Value Creation in the Hedge Fund Industry[⋆]

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Abstract

We develop an approach to jointly study four dimensions of hedge fund value creation—its drivers, split, dynamics, and optimality. This approach captures the large fund heterogeneity and controls for hedge fund complexities. We find that most funds add value via their unique skills but face strong scalability constraints—a feature that prevents them from systematically dominating mutual funds. Hedge fund investors slowly improve their fund capital allocation over time, which suggests an impactful but noisy learning process. Despite these efforts, they extract a modest fraction of the total value. These findings fit reasonably well with an equilibrium model featuring funds with heterogeneous skill and scalability and investors with limited bargaining power.

Keywords: Hedge funds, Hedge fund investors, Value-added, Capital allocation

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I. Introduction

The analysis of the active fund industry is a central topic in financial economics. It determines whether active funds create value from their unique investment skills, which, in turn, sheds light on their role in the economy. As discussed by Pedersen (2018), the fund industry may improve the allocation of resources by making asset prices more informative. This analysis also determines whether investors extract some of the value created by funds and whether they reallocate capital efficiently over time—an important experiment for understanding how agents make financial decisions (*e.g.*, Campbell and Ramadorai, 2025; Shiller, 2005). Finally, it determines whether the value created by active funds is consistent with equilibrium models, thus contributing to the debate on the optimal size of the financial sector (*e.g.*, Cochrane, 2013; Greenwood and Scharfstein, 2013).

In this paper, we focus on the value created by hedge funds—an industry with more than $6 trillion under management (Barth et al., 2021). There are several dimensions along which this industry is unique. First, hedge funds trade aggressively to exploit their information and provide liquidity (*e.g.*, Getmansky, Lee, and Lo, 2015; Pedersen, 2015). As a result of this trading activity, they may extract substantial value from capital markets. Second, hedge fund managers are known to follow complex strategies in specialized markets. The profile of these strategies in terms of profitability and scalability is likely to depart substantially from traditional long-only strategies. Third, hedge fund investors plausibly have sufficient bargaining power to extract value from funds (*e.g.*, Gârleanu and Pedersen, 2018; Glode and Green, 2011). Fourth, these investors are deemed sophisticated as evidenced by the light regulation on hedge funds (Lhabitant, 2007). Under this premise, we expect them to identify funds with high-value potential. Studying capital allocation across hedge funds provides a natural test of rational models of active management.

We measure value creation using the value-added of Berk and van Binsbergen (2015). It is defined for each fund as $va_i = E[\alpha_{i,t-1} w_{i,t-1}]$, where $\alpha_{i,t-1}$ is the gross alpha relative to the benchmark assets available to investors and $w_{i,t-1}$ is the equity capital. Intuitively, va_i mirrors the concept of net present value (NPV)—a fund with a positive va_i creates value for investors, just like an investment project with a positive NPV. Deducting fees, we can then measure the net value extracted by investors as $va_i^{\text{net}} = E[\alpha_{i,t-1}^{\text{net}} w_{i,t-1}]$, where $\alpha_{i,t-1}^{\text{net}}$ is the net alpha. In a world where hedge funds face scalability constraints, va_i^{net} is poorly measured by the average net alpha $E[\alpha_{i,t-1}^{\text{net}}]$ commonly used in previous studies on fund performance.

The cornerstone of our approach is the specification of the fund value-added as $va_i = a_i E[w_{i,t-1}] - b_i E[w_{i,t-1}^2]$ with $\alpha_{i,t-1} = a_i - b_i w_{i,t-1}$. This expression formalizes the intuition that the value created by the fund ultimately depends on two drivers—its skill to identify profitable ideas (captured by the first-dollar alpha a_i) and its exposure to scalability constraints (captured by the scale coefficient b_i). While our parametrized va_i is numerically equivalent to the non-parametric estimate proposed by Berk and van Binsbergen (2015), it allows us to study the value-added along four dimensions: (i) its drivers (skill versus scalability), (ii) its split with investors, (iii) its dynamics as investors learn and reallocate capital over time, and (iv) its optimality under a rational equilibrium model inspired by Berk and Green (2004).[1]

Armed with this specification, we develop a new approach for inferring the entire value-added distribution across funds. Extending the analysis beyond the average allows us to capture the suspected large heterogeneity in skill and scalability. Our approach tailored to hedge funds departs from the one proposed by Barras, Gagliardini, and Scaillet (2022; BGS hereafter) for mutual funds. First, we show how to control for the unobserved variation in leverage across funds via the fund-specific coefficients a_i and b_i. Second, we account for the complexity of benchmarking hedge funds as they follow alternative strategies that investors are unlikely to replicate (Agarwal, Green, and Ren, 2018; Cochrane, 2013). We show theoretically that these non-replicable strategies not only contribute to the value-added, but also produce cross-fund dependencies that substantially increase estimation noise.

We measure value creation using monthly data on 2,971 hedge funds. We carefully aggregate four databases and mitigate well-known biases (backfill, selectivity, and survivorship). The estimation of the value-added distribution requires as main inputs the coefficients $\hat{a}_i$, $\hat{b}_i$, which are obtained from a time-series regression of the gross return of each fund on its lagged capital and the benchmark factor returns. In our baseline analysis, we benchmark hedge funds using five factors: market, size, value, carry, and time-series (TS) momentum.[2] The rationale for this choice is based

[1]To the best of our knowledge, none of these four dimensions are examined in the hedge fund literature. The vast majority of papers focus exclusively on the average net alpha. A non-exhaustive list includes Avramov, Barras, and Kosowski (2013), Buraschi, Kosowski, and Trojani (2014), Capocci and Hübner (2004), Chen, Cliff, and Zhao (2017), Diez de los Rios and Garcia (2010), Kosowski, Naik, and Teo (2007)). More recently, Ling, Satchell, and Yao (2023) use the methodology of Berk and van Binsbergen (2015) to examine other aspects of hedge fund value creation, namely its persistence and its dependence on fee types (management versus performance fees).

[2]The market, size, and value factors are constructed by Cremers, Petajisto, and Zitzewitz (2012) using the SP500 and Russell indices. The carry and TS momentum factors are constructed by Koijen et al. (2018) and Moskowitz et al. (2012) for four asset classes (equity, bond, commodity, and currency).

on relevance and replicability—these factors capture popular strategies followed by hedge funds (Ardia et al., 2024) and are relatively easy to replicate by investors (Jorion, 2021).

Our analysis over the period 1994–2020 reveals that hedge funds create substantial value. More than 65% of them exhibit a positive value-added equal to \$4.7 mio. per year on average. We also confirm that the cross-sectional variation in value-added is substantial. Forming investment categories partly absorbs this heterogeneity—on average, arbitrage funds create \$8.5 mio. per year (versus \$3.7 mio. and \$1.5 mio. for equity and macro funds). However, each category features a subset of funds with stellar value-added. This result implies that value creation is fairly concentrated. The top decile contributes to 40% of the industrywide value-added. It also shows the limitations of the average as it hides the large fund heterogeneity and oversestimate the value created by the typical (median) fund (only equal to \$1.1 mio per year).

Examining the drivers of value creation sheds important light on the above results. We find that most hedge funds create value because they have unique skills—more than 80% have a positive first-dollar alpha equal to 12.2% per year on average (versus 3.2% for mutual funds). At the same time, their ability to create value is hampered by strong scalability constraints. On average, the gross alpha decreases by 2.0% per year for every \$10 mio. of additional equity capital (versus 0.1% for mutual funds). As they exploit their greater scalability, a sizable fraction of mutual funds deliver as much value as hedge funds. Our comparison therefore challenges the view that hedge fund managers systematically come on top because they are more sophisticated and incentivized.

The analysis of skill and scale also explains the observed heterogeneity across funds. We find that the most valuable follow strategies that moderately improve both skill and scalability. These balanced strategies deliver the highest value because the skill and scale coefficients a_i and b_i are strongly correlated—put simply, great ideas are difficult to scale up. The top funds also create value by exploiting superior information, instead of offering strategies that investors cannot replicate. Adding to the benchmark model more complex strategies that capture illiquidity, betting-against-beta, and variance factors, we find that the value-added remains largely unchanged.

An important question is how the value-added is split with investors. Overall, they extract modest benefits from their hedge fund investments—the average net value-added only equals \$0.3 mio. per year. Here again, the average hides substantial heterogeneity. On the one hand, investors extract some value for half the fund population, which reaches more than \$10 mio. per year in the top decile of the distribution. On the other hand, they misallocate capital to the remaining half as they end up paying excessive fees to investors. Zooming in on these value-destroying funds, we find that 40% of them are unskilled and thus unable to deliver value at any size level. The remaining 60% are skilled but suffer from overcapacity—investors endow them with capital beyond the tipping point at which the net alpha $\alpha_{i,t-1}^{\text{net}}$ turns negative.

The modest net value-added seems at odds with the large positive average net alpha $E[\alpha_{i,t-1}^{\text{net}}]$ estimated in previous studies—a finding that we confirm in our sample. However, it is perfectly possible for a fund to deliver both a positive $E[\alpha_{i,t-1}^{\text{net}}]$ and a negative va_i^{net}. The intuition is that times of poor performance (when $\alpha_{i,t-1}^{\text{net}}$ is negative) carry a large weight in the value-added calculation because they come with a large amount of capital $w_{i,t-1}$. As a result, the average net alpha is a poor measure of the actual value investors receive, given their changing capital allocation.

Next, we turn to the dynamics of value creation over the fund's lifecycle. We examine whether investors sharpen their capital allocation as they learn about hedge fund skill and scalability. To this end, we split the fund's observations into five subperiods and infer the value-added distribution when funds are young (subperiod 1) and old (subperiod 5). If investors favor the most valuable funds, we expect the value-added distribution to shift rightwards as funds age. Consistent with this prediction, the value created in the top decile rises from \$15.8 mio. to \$19.9 mio. per year. At the same time, the misallocation of capital does not disappear—the proportion of funds that charge excessive fees stays above 20% across all five subperiods.

The investors' reallocation process suggests a relatively complex learning mechanism. On the one hand, investors are able to identify value-creating funds. On the other hand, they systematically deploy too much capital midway through the fund's lifecycle. This overcapacity, which largely increases the proportion of value-destroying funds, is only partly corrected in the final subperiod. Whereas hedge fund investors do not perfectly allocate capital, they perform substantially better than mutual fund investors. Examining the net value-added across mutual funds, we find that investors pay excessive fees equal to a staggering \$7.6 mio per year on average. This value provides a simple metric to gauge the impact of investor sophistication on financial outcomes.

Finally, we examine how consistent hedge fund value creation is with economic rationale. We consider a simple extension of the rational model of Berk and Green (2004) in which funds with heterogeneous skill and scalability maximize their fee revenues under the constraint that investors receive a minimum return compensation κ to cover due diligence and monitoring costs (Stein, 2009). Setting κ equal to 1% per year (based on Stulz (2007)), we find the model does a reasonable job at explaining hedge fund value creation. In particular, the model captures the strong pairwise correlation of 0.83 between the total and net value-added (0.91 in the model), and the low fraction of value extracted by investors equal to 14% (15% in the model). Overall, these results suggest that hedge fund investors only have limited bargaining power in the fee negotiation.

The model also sheds light on two important sources of suboptimality: (i) the choice of fees by funds and (ii) the allocation decisions by investors. We find that the fees charged by hedge funds are generally too low compared to the values implied by the model. This suboptimal fee choice leads to a 26%-reduction in value-added relative to its optimal level. An additional 37%-reduction comes from the misallocation of capital by investors (possibly because of learning). In other words, capital misallocation is the prevalent source of suboptimality—it represents 60% of the gap from optimality.

The remainder of the paper is as follows. Section II.C presents our framework for measuring hedge fund value creation. Section III describes the methodology for inferring the value-added distribution. Section IV presents the hedge fund dataset. 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 ($i = 1, \ldots, n$) and each period by the subscript t ($t = 1, \ldots, T$). The variable $w_{i,t-1}$ denotes the lagged capital (in real terms) endowed by investors to the fund, $r_{i,t}$ denotes the gross excess return of the fund, and $r_{b,i,t}$ denotes the excess return of the fund benchmark which captures the best alternative investment available to investors. The benchmark return is given by $r_{b,i,t} = \beta_i' f_{R,t}$, where $f_{R,t}$ is the excess return vector of the trading strategies that investors are able to replicate themselves (R stands for replicable).[3]

[3]The use of constant betas is not restrictive because $f_{R,t}$ can include factor-timing strategies (managed portfolios) based on public information. To elaborate, suppose that investors can replicate a hedge fund strategy that consists

To measure the value created by each fund, we use the value-added proposed by Berk and van Binsbergen (2015) and defined as

$$va_i = E[\alpha_{i,t-1} w_{i,t-1}]\,, \tag{1}$$

where the gross alpha $\alpha_{i,t-1} = E[r_{i,t} - r_{b,i,t}|I_{t-1}]$ is the expectation of the difference between $r_{i,t}$ and $r_{b,i,t}$ conditional on the publicly available information set I_{t-1} which includes the fund capital $w_{i,t-1}$. Because the value-added is a dollar value that depends on the entire (benchmark-adjusted) fund payoff $\alpha_{i,t-1}w_{i,t-1}$, the gross alpha alone is not sufficient to infer fund value—a point forcefully made by Berk and van Binsbergen (2015). Intuitively, va_i is equivalent to the concept of net present value (NPV) applied to investment projects—a positive value-added signals that the hedge fund creates value, just like a positive NPV signals that the project creates value.

Equation (1) measures value creation from the viewpoint of investors—it determines whether the fund creates value relative to the best opportunity available to them (captured by $r_{b,i,t}$). Building on this insight, we can also define the value-added using the stochastic discount factor (SDF) valuation framework (see Cochrane, 2005). We can write the value attached by investors to the fund as $va_i^{sdf} = R_f E[m_t r_{i,t} w_{i,t-1}]$, where R_f is one plus the riskfree rate (assumed constant for simplicity) and the SDF m_t captures the investors' marginal utility of consumption. Noting that $E[m_t] = R_f^{-1}$ and $E[m_t r_{b,i,t}] = 0$ (by construction, m_t prices the factors $f_{R,t}$), we obtain $va_i^{sdf} = R_f E\left[m_t\left((r_{i,t} - r_{b,i,t})w_{i,t-1}\right)\right] = E[(r_{i,t} - r_{b,i,t})w_{i,t-1}] + R_f cov[m_t, (r_{i,t} - r_{b,i,t})w_{i,t-1}]$. If m_t depends linearly on investors' wealth (driven by the factors $f_{R,t}$), we have $cov[m_t, (r_{i,t} - r_{b,i,t})w_{i,t-1}] = 0$ (Chen and Knez, 1996; Ferson, 2013). As a result, the SDF value-added va_i^{sdf} is identical to the traditional value-added va_i: $va_i^{sdf} = E[(r_{i,t} - r_{b,i,t})w_{i,t-1}] = E[\alpha_{i,t-1}w_{i,t-1}] = va_i$.

II.B. Specification of the Value-Added

II.B.1. Main Assumptions

In this section, we present a simple specification that allows us to study the value-added along four dimensions: (i) its magnitude and drivers (fund skill and scalability), (ii) its split with investors, (iii) its time-variation as funds get older, and (iv) its optimality measured through the lens

of changing the market beta after observing a public signal z_{t-1} that predicts the equity market return $r_{m,t}$. We can absorb the time-variation in betas by including the scaled factor $z_{t-1}r_{m,t}$ in the vector $f_{R,t}$ (*e.g.*, Cochrane, 2005).

of a rational model a la Berk and Green (2004).

We assume that each fund has access to a fully collateralized active strategy whose average (benchmark-adjusted) excess return is denoted by a_i^{as}.[4] In addition, the fund must pay trading costs to implement the active strategy equal to a fraction b_i^{as} of the squared dollar amount invested in the active strategy. This convex cost function captures the intuitive idea that the active strategy cannot be scaled up without impacting its return.

We incorporate two salient features specific to the hedge fund industry. First, hedge funds can use leverage to increase the amount invested in the active strategy such that the total fund size $q_{i,t-1}$ (in real terms) is the sum of capital $w_{i,t-1}$ and debt $d_{i,t-1}$. Second, hedge funds face margin constraints and thus cannot take too much debt relative to capital (Lhabitant, 2007; Pedersen, 2015; Titman, 2010). We capture these features by expressing debt as a constant fraction of capital: $d_{i,t-1} = L_i w_{i,t-1}$, where L_i determines the fund leverage ratio $\pi_i = \frac{w_{i,t-1}+d_{i,t-1}}{w_{i,t-1}} = 1 + L_i$.

II.B.2. Baseline Specification

Using the equality $q_{i,t-1} = \pi_i w_{i,t-1}$, we can write the total expected fund revenue as $TR_{i,t} = a_i^{as}\pi_i w_{i,t-1}$, and the total cost as $TC_{i,t} = b_i^{as}\pi_i^2 w_{i,t-1}^2$. Taking the difference between $TR_{i,t}$ and $TC_{i,t}$ and dividing by $w_{i,t-1}$, we specify the gross alpha as a linear function of capital:

$$\alpha_{i,t-1} = a_i - b_i w_{i,t-1}\,, \tag{2}$$

where the coefficients $a_i = a_i^{as}\pi_i$ and $b_i = b_i^{as}\pi_i^2$ absorb the impact of the leverage ratio π_i. A key benefit of this specification is that the gross alpha only depends on capital $w_{i,t-1}$, but not debt $d_{i,t-1}$—a variable typically not reported in hedge fund databases.[5]

Replacing $\alpha_{i,t-1}$ with $a_i - b_i w_{i,t-1}$ in Equation (1), we obtain the following specification of the value-added:

$$va_i = a_i E[w_{i,t-1}] - b_i E[w_{i,t-1}^2]\,, \tag{3}$$

[4] 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 the position weights $x_{i,l}$ and $x_{i,s}$ sum to one (fully collateralized).

[5] Some databases, such as TASS, provide cross-sectional data on the average fund leverage. Because data is self-reported on a voluntary basis, the coverage is limited, and the calculation is not consistent across funds. Even worse, time-series information on hedge fund leverage is quasi-inexistent. 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. Barth, Hammond, and Monin (2020) work with data from the SEC on large hedge fund advisors having at least \$1.5 billion under management.

where va_i depends on the two coefficients that drive the gross alpha. Both a_i and b_i are fund-specific—a flexibility that departs from the standard panel specification which imposes constant scalability across funds ($b_i = b$). BGS show that this restriction is strongly rejected in the mutual fund population, leading to biased estimators of the value-added across funds. Similarly, our empirical results reveal that hedge fund value creation features substantial fund heterogeneity.

II.C. Analysis of the Value-Added

II.C.1. Magnitude and Drivers

The first benefit of Equation (3) is to measure the value-added and shed light on its main drivers. Ultimately, the value created by hedge funds depends on their skill to identify profitable ideas and their sensitivity to scalability constraints as they grow. Equation (3) formalizes the intuition by expressing va_i as a function of the fund skill and scalability (captured by a_i and b_i).

The skill coefficient a_i is equal to the alpha on the first dollar of equity capital (when $w_{i,t-1} = 0$). As such, it measures the profitability of the fund's ideas without the drag of real-world implementation (Perold and Salomon, 1991). Hedge funds can use two sources of information to generate a positive a_i. They can exploit superior information to implement stock picking or factor timing strategies. In addition, they can rely on public information to implement alternative strategies that investors are unable to replicate.[6] The scale coefficient b_i is equal to the sensitivity of the gross alpha to changes in fund capital. The magnitude of b_i captures multiple facets of diseconomies of scale. As the fund deploys more capital, it is less likely to execute trades cheaply. It may also require more staff, leading to the dissipation of talent and the rise of delegation costs.

There are several reasons why the skill and scale coefficients vary across funds. Some funds may have a higher a_i because they are run by extremely talented managers, while others may have a higher b_i because they focus on illiquid assets, trade more aggressively, or have a limited number of ideas to exploit (van Binsbergen et al., 2024; Busse et al., 2021). In addition, Equation (2) reveals that both a_i and b_i depend on leverage. One benefit of Equation (3) is that we can estimate a_i and b_i without explicitly modeling why they vary across funds—a daunting task given the complexity of hedge fund strategies and the scarcity of observable fund characteristics.

[6] 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."

In our baseline specification, the gross alpha is based on a constant leverage ratio π_i—an assumption largely consistent with the empirical evidence from proprietary hedge fund data.[7] That said, some hedge funds may find it optimal to adjust leverage over time—particularly in bad times to protect the present value of their future fees (Buraschi, Kosowski, and Sritrakul, 2014; Lan, Wang, and Yang, 2013). More generally, Equation (2) potentially omits other time-varying variables that drive the gross alpha such as non-linearities in fund capital or business cycle variables.

Even if we omit relevant variables, Equation (3) still provides a proper measure of the true value-added $E[\alpha_{i,t-1} w_{i,t-1}]$. To see this point, we suppose that the true alpha is given by $\alpha_{i,t-1} = a_{i,t-1} - b_{i,t-1} w_{i,t-1} = a_i + a'_{i,z} z_{i,t-1} - (b_i + b'_{i,z} z_{i,t-1}) w_{i,t-1}$, where $z_{i,t-1}$ is a demeaned vector of variables that drive the dynamics of $a_{i,t-1}$ and $b_{i,t-1}$. We can always linearly project $\alpha_{i,t-1}$ on $w_{i,t-1}$ to obtain $\alpha_{i,t-1} = proj(\alpha_{i,t-1}|w_{i,t-1}) + \epsilon_{\alpha,t-1}$, where $proj(\alpha_{i,t-1}|w_{i,t-1}) = a_i - b_i w_{i,t-1}$. Given that $E[\epsilon_{\alpha,t-1} w_{i,t-1}] = 0$ by construction, we have $va_i = E[\alpha_{i,t-1} w_{i,t-1}] = a_i E[w_{i,t-1}] - b_i E[w_{i,t-1}^2]$.

II.C.2. Split With Investors

The second dimension of our analysis pertains to the value split with investors. There are several reasons why hedge fund investors plausibly hold bargaining power in the fee negotiation. They may require compensation for due diligence and monitoring costs (Stein, 2009). They may also take advantage of soft information that is difficult for the fund to communicate to outsiders (Hochberg, Ljungqvist, and Vissing-Jørgensen, 2014) or threaten the fund to expropriate its investment ideas (Glode and Green, 2011).

To examine this issue, we denote by $fee_{i,t}$ the fee rate defined as the sum of management and performance fees divided by capital. We then define the net value-added received by investors as $va_i^{\text{net}} = E[\alpha_{i,t-1}^{net} w_{i,t-1}]$, where the net alpha $\alpha_{i,t-1}^{net} = E[r_{i,t}^{\text{net}} - r_{b,i,t}|I_{t-1}]$ is the conditional expectation of the difference between the fund net return $r_{i,t}^{\text{net}} = r_{i,t} - fee_{i,t}$ and $r_{b,i,t}$. Similar to the gross alpha $\alpha_{i,t}$ in Equation (2), we can project the net alpha on the fund capital to obtain $\alpha_{i,t-1}^{net} = a_i^{\text{net}} - b_i^{\text{net}} w_{i,t-1}$. Similar to Equation (3), we obtain an expression of the net value-added that depends on the two coefficients a_i^{net} and a_i^{net}:

$$va_i^{\text{net}} = a_i^{\text{net}} E[w_{i,t-1}] - b_i^{\text{net}} E[w_{i,t-1}^2]. \tag{4}$$

[7] Ang, Gorovyy, and van Inwegen (2011) find that gross leverage is very persistent with an autocorrelation of 0.97. Barth, Hammond, and Monin (2020) show that 89% of the variation in leverage is captured by fund fixed effects, which implies that leverage is largely a cross-sectional attribute.

To illustrate how fees affect the net skill and scale coefficients in Equation (4), we consider a simple example of a pure alpha fund (*i.e.*, no factor exposure). If this fund charges to investors a fraction f_i of capital (management fees) and a fraction p_i of the alpha (performance fees), we obtain $a_i^{\text{net}} = (1 - p_i)a_i - f_i$ and $b_i^{\text{net}} = (1 - p_i)b_i$. We see that fees have more pronounced impact of the first-dollar alpha a_i^{net} (via the term f_i) than the scale coefficient b_i^{net}.

II.C.3. Dynamics of the Fund's Lifecycle

The third dimension of our analysis focuses on the dynamics of value creation. The standard measure va_i in Equation (3) determines the value created by the fund over its entire existence. Therefore, it does not determine how the value-added varies over the fund's lifecycle. This variation is potentially large because investors may need time to learn about the fund skill and scale coefficients (Pástor and Stambaugh, 2012). As they update their views using fund return information, they reallocate capital which, in turn, changes the value-added.[8]

To examine this issue, we extend Equation (3) to obtain a dynamic version of the value-added. Following BGS, we split the observations on each fund into S subperiods of equal length. We then measure the value-added $va_i(s)$ for each subperiod s ($s = 1, ..., S$) as

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

where $\bar{w}_i(s)$ and $\bar{w}_{i,2}(s)$ denote the realized averages of the fund capital and its squared value in subperiod s. Using Equation (5), we can compare $va_i(1)$ and $va_i(S)$ to determine whether the value created by the fund increases as it gets older. Using the same approach, we can extend Equation (4) to examine the time-variation in the net value-added received by investors:

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

A notable advantage of Equations (5) and (6) is that the subperiod value-added depends on the skill and scale coefficients estimated over the entire sample period. We can, therefore, analyze shorter time intervals without increasing the noise of the estimated subperiod value-added.

[8] Investors' learning also provides an identification mechanism to the econometrician by inducing variation in fund capital over time. In the extreme case where investors perfectly know the fund skill and scalability a_i and b_i and are not hit by liquidity shocks, the fund capital is constant and a_i and b_i cannot be identified from the data.

II.C.4. Optimality

The final dimension of our analysis pertains to the optimality of the value-added. This normative analysis allows us to determine whether the actual value created by the hedge fund industry is consistent with economic rationale. Similar to Berk and Green (2004), we assume that each fund is endowed with specific levels of skill and scalability a_i and b_i and maximizes its total fee revenue $fee_i w_i$, where fee_i denotes the fee rate. The novelty of the model is that investors can extract value from the fund as they require a minimum (benchmark-adjusted) return κ per unit of capital as a compensation for due diligence and monitoring costs (see, for instance, Stein, 2009). With these assumptions, it is straightforward to show that the fund chooses constant leverage as in our baseline specification in Equation (3).[9]

The fund chooses capital w_i to maximize the value-added va_i minus the amount that must be given to investors κw_i, which yields the following maximization problem: $max_{w_i} a_i w_i - b_i w_i^2 - \kappa w_i$. The optimal level of capital $w_i^* = \frac{a_i - \kappa}{2b_i}$ is obtained by setting the fee rate at $fee_i^* = \frac{a_i - \kappa}{2}$.[10] The optimal value-added (total and net) is then given by

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

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

If investors have no bargaining power ($\kappa = 0$), we obtain the same results as in Berk and van Binsbergen (2015). The optimal value-added simplifies to $va_i^* = \frac{a_i^2}{4b_i} = \frac{(a_i^{as})^2}{4b_i^{as}}$ and can be interpreted as the profit of a monopolist, measured as the markup price of its product (alpha) multiplied by the total quantity sold (capital). As discussed in Section III, it is straightforward to estimate va_i^* and $va_i^{\text{net}*}$ and compare them to the actual value-added. Because of its tractability, the proposed model provides a natural starting point to rationalize the actual value-added and size of the hedge fund industry. That said, we acknowledge that our simple model does not incorporate key features including multi-period contracting, agency frictions, and investors' learning. The design of a general

[9] Fixing the total fund size at $\bar{q}_i$, we can write the total value-added as $\bar{va}_i(\bar{q}_i) = a_i^{as}\bar{q}_i - b_i^{as}\bar{q}_i^2$. Whereas $\bar{va}_i(\bar{q}_i)$ is independent of the equity-debt composition of $\bar{q}_i$, the extra cost of equity financing κw_i rises with w_i. For any size level $\bar{q}_i$, it is therefore optimal to maximize leverage at π_i.

[10] Similar to Glode and Green (2011), our simple model is silent on the types of fees that the fund should charge. There is an infinite combination of management and performance fees that allows the fund to maximimize the expected dollar revenue, as discussed by Goetzmann, Ingersoll, and Ross (2003).

equilibrium model with all these features is a difficult and still-open question.

III. Approach for Estimating Hedge Fund Value Creation

III.A. Motivation for a Fund-Level Approach

In this section, we describe our novel econometric approach for estimating hedge fund value creation. Specifically, we infer the entire value-added distribution across individual funds. This flexibility is important because hedge funds follow a large number strategies with unique skill and scale (captured by a_i and b_i). We therefore expect a large dispersion in value creation that cannot be captured by a simple average. For instance, the average is uninformative about the proportions of funds that create value or charge excessive fees to investors.

Our econometric approach builds on recent studies on estimation and inference in large cross-sectional datasets (*e.g.*, Ardia et al., 2024; Gagliardini, Ossola, and Scaillet, 2016). It is particularly appealing in our context for several reasons. 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 among 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 inferential theory. We derive the asymptotic properties of the estimated value-added distribution, which allows us to conduct proper statistical inference guided by econometric theory.

III.B. Estimation of the Fund Value-Added

The main inputs for the estimation of the value-added of each fund are the skill and scale coefficients a_i and b_i obtained from the following time-series regression:

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

We compute the least-square the coefficient vector in Equation (9) as $\hat{\gamma}_i = (\hat{a}_i, \hat{b}_i, \hat{\beta}'_{i,R})' = (\hat{Q}_{x,i})^{-1} \frac{1}{T_i} \sum_t I_{i,t} x_{i,t} r_{i,t}$, where $I_{i,t}$ is an indicator variable equal to one if $r_{i,t}$ is observable, $T_i = \sum_t I_{i,t}$, $x_{i,t} = (1, -w_{i,t-1}, f'_{R,t})'$ 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 value-added as

$$\hat{va}_i = \hat{a}_i \bar{w}_i - \hat{b}_i \bar{w}_{i,2}\,, \tag{10}$$

where $\bar{w}_i = \frac{1}{T_i}\sum_t I_{i,t} w_{i,t-1}$, $\bar{w}_{i,2} = \frac{1}{T_i}\sum_t I_{i,t} w_{i,t-1}^2$. To measure the net value-added, we re-run Equation (9) using the fund net return $r_{i,t}^{\text{net}}$. Replacing the estimated skill and scale coefficients $\hat{a}_i^{\text{net}}$ and $\hat{b}_i^{\text{net}}$ in Equation (4), we obtain

$$\hat{va}_i^{\text{net}} = \hat{a}_i^{\text{net}} \bar{w}_i - \hat{b}_i^{\text{net}} \bar{w}_{i,2}\,. \tag{11}$$

Finally, we plug $\hat{a}_i$, $\hat{b}_i$ and $\hat{a}_i^{\text{net}}$, $\hat{b}_i^{\text{net}}$ in Equations (5) and (6) to compute the value-added over subperiod s:

$$\hat{va}_i(s) = \hat{a}_i \bar{w}_i(s) - \hat{b}_i \bar{w}_{i,2}(s)\,, \tag{12}$$

$$\hat{va}_i^{\text{net}}(s) = \hat{a}_i^{\text{net}} \bar{w}_i(s) - \hat{b}_i^{\text{net}} \bar{w}_{i,2}(s)\,. \tag{13}$$

III.C. Benchmarking and Non-Replicable Factors

Hedge funds follow a large number of complex alternative strategies. They invest in many countries and asset classes and follow complex option and factor-timing strategies based on public information (see, *e.g.*, Avramov, Barras, and Kosowski, 2013; Ferson and Schadt, 1996; Karehnke and de Roon, 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 $f_t = (f'_{R,t}, f'_{NR,t})'$, where $f_{R,t}$ includes the replicable strategies and $f_{NR,t}$ includes the strategies that investors cannot replicate (NR stands for non-replicable).

The non-replicable factors $f_{NR,t}$ 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 f_t: $r_{i,t} = \alpha_{i,t}^* + \beta_{i,R}^{*\prime} f_{R,t} + \beta_{i,NR}^{*\prime} f_{NR,t} + \varepsilon_{i,t}^*$. We then regress $f_{NR,t}$ on $f_{R,t}$ to break the non-replicable factors into three components: $f_{NR,t} = \alpha_{NR} + \Psi_{NR,R} f_{R,t} + u_{NR,t}$, where α_{NR} is the vector of factor alphas, $\Psi_{NR,R}$ is the matrix of slope coefficients, and $u_{NR,t}$ is the vector of errors.

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

$$\varepsilon_{i,t} = \varepsilon_{i,t}^* + \beta_{i,NR}^{*\prime}u_{NR,t}\,. \tag{14}$$

Equation (14) reveals that the error terms $\varepsilon_{i,t}$ $(i = 1, ..., n)$ are strongly correlated across funds because they all depend on the error term of the non-replicable factors $u_{NR,t}$. As shown in Proposition 1 below, this result implies that the cross-sectional value-added distribution is estimated with substantial uncertainty. The intuition is straightforward—even if we have information about the estimated value-added across a large number of hedge funds (n is large), this information is noisy because it is primarily driven by the common component $u_{NR,t}$.

III.D. Statistical Properties of the Value-Added Distribution

III.D.1. Estimation of the Distribution Characteristics

We now focus on the statistical properties of the cross-sectional distribution of the value-added va_i. To save space, we refer the reader to the appendix for the analysis of the other formulations of the value-added (va_i^{net}, $va_i(s)$, $va_i^{\text{net}}(s)$) and the fund coefficients (a_i, b_i, a_i^{net}, $b_i^{\text{net}}(s)$), for which the statistical properties remain unchanged. The basic idea behind our approach is to interpret Equation (9) as a random coefficient model (*e.g.*, Hsiao, 2003) in which a_i, b_i, and thus va_i are not fixed parameters, but random realizations from a continuum of funds. Under this sampling scheme, we can invoke cross-sectional limits to infer the asymptotic properties of the value-added distribution across funds (see Gagliardini, Ossola, and Scaillet, 2016, for details).

To estimate the value-added distribution, we account for the unbalanced nature of the hedge fund sample. Following Gagliardini, Ossola, and Scaillet (2016), we introduce a formal selection rule $\mathbf{1}_i^{\chi}$ equal to one if the following conditions are met: $\mathbf{1}_i^{\chi} = \mathbf{1}\left\{\tau_{i,T} \leq \chi_{1,T}, CN_i \leq \chi_{2,T}\right\}$, where $\tau_{i,T} = T/T_i$, $CN_i = \sqrt{eig_{\max}\left(\hat{Q}_{x,i}^k\right)/eig_{\min}\left(\hat{Q}_{x,i}^k\right)}$ is the condition number of $\hat{Q}_{x,i}^k$, 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 $n_\chi = \sum_{i=1}^{n} \mathbf{1}_i^\chi$.

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 $(\hat{va}_1, ..., \hat{va}_{n_\chi})'$ obtained from Equation (10). The estimated mean, proportion, and quantile are given by

$$\hat{M} = \frac{1}{n_\chi} \sum_i \mathbf{1}_i^\chi \hat{va}_i \,, \tag{15}$$

$$\hat{P}(a) = \frac{1}{n_\chi} \sum_i \mathbf{1}_i^\chi \mathbf{1}\{\hat{va}_i \leq a\} \,, \tag{16}$$

$$\hat{Q}(u) = (\hat{P})^{-1}(u) \,. \tag{17}$$

III.D.2. Inference on the Distribution Characteristics

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

$$\sqrt{T}\left(\hat{M} - M\right) \to_d N(0, V[M]) \,, \tag{18}$$

$$\sqrt{T}\left(\hat{P}(a) - P(a)\right) \to_d N(0, V[P(a)]) \,, \tag{19}$$

$$\sqrt{T}\left(\hat{Q}(u) - Q(u)\right) \to_d N(0, V[Q(u)]) \,, \tag{20}$$

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

$$V[M] = E\left[\eta_{M_s}' \otimes \zeta_i' Q_{x,i}^{-1} B_i\right] \Omega_{ux}^k (E\left[\eta_{M_s} \otimes B_i' Q_{x,i}^{-1} \zeta_i\right] \,, \tag{21}$$

$$V[P(a)] = E\left[\eta_{P(a)}' \otimes \zeta_i' Q_{x,i}^{-1} B_i\right] \Omega_{ux}^k (E\left[\eta_{P(a)} \otimes B_i' Q_{x,i}^{-1} \zeta_i\right] \,, \tag{22}$$

$$V[Q(u)] = V[P(Q(u))]/\phi(Q(u))^2 \,, \tag{23}$$

where $\eta_M = \beta_{i,NR}^*$, $\zeta_i = e_1 E[w_{i,t-1}] + e_2 E[w_{i,t-1}^2]$, e_1 and e_2 are $(K+2)$ vectors with zeros everywhere except on the first and second positions, $\otimes$ denotes the Kronecker product, $Q_{x,i}$ =

$E[x_{i,t}x'_{i,t}]$, B_i is a $(K+2)\times(K+1)$ matrix whose first column is given by $[1, E[w_{i,t-1}], ..., 0]'$ and the j^{th} column is a vector with zeros everywhere except in the $j^{th}+1$ position, $\Omega_{ux} = \lim_{T\to\infty} V\left[\frac{1}{\sqrt{T}}\sum_t u_{NR,t}\otimes x_t\right]$, $x_t = (1, f'_{R,t})'$ is a $(K+1)$-vector, $\eta_{P(a)} = E[\beta^*_{i,NR}|va_i = a]\phi(a)$, $\beta^*_{i,NR}$ and $u_{NR,t}$ denote the vectors of betas and residuals associated with the non-replicable factors $f_{NR,t}$, and $\phi_{va}(a)$ is the value-added density evaluated at a.

Proof. *See the appendix.*

Proposition 1 reveals two key properties of the estimated distribution characteristics. First, they converge toward their respective values. We can estimate them without any error-in-variable (EIV) bias adjustment, even though we use as inputs noisy versions of the value-added (*i.e.*, we use $\hat{va}_i$ instead of va_i). Second, the characteristics are estimated with substantial noise because the convergence rate equals $1/\sqrt{T}$. This result may be surprising because we compute these characteristics by averaging across funds (not across time).

Both properties stem from the impact of the non-replicable hedge fund factors $f_{NR,t}$. Building on Equation (14), we see that the fund value-added $\hat{va}_i$ depends on the term $\bar{\varepsilon}_i = \bar{\varepsilon}^*_i + \beta^{*\prime}_{i,NR}\bar{u}_{NR}$, where $\bar{\varepsilon}_i$, $\bar{\varepsilon}^*_i$, and $\bar{u}_{NR}$ denote the time-series averages of $\hat{\varepsilon}_{i,t}$, $\hat{\varepsilon}^*_{i,t}$, and $\hat{u}_{NR,t}$. The error term $\bar{u}_{NR}$ due to the non-replicable factors determines the properties of the estimated characteristics because it has a pervasive impact on all funds. This common term only converges to zero at the rate equal to $1/\sqrt{T}$, which (i) slows down the convergence rate of the estimated characteristics to $1/\sqrt{T}$, and (ii) dwarfs the EIV bias, making any bias adjustment unnecessary.[11]

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 $u_{NR,t}$ 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 based on the observed fund residuals of each model $\hat{\varepsilon}_{i,t} = r_{i,t} - x'_{i,t}\hat{\gamma}_i$. Denoting by $\hat{C}\in\{\hat{M}_s, \hat{P}(a), \hat{Q}(u)\}$, we compute the asymptotic variances of $\sqrt{T}(\hat{C}-C)$ as

$$\hat{V}[\hat{C}] = \frac{1}{n_\chi^2 T}\sum_i\sum_j\sum_t \mathbf{1}^\chi_i\tau_{i,T}I_{i,t}\mathbf{1}^\chi_j\tau_{j,T}I_{j,t}\hat{a}_{i,t}(\hat{C})\hat{a}_{j,t}(\hat{C})', \tag{24}$$

where the terms $\hat{a}_{i,t}(\hat{C})$ are functions of $\hat{C}$ and defined in the appendix for brevity. The following proposition shows that $\hat{V}[\hat{C}]$ is a consistent variance estimator as the numbers of funds n and

[11] As shown by BGS, the EIV bias is of order $1/T$, which is smaller in magnitude than the variance term of order $1/\sqrt{T}$ in Proposition 1. Therefore, the bias term becomes negligible relative to the variance term as $T\to\infty$.

observations T grow large.

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

$$\hat{V}[\hat{C}] \to_p V[\hat{C}], \tag{25}$$

where $\to_p$ denotes convergence in probability.
Proof. *See the appendix.*

III.D.3. Formal Comparisons With Mutual Funds

We can extend Proposition 1 to allow for comparison tests with mutual funds. Contrary to hedge funds, mutual funds typically do not rely on many complex strategies to generate returns—instead, they primarily load on market, size, and value factors. Building on this observation, BGS make the assumption that mutual fund strategies are replicable ($f_t = f_{R,t}$). As the error term $\bar{\varepsilon}_i = \bar{\varepsilon}_i^*$ becomes weakly correlated across funds (*i.e.*, the term $\hat{u}_{NR,t}$ vanishes), they show that the characteristics of the value-added converge at a faster rate of $1/\sqrt{n}$ (instead of $1/\sqrt{T}$). Because of the increased precision obtained with mutual funds, we can treat their value-added characteristics as known in the comparison tests with hedge funds.

We compute the differences in distribution characteristics between the populations of hedge funds and mutual funds as $\Delta\hat{M} = \hat{M} - \hat{M}_{\text{mf}}$, $\Delta\hat{P}(a) = \hat{P}(a) - \hat{P}_{\text{mf}}(a)$, and $\Delta\hat{Q}(u) = \hat{Q}(u) - \hat{Q}_{\text{mf}}(u)$, where $\hat{M}_{\text{mf}}$, $\hat{P}_{\text{mf}}(a)$, and $\hat{Q}_{\text{mf}}(u)$ 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 $n, T \to \infty$, such that $T/n \to 0$, we obtain the following properties for the differences between the estimated characteristics of the distributions of the value-added va_i across hedge funds and mutual funds:*

$$\sqrt{T}\left(\Delta\hat{M} - \Delta M\right) \to_d N(0, V[M]), \tag{26}$$

$$\sqrt{T}\left(\Delta\hat{P}(a) - \Delta P(a)\right) \to_d N(0, V[P(a)]), \tag{27}$$

$$\sqrt{T}\left(\Delta\hat{M}Q(u) - \Delta Q(u)\right) \to_d N(0, V[Q(u)]), \tag{28}$$

where $\to_d$ 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

We conduct our empirical analysis between January 1994 and December 2020. We collect monthly data on net-of-fee returns and capital, as well as cross-sectional data on investment objectives, fees, and other characteristics from four databases (Barclayhedge, HFR, Morningstar, and TASS). In our baseline analysis, we exclude funds-of-funds and multi-strategy funds and take several steps to mitigate well-known sources of data biases. We reduce selection bias by combining four standard databases. We control for survivorship bias by keeping track of dead funds. Finally, we address backfill bias by removing the first 12 months of data for each fund. The appendix provides more detail on the construction of the dataset.

A key input for measuring the value-added is the unreported gross return of each fund. We manually compute the monthly gross return by estimating the monthly fees (management and performance fees) and adding them to the reported monthly net return. Contrary to mutual funds, inferring the time series of gross returns is not trivial because it requires a proper measurement of the accrued performance fees and the frequency at which they are paid—a process called crystallization. Because the crystallization frequency is generally not disclosed, we follow Jorion and Schwarz (2014) and assume that performance fees are paid annually (see the appendix for a detailed description of the computations). Another important input is the fund capital in real terms. To obtain this variable, we follow Berk and van Binsbergen (2015) and express the reported monthly fund capital in terms of January 1, 2000 dollars.

To account for the unbalanced nature of the hedge fund sample, we apply the fund selection rule described in Section III. Taking the same thresholds as BGS for mutual funds, we set the minimum number of return observations to 60 and the minimum condition number to 15. We also remove micro funds whose capital is below \$10 million for at least one third of the observations. Finally, we mitigate the impact of outliers by removing 1% of the funds with bottom and top values of $\hat{a}_i$, $\hat{b}_i$, and $\hat{va}_i$. Applying these selection rules, we obtain 2,971 funds over the entire period ($n_\chi = 2{,}971$).

While the original sample includes all dead funds, the above selection potentially introduces survivorship bias. If value-destroying funds disappear early, the value-added distribution is biased upwards. However, there are two offsetting effects. First, value-creating funds can disappear early after unexpectedly low realized returns—a phenomenon called reverse-survivorship bias (Linnainmaa, 2013). Second, the best funds are more likely to stop reporting to databases because their client base is sufficiently large. Therefore, the 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. Hedge Fund Benchmark Model

To estimate the value-added, we need to specify the investment opportunities available to investors. In our baseline analysis, we consider a simple extension of the three-factor model of Cremers, Petajisto, and Zitzewitz (2013), which adds global carry and time-series (TS) momentum to the standard market, size, and value factors. The carry and TS momentum strategies are constructed by Koijen et al. (2018) and Moskowitz, Ooi, and Pedersen (2012) and invest in assets with high carry and positive 12-month returns across four international asset classes (equity, bond, currency, commodity).

The rationale for selecting these factors is twofold. First, they capture mechanical strategies that hedge funds plausibly follow. As noted by Ardia et al. (2024), these factors are supported by economic intuition and explain a sizable fraction of the average returns earned by hedge funds. Second, it is reasonable to assume that hedge fund investors can take positions in these five factors. The market, size, and value factors track the S&P500 and Russell indices and can be replicated using passive products. By construction, they assign zero alphas to S&P500 and Russell 2000—two widely-used benchmark indices in the fund industry. The carry and TS momentum factors can also be traded using liquid futures markets or alternative premia funds offered by an increasing number of institutions (Jorion, 2021).[12]

The factor returns capture the gross-of-fee returns of the replicable factors. As a result, we exclude from the value-added the replication services that hedge funds provide to investors (see Berk and van Binsbergen, 2015). We exclude these services because they are also provided by passive products (contrary to the active hedge fund strategies). In the appendix, we show that all but one factor (value) deliver positive premia over the sample period. They also capture distinct

[12]Our benchmark choice geared towards factor replication departs from that of Ling, Satchell, and Yao (2023) in their study of hedge fund value creation. For each fund, they form a benchmark portfolio that invests in six HFR-style indices. Since each index includes 500 individual hedge funds, this benchmark portfolio is difficult to replicate.

strategies—none of the pairwise correlations is above 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 entire fund population includes (i) 1,179 equity funds (long-short and market neutral), which rely on discretionary or quantitative analysis to detect mispriced stocks, (ii) 783 macro funds (global macro and managed futures), which take directional bets across asset classes using broad economic and financial indicators, and (iii) 1,009 arbitrage funds (relative value and event driven), which exploit various sources of mispricing primarily in the debt market. For comparison purposes, we compute the same statistics for the sample of 2,247 U.S. equity mutual funds constructed using the procedure proposed by BGS.

Panel A shows that the portfolio of all funds achieves an average gross return equal to 9.8% per year. The average portfolio return drops to 6.6% per year after accounting for management fees (1.4% per year) and performance fees (1.7% per year). Overall, the results are similar to those reported by previous studies on gross and net hedge fund returns (*e.g.*, Elaut, Frömmel, and Sjödin, 2015; Jorion and Schwarz, 2014). Hedge funds are significantly smaller than mutual funds—the time-series average of the cross-sectional average (median) capital is equal to \$196 mio. (\$58 mio.), versus \$906 mio. (\$243 mio.) for mutual funds.

In Panel B, we report the estimated portfolio betas for the five factors (market, size, value, carry, TS momentum). The betas of the aggregate hedge fund portfolio are all positive. This result is consistent with the view that hedge funds take on market risk, favor small-cap and value stocks, buy cheap assets with high carry, and follow trends to boost their average returns (*e.g.*, Pedersen, 2015). Equity funds have the highest exposure to the equity market (0.47), whereas macro funds load more aggressively on TS momentum (0.34) as they rely on past returns to exploit trends caused by behavioral biases, frictions, or slow-moving capital. Examining the fit of the benchmark model, we find that it only explains 42% of the average return of the portfolio and 68% of its time-series variation (versus 95% and 99% for mutual funds). Put differently, hedge funds follow strategies that are not captured by the five factors—a finding that emphasizes the relevance of our methodology which explicitly controls for the non-replicable factors $f_{NR,t}$.

Please insert Table I here

V. Main Empirical Results

V.A. Magnitude and Drivers of Value Creation

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

In this section, we focus on the drivers of value creation in the hedge fund industry. Applying the methodology in Section III, we begin by estimating the entire distribution of the value-added va_i defined in Equation (3). We compute the cross-sectional mean and median, the proportions of funds with negative and positive value-added, and the quantiles at 10% and 90%. To compute the standard deviation of the estimated characteristics, we replace $T = 324$ with $T_\chi = \frac{1}{n_\chi} \sum_{i=1}^{n} \mathbf{1}_i^\chi T_i = 125$ to control for the increased estimation noise caused by the unbalanced hedge fund panel.

Panel A of Table II provides robust evidence of hedge fund value creation. In the entire population, 66.6% of the funds exhibit a positive value-added. The average is equal to \$4.7 mio. per year on average and is statistically highly significant. These results provide suggestive evidence that hedge funds contribute to price informativeness through their investment activities. Performing this role is socially valuable for the allocation of resources in the economy because it improves the decisions made by capital providers, managers, employees, and regulators (*e.g.*, Pedersen, 2018; Bond, Edmans, and Goldstein, 2012).

In line with the large number of strategies followed by hedge funds, we observe a substantial dispersion in value-added. Part of the observed heterogeneity is captured by investment categories. We find that value creation is substantially larger among arbitrage funds as 80.3% of them create value (versus 65.4% and 51.0% for equity and macro funds). That said, the within-group heterogeneity remains large—in all three categories, funds in the top decile produce a value-added more than 3 times higher than the average. These results imply that the value created by the hedge fund industry is fairly concentrated. A lower bound for the total value in the top decile is \$54,963 mio. (18,5· 2,971), which represents 39.4% of the total value created. They also imply that the average provides limited informationabout hedge fund value creation. It fails to capture the large dispersion across funds and is not representative of the typical hedge fund as evidenced by the large gap with the median (\$4.7 mio. versus \$1.1 mio. per year).

Please insert Table II here

V.A.2. Skill and Scalability

We now focus on the drivers of value creation to understand why most funds create value and why the heterogeneity among them is large. Hedge funds create value because they are able to generate profitable investment ideas. To verify this claim, we estimate the cross-sectional distribution of the skill coefficient a_i. Panel B of Table II confirms that 85.8% of them exhibit a positive alpha on their first dollar of capital whose average equals 12.2% per year. At the same time, value creation is limited by capacity constraints. Panel C shows that a \$10 mio. increase in capital decreases the gross alpha by 2.0% per year on average, which is consistent with previous studies (*e.g.*, Fung et al., 2008). That said, our results go one step further by showing that the scale coefficient is not only positive on average, but for more than 80% of the hedge funds. It therefore provides a strong justification for equilibrium models of active management featuring diseconomies of scale (Berk and Green, 2004; Pástor and Stambaugh, 2012)

The heterogeneity in value creation arises from the dispersion in skill and scalability. First, we examine why investment categories produce different value. Panel B reveals the average first-dollar alphas are remarkably similar. Therefore, the domination of arbitrage funds stems from their lower scale coefficient—as shown in Panel C, it is equal to 1.2% per year on average (versus 2.5% for equity funds and 2.2% for macro funds). This result seems at odds with the view that arbitrage funds trade assets with limited liquidity (such as convertible bonds). However, asset liquidity is not the only determinant of the scale coefficient. As mentioned, reduced levels of leverage and turnover lower b_i and may offset the positive impact of illiquidity. Consistent with this argument, Barth, Hammond, and Monin (2020) show that arbitrage funds choose lower leverage than macro funds.[13] It is also plausible that these funds trade less frequently than high-frequency equity funds and trend-following macro funds. Whereas we lack data to test this hypothesis, differences in trading can have a large impact on b_i—using transaction data on mutual funds, van Binsbergen et al. (2024) find that turnover is the most important determinant of scalability.

Second, we examine why the top decile funds are so valuable. Table III shows these top funds not generate the most profitable ideas. Instead, they follow unique strategies that balance skill and scalability. A simple way to make this point is to sort $\hat{a}_i$ and $\hat{b}_i$ for each fund into deciles to

[13] In Figure 1 presented below, we show that once we adjust for leverage differences, the unlevered scale coefficient becomes higher for arbitrage funds.

create a scoring system from 1 to 10 (1=lowest, 10=highest). We find that the median skill and scalability scores of the top funds in the population are equal to 8 and 3. In addition, only 14.6% (0.0%) of them achieve the highest skill (scale) score of 10 (1). These balanced strategies produce the highest value-added because of the trade-off between skill and scale—the pairwise correlation between $\hat{a}_i$ and $\hat{b}_i$ is close to 0.6. This strong correlation arises for several reasons. First, hedge funds favor volatile and illiquid assets. These assets are more risky and costly to trade (higher b_i) and thus exhibit higher levels of mispricing (higher a_i). Second, hedge funds use leverage which jointly increases a_i and b_i (as per Equation (2)).

The top funds are either skilled at exploiting unique information or offering non-replicable strategies. To distinguish between these two sources of profitability, we control for three strategies that investors cannot easily replicate: illiquidity, betting-against-beta (BAB), and variance.[14] Adding these factor returns to the benchmark model, we re-compute the value created by hedge funds. Panel B do not reveal major changes in the mean and median value-added. The highest average contribution of these strategies to value creation equals 23% for arbitrage funds (12.0/51.8) as they load on variance risk (see Ardia et al., 2024). These results suggest that superior information is the main skill driver among the top funds.

Please insert Table III here

V.A.3. The Impact of Leverage

A key insight from Table II is that hedge fund strategies are both highly profitable and highly unscalable. A natural explanation for this result is leverage—as shown in Equation (2), both a_i and b_i scale up with the leverage ratio. Given the lack of data on hedge fund leverage, we borrow from 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 compute the average unlevered skill and scale coefficients as $\hat{M}_a^u = \frac{\hat{M}_a}{\hat{\pi}}$ and $\hat{M}_b^u = \frac{\hat{M}_b}{\hat{\pi}^2}$, where $\hat{M}_a = \frac{1}{n_\chi}\sum_i \mathbf{1}_i^\chi \hat{a}_i$ and $\hat{M}_b = \frac{1}{n_\chi}\sum_i \mathbf{1}_i^\chi \hat{b}_i$. Figure 1 shows that the leverage-adjusted average

[14] Ardia et al. (2024), Asness, Moskowitz, and Pedersen (2013), and Pedersen (2015) provide evidence that some hedge funds follow these strategies. The illiquidity strategy of Pástor and Stambaugh (2003) captures marketwide changes in market liquidity. The BAB strategy of Frazzini and Pedersen (2014) exploits the price distortions caused by leverage-constrained investors on low- and high-beta stocks. The variance strategy tracks the realized variance of the S&P 500.

skill and scale coefficients equal 3.7% and 0.2% per year and only represent 30.3% and 9.1% of the unadjusted coefficients reported in Table II (3.7/12.2 and 0.18/1.96). These results confirm that leverage plays a central role in driving the magnitude of the skill and scale coefficients.

Please insert Figure 1 here

V.A.4. Comparison with Mutual Funds

A common view is that hedge fund managers deliver strong profitability because they are more sophisticated and incentivized than their mutual fund peers. Consistent with this view, the appendix shows that the first-dollar alpha of mutual funds is equal to 2.5% per year on average (versus 12.2% for hedge funds). Another common argument is that hedge funds are more flexible as they take both long and short positions. They can therefore scale more as they spread trades on multiple ideas (Harvey et al., 2021). Instead, we find that the traditional long-only strategies followed by mutual funds are substantially more scalable—a \$10 mio. increase in capital leads to a mere 0.1% decrease in annual alpha on average (versus 2.0% for hedge funds).

It is unclear whether hedge funds create more value because they follow strategies that are highly profitable, but far less scalable. To examine this issue, we compare in Figure 2 the average value created by hedge funds and mutual funds. We consider the entire population of mutual funds as well as various groups sorted on stock size (small- and large-cap), turnover (low- and high turnover), and distribution channel (direct- and broker-sold). In the entire population, we find that hedge funds are able to create more value—the estimated difference equals \$4 mio. per year and is statistically significant.[15] However, this superiority is primarily driven by arbitrage funds. The other two categories—equity and macro funds—produce a comparable or even lower value-added than several mutual fund groups (small-cap, low-turnover, and direct-sold funds). Overall, these results reveal that the low scalability of hedge funds prevent them from systematically dominating mutual funds.

Please insert Figure 2 here

[15] The value-added of mutual funds is positive but smaller in magnitude than the values reported by BGS and Berk and van Binsbergen (2015) because we use a different benchmark model and a shorter period (1994-2020).

V.B. Value Split with Investors

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

We now examine how the value created by hedge funds is split with their investors. For each fund, we estimate the net value-added va_i^{net} defined in Equation (4) and apply our methodology to compute the mean and median, the proportions of funds with negative and positive coefficients, and the quantiles at 10% and 90%. The results are reported in Panel A of Table IV.

Similar to Table II, we observe a large heterogeneity in net value-added. Some of this heterogeneity reflects the actual value created by hedge funds. The proportion of funds with positive net value-added is equal to 50.5% of all funds and rises up to 65.1% in the most valuable category (arbitrage funds). When positive, the extracted value is economically important—in the top decile, it is higher than $10 mio. per year. The remaining heterogeneity is caused by capital misallocation—we find that investors pay excessive fees to 49.5% of the funds in the population. Combining these results, we find that investors do not extract large benefits from hedge funds—the average barely reaches $0.3 mio. per year and is not statistically different from zero.

A common explanation for value destruction is the existence of unskilled funds—that is, funds with a first dollar alpha too low relative to the fees ($a_i^{\text{net}} < 0$). Because these funds destroy value regardless of the size at which they operate, they can only survive by attracting investors with high search costs (via marketing efforts). To quantify the importance of these funds, we estimate the distribution of the net skill coefficient a_i^{net}. Panel B shows that 19.0% of the funds have a negative skill coefficient. This result implies that 38% of the value-destroying funds are unskilled (19.0/49.6). The remaining funds (62%) are skilled, but grow too large. In the presence of hedge fund fees, the fund capital quickly reaches the tipping point at which the net value-added turns negative. As shown in Panel B, fees bring down the average first-dollar alpha a_i^{net} to 9.0% per year on average (versus 12.2% for a_i). In addition, we find that performance fees do not cushion the negative impact of scalability constraints—Panel C shows that the distribution of the net scale coefficient b_i^{net} is largely similar to that of b_i.

Please insert Table IV here

V.B.2. Net Value-Added Versus Net Alpha

The sizable proportion of value-destroying funds in Table IV seems at odds with the strong performance in previous studies.[16] Consistent with these studies, we also find a positive performance—the average net alpha $\alpha_i^{\text{net}} = E[\alpha_{i,t-1}^{\text{net}}] = a_i^{\text{net}} - b_i^{\text{net}} E[w_{i,t-1}]$ is positive for 65% of the funds and equal to 1.7% per year on average (see the appendix). A central insight for reconciling these results is that times of poor performance (when $\alpha_{i,t-1}^{\text{net}}$ is negative) carry a larger weight in the value-added computation because they come with a large amount of invested capital $w_{i,t-1}$.

To illustrate, we consider a two-period example in which investors invest (i) a small amount of capital in the first period such that the net alpha is positive ($\alpha_{i,1}^{\text{net}} = a_i^{\text{net}} - b_i^{\text{net}} w_{i,1} > 0$), and (ii) a large amount of capital in the second period, resulting in a negative net alpha ($\alpha_{i,2}^{\text{net}} = a_i^{\text{net}} - b_i^{\text{net}} w_{i,2} < 0$). If the variation in capital over these two periods is sufficiently strong, we can have a positive average net alpha ($\alpha_i^{\text{net}} = (\alpha_{i,1}^{\text{net}} + \alpha_{i,2}^{\text{net}})/2 > 0$) and a negative net value-added ($va_i^{\text{net}} = (va_{i,1}^{\text{net}} + va_{i,2}^{\text{net}})/2 < 0$).[17] Put differently, the net alpha is a poor indicator of the actual value extracted by hedge funds investors given their time-varying capital allocation decisions.

V.B.3. Comparison with Mutual Fund Investors

In Figure 3, we examine how much value mutual fund investors are able to extract. Similar to BGS and Cooper, Halling, and Yang (2021), we find overwhelming evidence of excessive mutual fund fees. In the population, the net value-added drops to -\$7.6 mio. per year on average. In addition, the average is consistently negative in all fund groups as it ranges between -\$1.3 mio. for small-cap funds and -\$10.9 mio. for large-cap funds. These results point towards a severe capital misallocation by mutual fund investors

The gap of \$7.9 mio. per year relative to hedge funds is economically large and statistically significant. It provides a simple metric to assess the impact of investor sophistication. Whereas hedge funds primarily target institutions and high net-worth individuals, mutual funds primarily target retail investors. These investors are more likely to be ignorant of underperformance (Gruber,

[16] A non-exhaustive list of hedge fund studies documenting positive average net alphas includes Ardia et al. (2024), Avramov, Barras, and Kosowski (2013), Buraschi, Kosowski, and Sritrakul (2014), Capocci and Hübner (2004), Chen, Cliff, and Zhao (2017), Diez de los Rios and Garcia (2010), and Kosowski, Naik, and Teo (2007).

[17] This result is an application of Jensen's inequality. With scalability constraints ($b_i > 0$), the net value-added function $va^{\text{net}}(w_{i,t-1}) = (a_i^{\text{net}} - b_i^{\text{net}} w_{i,t-1}) w_{i,t-1}$ is concave in $w_{i,t-1}$, which implies that $va_i^{\text{net}} = E[va^{\text{net}}(w_{i,t-1})] = \alpha_i^{\text{net}} E[w_{i,t-1}] - b_i^{\text{net}} V[w_{i,t-1}] < va^{\text{net}}(E[w_{i,t-1}]) = \alpha_i^{\text{net}} E[w_{i,t-1}]$.

1996), constrained by high search costs (Roussanov, Ruan, and Wei, 2021), and willing to pay extra fees for financial advice (Del Guercio and Reuter, 2014).

Please insert Figure 3 here

V.C. The Dynamics of Value Creation

V.C.1. The Value-Added over the Fund's Lifecycle

Table IV provides evidence of capital misallocation. Half the funds manage too much capital, resulting in a negative value-added net of fees. When investors pay excessive fees, they have strong incentives to withdraw their capital and seek more profitable opportunities. As they adjust their capital allocation, it changes the value created by hedge funds.

To examine this issue, we examine how the value-added evolves over the fund's lifecycle. Applying our methodology, we estimate the cross-sectional distribution of the subperiod value-added $va_i(s)$ defined in Equation (5) ($s = 1, ..., S$) and measured using capital observations over the s^{th} partition of the fund's entire sample. We consider a total of five subperiods ($S = 5$) to allow for a gradual adjustment process as investors learn about the skill and scale coefficients using past fund returns (Pástor and Stambaugh, 2012) and overcome frictions in moving capital in and out of hedge funds (Joenväärä, Kosowski, and Tolonen, 2019).

Panel A of Table V reports the distribution characteristics of the value-added in each subperiod. If investors use sharper skill and scale estimates, the allocation of capital becomes more efficient and the value-added distribution shifts to the right. Consistent with this prediction, we find more evidence of stellar value creation when funds enter the later stages of their lifecycle. The 90%-quantile increases from \$15 mio. to \$19 mio. per year between the first and last subperiods. However, there is no evidence that investors eliminate value-destroying funds—their proportion actually slightly increases from 22.1% to 28.1% as we reach the last subperiod. These patterns are remarkably similar across equity, macro, and arbitrage funds shown in Panels B to D. In each category, we observe an increase in the right tail accompanied by a persistently thick left tail.

Please insert Table V here

Next, we measure the value received by investors over the five subperiods using the net subperiod value-added $va_i^{net}(s)$ defined in Equation (6). Table VI shows that investors consistently extract value from a minority of the fund population—the 90% quantile ranges between \$10.0 mio. and \$12.4 mio. per year across the five subperiods. At the same time, they let an increasing proportion of funds grow too large and charge excessive fees. As this proportion reaches 46.2% in subperiod 4, the average net value-added turns negative (-\$1.1 mio. per year). This excess capital is the main culprit for the modest value created by the hedge fund industry over the entire period (\$0.3 mio. per year in Table II).

Please insert Table VI here

V.C.2. Investors' Capital Reallocation

We now examine how investors reallocate capital over the five subperiods. For each fund, we measure the ratio $\Delta\bar{w}_i(s) = \bar{w}_i(s)/\bar{w}_i$, where $\bar{w}_i(s)$, $\bar{w}_i$ denote the average levels of capital invested in subperiod s and over the full period. We then compute the cross-sectional average of $\Delta\bar{w}_i(s)$ for the entire population and each investment category (equity, macro, arbitrage) across the five subperiods (we obtain similar results with the median in the appendix).

Figure 4 shows that the capital allocated to hedge funds over their lifecycle can decomposed into three phases. During the initial phase (subperiod 1), the invested capital is relatively low—on average, it only represents 80% of the fund capital over the full period. During the intermediary phase (subperiods 2 to 4), we observe a strong capacity build up as capital overshoots its full-period level (on average, $\Delta\bar{w}_i(s)$ equals 1.1 in subperiod 4). This phase corresponds to an increased cross-sectional dispersion in value-added as the top (bottom) decile creates (destroys) more value (see Table V). During the final phase (subperiod 5), investors reduce capital as the average ratio falls down close to one.

Overall, the evidence in Figure 4 suggests a relatively complex reallocation process. On the one hand, investors are slow to punish funds that charge excessive fees. If a fund initially delivers a negative net value-added, we estimate a probability of 54% that it keeps doing so in the last subperiod. In addition, investors lose money on average in subperiod 4 as they endow funds with excess capital—possibly because they overreact to positive performance in earlier subperiods.[18] On the other hand, investors seem able to rationally distinguish between funds that create and destroy

[18]This interpretation is consistent with the study by Baquero and Verbeek (2022), who show that hedge fund investors overreact to past winning streaks—a behavioral bias referred to as the hot-hand fallacy (Rabin, 2002).

value. First, the progressive increase in value creation among the top funds provides evidence that a portion of investors' capital is efficently allocated. Second, the reduction in capital in the last subperiod is a rational response to the disappointing net value-added in the previous subperiod.

Please insert Figure 4 here

V.D. Value Optimality and Equilibrium Considerations

V.D.1. Estimation of the Model

Our results so far reveals that the majority of hedge funds create value. At the same time, we find evidence that investors pay excessive fees as they let funds grow too large. These contrasting findings beg the question of the overall efficiency of the hedge fund industry. In this section, we examine how consistent the actual value-added is with economic rationale. We estimate the optimal value-added va_i^* of each fund using the model presented in Section II.C in which (i) funds with heterogeneous skill and scale coefficients maximize their fee revenues and (ii) investors require a minimum compensation κ per unit of capital to cover due-diligence and monitoring costs.[19]

If the fund chooses the fee rate optimally at $fee_i^* = \frac{a_i-\kappa}{2}$, it produces the highest value-added $va_i^* = a_i w_i^* - b_i(w_i^*)^2 = \frac{a_i^2-\kappa^2}{4b_i}$ under the constraint that investors break even and receive $va_i^{\text{net},*} = a_i w_i^* - b_i(w_i^*)^2 - fee_i^* w_i^* = \kappa w_i^* = \frac{\kappa(a_i-\kappa)}{2b_i}$, where the optimal capital is given by $w_i^* = \frac{a_i-\kappa}{2b_i}$. The empirical counterparts of these optimal quantities are given by $\hat{fee}_i^* = \frac{\hat{a}_i-\kappa}{2}$, $\hat{va}_i^* = \frac{\hat{a}_i^2-\kappa^2}{4\hat{b}_i}$, and $\hat{va}_i^{\text{net},*} = \frac{\kappa(\hat{a}_i-\kappa)}{2\hat{b}_i}$. We can then compare these optimal values with the actual ones given by $\hat{fee}_i = \frac{1}{T_i}\sum_t I_{i,t} fee_{i,t}$, $\hat{va}_i$ and $\hat{va}_i^{\text{net}}$ (the full-period estimates).

Our normative analysis requires a value for the compensation κ. Contrary to a_i and b_i, which can be inferred from the data, κ is not directly observable. In our baseline analysis, we follow Stulz (2007) and set κ equal to 1% per year.[20] Another requirement is that va_i^* is positive. To incorporate this condition, we focus on the top 25% of funds with the highest estimated optimal values $\hat{va}_i^* = \frac{\hat{a}_i^2-\kappa^2}{4\hat{b}_i}$. Finally, we impose that $\hat{a}_i$ is above $\hat{fee}_i + \kappa$ such that investors find it rational

[19] Our analysis measures optimality from a private viewpoint and is silent on the social optimality of active management. On the one hand, hedge funds perform the socially valuable function of making prices more informative.On the other hand, hedge funds may be engaged in rent-seeking and socially wasteful activities at the expense of other investors in the market (Greenwood and Scharfstein, 2013; Tobin, 1984). Measuring the social value of active management therefore requires that one determines the relative importance of these two effects (*e.g.*, Kurlat, 2019).

[20] Stulz (2007) writes that a frequently heard price tag for hedge fund due-diligence costs is $50,000. If we take a five-year investment period as in Khorana, Servaes, and Tufano (2009) and a $1 mio. investment, we obtain $\kappa = 1\%$.

to invest a positive amount in the fund. This selection rule yields a total of 537 funds (in the appendix, we find similar results with alternative filters).

V.D.2. Comparison of Actual and Optimal Values

Table VII summarizes the results for the entire sample and three groups sorted on the actual fee rate (low, medium, high). For the fee comparison, we measure the difference between the cross-sectional means of the actual and optimal fees, denoted by $\hat{M}_{fee}$ and $\hat{M}_{fee^*}$ (both in level and in percentage of $\hat{M}_{fee^*}$). To address the concern that the average is not representative of the typical fund, we also examine the differences between the cross-sectional medians, denoted by $\hat{Q}_{fee}(0.5)$ and $\hat{Q}_{fee^*}(0.5)$ (both in level and in percentage of $\hat{Q}_{fee^*}(0.5)$). We compute the same statistics for the value-added (total and net).[21]

Panel A shows that actual and optimal fees are aligned. Low-fee funds have a lower skill coefficient and thus lower optimal fees relative to high-fee funds. These differences are economically large—12.4% and 6.2% per year for the average skill coefficient and optimal fees. However, the model is unable to quantitatively match the observed fees. For the vast majority of funds (502 out of 53), actual fees are lower than the optimal values (3.5% versus 9.3% per year on average).

In Panel B, we examine the value-added. The model rationalizes the value-added as an optimal trade-off between the fund skill and scalability. This simple mechanism does a reasonable job at explaining hedge fund value creation. The ratio of actual to optimal value-added equals 37% with the mean and rises up to 46% with the median. If the model holds, we expect a convergence of the value-added towards optimality as funds age. Examining the last subperiod value-added $\hat{va}_i(5)$ (instead of $\hat{va}_i$), we find that the median ratio does increase from 46% to 52%. However, this difference is small and reflects the slow change in the value-added across the five subperiods (see Tables V and VI). In Panel C, we focus on the value extracted by investors. Overall, the model does a better job at fitting the net value-added. For instance, the difference between the medians of $\hat{va}_i^{\text{net}}$ and $\hat{va}_i^{\text{net},*}$ is equal to 3.6 mio. per year, which represents 10.0% of the median optimal value-added.

Please insert Table VII here

[21]To facilitate the interpretation of the percentage difference, we use the common denominator $\hat{M}_{va}^*$ (mean) or $\hat{Q}_{va}^*(0.5)$ (median) for both the value-added and the net value-added.

In the traditional Berk and Green (2004) model, funds do not share the value created with investors. As a result, the net value-added is null and uncorrelated with the total value-added. This prediction is at odds with the data—we find that the pairwise correlation between $\hat{va}_i$ and $\hat{va}_i^{\text{net}}$ reaches 0.83. To capture this correlation, it is therefore necessary to allow investors some bargaining power. Our proposed model incorporates this feature via the parameter κ and delivers a strong correlation of 0.91 between $\hat{va}_i^*$ and $\hat{va}_i^{\text{net},*}$.

Finally, the model can match the fraction of the total value extracted by hedge fund investors. Using the average values of $\hat{va}_i^{\text{net}}$ on $\hat{va}_i$, we find that investors extract 14% of the total value created. Whereas the model makes different predictions for the levels of total and net value-added, their ratio remains remarkably similar at 15%. Overall, the combined findings from the data and the model suggest that hedge fund investors have limited bargaining power in the fee negociation.

V.D.3. Sources of Suboptimality

We now examine the reasons why the actual value-added departs from its optimal level. Under the model, there are two sources of suboptimality: (i) the choice of fees by funds and (ii) the capital allocation by investors. We illustrate the impact of suboptimal fees on equilibrium outcomes in Figure 5. In Panel A, we suppose that the fund sets fees too low ($fee_i < fee_i^*$). In this case, the equilibrium capital w_i^e at which investors break even ($va_i^{\text{net},e} = a_i w_i^e - b_i (w_i^e)^2 - fee_i = \kappa w_i^e$) is higher than its optimal value w_i^*. As a result, the equilibrium value-added is lower than optimal ($va_i^e = a_i w_i^e - b_i (w_i^e)^2 < va_i^*$), while the equilibrium net value-added is higher than optimal ($va_i^{\text{net},e} > va_i^{\text{net},*}$).[22] In Panel B, the fund sets fees too high ($fee_i > fee_i^*$). As a result, the equilibrium capital is too low ($w_i^e < w_i^*$) and both va_i^e and $va_i^{\text{net},e}$ are lower than optimal.

Please insert Figure 5 here

The second source of suboptimality—capital misallocation—arises from the gap between the actual capital $\bar{w}_i$ and its equilibrium value w_i^e (under the chosen fee rate $fees_i$). While this gap should vanish over time as investors learn and reallocate capital, it can have sizable short-term effects on value creation. Figure 6 illustrates these effects in the common situation where fees are set too low (such that $w_i^e > w_i^*$). In Panel A, we focus on overcapacity which occurs when

[22] In theory, it is possible that va_i^e rises above va_i^* if w_i^e corresponds to the value 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, none of the funds satisfy this condition.

the actual capital is above equilibrium ($\bar{w}_i > w_i^e$). As a result, both the value-added and the net value-added are below their equilibrium values ($va_i = a_i\bar{w}_i - b_i(\bar{w}_i)^2 < va_i^e$ and $va_i^{\text{net}} = a_i\bar{w}_i - b_i(\bar{w}_i)^2 - \mathit{fee}_i\bar{w}_i < va_i^{\text{net},e}$). In Panel B, we have undercapacity as capital is below equilibrium ($\bar{w}_i < w_i^e$). In this case, the effect on the value-added is uncertain and depends on the magnitude of the gap between $\bar{w}_i$ and w_i^e (in this example, both va_i and va_i^{net} are higher).

Please insert Figure 6 here

To examine the relative importance of these two sources of suboptimality, we split the difference between the actual and optimal value-added in two parts:

$$\hat{va}_i - \hat{va}_i^* = (\hat{va}_i^e - \hat{va}_i^*) + (\hat{va}_i - \hat{va}_i^e), \tag{29}$$

$$\hat{va}_i^{\text{net}} - \hat{va}_i^{\text{net},*} = (\hat{va}_i^{\text{net},e} - \hat{va}_i^{\text{net},*}) + (\hat{va}_i^{\text{net}} - \hat{va}_i^{\text{net},e}), \tag{30}$$

where the estimates of the equilbrium value-added are computed as $\hat{va}_i^e = \hat{a}_i\hat{w}_i^e - \hat{b}_i(\hat{w}_i^e)^2$ and $\hat{va}_i^{\text{net},e} = \hat{a}_i\hat{w}_i^e - \hat{b}_i(\hat{w}_i^e)^2 - \hat{\mathit{fee}}_i\hat{w}_i^e$and the equilbrium capital is given by $\hat{w}_i^e = \frac{\hat{a}_i - \hat{\mathit{fee}}_i - \kappa}{\hat{b}_i}$. The first term on the righthand side of each equation captures the impact of suboptimal fees on value creation (without any capital misallocation). The second term captures the impact of capital misallocation on value added (without suboptimal fees).

Our analysis in Table VIII reveals that capital misallocation the prevalent source of suboptimality. In Panel A, the average equilibrium value-added (under the chosen fees) represents 84% of the average optimal value. Therefore, suboptimal fees lead to a 26%-reduction in value creation. Panel B reveals that investors' capital decisions lead to an additional 37%-reduction in value creation. Combining both results, we conclude that capital misallocation represents around 60% (37/53) of the gap between the actual and optimal value-added.

Turning to the analysis of the equilibrium net value-added in Panel A, we find that it is above the optimal level (\$10.6 mio versus \$7.7 mio. per year). This result is consistent with Figure 6 showing that low fees leads to a higher capital base which, in turn, raises the dollar compensation required by investors. Interestingly, the impact of capital misallocation goes in the other direction and leads to a reduction in the actual net value-added on average (\$7.5 mio. versus \$10.6 mio. per year). This result is entirely driven by excess capacity (*i.e.*, $\bar{w}_i > w_i^e$)—the appendix shows that the gap between $\hat{va}_i^{\text{net}}$ and $\hat{va}_i^{\text{net},e}$ among bloated funds reaches -\$31.0 mio. per year on average.

Please insert Table VIII here

VI. Conclusion

In this paper, we conduct an in-depth analysis of value creation in the hedge fund industry. Hedge funds are considered as the most active investors and could therefore extract substantial value from capital makets. They follow complex alternative strategies whose profile in terms of profitability and scalability may depart substantially from the long-only strategies followed by mutual funds. Our analysis also considers the unique features of hedge fund investors. They plausibly have more bargaining power in the fee negociation and higher levels of sophistication than their mutual fund peers. Under this premise, we expect them to extract value from their fund investments and allocate capital more efficiently over time.

We develop a new econometric approach to infer the entire distribution of the value-added. This approach captures the large heterogeneity across hedge funds, while controling for the complexities of hedge fund industry in terms of leverage and benchmarking. The cornerstone of our approach is the specification of the fund value-added as $va_i = a_i E[w_{i,t-1}] - b_i E[w_{i,t-1}^2]$. This specification captures the idea that value creation depends on skill (captured by a_i) and scalability (captured by b_i). Ultimately, it provides a unified framework to study the drivers, split, dynamics, and optimality of hedge fund value-added.

Our empirical analysis brings several insights. First, most hedge funds create value by exploiting their unique investment skills. Their levered strategies are highly profitable but remain unscalable. As a result, hedge funds do not systematically create more value than mutual funds. Second, we find that investors extract little value from hedge funds on average—a result that contrasts with the large net alphas documented in previous studies. This result hides a large heterogeneity as investors extract positive value from one half of the population, while paying excessive fees to the other half. Third, hedge fund investors are able to identify funds with high value potential over time. However, they also tend to deploy too much capital through the fund's lifecycle. The process of capital reallocation across funds suggests a learning process that is impactful but noisy. Finally, we find that a rational model of active management does a good job at explaining fees and value creation in the hedge fund industry. Consistent with the data, this model also concludes that hedge fund investors have limited power in the fee negociation.

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TABLE I. Descriptive Statistics

Panel A provides summary statistics for an equal-weighted portfolio of all existing hedge funds at the start of each month in the entire population and three investment categories: (i) equity funds (long-short, market neutral), (ii) macro funds (global macro, managed futures), and (iii) arbitrage funds (relative value, event driven). We report the mean and standard deviation of the portfolio gross and net returns (over the riskfree rate), the mean of the portfolio management and performance fees, and the time-series average of the cross-sectional mean (median) of capital across funds. The number in parentheses denotes the total number of funds in each category over the sample period. The return and fee statistics are reported in percentage per year and capital is expressed in \$ mio. in terms of January 1, 2000 dollars. Panel B summarizes the results of the time-series regression of the gross return of the equal-weighted portfolio on the returns of the five factors included in the benchmark model. It reports the estimated portfolio beta on the market, size, value, carry, and time-series (TS) momentum factors. It also reports the relative contribution of the five factors to the average gross return of the portfolio and the adjusted R^2 of the regression. The statistics are computed using monthly data between January 1994 and December 2020.

Panel A: Return & Capital Statistics

	Gross Returns (% p.a.)		Net Returns (% p.a.)		Fees (% p.a.)		Capital ($ mio.)	
	Mean	Std Dev.	Mean	Std Dev.	MF	PF	Mean	Median
All Funds	9.84	6.06	6.67	5.59	1.43	1.73	196	58
Equity	11.13	9.07	7.90	8.41	1.27	1.97	155	45
Long/Short	11.71	10.03	8.40	9.30	1.27	2.05	148	44
Market Neutral	6.72	3.30	4.09	2.99	1.29	8.41	208	64
Macro	8.82	7.88	5.62	6.91	1.68	1.50	250	59
Global Macro	9.73	7.83	6.22	6.94	1.70	1.78	287	72
Managed Futures	8.19	8.33	5.20	7.27	1.66	1.31	218	51
Arbitrage	9.15	5.53	6.09	5.18	1.39	1.67	204	79
Event Driven	9.57	6.65	6.33	6.15	1.45	1.80	186	76
Relative Value	8.79	5.00	5.87	4.75	1.34	1.58	214	81
Mutual Funds	8.97	15.58	7.75	15.58	1.22		906	243

Panel B: Benchmark Model

	Factor Exposures					Model Fit	
	Market	Size	Value	Carry	TS Mom.	RC	R^2
All Funds	0.29	0.17	0.02	0.08	0.10	0.43	0.68
Equity	0.47	0.31	-0.04	0.08	0.05	0.47	0.84
Long/Short	0.52	0.35	-0.05	0.09	0.05	0.48	0.84
Market Neutral	0.11	0.01	-0.01	0.03	0.06	0.26	0.26
Macro	0.08	0.03	0.10	0.04	0.34	0.52	0.29
Global Macro	0.14	0.07	0.08	0.02	0.30	0.47	0.26
Managed Futures	0.03	0.01	0.11	0.05	0.37	0.56	0.32
Arbitrage	0.24	0.13	0.04	0.15	-0.01	0.32	0.60
Event Driven	0.31	0.19	0.05	0.10	-0.01	0.33	0.65
Relative Value	0.19	0.09	0.03	0.20	-0.02	0.32	0.48
Mutual Funds	0.95	0.38	-0.06	0.04	-0.00	0.94	0.99

TABLE II. The Value-Added and Its Drivers

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 mean and median, the proportions of funds with a negative and positive value-added, and the quantiles at 10% and 90%. The value-added (capital) is expressed in \$mio. per year (in \$mio.) in terms of January 1, 2000 dollars. Panel B contains summary statistics for the cross-sectional distribution of the skill coefficient measured as the first-dollar alpha. This cofficient is expressed in percentage per year. 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 mio. increase in capital. This coefficient is expressed in percentage per year. Figures in parentheses denote the standard deviation of each estimator.

Panel A: Cross-Sectional Distribution of Value-Added

			Proportions (%)		Quantiles ($ mio. p.a.)	
	Mean ($ mio. p.a.)	Median ($ mio. p.a)	Negative	Positive	10%	90%
All Funds	4.73	1.12	33.36	66.64	-4.77	18.51
Equity	3.69	0.89	34.61	65.39	-3.58	12.30
Macro	1.47	0.06	49.04	50.96	-10.51	14.16
Arbitrage	8.48	3.18	19.72	80.28	-2.08	26.56

Panel B: Cross-Sectional Distribution of Skill

			Proportions (%)		Quantiles (% p.a.)	
	Mean (% p.a.)	Median (% p.a.)	Negative	Positive	10%	90%
All Funds	12.23	10.21	14.17	85.83	-1.95	28.86
Equity	12.89	10.55	13.66	86.34	-1.85	30.36
Macro	11.19	8.60	19.28	80.72	-4.16	27.73
Arbitrage	12.28	10.58	10.80	89.20	-0.42	27.32

Panel C: Cross-Sectional Distribution of Scalability

			Proportions (%)		Quantiles (% p.a.)	
	Mean (% p.a.)	Median (% p.a.)	Negative	Positive	10%	90%
All Funds	1.96	0.47	18.55	81.45	-0.32	6.23
Equity	2.45	0.77	18.91	81.09	-0.31	8.03
Macro	2.17	0.51	15.96	84.04	-0.29	6.43
Arbitrage	1.22	0.29	20.12	79.88	-0.33	4.23

TABLE III. The Analysis of the Most Valuable Funds

This table provides summary statistics for the top decile of funds sorted on the estimated value-added. Panel A reports the cross-sectional mean (median) of the value-added, the skill coefficient, the scale coefficient, and the average fund capital for the top funds and the entire population. The value-added is expressed in $mio. per year in terms of January 1, 2000 dollars. The skill coefficient is measured as the first-dollar alpha and is expressed in percentage per year. The scale coefficient is measured as the change in the gross alpha for a $10 mio. increase in capital and is expressed in percentage per year. Figures in parentheses denote the mean (median) rank of the coefficients of the top funds (1=low, 10=high). Panel B reports the cross-sectional mean (median) of the value-added after controling for three additional strategies (illiquidity, betting-against-beta (BAB), and variance). It also reports the difference with the mean (median) value-added in the baseline case.

Panel A: Value-Added and Its Drivers

	Value-Added ($ mio. p.a.)		AUM ($ mio.)		Skill (% p.a.)		Scale (% p.a.)	
	Top	All	Top	All	Top	All	Top	All
Cross-Sectional Average								
All Funds	40.84	4.73	637	191	17.56 (7)	12.23	0.15 (7)	1.96
Equity	31.80	3.69	515	146	16.05 (6)	12.89	0.13 (7)	2.45
Macro	35.68	1.47	695	229	17.17 (7)	11.19	0.24 (7)	2.17
Arbitrage	51.85	8.48	689	213	19.83 (7)	12.28	0.16 (7)	1.22
Cross-Sectional Median								
All Funds	31.05	1.12	489	73	14.68 (7)	10.21	0.09 (8)	0.47
Equity	24.29	0.89	339	56	11.88 (6)	10.55	0.07 (8)	0.77
Macro	26.14	0.06	529	75	14.21 (7)	8.60	0.07 (8)	0.51
Arbitrage	40.03	3.18	615	105	15.58 (7)	10.58	0.10 (8)	0.29

Panel B: Impact of Non-Replicable Strategies

	Value-Added				Difference With Base Case			
	Liquidity	BAB	Variance	All	Liquidity	BAB	Variance	All
Cross-Sectional Average								
All Funds	40.86	37.40	33.62	33.99	-0.02	3.43	7.22	6.85
Equity	32.00	28.07	26.22	25.74	-0.20	3.73	5.58	6.06
Macro	35.82	34.67	34.17	35.28	-0.14	1.01	1.51	0.40
Arbitrage	51.44	46.65	39.86	39.56	0.42	5.20	11.99	12.29
Cross-Sectional Median								
All Funds	32.52	29.22	27.16	26.36	-1.47	1.83	3.89	4.69
Equity	25.15	22.33	20.21	19.95	-0.86	1.96	4.08	4.34
Macro	27.56	25.73	28.26	25.20	-1.42	0.40	-2.12	0.94
Arbitrage	41.19	38.63	29.78	30.97	-1.15	1.40	10.25	9.07

TABLE IV. The Net Value-Added and Its Drivers

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

Panel A: Cross-Sectional Distribution of Net Value-Added						
			Proportions (%)		Quantiles ($ mio. p.a.)	
	Mean ($ mio. p.a.)	Median ($ mio. p.a)	Negative	Positive	10%	90%
All Funds	0.32	0.03	49.55	50.45	-8.40	10.06
Equity	0.12	-0.07	51.91	48.09	-6.38	5.93
Macro	-3.05	-0.72	64.88	35.12	-15.82	6.67
Arbitrage	3.16	0.93	34.89	65.11	-4.75	15.01

Panel B: Cross-Sectional Distribution of Skill						
			Proportions (%)		Quantiles (% p.a.)	
	Mean (% p.a.)	Median (% p.a.)	Negative	Positive	10%	90%
All Funds	8.96	7.18	19.02	80.98	-3.73	23.38
Equity	9.60	7.86	18.83	81.17	-3.54	24.98
Macro	7.90	6.08	24.78	75.22	-6.00	22.42
Arbitrage	9.02	7.50	14.77	85.23	-1.73	21.83

Panel C: Cross-Sectional Distribution of Scalability						
			Proportions (%)		Quantiles (% p.a.)	
	Mean (% p.a.)	Median (% p.a.)	Negative	Positive	10%	90%
All Funds	1.79	0.44	18.01	81.99	-0.27	5.67
Equity	2.26	0.69	17.64	82.36	-0.26	7.49
Macro	1.93	0.47	15.58	84.42	-0.24	5.82
Arbitrage	1.13	0.25	20.32	79.68	-0.30	3.91

TABLE V. The Value-Added Over the Fund's Lifecycle

Panel A contains summary statistics for the cross-sectional distribution of the value-added across the five subperiods of the fund's lifecycle (measured by splitting the fund observations into five equal subperiods). It reports the mean and median, the proportions of funds with a negative and positive value-added, and the quantiles at 10% and 90%. The subperiod value-added is expressed in $mio. per year in terms of January 1, 2000 dollars. Panels B to D report the same summary statistics for the three investment categories (equity, macro, and arbitrage funds). Figures in parentheses denote the estimated standard deviation of each estimator.

Panel A: All Funds

			Proportions (%)		Quantiles ($ mio. p.a.)	
	Mean ($ mio. p.a.)	Median ($ mio. p.a)	Negative	Positive	10%	90%
Subperiod 1	3.90	1.60	22.11	77.89	-3.08	15.79
Subperiod 2	5.48	1.72	26.52	73.48	-4.81	20.92
Subperiod 3	5.38	1.50	30.16	69.84	-5.10	21.74
Subperiod 4	3.94	1.12	33.19	66.81	-6.48	20.47
Subperiod 5	4.99	1.15	28.14	71.86	-3.42	19.90

Panel B: Equity Funds

			Proportions (%)		Quantiles ($ mio. p.a.)	
	Mean ($ mio. p.a.)	Median ($ mio. p.a)	Negative	Positive	10%	90%
Subperiod 1	2.52	1.45	22.31	77.69	-2.92	12.03
Subperiod 2	4.29	1.48	28.50	71.50	-4.09	14.21
Subperiod 3	4.88	1.30	30.28	69.72	-3.36	13.72
Subperiod 4	3.38	0.82	35.37	64.63	-4.77	12.57
Subperiod 5	3.41	0.95	28.92	71.08	-2.48	12.93

Panel C: Macro Funds

			Proportions (%)		Quantiles ($ mio. p.a.)	
	Mean ($ mio. p.a.)	Median ($ mio. p.a)	Negative	Positive	10%	90%
Subperiod 1	2.11	0.78	31.55	68.45	-7.08	13.44
Subperiod 2	2.36	0.61	37.55	62.45	-10.77	17.14
Subperiod 3	0.98	0.34	43.81	56.19	-12.85	18.46
Subperiod 4	-0.97	0.12	46.87	53.13	-14.59	15.07
Subperiod 5	2.85	0.41	39.59	60.41	-7.74	18.43

Panel D: Arbitrage Funds

			Proportions (%)		Quantiles ($ mio. p.a.)	
	Mean ($ mio. p.a.)	Median ($ mio. p.a)	Negative	Positive	10%	90%
Subperiod 1	6.89	2.75	14.57	85.43	-1.13	22.19
Subperiod 2	9.30	3.59	15.66	84.34	-1.55	29.60
Subperiod 3	9.37	3.19	19.43	80.57	-3.37	31.98
Subperiod 4	8.41	2.83	20.02	79.98	-2.97	29.59
Subperiod 5	8.48	2.70	18.33	81.67	-1.99	28.95

TABLE VI. The Net Value-Added Over the Fund's Lifecycle

Panel A contains summary statistics for the cross-sectional distribution of the net value-added across the five subperiods of the fund's lifecycle (measured by splitting the fund observations into five equal subperiods). It reports the mean and median, the proportions of funds with a negative and positive value-added, and the quantiles at 10% and 90%. The subperiod net value-added is expressed in $mio. per year in terms of January 1, 2000 dollars. Panels B to D report the same summary statistics for the three investment categories (equity, macro, and arbitrage funds). Figures in parentheses denote the estimated standard deviation of each estimator.

Panel A: All Funds

			Proportions (%)		Quantiles ($ mio. p.a.)	
	Mean ($ mio. p.a.)	Median ($ mio. p.a)	Negative	Positive	10%	90%
Subperiod 1	0.87	0.76	31.00	69.00	-5.51	9.99
Subperiod 2	0.93	0.62	38.30	61.70	-9.27	12.35
Subperiod 3	0.34	0.35	43.66	56.34	-9.35	12.13
Subperiod 4	-1.09	0.14	46.18	53.82	-10.14	11.14
Subperiod 5	0.52	0.34	40.66	59.34	-6.29	11.43

Panel B: Equity Funds

			Proportions (%)		Quantiles ($ mio. p.a.)	
	Mean ($ mio. p.a.)	Median ($ mio. p.a)	Negative	Positive	10%	90%
Subperiod 1	-0.25	0.63	32.65	67.35	-5.20	6.77
Subperiod 2	0.42	0.48	40.63	59.37	-7.49	8.55
Subperiod 3	0.89	0.22	45.97	54.03	-7.13	7.62
Subperiod 4	-0.45	0.03	48.52	51.48	-8.26	6.47
Subperiod 5	0.01	0.22	42.41	57.59	-4.48	6.12

Panel C: Macro Funds

			Proportions (%)		Quantiles ($ mio. p.a.)	
	Mean ($ mio. p.a.)	Median ($ mio. p.a)	Negative	Positive	10%	90%
Subperiod 1	-0.55	0.25	40.49	59.51	-9.76	8.75
Subperiod 2	-2.00	-0.01	50.45	49.55	-15.96	9.03
Subperiod 3	-4.43	-0.36	56.58	43.42	-18.37	10.08
Subperiod 4	-6.44	-0.47	59.64	40.36	-19.26	7.66
Subperiod 5	-1.89	-0.04	52.11	47.89	-12.62	10.22

Panel D: Arbitrage Funds

			Proportions (%)		Quantiles ($ mio. p.a.)	
	Mean ($ mio. p.a.)	Median ($ mio. p.a)	Negative	Positive	10%	90%
Subperiod 1	3.29	1.43	21.70	78.30	-3.24	14.72
Subperiod 2	3.80	1.53	26.16	73.84	-5.38	18.47
Subperiod 3	3.39	1.29	30.92	69.08	-6.90	17.54
Subperiod 4	2.31	0.94	33.00	67.00	-7.11	16.57
Subperiod 5	2.99	1.14	29.73	70.27	-4.91	16.91

TABLE VII. Comparison of Actual and Optimal Values

Panel A reports the cross-sectional mean (median) of the actual fees and optimal fees, as well as their difference (in level and in proportion of the mean (median) optimal fees) for the entire sample of funds and three groups sorted on actual fees (low, medium, high). It also reports the cross-sectional mean (median) of management fees, performance fees, and the skill coefficient measured as the first-dollar alpha. The fees and the skill coefficient are expressed in percentage per year. Panel B reports the cross-sectional mean (median) of the actual value-added over the full period and the optimal value-added, as well as their difference (in level and in proportion of the mean (median) optimal value-added). It also reports the same statistics for the value-added over the last subperiod. Panel C reports the cross-sectional mean (median) of the net actual value-added over the full period and the optimal net value-added, as well as their difference (in level and in proportion of the mean (median) optimal value-added). It also reports the same statistics for the net value-added over the last subperiod. The value-added is expressed in $ mio. per year in terms of January 1, 2000 dollars.

Panel A: Fees

	Comparison				Additional Info		
	Actual	Optimal	Diff.	Diff.(%)	MF	PF	Skill
Cross-Sectional Average							
All Funds	3.49	9.32	-5.82	0.63	1.49	2.00	19.64
Low Fee	2.03	6.47	-4.44	0.69	1.16	0.87	13.95
Medium Fee	3.51	8.40	-4.89	0.58	1.55	1.96	17.81
High Fee	4.94	13.07	-8.13	0.62	1.75	3.18	27.14
Cross-Sectional Median							
All Funds	3.53	7.92	-4.39	0.55	1.50	1.93	16.84
Low Fee	2.32	5.35	-3.03	0.57	1.13	0.87	11.70
Medium Fee	3.53	6.93	-3.40	0.49	1.50	1.92	14.86
High Fee	4.55	11.55	-7.00	0.61	2.01	2.97	24.10

Panel B: Value-Added

	Comparison Full Period				Comparison Last Period			
	Actual	Optimal	Diff.	Diff.(%)	Actual	Optimal	Diff.	Diff.(%)
Cross-Sectional Average								
All Funds	21.40	56.86	-35.46	0.62	20.32	56.86	-36.54	0.64
Low Fee	16.70	60.65	-43.95	0.72	16.71	60.65	-43.94	0.72
Medium Fee	21.16	50.59	-29.43	0.58	22.87	50.59	-27.72	0.55
High Fee	26.34	59.31	-32.97	0.56	21.40	59.31	-37.91	0.64
Cross-Sectional Median								
All Funds	16.61	36.32	-19.70	0.54	18.79	36.32	-17.52	0.48
Low Fee	14.48	32.59	-18.11	0.56	17.91	32.59	-14.68	0.45
Medium Fee	17.65	36.97	-19.32	0.52	19.12	36.97	-17.85	0.48
High Fee	18.54	39.55	-21.01	0.53	19.21	39.55	-20.34	0.51

Panel C: Net Value-Added

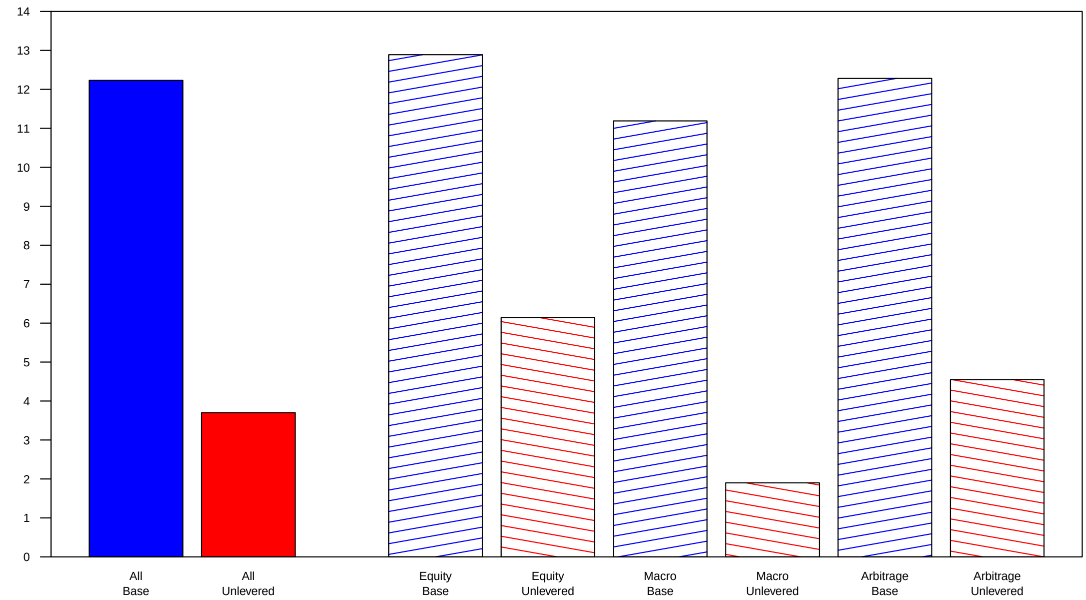
	Comparison Full Period				Comparison Last Period			
	Actual	Optimal	Diff.	Diff.(%)	Actual	Optimal	Diff.	Diff.(%)
Cross-Sectional Average								
All Funds	7.46	7.67	-0.20	0.00	4.99	7.67	-2.68	0.05
Low Fee Group	3.23	10.71	-7.47	0.12	2.29	10.71	-8.42	0.14
Medium Fee Groups	6.83	7.03	-0.20	0.00	8.28	7.03	1.26	0.02
High Fee Group	12.32	5.26	7.06	0.12	4.42	5.26	-0.84	0.01
Cross-Sectional Median								
All Funds	7.97	4.40	3.57	0.10	10.63	4.40	6.23	0.17
Low Fee	6.52	5.69	0.83	0.03	10.76	5.69	5.07	0.16
Medium Fee	7.90	4.49	3.41	0.09	10.81	4.49	6.32	0.17
High Fee	10.09	3.15	6.95	0.18	10.10	3.15	6.95	0.18

TABLE VIII. Departure From Optimality

		Panel A: Impact of Suboptimal Fees							
		Value-Added				Net Value-Added			
	N	Equilibrium	Optimal	Diff.	Diff.(%)	Equilibrium	Optimal	Diff.	Diff.(%)
Cross-Sectional Average									
All Funds	536	42.23	56.86	-14.63	0.26	10.61	7.67	2.94	0.05
Low Fee	179	45.26	60.65	-15.39	0.25	15.88	10.71	5.17	0.09
Medium Fee	178	39.18	50.59	-11.41	0.23	8.73	7.03	1.70	0.03
High Fee	179	42.24	59.31	-17.07	0.29	7.22	5.26	1.96	0.03
Cross-Sectional Median									
All Funds	536	26.69	36.32	-9.62	0.26	6.35	4.40	1.95	0.05
Low Fee	179	24.58	32.59	-8.01	0.25	8.08	5.69	2.39	0.07
Medium Fee	178	27.60	36.97	-9.37	0.25	6.27	4.49	1.77	0.05
High Fee	179	26.54	39.55	-13.01	0.33	4.80	3.15	1.65	0.04
		Panel B: Impact of Capital Misallocation							
		Value-Added				Net Value-Added			
	N	Actual	Equilibrium	Diff.	Diff.(%)	Actual	Equilibrium	Diff.	Diff.(%)
Cross-Sectional Average									
All Funds	536	21.40	42.23	-20.83	0.37	7.46	10.61	-3.15	0.06
Low Fee	179	16.70	45.26	-28.56	0.47	3.23	15.88	-12.64	0.21
Medium Fee	178	21.16	39.18	-18.02	0.36	6.83	8.73	-1.90	0.04
High Fee	179	26.34	42.24	-15.90	0.27	12.32	7.22	5.11	0.09
Cross-Sectional Median									
All Funds	536	16.61	26.69	-10.08	0.28	7.97	6.35	1.62	0.04
Low Fee	179	14.48	24.58	-10.09	0.31	6.52	8.08	-1.56	0.05
Medium Fee	178	17.65	27.60	-9.95	0.27	7.90	6.27	1.64	0.04
High Fee	179	18.54	26.54	-8.00	0.20	10.09	4.80	5.30	0.13

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 and is expressed in percentage per year. 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 mio. increase in capital and is expressed in percentage per year.

Panel A Average Skill Coefficient (% p.a.)



Panel B Average Scale Coefficient (% p.a.)

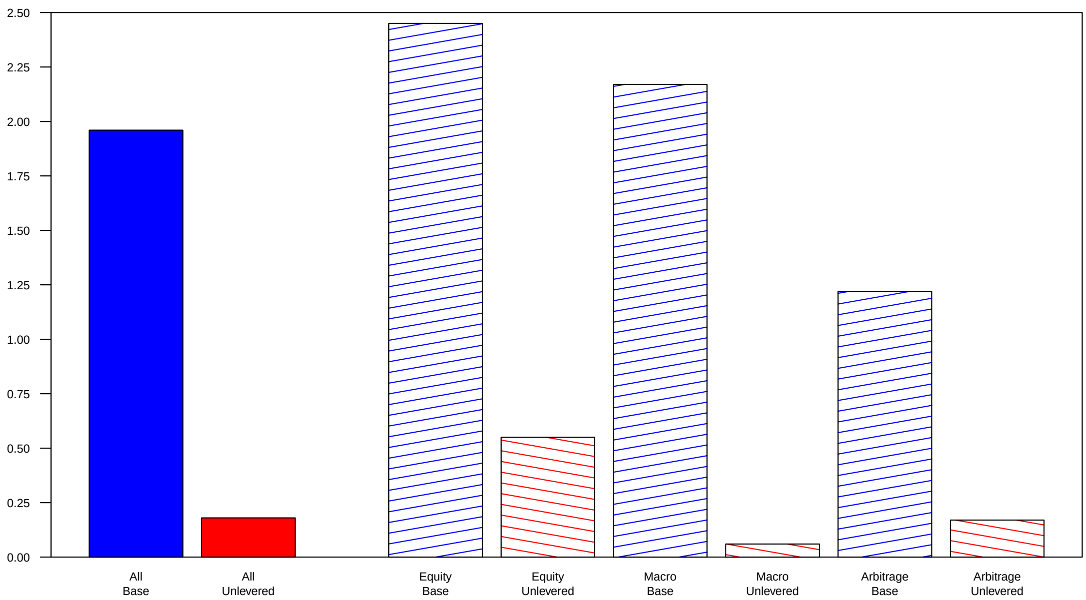


Figure 2. Comparison of the Value-Added With Mutual Funds
This figure compares the average value-added for hedge funds and mutual funds. The leftmost bars show the average values for all hedge funds in the population and the three investment categories (equity, macro, and arbitrage funds). The rightmost 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 $ mio. per year in terms of January 1, 2000 dollars.

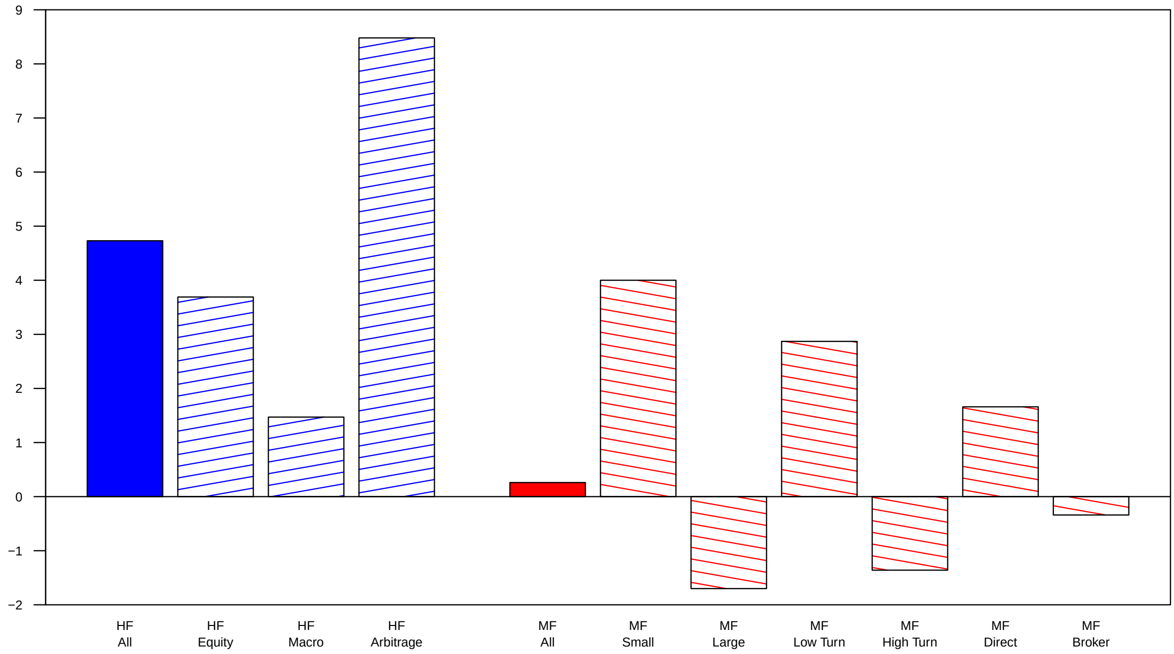


Figure 3. Comparison of the Net Value-Added With Mutual Funds

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 $ mio. per year in terms of January 1, 2000 dollars.

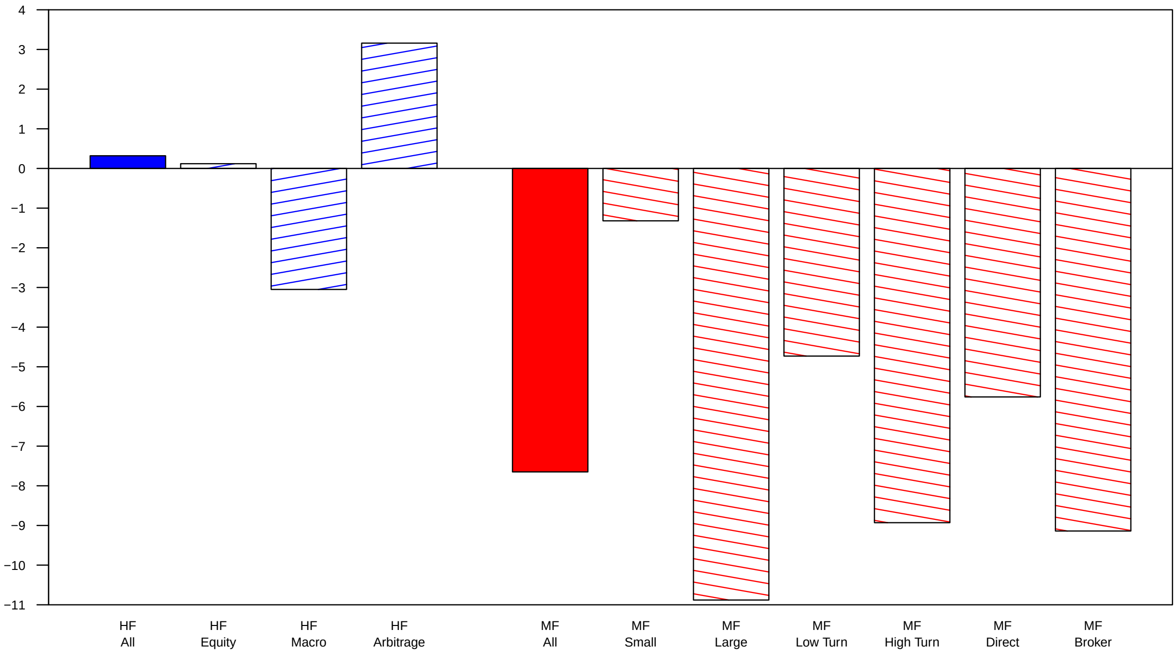


Figure 4. Variation in Capital Over the Fund's Lifecycle
This figure plots the cross-sectional mean of the ratio of the average fund capital during each subperiod of its lifecycle (measured by splitting the fund observations into five equal subperiods) on the average fund capital over the entire period. We conduct this analysis for the entire population and the three investment categories (equity, macro, and arbitrage funds). The capital is expressed in $ mio. in terms of January 1, 2000 dollars.

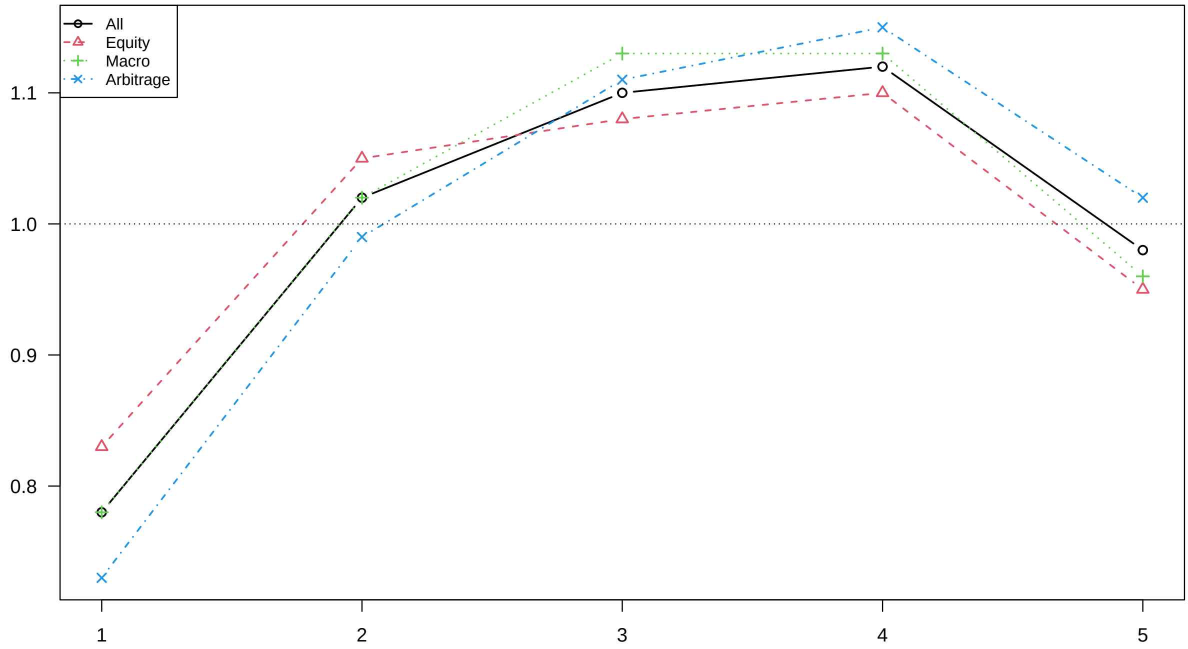
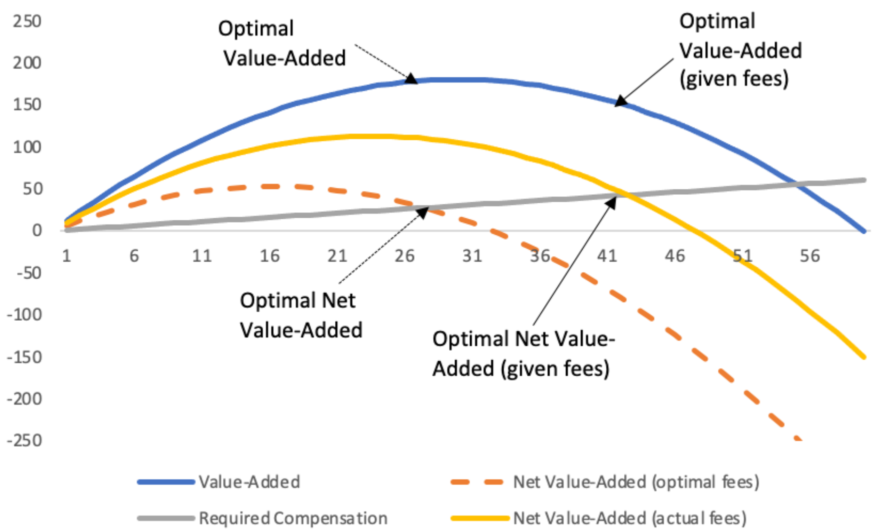


Figure 5. Impact of Subtimal Fees

This figure illustrates how the choice of fees by the fund affects the equilibrium value-added. Panel A plots the case where fees are too low relative to their optimal value. As a result, the equilibrium capital is above its optimal level, and the equilibrium (net) value-added is below (above) its optimal level. Panel B plots the case where fees are too high relative to their optional value. As a result, the equilibrium capital is below its optimal level, the equilibrium (net) value-added is below (below) its optimal level.

Panel A Low Fees



Panel B High Fees

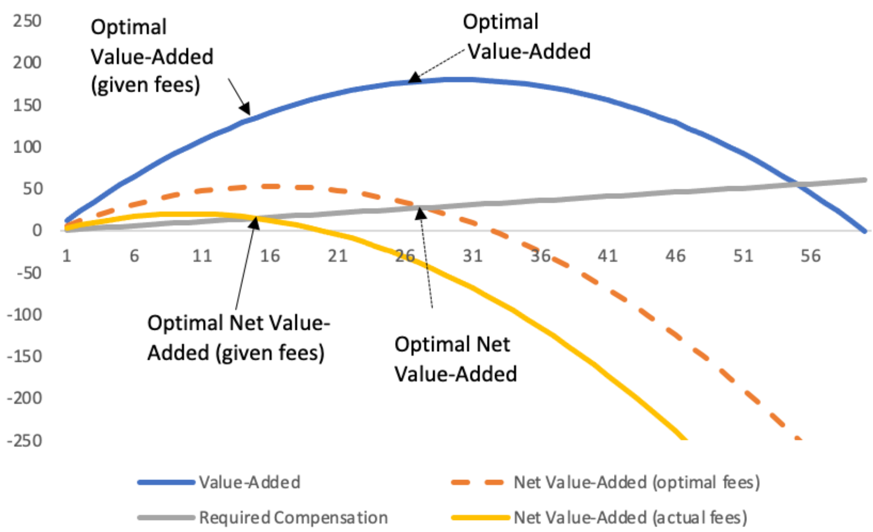
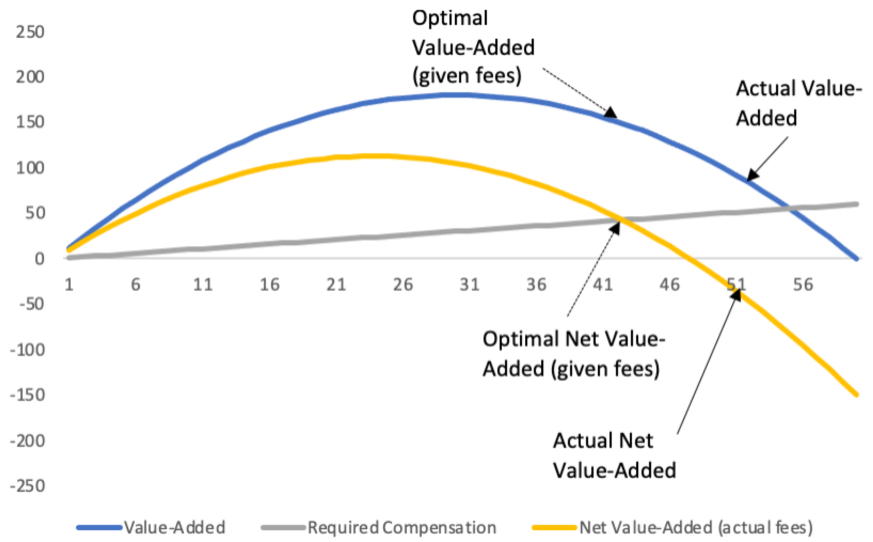


Figure 6. Impact of Capital Misallocation

This figure illustrates how the capital allocation by investors can imply a short-run departure of the value-added from its optimal value. Panel A plots the case where the actual capital is temporarily below its equilibrium level. As a result, the net value-added is above its optimal level, while the impact on the value-added is uncertain. Panel B plots the case where the actual capital is temporarily above its equilibrium level. As a result, the (net) value-added is below (below) its optimal level.

Panel A Capital Undercapacity



Panel B Capital Overcapacity