From Funds to Families: Organizational Scale in Value Creation

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Abstract

We study how family size shapes both the investment skill and scalability of affiliated mutual funds. We show that family scale has economically large but opposing effects—it reduces fund skill while improving scalability for a majority of funds. On net, these family effects enhance value creation and allow funds to sustain a positive value-added despite managing large amounts of capital. A normative analysis further reveals that families operate far beyond their value-maximizing size. Despite this excess capacity, family fee revenues remain close to optimal levels, indicating that families capture substantial rents through asset growth rather than value-maximizing capital allocation.

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I. Introduction

A large body of research examines how the size of actively-managed funds affects their future returns. Consistent with the model of Berk and Green (2004), several studies document that funds are, on average, subject to capacity constraints (*e.g.*, Fung et al., 2008; Yan, 2008; Zhu, 2018). More recently, Barras, Gagliardini, and Scaillet (2022, BGS hereafter) adopt a fund-level approach and show that the severity of these constraints varies substantially across funds. By contrast, much less is known about how family size shapes the returns of affiliated funds. This gap is noteworthy given the dominant role of families in the industry—the 50 largest families now control more than 90% of U.S. mutual fund assets (Morningstar Research, 2021).

There are opposing views on the effects of family size. One perspective holds that families have little influence on fund investment decisions, serving primarily to reduce fixed operating costs and leverage distribution networks to accelerate fund growth. The alternative view sees larger families as playing at least three important roles: (i) managing common assets such as brand reputation and institutional knowledge (e.g., Cici, Dahl, and Kempf, 2018; Holmstrom and Roberts, 1998); (ii) designing managerial incentives (e.g., Evans et al., 2020; Holmstrom, 1999); and (iii) allocating scarce resources, including human capital and unique investment opportunities (e.g., Berk, van Binsbergen, and Liu, 2017; Gaspar, Massa, and Matos, 2006). Through these channels, families may significantly influence the returns achieved by their affiliated funds.

In this paper, we quantify these family size effects. Our approach builds on the premise that as families expand, they can simultaneously affect both the quality and the scalability of fund ideas. Guided by this premise, we examine how family size influences funds along two core dimensions: (i) their skill in identifying profitable opportunities and (ii) their exposure to scalability constraints.[1] Another key feature of our approach is that we measure family size effects at the in-

[1]The dual impact of families is well summarized by The Economist (2025): "The idea [of the multi-manager model] is that, over the long run, it is more efficient for top investors—Mr. Griffin at Citadel, Israel Englander at Millennium, or Steven Cohen at Point72—to choose stockpickers and the conditions under which they operate than to make all the trades themselves. Portfolio managers enjoy economies of scale in technology and financing, but sign up for lengthy non-compete clauses and a level of subservience instinctively antithetical to placing billion-dollar bets."

dividual fund level. This granularity allows funds within the same family to respond differently to the multidimensional influence of family organization through the management of common assets, managerial talents, and resources. In doing so, we depart from the few panel studies on family size (*e.g.*, Chen et al., 2004; Evans et al., 2020), which focuses on fund skill—but not scalability—and imposes homogeneous family effects across funds.

In our baseline specification, we model the gross alpha of each fund as $\alpha_i = a_i - b_i q_{i,t-1}$. The skill coefficient a_i captures the fund alpha on the first dollar of capital, while the scale coefficient b_i measures how alpha declines as fund size $q_{i,t-1}$ increases. Unlike the standard model of Berk and Green (2004), which assumes constant skill and scale coefficients, we allow both coefficients to vary linearly with family size $q_{j,t-1}$: $a_i = a_{i,0} + a_{i,f} q_{j,t-1}$ and $b_i = b_{i,0} + b_{i,f} q_{j,t-1}$. Measured at the average family size $E[q_{j,t-1}]$, the induced family effects on fund skill and scalability are given by $a^s_{i,f} = a_{i,f} E[q_{j,t-1}]$ and $b^s_{i,f} = b_{i,f} E[q_{j,t-1}]$. We then measure the contribution of these effects to the total value created by the fund defined as $va_i = E[\alpha_{i,t-1} q_{i,t-1}]$ (Berk and van Binsbergen, 2015). Analogously to the concept of net present value, va_i determines whether a fund creates value relative to the best investment alternative available to investors. Substituting for α_i, we obtain $va_i = va_{i,0} + va_{i,f}$, where the $va_{i,0}$ is the baseline value-added and $va_{i,f} = a_{i,f} E[q_{i,t-1} q_{j,t-1}] - b_{i,f} E[q^2_{i,t-1} q_{j,t-1}]$ captures the dollar value of the dual family effects on skill and scalability (interaction between fund and family).

The central focus of our empirical analysis are the cross-sectional distributions of the family effects $a^s_{i,f}$, $b^s_{i,f}$, and their dollar value $va_{i,f}$. To recover these distributions, we extend the methodology of BGS which does not account for family effects. Our estimation uses as inputs the fund-level measures $\hat{a}^s_{i,f}$, $\hat{b}^s_{i,f}$, and $\hat{va}_{i,f}$ obtained from a time-series regression of the fund gross return on the size variables $(q_{i,t-1}, q_{j,t-1}, q_{i,t-1} q_{j,t-1})'$, and the market, size, value, and momentum factors of Cremers, Petajisto, and Zitzewitz (2013), which proxy for the investment opportunities available to investors. A key econometric challenge is that we observe only the noisy estimates $\hat{a}^s_{i,f}$, $\hat{b}^s_{i,f}$, and $\hat{va}_{i,f}$ rather than their true values, giving rise to an error-in-variables (EIV) bias. We derive closed-form expressions for this bias and use them to correct the estimated distributions.

Our analysis of U.S. equity funds from 1999 to 2022 reveals that family scale exerts economically large effects on the skill and scalability of affiliated funds. As they reach their average size, families reduce the first-dollar alpha for a majority of funds, with an average decline of 1.6% per year. By contrast, families mitigate scalability constraints for more than 60% of funds. Following a one-standard-deviation increase in fund size, family support attenuates the associated decline in fund alpha by about 1.4% per year on average. Overall, these findings run counter to the notion that families play a purely passive role limited to reducing fixed costs.

The overall evidence indicates that large families impose hierarchy costs that limit the profitability of fund investment ideas (e.g., Stein, 2002). This conclusion contrasts with Chen et al. (2004), who document a positive impact of family size on fund skill. The difference stems from a key modeling choice—their specification allows family size to affect fund skill but not scalability. As a result, the estimated skill effect is contaminated by the scalability benefits associated with larger families. These benefits point to the accumulation of institutional trading knowledge within families. As they expand, families may develop proprietary execution algorithms, invest in advanced analytical infrastructure, and cultivate strong relationships with liquidity providers.

Our analysis sheds new light on the role played by families. First, the incentive structure established by families is of primary importance. While greater managerial collaboration within families can relax scalability constraints through idea sharing, it may also weaken individual incentives to generate high-quality ideas. Consistent with this trade-off, increases in the size of cooperative families reduce the skill and scale coefficients by 2.9% and 2.4% per year, compared with reductions of 0.5% and 0.9% in competitive families. Second, family effects are weaker among small-cap and value funds, which invest more heavily in illiquid and hard-to-value securities. This pattern suggests that hierarchy costs arise less from information frictions and more from the centralization of investment decisions. Third, funds with stronger skill and scalability benefit the least from family support. In other words, families generally allocate internal resources to cross-subsidize funds, rather than disproportionately favoring their top-performing funds.

The overall effect of family size on value creation is positive. Although the skill-related effect reduces fund value by $19.1 million per year on average, this loss is more than offset by scalability gains associated with family support. On net, the dollar value of family effects averages $24.2 million and is positive for nearly 80% of funds in the population. These findings resonate with prior research showing that families contribute to value creation by reallocating managers (Berk, van Binsbergen, and Liu, 2017; Luo, Manconi, and Schumacher, 2023) and suggest that scalability—rather than skill—is the primary channel through which these reallocation add value. Despite the strong contribution of family support, funds generate only $1.5 million in value on average because they operate at sizes where scalability constraints are steep. Family support is therefore essential for enabling funds to maintain positive value-added at their observed scale.

Motivated by these findings, we next conduct a normative analysis of the mutual fund industry. We assess whether the large observed fund sizes are consistent with economic fundamentals. A key implication of our framework is that, in the presence of family effects, the value-maximizing fund size must be determined jointly across all funds within a family, and not only on a stand-alone basis. Although this optimization does not admit a closed-form solution, it can be solved numerically. The results reveal pervasive excess capacity across all fund categories. While the average fund size is $792 million, the model predicts an optimal size of only $182 million. Consequently, funds operate far beyond their value-maximizing scale, leaving an average of $12.7 million per year in unrealized value.

It is standard practice to base the normative analysis on the Berk and Green (2004) model (e.g., BGS; Roussanov, Ruan, and Wei, 2021; Zhu, 2018). While analytically convenient, the model predictions lack a clear structural interpretation in the presence of family effects. For a subset of skilled funds, the model assigns an optimal size and value-added equal to zero because the omitted family size spuriously drives the estimated skill coefficient into negative territory. As a result, the model narrows the gap between actual and optimal value-added by about 50%, thereby masking the true economic impact of excess capacity on value creation.

Finally, we examine the implications of this excess capacity for investors and families. We assess whether investors extract any value by measuring the net-of-fee fund value-added $va_i^{net} = va_i - rev_i$, where $va_i = E[\alpha_{i,t-1} q_{i,t-1}]$ is the gross fund value-added and $rev_i = E[fee_{i,t-1} q_{i,t-1}]$ is the fund fee revenue. The negative impact of excess fund capacity on investors is substantial. We find that the net value-added is negative for 99.1% of funds and averages –\$7.7 million per year. This pattern holds across all fund groups and contradicts the predictions of rational asset management models in which investors allocate capital until they break even ($va_i^{net} = 0$). While several forces may explain these results—including financial illiteracy (Gruber, 1996) and search costs (Roussanov, Ruan, and Wei, 2021)—these frictions must be economically large to sustain the negative net value-added observed in the data.

Our results also highlight the limitations of average net alpha $E[\alpha_{i,t-1}^{net}]$ as a performance measure. Despite its widespread use, it understates the true cost of active management for investors for two reasons. First, average net alpha is not a dollar measure because it ignores the scale $E[q_{i,t-1}]$ at which the fund operates. Second, it ignores the time-varying nature of investor capital allocation. Periods of negative net alpha receive a huge weight in value-added calculations because they occur when funds manage large capital amounts. As a result, using the net alpha incorrectly suggests that about 40% of funds create value for investors—rather than only 0.9%.

Excess capacity has sharply different implications for fund families. While it reduces the value-added of the family to only \$24.4 million per year on average, it increases its total fee revenues to \$76.2 million. Remarkably, this amount is close to the maximum value-added families could generate at the optimal size. In other words, families earn fee revenues comparable to those predicted by rational asset management models, but through asset growth rather than value-maximizing capital allocation. Consequently, excess capacity imposes substantial losses on investors while leaving family revenues largely intact.

The remainder of the paper is as follows. Section II presents our specification of the family size effects. Section III describes the methodology for measuring these effects. Section IV presents the mutal fund dataset. Section V contains the empirical analysis, and Section VI concludes. The appendix provides additional information on the methodology, the data, and the empirical results.

II. Fund Returns and Family Size Effects

II.A. The Standard Model of Berk and Green

To begin, we provide a brief overview of the standard model of Berk and Green (2004), which offers an intuitive framework for defining fund skill, scalability, and value creation—concepts that underpin our motivation and modeling of family effects.[2] We consider a population of n mutual funds, where we denote each fund by the subscript i $(i = 1, ..., n)$. The gross alpha of each fund is given by

$$\alpha_i^{\text{BG}} = a_i - b_i q_i, \tag{1}$$

where q_i denotes the fund size (in real terms). Equation (1) delivers simple measures of the skill and scalability of each fund. The skill coefficient a_i is equal to the alpha on the first dollar of invested capital ($q_i = 0$). This coefficient measures the profitability of the fund ideas without the drag of real-world implementation (Perold and Salomon, 1991).

The scale coefficient b_i is equal to the sensitivity of the gross alpha to changes in fund size. The magnitude of b_i captures multiple facets of diseconomies of scale. As the fund deploys more capital, it is less likely to execute trades cheaply—larger positions move prices, raise trading costs, and dilute high-conviction ideas. These frictions make it increasingly difficult to sustain the same alpha as when the fund was smaller.

Building on Equation (1), we can define the total value created by the fund as

$$va_i^{\text{BG}} = \alpha_i^{\text{BG}} q_i = a_i q_i - b_i q_i^2. \tag{2}$$

[2] A non-exhaustive list of papers that apply this model empirically includes BGS, Berk and van Binsbergen (2015), Roussanov, Ruan, and Wei (2021), and Zhu (2018).

Intuitively, va_i^{BG} is equivalent to the concept of net present value (NPV) applied to investment projects. A positive value-added signals that the hedge fund creates value for investors, just like a positive NPV signals that the project creates value for shareholders. Because va_i^{BG} is a dollar value that depends on the scale q_i at which the fund operates, the gross alpha alone is not sufficient to infer fund value—a point forcefully made by Berk and van Binsbergen (2015). If investors behave competitively, the fund extracts all the rents from its investment skill and set fees optimally so as to maximize the value-added.

The standard model outlined above accounts for fund size but abstracts from family size. At most, families may help reduce fixed costs associated with launching and operating funds—such as compliance, regulatory reporting, or data management. They may also leverage their client networks to accelerate fund growth toward the optimal size. Crucially, however, the organizational scale of the family has no direct impact on fund returns—an implication that sits uneasily with the reality of today's mutual fund industry. Given the substantial growth of fund families over recent decades, it is plausible that scale effects at the family level meaningfully shape the investment strategies of affiliated funds.

II.B. Family Size Effects

II.B.1. Motivating Family Size Effects

There are several non-exclusive channels through which fund families can influence the skill and scalability of their funds. First, fund families are responsible for managing common assets such as brand reputation and proprietary know-how. As Holmstrom and Roberts (1998) argue, common assets are more effectively managed within firms than through market-based contracting. In the mutual fund context, families may develop proprietary investment frameworks, build advanced analytical tools, refine trading algorithms, and cultivate privileged relationships with liquidity providers, brokers, and other market participants. When effectively shared, this knowledge can raise the gross alpha across affiliated funds. For example, Cici, Dahl, and Kempf (2018) document that families with more efficient trading desks trade more aggressively and hold less liquid positions. However, the management of common assets can also dilute individual fund skill as families centralize decision-making to preserve brand consistency.

Second, families are responible for shaping managerial incentives. In the broader context of firm boundaries, Holmstrom (1999) argues that a central reason why firms exist is to enable the use of a wide array of instruments to influence employee behavior. Fund families, for example, can favor intra-family competition to motivate managers to exert effort (e.g., Dannhauser and Spilker, 2023; Chevalier and Ellison, 1997; Kempf and Ruenzi, 2008). Alternatively, families might rely on lower-powered incentives to promote more collaboration among managers (Evans et al., 2020). Such collaboration may ease scalability constraints by expanding the pool of investment ideas, favoring the creation of team-managed funds, and increasing cross-trading within the family.

Third, families have the authority to allocate resources across funds. Families allocate human capital by assigning managers to specific funds (Berk, van Binsbergen, and Liu, 2017; Fang, Kempf, and Trapp, 2014). In addition, families decide on the distribution of key support functions (e.g., analysts, data scientists) and the allocation of unique investment opportunities (e.g., succesful IPOs). These resources could be equally shared or targeted at specific funds. For instance, some families may prioritize high-value or flagship funds as shown by Gaspar, Massa, and Matos (2006), while others may cross-subsidize funds—either due to internal rent-seeking behavior (Scharfstein and Stein, 2000) or as part of a broader proliferation strategy (Massa, 2003).

II.B.2. Modeling Family Size Effects

Our specification builds on the premise that the role played by families depends on the scale at which they operate. Intuitively, larger families have greater capacity to manage common assets, design comprehensive incentive schemes, and allocate resources effectively. Consistent with this view, prior research shows that the magnitude of several family decisions—such as cross-trading, intra-family competition, and fund–manager matching—varies systematically with family size (e.g., Dannhauser and Spilker, 2023; Gaspar, Massa, and Matos, 2006; Luo, Manconi, and Schumacher, 2023).

Specifically, we consider a population of J families, where we denote each family by the subscript j ($j = 1, ..., J$). For each fund i in family j, we specify its skill and scale coefficients as functions of the family size q_j (in real terms and excluding fund i):

$$a_i(q_j) = a_{i,0} + a_{i,f} q_j, \tag{3}$$

$$b_i(q_j) = b_{i,0} + b_{i,f} q_j. \tag{4}$$

Both equations formalize the idea that family size influences both the skill and scalability of affiliated funds. The magnitude of these effects is captured by the coefficients $a_{i,f}$ and $b_{i,f}$. The remaining coefficients $a_{i,0}$ and $b_{i,0}$ measure skill and scalability in the absence of family size effects. In particular, $a_{i,0}$ measures the fund alpha in a hypothetical world in which both the fund and family sizes are equal to zero ($q_i = 0$ and $q_j = 0$).[3] A distinctive feature of our approach is that we allow all coefficients—$a_{i,0}$, $a_{i,f}$, $b_{i,0}$, and $b_{i,f}$—to vary across funds. This contrasts with much of the existing panel literature, which assumes constant coefficients across funds.[4] We instead treat each coefficient as a random draw from its underlying cross-sectional distribution that we estimate from the data.

Allowing for heterogeneous coefficients is important for two reasons. First, the family environment—through the management of common assets, talents, and resources—may not enhance or constrain skill formation and scalability uniformly across all funds. Second, it uncovers cross-fund relationships among coefficients. As shown by BGS, the fund skill and scale coefficients are strongly positively correlated, implying that the best ideas tend to be the hardest to scale. Similar relationships may arise between $a_{i,0}$ and $a_{i,f}$ and between $b_{i,0}$ and $b_{i,f}$, a question that we address

[3]It is tempting to interpret $a_{i,0}$ and $b_{i,0}$ as the skill and scalabilty of the fund as a stand-alone entity. This interpretation is, however, incorrect since these coefficients can still be shaped by the fund's mere affiliation with a family. Disentangling the fund-specific and family-specific components of these coefficients in a large cross-section of funds constitutes a challenging identification problem (e.g., Bonhomme and Denis, 2024).

[4]For example, the large literature on diseconomies of scale in active management commonly assumes that the scale coefficient for fund size is constant across funds (*e.g.*, Chen et al., 2004; Fung et al., 2008; Naik, Ramadorai, and Stromqvist, 2007; Pástor, Stambaugh, and Taylor, 2015; Zhu, 2018).

empirically below.

Several fund- and family-level characteristics may shape the cross-sectional distributions of the coefficients $a_{i,0}$, $a_{i,f}$, $b_{i,0}$, and $b_{i,f}$. These coefficients likely reflect the unique investment and trading abilities of individual funds and their families, as well as many other sources of heterogeneity across funds and families. For example, the fund investment style influences the portfolio liquidity and turnover, thereby affecting the skill and scale coefficients $a_{i,0}$ and $b_{i,0}$ (e.g., van Binsbergen et al., 2024). Similarly, the distributions of the family-specific coefficients $a_{i,f}$ and $b_{i,f}$ are likely shaped by the overall style orientation of the family and its incentive structure—whether it emphasizes cooperation or competition among managers (Evans et al., 2020). While we explore these relationships empirically, a key advantage of Equations (3)-(4) is that they allow us to estimate all coefficients without needing to explicitly model their determinants—an inherently complex task given the large set of potential fund and family characteristics.

II.C. An Extended Model with Family Size Effects

II.C.1. Specification of the Gross Alpha and Value-Added

We can now build on Equations (3)-(4) to add family effects into the Berk and Green (2004) model. Replacing a_i and b_i with $a_i(q_j)$ and $b_i(q_j)$ in Equation (1), we write the gross alpha as

$$\alpha_i(q_i, q_j) = a_i(q_j) - b_i(q_j)q_i = a_{i,0} + a_{i,f}q_j - (b_{i,0} + b_{i,f}q_j)q_i, \tag{5}$$

which implies the following expression for the value-added:

$$va_i(q_i, q_j) = va_{i,0}(q_i) + va_{i,f}(q_i, q_j) = a_{i,0}q_i - b_{i,0}q_i^2 + a_{i,f}q_iq_j - b_{i,f}q_i^2q_j. \tag{6}$$

The term $va_{i,0}(q_i)$ measures the value created by the fund measures the value created by the fund in the absence of family effects ($q_j = 0$) and therefore depends only on the coefficients $a_{i,0}$ and $b_{i,0}$. The term $va_{i,f}(q_i, q_j)$ captures the dollar value of the family size effects on both skill and scalability. It includes the dollar value of the skill-related effect $a^{\$}_{i,f}(q_i, q_j) = a_{i,f} q_i q_j$ and the dollar value of the scale-related effect $b^{\$}_{i,f}(q_i, q_j) = -b_{i,f} q_i^2 q_j$.

If investors lack bargaining power as in the Berk and Green (2004) model, the family extracts the entire value-added through fees. A key difference in our setting, however, is that the optimization of the value-added cannot be carried out independently for each fund. Instead, it must be solved jointly across the n_j funds within the family—a point discussed in detail in Section V.C.

II.C.2. Model Identification

Our presentation so far does not address how to bring the model to the data. If funds set fees optimally and investors immediately allocate the optimal capital q_i^* to each fund, the model is unidentified. With constant fund and family sizes, there is no variation for the econometrician to exploit in order to recover the key coefficients $a_{i,0}$, $a_{i,f}$, $b_{i,0}$, and $b_{i,f}$—the core inputs of our methodology described in Section III.

In practice, the sizes of funds and families do vary over time. A key driver of this variation is learning—investors need time to learn about skill and scalability (Pástor and Stambaugh, 2012). As they update their views using fund return information, they reallocate capital generating the variation in sizes that is necessary for identification. Building on this insight, we now introduce the time dimension into the model. We consider a total of T periods, where each period is denoted by subscript t ($t = 1, ..., T$). The fund gross alpha at time t is given by

$$\alpha_{i,t} = a_{i,0} + a_{i,f} q_{j,t-1} - (b_{i,0} + b_{i,f} q_{j,t-1}) q_{i,t-1}, \tag{7}$$

where $q_{i,t-1}$ and $q_{j,t-1}$ are the fund and family sizes at time $t-1$. We then follow Berk and van Binsbergen (2015) and define the value-added as the average value created by the fund over its entire lifecycle: $va_i = E[\alpha_{i,t-1} q_{i,t-1}]$. Substituting the specification of the gross alpha from

Equation (7), we obtain

$$va_i = va_{i,0} + va_{i,f} = a_{i,0}E[q_{i,t-1}] - b_{i,0}E[q_{i,t-1}^2] + a_{i,f}E[q_{j,t-1}q_{i,t-1}] - b_{i,f}E[q_{i,t-1}q_{j,t-1}^2]. \quad (8)$$

As explained below, estimating family size effects and their implications for value creation across individual funds boils down to computing the empirical counterparts of Equations (7)-(8).

III. Methodology

III.A. Overview of the Methodology

We now describe our approach for measuring the family size effects across funds. We estimate the full cross-sectional distributions of these effects, as well as their combined dollar value. Focusing on these distributions allows us to capture the heterogeneity across funds and the multifaceted ways in which families influence the skill, scalability, and value-added among affiliated funds.

Our econometric strategy builds on recent advances in estimation and inference using large cross-sectional datasets (e.g., Ardia et al., 2024; Gagliardini, Ossola, and Scaillet, 2016). This approach is particularly well suited to our setting for several reasons. Unlike standard parametric or Bayesian methods (e.g., Harvey and Liu, 2018; Jones and Shanken, 2005), it does not require a full-fledged specification of the true distributions of family size effects—a specification for which theory provides limited guidance. It is also computationally efficient and easy to implement, even in samples involving thousands of mutual funds. At a basic level, the method amounts to constructing a (smoothed) histogram, avoiding the complexity of intensive techniques such as Gibbs sampling or expectation-maximization algorithms. Finally, it comes with a well-developed inferential framework as we characterize the asymptotic behavior of each estimated distribution, which enables rigorous statistical inference grounded in econometric theory.

III.B. Estimation of the Family Size Effects

We begin with the estimation of the coefficients of the time-series regression of the fund gross excess return $r_{i,t}$ on the size variables and the excess return vector f_t of K factors:

$$r_{i,t} = a_{i,1} + a_{i,f}\tilde{q}_{j,t-1} - b_{i,1}q_{i,t-1} - b_{i,f}\tilde{q}_{j,t-1}q_{i,t-1} + \beta_i' f_t + \varepsilon_{i,t} \,. \tag{9}$$

where $a_{i,1} = a_{i,0} + a_{i,f}E[q_j]$, $b_{i,1} = b_{i,0} + b_{i,f}E[q_j]$, $\tilde{q}_{j,t-1}$ denotes the centered family size, and $\beta_i' f_t$ is the benchmark portfolio that capture the investment opportunities available to investors. We compute the least-squares estimate as $\hat{\gamma}_i = (\hat{a}_{i,1}, \hat{a}_{i,f}, \hat{b}_{i,1}, \hat{b}_{i,f}, \hat{\beta}_i')' = (\hat{Q}_{x,i})^{-1}\frac{1}{T_i}\sum_t I_{i,t}x_{i,t}r_{i,t}$, where $T_i = \sum_t I_{i,t}$, $x_{i,t} = (1, \tilde{q}_{j,t-1}, -q_{i,t-1}, -q_{i,t-1}\tilde{q}_{j,t-1}, f_t')'$ is a $(K+4)$-vector, $\hat{Q}_{x,i} = \frac{1}{T_i}\sum_t I_{i,t}x_{i,t}x_{i,t}'$, and $I_{i,t}$ is an indicator variable equal to one if $x_{i,t}$ and $r_{i,t}$ are observable.

We assume for the inferential theory that fund and family sizes are asymptotically stationary as the time index t grows large (Pötscher and Prucha, 1989). Under this assumption, $q_{i,t-1}$ and $q_{j,t-1}$ can perfectly trend up during the early years when the impact of investor learning is strong. In theory, long-run stationarity in fund size is compatible with any model that incorporates diseconomies of scale at either the fund or industry level. For example, Pástor and Stambaugh (2012) demonstrate that fund size converges to an equilibrium regardless of risk preferences of investors or their bargaining power vis-à-vis fund managers. The long-run stationarity in family size further requires that the number of funds per family is bounded—an assumption that is consistent with empirical evidence.[5] Equation (9) is a standard time-series regression that yields consistent estimators of all fund-specific coefficients as T grows large. In contrast to the widely-used panel data methododology commonly, we do not impose that the coefficients are identical across funds. As a result, we avoid the incidental parameters problem which generates a bias that does not disappear asymptotically and is challenging to correct (see BGS for details).

To ease interpretation, we evaluate the family size effects on skill and scalability at the average

[5]In the appendix, we show that the average number of funds per family is remarkably stable around 5 over the sample period.

family size $E[q_j]$ by focusing on the coefficients $a^s_{i,f} = a_{i,f}E[q_j]$ and $b^s_{i,f} = b_{i,f}E[q_j]$. Using the generic notation $\hat{m}_{i,j}$ for each effect, we obtain

$$\text{Family size effect on skill}: \hat{m}_i = \hat{a}^s_{i,f} = \hat{a}_{i,f}\bar{q}_j, \tag{10}$$

$$\text{Family size effect on scalability}: \hat{m}_i = \hat{b}^s_{i,f} = -\hat{b}_{i,f}\bar{q}_j, \tag{11}$$

$$\text{Family size effect on value-added}: \hat{m}_i = \hat{va}_{i,f} = \hat{a}^{\$}_{i,f} + \hat{b}^{\$}_{i,f} = \hat{a}_{i,f}\bar{q}_{i,j} - \hat{b}_{i,f}\bar{q}_{i,j,2}, \tag{12}$$

where $\bar{q}_j$ denotes the average of the family size, while $\bar{q}_{i,j}$ and $\bar{q}_{i,j,2}$ denote the averages of the interactions between fund and family sizes and between squared fund and family sizes.

III.C. The Distribution of Family Size Effects

III.C.1. Estimation of the Distribution Characteristics

We now describe the statistical properties of the cross-sectional distribution of each measure $m_i \in \{a^s_{i,f}, b^s_{i,f}, va_{i,f}\}$. The basic idea behind our approach is to interpret each measure m_i as a random realization from a continuum of funds. Under this sampling scheme, we can invoke cross-sectional limits to infer the asymptotic properties of each estimated distribution. Our approach largely builds on previous work by BGS who derive the asymptotic properties of the skill, scale, and value-added densities in a world without family size effects. Here, we incorporate these effects and summarize the shape of the distribution using a set of key characteristics: (i) the cross-sectional mean M, (ii) the proportion of funds with a measure below a given value a, denoted by $P(a) = prob(m_i < a)$, and (iii) the quantile at a given percentile level u, denoted by $Q(u) = (P)^{-1}(u)$. Focusing on these characteristics instead of the density greatly simplifies the econometric analysis while preserving all relevant cross-sectional information.

To estimate the above characteristics, we account for the unbalanced nature of the mutual fund sample. Following Gagliardini, Ossola, and Scaillet (2016), we introduce a formal selection rule $\mathbf{1}^\chi_i$ equal to one if the following conditions are met: $\mathbf{1}^\chi_i = \mathbf{1}\left\{\tau_{i,T} \leq \chi_{1,T}, CN_i \leq \chi_{2,T}\right\}$, where

$\tau_{i,T} = T/T_i$, $CN_i = \sqrt{eig_{\max}\left(\hat{Q}_{x,i}\right)/eig_{\min}\left(\hat{Q}_{x,i}\right)}$ 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 observations, we estimate the coefficients with greater accuracy, which allows for a less stringent selection rule.

Applying the selection rule, we work with a population size equal to $n_\chi = \sum_{i=1}^{n} \mathbf{1}_i^\chi$. We then compute the estimated mean, proportion, and quantile as

$$\hat{M} = \frac{1}{n_\chi}\sum_i \mathbf{1}_i^\chi \hat{m}_i\,, \tag{13}$$

$$\hat{P}(a) = \frac{1}{n_\chi}\sum_i \mathbf{1}_i^\chi \mathbf{1}\{\hat{m}_i \leq a\}\,, \tag{14}$$

$$\hat{Q}(u) = (\hat{P})^{-1}(u), \tag{15}$$

where we replace the true fund measure m_i with the estimated measure $\hat{m}_i$.

III.C.2. Inference on the Distribution Characteristics

In the following proposition, we derive the asymptotic distributions of the estimated characteristics $\hat{M}$, $\hat{P}(a)$, and $\hat{Q}(u)$ obtained with the estimated fund measures $\hat{m}_i$ ($i = 1, ..., n_\chi$). We consider a setup where the numbers of funds n and observations T grow large (simultaneous double asymptotics with $n, T \to \infty$).[6] To capture the large cross-sectional dimension of the mutal fund population observed in the data, we require that n is larger than T.

Proposition 1. *As $n, T \to \infty$, such that $T/n \to 0$, we obtain the following properties for the*

[6] In our baseline specification, we assume that the number of funds per family is bounded (to match our empirical evidence), implying that as n grows large, the number of families J must also increase. Alternatively, we can take the number of families to be bounded, while the number of funds per family grows large. What matters for the asymptotic analysis is that their product n diverges to infinity.

estimated mean, proportion and quantile of the cross-sectional distribution of m_i:

$$\sqrt{T}\left(\hat{M} - M\right) \to_d N(0, V[M]) \,, \tag{16}$$

$$\sqrt{T}\left(\hat{P}(a) - P(a) - B(P(a))\right) \to_d N(0, V[P(a)]) \,, \tag{17}$$

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

where $\to_d$ denotes convergence in distribution. The variance terms are given by $V[M] = E(m_i - M)^2$, $V[P(a)] = P(a)(1 - P(a))$ and $V[Q(u)] = u(1-u)/\phi(Q(u))^2$, where $\phi(x)$ is the density function of m_i at x. The bias terms for the proportion and quantile estimators are given by

$$B(P(a)) = \frac{1}{2T}\psi^1(a) \,, \tag{19}$$

$$B(Q(u)) = -\frac{1}{2T}\frac{\psi^1(Q(u))}{\phi(Q(u))} . \tag{20}$$

The function $\psi^1(x)$ is the first derivative of $\psi(x) = \omega(x)\phi(x)$, where $\omega(x) = E[S_i|m_i = x]$ and S_i is the asymptotic variance of the estimated centered measure $\sqrt(T)(\hat{m}_i - m_i)$.

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

Proposition 1 reveals that both the estimated proportion and quantile are biased estimators of their true counterparts. This error-in-variable (EIV) bias arises from estimation noise—we can only estimate $P(a)$ and $Q(u)$ using the estimated fund measures $\hat{m}_i$, rather than the true ones m_i. Consistent with intuition, the bias terms $B(P(a))$ and $B(Q(u))$ depend on T—the available number of observations for computing $\hat{m}_i$. As a result, they do not vanish even if the fund population n gets large. Interestingly, the estimated mean $\hat{M}$ is the only characteristic immune to the EIV bias. This result arises because the estimation noise of $\hat{M}$ a linear combination of the individual estimation errors $\hat{m}_i - m_i$ ($i = 1, ..., n_\chi$), which are mean zero by construction.

A common argument against the use of the fund-specific measures—and in favor of imposing panel restrictions ($m_i = m$)—is that they are too noisy to be informative. However, our results in Proposition 1 challenge this view. We show that the estimation error in $\hat{m}_i$ only affects the magnitude of the EIV bias, not the asymptotic variance of $\hat{M}$, $\hat{P}(a)$, and $\hat{Q}(u)$. As long as the EIV bias is properly accounted for, these characteristics can be estimated with the same asymptotic precision, even when the sampling variability in each individual fund estimate $\hat{m}_i$ is large.

III.D. Adjustment for the Error-in-Variable Bias

III.D.1. Derivation of the Bias Terms

We now explain how to adjust for the EIV bias. To estimate the two terms $B(P(a))$ and $B(Q(u))$, we use a simple Gaussian model in which m_i and the log of its asymptotic variance $s_i = log(S_i)$ follow a bivariate normal distribution where $m_i \sim N(\mu_m, \sigma_m^2)$, $s_i \sim N(\mu_s, \sigma_s^2)$, and $corr(m_i, s_i) = \rho$. Using a Gaussian reference model instead of a fully nonparametric estimation is appealing because the bias terms (i) are easy to compute in closed form, and (ii) are precisely estimated because they only depend on the five parameters $\theta = (\mu_m, \sigma_m^2, \mu_s, \sigma_s^2, \rho)$. We refer the reader to BGS who provide a detailed analysis of the bias under the Gaussian model and show that it provides a good approximation of the true bias in Monte-Carlo simulations.

Armed with this reference model, we obtain closed-form expressions for the functions $\psi^1(x)$ and $\phi(x)$—the two elements in the bias terms $B(P(a))$ and $B(Q(u))$.

Proposition 2. *As $n, T \rightarrow \infty$, such that $T/n \rightarrow 0$, we obtain under the Gaussian reference model:*

$$\psi^1(x) = \frac{1}{\sigma_m}\left(\varphi\left(\frac{m-\mu_m-\rho\sigma_m\sigma_s}{\sigma_m}\right) - exp\left(\mu_s + \frac{1}{2}\sigma_s^2\right)\left(\frac{m-\mu_m-\rho\sigma_m\sigma_s}{\sigma_m}\right)\right), \quad (21)$$

$$\phi(x) = \frac{1}{\sigma_m}\left(\varphi\left(\frac{m-\mu_m}{\sigma_m}\right)\right), \quad (22)$$

where $\varphi(x) = \frac{1}{\sqrt{2\pi}}exp\left(-\frac{1}{2}x^2\right)$ is the standard normal density.
Proof. *See the appendix.*

Using Proposition 2, we perform the EIV bias adjustment as follows. First, we estimate the parameter vector θ using the estimated quantities m_i and s_i ($i = 1, ..., n_\chi$). To compute $s_i = log(S_i)$, we use the standard variance estimator of Newey and West (1987):

$$S_i = \frac{T}{T_i^2}\sum_{t=1}^{T} I_{i,t}\hat{u}_{i,t}^2 + 2\sum_{l=1}^{L}\left(1 - \frac{l}{L+1}\right)\left[\frac{T}{T_i^2}\sum_{t=1}^{T-l} I_{i,t}I_{i,t+l}\hat{u}_{i,t}\hat{u}_{i,t+l}\right]. \quad (23)$$

where the residual term $\hat{u}_{i,t}$ depends on the fund measure m_i and L is the number of lags to capture potential serial correlation (we set $L = 3$ in the baseline specification). We have $\hat{u}_{i,t} = \bar{q}_j E_2 \hat{Q}_{x,i}^{-1} \hat{\varepsilon}_{i,t} + \hat{a}_{i,f}(q_{j,t-1} - \bar{q}_j)$ for $a_{i,f}^s$, $\hat{u}_{i,t} = \bar{q}_j E_4 \hat{Q}_{x,i}^{-1} \hat{\varepsilon}_{i,t} + \hat{b}_{i,f}(q_{j,t-1} - \bar{q}_j)$ for $b_{i,f}^s$, and $\hat{u}_{i,t} = \bar{q}_{i,j} E_2 \hat{Q}_{x,i}^{-1} \hat{\varepsilon}_{i,t} + \hat{a}_{i,f}(q_{i,t-1} q_{j,t-1} - \bar{q}_{i,j}) + \bar{q}_{i,j,2} E_4 \hat{Q}_{x,i}^{-1} \hat{\varepsilon}_{i,t} - \hat{b}_{i,f}(q_{i,t-1}^2 q_{j,t-1} - \bar{q}_{i,j,2})$ for $va_{i,f}$, where E_j is a $(K + 4)$-vector with zeros except in the j position. Second, we compute the bias terms $\hat{B}(P(a))$ and $\hat{B}(Q(u))$ after computing $\hat{\psi}^1$ and $\hat{\phi}$ using the estimated vector $\hat{\theta}$:

$$\hat{B}(P(a)) = \frac{1}{2T} \hat{\psi}^1(a)\,, \tag{24}$$

$$\hat{B}(Q(u)) = -\frac{1}{2T} \frac{\hat{\psi}^1(Q(u))}{\hat{\phi}(Q(u))}. \tag{25}$$

Third, we obtain the bias-adjusted characteristics:

$$\tilde{M} = \hat{M}, \tag{26}$$

$$\tilde{P}(a) = \hat{P}(a) - \hat{B}(P(a)), \tag{27}$$

$$\tilde{Q}(u) = \hat{Q}(u) - \hat{B}(P(a)). \tag{28}$$

Using Equation (27), it is also straightforward to compute the proportion of funds with a measure above a as $\tilde{P}^+(a) = prob(m_i > a) = 1 - \tilde{P}(a)$ or $\tilde{P}^+(a) = \hat{P}^+(a) - \hat{B}^+(P(a))$, where $\hat{P}^+(a) = 1 - \hat{P}(a)$ is the bias-unadjusted estimate and $\hat{B}^+(P(a)) = -\hat{B}(P(a))$ is the bias of $\hat{P}^+(a)$.

III.D.2. Analysis of the Bias Adjustment

The reference model builds solid intuition for the nature of the EIV bias. The bias adjustment alters the cross-sectional distribution obtained with the estimated measures $\hat{m}_i$ $(i = 1, ..., n_\chi)$ in two ways. First, it moves the probability mass from the tails to the center of the distribution, as estimation noise tends to generate extreme values of $\hat{m}_i$ relative to the true m_i. To illustrate this effect, Panels A and B of Figure 1 plots the shape of the bias adjustment applied to (i) the estimated proportion $\hat{P}(a)$ when a is below the mean μ_m and its complement $\hat{P}^+(a) = 1 - \hat{P}(a)$

when a is above μ_m, and (ii) the estimated quantile $\hat{Q}(u)$. For interpretive clarity, we set $\mu_m = 0$ and $\rho = 0$. stimation noise implies that the estimated probability of observing large values is overstated. To correct for this distortion, the bias adjustment is strongly negative when $|a|$ is large. As we move toward the center of the distribution, the severity of the bias diminishes and the adjustment converges to zero when $a = 0$. Similarly, the quantiles are compressed toward zero—the bias adjustment increases (decreases) $\hat{Q}(u)$ when u is large and negative (positive).

Second, the bias adjustment can be asymmetric around the mean μ_m, depending on the correlation ρ. When ρ is negative, funds with lower true values m_i also have greater estimation variance S_i. As a result, the right tail of the estimated distribution becomes artificially thick, since funds with low m_i are more likely to generate spuriously high estimates $\hat{m}_i$. To correct this distortion, the bias adjustment shifts probability mass from the right of μ_m to the left. Panel C illustrates this transfer. We observe a discontinuity at $a = \mu_m$, where the bias adjustment is negative to the right of μ_m and positive to the left.

Please insert Figure 1 here

IV. Data Description

IV.A. Construction of the Mutual Fund Dataset

We conduct our analysis using the full population of open-end, actively managed U.S. equity mutual funds. Monthly data on net returns and fund size, along with annual data on fees, turnover, investment objectives, and family affiliation, are obtained from the CRSP mutual fund database over the period January 1999 to December 2022 (288 months). We start the sample in January 1999 due to extensive missing family information in earlier years. These data allow us to construct time series for each fund gross returns and size, as well as for the family size. Following Berk and van Binsbergen (2015), we express all fund and family size values in real terms using January 1, 2000 dollars. Additional details on the construction of the mutual fund dataset and the fund-family matching process are provided in the appendix.

We estimate the fund coefficients in Equation (9) using the model of Cremers, Petajisto, and Zitzewitz (2013), which includes the vector of factors $f_t = (r_{m,t}, r_{smb,t}, r_{hml,t}, r_{mom,t})$, where $r_{m,t}$, $r_{smb,t}$, $r_{hml,t}$, $r_{mom,t}$ capture the gross excess returns of the market, size, value, and momentum factors. This model departs from the traditional model of Carhart (1997) in two respects: (i) the market factor is proxied by the excess return of the SP500 (instead of the CRSP index), and (ii) the size and value factors are measured using Russell index data. By design, this model assigns a zero alpha to both the S&P 500 and the Russell 2000—two indices that collectively represent approximately 85% of total market capitalization and serve as common benchmarks for active equity funds. The factor returns capture the gross-of-fee returns of the replicable factors, which implies that we exclude from the value-added the replication services that mutual funds provide to investors (Berk and van Binsbergen, 2015). We exclude these services because they are also provided by passive products.

To account for the unbalanced nature of the mutual fund sample, we apply the fund selection rule described in Section III. Taking the same thresholds as BGS, we set the minimum number of return observations to 60 and the minimum condition number to 15. We also remove micro funds whose capital is below $15 million for at least one third of the observations. Finally, we limit the influence of outliers by removing the most extreme 1% of observations based on the estimated coefficients and their asymptotic variances. Applying these selection rules yields a sample of 1,544 funds over the full period ($n_\chi = 1,544$).

IV.B. Summary Statistics

Table I reports summary statistics for an equal-weighted portfolio of all funds available at the start of each month. We present results for the full sample as well as for subgroups of funds defined by investment styles which cover the small-/large-cap and value/growth dimensions. We also consider family characteristics as we compare the bottom and top terciles of funds sorted by the levels of style diversification/concentration and competition/cooperation within the family.[7]

[7] We thank Rafael Zembrana for kindly providing us the family index of competition/cooperation.

Further details on the group formation are provided in the appendix.

In the full sample, Panel A shows that the equal-weighted portfolio exhibits a mean–volatility trade-off comparable to that of the aggregate stock market, with annualized return and volatility of 7.5% and 17.6%. Similar patterns obtain across most fund categories, except for small-cap funds, which display both higher average returns and greater volatility (9.3% and 20.3%). Median fund and family sizes in the overall sample are \$325 million and \$6,648 million. These sizes are substantially smaller for small-cap funds (\$191 million and \$4,247 million) and for funds belonging to style-concentrated families (\$176 million and \$1,201 million).

Panel B reports the portfolio betas with respect to the four benchmark factors. As expected, small-cap funds display strong exposure to the size factor (0.82), while value funds load positively on the value factor (0.31). Overall, the benchmark model provides a good fit to the data, explaining 90% or more of the time-series variation in portfolio returns. These high R^2 values suggest that omitted risk factors are unlikely to materially affect the magnitude of the estimated alphas.

Please insert Table I here

V. Empirical Results

V.A. Family Size Effects on Skill and Scalability

V.A.1. Magnitude of the Family Size Effects

We begin our empirical analysis by examining how family size impacts the skill and scale coefficients across funds. Applying the methodology in Section III, we estimate the cross-sectional distributions of the family effects $a_{i,f}^s$ and $b_{i,f}^s$. Using the estimated values $\hat{a}_{i,f}^s$ and $\hat{b}_{i,f}^s$ for all funds, we report in Table II the mean, as well as the bias-adjusted median, the bias-adjusted proportions of funds with negative and positive coefficients, and the bias-adjusted 25th and 75th quantiles. To ease the interpretation, we standardize the estimated coefficient $\hat{b}_{i,f}^s$ so that it measures the change in fund alpha in response to a one-standard-deviation change in fund size.

We find that family size effects are economically large when evaluated at the average family size. On the skill dimension, family scale lowers the first-dollar alpha by 1.6% per year on average. This decline is consistent with the idea that large family organizations impose hierarchy costs which limit the profitability of fund investment ideas (e.g., Pollet and Wilson, 2008; Stein, 2002). In contrast, family size helps ease scalability constraints. Following a one-standard-deviation increase in fund size, the negative impact on the fund alpha is mitigated by 1.4% per year due to family support. Overall, these results stand in sharp contrast to the view that fund families play a passive role, merely serving to reduce the fixed costs of launching and operating funds without interfering in their investment operations.

Whereas the magnitude of family size effects differs across funds, their signs display strong commonality. An increase in family size reduces the skill and scale coefficients for 56.8% and 63.3% of the funds. Moreover, the average family effect is broadly representative of the typical fund, as evidenced by the close alignment between mean and median effects for both skill (-1.6% vs. -1.3% per year) and scalability (-1.4% vs. -1.3% per year).

The evidence that growing families impose hierarchy costs on affiliated funds contrasts with Chen et al. (2004), who document a positive relation between family size and fund skill. Their specification, however, allows family size to only affect fund skill but not scalability—the second dimension of value creation. By omitting the interaction term $q_{i,t-1}q_{j,t-1}$, their estimate of the skill-related family effect is upward biased, as it inadvertently captures the positive impact of families on fund scalability. Consistent with this interpretation, we find that the coefficient $a_{i,f}^{s}$ turns positive on average once we exclude $q_{i,t-1}q_{j,t-1}$ from our baseline specification.

Please insert Table II here

V.A.2. Variation across Fund Groups

We can gain further insight by examining the heterogeneity in family size effects across fund groups. A first takeaway from Table III is that the direction of these effects is remarkably stable—

across all groups, most funds experience declines in both their skill and scale coefficients as families grow in size. The most pronounced differences arise between funds operating in competitive and cooperative families. While greater managerial collaboration may ease scalability constraints through idea sharing, it can also weaken individual incentives to generate high-quality ideas. Our estimates indicate that this trade-off is economically meaningful. In cooperative environments, increases in family size reduce fund skill by -2.9% per year while alleviating capacity constraints by 2.4% per year. In contrast, these effects are substantially weaker in competitive families, where the corresponding magnitudes fall to -0.5% and -0.9%. Taken together, these findings suggest that the incentive structure set up by families plays a central role in shaping fund skill and scalability.

Table III also sheds light on the nature of the hierarchy costs imposed by families. One might expect these costs to be more severe for small-cap and value funds, since these funds invest in smaller and less liquid stocks whose valuation depends on soft information that is difficult to communicate (Stein, 2002). Yet the empirical evidence points in the opposite direction. This pattern suggests that hierarchy costs stem less from information frictions and more from the centralization of investment decisions. To protect their brand, families may impose stricter oversight on large-cap and growth funds, which often serve as flagship products. Consistent with this centralization view, hierarchy costs are also stronger in style-diverse families, where a one-size-fits-all approach makes it harder for managers to push their best ideas through.

Finally, the widespread reduction in scalability constraints across groups suggests that families accumulate institutional knowledge in trading. As they expand, families may build proprietary execution algorithms, develop advanced analytical infrastructure, and cultivate strong relationships with liquidity providers (e.g., Cici, Dahl, and Kempf, 2018). Families may also enhance information sharing through analysts, research capacity, or data resources. Fang, Kempf, and Trapp (2014) show that faster information flows within families increase the returns of style-diverse funds, consistent with our finding that scalability gains are larger in such families.

Please insert Table III here

V.A.3. Decomposing Fund Skill and Scalability

We now examine the overall fund skill and scalability evaluated at the average family size. For each fund, we measure them using the coefficients $\hat{a}_{i,1}$ and $\hat{b}_{i,1}$ in Equation (9). We then compare these coefficients with the corresponding coefficients in the absence of family size effects ($q_j = 0$), which we estimate as $\hat{a}_{i,0} = \hat{a}_{i,1} - \hat{a}^s_{i,f}$ and $\hat{b}_{i,0} = \hat{b}_{i,1} - \hat{b}^s_{i,f}$. Applying our methodology to these estimates, we compare in Figure 2 the bias-adjusted distributions for all four coefficients $a_{i,0}$, $b_{i,0}$, $a_{i,1}$, and $b_{i,1}$ (see the appendix for details).

In the absence of family size effects, the skill coefficient averages 5.8% per year, with 25% of funds delivering first-dollar alphas in excess of 12% annually. In practice, however, such exceptional returns are rarely observed because they are attenuated by family size effects. Once these effects are incorporated, we observe an average drop in overall fund skill to 4.2% per year, accompanied by a pronounced compression in the upper tail of the distribution as the 75th percentile falls to 7.0% per year. This compression reflects the fact that funds with the most profitable ideas suffer the most from the hierarchy costs imposed by large families.

The analysis of fund scalability reinforces the central role of scalability in the mutual fund industry. In the absence of family support, we find that scalability constraints are particularly tight—a one–standard-deviation increase in fund size lowers the gross alpha by 3.5% per year. Once family size effects are taken into account, the overall scale coefficient falls to 2.0% per year. We also observe a marked reduction in the scale coefficients in the right tail of the distribution, as the 75th percentile falls from 7.4% to 3.4%. In other words, funds facing the tightest scalability constraints benefit the most from family support.

The compression in the right tail of the overall skill (scale) distribution reflects the strong correlation between $\hat{a}_{i,0}$ and $\hat{a}^s_{i,f}$ ($\hat{b}_{i,0}$ and $\hat{b}^s_{i,f}$). This correlation is informative about the resource allocation process within families. While some studies report that families occasionally favor their top-performing funds (Gaspar, Massa, and Matos, 2006), such selective treatment appears to be the exception rather than the norm. Our findings instead suggest that families often level the playing field, channeling more support toward funds with weaker skill or tighter scalability constraints. A concrete illustration of this behavior is provided by Bhattacharya, Lee, and Pool (2013), who show that affiliated funds-of-funds supply liquidity backstops to underperforming funds in order to prevent fire sales.

Please insert Figure 2 here

V.B. Family Size Effects on Value Creation

V.B.1. The Dollar Value of Family Size Effects

Our previous analysis reveals that growing families exert both a positive and a negative influence on value creation. On one hand, they reduce the profitability of fund ideas (i.e., $a_{i,f} < 0$ for most funds). On the other hand, they allow funds to scale these ideas more aggressively (i.e., $b_{i,f} < 0$ for most funds). To assess the net impact, we examine the distribution of the dollar value of family size effects, measured as $va_{i,f} = a^{\$}_{i,f} + b^{\$}_{i,f}$. The first component $a^{\$}_{i,f} = a_{i,f} E[q_{i,t-1} q_{j,t-1}]$ captures the skill-related effect, while the second $b^{\$}_{i,f} = -b_{i,f} E[q^2_{i,t-1} q_{j,t-1}]$ reflects the scale-related effect. Applying our methodology on the estimated values $\hat{a}^{\$}_{i,f} = \hat{a}_{i,f} \bar{q}_{i,j}$ and $\hat{b}^{\$}_{i,f} = -\hat{b}_{i,f} \bar{q}_{i,j,2}$, we can infer the bias-adjusted distributional characteristics of $va_{i,f}$.

Table IV reveals that the dollar value of skill-related family effect amounts to \$19.1 million per year on average. This negative contribution, however, is more than offset by scalability gains, which add \$43.3 million. On net, the dollar value of family size effects averages \$24.2 million and is positive for nearly 80% of funds in the population. The dollar value of these effects is large because it reflects the scale at which funds operate. As shown in Table I, the average fund size reaches \$1.6 billion, implying that family effects influence substantial amounts of managed capital.

Table V reveals similar patterns across all fund groups. The dollar impact of family size on skill is negative in all but one category (small-cap), whereas its effect on scalability is uniformly positive and economically large. As a result, family support brings positive value for at least 64% of funds. The cross-sectional average ranges from \$9.8 million for funds in concentrated families to \$33.1 million for funds in diversified families, underscoring the substantial value created through improved scalability.

Correcting for the error-in-variables (EIV) bias is particularly important in this setting. In the bias-unadjusted distribution of the family effect $va_{i,f}$, the left tail is excessively thick. As discussed in Section III.D.2, this pattern arises because positive values of $va_{i,f}$ are associated with greater estimation noise ($\rho > 0$), which makes it more likely that their estimates $\hat{va}_{i,f}$ appear negative. Relying on the unadjusted distribution therefore yields a severely biased inference as it suggests that only half of funds benefit from family support (versus nearly 80% in Table IV).

Our conclusion that family size enhances the fund value-added resonates with prior research on manager assignment. Luo, Manconi, and Schumacher (2023) find that larger families can allocate managers to more specialized funds that better match their areas of expertise. Similarly, Berk, van Binsbergen, and Liu (2017) document that families possess unique information that improves the matching between funds and managers. Taken together with our evidence, these findings suggest that family reallocation decisions enhance value primarily by improving the scalability of affiliated funds rather than by increasing their skill.

Please insert Table IV & Table V here

V.B.2. Decomposing the Fund Value-Added

Using our framework, we can decompose the actual fund value-added $\hat{va}_i$ into two components. The first component captures the value-added in the absence of family size effects ($q_j = 0$). It is computed as $\hat{va}_{i,0} = \hat{a}_{i,0}\bar{q}_i - \hat{b}_{i,0}\bar{q}_{i,2}$, where $\bar{q}_i$ and $\bar{q}_{i,2}$ the realized averages of the fund size and its squared value. The second component $\hat{va}_{i,j}$ is the dollar value of family size effects reported in Table IV. Estimating these two components for all funds, we summarize their bias-adjusted distribution characteristics in Figure 3.

Absent family size effects, funds would destroy value at their actual sizes. In the bottom quartile, the value destroyed exceeds \$74 million per year. Even across the entire population, the average component $\hat{va}_{i,0}$ remains negative at -\$22.6 million. Once family effects are incorporated, this result is reversed—the average becomes positive at \$1.5 million, and more than 60% of funds create value. Family support thus appears essential for enabling funds to operate at their observed scale while maintaining positive value creation. However, this conclusion does not hold across all categories. As shown in the appendix, family effects are insufficient to sustain a positive average value-added among large-cap and growth funds. This pattern suggests that some families fail to maximize value creation as some of its affiliated funds operate at excessive scale. Motivated by these findings, we next conduct a normative analysis of value added.

Please insert Figure 3 here

V.C. Normative Analysis with Family Size Effects

V.C.1. Estimation of the Model

A striking feature of the active mutual fund industry is its size—U.S. funds collectively managed close to \$30 trillion by the end of 2022 (Investment Company Institute, 2023). An important question is whether this magnitude is consistent with economic fundamentals. To address this issue, we conduct a normative analysis of the mutual fund industry using our framework which explicitly incorporates family size effects.

In contrast to the standard Berk and Green (2004) model, the optimization cannot be carried out fund by fund because the value-added depends on family size. Instead, it must be conducted at the level of the entire family. To formalize this point, we denote the value-added of family j by $va_j = \sum_{i=1}^{n_j} va_i(q_j^v)$, where the value-added of each affiliated fund depends on the vector of fund sizes $q_j^v = (q_1, \ldots, q_{n_j})'$. Maximizing va_j with respect to q_j^v yields a system of n_j first-order conditions whose ith element is given by

$$\frac{\partial va_j}{\partial q_i} = \frac{\partial va_i}{\partial q_i} + \sum_{l,l\neq i} \frac{\partial va_l}{\partial q_j} = a_{i,0} + a_{i,f} q_j - 2(b_{i,0} + b_{i,f} q_j) q_i + \sum_{l,l\neq i} (a_{l,f} q_l - b_{l,f} q_l^2). \qquad (29)$$

Equation (30) shows that a change in fund size has a direct effect on its own value-added by altering revenues and costs by $a_{i,0} + a_{i,f}q_j$ and $-2(b_{i,0} + b_{i,f}q_j)q_i$. In addition, it has an indirect effect on the value-added of every other fund l by affecting its skill and scale coefficients through the terms $a_{l,f}q_l$ and $b_{l,f}q_l^2$. Although this optimization problem does not generally admit a closed-form solution, we show in the appendix that we can solve it numerically.[8]

The optimization requires as inputs the estimated skill and scale coefficients for all n_j funds, which we obtain from Equation (9). To reduce the sensitivity of the optimization procedure to estimation noise, we follow Frazzini and Pedersen (2014) and Vasicek (1973) and shrink each estimated coefficient $\hat{\psi}_i \in \{\hat{a}_{i,0}, \hat{a}_{i,f}, \hat{b}_{i,0}, \hat{b}_{i,f}\}$ toward its family-level mean $\hat{\psi}_j = \frac{1}{n_j}\sum_{n_j}\hat{\psi}_i$:

$$\hat{\psi}_i^a = \hat{w}_i\hat{\psi}_i + (1 - \hat{w}_i)\hat{\psi}_j. \tag{30}$$

The weight is defined as $\hat{w}_i = 1 - \frac{\hat{\sigma}_i}{\hat{\sigma}_i + \hat{\sigma}_j}$, where $\hat{\sigma}_i$ denotes the variance of the fund-level estimate and $\hat{\sigma}_j$ is the cross-sectional variance of the estimates within the family. This estimator places more weight on $\hat{\psi}_i$ when its variance is low or when dispersion within the family is high. The normative analysis requires funds to have a positive optimal size. To satisfy this condition, we exclude all funds whose optimal size is negative under either model. We also limit the influence of outliers by removing the top 1% of funds based on their actual and optimal sizes and value-added. Applying these filters reduces the sample to 926 funds.

V.C.2. Optimality of Fund Size and Value-Added

Our normative analysis with family effects in Table VI uncovers pervasive excess capacity in the mutual fund industry. While the average fund size equals \$792 million in the data, the model implies a substantially smaller optimal size of only \$182 million. As a result, funds operate far beyond their value-maximizing scale. On average, the value gap between the optimal and actual

[8]We can find a closed-form solution but only in the unrealistic case of n_j funds which all share the same coefficients, namely $a_{i,0} = a_0$, $b_{i,0} = b_0$, $a_{i,f} = a_f$, and $b_{i,f} = b_f$, $i = 1, ..., n_j$ (symmetric case of homogeneous funds within a family).

value-added reaches \$12.7 million per year. This conclusion is not driven by a small subset of extreme funds—the median value gap remains economically large at \$4.2 million, confirming that excess capacity is a widespread phenomenon across funds.

Our results across investment groups are qualitatively similar but reveal differences. Overcapacity is most pronounced among large-cap and growth funds, averaging about \$700 million. As a result, their average value added is negative at –\$6.2 million per year, far below the optimal levels of \$9.7 million and \$13.9 million they could achieve. By contrast, small-cap funds and funds in competitive families operate closer to optimal scale, with excess capacity of roughly \$200 million. Although their average value gap remains economically meaningful, it is considerably smaller and falls below \$10 million per year.

Please insert Table VI here

V.C.3. Comparison with the Model of Berk and Green

Previous studies rely on the standard Berk and Green (2004) model to conduct a normative analysis of the mutual fund industry (e.g., BGS; Roussanov, Ruan, and Wei, 2021; Zhu, 2018). Because this model abstracts from family effects, the value-added can be optimized independently for each fund. This optimization yields closed-form expressions for the optimal fund size and value added: $q_i^{\mathrm{BG}} = \frac{a_i}{2b_i}$ and $va_i^{\mathrm{BG}} = \frac{a_i^2}{4b_i}$, where a_i and b_i are the coefficients of the regression of the fund alpha $\alpha_{i,t}$ on its size $q_{i,t-1}$.

While this model is analytically convenient, the coefficients a_i and b_i lack a clear structural interpretation because they are contaminated by the family-size variables q_j and $q_i q_j$ omitted from the Berk–Green specification. Using standard omitted-variable bias formulas, we obtain:

$$a_i = a_{i,0} + a_{i,f} a_{i,q_j} + b_{i,f} a_{i,q_i q_j}, \tag{31}$$

$$b_i = b_{i,0} + a_{i,f} b_{i,q_j} + b_{i,f} b_{i,q_i q_j}, \tag{32}$$

where a_{i,q_j} and b_{i,q_j} denote the intercept and slope coefficients from the projection of the omitted family-size variable $q_{j,t-1}$ on fund size $q_{i,t-1}$, and a_{i,q_iq_j} and b_{i,q_iq_j} denote the corresponding projection coefficients for the interaction term $q_{i,t-1}q_{j,t-1}$ (projected on $q_{i,t-1}$). In other words, large family size in the data can mechanically load into the fitted intercept and slope, so that the implied optimal values $q_i^{\text{BG}*}$ and $va_i^{\text{BG}*}$ reflect omitted family effects rather than true structural parameters.[9] To examine this issue, we infer $\hat{a}_i$ and $\hat{b}_i$ from the coefficients $\hat{a}_{i,0}$, $\hat{a}_{i,f}$, $\hat{b}_{i,0}$, and $\hat{b}_{i,f}$ using Equations (31)–(32), and compute the implied optimal size and value-added as $\hat{q}_i^{\text{BG}*} = \frac{\hat{a}_i}{2\hat{b}_i}$ and $\hat{va}_i^{\text{BG}*} = \frac{\hat{a}_i^2}{4\hat{b}_i}$.[10] The results of this analysis are reported in Table VI.

Using the Berk–Green model further amplifies the measured excess capacity in the mutual fund industry. The optimal fund size falls from \$180 million to \$129 million, increasing the gap between actual and optimal size from \$610 million to \$706 million. This amplification arises because family size effects spuriously drive the estimated skill coefficient $\hat{a}_i$ below zero for around 20% of funds. Although these funds have positive standalone skill ($\hat{a}_{i,0} > 0$), the Berk–Green model assigns them an optimal size of zero, mechanically lowering the cross-sectional average optimal size. The same mechanism applies to the value-added, as the model also assigns these funds an optimal value-added $\hat{va}_i^{\text{BG}}$ equal to zero. As a result, the cross-sectional average optimal value added shrinks toward zero and becomes artificially close to the actual value added—the average value gap declines from \$12.7 million to \$7.9 million, thereby masking the true economic impact of excess capacity on value creation.[11]

[9] Whereas the Berk–Green and family-based models yield different implications for optimal size and value added, their implications for the actual value added are identical. To elaborate, suppose that the family model is correctly specified such that $\alpha_{i,t}$ is given by Equation (7). We can always write $\alpha_{i,t} = \alpha_{i,t}^{\text{BG}} + e_{\alpha,t}$, where $\alpha_{i,t}^{\text{BG}} = a_i - b_i q_{i,t-1}$ is the linear projection of $\alpha_{i,t}$ on fund size and $e_{\alpha,t}$ is orthogonal to $q_{i,t-1}$ by construction. Consequently, the actual value-added under both models is the same, i.e., $E[\alpha_{i,t}q_{i,t-1}] = E[\alpha_{i,t}^{\text{BG}} q_{i,t-1}]$.

[10] For 86 funds in the sample, the optimal Berk–Green size is undefined because the estimated skill coefficient $\hat{a}_i$ is positive while the scale coefficient $\hat{b}_i$ is negative, implying no finite interior optimum. In our baseline analysis, we set the optimal size of these funds to zero. The appendix shows that excluding these funds does not affect our conclusions.

[11] Our results are not directly comparable to those in BGS, who use a multiple-testing procedure to retain only funds with positive and significant optimal size. When we restrict our analysis to funds with a positive estimated optimal size $\hat{q}_i^{\text{BG}*}$, the average optimal value-added $\hat{va}_i^{\text{BG}*}$ equals \$11.2 million, which is comparable to the \$18.6 million reported by BGS under their least conservative selection procedure.

V.D. Implications of Excess Fund Capacity

V.D.1. The Net Value-Added to Investors

Our normative analysis shows that funds operate at scales exceeding the level that maximizes value added. This finding raises the question of how such excess capacity affects investors. To illustrate the underlying mechanism, consider a simple setting in which the family consists of a single fund whose value-maximizing size is q_i^*. Suppose investors instead allocate capital $q_i > q_i^*$. This excess size harms investors along two margins. First, total value creation declines because are scalability constraints tighter at q_i. Second, investors pay fees on the additional capital $q_i - q_i^*$ allocated to the fund.

To quantify these effects, we measure the net-of-fee value-added defined as $va_i^{net} = E[\alpha_{i,t-1}^{net} q_{i,t-1}]$, where $\alpha_{i,t-1}^{net} = \alpha_{i,t-1} - \mathit{fee}_{i,t-1}$ denotes the net-of-fee alpha, and $\mathit{fee}_{i,t-1}$ is the fee rate. Substituting the specification of the gross alpha from Equation (7), we obtain

$$va_i^{net} = a_{i,0} E[q_{i,t-1}] - b_{i,0} E[q_{i,t-1}^2] + a_{i,f} E[q_{j,t-1} q_{i,t-1}] - b_{i,f} E[q_{i,t-1}^2 q_{j,t-1}] - rev_i, \tag{33}$$

where $rev_i = E[\mathit{fee}_{i,t-1} q_{i,t-1}]$ is the fund fee revenue. Equation (33) admits a straightforward interpretation—a positive va_i^{net} implies that investors extract some of the value created by the fund, while a negative va_i^{net} implies that investors pay fees in excess of the value generated. We compute the net value-added as $\hat{va}_i^{net} = \hat{a}_{i,0}\bar{q}_i - \hat{b}_{i,0}\bar{q}_{i,2} + \hat{a}_{i,f}\bar{q}_{i,j} - \hat{b}_{i,f}\bar{q}_{i,j,2} - r\hat{e}v_i$, where $r\hat{e}v_i = \frac{1}{T_i}\sum_{t=1}^{T_i} \mathit{fee}_{i,t}\, q_{i,t}$. Using these estimates across all funds, we show in Table VII the characteristics of the net value-added distribution.

The negative consequences of excess fund capacity for investors are substantial. For 99.1% of funds, net value added is negative, averaging –\$7.7 million per year. This pattern holds across all fund groups—in all but one group (small-cap), more than 90% of funds generate negative net value added. Excessive fees are particularly pronounced among large-cap and growth funds, which exhibit average net value added of –\$11.6 million and –\$10.1 million per year.

Rational mutual fund models—whether or not they incorporate family size effects—predict that investors withdraw capital from funds charging excessive fees, allowing value creation to recover until investors break even. However, this prediction is not supported by the results in Table VII. Several explanations are proposed in the literature for why investors pay excessive fees. For example, mutual fund investors may lack the financial literacy needed to evaluate performance (Gruber, 1996). They may also face high search costs that limit their ability to reallocate capital toward better-performing funds (Roussanov, Ruan, and Wei, 2021). Finally, investors may be willing to pay additional fees for financial advice covering their broader portfolio (Del Guercio and Reuter, 2014). Whatever the underlying mechanisms, our results indicate that these frictions must be economically significant to sustain the negative net value added observed in the data.

The standard approach for assessing whether funds deliver value to investors relies on the average net alpha $E[\alpha_{i,t}^{\text{net}}]$.[12] However, this measure understates the magnitude of the excessive fees paid by investors for two reasons. First, the average net alpha is not a dollar measure because it ignores the scale $E[q_{i,t}]$ at which the fund operates—a limitation analogous to that highlighted by Berk and van Binsbergen (2015) in the context of gross alpha. Second, even after controlling for average scale, the resulting measure $E[\alpha_{i,t}^{\text{net}}]E[q_{i,t}]$ ignores the time-varying nature of investor capital allocation. This discrepancy arises because poor performance tends to occur when funds manage large amounts of capital and face tighter scale constraints, giving these periods greater weight in the value-added calculation.[13] Using $E[\alpha_{i,t}^{\text{net}}]E[q_{i,t}]$, the average equals -\$0.1 million per year, and 40% of funds appear to create value for investors—figures substantially higher than those reported in Table VII.

Please insert Table VII here

[12] A non-exhaustive list includes Baks, Metrick, and Wachter (2001); Barras, Scaillet, and Wermers (2010); Carhart (1997); Elton et al. (1993); Jensen (1968); Kosowski et al. (2006); Pástor and Stambaugh (2002).

[13] This result is an application of Jensen's inequality. With scalability constraints, the net value-added function $va^{\text{net}}(q_{i,t}) = (a_i(q_j) - fee_{i,t} - b_i(q_j)q_{i,t})q_{i,t}$ is concave in $q_{i,t}$, which implies that $va_i^{\text{net}} = E[va^{\text{net}}(q_{i,t})] < va^{\text{net}}(E[q_{i,t}]) = \alpha_i^{\text{net}}E[q_{i,t}]$. We further have $E[va^{\text{net}}(q_{i,t})] - va^{\text{net}}(E[q_{i,t}]) = -b_i^{\text{net}}V[q_{i,t}]$. Hence, greater variation in size over time increases the gap between these two measures.

V.D.2. Family Fee Revenues

We next turn to the analysis of fund families. In a setting where investors overallocate capital, a wedge should emerge between the total value created by a family and its fee revenues. While families benefit from higher fee revenues as additional capital flows into their funds, capacity constraints reduce the value generated by this capital, causing the total value-added to fall below its optimal level. To examine this issue, we define the family value-added and fee revenues as $va_j = \sum_{i=1}^{n_j} va_i$ and $rev_j = \sum_{i=1}^{n_j} rev_i$, where $va_i = E[\alpha_{i,t-1} q_{i,t-1}]$ and $rev_i = E[fee_{i,t-1} q_{i,t}]$. We then compute both measures for each family as $\hat{va}_j = \sum_{i=1}^{n_j} \hat{va}_i$ and $rev_j = \sum_{i=1}^{n_j} r\hat{e}v_i$. Using these estimates across all families, we show in Table VII the characteristics of the value-added and revenue distribution.

Consistent with this intuition, we find that family fee revenues are large relative to the value created. The average and median value added equal \$24.4 and \$0.9 million per year, respectively, whereas the corresponding values for fee revenues are substantially higher at \$76.2 and \$12.4 million. While all families generate positive fee revenues, only 72.3% extract a positive value-added from capital markets.

An important question is whether the fee revenues earned by families differ from the maximum value-added they could generate at the optimal size. To address this issue, Figure 4 focuses on the subset of families whose funds are included in the normative analysis in Section V.C. Among these families, average fee revenue amounts to \$60.5 million per year—a value remarkably close to the average optimal value added of \$69.9 million. For cooperative families, total fee revenues are even higher than the maximum value added attainable at the optimal size. These results suggest that families earn revenues comparable to those predicted by rational asset management models, but through a fundamentally different mechanism. Rather than operating at value-maximizing capital levels, families appear to pursue asset-growth strategies. As a result, excess capacity imposes substantial losses on investors while leaving family revenues largely intact.

Please insert Table VIII & Figure 4 here

VI. Conclusion

Fund families play several key organizational roles—they manage shared assets such as brand reputation and institutional knowledge, design managerial incentives, and allocate scarce resources across funds. Through these channels, family size may directly influence the returns of affiliated funds. Motivated by these considerations, we examine how family size affects funds along two core dimensions: (i) their skill in identifying profitable investment opportunities and (ii) their exposure to scalability constraints.

A notable feature of our approach is that we measure family size effects at the individual fund level. Formally, we specify the gross alpha of each fund as $\alpha_i = a_i - b_i q_{i,t-1}$, where the skill and scale coefficients a_i and b_i depend on family size through fund-specific coefficients $a_{i,f}$ and $b_{i,f}$. This formulation allows funds within the same family to respond differently to the multidimensional influence of family organization, including the management of shared assets, managerial talent, and internal resources. In doing so, we depart from the few existing panel studies of family size, which focus exclusively on fund skill—while abstracting from scalability—and impose homogeneous family effects across funds.

This paper shows that fund families play a central and previously underappreciated role in shaping value creation in the mutual fund industry. While larger families impose hierarchy costs that reduce the profitability of investment ideas, they also provide organizational support that relaxes scalability constraints, allowing funds to deploy capital more efficiently. On net, these family effects enhance value creation for most funds and are essential for sustaining positive value-added at the large scales observed in practice. However, our normative analysis reveals pervasive excess capacity—funds operate far beyond their value-maximizing sizes, leaving substantial value unrealized. This overexpansion has sharply asymmetric consequences. Investors bear large losses, as nearly all funds generate negative net value-added after fees, whereas families maintain fee revenues close to their optimal levels by pursuing asset-growth strategies rather than value-maximizing capital allocation.

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TABLE I. Summary Statistics

This table reports summary statistics for an equal-weighted portfolio of all funds available at the start of each month. Results are shown for the full sample and for subgroups defined by investment style (small-/large-cap and value/growth) and family characteristics (bottom and top terciles of families sorted by style diversification/concentration and competition/cooperation). Panel A reports the mean and standard deviation of gross and net portfolio returns (annualized, % p.a.), together with the cross-sectional mean and median of fund size and family size (in $M), computed each month and then averaged over time. Panel B reports the portfolio gross alpha and factor loadings from regressing monthly gross portfolio returns on the market, size, value, and momentum factors, together with the regression R^2.

Panel A: Portfolio Return

Group	Gross (% p.a.)		Net (% p.a.)		Fund Size ($ Million)		Family Size ($ Million)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Median	Mean	Median
All Funds	7.54	17.55	6.39	17.55	1,644.38	325.80	29,385.30	6,648.02
Small-cap Funds	9.25	20.31	7.99	20.31	494.67	191.47	15,591.36	4,247.16
Large-cap Funds	6.05	16.51	4.95	16.51	2,589.51	465.61	37,379.14	7,812.95
Value Funds	7.47	16.22	6.35	16.22	1,675.36	344.46	31,106.49	7,168.26
Growth Funds	7.58	18.99	6.37	18.99	2,045.41	416.47	27,465.69	7,148.24
Funds in Style Concentrated Families	8.14	17.74	6.94	17.74	1,671.30	176.34	9,509.37	1,201.51
Funds in Style Diversified Families	6.94	17.43	5.81	17.43	1,256.16	466.62	20,555.27	14,237.59
Funds in Competitive Families	8.30	17.52	7.08	17.52	1,200.48	348.65	12,262.09	3,690.87
Funds in Cooperative Families	7.29	17.45	6.16	17.45	2,016.44	408.00	20,282.31	8,286.04

Panel B: Portfolio Beta

Group	Gross Alpha (% p.a.)	Market	Size	Value	Momentum	R^2
All Funds	0.82	0.98	0.35	-0.05	0.01	0.91
Small-cap Funds	1.42	1.00	0.82	-0.02	0.01	0.91
Large-cap Funds	0.25	0.99	0.11	-0.06	0.01	0.93
Value Funds	1.25	0.95	0.24	0.31	-0.03	0.92
Growth Funds	0.53	1.00	0.42	-0.43	0.05	0.90
Funds in Style Concentrated Families	1.20	0.97	0.38	-0.05	-0.00	0.90
Funds in Style Diversified Families	0.44	0.98	0.36	-0.06	0.01	0.92
Funds in Competitive Families	1.40	0.97	0.38	-0.04	-0.00	0.90
Funds in Cooperative Families	0.21	0.99	0.35	-0.11	0.01	0.93

TABLE II. Family Size Effects on Skill and Scalability

This table reports summary statistics for the cross-sectional distribution of fund-level family size effects on skill and scalability (annualized, % p.a.). The effect on skill corresponds to the family component of the fund's first-dollar alpha, $\hat{a}^s_{i,f}$. The effect on scalability corresponds to the family component of the fund's scale coefficient, $\hat{b}^s_{i,f}$, standardized so that it measures the change in fund alpha associated with a one-standard-deviation increase in fund size. The table reports the mean, the bias-adjusted median, the bias-adjusted proportions (%) of funds with negative and positive effects, and the bias-adjusted 25th and 75th percentiles. Figures in parentheses denote the estimated standard deviation of each estimator.

	Moments (% p.a.)		**Proportions (%)**		**Quantiles (% p.a.)**	
	Mean	**Median**	**Negative**	**Positive**	**Q25**	**Q75**
Effect on Skill	-1.60 (0.5)	-1.34 (0.0)	56.88 (1.3)	43.12 (1.3)	-7.79 (0.2)	4.20 (0.0)
Effect on Scalability	-1.44 (0.2)	-1.30 (0.0)	63.33 (1.3)	36.67 (1.3)	-4.72 (0.0)	1.37 (0.1)

TABLE III. Family Size Effects across Fund Groups

This table reports summary statistics for the cross-sectional distribution of fund-level family size effects across fund groups (annualized, % p.a.). Panel A reports the effect on skill, defined as the family component of the fund's first-dollar alpha, $\hat{a}^s_{i,f}$. Panel B reports the effect on scalability, defined as the family component of the fund's scale coefficient, $\hat{b}^s_{i,f}$, standardized so that it measures the change in fund alpha associated with a one-standard-deviation increase in fund size. Results are shown for subgroups defined by investment style (small-/large-cap and value/growth) and family characteristics (style concentrated/diversified families and competitive/cooperative families). The table reports the mean, the bias-adjusted median, the bias-adjusted proportions (%) of negative and positive effects, and the bias-adjusted 25th and 75th percentiles. Figures in parentheses denote the estimated standard deviation of each estimator.

	Moments (% p.a.)		Proportions (%)		Quantiles (% p.a.)	
	Mean	**Median**	**Negative**	**Positive**	**Q25**	**Q75**
Panel A: Effect on Skill						
Small-cap Funds	-1.02 (1.2)	-0.84 (0.5)	54.07 (2.7)	45.93 (2.7)	-6.95 (0.1)	5.69 (0.4)
Large-cap Funds	-1.84 (0.7)	-1.47 (0.4)	58.58 (2.0)	41.42 (2.0)	-7.35 (0.6)	3.33 (0.0)
Value Funds	-0.03 (0.9)	-0.26 (0.2)	51.58 (2.5)	48.42 (2.5)	-5.83 (0.6)	5.19 (0.5)
Growth Funds	-2.22 (1.0)	-1.43 (0.3)	56.38 (2.3)	43.62 (2.3)	-9.56 (0.0)	4.54 (0.6)
Funds in Style Concentrated Families	-1.14 (0.8)	-0.97 (0.1)	56.81 (2.3)	43.19 (2.3)	-6.10 (0.5)	3.96 (0.2)
Funds in Style Diversified Families	-1.27 (1.0)	-1.11 (0.3)	55.55 (2.3)	44.45 (2.3)	-7.74 (0.7)	5.01 (1.4)
Funds in Competitive Families	-0.48 (0.9)	-0.18 (0.2)	51.43 (2.4)	48.57 (2.4)	-6.01 (0.0)	5.63 (0.3)
Funds in Cooperative Families	-2.89 (0.9)	-2.75 (0.6)	62.85 (2.3)	37.15 (2.3)	-10.20 (0.2)	2.60 (0.2)
Panel B: Effect on Scalability						
Small-cap Funds	-1.12 (0.6)	-0.97 (0.0)	58.74 (2.7)	41.26 (2.7)	-4.25 (0.6)	1.84 (0.1)
Large-cap Funds	-1.35 (0.3)	-1.21 (0.1)	64.62 (2.0)	35.38 (2.0)	-4.03 (0.3)	1.12 (0.1)
Value Funds	-1.34 (0.4)	-1.54 (0.1)	64.91 (2.4)	35.09 (2.4)	-4.03 (0.3)	1.26 (0.0)
Growth Funds	-1.55 (0.5)	-1.13 (0.0)	62.63 (2.2)	37.37 (2.2)	-5.77 (0.1)	1.82 (0.1)
Funds in Style Concentrated Families	-0.64 (0.4)	-0.63 (0.2)	58.67 (2.3)	41.33 (2.3)	-3.19 (0.1)	1.73 (0.0)
Funds in Style Diversified Families	-1.65 (0.4)	-1.58 (0.1)	65.19 (2.2)	34.81 (2.2)	-4.81 (0.2)	1.39 (0.3)
Funds in Competitive Families	-0.89 (0.5)	-0.82 (0.1)	58.11 (2.4)	41.89 (2.4)	-4.07 (0.5)	2.00 (0.1)
Funds in Cooperative Families	-2.36 (0.4)	-2.38 (0.1)	74.12 (2.1)	25.88 (2.1)	-5.92 (0.1)	0.10 (0.1)

TABLE IV. Dollar Value of Family Size Effects: Whole Population

This table reports summary statistics for the cross-sectional distribution of the annual dollar value of family size effects on fund value-added in the whole population (in $ Million p.a.). The "value effect on skill" captures the contribution of family size through its impact on skill (first-dollar alpha). The "value effect on scalability" captures the contribution of family size through its impact on scale constraints. The "net value effect" is the sum of the skill and scalability components. The table reports the mean, the bias-adjusted median, the bias-adjusted proportions (%) of negative and positive values, and the bias-adjusted 25th and 75th percentiles. Figures in parentheses denote the estimated standard deviation of each estimator. Dollar quantities are expressed in real terms as of January 1, 2000.

	Moments ($ Million p.a.)		**Proportions (%)**		**Quantiles ($ Million p.a.)**	
	Mean	**Median**	**Negative**	**Positive**	**Q25**	**Q75**
Value Effect on Skill	-19.09 (4.8)	-14.12 (0.6)	72.99 (1.2)	27.01 (1.2)	-66.28 (3.4)	0.76 (0.0)
Value Effect on Scalability	43.28 (5.7)	49.36 (2.0)	16.98 (1.0)	83.02 (1.0)	5.03 (0.5)	158.21 (5.3)
Net Value Effect	24.18 (3.7)	21.23 (1.0)	21.04 (1.1)	78.96 (1.1)	1.23 (0.1)	83.46 (3.9)

TABLE V. Dollar Value of Family Effects across Fund Groups
This table reports summary statistics for the cross-sectional distribution of the annual dollar value of family effects across fund groups (in $ Million p.a.). Panel A reports the dollar value of the family effect operating through skill (first-dollar alpha). Panel B reports the dollar value of the family effect operating through scalability (scale constraints). Panel C reports the dollar value of the net family effect (skill plus scalability). Results are shown for subgroups defined by investment style (small-/large-cap and value/growth) and family characteristics (style concentrated/diversified families and competitive/cooperative families). The table reports the mean, the bias-adjusted median, the bias-adjusted proportions (%) of negative and positive values, and the bias-adjusted 25th and 75th percentiles. Figures in parentheses denote the estimated standard deviation of each estimator. Dollar quantities are expressed in real terms as of January 1, 2000.

	Moments ($ Million p.a.)		Proportions (%)		Quantiles ($ Million p.a.)	
	Mean	**Median**	**Negative**	**Positive**	**Q25**	**Q75**
Panel A: Dollar Value of Value Effect on Skill						
Small-cap Funds	0.48 (6.6)	-0.00 (0.5)	49.73 (2.7)	50.27 (2.7)	-12.53 (0.8)	14.79 (1.3)
Large-cap Funds	-29.83 (7.9)	-34.83 (5.9)	83.59 (1.5)	16.41 (1.5)	-116.66 (7.1)	-4.41 (0.5)
Value Funds	-9.22 (8.8)	-11.33 (4.3)	69.35 (2.3)	30.65 (2.3)	-44.70 (0.2)	3.96 (0.0)
Growth Funds	-21.46 (8.4)	-24.25 (4.5)	74.35 (1.9)	25.65 (1.9)	-82.55 (4.7)	0.30 (0.3)
Funds in Style Concentrated Families	-20.25 (6.9)	-7.25 (3.0)	68.62 (2.1)	31.38 (2.1)	-51.60 (10.5)	1.78 (0.8)
Funds in Style Diversified Families	-15.86 (9.1)	-10.41 (1.3)	63.16 (2.2)	36.84 (2.2)	-50.58 (6.1)	10.57 (0.3)
Funds in Competitive Families	-14.23 (8.0)	-8.94 (1.6)	68.08 (2.2)	31.92 (2.2)	-48.10 (2.8)	3.06 (0.6)
Funds in Cooperative Families	-19.52 (7.0)	-16.76 (1.5)	73.39 (2.1)	26.61 (2.1)	-63.11 (3.7)	0.86 (0.2)
Panel B: Dollar Value of Value Effect on Scalability						
Small-cap Funds	17.97 (8.1)	9.55 (0.8)	33.30 (2.5)	66.70 (2.5)	-3.77 (1.2)	53.09 (6.7)
Large-cap Funds	51.20 (9.2)	106.24 (5.1)	9.04 (1.2)	90.96 (1.2)	13.60 (0.2)	211.39 (6.7)
Value Funds	34.66 (10.1)	43.88 (0.9)	15.36 (1.8)	84.64 (1.8)	6.96 (0.2)	133.56 (1.2)
Growth Funds	52.76 (10.4)	90.28 (16.7)	12.64 (1.5)	87.36 (1.5)	10.37 (0.8)	207.15 (7.8)
Funds in Style Concentrated Families	30.05 (7.7)	16.60 (2.6)	22.43 (1.9)	77.57 (1.9)	0.73 (0.1)	101.80 (3.0)
Funds in Style Diversified Families	48.99 (10.7)	41.92 (1.6)	22.90 (1.9)	77.10 (1.9)	1.75 (1.0)	142.92 (1.4)
Funds in Competitive Families	39.81 (10.1)	27.97 (2.5)	23.20 (2.0)	76.80 (2.0)	0.93 (0.5)	125.75 (12.0)
Funds in Cooperative Families	39.95 (8.8)	42.60 (2.3)	15.88 (1.7)	84.12 (1.7)	6.91 (0.8)	114.26 (3.4)
Panel C: Dollar Value of Net Value Effect						
Small-cap Funds	18.45 (6.2)	4.32 (0.2)	35.39 (2.6)	64.61 (2.6)	-4.02 (0.3)	34.87 (3.3)
Large-cap Funds	21.37 (5.5)	37.00 (0.1)	9.75 (1.2)	90.25 (1.2)	5.97 (0.3)	84.46 (2.1)
Value Funds	25.44 (5.3)	41.91 (0.1)	6.19 (1.2)	93.81 (1.2)	7.85 (1.0)	91.20 (2.7)
Growth Funds	31.29 (8.3)	21.54 (2.4)	26.94 (2.0)	73.06 (2.0)	-0.67 (0.4)	108.10 (8.7)
Funds in Style Concentrated Families	9.80 (4.8)	5.89 (0.5)	30.12 (2.1)	69.88 (2.1)	-1.24 (0.2)	29.93 (0.4)
Funds in Style Diversified Families	33.13 (7.6)	14.97 (0.2)	30.23 (2.1)	69.77 (2.1)	-2.33 (0.3)	75.27 (1.9)
Funds in Competitive Families	25.58 (7.3)	15.02 (0.8)	22.41 (2.0)	77.59 (2.0)	0.65 (1.1)	77.22 (6.0)
Funds in Cooperative Families	20.43 (5.5)	13.48 (1.5)	28.55 (2.2)	71.45 (2.2)	-0.91 (0.4)	55.51 (3.7)

TABLE VI. Actual versus Optimal Fund Size and Value-Added

This table compares actual versus optimal fund size and value-added. "Actual" size and value-added are computed using realized fund size over the sample period. "Optimal" size and value-added are computed by maximizing implied value-added under the corresponding model. "Diff." is defined as Actual minus Optimal. Results are reported as cross-sectional means and medians, for size (in $ Million) and value-added (in $ Million p.a.). Panel A reports results under the family model with family size effects. Panel B reports results under the Berk–Green (BG) model without family size effects. The sample excludes funds for which the implied BG coefficients do not yield a finite interior optimum (i.e., funds with $a_{\text{impl}} > 0$ and $b_{\text{impl}} < 0$). We then apply a joint top 1% trimming rule and drop the union of funds that fall in the top 1% of (i) actual size or actual value-added, (ii) BG-optimal size or BG-optimal value-added, or (iii) family-model optimal size or family-model optimal value-added. Dollar quantities are expressed in real terms as of January 1, 2000.

Panel A: Model with Family Size Effects

	Mean						Median					
	Size ($ Million)			Value-Added ($ Million p.a.)			Size ($ Million)			Value-Added ($ Million p.a.)		
	Actual	Optimal	Diff.	Actual	Optimal	Diff.	Actual	Optimal	Diff.	Actual	Optimal	Diff.
All Funds	792.01	181.79	610.21	-1.12	11.64	-12.76	299.74	104.18	161.56	-0.26	3.51	-4.17
Small-cap Funds	406.33	172.95	233.37	2.91	11.43	-8.52	211.62	103.76	74.56	0.32	3.51	-3.09
Large-cap Funds	919.03	169.03	749.99	-6.20	9.73	-15.93	338.03	89.95	226.33	-0.62	3.47	-4.42
Value Funds	792.25	180.39	611.86	4.34	10.44	-6.09	300.10	99.14	168.38	0.55	3.53	-3.34
Growth Funds	898.21	205.49	692.71	-6.17	13.94	-20.11	336.26	104.69	185.71	-1.04	3.53	-5.96
Funds in Style Concentrated Families	591.28	192.83	398.45	-1.52	21.25	-22.77	223.77	95.05	81.83	-0.27	2.89	-5.02
Funds in Style Diversified Families	808.65	228.53	580.12	-0.62	9.99	-10.61	402.62	153.45	187.53	-0.45	4.30	-5.00
Funds in Competitive Families	390.18	193.91	196.27	1.64	13.23	-11.59	213.03	79.24	74.83	0.10	2.02	-2.13
Funds in Cooperative Families	675.74	111.70	564.03	-2.44	5.72	-8.17	323.68	97.16	208.13	-0.68	2.39	-3.88

Panel B: Berk-Green Model

	Mean						Median					
	Size ($ Million)			Value-Added ($ Million p.a.)			Size ($ Million)			Value-Added ($ Million p.a.)		
	Actual	Optimal	Diff.	Actual	Optimal	Diff.	Actual	Optimal	Diff.	Actual	Optimal	Diff.
All Funds	834.99	129.32	705.68	-1.27	6.64	-7.91	317.39	63.79	205.13	-0.35	1.41	-2.82
Small-cap Funds	423.04	118.51	304.53	3.36	4.18	-0.81	211.68	58.16	108.04	0.30	1.28	-1.39
Large-cap Funds	977.43	124.91	852.53	-6.88	6.52	-13.39	380.17	60.95	273.72	-0.74	1.33	-3.34
Value Funds	830.38	138.11	692.27	4.60	8.48	-3.88	315.29	73.19	188.66	0.53	1.83	-2.03
Growth Funds	953.80	143.20	810.60	-6.52	7.69	-14.22	360.81	67.08	242.74	-1.06	1.42	-3.73
Funds in Style Concentrated Families	624.79	136.50	488.29	-1.81	4.98	-6.79	248.10	62.09	104.29	-0.46	1.15	-2.47
Funds in Style Diversified Families	864.68	151.45	713.23	-0.70	6.06	-6.77	438.31	98.64	281.91	-0.50	1.61	-3.13
Funds in Competitive Families	401.48	155.88	245.60	1.82	6.63	-4.81	225.44	83.66	78.16	0.08	1.79	-2.15
Funds in Cooperative Families	703.58	107.86	595.72	-2.61	5.95	-8.56	332.81	53.64	239.92	-0.73	0.57	-2.63

TABLE VII. Net Value-Added
This table reports summary statistics for the cross-sectional distribution of net value-added to investors (in $ Million p.a.). Net value-added is defined as fund value-added minus fee revenue, so a negative value indicates that investors pay fees in excess of the value generated. Results are shown for the full sample and for subgroups defined by investment style (small-/large-cap and value/growth) and family characteristics (style concentrated/diversified families and competitive/cooperative families). The table reports the mean, the bias-adjusted median, the bias-adjusted proportions (%) of negative and positive net value-added, and the bias-adjusted 25th and 75th percentiles. Figures in parentheses denote the estimated standard deviation of each estimator. Dollar quantities are expressed in real terms as of January 1, 2000.

	Moments ($ Million p.a.)		Proportions (%)		Quantiles ($ Million p.a.)	
	Mean	Median	Negative	Positive	Q25	Q75
All Funds	-7.73 (0.5)	-8.31 (0.4)	99.07 (0.3)	0.93 (0.3)	-19.35 (0.3)	-2.27 (0.0)
Small-cap Funds	-2.65 (0.7)	-2.00 (0.2)	79.54 (2.2)	20.46 (2.2)	-5.44 (0.4)	-0.20 (0.1)
Large-cap Funds	-11.64 (0.8)	-13.36 (0.4)	97.88 (0.6)	2.12 (0.6)	-35.80 (0.6)	-2.34 (0.1)
Value Funds	-6.42 (0.9)	-6.21 (0.4)	90.02 (1.5)	9.98 (1.5)	-16.47 (0.3)	-1.28 (0.1)
Growth Funds	-10.06 (0.9)	-12.83 (0.6)	100.00 (0.0)	0.00 (0.0)	-25.45 (0.9)	-3.36 (0.6)
Funds in Style Concentrated Families	-5.53 (0.8)	-6.11 (0.3)	100.00 (0.0)	0.00 (0.0)	-14.02 (0.3)	-1.64 (0.0)
Funds in Style Diversified Families	-9.48 (0.9)	-9.43 (0.1)	97.97 (0.6)	2.03 (0.6)	-19.10 (0.4)	-2.89 (0.1)
Funds in Competitive Families	-4.25 (0.9)	-3.69 (0.3)	92.65 (1.2)	7.35 (1.2)	-9.46 (0.1)	-1.20 (0.1)
Funds in Cooperative Families	-8.48 (0.8)	-7.27 (0.0)	97.53 (0.7)	2.47 (0.7)	-17.41 (0.8)	-2.80 (0.0)

TABLE VIII. Family-Level Value-Added and Fee Revenue

This table reports summary statistics for the cross-sectional distribution of family-level value-added and fee revenue (in $ Million p.a.). Family value-added is computed by aggregating fund value-added across all funds within a family. Family fee revenue is computed by aggregating fund fee revenues across the family. Panel A reports the distribution of family value-added. Panel B reports the distribution of family fee revenue. Results are shown for all families and for subgroups defined by family characteristics (style concentrated/diversified families and competitive/cooperative families). The table reports the mean, median, proportions (%) of negative and positive outcomes, and the 25th and 75th percentiles. Figures in parentheses denote the estimated standard deviation of each estimator. Dollar quantities are expressed in real terms as of January 1, 2000.

Panel A: Family Value-Added

	Moments ($ Million p.a.)		**Proportions (%)**		**Quantiles ($ Million p.a.)**	
	Mean	**Median**	**Negative**	**Positive**	**Q25**	**Q75**
All Families	24.42 (12.0)	2.07 (0.2)	35.15 (3.0)	64.85 (3.0)	-2.26 (0.2)	17.83 (0.6)
Style Concentrated Families	24.74 (17.7)	0.89 (0.0)	36.41 (4.0)	63.59 (4.0)	-2.00 (0.1)	6.72 (0.8)
Style Diversified Families	10.05 (16.1)	0.57 (1.7)	47.79 (7.6)	52.21 (7.6)	-10.94 (3.6)	25.02 (10.3)
Competitive Families	20.22 (5.4)	4.11 (0.9)	25.99 (4.0)	74.01 (4.0)	-0.09 (0.2)	92.69 (8.5)
Cooperative Families	57.64 (78.4)	-4.07 (5.4)	53.97 (7.3)	46.03 (7.3)	-25.68 (13.7)	7.68 (2.9)

Panel B: Family Fee Revenue

	Moments ($ Million p.a.)		**Proportions (%)**		**Quantiles ($ Million p.a.)**	
	Mean	**Median**	**Negative**	**Positive**	**Q25**	**Q75**
All Families	76.17 (15.4)	12.37 (0.7)	0.00 (0.0)	100.00 (0.0)	3.73 (0.0)	52.68 (5.2)
Style Concentrated Families	41.31 (15.5)	6.28 (0.2)	0.00 (0.0)	100.00 (0.0)	2.01 (0.0)	23.60 (2.3)
Style Diversified Families	131.12 (24.7)	57.08 (2.9)	0.00 (0.0)	100.00 (0.0)	18.95 (0.0)	180.47 (82.9)
Competitive Families	34.16 (7.2)	7.95 (1.8)	0.00 (0.0)	100.00 (0.0)	3.03 (0.2)	23.68 (1.6)
Cooperative Families	139.68 (45.8)	51.23 (11.9)	0.00 (0.0)	100.00 (0.0)	11.61 (0.5)	120.63 (24.7)

Figure 1. Bias-adjustment functions for the coefficient $a_{i,f}$ under the Gaussian reference model. Panels (A,C) report the implied adjustment to tail probabilities as a function of the centered cutoff value a. Panels (B,D) report the corresponding adjustment to quantiles.

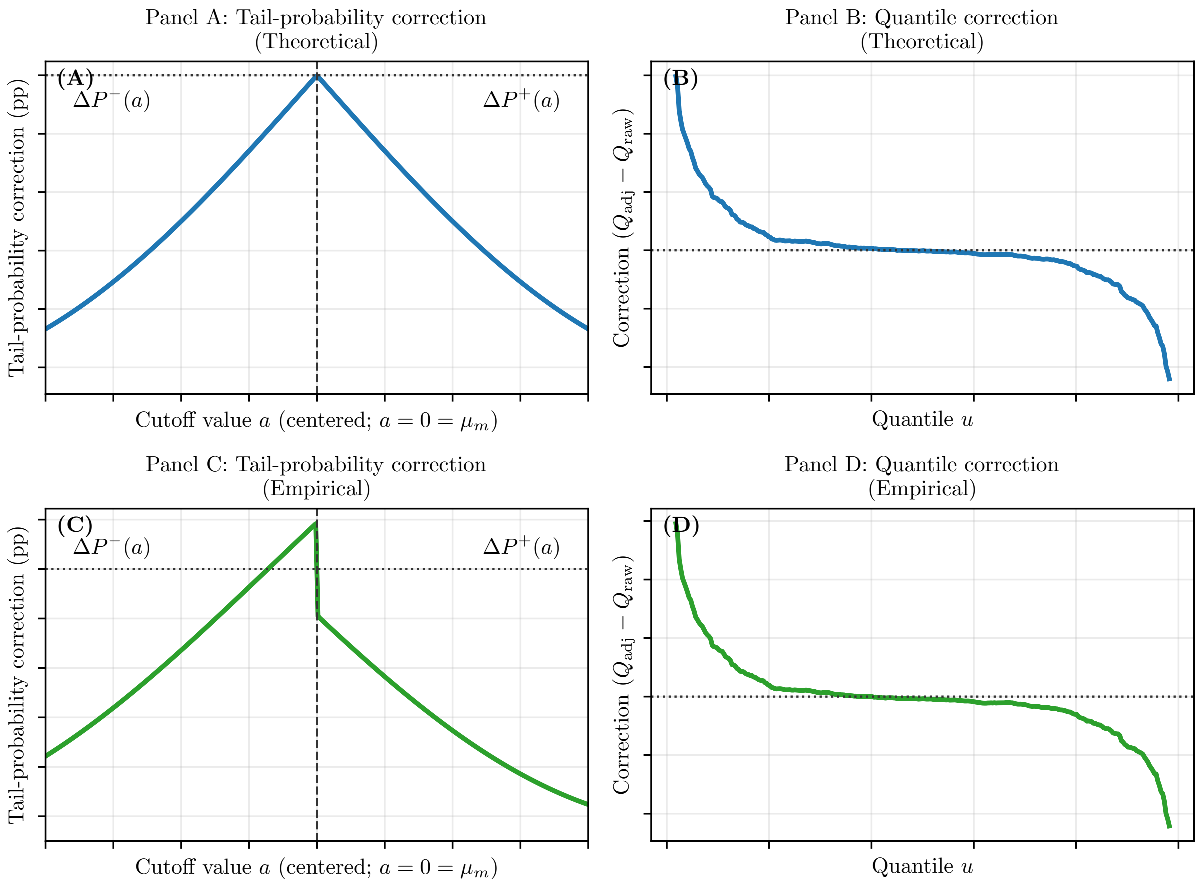

Figure 2. Skill and scalability with and without family effects. The figure reports the bias-adjusted 25th percentile, mean, and 75th percentile for skill (Panel A) and scalability (Panel B).

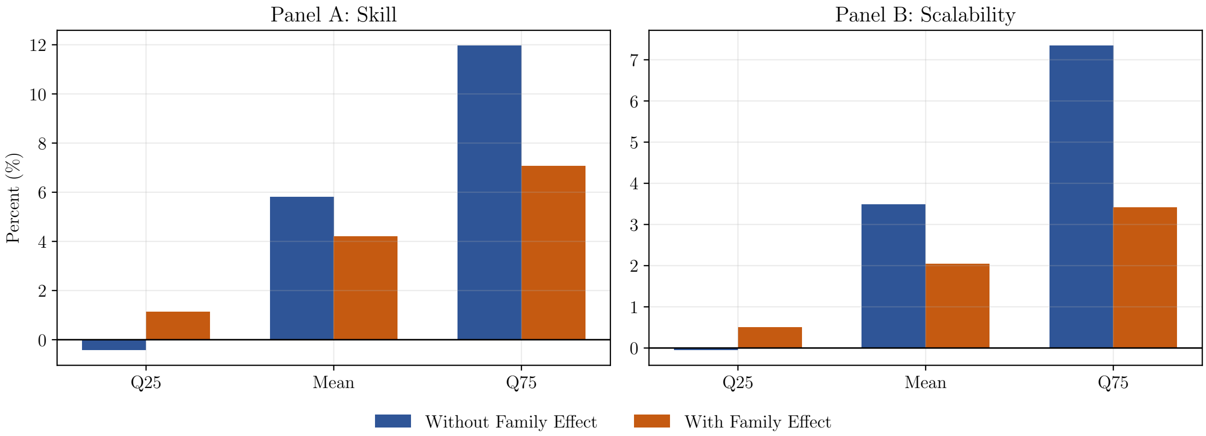

Figure 3. Value added with and without family effects. The figure reports the bias-adjusted 25th percentile, mean, and 75th percentile of annualized value added.

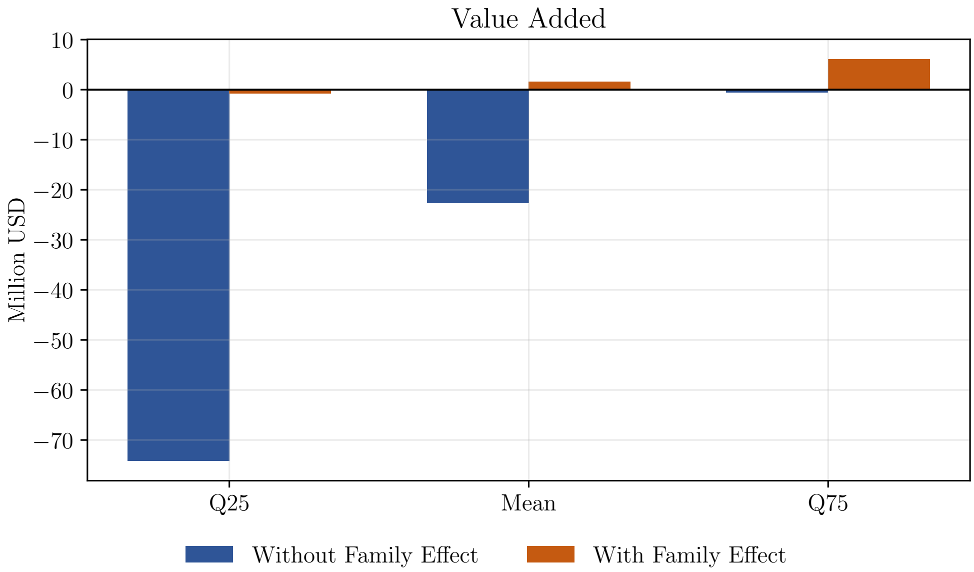

Figure 4. Selected sample: Optimal value added versus fee revenue. The figure reports group-level means for all families, style concentrated families, style diversified families, competitive families, and cooperative families.