

Hedge Fund Value Creation

First version: March 5, 2024

This Version: February 1, 2026

Abstract

We measure value creation in the hedge fund industry—an ideal setting to study how manager and investor sophistication shape the magnitude, sharing, dynamics, and optimality of the value-added. Our fund-level analysis reveals that most hedge funds add value by leveraging profitable but hard-to-scale strategies, which limits their ability to consistently outperform mutual funds. Investors allocate capital far more efficiently than in the mutual fund sector, yet they extract no value on average. Finally, a simple extension of the Berk–Green model matches the observed heterogeneity across funds, but reveals that the hedge fund industry operates at excess capacity.

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

I. Introduction

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

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

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

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

To address these issues, we develop a novel methodology with two main ingredients. First, we specify the gross alpha as $\alpha_{i,t} = a_i - b_i w_{i,t}$, which formalizes the intuition that the value created by the hedge fund ultimately depends on (i) its skill at identifying profitable strategies—captured by the first-dollar alpha a_i —and (ii) its scalability constraints as it grows in size—captured by the coefficient b_i . While this parameterization of the value-added is numerically equivalent to the nonparametric approach of Berk and van Binsbergen (2015), it is necessary to derive closed-form expressions for studying the dynamics and optimality of value creation. Second, we take a fund-level approach and infer the entire distribution of value-added across funds. Hedge funds differ widely in their skill and scalability reflected in the coefficients a_i and b_i . Because of this heterogeneity, simple averages provide limited information about hedge fund value creation. For example, it is silent on the unique characteristics of the most valuable funds or the proportion of funds that charge excessive fees to investors.

Our econometric framework is tailored to hedge funds and departs markedly from that of Barras, Gagliardini, and Scaillet (2022, BGS) for mutual funds. A key distinction is that we address the benchmarking challenge posed by hedge funds as they pursue alternative strategies that investors cannot easily replicate (*e.g.*, Cochrane, 2013). We show theoretically that these non-replicable strategies not only contribute to the value-added, but also generate cross-fund dependencies that substantially amplify estimation noise. Our approach also allows skill and scalability to vary across funds without requiring explicit identification of their underlying sources. The fund-specific coefficients a_i and b_i therefore absorb the effects of a potentially large set of characteristics—including leverage—that are not reported in standard databases.

We measure value created by 2,517 hedge funds across four major databases and three categories (equity, macro, arbitrage). The main inputs for our analysis are the fund-specific coefficients a_i and b_i obtained from time-series regressions of monthly gross returns on lagged capital and factor returns. In our main specification, we benchmark funds against five factors—market, size, value, carry, and time-series (TS) momentum.² This choice reflects both relevance and replicability as these factors capture common hedge fund strategies that can be implemented by investors (Ardia et al., 2024; Jorion, 2021; Pedersen, 2015).

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

Our analysis between 1994 and 2020 reveals that hedge funds create substantial value. Close to 70% of them deliver positive value-added, averaging \$5.7 million per year or about \$1.2 million per manager. In aggregate, this amounts to \$86 billion—roughly 35% of the total value generated by the securities sector. Hedge funds create value because they possess investment skills, consistent with evidence that their trading activities enhance price efficiency (Ha, Hu, and Tang, 2024). The first-dollar alpha is positive for more than 85% of funds and is economically large, averaging 12.5% per year. At the same time, they struggle to scale up these strategies—on average, the gross alpha declines by 1.5% per year for every additional \$10 million of capital.

We also document substantial heterogeneity in value creation across funds. Arbitrage funds create more value as roughly 80% of them generate a positive value-added, compared with 67% for equity funds and 51.6% for macro funds. These patterns are consistent with recent studies showing that arbitrage funds trade complex assets with attractive risk–return trade-offs (Eisfeldt, Lustig, and Zhang, 2023; Haddad and Muir, 2021). We also find that value creation is highly concentrated within each category—the top 10% of funds account for at least 60% of total value added. These funds do not focus on the most profitable ideas, which are inherently difficult to scale. Instead, they strike a unique balance between skill and scalability. Moreover, the top funds tend to exploit informational advantages rather than rely on mechanical, hard-to-replicate strategies. Controlling for more complex factors linked to illiquidity, betting-against-beta, and variance, we find that the value-added remains largely unchanged.

Our comparison with mutual funds reveals striking differences in skill and scalability. On average, the first-dollar alpha of mutual funds is only equal to 2.6% per year and their gross alpha declines by just 0.2% per year for every additional \$10 million of capital. These differences do not stem from hedge funds having fundamentally better ideas or trading technologies. Rather, they are largely explained by the leverage employed by hedge funds—a conclusion supported by proprietary leverage data from Barth, Hammond, and Monin (2020). Whereas the value gap with mutual funds is large at \$5.3 million per year, it is primarily driven by arbitrage funds. Once this category is excluded, several mutual fund groups—most notably small-cap and low-turnover funds—exploit lower scalability constraints to rival or even surpass hedge funds in value creation. Taken together, these results cast doubt on the notion that hedge fund sophistication translates into systematically superior economic value.

An important question is whether hedge funds share the value they create with investors. On average, the net-of-fee value-added to investors is close to zero—a finding with two important implications. First, it departs from the strong net alphas documented in prior studies.³ The discrepancy arises because poor performance tends to occur when funds manage large amounts of capital and face tight scale constraints, giving these periods disproportionate weight in the value-added calculation. Therefore, the net alpha fails to measure the net value-added as it ignores both the level and time-variation of investors’ capital allocation. Second, our findings do not support the view that hedge fund investors suffer from agency problems that lead them to overpay for active management (*e.g.*, Greenwood and Scharfstein, 2013). This stands in sharp contrast with mutual fund investors who, on average, pay nearly \$8 million per year in excessive fees—a pattern widely attributed to their lower financial literacy (*e.g.*, French, 2008).

The near-zero average value for investors might suggest that funds extract all rents, consistent with the prediction of Berk and Green (2004). However, this interpretation is misleading as it conceals substantial heterogeneity across funds—half of them generate a positive net value-added. This pattern is particularly pronounced among arbitrage funds, plausibly because their complex strategies attract specialized investors better able to allocate scarce capital efficiently. Conversely, we find that the other half of the population destroys investor wealth. Among these funds, 63.6% appear skilled but operate at an inefficiently large scale. Therefore, excessive capital rather than lack of skill is the primary source of negative value-added.

Next, we examine whether investors improve their capital allocation by learning from past fund returns. We find that they are able to distinguish between skilled and unskilled funds. To show this, we track the evolution of capital over each fund’s lifecycle, dividing its full history into five subperiods. Whereas capital in unskilled funds declines steadily, skilled funds attract increasing allocations. Focusing on the latter, we show that investors progressively identify the most valuable funds. The value-added in the top decile rises from \$18.5 to \$24.0 million between the first and last subperiods. However, the negative net value-added persists over time—nearly one third of funds continue to destroy investor value even at the final stage of their lifecycle. This mixed evidence suggests that, despite their sophistication, hedge fund investors adjust capital only partially.

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

We conclude with a normative analysis of value creation. As noted by Barth et al. (2023), hedge funds collectively manage more than \$6 trillion, prompting the question of whether an industry of this size is consistent with economic logic. We consider an extended version of the rational model of Berk and Green (2004), in which funds maximize rents from their skill subject to a minimum compensation constraint that reflects investors’ due-diligence costs (Stein, 2009). We show that the model matches the data reasonably well. The actual and optimal value-added are closely aligned, with a pairwise correlation of 0.81. It also reproduces the strong correlation between total and net value-added—a feature absent from the original Berk and Green (2004) model in which funds extract all rents. Finally, the model predicts that investors capture only about 10% of the total value created, consistent with the low average bargaining power observed in the data.

At the same time, the actual value-added reaches only 36.1% of its optimal level. This gap arises because hedge funds operate at excessive scale. While the value-maximizing size averages \$164 million, the estimated value-added implies an actual size of \$288 million. We attribute this excess capacity to two roughly equal forces. First, funds set fees too low, inducing investors to increase their capital allocation. Second, even at prevailing fee levels, investors allocate excessive capital relative to the level predicted by the model. This misallocation is particularly pronounced among macro funds which explains why these funds deliver a negative net value-added to investors and why they would generate more value in a counterfactual setting without leverage.

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

II. Hedge Fund Value Creation

II.A. Definition of the Value-Added

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

which represents the best alternative investment available to investors. The benchmark return is defined as $r_{b,i,t+1} = \beta'_{i,R} f_{R,t+1}$, where $f_{R,t+1}$ is the excess return vector of the trading strategies that investors are able to replicate (R stands for replicable).⁴

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

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

where the gross alpha $\alpha_{i,t} = E[r_{i,t+1} - r_{b,i,t+1} | I_t]$ is the expectation of the difference between $r_{i,t+1}$ and $r_{b,i,t+1}$ conditional on the publicly available information set I_t which includes the fund equity capital $w_{i,t}$. The value-added is a dollar value that depends on the entire fund payoff $\alpha_{i,t} w_{i,t}$. Therefore, the gross alpha alone is uninformative about value creation because it ignores the size at which the fund operates. As emphasized by Berk and van Binsbergen (2015), a manager who generates a gross alpha of 1% on a \$10 billion fund creates more value than a manager who generates 10% on a \$1 million fund.

Equation (1) measures value creation from the perspective of investors by assessing whether a fund delivers value relative to their best alternative investment opportunity captured by $f_{R,t+1}$. Building on this insight, the value-added can also be expressed within the stochastic discount factor (SDF) valuation framework (see Cochrane, 2005). Denoting the marginal utility of consumption of hedge fund investors by m_{t+1} , we can write the valuation of the fund payoff as $va_i^{sdf} = E[m_{t+1}(r_{i,t+1} w_{i,t})]$. If m_{t+1} is a linear function of $f_{R,t+1}$ (e.g., Ferson, 2013), we show in the appendix that the SDF-based measure va_i^{sdf} coincides with the traditional value-added va_i .

II.B. Framework for Measuring the Value-Added

II.B.1. Specification of the Gross Alpha

We now impose additional structure on Equation (1) to estimate the value created by hedge funds. We write the expected (benchmark-adjusted) revenue and cost of each fund as $TR_{i,t} = a_i w_{i,t}$ and $TC_{i,t} = b_i w_{i,t}^2$. This convex cost function reflects the idea that the active strategy cannot be scaled without eroding returns. Taking the difference between $TR_{i,t}$ and $TC_{i,t}$ and dividing by $w_{i,t}$

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

yields a linear specification for the gross alpha:

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

where the skill and scale coefficients a_i and b_i are fund-specific, in contrast to the standard panel specification that imposes constant scalability across funds ($b_i = b$).⁵ This flexibility allows us to absorb the potentially large and unobservable set of fund characteristics that drive the cross-sectional differences in skill and scalability.

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

II.B.2. Interpretation of the Coefficients

The notions of skill and scalability captured by a_i and b_i should be interpreted broadly. A high a_i may reflect unique investment abilities and a low b_i may result from a unique trading infrastructure. Yet both coefficients can absorb other sources of variation across funds. For instance, some funds may exhibit higher a_i because they operate in less efficient markets (*e.g.*, Fang, Kempf, and Trapp, 2014), whereas others may display higher b_i because they invest in illiquid assets and trade more often (van Binsbergen et al., 2024; Busse et al., 2021).

A particularly relevant determinant for hedge funds is leverage, which mechanically increases both coefficients. To see this, we denote by a_i^u and b_i^u the skill and scale coefficients of the unlevered (fully collateralized) active fund strategy, for which the gross asset exposure equals the

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

⁶This 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.'"

fund capital.⁷ If the fund applies leverage to its active strategy, the gross asset exposure becomes $q_{i,t} = \pi_i w_{i,t}$, where the leverage ratio $\pi_i = \frac{q_{i,t}}{w_{i,t}} > 1$. Rewriting the fund revenue and cost as $TR_{i,t} = a_i w_{i,t} = a_i^u q_{i,t} = a_i^u \pi_i q_{i,t}$ and $TC_{i,t} = b_i w_{i,t}^2 = b_i^u q_{i,t}^2 = b_i^u \pi_i^2 q_{i,t}$, it follows that leverage scales both coefficients as $a_i = a_i^u \pi_i$ and $b_i = b_i^u \pi_i^2$.

As discussed in Section III.A, we can estimate a_i and b_i without modeling the underlying sources of their cross-sectional variation. This flexibility is especially valuable for hedge funds for two reasons. First, it is practically impossible to specify all the characteristics that shape the complex strategies these funds pursue. Second, the set of observable hedge fund characteristics is limited. For example, leverage—a key determinant of returns—is typically unreported in standard databases.⁸ We sidestep this issue by expressing $TR_{i,t}$ and $TC_{i,t}$ exclusively as functions of equity capital, with unobserved leverage effects absorbed into the coefficients a_i and b_i .

II.C. The Four Measures of Value-Added

II.C.1. The Value-Added

In this section, we apply the framework developed above to study value creation in the hedge fund industry. This framework allows us to estimate four complementary measures of value creation in a parsimonious and unified manner. Using the gross alpha specification in Equation (2), we derive simple expressions that link each measure directly to the underlying skill and scalability coefficients a_i and b_i .

We begin by deriving the expression for the value-added. Substituting $\alpha_{i,t}$ with $a_i - b_i w_{i,t}$ in Equation (1), we can write the value created by the fund as

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

which formalizes the intuition that the fund value-added ultimately depends on (i) its skill at identifying profitable investment opportunities and (ii) its constraints on scaling these opportunities

⁷To 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 $a_i^u = x_{i,l} a_{i,l} + x_{i,s} a_{i,s}$, where $x_{i,l} + x_{i,s} = 1$ such that the gross asset exposure $x_{i,l} w_{i,t} + x_{i,s} w_{i,t} = w_{i,t}$.

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

efficiently as capital increases. Equation (3) enables us to quantify the relative contributions of skill and scalability to hedge fund value creation.

II.C.2. The Net Value-Added

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

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

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

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

II.C.3. The Subperiod Value-Added

Equation (3) captures the average level of value-added, but provides no insight into its evolution over the fund's lifecycle. When the fund destroys value, investors have strong incentives to withdraw capital. As the fund shrinks and becomes less constrained by scale, it creates more value,

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

which reduces the persistence of poor performance. Consistent with this mechanism, prior studies show that hedge fund flows respond to past performance (*e.g.*, Agarwal, Green, and Ren, 2018; Baquero and Verbeek, 2021; Fung et al., 2008). The strength of this reallocation depends on the speed at which investors learn about fund skill and scalability (Berk and Green, 2004; Pástor and Stambaugh, 2012).¹⁰

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

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

where $\bar{w}_i(s)$ and $\bar{w}_{i,2}(s)$ denote the realized averages of capital and its squared value in subperiod s . Importantly, $va_i(s)$ is computed using the coefficients a_i and b_i estimated over the full sample. This specification allows us to analyze the dynamics of value creation over shorter horizons without introducing additional estimation noise. Applying the same approach to the net value-added in Equation (4), we obtain

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

II.C.4. The Optimal Value-Added

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

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

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

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

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

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

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

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

II.D. Remarks About the Specification

Our framework imposes that the skill and scale coefficients are constant over time. This specification implies a constant leverage ratio, which is broadly consistent with empirical evidence from proprietary hedge fund data.¹³ Nonetheless, some hedge funds may adjust their leverage over time to protect the present value of future fees or in response to constraints imposed by their prime brokers (e.g., Lan, Wang, and Yang, 2013). More generally, the gross alpha may depend on additional state variables, such as business cycle conditions or industry competition (Avramov, Barras, and Kosowski, 2013; Hoberg, Kumar, and Prabhala, 2018; Pástor, Stambaugh, and Taylor, 2015). To

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

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

¹³Ang, Gorovyy, and van Inwegen (2011) document that gross leverage is highly persistent, with an autocorrelation of 0.97. Similarly, Barth, Hammond, and Monin (2020) find that 89% of the variation in fund leverage in a panel regression is explained by fund fixed effects, indicating that leverage is largely a cross-sectional, rather than time-varying, characteristic.

illustrate, suppose that the regression coefficients depend on a demeaned vector of state variables z_t . Then, the true alpha is $\alpha_{i,t} = a_{i,t} - b_{i,t}w_{i,t} = a_i + a'_{i,z}z_{i,t} - (b_i + b'_{i,z}z_{i,t})w_{i,t}$, implying that Equation (2) is misspecified as it omits the relevant terms $z_{i,t}$ and $z_{i,t}w_{i,t}$.

Misspecification has no impact on our analysis of the magnitude and sharing of value creation. Equations (3)-(4) are numerically equivalent to the value-added measures obtained with the non-parametric approach proposed by Berk and van Binsbergen (2015). To see this, let us focus on the value-added whose nonparametric representation is given by $va_i = E[\alpha_{i,t}w_{i,t}]$ (the same analysis applies to $va_i^{\text{net}} = E[\alpha_{i,t}^{\text{net}}w_{i,t}]$). For any time-series process for $\alpha_{i,t}$, we can always take its linear projection on $w_{i,t}$: $\alpha_{i,t} = \text{proj}(\alpha_{i,t}|w_{i,t}) + \epsilon_{\alpha,i,t}$, where $\text{proj}(\alpha_{i,t}|w_{i,t}) = a_i - b_iw_{i,t}$. By construction, the projection error satisfies $E[\epsilon_{\alpha,i,t}w_{i,t}] = 0$, which implies that $va_i = E[\alpha_{i,t}w_{i,t}]$ is equal to the parametric representation $a_iE[w_{i,t}] - b_iE[w_{i,t}^2]$ given in Equation (3).

However, the expressions for the subperiod and optimal value-added in Equations (5)-(8) are sensitive to model misspecification. To illustrate, consider the optimal value-added $va_i^o = \frac{a_i^2 - \kappa^2}{4b_i}$. If Equation (2) does not hold, the coefficients a_i and b_i lose their structural interpretation because they become biased when $z_{i,t}$ or $z_{i,t}w_{i,t}$ are omitted. Consequently, va_i^o and $va_i^{\text{net},o}$ need not represent the true optimal values. To gauge the empirical importance of this concern, we follow BGS and conduct formal specification tests for all funds in the sample. The results, summarized in Section V.A, indicate that the linear specification $\alpha_{i,t} = a_i - b_iw_{i,t}$ provides a reasonable approximation to the gross alpha.

III. Methodology

III.A. Estimation of the Value-Added Distribution

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

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

The intuition behind our approach is to interpret Equation (2) as a random coefficient model (e.g., Hsiao, 2003), in which a_i and b_i are random realizations from a continuum of funds. Under

this sampling scheme, we can invoke cross-sectional limits to infer the distribution of value-added (*e.g.*, Gagliardini, Ossola, and Scaillet, 2016). To save space, we focus on the value-added va_i and relegate to the appendix the treatment of the other measures presented in Section II.C, which share the same properties as va_i .

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

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

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

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

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

The non-replicable factors $f_{NR,t+1}$ are absorbed by the various elements of Equation (9). To see this point, we write the fund return as a function of the full set of factors: $r_{i,t+1} = \alpha_{i,t}^* + \beta_{i,R}^* f_{R,t+1} + \beta_{i,NR}^* f_{NR,t+1} + \varepsilon_{i,t+1}^*$. We then regress $f_{NR,t+1}$ on $f_{R,t+1}$ to break the non-replicable

factors into three components: $f_{NR,t+1} = \alpha_{NR} + \Psi_{NR,R}f_{R,t+1} + u_{NR,t+1}$, where α_{NR} is the vector of factor alphas, $\Psi_{NR,R}$ is the matrix of slope coefficients, and $u_{NR,t+1}$ is the vector of errors.

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

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

Equation (10) shows that estimation errors are strongly correlated across funds, as they all load on the common error component of the non-replicable factors, $u_{NR,t+1}$. As a result, the cross-sectional distribution of value-added is estimated with substantial uncertainty—a point we formalize in Proposition 1 below.

III.A.3. Estimation of the Distribution Characteristics

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

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

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

We then account for the unbalanced nature of the hedge fund sample. Following Gagliardini, Ossola, and Scaillet (2016), we introduce a formal selection rule $\mathbf{1}_i^x$ equal to one if the following conditions are met: $\mathbf{1}_i^x = \mathbf{1} \{ \tau_{i,T} \leq \chi_{1,T}, CN_i \leq \chi_{2,T} \}$, where $\tau_{i,T} = T/T_i$, $CN_i = \sqrt{\text{eig}_{\max}(\hat{Q}_{x,i}) / \text{eig}_{\min}(\hat{Q}_{x,i})}$ is the condition number of $\hat{Q}_{x,i}$, and $\chi_{1,T}$, $\chi_{2,T}$ denote the two

threshold values. The first condition $\tau_{i,T} \leq \chi_{1,T}$ excludes funds for which the sample size is too small. The second condition $CN_i \leq \chi_{2,T}$ excludes funds for which the time-series regression is subject to multicollinearity problems (*e.g.*, Belsley, Kuh, and Welsch, 2004). Both thresholds $\chi_{1,T}$ and $\chi_{2,T}$ increase with the sample size T —with more return observations, we estimate the fund coefficients with greater accuracy, which allows for a less stringent selection rule. Applying this selection rule, we work with a population size equal to $n_\chi = \sum_{i=1}^n \mathbf{1}_i^\chi$.

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

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

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

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

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

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

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

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

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

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

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

where $\rightarrow_d$ denotes convergence in distribution and $V[M]$, $V[P(a)]$, and $V[Q(u)]$ denote the asymptotic variance terms.

Proof. See the appendix.

Proposition 1 establishes two key properties that differ from those derived by BGS for mutual funds. First, the estimators are intrinsically noisy as their convergence rate is only $1/\sqrt{T}$. Although each characteristic is computed across funds n , it does not converge to the true value at the usual $1/\sqrt{n}$ rate. Second, the estimated characteristics are asymptotically unbiased. Because the true values va_i are unobservable, we must rely on their estimated values $\hat{va}_i$ which embed the estimation noise from $\hat{a}_i$ and $\hat{b}_i$. Proposition 1 reveals that this noise does not distort the estimation, allowing us to recover the characteristics without any error-in-variable (EIV) bias correction.

Both properties are driven by the presence of the non-replicable hedge fund factors $f_{NR,t+1}$. From Equation (10), the estimated fund value-added $\hat{va}_i$ depends on $\bar{\varepsilon}_i = \bar{\varepsilon}_i^* + \beta_{i,NR}' \bar{u}_{NR}$, where $\bar{\varepsilon}_i$, $\bar{\varepsilon}_i^*$, and $\bar{u}_{NR}$ denote the time-series averages of the residuals. Even if n is large, all funds depend on the common component $\bar{u}_{NR}$ which converges to zero at the rate $1/\sqrt{T}$. Because this term dominates the sampling variation in the estimated characteristics, (i) the convergence rate only equals $1/\sqrt{T}$, and (ii) the variance induced by $\bar{u}_{NR}$ dominates the EIV bias, making any explicit bias correction unnecessary.¹⁴

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

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

$$\hat{V}[\hat{C}] \rightarrow_p V[\hat{C}], \quad (18)$$

where $\rightarrow_p$ denotes convergence in probability.

Proof. See the appendix.

III.B.2. Formal Comparisons With Mutual Funds

We can extend Proposition 1 to enable comparison tests with mutual funds. Unlike hedge funds, mutual funds typically do not rely on complex strategies as they load on standard factors

¹⁴ As shown by BGS, the EIV bias is of order $1/T$, which is asymptotically negligible relative to the variance term of order $1/\sqrt{T}$ in Proposition 1.

such as market, size, and value. Building on this observation, we follow BGS and assume that the mutual fund strategies are fully replicable ($f_{t+1} = f_{R,t+1}$). Because the common term $\hat{u}_{NR,t+1}$ vanishes, the characteristics of the mutual fund value-added converge at the faster rate of $1/\sqrt{n}$ and can be treated as known in the comparison tests.

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

$$\sqrt{T} \left(\Delta\hat{M} - \Delta M \right) \rightarrow_d N(0, V[M]), \quad (19)$$

$$\sqrt{T} \left(\Delta\hat{P}(a) - \Delta P(a) \right) \rightarrow_d N(0, V[P(a)]), \quad (20)$$

$$\sqrt{T} \left(\Delta\hat{Q}(u) - \Delta Q(u) \right) \rightarrow_d N(0, V[Q(u)]), \quad (21)$$

where $\rightarrow_d$ denotes convergence in distribution, and the variance terms coincide with those in Proposition 1.

Proof. See the appendix.

IV. Data Description

IV.A. Construction of the Hedge Fund Dataset

Our empirical analysis covers the period from January 1994 to December 2020. We collect monthly data on net-of-fee returns and capital, along with cross-sectional information on investment objectives, fees, and other fund characteristics from standard hedge fund databases. In the baseline analysis, we exclude funds-of-funds and multi-strategy funds, and take several steps to mitigate well-known data biases (e.g., Getmansky, Lee, and Lo, 2015). To reduce selection bias, we merge four major databases (BarclayHedge, HFR, Morningstar, and TASS). To address survivorship bias, we retain both live and dead funds. Finally, we remove the first 12 months of reported data for each fund to correct for backfill bias.

A key input for measuring the value-added is the unreported monthly gross return of each fund. We construct this variable manually by estimating monthly management and performance fees and

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

To address the unbalanced panel of hedge funds, we apply the fund selection rules described in Section III.A. Similar to BGS, we require a minimum of 60 capital-return observations and a minimum condition number of 15. We also exclude micro funds whose capital falls below \$10 million for at least one-third of the sample period. To further mitigate the influence of outliers, we drop the 1% of funds with extreme values of $\hat{a}_i$, $\hat{b}_i$, or $\hat{v}a_i$. After applying these filters, our final sample consists of 2,517 funds over the full period. While the original sample includes all dead funds, these selection rules may introduce survivorship bias. If value-destroying funds disappear early, the value-added distribution is biased upward. Several offsetting forces, however, mitigate this concern. First, value-creating funds may also disappear early following unexpectedly poor returns—a phenomenon known as reverse survivorship bias (Linnainmaa, 2013). Second, many successful hedge funds choose not to report to commercial databases once their client base is established. Using proprietary data, Barth et al. (2023) show that non-reporting funds deliver higher performance than reporting funds. Taken together, these considerations suggest that our estimates likely understate the true extent of hedge fund value creation.

IV.B. Construction of the Benchmark Model

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

The rationale for selecting these five factors is twofold. First, they capture mechanical strategies that hedge funds plausibly follow. As noted by Ardia et al. (2024), Carhart et al. (2014), and Pedersen (2015), these factors are grounded in economic intuition and explain a sizable share of hedge fund average returns. Second, it is reasonable to assume that hedge fund investors can take positions in these factors. The market, size, and value factors from Cremers, Petajisto, and Zitzewitz (2013) track the S&P 500 and Russell indices and can be replicated using passive products. By construction, they assign zero alpha to the S&P 500 and Russell 2000—two widely used benchmarks in the fund industry. The carry and TS momentum factors can also be traded through liquid futures markets or alternative premia funds increasingly offered by financial institutions (Jorion, 2021). Consistent with this rationale, Ardia et al. (2024) show that hedge fund investors chase funds with high past alphas, but do not chase funds whose past returns primarily reflect exposures to these five factors. This evidence suggests that investors are sufficiently sophisticated to replicate these factor exposures on their own.^{15,16}

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

IV.C. Summary Statistics

Table I reports summary statistics for an equal-weighted portfolio of all existing funds at the start of each month. The full hedge fund sample consists of (i) 974 equity funds (long–short and market neutral), which rely on discretionary or quantitative analysis to detect mispriced stocks; (ii) 631 macro funds (global macro and managed futures), which take directional positions across asset classes using broad economic and financial indicators; and (iii) 912 arbitrage funds (relative value

¹⁵We also consider alternative benchmark models in which investors have access to (i) only the equity market factor, (ii) the equity market, size, and value factors, and (iii) the equity market and the five bonds factors of Dick-Nielsen et al. (2025). The last specification is particularly relevant for pension funds—major hedge fund investors which typically hold portfolios of stocks and bonds. The results reported in the appendix are largely unchanged.

¹⁶Our benchmark choice for measuring value creation is oriented toward factor replication and differs from that of Ling, Satchell, and Yao (2023) who form for each fund a benchmark portfolio of six HFR-style indices. Since each index aggregates about 500 hedge funds, this benchmark portfolio is difficult for investors to replicate.

and event-driven), which primarily exploit mispricings in debt markets. For comparison, we also compute the same statistics for a sample of 2,238 U.S. equity mutual funds constructed following the procedure of BGS.

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

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

Please insert Table I here

V. Main Empirical Results

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

V.A.1. *The Value-Added and its Drivers*

We begin our empirical analysis by measuring the value created by the hedge fund industry. Specifically, we infer the entire cross-sectional distribution of value-added using as inputs the estimated value-added $\hat{v}a_i = \hat{a}_i\bar{w}_i - \hat{b}_i\bar{w}_{i,2}$ across funds. We summarize the shape of the distribution

using the mean and median, the proportions of funds with positive and negative value-added, and the 10th and 90th quantiles.

Panel A of Table II provides robust evidence of hedge fund value creation. Across the full sample, nearly 70% of funds are able to create value through their investment skills. The value-added reaches \$5.7 million per year and is highly significant, despite the substantial estimation noise inherent in hedge fund return data. If we set the entire hedge fund population equal to 15,000 (Barth et al., 2023), the value-added of the industry amounts to \$85.5 billion, or roughly 35% of the aggregate value-added of the securities sector computed by the Bureau of Economic Analysis (BEA) and summarized in Greenwood and Scharfstein (2013) ($85.5/241$).¹⁷ Assuming an average of 2.8 managers per fund (Berk, van Binsbergen, and Liu, 2017), the estimated value-added implies an average compensation of approximately \$1.2 million per manager per year.¹⁸

The ability of hedge funds to create value suggests that their trading activity enhances asset price efficiency—a channel often invoked to justify their economic importance. Improvements in price informativeness are socially valuable because they enhance the decisions by capital providers, managers, employees, and regulators (Bond, Edmans, and Goldstein, 2012). Although this mechanism is difficult to verify, Ha, Hu, and Tang (2024) study the daily trades of institutional investors and provide evidence that only hedge funds enhance the efficiency of capital markets.

Given the prevalence of value creation among hedge funds, we expect most of them to be skilled at designing profitable investment strategies. To test this idea, we infer the cross-sectional distribution of the skill coefficient. Table II confirms this prediction as 86.4% of funds generate profitable investment ideas. The average first-dollar alpha reaches 12.5% per year and is therefore the primary engine of hedge fund value creation. On the downside, hedge funds suffer from severe scalability constraints. A \$10 million increase in capital reduces the gross alpha by 1.5% per year on average. Although hedge funds can spread capital across multiple ideas by taking long and short positions, this flexibility does not translate into high scalability. Our fund-level estimates contribute to the literature by showing that the scale coefficient is positive not only on average (*e.g.*, Fung et al., 2008; Naik, Ramadorai, and Stromqvist, 2007), but for the vast majority of funds. This

¹⁷The value-added of the securities sector computed by the BEA equals total revenue minus input costs for asset managers, hedge funds, investment advisers, broker–dealers, trading desks, and market making firms.

¹⁸For this computation, we assume that operating costs are equal to a conservative 1% of the average fund capital of \$226 million (Colon, 2018), and that the fund extracts the entire value-added through fees. Under these assumptions, the implied compensation in equals $(5.7 - 0.01 \times 226)/2.8 = \1.2 million.

evidence provides strong support for equilibrium models of active management with diseconomies of scale (*e.g.*, Berk and Green, 2004; Glode and Green, 2011).

For a minority of funds, Panel C yields the counterintuitive result that scale improves returns ($b_i < 0$). One plausible explanation is estimation noise—the lower bound of the 95% confidence interval barely exceeds 7.3%. Alternatively, these cases may reflect model misspecification due to omitted nonlinearities or relevant predictors of alpha. To assess this possibility, we follow BGS and conduct a test of the null hypothesis $H_{0,i}$ that $\alpha_{i,t} = a_i - b_i w_{i,t}$ is correctly specified against the alternative $H_{a,i}$ that the alpha follows the more general expression $\alpha_{i,t} = a_i - b_i w_{i,t} + c_i' p_{i,t}$, where $p_{i,t}$ is the set of additional predictors that drive the fund alpha, including changing economic conditions and nonlinearities (see the appendix). After accounting for false discoveries—that is, erroneous rejections of $H_{0,i}$ when it is true—we reject $H_{0,i}$ (at the 5% level) for fewer than **XXX** % of funds. Although not perfect, the linear specification appears to provide a reasonable approximation for the vast majority of hedge funds.

Please insert Table II here

V.A.2. *Variation Across Investment Styles*

Another insight from Table II is that value creation varies sharply across investment styles. More than 80% of arbitrage funds create value, compared with 67% of equity funds and 51.7% of macro funds. This superiority is not driven by exposure to bond risk factors—augmenting the CAPM with the five bond factors proposed by Dick-Nielsen et al. (2025) leaves the value-added across categories largely unchanged (see the appendix). Overall, these findings are consistent with recent evidence that arbitrage funds trade complex assets with limited direct participation and attractive risk–return trade-offs (Eisfeldt, Lustig, and Zhang, 2023; Haddad and Muir, 2021).

Importantly, the value created by arbitrage funds does not stem from more profitable investment ideas. Across all three investment categories, the average skill coefficient exceeds 11% per year. Instead, arbitrage funds operate more efficiently at scale. A \$10 million increase in capital reduces gross alpha by only 1.0% per year, compared with 1.9% for equity funds and 1.5% for macro funds. As emphasized by Duarte, Longstaff, and Yu (2006), arbitrage strategies rely heavily on intellectual capital and sophisticated implementation. Our results suggest that these inputs are central to achieving efficient trading at scale.

Hedge fund strategies are both highly profitable and difficult to scale (i.e., both a_i and b_i are large). A plausible explanation is leverage. As discussed in Section II.B, leverage mechanically increases both the skill and scale coefficients by amplifying the first-dollar alpha and the trading costs incurred per dollar of equity capital.¹⁹ Given the lack of data on hedge fund leverage, we rely on Barth, Hammond, and Monin (2020), who report leverage statistics for their proprietary 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 (see the appendix for details). We then recover the average of the unlevered coefficients a_i^u and b_i^u by dividing the average skill coefficient by $\hat{\pi}$ and the average scale coefficient by $\hat{\pi}^2$.

Figure 1 shows that leverage is the primary driver of the high skill and scale coefficients observed for hedge fund strategies. Once we strip out the effect of leverage, the average skill and scale coefficients fall to 3.8% and 0.2% per year—only 30.4% and 13.3% of their levered counterparts reported in Table II (3.8/12.5 and 0.2/1.5). Focusing on the unlevered coefficients further clarifies the trading efficiency of arbitrage funds. An unlevered \$10 million increase in capital reduces the gross alpha by just 0.1% per year—nearly identical to macro funds, which operate in substantially more liquid markets.²⁰

Please insert Figure 1 here

V.A.3. Analysis of the Most Valuable Funds

Even after controlling for investment style, substantial heterogeneity remains across funds. Within each category, the 90th quantile is more than three times the group average. Motivated by this dispersion, we examine the distinguishing characteristics of the top decile of value-creating funds relative to the rest of the population in Table III.

A striking feature of the hedge fund industry is the high concentration of value creation. The top 10% of funds account for more than 80% of total value-added ($\frac{46.9 \times 0.1}{5.7} = 0.82$). In other

¹⁹ As discussed by BGS, market forces also contribute to the positive correlation between a_i and b_i . Costly strategies must deliver sufficiently high expected returns to justify their implementation. For example, van Binsbergen et al. (2024) show that high-turnover strategies entail substantial trading costs (high b_i) and are adopted only when their profitability is high enough to compensate for those costs (high a_i).

²⁰ Under our specification, value creation is independent of the financing choice. For a given asset exposure q_i , replacing debt with equity leaves the value-added unchanged: $va_i = a_i E[w_{i,t}] - b_i E[w_{i,t}^2] = a_i^u E[q_{i,t}] - b_i^u E[q_{i,t}^2]$. We nonetheless explore in Section V.D how the value added would change in a counterfactual setting in which hedge funds only take unlevered positions.

words, a small number of funds possess distinctive capabilities that are difficult for competitors to replicate. This concentration resonates with the model of Eisfeldt, Lustig, and Zhang (2023) in which some investors have unique abilities to trade complex assets, thereby deterring entry by less skilled competitors.

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

As discussed in Section III.A, hedge funds can create value by exploiting superior information or by following strategies that investors cannot replicate. To distinguish between these two channels, we augment the benchmark model with three hard-to-replicate strategies commonly used by hedge funds: illiquidity, betting-against-beta (BAB), and variance.²¹ Controlling for these factors leaves both the mean and median value-added essentially unchanged. Panel B shows that the largest average contribution of these strategies is 23.8% for arbitrage funds (14.0/58.7), reflecting their exposure to variance risk (see Ardia et al., 2024). Overall, these results indicate that distinctive informational advantages—rather than reliance on hard-to-replicate strategies—are the primary source of value among top funds.

Please insert Table III here

V.A.4. *Comparison With Mutual Funds*

The comparison of skill and scalability reveals stark differences between hedge funds and mutual funds. Mutual funds exhibit a much lower first-dollar alpha, averaging only 2.6% per year, compared with 12.5% for hedge funds. At the same time, mutual fund strategies are far more scalable—a \$10 million increase in capital reduces annual alpha by just 0.2% on average, versus

²¹Ardia et al. (2024), Carhart et al. (2014), and Pedersen (2015) provide evidence that hedge funds pursue these strategies. The illiquidity factor of Pástor and Stambaugh (2003) captures marketwide liquidity shocks, the BAB strategy of Frazzini and Pedersen (2014) exploits mispricing created by leverage-constrained investors, and the variance strategy tracks the realized S&P 500 variance.

1.5% for hedge funds. As a result, the implications for value creation are not obvious ex ante. To assess this trade-off, we compare the average value-added of hedge funds and mutual funds. For mutual funds, we examine the full population as well as subgroups sorted by stock size (small- and large-cap), turnover (low- and high-turnover), and distribution channel (direct- and broker-sold).

Figure 2 shows that hedge funds generate about \$5.3 million more in value-added per year.²² This large advantage, however, is largely driven by arbitrage funds. The other two hedge fund categories generate a value-added that is comparable to, or even lower than, that of several mutual fund groups. For example, small-cap mutual funds create \$4.1 million, yielding differences with equity and macro hedge funds that are not statistically significant at the 10% level. Taken together, these results challenge the view that the greater sophistication of hedge fund managers translates into systematically higher value creation than in the mutual fund industry.

Please insert Figure 2 here

V.B. Sharing of the Value-Added With Investors

V.B.1. The Net Value-Added

Our earlier results show that hedge funds create substantial value. The next step is to ask how this value is shared between funds and investors. To address this question, we compute the net value-added received by investors as $\hat{v}_i^{\text{net}} = \hat{a}_i^{\text{net}} \bar{w}_i - \hat{b}_i^{\text{net}} \bar{w}_{i,2} = (\hat{a}_i - \hat{a}_i^{\text{fee}}) \bar{w}_i - (\hat{b}_i - \hat{b}_i^{\text{fee}}) \bar{w}_{i,2}$, where $\hat{a}_i^{\text{fee}}$ and $\hat{b}_i^{\text{fee}}$ are obtained by regressing fund fees on capital. We then apply our methodology to infer the distribution of the net value-added across all funds.

Table IV shows that investors do not, on average, benefit from the value created by hedge funds. The mean net value-added is -\$0.2 million per year, while the median is zero. At face value, this finding might suggest that hedge fund investors have limited bargaining power—consistent with the prediction of Berk and Green (2004) that funds extract all rents generated by their investment skill. This interpretation is, however, misleading because the average masks a large mass of funds for which net value-added is meaningfully different from zero.

We find that investors extract positive value-added from roughly half of the funds in the population. When positive, these amounts are economically meaningful—in the top decile, investors

²²The value-added of mutual funds is positive at \$0.3 million but smaller than the estimates reported by BGS and Berk and van Binsbergen (2015), reflecting our different benchmark model and shorter sample period (1994–2020).

receive more than \$11 million per year. These patterns are particularly pronounced among arbitrage funds, where 64.1% deliver a positive net value-added to investors. As noted by Duarte, Longstaff, and Yu (2006) and Pedersen (2015), arbitrage funds pursue complex strategies which likely attract specialized investors who are better positioned to allocate scarce capital efficiently over time—a hypothesis we examine in Section V.C.

At the same time, we find that half of the funds deliver a negative value-added net of fees. A common explanation for such wealth destruction is the presence of unskilled funds—those whose first-dollar alpha is too low to cover fees ($a_i^{\text{net}} < 0$). As shown in Panel B, hedge fund fees have a pronounced effect on net profitability—on average, the difference between a_i and a_i^{net} amounts to 3.8% per year (12.5% versus 8.7%). However, only 18.3% of funds exhibit a negative a_i^{net} , implying that merely 36.4% of the wealth-destroying funds are unskilled ($18.3/50.3$).²³ The remaining 63.6% destroy wealth by operating at an excessive scale. Put differently, capital misallocation rather than lack of skill appears to be the primary driver of negative net value-added.

Please insert Table IV here

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

The prevalence of value-destroying funds in Table IV appears at odds with the strong hedge fund performance documented in previous studies (*e.g.*, Ackermann, McEnally, and Ravenscraft, 1999; Chen, Cliff, and Zhao, 2017; Liang, 1999; Kosowski, Naik, and Teo, 2007). Consistent with this literature, we also find evidence of positive performance, as measured by the average net alpha $\alpha_i^{\text{net}} = E[\alpha_{i,t}^{\text{net}}] = a_i^{\text{net}} - b_i^{\text{net}} E[w_{i,t}]$. Applying our methodology to the estimated values $\hat{\alpha}_i^{\text{net}} = \hat{a}_i^{\text{net}} - \hat{b}_i^{\text{net}} \bar{w}_i$, we find that close to 70% of funds exhibit a positive alpha, with a cross-sectional average of 1.8% per year (see the appendix).

The difference in sign between α_i^{net} and va_i^{net} arises from the time-variation in fund capital. The average net alpha reflects the value of investing one dollar each period, but it does not capture the value investors receive given their actual capital allocation. To illustrate, consider a simple two-period example. In the first period, investors allocate a small amount of capital such that

²³It is possible that investors allocate capital to unskilled funds because their non-replicable strategies provide insurance benefits, even at the cost of a negative a_i^{net} . We cannot rule out this interpretation given that we do not observe these non-replicable strategies. However, it appears unlikely in light of the evidence in Ardia et al. (2024) who show that most hedge funds rely on mechanical strategies to boost their average returns.

the net alpha is positive ($\alpha_{i,1}^{\text{net}} = a_i^{\text{net}} - b_i^{\text{net}}w_{i,1} > 0$). In the second period, they invest a much larger amount of capital, driving the net alpha negative ($\alpha_{i,2}^{\text{net}} = a_i^{\text{net}} - b_i^{\text{net}}w_{i,2} < 0$). Because this period of poor performance coincides with greater capital allocation ($w_{i,2} > w_{i,1}$), it receives more weight in the computation of the value-added. As a result, the fund can display a positive net alpha over the entire sample ($\alpha_i^{\text{net}} = (\alpha_{i,1}^{\text{net}} + \alpha_{i,2}^{\text{net}})/2 > 0$), but a negative net value-added ($va_i^{\text{net}} = (\alpha_{i,1}^{\text{net}}w_{i,1} + \alpha_{i,2}^{\text{net}}w_{i,2})/2 < 0$).²⁴

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

V.B.3. Comparison With Mutual Funds

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

Figure 3 reports the average net value-added in the mutual fund industry. The average is negative across all mutual fund categories and equals -\$7.7 million per year for the population, consistent with BGS and Cooper, Halling, and Yang (2021), who show that mutual funds systematically charge excessive fees to their clients. Comparing these values with the net value added across the three hedge fund categories reveals statistically significant differences in 14 out of 18 pairwise comparisons at the 10% level. This result is consistent with the view that mutual funds predominantly cater to less sophisticated retail investors, who are more likely to be unaware of underperformance (Gruber, 1996), face high search costs (Roussanov, Ruan, and Wei, 2021), and are willing to pay higher fees for financial advice (Del Guercio and Reuter, 2014).

²⁴This result is an application of Jensen's inequality. With scalability constraints, the net value-added function $va_i^{\text{net}}(w_{i,t}) = (a_i^{\text{net}} - b_i^{\text{net}}w_{i,t})w_{i,t}$ is concave in $w_{i,t}$, which implies that $va_i^{\text{net}} = E[va_i^{\text{net}}(w_{i,t})] < va_i^{\text{net}}(E[w_{i,t}]) = \alpha_i^{\text{net}} E[w_{i,t}]$. We further have $E[va_i^{\text{net}}(w_{i,t})] - va_i^{\text{net}}(E[w_{i,t}]) = -b_i^{\text{net}}V[w_{i,t}]$. Hence, greater variation in capital over time increases the likelihood that the net value-added and the net alpha differ in sign.

Please insert Figure 3 here

V.C. Dynamics of the Value-Added over the Fund's Lifecycle

V.C.1. Analysis of Capital Allocation

Our earlier findings provide evidence of capital misallocation, as half of all funds destroy value due to either insufficient skill or excessive scale. A natural question is whether this misallocation dissipates over time. Motivated by this evidence, we study how fund capital and value-added evolve over the fund's lifecycle. We begin by examining how investors allocate capital between unskilled and skilled funds. Because unskilled funds have a negative net skill coefficient ($a_i^{\text{net}} < 0$), they destroy value regardless of how much capital they manage. Investors should therefore withdraw capital as they learn to identify such funds over time.

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

Figure 4 shows that investors are able to distinguish between unskilled and skilled funds. Capital invested in unskilled funds declines steadily over time, falling to about 65% of its average level by the final subperiod. In contrast, investors gradually increase their capital allocation to skilled funds. The capital ratio starts around 0.7 in the first subperiod, rises above 1.1 by subperiod 4, and settles slightly above one in the final subperiod.

Please insert Figure 4 here

V.C.2. The Subperiod Value-Added

We next zoom in on skilled funds to study the dynamics of value-added. At inception, investors are likely to allocate similar amounts of capital across funds, as they rely primarily on prior information. As learning about the specific skill and scalability of each fund unfolds, investors should reallocate capital more efficiently across funds. Consequently, the left tail of the value-added distribution should thin as value-destroying funds are increasingly penalized, while the right

tail should thicken as investors direct more capital toward value-creating funds. To test these predictions, we compute the subperiod value-added measures as $\hat{v}a_i(s) = \hat{a}_i\bar{w}_i(s) - \hat{b}_i\bar{w}_{i,2}(s)$ and $\hat{v}a_i^{\text{net}}(s) = \hat{a}_i^{\text{net}}\bar{w}_i(s) - \hat{b}_i^{\text{net}}\bar{w}_{i,2}(s)$. Applying our methodology, we then estimate the distribution of each subperiod measure. The results are reported in Figures 5 and 6, which plot the evolution of the left and right tails of the value-added distribution.

We do not find that investors limit the prevalence of value-destroying funds. As shown in Panel A of Figure 5, the share of funds with a negative net value-added rises sharply above 40% by subperiod 4. This rise indicates that the surge in capital documented in Figure 4 results in widespread overcapacity across the industry. Although investors eventually respond to poor performance by withdrawing capital, nearly one-third of funds still destroy value in the final subperiod. Consistent with this slow moving capital, the value-added is persistent—if a fund initially delivers a negative net value-added, the probability that it continues to do so in the last subperiod is 58%. At the same time, Figure 6 provides evidence that investors’ capital reallocation improves value creation at the top of the distribution. The 90th percentile of value-added increases from \$18.5 million to \$24.0 million per year between the first and last subperiods. Importantly, this improvement is also shared with investors—the 90th percentile of net value-added rises from \$11 million to \$13.5 million over the same horizon.

Examining the three investment categories reveals similar patterns, but with markedly different magnitudes. Capital misallocation is most severe among macro funds—nearly 60% destroy investor wealth by subperiod 4.²⁵ By contrast, value creation in the upper tail improves more strongly among arbitrage funds—the 90th percentile of value added increases from \$24.6 million to \$32.3 million. Taken together, these results reveal that investors’ capital allocation is better aligned with value creation in the arbitrage category than in the macro category.

Overall, we find mixed evidence that hedge fund investors reallocate capital efficiently over time. This conclusion likely reflects the interaction of opposing forces. On the one hand, hedge fund investors—primarily institutions and high-net-worth individuals—are sophisticated and therefore well equipped to extract information from past performance. On the other hand, learning about hedge funds is inherently difficult given the large number of strategies and the limited length of

²⁵The appendix shows that most of the value destruction within the macro category originates from managed futures rather than global macro funds. Excess capacity is so pronounced that managed futures is the only hedge fund subcategory that generates negative value added even before fees.

most return histories. In addition, investors face contractual frictions such as lockup and notice periods, which further slow the reallocation of capital (Joenväärä, Kosowski, and Tolonen, 2019).²⁶

Please insert Figure 5 and Figure 6 here

V.D. Optimality of the Value-Added

V.D.1. Estimation of the Model

Given its sophistication, the hedge fund industry offers an ideal laboratory for testing rational models of active management. We perform a normative analysis to determine how well such a model explains both the cross-sectional variation and the overall magnitude of the value-added. We consider the rational model in Section II.C, in which funds maximize the fee revenue from exploiting their investment skill under the constraint that investors require a compensation κ per unit of capital to cover due diligence costs.²⁷

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

Contrary to the estimated values $\hat{a}_i$ and $\hat{b}_i$, which can be inferred from the data, κ is not directly observable. In our baseline analysis, we follow Stulz (2007) and set κ equal to 1% per year.²⁸ We require $\hat{a}_i > \bar{fee}_i + \kappa$ to ensure that investors optimally allocate a positive amount of capital to the fund at the prevailing fee rate computed as $\bar{fee}_i = \frac{\frac{1}{T_i} \sum_t I_{i,t} fee_{i,t+1} w_{i,t}}{\frac{1}{T_i} \sum_t I_{i,t} w_{i,t}}$. We further restrict $\hat{b}_i > 0.05\%$ per year to guarantee a well-defined and non-explosive optimal value-added as $\hat{b}_i$ approaches zero. After applying these filters, our final sample includes 1,733 funds.

²⁶To further explore these channels, we test whether the proportion of funds with negative net value-added is lower in the final subperiod when investors (i) are more sophisticated (proxied by the fund's offshore status (Aragon, Liang, and Park, 2014), and (ii) have more time to learn (proxied by fund age). As shown in the appendix, this is indeed the case, although the differences are modest.

²⁷Our analysis examines whether the value created is privately optimal for funds and investors. It is therefore silent on the social value of active management. On one hand, hedge funds enhance price efficiency, which is socially beneficial. On the other hand, they may engage in socially wasteful rent-seeking activities that redistribute wealth at the expense of other market participants. Quantifying the net social value of the industry thus requires assessing the relative strength of these opposing forces (e.g., Kurlat, 2019).

²⁸Stulz (2007) writes that a frequently heard price tag for hedge fund due diligence costs is \$50,000. Assuming a five-year investment horizon (e.g., Khorana, Servaes, and Tufano, 2009) and a typical investment size of \$1 mio. (e.g., Burns, 2023), this corresponds to $\kappa = 1\%$.

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

We begin our comparison analysis by computing the pairwise correlation between $\hat{v}a_i$ and $\hat{v}a_i^o$ ($\hat{v}a_i^{net}$ and $\hat{v}a_i^{net,o}$). This analysis provides a simple diagnostic of whether the actual and optimal values are qualitatively aligned. The correlation for the gross value-added is high at 0.81, confirming that funds with greater potential for value creation do create more value. For the net value-added, the correlation remains positive but more modest at 0.41. The model also successfully replicates the strong correlation of 0.90 between $\hat{v}a_i$ and $\hat{v}a_i^{net}$. In the model of Berk and Green (2004), this correlation is equal to zero as funds extract all rents from their skills, driving the net value-added to zero across funds. By contrast, our model allows investors to retain some bargaining power through the parameter κ , generating a substantial correlation of 0.87 between $\hat{v}a_i^o$ and $\hat{v}a_i^{net,o}$.

Next, we compare the magnitude of the actual and optimal value-added. Table V shows that the model reasonably captures the extent of value creation. On average, the actual value-added amounts to 36.1% of the optimal level of \$15.4 million per year. The fit is weaker for the net value-added, which reaches 27.1% of its optimal level of \$1.6 million. The model also predicts that investors extract only a small share of the total value created—about 10% (1.6/15.4)—a figure broadly consistent with the 7.1% observed in the data (0.4/5.6).

Please insert Table V here

V.D.3. Impact of Fee Policy

The previous analysis shows that the model captures the cross-sectional variation in value-added, but only partially its economic magnitude. We now quantify the two forces that drive the gap between actual and optimal value-added. First, funds may set fees that deviate from their optimal levels. In this case, the equilibrium capital w_i^e and value-added implied by the model differ from the optimal ones. Solving for the condition that investors get their required compensation, we obtain $w_i^e = \frac{a_i - \bar{f}e_i - \kappa}{b_i}$, which implies the following equilibrium value-added measures: $va_i^e = a_i w_i^e - b_i (w_i^e)^2$ and $va_i^{net,e} = a_i w_i^e - b_i (w_i^e)^2 - \bar{f}e_i w_i^e$. Second, investors may misallocate capital relative to the equilibrium value implied by the model. When this occurs, the actual capital w_i and the corresponding value-added measures va_i and va_i^{net} differ from their equilibrium counterparts.

To assess the relative importance of these two channels, we decompose the gap between the

optimal and actual value-added as

$$va_i - va_i^o = (va_i - va_i^e) + (va_i^e - va_i^o), \quad (22)$$

$$va_i^{\text{net}} - va_i^{\text{net},o} = (va_i^{\text{net}} - va_i^{\text{net},e}) + (va_i^{\text{net},e} - va_i^{\text{net},o}), \quad (23)$$

where the first term captures the effect of capital misallocation and the second term captures the effect of fees. The empirical counterparts of these expressions are obtained by using the following expressions: $\hat{va}_i^e = \hat{a}_i \hat{w}_i^e - \hat{b}_i (\hat{w}_i^e)^2$ and $\hat{va}_i^{\text{net},e} = \hat{a}_i \hat{w}_i^e - \hat{b}_i (\hat{w}_i^e)^2 - \bar{fee}_i \hat{w}_i^e$ with $\hat{w}_i^e = \frac{\hat{a}_i - \bar{fee}_i - \kappa}{\hat{b}_i}$.

Panel A of Table VI summarizes the effect of the fee policy. As predicted by the model, funds with higher skill tend to charge higher fees—the pairwise correlation between $\hat{a}_i$ and $\bar{fee}_i$ is 0.37. However, the optimal target fees are substantially higher than the fees actually charged. On average, the gap amounts to 5.8% per year. Figure 7 illustrates the consequences of this fee gap. When the fund sets fees too low, investors are incentivized to invest more capital than is optimal ($w_i^o < w_i^e$), causing the equilibrium value-added to fall short of its optimal level ($va_i^o > va_i^e$).²⁹ In contrast, the equilibrium net value-added increases because investors must be compensated for deploying a larger amount of capital ($va_i^{\text{net},o} > va_i^{\text{net},e}$). Consistent with this mechanism, Panel A shows that the equilibrium capital averages \$253 million, compared with only \$164 million for the optimal level. Likewise, the average difference is negative for the value-added (−\$5.5 million) and positive for the net value-added (\$0.9 million).³⁰

Please insert Table VI and Figure 7 here

V.D.4. Impact of Capital Misallocation

We next examine the extent of capital misallocation by investors. For each fund, we infer the actual capital level $\hat{w}_i$ as the constant amount that rationalizes the observed net value-added $\hat{va}_i^{\text{net}}$. Panel B of Table VI reveals that, on average, investors allocate excessive capital to hedge funds—the actual capital averages \$288 million, compared with the model-implied equilibrium

²⁹In principle, va_i^e could exceed va_i^o if w_i^e coincides with the capital level that maximizes the unconstrained value-added, that is, $\max_{w_i} va_i = \frac{a_i^2}{4b_i} > va_i^o = \frac{(a_i - \kappa)^2}{4b_i}$. Empirically, no fund in our sample satisfies this condition.

³⁰In the Berk and Green (2004) model, funds can set low fees without reducing the value-added because they can costlessly index the excess capital $w_i^e - w_i^o$. By contrast, the decline in value-added in Table V suggests that hedge funds cannot rely on this mechanism because (i) costless indexing is not available, and (ii) investors must be compensated for the additional capital they are required to deploy at w_i^e .

level of \$253 million. Figure 8 illustrates the implications of this overinvestment. Excess capital depresses both value-added measures, pushing them below their equilibrium levels ($va_i^e > va_i$ and $va_i^{\text{net},e} > va_i^{\text{net}}$). Panel B quantifies these reductions which amount to \$4.3 million for the value-added and \$2.1 million for the net value-added. Capital misallocation is particularly severe among macro funds, where excess capital reduces the value-added by \$7.5 million and the net value-added by \$5.7 million. These findings align with the large fraction of macro funds that destroy investor wealth documented in Table IV.

Overall, the model implies that the hedge fund industry operates at a scale well above its value-maximizing level (\$288 million versus \$164 million). This excess capacity is jointly driven by suboptimal fee setting and persistent capital misallocation. These channels reduce the total value-added by \$5.5 and \$4.3 million on average, together accounting for the \$9.8 million gap between actual and optimal value reported in Table V. From investors' perspective, however, the negative effect of capital misallocation dominates the positive effect of fee policy, resulting in an overall reduction of \$1.2 million in net value-added.

Given this excess capacity, an open question is whether some hedge fund categories would create more value by reducing leverage. To assess this possibility, we conclude our analysis by estimating unlevered value added $va_i^u = a_i^u E[w_{i,t}] - b_i^u E[w_{i,t}^2]$ where a_i^u and b_i^u are the unlevered skill and scale coefficients estimated in Section V.A. Results reported in the appendix show that two of the three categories—equity and macro funds—would create more value as unlevered entities. On average, the value-added increases from \$1.8 million to \$4.3 million per year for equity funds and from \$1.8 million to \$4.3 million per year for macro funds.

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

VI. Conclusion

In this paper, we measure the value created by hedge funds. The sophistication of this industry offers distinctive insights into how value is produced and shared. Hedge fund managers take long and short positions, employ leverage, and use complex trading techniques to exploit information and provide liquidity. Ex ante, these capabilities suggest that hedge funds should generate more value than mutual funds, both by uncovering more profitable opportunities and by scaling them more effectively. Their investors—primarily institutions and high-net-worth clients—are

also viewed as more sophisticated. They may therefore possess greater bargaining power and a stronger ability to learn from performance and reallocate capital. Taken together, these features make hedge funds an ideal laboratory for testing rational models of active management.

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

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

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TABLE I. Summary Statistics

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

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

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

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

Panel A: Distribution of the Value-Added						
	Mean (\$ mio. p.a.)	Median (\$ mio. p.a.)	Proportions (%)		Quantiles (\$ mio. p.a.)	
			Negative	Positive	10%	90%
All Funds	5.67 (1.54)	1.77 (0.36)	31.59 (1.76)	68.41 (1.76)	-5.52 (0.38)	21.55 (0.60)
Equity	4.38 (0.73)	1.36 (0.25)	32.96 (1.45)	67.04 (1.45)	-4.06 (0.27)	14.30 (0.64)
Macro	1.75 (2.07)	0.14 (0.49)	48.34 (2.09)	51.66 (2.09)	-12.95 (1.37)	18.70 (0.84)
Arbitrage	9.77 (3.25)	3.85 (1.00)	18.53 (3.21)	81.47 (3.21)	-2.18 (0.83)	29.24 (2.53)
Panel B: Distribution of the Skill Coefficient						
	Mean (% p.a.)	Median (% p.a.)	Proportions (%)		Quantiles (% p.a.)	
			Negative	Positive	10%	90%
All Funds	12.50 (4.44)	10.47 (3.53)	13.63 (2.38)	86.37 (2.38)	-1.54 (0.75)	28.91 (2.91)
Equity	13.20 (4.28)	11.04 (3.92)	12.83 (4.24)	87.17 (4.24)	-1.36 (1.59)	30.21 (3.30)
Macro	11.45 (3.87)	9.04 (3.93)	19.02 (6.31)	80.98 (6.31)	-3.82 (1.31)	28.26 (2.91)
Arbitrage	12.48 (7.32)	10.84 (5.90)	10.75 (3.80)	89.25 (3.80)	-0.34 (1.75)	28.12 (5.07)
Panel C: Distribution of the Scale Coefficient						
	Mean (% p.a.)	Median (% p.a.)	Proportions (%)		Quantiles (% p.a.)	
			Negative	Positive	10%	90%
All Funds	1.47 (0.49)	0.40 (0.17)	17.92 (4.62)	82.08 (4.62)	-0.20 (0.14)	4.41 (0.26)
Equity	1.94 (0.68)	0.63 (0.26)	18.58 (4.82)	81.42 (4.82)	-0.25 (0.21)	5.84 (0.42)
Macro	1.45 (0.31)	0.40 (0.10)	15.06 (2.64)	84.94 (2.64)	-0.13 (0.11)	3.99 (0.42)
Arbitrage	0.99 (0.48)	0.26 (0.27)	19.19 (8.86)	80.81 (8.86)	-0.24 (0.23)	3.23 (0.46)

TABLE III. Analysis of the Most Valuable Funds

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

Panel A: Value-Added and Other Characteristics								
	Value-Added (\$ mio. p.a.)		Skill (% p.a.)			Scale (% p.a.)		
	Top	All	Top	All	Rank	Top	All	Rank
Cross-Sectional Average								
All Funds	46.85	5.67	17.98	12.50	7	0.13	1.47	7
Equity	35.45	4.38	15.73	13.20	6	0.09	1.94	8
Macro	42.05	1.75	17.67	11.45	7	0.22	1.45	7
Arbitrage	58.70	9.77	20.57	12.48	7	0.16	0.99	7
Cross-Sectional Median								
All Funds	36.37	1.77	15.04	10.47	7	0.09	0.40	8
Equity	27.69	1.36	11.62	11.04	6	0.07	0.63	8
Macro	30.47	0.14	14.96	9.04	7	0.07	0.40	8
Arbitrage	45.45	3.85	15.90	10.84	7	0.09	0.26	8
Panel B: Impact of Non-Replicable Strategies								
	Value-Added (\$ mio. p.a.)				Difference With Base Case (\$ mio. p.a.)			
	Liquidity	BAB	Variance	All	Liquidity	BAB	Variance	All
Cross-Sectional Average								
All Funds	46.78	42.70	38.53	38.64	0.07	4.15	8.32	8.21
Equity	35.66	31.55	29.06	29.00	-0.21	3.89	6.39	6.45
Macro	42.02	40.51	40.75	41.00	0.03	1.54	1.30	1.05
Arbitrage	58.21	52.62	44.66	44.82	0.49	6.08	14.04	13.88
Cross-Sectional Median								
All Funds	36.57	33.78	30.02	30.42	-0.20	2.58	6.35	5.95
Equity	28.68	26.41	25.60	24.21	-0.99	1.28	2.09	3.48
Macro	33.71	33.04	33.64	31.22	-3.24	-2.57	-3.16	-0.75
Arbitrage	48.75	43.24	37.07	37.62	-3.30	2.22	8.38	7.83

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

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

Panel A: Distribution of the Net Value-Added						
	Mean (\$ mio. p.a.)	Median (\$ mio. p.a.)	Proportions (%)		Quantiles (\$ mio. p.a.)	
			Negative	Positive	10%	90%
All Funds	-0.17 (1.45)	-0.01 (0.37)	50.26 (2.37)	49.74 (2.37)	-11.47 (0.49)	11.26 (0.73)
Equity	-0.46 (0.66)	-0.25 (0.27)	54.00 (2.09)	46.00 (2.09)	-8.43 (0.29)	6.71 (0.46)
Macro	-4.70 (1.83)	-1.44 (0.50)	65.29 (2.15)	34.71 (2.15)	-20.24 (1.16)	8.56 (0.87)
Arbitrage	3.27 (3.09)	0.98 (0.90)	35.86 (4.42)	64.14 (4.42)	-6.03 (1.04)	16.47 (2.56)
Panel B: Distribution of the Net Skill Coefficient						
	Mean (% p.a.)	Median (% p.a.)	Proportions (%)		Quantiles (% p.a.)	
			Negative	Positive	10%	90%
All Funds	8.69 (4.19)	6.96 (3.34)	19.98 (4.11)	80.02 (4.11)	-3.86 (0.66)	22.81 (2.45)
Equity	9.23 (4.02)	7.21 (3.66)	20.74 (6.29)	79.26 (6.29)	-3.71 (1.49)	23.37 (2.93)
Macro	7.57 (3.45)	5.88 (3.52)	26.78 (8.02)	73.22 (8.02)	-6.64 (1.44)	22.49 (2.30)
Arbitrage	8.89 (7.02)	7.48 (5.64)	14.47 (6.61)	85.53 (6.61)	-1.84 (1.54)	22.00 (4.95)
Panel C: Distribution of Net Scale Coefficient						
	Mean (% p.a.)	Median (% p.a.)	Proportions (%)		Quantiles (% p.a.)	
			Negative	Positive	10%	90%
All Funds	1.32 (0.46)	0.36 (0.17)	18.32 (5.02)	81.68 (5.02)	-0.19 (0.14)	4.02 (0.22)
Equity	1.75 (0.64)	0.55 (0.26)	18.89 (5.22)	81.11 (5.22)	-0.24 (0.20)	5.22 (0.42)
Macro	1.27 (0.28)	0.37 (0.10)	15.37 (2.22)	84.63 (2.22)	-0.12 (0.07)	3.47 (0.35)
Arbitrage	0.90 (0.46)	0.23 (0.25)	19.74 (9.29)	80.26 (9.29)	-0.18 (0.22)	2.87 (0.46)

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

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

	Value-Added (\$ mio. p.a.)				Net Value-Added (\$ mio. p.a.)			
	Actual	Optimal	Diff.	Ratio (%)	Actual	Optimal	Diff.	Ratio (%)
Cross-Sectional Average								
All Funds	5.55	15.38	-9.83	36.12	0.44	1.64	-1.19	27.07
Equity	3.85	11.22	-7.38	34.27	-0.09	1.19	-1.28	-7.81
Macro	2.34	15.66	-13.32	14.92	-3.16	1.62	-4.78	-194.67
Arbitrage	9.40	19.61	-10.21	47.93	3.28	2.12	1.16	154.91
Cross-Sectional Median								
All Funds	1.73	6.33	-4.60	27.32	0.07	0.78	-0.71	9.23
Equity	1.39	4.91	-3.52	28.34	-0.15	0.52	-0.66	-28.09
Macro	0.31	5.86	-5.55	5.25	-1.05	0.75	-1.80	-138.85
Arbitrage	3.57	8.74	-5.18	40.79	0.90	1.24	-0.34	72.60

TABLE VI. Fee Policy and Capital Misallocation

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

Panel A: Fee Policy by Funds													
Fee Policy (% p.a.)				Implications For									
			Diff.	Capital (\$ mio.)			Value-Added (\$ mio. p.a.)			Net Value-Added (\$ mio. p.a.)			
Chosen	Target			Equilib.	Optimal	Diff.	Equilib.	Optimal	Diff.	Equilib.	Optimal	Diff.	
Cross-Sectional Average													
All Funds	2.75	8.52	-5.76	253	164	89	9.90	15.38	-5.48	2.53	1.64	0.89	
Equity	2.84	8.91	-6.06	178	119	60	7.22	11.22	-4.00	1.78	1.19	0.60	
Macro	2.64	8.56	-5.92	255	162	93	9.80	15.66	-5.86	2.55	1.62	0.93	
Arbitrage	2.73	8.07	-5.35	330	212	118	12.79	19.61	-6.82	3.30	2.12	1.18	
Cross-Sectional Median													
All Funds	2.75	7.00	-4.25	116	78	38	4.15	6.33	-2.19	1.16	0.78	0.38	
Equity	2.86	7.65	-4.79	80	52	28	3.10	4.91	-1.81	0.80	0.52	0.28	
Macro	2.49	6.78	-4.28	111	75	35	3.86	5.86	-2.00	1.11	0.75	0.35	
Arbitrage	2.79	6.59	-3.80	177	124	53	6.48	8.74	-2.27	1.77	1.24	0.53	
Panel B: Capital Misallocation by Investors													
				Capital Misallocation (\$ mio.)			Implications For						
				Diff.				Value-Added (\$ mio. p.a.)			Net Value-Added (\$ mio. p.a.)		
			Chosen		Target		Actual	Equilib.	Diff.	Actual	Equilib.	Diff.	
Cross-Sectional Average													
All Funds				288	253	36	5.55	9.90	-4.34	0.44	2.53	-2.08	
Equity				216	178	37	3.85	7.22	-3.38	-0.09	1.78	-1.88	
Macro				313	255	58	2.34	9.80	-7.46	-3.16	2.55	-5.71	
Arbitrage				349	330	20	9.40	12.79	-3.39	3.28	3.30	-0.01	
Cross-Sectional Median													
All Funds				142	116	26	1.73	4.15	-2.42	0.07	1.16	-1.09	
Equity				97	80	16	1.39	3.10	-1.71	-0.15	0.80	-0.95	
Macro				154	111	43	0.31	3.86	-3.55	-1.05	1.11	-2.15	
Arbitrage				208	177	31	3.57	6.48	-2.91	0.90	1.77	-0.87	

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

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

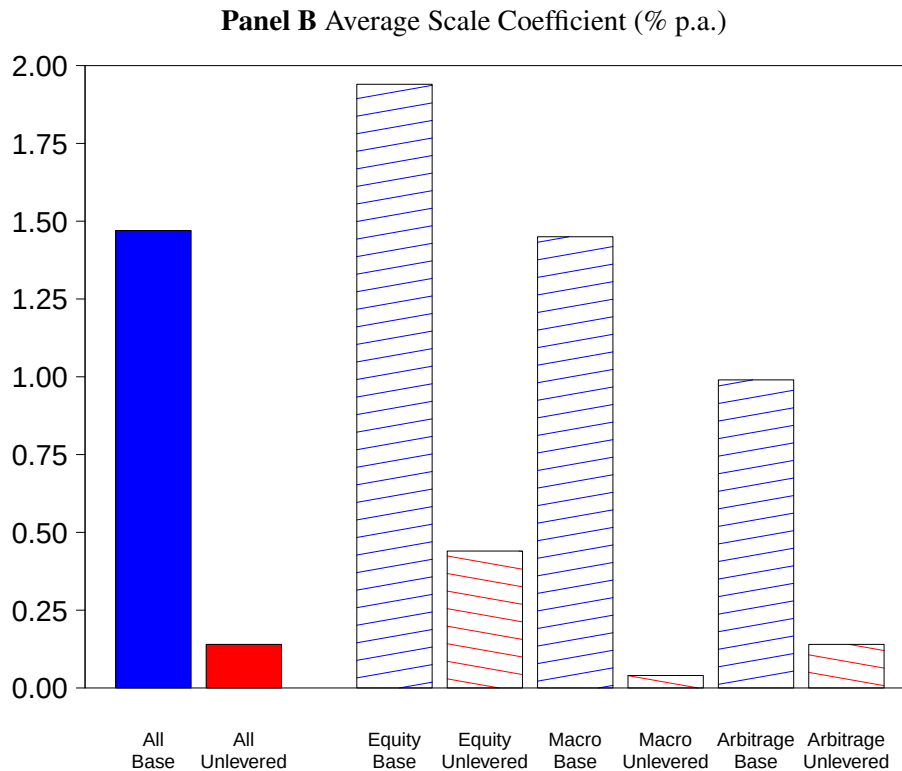
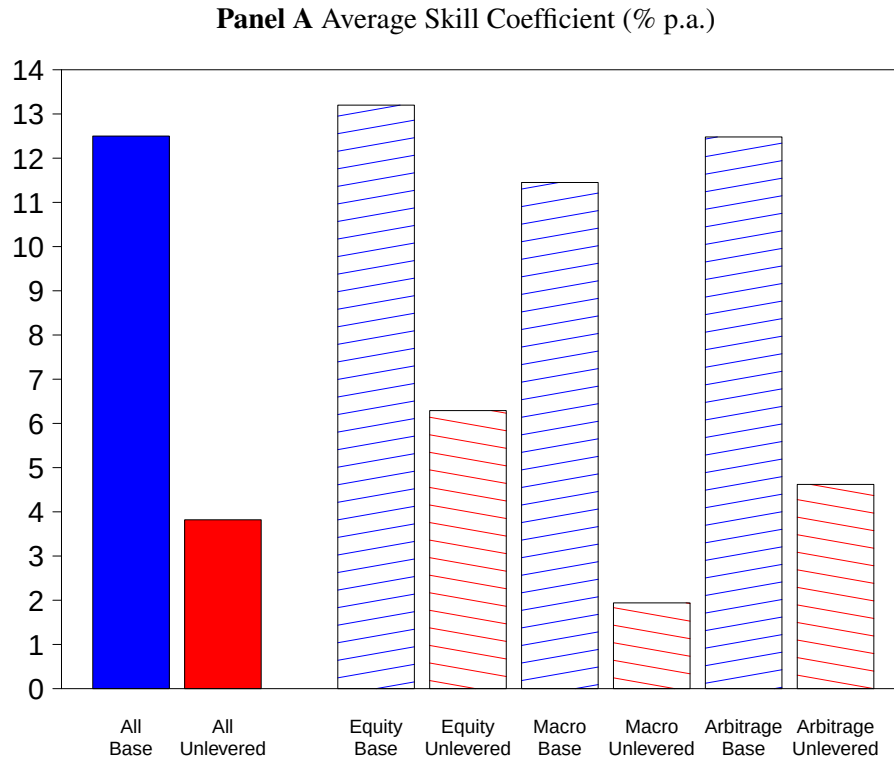


Figure 2. Comparison of the Value-Added With Mutual Funds

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

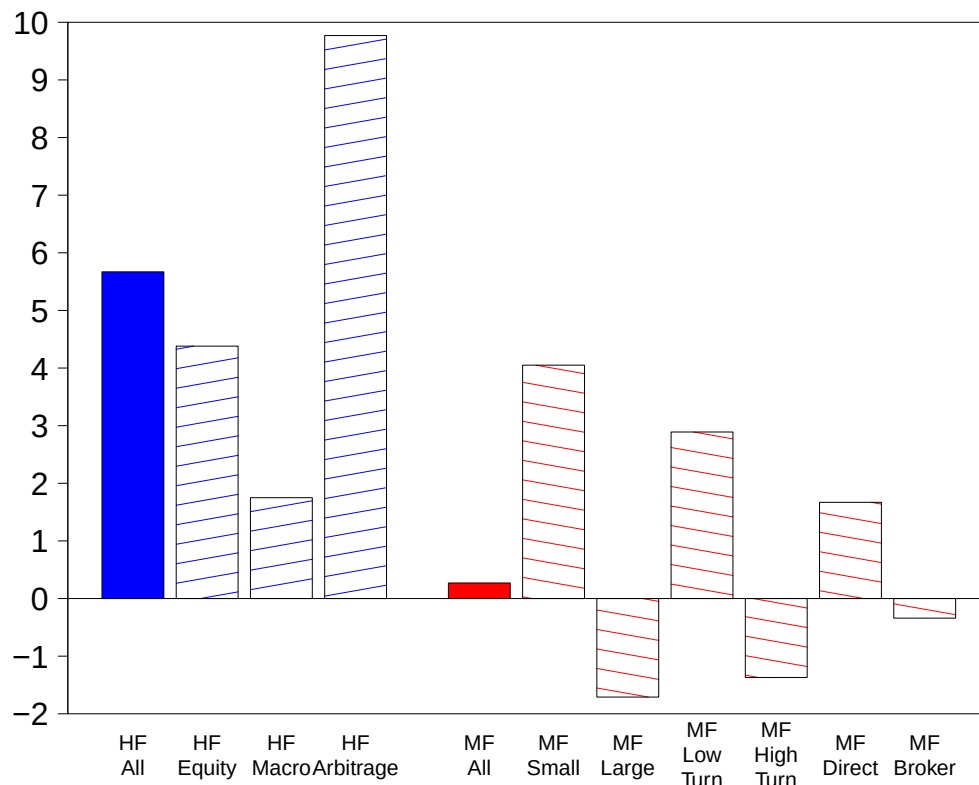


Figure 3. Comparison of the Net Value-Added With Mutual Funds

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

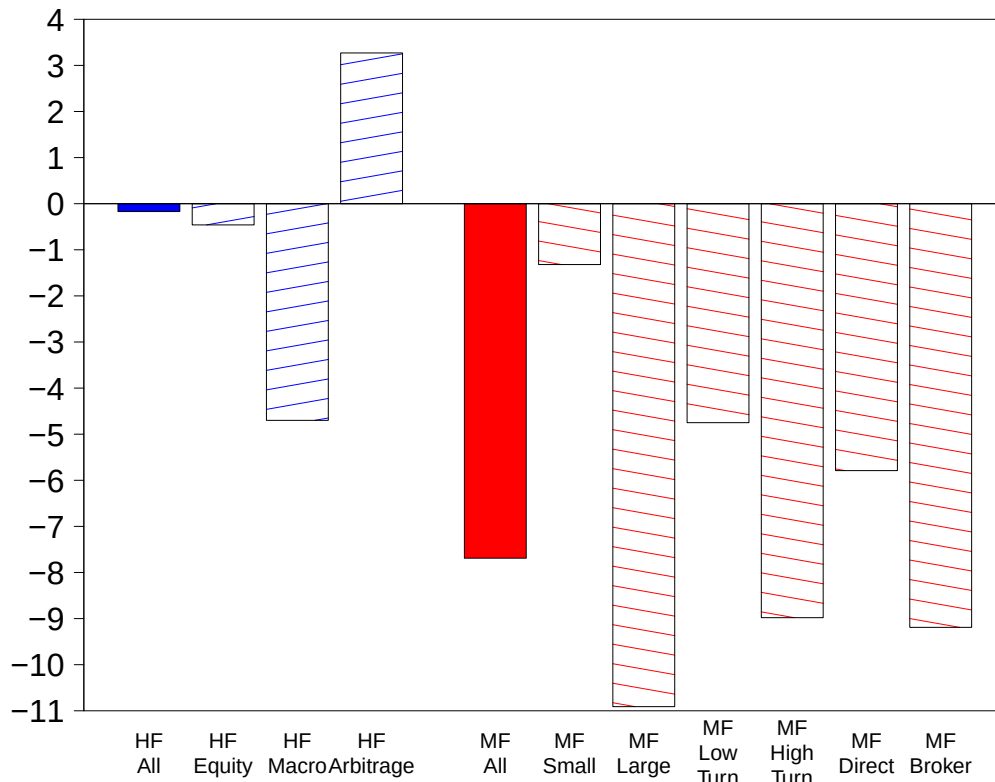


Figure 4. Evolution of Capital Allocation

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

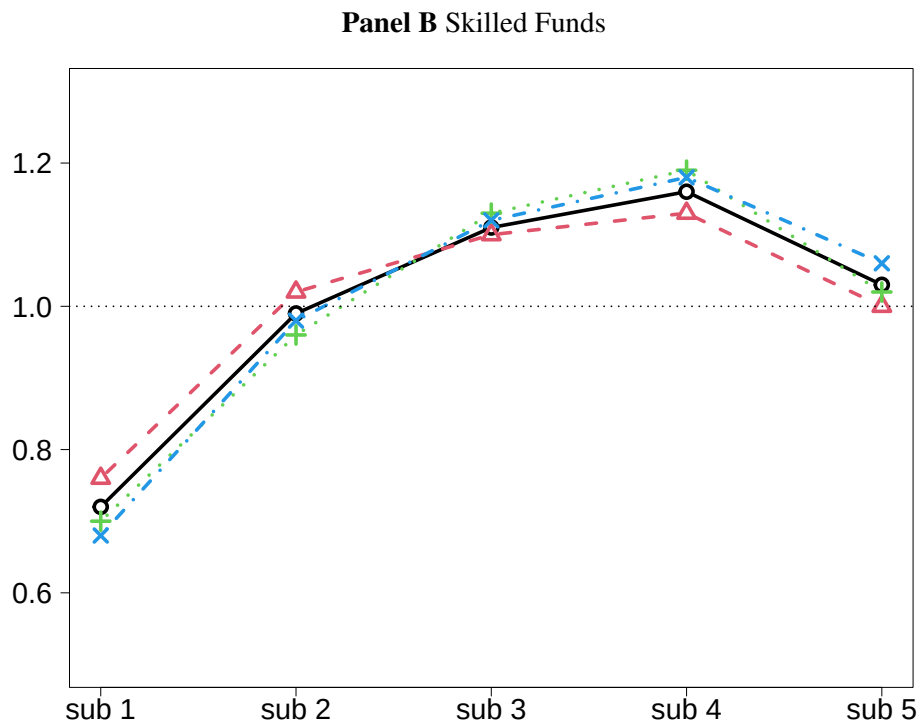
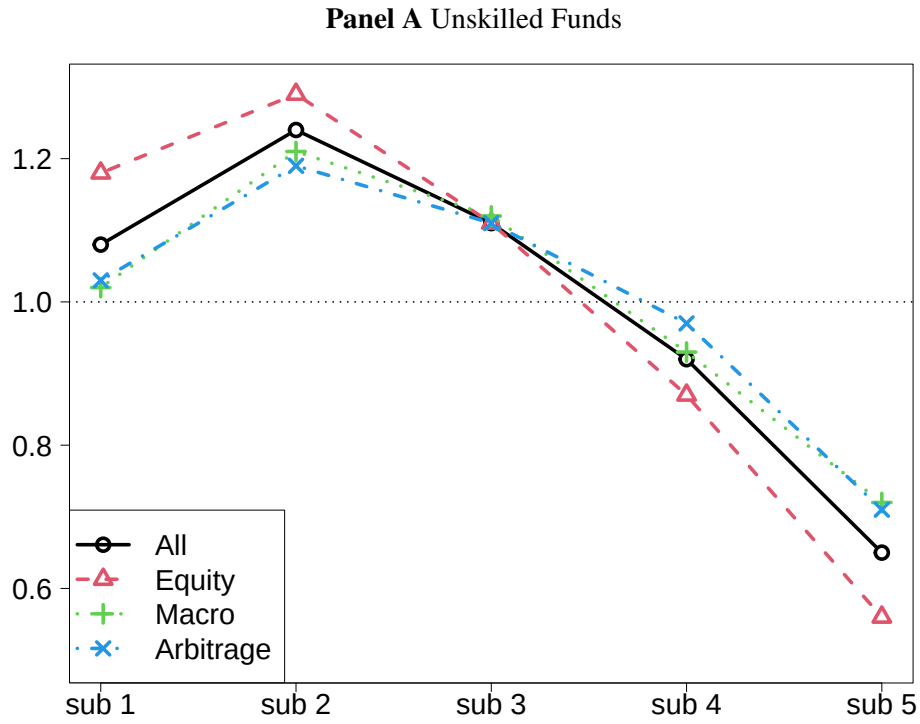
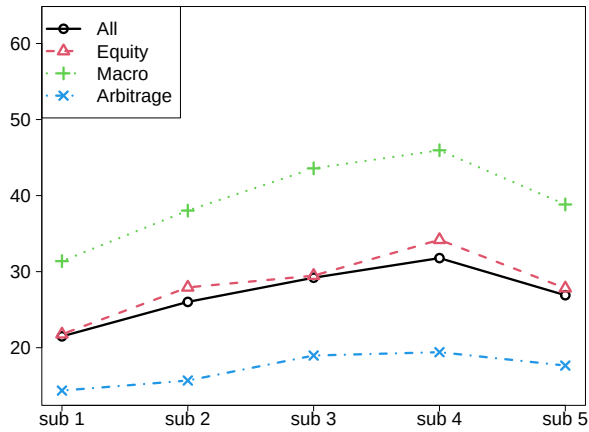


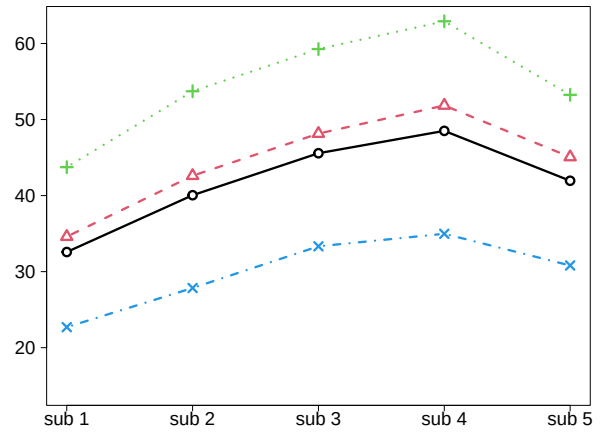
Figure 5. Evolution of the Left Tail of the Value-Added Distribution

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

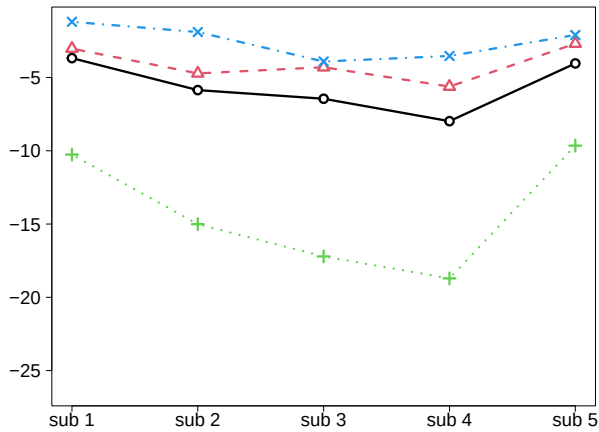
Panel A Negative Proportion - Value-Added



Panel B Negative Proportion - Net Value-Added



Panel C Quantile 10% - Value-Added



Panel D Quantile 10% - Net Value-Added

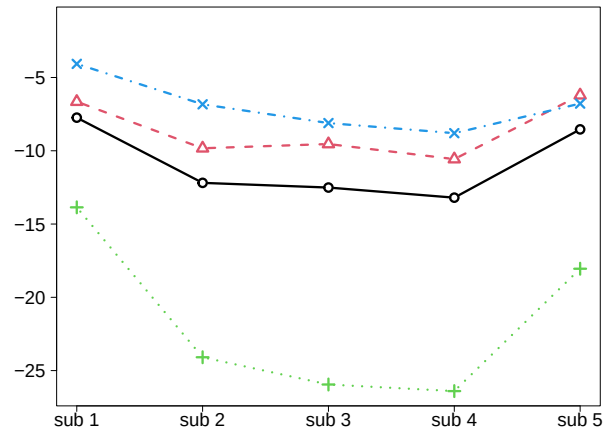
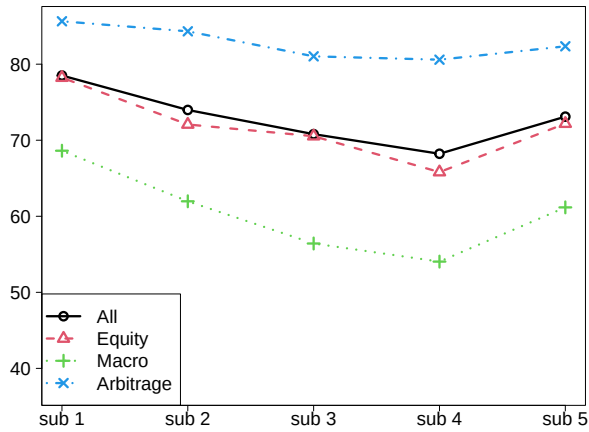


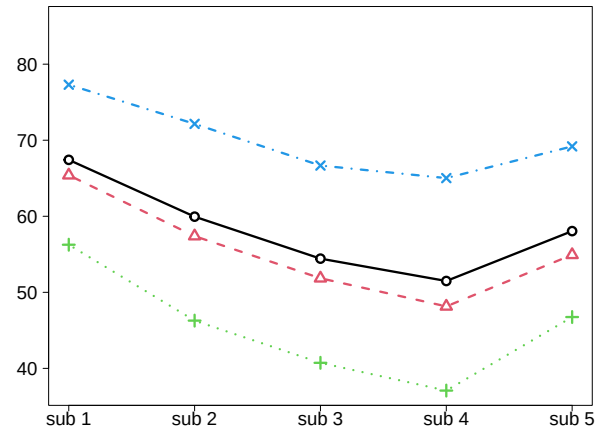
Figure 6. Evolution of the Right Tail of the Value-Added Distribution

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

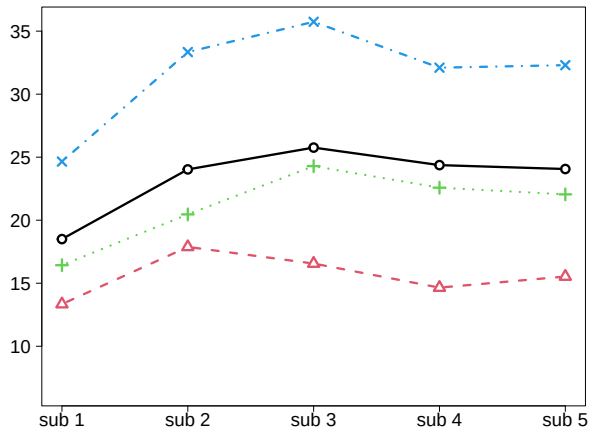
Panel A Positive Proportion - Value-Added



Panel B Positive Proportion - Net Value-Added



Panel C Quantile 90% - Value-Added



Panel D Quantile 90% - Net Value-Added

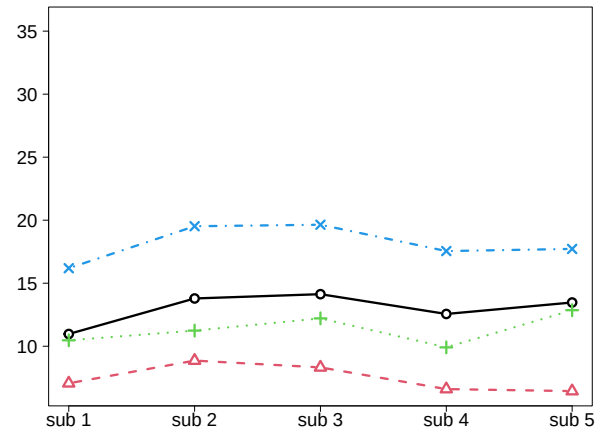


Figure 7. Fee Policy - Impact of Low Fees

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

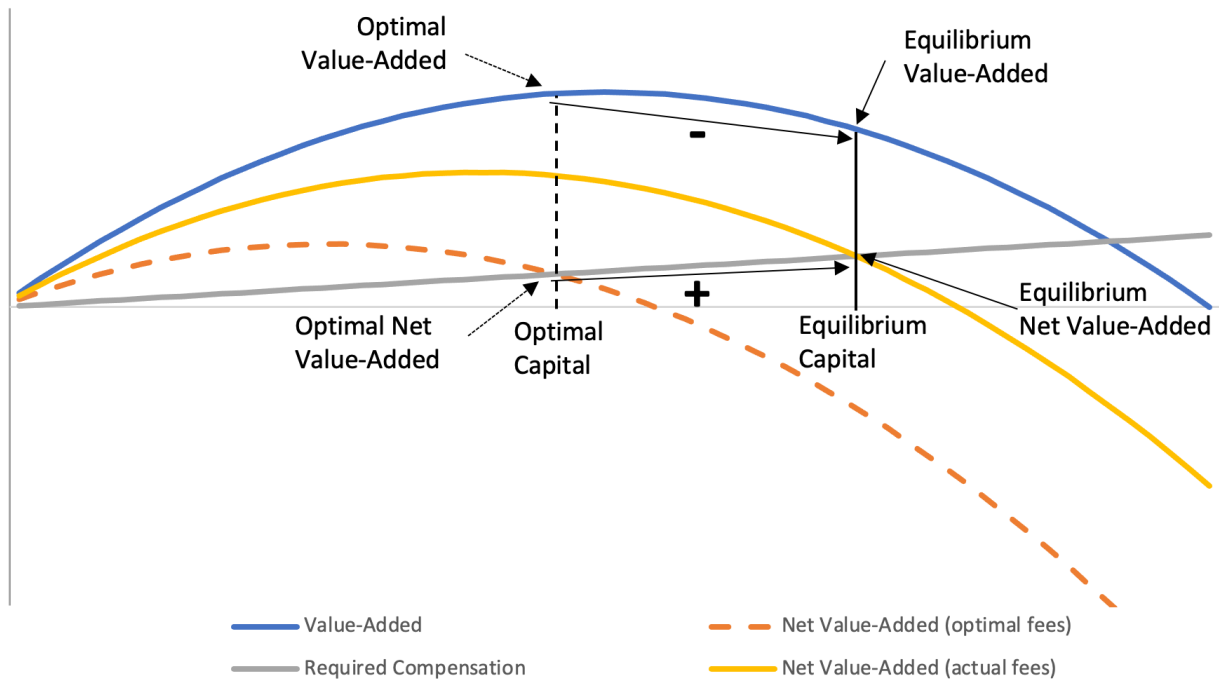


Figure 8. Capital Misallocation - Impact of Excess Capacity

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

