the quantiles at 10% and 90%.

If investors form sharper estimates of skill and scalability over time, capital allocation should improve and the subperiod value-added distribution should gradually shift to the right. Consistent with this prediction, Panel D of Figure 5 reveals stronger value creation as funds progress through their lifecycle. The 90th-quantile increases from \$18.5 million to \$24.0 million per year between the first and last subperiods. In the arbitrage category, this improvement is even more pronounced as the value-added rises from 24.6 to 32.3 million per year.

Please insert Figure 5 here

At the same time, we do not find that investors limit the prevalence of value-destroying funds. As shown in Panel A of Figure 6, the share of funds with a negative net value-added rises sharply from 30.6% to 45.2% by subperiod 4. This pattern is even more pronounced among macro funds, where nearly 60% destroy value by subperiod 4. This increase confirms that the earlier surge in invested capital leads to widespread overcapacity across hedge funds.<sup>23</sup> On the positive side, investors eventually respond to poor performance by withdrawing capital. Nevertheless, nearly one-third of funds still destroy value in the final subperiod.

To summarize, we find that investors can distinguish between funds with positive and negative value-added, yet the resulting capital reallocation is slow and noisy. This mixed evidence likely reflects the interaction of opposing forces. On the one hand, hedge fund investors—primarily institutions and high-net-worth individuals—are relatively sophisticated and therefore well equipped

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<sup>23</sup>The appendix further shows that most of the value destruction within the macro category comes from managed futures funds rather than global macro funds. Excess capacity is so severe that managed futures is the only hedge fund subcategory that generates a negative value-added even before fees.

to extract information from past performance. On the other hand, learning about hedge funds is inherently difficult given the complexity of their strategies and the limited length of most return histories. In addition, investors face contractual frictions such as lockup and notice periods, which further slow the reallocation of capital (Joenväärä, Kosowski, and Tolonen, 2019).<sup>24</sup>

Please insert Figure 6 here

## V.D. Normative Analysis of the Value-Added

### V.D.1. Estimation of the Model

Given the sophistication of managers and investors, the hedge fund industry offers an ideal laboratory for testing rational models of active management. We perform a normative analysis to determine how well such a model explains both the cross-sectional variation and the overall magnitude the value-added. We consider the rational model in Section II.C, in which (i) funds with heterogeneous skill and scalability maximize fee revenues, and (ii) investors require a compensation  $\kappa$  per unit of capital to cover due diligence and monitoring costs.<sup>25</sup>

To estimate the model-implied optimal quantities for each fund, we proceed as follows. When the fund sets fees optimally at  $fee_i^o = \frac{a_i - \kappa}{2}$ , the optimal capital level is  $w_i^o = \frac{a_i - \kappa}{2b_i}$ , which yields the following optimal measures for value creation:  $va_i^o = a_i w_i^o - b_i (w_i^o)^2 = \frac{a_i^2 - \kappa^2}{4b_i}$  and  $va_i^{\text{net},o} = a_i w_i^o - b_i (w_i^o)^2 - fee_i^o w_i^o = \kappa w_i^o = \frac{\kappa(a_i - \kappa)}{2b_i}$ . We compute the empirical counterparts of these quantities as  $\hat{va}_i^o = \frac{\hat{a}_i^2 - \kappa^2}{4\hat{b}_i}$  and  $\hat{va}_i^{\text{net},o} = \frac{\kappa(\hat{a}_i - \kappa)}{2\hat{b}_i}$ . We can then compare these optimal values with the actual ones given by the estimates  $\hat{va}_i$  and  $\hat{va}_i^{\text{net}}$ .

Contrary to the estimated values  $\hat{a}_i$  and  $\hat{b}_i$ , which can be inferred from the data,  $\kappa$  is not directly observable. In our baseline analysis, we follow Stulz (2007) and set  $\kappa$  equal to 1% per year.<sup>26</sup> We require  $\hat{a}_i > \bar{fee}_i + \kappa$  to ensure that investors optimally allocate a positive amount of capital to the

<sup>24</sup>To further explore these channels, we test whether the proportion of funds with negative net value-added is lower in the final subperiod when investors (i) are more sophisticated (proxied by the fund's offshore status (Aragon, Liang, and Park, 2014), and (ii) have more time to learn (proxied by fund age). As shown in the appendix, this is indeed the case, although the differences are modest.

<sup>25</sup>Our analysis examines whether the value created is privately optimal for funds and investors. It is therefore silent on the social value of active management. On one hand, hedge funds enhance price efficiency, which is socially beneficial. On the other hand, they may engage in socially wasteful rent-seeking activities that redistribute wealth at the expense of other market participants. Quantifying the net social value of the industry thus requires assessing the relative strength of these opposing forces (e.g., Kurlat, 2019).

<sup>26</sup>Stulz (2007) writes that a frequently heard price tag for hedge fund due diligence costs is \$50,000. Assuming a five-year investment horizon (e.g., Khorana, Servaes, and Tufano, 2009) and a typical investment size of \$1 mio. (e.g., Burns, 2023), this corresponds to  $\kappa = 1\%$ .

fund at the prevailing fee level. We further restrict  $\hat{b}_i > 0.05\%$  per year to guarantee a well-defined and non-explosive optimal value-added as  $\hat{b}_i$  approaches zero. After applying these filters, our final sample includes 1,729 funds.

#### *V.D.2. Actual versus Optimal Value-Added*

We begin our comparison analysis by computing the pairwise correlation between  $\hat{v}a_i$  and  $\hat{v}a_i^o$  ( $\hat{v}a_i^{net}$  and  $\hat{v}a_i^{net,o}$ ). This analysis provides a simple diagnostic of whether the actual and optimal values are qualitatively aligned. The correlation for the gross value-added is high at 0.81, confirming that funds with higher value-added have greater potential for value creation. For the net value-added, the correlation remains positive but is more modest at 0.46. The model also successfully replicates the strong empirical correlation of 0.92 between  $\hat{v}a_i$  and  $\hat{v}a_i^{net}$ . In the model of Berk and Green (2004), this correlation is equal to zero as funds extract all rents from their skills. By allowing investors to retain some bargaining power through the parameter  $\kappa$ , our framework instead generates a sizable correlation of 0.87 between  $\hat{v}a_i^o$  and  $\hat{v}a_i^{net,o}$ .

Next, we compare the magnitude of the actual and optimal value-added. Table V shows that the model reasonably captures the extent of value creation. On average, the actual value-added amounts to 36.3% of the optimal level of \$15.4 million per year. The fit is stronger for the net value-added, which reaches 61.8% of its optimal level of \$1.6 million. The model further implies that investors retain only a small share of the total value created—about 10% (1.6/15.4)—a figure broadly consistent with the 17.8% observed in the data (1.0/5.6). Examining the three investment styles, the model correctly ranks arbitrage funds as the largest value creators (\$19.7 million). However, it does not capture the differences in net value-added across categories. For macro funds, the optimal net value-added equals \$1.6 million, yet investors end up paying excessive fees of \$2.3 million. In contrast, hedge fund investors extract more value from arbitrage funds than the model predicts (\$3.7 versus \$2.1 million).

Please insert Table V here

#### *V.D.3. Fee Policy and Capital Misallocation*

The previous analysis shows that the model captures the cross-sectional variation in value-added but only partially its economic magnitude. We now quantify the two forces that explain this discrepancy: (i) the fee-setting policy chosen by funds and (ii) the capital allocation chosen by



investors. First, funds may set fees that deviate from their optimal levels. In this case, the equilibrium capital and value-added implied by the model differ from the optimal ones. The equilibrium capital  $w_i^e$  is now determined by the condition that the net value-added to investors equals their required compensation. Solving this condition yields  $w_i^e = \frac{a_i - \bar{f}e_i - \kappa}{b_i}$ , which implies the following equilibrium value-added measures:  $va_i^e = a_i w_i^e - b_i (w_i^e)^2$  and  $va_i^{\text{net},e} = a_i w_i^e - b_i (w_i^e)^2 - \bar{f}e_i w_i^e$ . Second, investors may misallocate capital relative to the equilibrium value implied by the model. When this occurs, the actual capital  $w_i$  and the corresponding value-added measures  $va_i$  and  $va_i^{\text{net}}$  differ from their equilibrium counterparts.

To assess the relative importance of these two channels, we decompose the gap between the optimal and actual value-added as

$$va_i - va_i^o = (va_i - va_i^e) + (va_i^e - va_i^o), \quad (25)$$

$$va_i^{\text{net}} - va_i^{\text{net},o} = (va_i^{\text{net}} - va_i^{\text{net},e}) + (va_i^{\text{net},e} - va_i^{\text{net},o}), \quad (26)$$

where the first term captures the effect of capital misallocation and the second term captures the effect of fees. The empirical counterparts of these expressions are given by

$$\hat{va}_i - \hat{va}_i^o = (\hat{va}_i - \hat{va}_i^e) + (\hat{va}_i^e - \hat{va}_i^o), \quad (27)$$

$$\hat{va}_i^{\text{net}} - \hat{va}_i^{\text{net},o} = (\hat{va}_i^{\text{net}} - \hat{va}_i^{\text{net},e}) + (\hat{va}_i^{\text{net},e} - \hat{va}_i^{\text{net},o}), \quad (28)$$

where  $\hat{va}_i^e = \hat{a}_i \hat{w}_i^e - \hat{b}_i (\hat{w}_i^e)^2$  and  $\hat{va}_i^{\text{net},e} = \hat{a}_i \hat{w}_i^e - \hat{b}_i (\hat{w}_i^e)^2 - \bar{f}e_i \hat{w}_i^e$  with  $\hat{w}_i^e = \frac{\hat{a}_i - \bar{f}e_i - \kappa}{\hat{b}_i}$ .

Panel A of Table VI summarizes the effect of the fee policy. As predicted by the model, funds with higher skill tend to charge higher fees—the pairwise correlation between  $\hat{a}_i$  and  $\bar{f}e_i$  is 0.44. However, the optimal target fees are substantially higher than the fees actually charged. On average, the gap amounts to 5.4% per year. Figure 7 illustrates the consequences of this fee gap. When the fund sets fees too low, investors are incentivized to invest more capital than is optimal ( $w_i^* < w_i^e$ ), causing the equilibrium value-added to fall short of its optimal level ( $va_i^* > va_i^e$ ).<sup>27</sup> At the same time, the equilibrium net value-added increases because investors must be compensated for deploying a larger amount of capital ( $va_i^{\text{net},*} > va_i^{\text{net},e}$ ). Consistent with this

<sup>27</sup>In principle,  $va_i^e$  could exceed  $va_i^*$  if  $w_i^e$  coincides with the capital level that maximizes the unconstrained value-added, that is,  $\max_{w_i} va_i = \frac{a_i^2}{4b_i} > va_i^* = \frac{(a_i - \kappa)^2}{4b_i}$ . Empirically, no fund in our sample satisfies this condition.

mechanism, Panel A shows that the equilibrium capital averages \$245 million, compared with only \$164 million for the optimal level. Likewise, the average difference is negative for the value-added (-\$4.8 million) and positive for the net value-added (\$0.8 million).<sup>28</sup>

We then assess the extent of capital misallocation in Panel B. For each fund, we infer the actual capital  $\hat{w}_i$  as the constant level that rationalizes the actual value-added  $\hat{va}_i$ . Consistent with earlier findings, the hedge fund industry exhibits substantial excess capacity. On average, actual capital is \$316 million, compared with the model-implied target of \$245 million. Figure 8 illustrates the consequences of this misallocation. In contrast to the fee-setting policy shown in Figure 7, excess capacity pushes both value-added measures below their equilibrium levels ( $va_i^e > va_i$  and  $va_i^{\text{net},e} > va_i^{\text{net}}$ ). Panel B quantifies these effects, showing that the average value-added measures decrease by \$5 and \$1.4 million, respectively.

Overall, the model suggests that the hedge fund industry operates at a scale that exceeds its optimal size (316 vs. 164 million)—a conclusion consistent with the sizable share of funds exhibiting negative net value-added (Table IV). This excess capacity is driven jointly by suboptimal fees and persistent capital misallocation. Each channel depresses the total value created by the industry by around \$5.0 million on average, explaining half of the total gap between the actual and optimal values in Table V. For the net value-added, their combined effect is ambiguous. Empirically, we find that the negative impact of capital misallocation dominates the positive impact of the fee policy, which leads to an overall reduction in the value extracted by investors (-\$0.6 million).

The extent of capital misallocation further explains the observed variation across investment categories. For macro funds, excess capacity is so prevalent that that funds create little value (\$2.5 million) and investors end up paying excessive fees (-\$2.3 million). In contrast, capital misallocation is milder among arbitrage funds which, combined with low fees, implies that investors extract more value than the optimal level implied by the model (\$3.7 million versus \$2.1 million).

Please insert Table VI, Figure 7, and Figure 8 here

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<sup>28</sup>In the Berk and Green (2004) model, funds can set low fees without reducing the value-added because they can costlessly index the excess capital  $w_i^e - w_i^*$ . By contrast, the decline in value-added in Table V suggests that hedge funds cannot rely on this mechanism: (i) costless indexing is not available, and (ii) investors must be compensated for the additional capital they are required to deploy at  $w_i^e$ .

## VI. Conclusion

In this paper, we measure the value created by hedge funds. The sophistication of this industry offers distinctive insights into how value is produced and shared. Hedge fund managers take long and short positions, employ leverage, and use complex trading techniques to exploit information and provide liquidity. Ex ante, these capabilities suggest that hedge funds should generate more value than mutual funds, both by uncovering more profitable opportunities and by scaling them more effectively. Their investors—primarily institutions and high-net-worth clients—are also viewed as more sophisticated. They may therefore possess greater bargaining power and a stronger ability to learn from performance and reallocate capital. Taken together, these features make hedge funds an ideal laboratory for testing rational models of active management.

We develop a novel methodology to measure hedge fund value creation. Its core is a simple specification of the value-added  $va_i = a_i E[w_{i,t}] - b_i E[w_{i,t}^2]$ , which formalizes the idea that value creation depends jointly on skill and scalability (captured by  $a_i$  and  $b_i$ ). This framework unifies the analysis of value-added by allowing us to examine its magnitude, sharing, dynamics, and optimality within a single structure. Our fund-level approach recovers the full cross-sectional distribution of value-added, revealing substantial heterogeneity that standard panel methods obscure. It also incorporates unobserved leverage differences across funds and addresses the benchmarking challenge specific to hedge funds by relying on factors that investors can replicate.

Our main results can be summarized as follows. First, most hedge funds create value by forming levered strategies that are highly profitable but difficult to scale. As a result, they do not systematically create more value than mutual funds. Value creation is also highly concentrated as a minority of hedge funds strike a unique balance between skill and scalability. Second, hedge fund investors avoid paying excessive as mutual fund investors do. However, they extract little value on average, which suggests that their greater sophistication does not translate into stronger bargaining power. Third, hedge fund investors reallocate capital in an impactful but noisy way. Whereas they are able to distinguish between unskilled and skilled funds, they tend to deploy too much capital through the fund’s lifecycle—an excess capacity that is not fully addressed as time passes by. Finally, we find that the value created by hedge funds is broadly aligned with the predictions a rational model of active management. This model nonetheless confirms that the hedge fund industry is too large as funds set fees too low and investors make persistent allocation mistakes.

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**TABLE I. Summary Statistics**

Panel A reports summary statistics for an equal-weighted portfolio of all hedge funds active at the start of each month, as well as for three investment styles: (i) equity funds (long–short, market neutral), (ii) macro funds (global macro, managed futures), and (iii) arbitrage funds (relative value, event driven). For comparison, we also provide statistics for an equal-weighted portfolio of U.S. equity mutual funds. We report the time-series mean and standard deviation of the portfolio gross and net excess returns, the time-series mean of portfolio management and performance fees, and the time-series mean of the cross-sectional mean (median) of the fund capital. Panel B summarizes the results from regressing the portfolio gross excess return on the five benchmark factors. It reports the estimated portfolio betas with respect to the market, size, value, carry, and time-series (TS) momentum factors, the relative contribution of the five factors to the average portfolio return, and the adjusted  $R^2$ . Returns and fees are expressed in percent per year. The capital is reported in million of January 1, 2000 dollars. All statistics are computed from monthly data spanning January 1994 to December 2020.

|                 | Panel A: Return & Capital Statistics |          |                      |          |               |                 |                      |        |
|-----------------|--------------------------------------|----------|----------------------|----------|---------------|-----------------|----------------------|--------|
|                 | Gross Returns (% p.a.)               |          | Net Returns (% p.a.) |          | Fees (% p.a.) |                 | Capital (\$ million) |        |
|                 | Mean                                 | Std Dev. | Mean                 | Std Dev. | Mgmt          | Perf.           | Mean                 | Median |
| All Funds       | 9.89                                 | 5.99     | 6.71                 | 5.53     | 1.42          | 1.75            | 226                  | 74     |
| Equity          | 11.15                                | 8.89     | 7.89                 | 8.22     | 1.28          | 1.98            | 177                  | 57     |
| Long/Short      | 11.71                                | 9.80     | 8.37                 | 9.06     | 1.28          | 2.07            | 168                  | 55     |
| Market Neutral  | 6.73                                 | 3.44     | 4.09                 | 3.10     | 1.32          | 1.34            | 248                  | 94     |
| Macro           | 8.94                                 | 7.89     | 5.75                 | 6.94     | 1.67          | 1.50            | 298                  | 85     |
| Global Macro    | 9.96                                 | 8.14     | 6.44                 | 7.25     | 1.71          | 1.78            | 329                  | 92     |
| Managed Futures | 8.13                                 | 8.19     | 5.20                 | 7.15     | 1.63          | 1.28            | 270                  | 79     |
| Arbitrage       | 9.16                                 | 5.52     | 6.07                 | 5.17     | 1.40          | 1.69            | 228                  | 94     |
| Event Driven    | 9.80                                 | 6.62     | 6.49                 | 6.11     | 1.48          | 1.84            | 205                  | 88     |
| Relative Value  | 8.56                                 | 5.03     | 5.64                 | 4.77     | 1.35          | 1.57            | 242                  | 98     |
| Mutual Funds    | 8.97                                 | 15.58    | 7.75                 | 15.58    | 1.22          | —               | 908                  | 245    |
|                 | Panel B: Benchmark Model             |          |                      |          |               |                 |                      |        |
|                 | Factor Exposures                     |          |                      |          |               | Model Fit       |                      |        |
|                 | Market                               | Size     | Value                | Carry    | TS Mom.       | Return Contrib. | $R^2$                |        |
| All Funds       | 0.29                                 | 0.17     | 0.02                 | 0.09     | 0.10          | 42.29           | 68.85                |        |
| Equity          | 0.46                                 | 0.30     | -0.03                | 0.08     | 0.05          | 46.00           | 83.57                |        |
| Long/Short      | 0.51                                 | 0.34     | -0.04                | 0.08     | 0.05          | 47.37           | 84.11                |        |
| Market Neutral  | 0.10                                 | 0.01     | -0.00                | 0.04     | 0.07          | 28.43           | 25.06                |        |
| Macro           | 0.09                                 | 0.04     | 0.10                 | 0.05     | 0.34          | 52.44           | 28.90                |        |
| Global Macro    | 0.15                                 | 0.07     | 0.08                 | 0.03     | 0.30          | 46.88           | 25.23                |        |
| Managed Futures | 0.04                                 | 0.01     | 0.12                 | 0.08     | 0.37          | 58.74           | 32.53                |        |
| Arbitrage       | 0.24                                 | 0.13     | 0.04                 | 0.16     | -0.01         | 32.30           | 57.98                |        |
| Event Driven    | 0.30                                 | 0.18     | 0.05                 | 0.10     | -0.01         | 32.24           | 63.36                |        |
| Relative Value  | 0.19                                 | 0.09     | 0.04                 | 0.21     | -0.02         | 32.31           | 46.09                |        |
| Mutual Funds    | 0.95                                 | 0.38     | -0.06                | 0.04     | 0.00          | 94.42           | 98.68                |        |

**TABLE II. Cross-Sectional Distribution of the Value-Added**

Panel A contains summary statistics for the cross-sectional distribution of the value-added for all funds in the population and the three investment categories (equity, macro, and arbitrage funds). It reports the cross-sectional mean and median, the proportions of funds with a negative and positive value-added, and the quantiles at 10% and 90%. Panel B contains summary statistics for the cross-sectional distribution of the skill coefficient measured as the first-dollar alpha. Panel C contains summary statistics for the cross-sectional distribution of the scale coefficient measured as the change in the gross alpha for a \$10 million increase in capital. The value-added is expressed in million per year in terms of January 1, 2000 dollars. The skill and scale coefficients are expressed in percentage per year. Figures in parentheses denote the standard deviation of each estimator.

| Panel A: Distribution of the Value-Added       |                     |                       |                 |               |                          |              |
|------------------------------------------------|---------------------|-----------------------|-----------------|---------------|--------------------------|--------------|
|                                                | Mean (\$ mio. p.a.) | Median (\$ mio. p.a.) | Proportions (%) |               | Quantiles (\$ mio. p.a.) |              |
|                                                |                     |                       | Negative        | Positive      | 10%                      | 90%          |
| All Funds                                      | 5.67 (1.46)         | 1.77 (0.52)           | 31.59 (2.63)    | 68.41 (2.63)  | -5.52 (0.63)             | 21.55 (0.67) |
| Equity                                         | 4.38 (1.70)         | 1.36 (0.58)           | 32.96 (3.77)    | 67.04 (3.77)  | -4.06 (0.77)             | 14.30 (1.23) |
| Macro                                          | 1.75 (2.09)         | 0.14 (0.79)           | 48.34 (3.33)    | 51.66 (3.33)  | -12.95 (1.84)            | 18.70 (1.36) |
| Arbitrage                                      | 9.77 (2.29)         | 3.85 (0.90)           | 18.53 (2.97)    | 81.47 (2.97)  | -2.18 (0.77)             | 29.24 (1.68) |
| Panel B: Distribution of the Skill Coefficient |                     |                       |                 |               |                          |              |
|                                                | Mean (% p.a.)       | Median (% p.a.)       | Proportions (%) |               | Quantiles (% p.a.)       |              |
|                                                |                     |                       | Negative        | Positive      | 10%                      | 90%          |
| All Funds                                      | 12.50 (6.06)        | 10.47 (4.51)          | 13.63 (4.26)    | 86.37 (4.26)  | -1.54 (1.49)             | 28.91 (3.78) |
| Equity                                         | 13.20 (7.76)        | 11.04 (7.33)          | 12.83 (11.84)   | 87.17 (11.84) | -1.36 (4.69)             | 30.21 (4.15) |
| Macro                                          | 11.45 (4.88)        | 9.04 (4.25)           | 19.02 (7.06)    | 80.98 (7.06)  | -3.82 (2.38)             | 28.26 (4.47) |
| Arbitrage                                      | 12.48 (7.76)        | 10.84 (5.87)          | 10.75 (5.12)    | 89.25 (5.12)  | -0.34 (2.41)             | 28.12 (6.57) |
| Panel C: Distribution of the Scale Coefficient |                     |                       |                 |               |                          |              |
|                                                | Mean (% p.a.)       | Median (% p.a.)       | Proportions (%) |               | Quantiles (% p.a.)       |              |
|                                                |                     |                       | Negative        | Positive      | 10%                      | 90%          |
| All Funds                                      | 1.47 (0.78)         | 0.40 (0.22)           | 17.92 (5.82)    | 82.08 (5.82)  | -0.20 (0.17)             | 4.41 (0.36)  |
| Equity                                         | 1.94 (1.18)         | 0.63 (0.56)           | 18.58 (10.26)   | 81.42 (10.26) | -0.25 (0.43)             | 5.84 (0.65)  |
| Macro                                          | 1.45 (0.45)         | 0.40 (0.08)           | 15.06 (0.41)    | 84.94 (0.41)  | -0.13 (0.52)             | 3.99 (0.43)  |
| Arbitrage                                      | 0.99 (0.77)         | 0.26 (0.24)           | 19.19 (7.50)    | 80.81 (7.50)  | -0.24 (0.19)             | 3.23 (0.41)  |



**TABLE III. Analysis of the Most Valuable Funds**

This table provides summary statistics for the top decile of funds sorted on estimated value-added in the population and the three investment categories (equity, macro, and arbitrage funds). Panel A reports the cross-sectional mean (median) of the value-added, the average fund capital, and the corresponding skill and scale coefficients for both the top funds and all funds. The skill coefficient is measured as the first-dollar alpha and the scale coefficient as the change in the gross alpha associated with a \$10 million increase in capital. Figures in parentheses denote the cross-sectional mean (median) rank of the coefficients for the top funds (1 = low, 10 = high). Panel B reports the cross-sectional mean (median) of the value-added after controlling for the illiquidity, betting-against-beta (BAB), and variance factors, along with the difference relative to the baseline value-added. The value-added (capital) is expressed in million per year (in million) in terms of January 1, 2000 dollars. The skill and scale coefficients are expressed in percentage per year.

| Panel A: Value-Added and Other Characteristics |                            |       |                   |       |                                          |       |                |       |
|------------------------------------------------|----------------------------|-------|-------------------|-------|------------------------------------------|-------|----------------|-------|
|                                                | Value-Added (\$ mio. p.a.) |       | Capital (\$ mio.) |       | Skill (% p.a.)                           |       | Scale (% p.a.) |       |
|                                                | Top                        | All   | Top               | All   | Top                                      | All   | Top            | All   |
| Cross-Sectional Average                        |                            |       |                   |       |                                          |       |                |       |
| All Funds                                      | 46.85                      | 5.67  | 714               | 225   | 17.98 (7)                                | 12.5  | 0.13 (7)       | 1.47  |
| Equity                                         | 35.45                      | 4.38  | 546               | 172   | 15.73 (6)                                | 13.2  | 0.09 (8)       | 1.94  |
| Macro                                          | 42.05                      | 1.75  | 805               | 285   | 17.67 (7)                                | 11.45 | 0.22 (7)       | 1.45  |
| Arbitrage                                      | 58.70                      | 9.77  | 769               | 239   | 20.57 (7)                                | 12.48 | 0.16 (7)       | 0.99  |
| Cross-Sectional Median                         |                            |       |                   |       |                                          |       |                |       |
| All Funds                                      | 36.37                      | 1.77  | 562               | 96    | 15.04 (7)                                | 10.47 | 0.09 (8)       | 0.40  |
| Equity                                         | 27.69                      | 1.36  | 418               | 73    | 11.62 (6)                                | 11.04 | 0.07 (8)       | 0.63  |
| Macro                                          | 30.47                      | 0.14  | 655               | 103   | 14.96 (7)                                | 9.04  | 0.07 (8)       | 0.40  |
| Arbitrage                                      | 45.45                      | 3.85  | 646               | 120   | 15.90 (7)                                | 10.84 | 0.09 (8)       | 0.26  |
| Panel B: Impact of Non-Replicable Strategies   |                            |       |                   |       |                                          |       |                |       |
|                                                | Value-Added (\$ mio. p.a.) |       |                   |       | Difference With Base Case (\$ mio. p.a.) |       |                |       |
|                                                | Liquidity                  | BAB   | Variance          | All   | Liquidity                                | BAB   | Variance       | All   |
| Cross-Sectional Average                        |                            |       |                   |       |                                          |       |                |       |
| All Funds                                      | 46.78                      | 42.70 | 38.53             | 38.64 | 0.07                                     | 4.15  | 8.32           | 8.21  |
| Equity                                         | 35.66                      | 31.55 | 29.06             | 29.00 | -0.21                                    | 3.89  | 6.39           | 6.45  |
| Macro                                          | 42.02                      | 40.51 | 40.75             | 41.00 | 0.03                                     | 1.54  | 1.30           | 1.05  |
| Arbitrage                                      | 58.21                      | 52.62 | 44.66             | 44.82 | 0.49                                     | 6.08  | 14.04          | 13.88 |
| Cross-Sectional Median                         |                            |       |                   |       |                                          |       |                |       |
| All Funds                                      | 36.57                      | 33.78 | 30.02             | 30.42 | -0.20                                    | 2.58  | 6.35           | 5.95  |
| Equity                                         | 28.68                      | 26.41 | 25.60             | 24.21 | -0.99                                    | 1.28  | 2.09           | 3.48  |
| Macro                                          | 33.71                      | 33.04 | 33.64             | 31.22 | -3.24                                    | -2.57 | -3.16          | -0.75 |
| Arbitrage                                      | 48.75                      | 43.24 | 37.07             | 37.62 | -3.30                                    | 2.22  | 8.38           | 7.83  |

**TABLE IV. Cross-Sectional Distribution of the Net Value-Added**

Panel A contains summary statistics for the cross-sectional distribution of the net value-added to investors for all funds in the population and the three investment categories (equity, macro, and arbitrage funds). It reports the cross-sectional mean and median, the proportions of funds with a negative and positive value-added, and the quantiles at 10% and 90%. Panel B contains summary statistics for the cross-sectional distribution of the net skill coefficient measured as the first-dollar alpha. Panel C contains summary statistics for the cross-sectional distribution of the net scale coefficient measured as the change in the net alpha for a \$10 million increase in capital. The value-added is expressed in million per year in terms of January 1, 2000 dollars. The skill and scale coefficients are expressed in percentage per year. Figures in parentheses denote the standard deviation of each estimator.

| Panel A: Distribution of the Net Value-Added       |                     |                       |                 |               |                          |              |
|----------------------------------------------------|---------------------|-----------------------|-----------------|---------------|--------------------------|--------------|
|                                                    | Mean (\$ mio. p.a.) | Median (\$ mio. p.a.) | Proportions (%) |               | Quantiles (\$ mio. p.a.) |              |
|                                                    |                     |                       | Negative        | Positive      | 10%                      | 90%          |
| All Funds                                          | 0.46 (1.32)         | 0.13 (0.48)           | 48.15 (3.09)    | 51.85 (3.09)  | -10.35 (0.79)            | 11.75 (0.79) |
| Equity                                             | 0.18 (1.50)         | -0.07 (0.50)          | 51.44 (3.92)    | 48.56 (3.92)  | -7.36 (1.17)             | 7.43 (0.79)  |
| Macro                                              | -3.86 (1.84)        | -1.24 (0.94)          | 63.87 (3.96)    | 36.13 (3.96)  | -18.41 (2.17)            | 9.61 (1.27)  |
| Arbitrage                                          | 3.75 (2.14)         | 1.15 (0.76)           | 33.77 (3.99)    | 66.23 (3.99)  | -5.63 (0.94)             | 16.67 (1.65) |
| Panel B: Distribution of the Net Skill Coefficient |                     |                       |                 |               |                          |              |
|                                                    | Mean (% p.a.)       | Median (% p.a.)       | Proportions (%) |               | Quantiles (% p.a.)       |              |
|                                                    |                     |                       | Negative        | Positive      | 10%                      | 90%          |
| All Funds                                          | 9.21 (5.54)         | 7.45 (4.02)           | 18.20 (6.67)    | 81.80 (6.67)  | -3.30 (1.34)             | 23.36 (3.16) |
| Equity                                             | 9.90 (7.16)         | 8.02 (6.55)           | 18.17 (15.00)   | 81.83 (15.00) | -3.12 (4.29)             | 24.63 (3.58) |
| Macro                                              | 8.21 (4.35)         | 6.53 (3.72)           | 23.77 (8.96)    | 76.23 (8.96)  | -5.39 (2.31)             | 22.43 (3.50) |
| Arbitrage                                          | 9.16 (7.20)         | 7.68 (5.11)           | 14.36 (8.01)    | 85.64 (8.01)  | -1.73 (2.31)             | 22.28 (5.85) |
| Panel C: Distribution of Net Scale Coefficient     |                     |                       |                 |               |                          |              |
|                                                    | Mean (% p.a.)       | Median (% p.a.)       | Proportions (%) |               | Quantiles (% p.a.)       |              |
|                                                    |                     |                       | Negative        | Positive      | 10%                      | 90%          |
| All Funds                                          | 1.35 (0.71)         | 0.36 (0.21)           | 17.40 (6.04)    | 82.60 (6.04)  | -0.17 (0.16)             | 4.07 (0.30)  |
| Equity                                             | 1.80 (1.09)         | 0.57 (0.51)           | 17.35 (10.31)   | 82.65 (10.31) | -0.16 (0.41)             | 5.24 (0.63)  |
| Macro                                              | 1.31 (0.42)         | 0.38 (0.07)           | 14.58 (10.95)   | 85.42 (10.95) | -0.10 (0.40)             | 3.44 (0.44)  |
| Arbitrage                                          | 0.91 (0.71)         | 0.23 (0.21)           | 19.41 (7.59)    | 80.59 (7.59)  | -0.21 (0.18)             | 2.92 (0.39)  |

**TABLE V. Comparison of the Actual and Optimal Value-Added Measures**

This table reports the results of the normative analysis of the value-added measures for all funds in the population and the three investment categories (equity, macro, and arbitrage funds). It reports the cross-sectional mean (median) of the actual and optimal values for the value-added and net value-added. It also reports the difference and ratio of these cross-sectional statistics. All value-added measures are expressed in million per year in January 1, 2000 terms.

|                         | Value-Added (\$ mio. p.a.) |         |        |           | Net Value-Added (\$ mio. p.a.) |         |       |           |
|-------------------------|----------------------------|---------|--------|-----------|--------------------------------|---------|-------|-----------|
|                         | Actual                     | Optimal | Diff.  | Ratio (%) | Actual                         | Optimal | Diff. | Ratio (%) |
| Cross-Sectional Average |                            |         |        |           |                                |         |       |           |
| All Funds               | 5.59                       | 15.41   | -9.82  | 36.29     | 1.01                           | 1.64    | -0.63 | 61.84     |
| Equity                  | 3.84                       | 11.20   | -7.37  | 34.25     | 0.43                           | 1.19    | -0.76 | 36.23     |
| Macro                   | 2.47                       | 15.76   | -13.30 | 15.64     | -2.32                          | 1.63    | -3.95 | -142.23   |
| Arbitrage               | 9.43                       | 19.67   | -10.24 | 47.93     | 3.73                           | 2.13    | 1.60  | 175.49    |
| Cross-Sectional Median  |                            |         |        |           |                                |         |       |           |
| All Funds               | 1.73                       | 6.36    | -4.63  | 27.22     | 0.28                           | 0.79    | -0.50 | 35.83     |
| Equity                  | 1.36                       | 4.88    | -3.51  | 27.99     | 0.04                           | 0.52    | -0.48 | 7.79      |
| Macro                   | 0.33                       | 5.99    | -5.66  | 5.47      | -0.76                          | 0.76    | -1.52 | -100.32   |
| Arbitrage               | 3.61                       | 8.76    | -5.15  | 41.25     | 1.06                           | 1.25    | -0.19 | 84.91     |

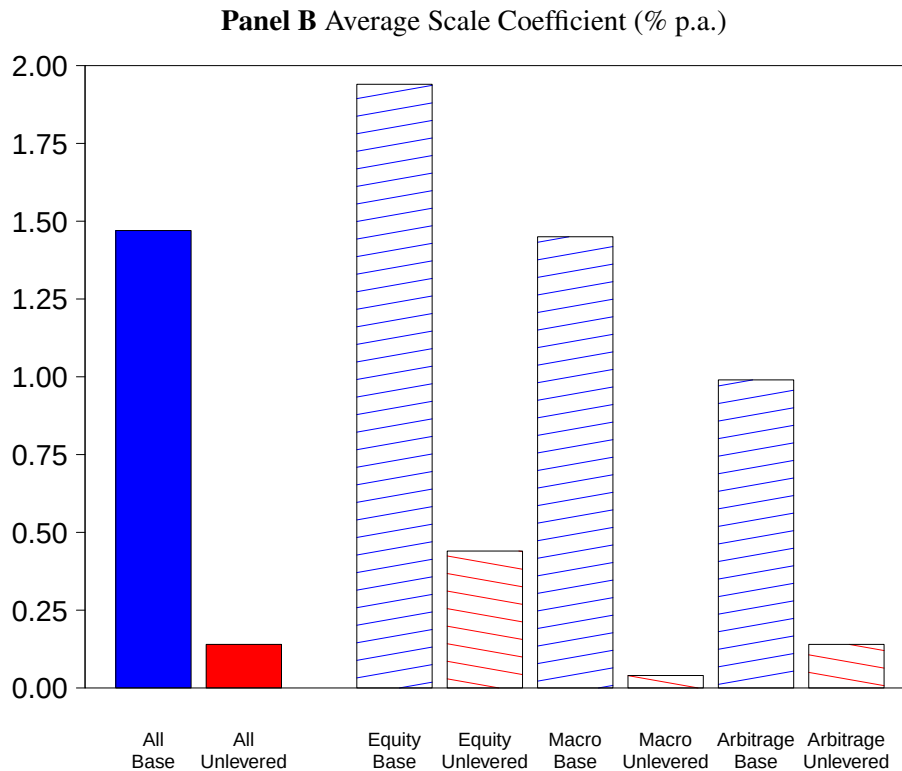
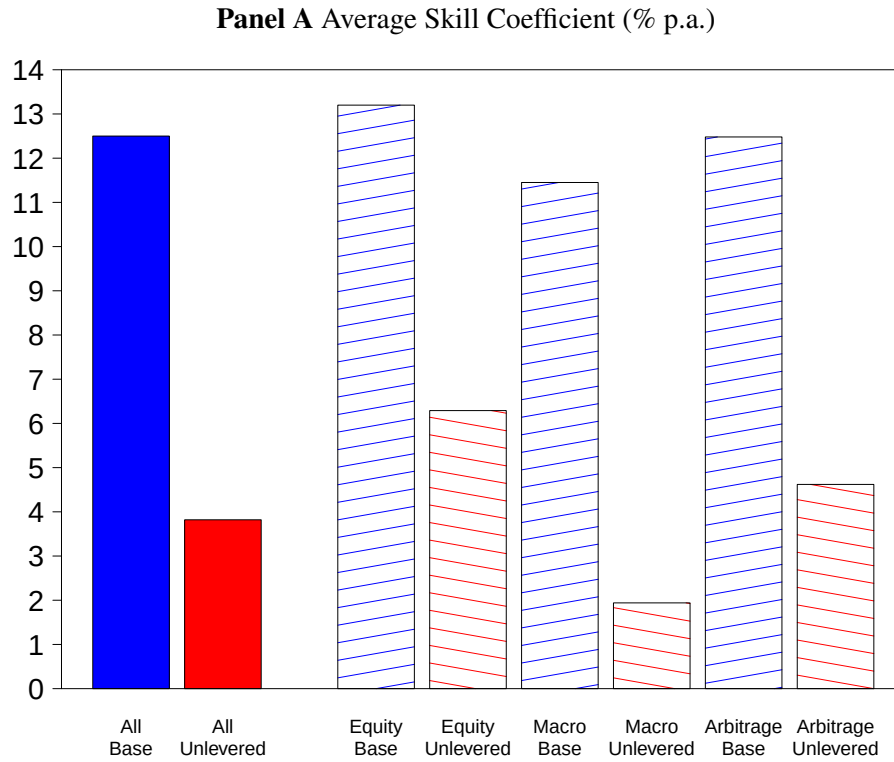
**TABLE VI. Fee Policy and Capital Misallocation**

This table quantifies the effects of the fee policy and capital misallocation on the value-added measures for all funds and the three investment categories (equity, macro, and arbitrage). Panel A examines the fee policy by funds. It reports the cross-sectional mean (median) of the actual and optimal fee rates, along with their differences. It then shows the implied consequences for the capital and value-added measures, reporting the mean (median) of the equilibrium and optimal values predicted by the model and their differences. Panel B examines the capital misallocation by investors. It reports the mean (median) of the actual and equilibrium capital levels, together with their differences. It then shows the implied consequences for the value-added measures reporting the mean (median) of the actual and equilibrium values. Fees are expressed in percent per year. The value-added measures (capital) are expressed in million per year (million) of January 1, 2000 dollars.

| Panel A: Fee Policy by Funds            |        |        |       |                   |         |                            |                            |         |                                |                                |         |       |
|-----------------------------------------|--------|--------|-------|-------------------|---------|----------------------------|----------------------------|---------|--------------------------------|--------------------------------|---------|-------|
| Fee Policy (% p.a.)                     |        |        |       | Implications For  |         |                            |                            |         |                                |                                |         |       |
|                                         |        |        |       | Capital (\$ mio.) |         |                            | Value-Added (\$ mio. p.a.) |         |                                | Net Value-Added (\$ mio. p.a.) |         |       |
|                                         | Chosen | Target | Diff. | Equilib.          | Optimal | Diff.                      | Equilib.                   | Optimal | Diff.                          | Equilib.                       | Optimal | Diff. |
| Cross-Sectional Average                 |        |        |       |                   |         |                            |                            |         |                                |                                |         |       |
| All Funds                               | 3.10   | 8.53   | -5.44 | 245               | 164     | 81                         | 10.59                      | 15.41   | -4.82                          | 2.45                           | 1.64    | 0.81  |
| Equity                                  | 3.18   | 8.90   | -5.71 | 173               | 119     | 54                         | 7.66                       | 11.20   | -3.54                          | 1.73                           | 1.19    | 0.54  |
| Macro                                   | 3.06   | 8.61   | -5.55 | 246               | 163     | 83                         | 10.78                      | 15.76   | -4.98                          | 2.46                           | 1.63    | 0.83  |
| Arbitrage                               | 3.02   | 8.10   | -5.07 | 321               | 213     | 109                        | 13.59                      | 19.67   | -6.08                          | 3.21                           | 2.13    | 1.09  |
| Cross-Sectional Median                  |        |        |       |                   |         |                            |                            |         |                                |                                |         |       |
| All Funds                               | 3.11   | 7.01   | -3.90 | 113               | 79      | 35                         | 4.37                       | 6.36    | -1.99                          | 1.13                           | 0.79    | 0.35  |
| Equity                                  | 3.22   | 7.62   | -4.40 | 78                | 52      | 27                         | 3.19                       | 4.88    | -1.69                          | 0.78                           | 0.52    | 0.27  |
| Macro                                   | 2.93   | 6.81   | -3.88 | 105               | 76      | 29                         | 4.03                       | 5.99    | -1.96                          | 1.05                           | 0.76    | 0.29  |
| Arbitrage                               | 3.13   | 6.61   | -3.48 | 172               | 125     | 48                         | 6.63                       | 8.76    | -2.13                          | 1.72                           | 1.25    | 0.48  |
| Panel B: Capital Misallocation by Funds |        |        |       |                   |         |                            |                            |         |                                |                                |         |       |
| Capital Misallocation (\$ mio.)         |        |        |       |                   |         | Implications For           |                            |         |                                |                                |         |       |
|                                         |        |        |       |                   |         | Value-Added (\$ mio. p.a.) |                            |         | Net Value-Added (\$ mio. p.a.) |                                |         |       |
|                                         | Chosen | Target | Diff. |                   |         | Actual                     | Equilib.                   | Diff.   | Actual                         | Equilib.                       | Diff.   |       |
| Cross-Sectional Average                 |        |        |       |                   |         |                            |                            |         |                                |                                |         |       |
| All Funds                               |        |        |       | 316               | 245     | 71                         | 5.59                       | 10.59   | -5.00                          | 1.01                           | 2.45    | -1.44 |
| Equity                                  |        |        |       | 231               | 173     | 58                         | 3.84                       | 7.66    | -3.82                          | 0.43                           | 1.73    | -1.30 |
| Macro                                   |        |        |       | 339               | 246     | 93                         | 2.47                       | 10.78   | -8.31                          | -2.32                          | 2.46    | -4.78 |
| Arbitrage                               |        |        |       | 392               | 321     | 71                         | 9.43                       | 13.59   | -4.16                          | 3.73                           | 3.21    | 0.51  |
| Cross-Sectional Median                  |        |        |       |                   |         |                            |                            |         |                                |                                |         |       |
| All Funds                               |        |        |       | 158               | 113     | 45                         | 1.73                       | 4.37    | -2.63                          | 0.28                           | 1.13    | -0.85 |
| Equity                                  |        |        |       | 106               | 78      | 27                         | 1.36                       | 3.19    | -1.82                          | 0.04                           | 0.78    | -0.74 |
| Macro                                   |        |        |       | 159               | 105     | 54                         | 0.33                       | 4.03    | -3.70                          | -0.76                          | 1.05    | -1.82 |
| Arbitrage                               |        |        |       | 240               | 172     | 68                         | 3.61                       | 6.63    | -3.02                          | 1.06                           | 1.72    | -0.66 |

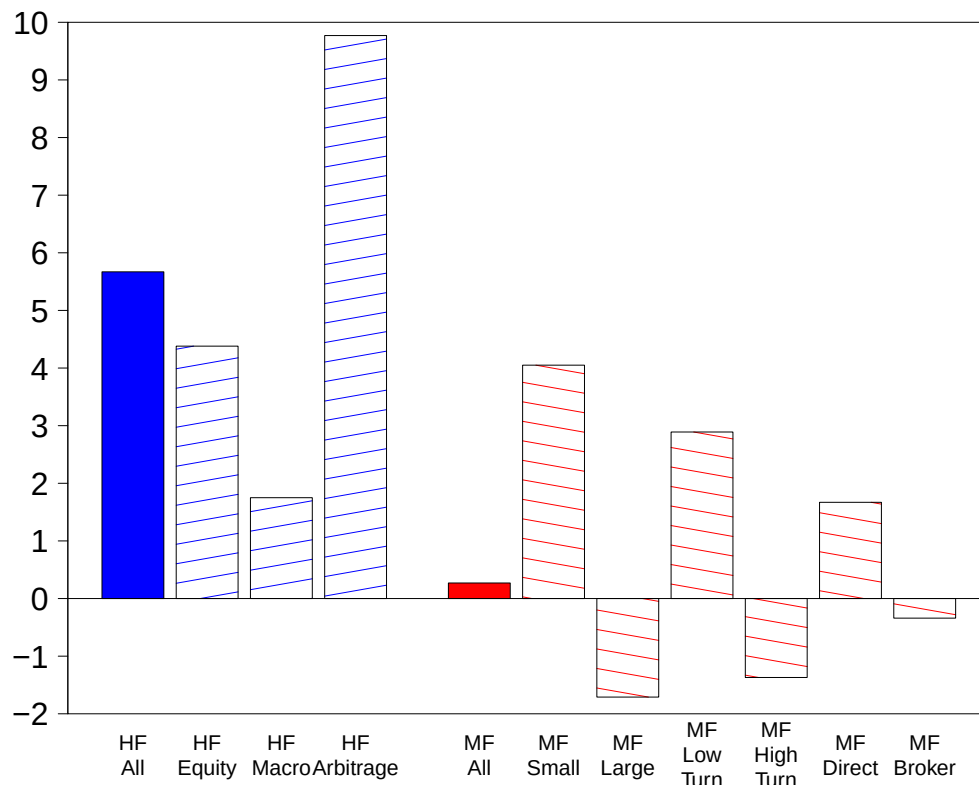
### Figure 1. Impact of Leverage on the Skill and Scale Coefficients

Panel A reports the average skill coefficient and its unlevered version for all funds in the population and the three investment categories (equity, macro, and arbitrage funds). The skill coefficient is measured as the first-dollar alpha. Panel B reports the average scale coefficient and its unlevered version. The scale coefficient is measured as the change in the gross alpha for a \$10 million increase in capital. Both coefficients are expressed in percentage per year.



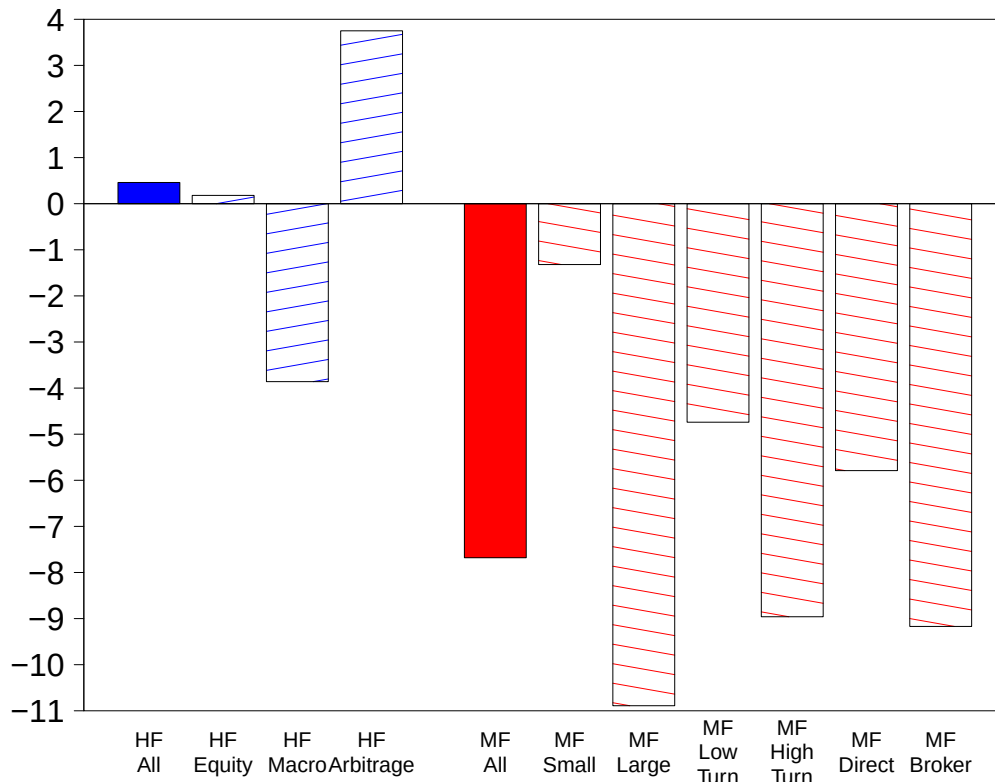
**Figure 2. Comparison of the Value-Added With Mutual Funds**

This figure compares the average value-added for hedge funds and mutual funds. The leftmost bars show the average values for all hedge funds in the population and the three investment categories (equity, macro, and arbitrage funds). The rightmost bars show the average values for all mutual funds in the population and the six fund groups (small/large cap, low-/high-turnover, direct-/broker sold). The value-added is expressed in million per year in terms of January 1, 2000 dollars.



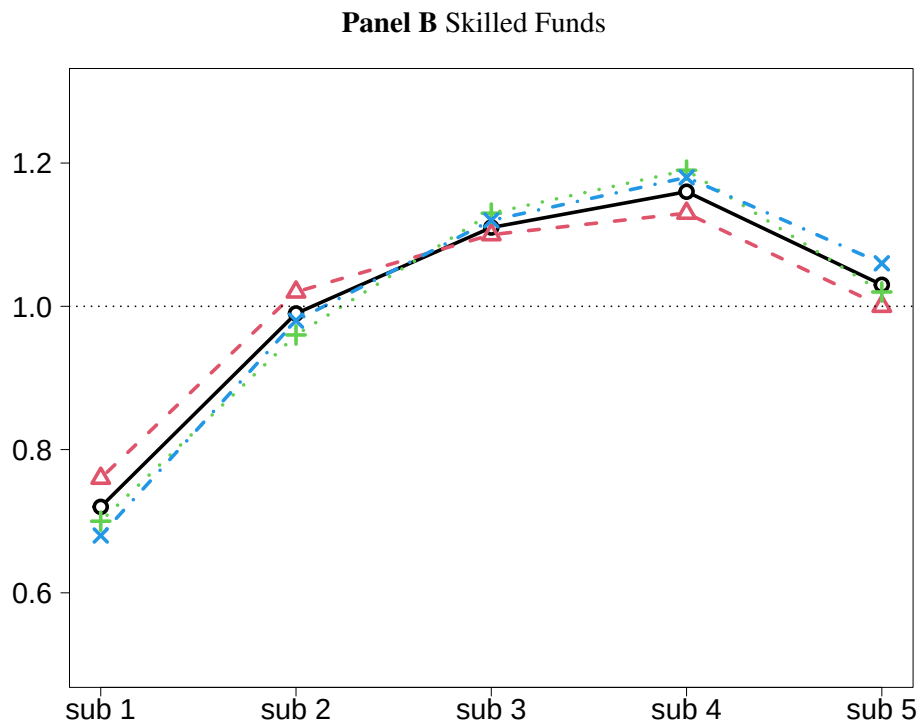
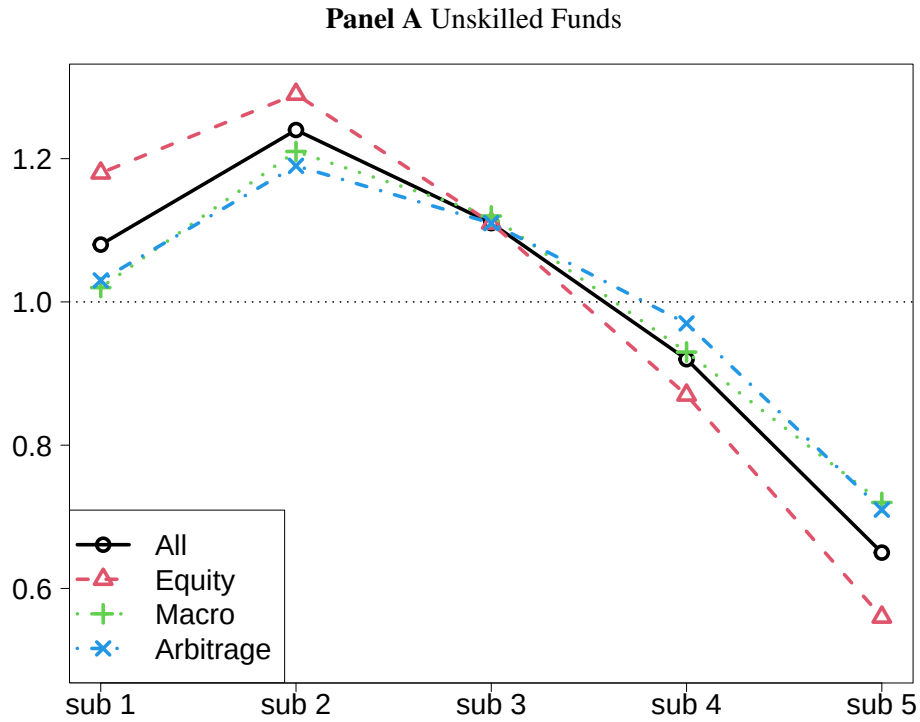
### Figure 3. Comparison of the Net Value-Added With Mutual Funds

This figure compares the average net value-added for hedge funds and mutual funds. The leftmost bars show the average values for all hedge funds in the population and the three investment categories (equity, macro, and arbitrage funds). The rightmost bars show the average values for all mutual funds in the population and the six fund groups (small/large cap, low-/high-turnover, direct-/broker sold). The net value-added is expressed in million per year in terms of January 1, 2000 dollars.



#### Figure 4. Evolution of the Subperiod Capital

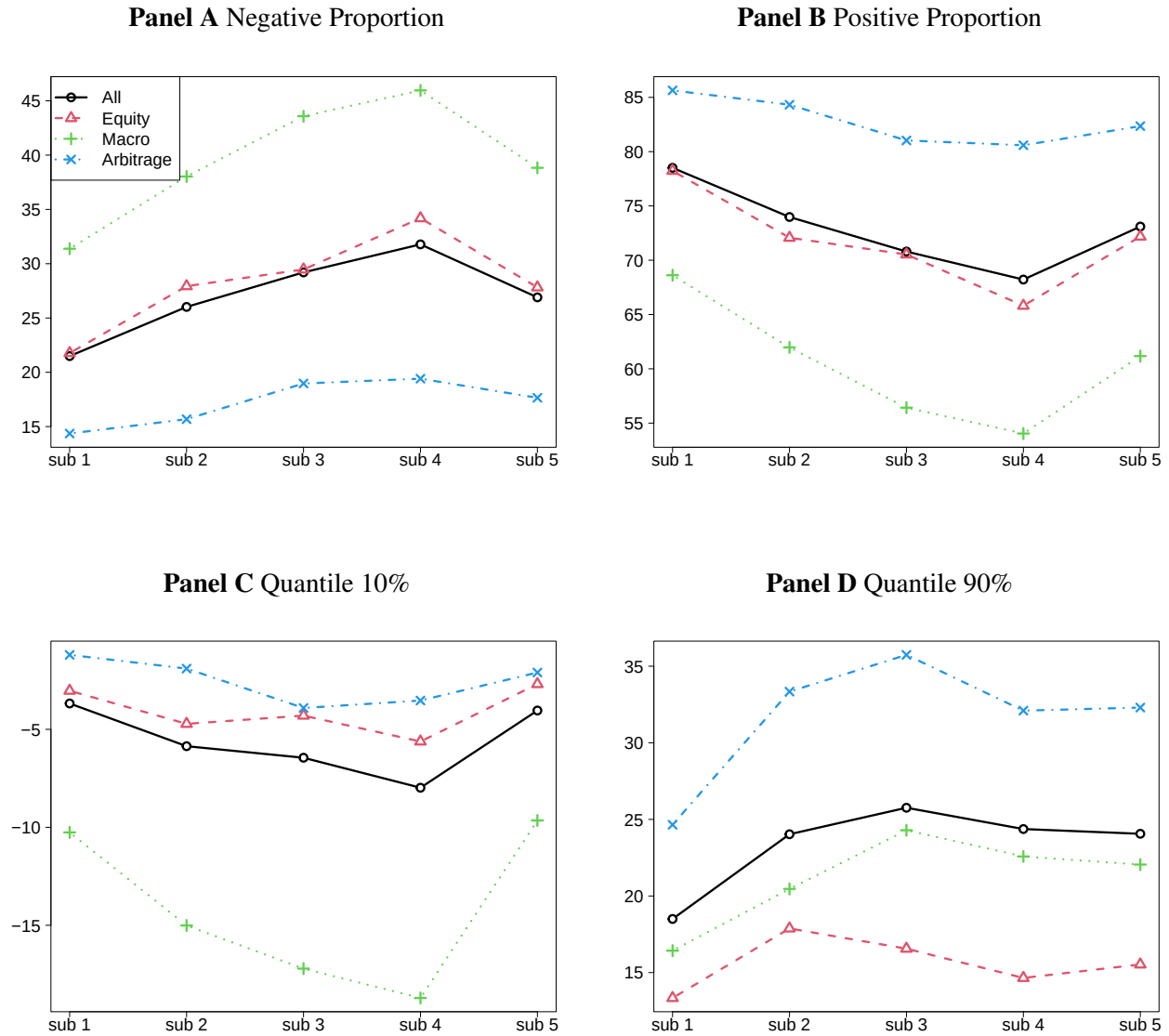
This figure examines the evolution of capital over the fund's lifecycle for all funds in the population and the three investment categories (equity, macro, and arbitrage funds). For each fund, we split its full sample of observations into five equal-sized subperiods and compute the ratio of average capital in each subperiod to its full-sample average. Panel A plots the evolution of the average ratio across unskilled funds, defined as those with a negative net-of-fee skill coefficient ( $\hat{a}_i^{net} < 0$ ). Panel B plots the evolution of the average ratio across skilled funds, defined as those with a positive net-of-fee skill coefficient ( $\hat{a}_i^{net} > 0$ ). The subperiod capital is expressed in million in terms of January 1, 2000 dollars.





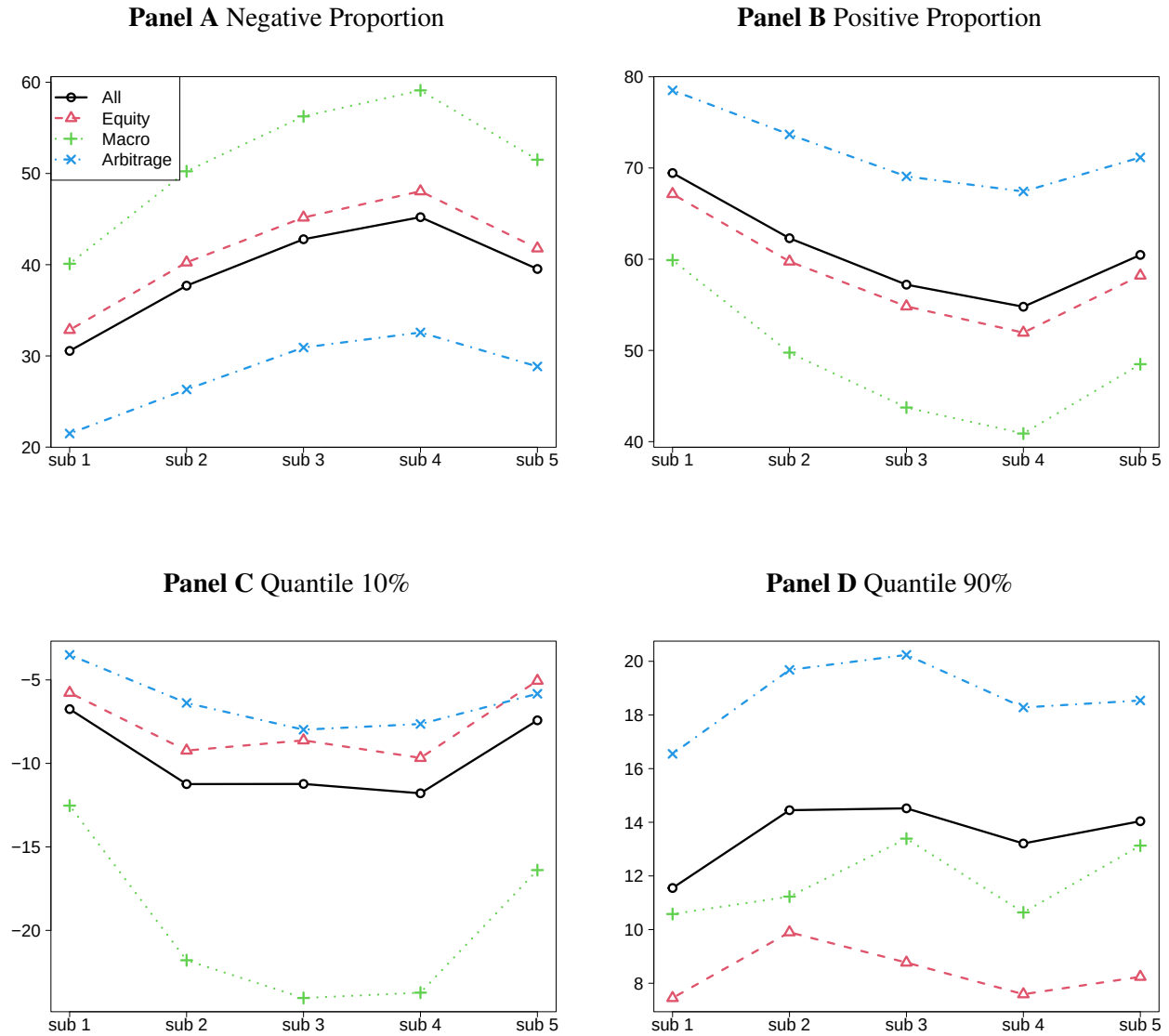
### Figure 5. Evolution of the Subperiod Value-Added

This figure examines the evolution of the value-added over the fund's lifecycle for all funds in the population and the three investment categories (equity, macro, and arbitrage funds). For each fund, we split its full sample of observations into five equal-sized subperiods and compute the value-added in each subperiod. Panel A and B plot the evolution of the proportion of funds with negative and positive subperiod value-added. Panels C and D plot the evolution of the quantiles at 10% and 90%. The subperiod value-added is expressed in million per year in terms of January 1, 2000 dollars.



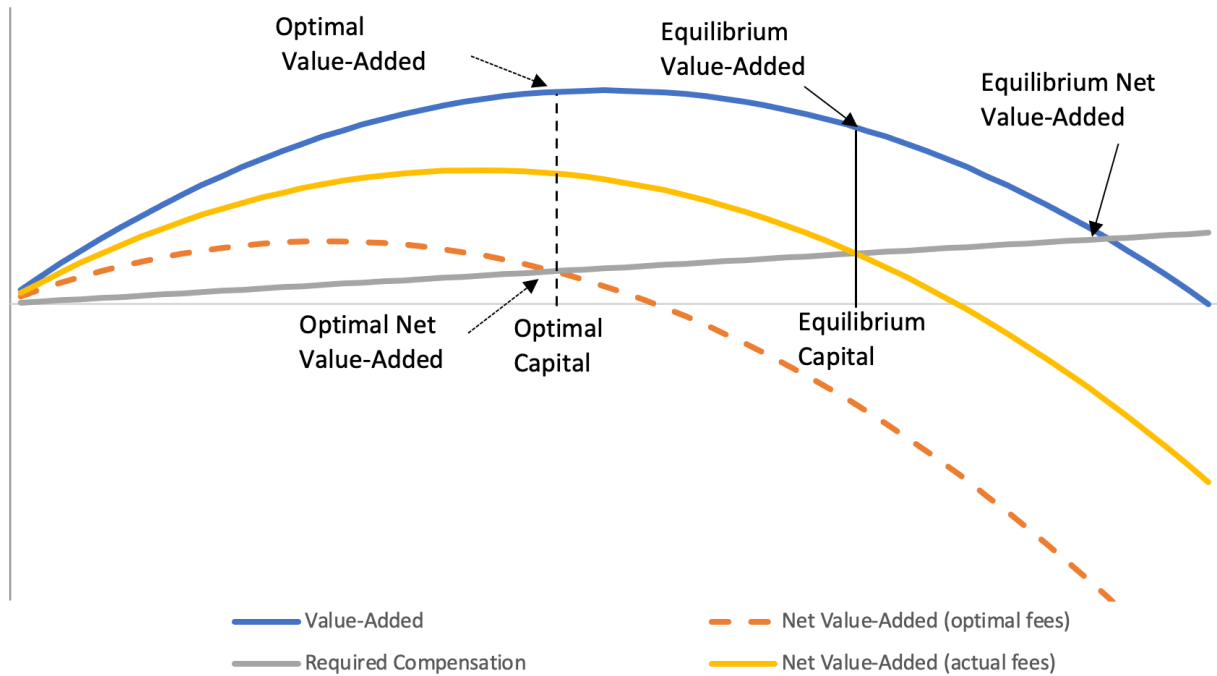
### Figure 6. Evolution of the Subperiod Net Value-Added

This figure examines the evolution of the net value-added over the fund's lifecycle for all funds in the population and the three investment categories (equity, macro, and arbitrage funds). For each fund, we split its full sample of observations into five equal-sized subperiods and compute the net value-added in each subperiod. Panel A and B plot the evolution of the proportion of funds with negative and positive subperiod net value-added. Panels C and D plot the evolution of the quantiles at 10% and 90%. The subperiod net value-added is expressed in million per year in terms of January 1, 2000 dollars.



### Figure 7. Fee Policy - Impact of Low Fees

This figure illustrates how the fee policy affects the equilibrium implied by the model. When a fund sets fees below the optimal level, investors allocate more capital than is optimal. Consequently, the equilibrium value-added falls below its optimal level, while the equilibrium net value-added rises above it.



### Figure 8. Capital Misallocation - Impact of Excess Capacity

This figure illustrates how capital misallocation affects the actual value-added measures. When investors allocate more capital than the equilibrium level implied by the model, both the gross and net value-added fall below their equilibrium levels.

