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Mutual Fund Flows and Cross-Fund Learning within Families

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ABSTRACT

We develop a model of performance evaluation and fund flows for mutual funds in a family. Family performance has two effects on a member fund's estimated skill and inflows: a positive common-skill effect, and a negative correlated-noise effect. The overall spillover can be either positive or negative, depending on the weight of common skill and correlation of noise in returns. Its absolute value increases with family size, and declines over time. The sensitivity of flows to a fund's own performance is affected accordingly. Empirical estimates of fund flow sensitivities show patterns consistent with rational cross-fund learning within families.

WITH A TOTAL OF $26.8 TRILLION assets under management worldwide, mutual funds are a major player in financial markets, and a primary investment vehicle for households in many countries. In the United States, the $13.0 billion mutual fund industry attracts 44.4% of households, among which 68% hold more than half of their financial assets in mutual funds.[1] As such, mutual fund investments have a significant impact on the wealth of a large fraction of the population. They also indirectly affect the efficiencies of stock, bond, and money markets, by determining the allocation of assets across fund managers participating in those markets. Not surprisingly, there is strong interest in understanding investment decisions of mutual fund investors, whether they are sophisticated, and whether they act rationally. Empirical studies in this

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[1] These are statistics for the end of 2012, reported in the 2013 *Investment Company Fact Book* of the Investment Company Institute (ICI).

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area produce mixed results. On the one hand, Gruber (1996) and Zheng (1999) find that investors appear to invest in funds that subsequently perform well. On the other hand, Sapp and Tiwari (2004) attribute this "smart money" effect to stock return momentum and investors naively chasing recent performance. Furthermore, Frazzini and Lamont (2008) and Bailey, Kumar, and Ng (2011) conclude that fund flows represent "dumb money" that is driven by behavioral biases instead of rational learning about managerial skill.[2]

In this paper, we develop a novel test of investor sophistication by extending the Berk and Green (2004) framework to allow for cross-fund learning within fund families. Most mutual funds belong to a family. This provides rich possibilities for cross-fund learning that are not available when funds are stand-alone. We investigate whether investors rationally use information contained in the performance of all funds in a family to evaluate an individual fund, instead of evaluating each fund in isolation.

One source of cross-fund learning is common skill or resources shared by funds in the family. For example, funds in a family may share a common manager or management team, and managers in a family may share information, opinions, and expertise with each other even if they manage different funds. Furthermore, funds in a family often have access to the same pool of financial analysts, trading desks, legal counselors, and outside experts. As a result, a fund's performance reflects not only its fund-specific characteristics, such as its investment strategies, but also the quality of the skill and resources shared across funds.

Another source of cross-fund learning is correlation in unobservable shocks to the returns of funds in a family, due in part to the reliance on common skill. Some aspects of common skill may affect fund alphas without systematically affecting exposures to risk. Examples include operating efficiency, the quality of trading desks and supporting staff, and the effectiveness of fund governance and manager compensation schemes. However, when funds rely on shared sources of information, they are likely to tilt their portfolios in similar directions relative to their benchmarks. For example, an idea from one analyst can lead several funds to simultaneously change their positions in a security. These funds are then subject to correlated shocks to their performance.

Given the considerations above, how should a rational investor evaluate the alpha-generating skill of a mutual fund in a family? More specifically, how does an estimate of skill depend on a fund's own performance, and how does it depend on the performance of other funds in the family? Furthermore, how do the sensitivities of the estimate to fund and family performance change with fund and family characteristics, including the number of funds in the family? And, finally, do investors respond to fund and family performance in a manner that is consistent with optimal learning?

To answer these questions, we develop a continuous-time model in which a fund's alpha is driven by a combination of a fund-specific component and a

[2] See Christoffersen, Musto, and Wermers (2014) for a review of the literature on mutual fund flows.

common component shared by all funds in the family. We refer to this combination as composite skill, the fund-specific component as fund skill, and the common component as family skill. The returns of funds within a family are subject to correlated idiosyncratic shocks, which are unobservable. Both fund skill and family skill are unknown constants. A fund's alpha increases with its composite skill, and decreases with fund size. Investors estimate funds' composite skill by observing the returns of all funds in the family, and allocate wealth across funds, as in Berk and Green (2004).

We derive the sensitivities of the optimal estimate of the composite skill and fund flows to both fund and family performance, where family performance for a given fund is defined as the average performance of other funds in its family. Our model highlights two competing effects of family performance on the estimated skill and fund flows of a member fund: a positive common-skill effect and a negative correlated-noise effect. The positive effect arises because family performance contains information about family skill. The negative effect arises because family performance is also a signal about unobservable shocks that affect all funds in the family. The overall spillover effect of family performance can be either positive or negative, depending on the relative strength of these two effects. It increases with the weight of family skill, and decreases with the correlation of noise in fund returns. Its absolute value increases with the number of funds in the family, and declines over time, as investors become more certain about the composite skill. The sensitivity to a fund's own performance is positive, declines over time, and varies with other fund characteristics in a direction opposite to that of the cross-sensitivity.

We test our model using a sample of actively managed domestic equity funds drawn from the CRSP survivor-bias-free mutual fund database, and we find patterns remarkably consistent with rational cross-fund learning. We measure the weight of the common component in a fund's composite skill using the average manager overlap rate between the fund and the rest of its family, and measure the correlation of noise between one fund and other member funds using the average pairwise correlation of idiosyncratic returns. We find that flows to a member fund respond positively on average to family performance, suggesting the dominance of the common-skill effect. The sensitivity of fund flows to family performance is higher when the manager overlap rate is high, the correlation of idiosyncratic returns is low, and the number of funds in the family is large. The sensitivity of flows to a fund's own performance declines with the manager overlap rate and the number of funds in the family, and increases with the correlation of idiosyncratic fund returns. Both sensitivities decline with fund age. These patterns support our model, and suggest that investors learn rationally from both fund and family performance.

In stark contrast to the positive spillover effect in the full sample, for a subsample of funds with a below-median family size-adjusted manager overlap rate, an above-median family size-adjusted correlation of idiosyncratic returns, and a below-median family size, the response of fund flows to family performance is significantly negative. This demonstrates the dominance of the correlated-noise effect in a sizable fraction of funds.

We consider four alternative explanations for our findings, including effects of a star or dog fund in a family, asset allocation by affiliated funds of mutual funds (AFoMFs), cannibalization within families, and effects of style performance. None of the alternatives explain the rich patterns of fund flow sensitivities we document.

This work contributes to the understanding of the behavior of mutual fund investors. It is well known that investors chase good past performance (see, for example, Sirri and Tufano (1998)). Berk and Green (2004) reconcile this behavior with the well-documented lack of persistence in fund performance by considering investor learning about managerial skill and diseconomies of scale in portfolio management. Within the rational learning framework, Lynch and Musto (2003) and Huang, Wei, and Yan (2007) explain the convexity in the flow-performance relation by considering managers' incentive to abandon unsuccessful strategies and investors' participation costs, respectively. Dangl, Wu, and Zechner (2008) jointly model fund flows and the firing of the fund manager in response to past performance. Pástor and Stambaugh (2012) model learning about the parameter governing the degree of decreasing returns to scale. Franzoni and Schmalz (2014) model learning about the exposure to a risk factor. None of these studies consider cross-fund learning within families. Nanda, Wang, and Zheng (2004) find that the stellar performance of one fund has a positive spillover onto the inflows of other funds in the same family. Sialm and Tham (2015) find that the prior stock price performance of a fund management company predicts flows into its affiliated funds. Choi, Kahraman, and Mukherjee (2014) examine pairs of funds managed by the same manager, and find that flows into one fund respond positively to the performance of the other fund. Our model of cross-fund learning provides a rational explanation for these findings. Beyond a positive spillover effect found in these studies, our equilibrium model also delivers many previously unexplored implications of rational learning that we verify empirically.

Our paper also contributes to the literature on mutual fund performance evaluation.[3] Most methods of evaluation rely solely on a fund's own record. Several recent papers propose the use of additional information. Pástor and Stambaugh (2002) estimate the alpha of an actively managed fund using returns on "seemingly unrelated" nonbenchmark passive assets. Cohen, Coval, and Pástor (2005) evaluate a fund manager's skill by considering the correlation between his investment decisions and those of managers with distinguished track records. Jones and Shanken (2005) measure performance using the distribution of other funds' alphas in addition to the information in a fund's own return history. Our performance evaluation strategy is in the spirit of this literature, but differs in two important respects. First, we exploit the information embedded in the performance of a fund's family. Second, while these studies focus on the cross-fund learning arising from common skill, we consider both common-skill and correlated-noise effects.

[3] See Aragon and Ferson (2006) for an extensive review of this literature.

Our study extends an important insight of the theory of relative performance evaluation, which forms the foundation of most benchmark-adjusted performance measures. Recognizing that peer performance reveals information about common shocks to multiple agents, the relative performance evaluation literature generally postulates a negative relation between the estimated skill or effort of an agent and the performance of his peers (Holmstrom (1982)). By allowing both unobservable skill and noise to be correlated, we show that this relation can be either positive or negative. Although our model is developed in the context of mutual funds, this insight is relevant for other settings, which we briefly discuss in the conclusion.

The paper is organized as follows. Section I introduces our model of a mutual fund family. Section II derives the dynamics of beliefs about composite skill and equilibrium fund flows. Section III derives the sensitivities of the optimal estimate of composite skill to both fund and family performance. We present our empirical findings on fund flows in Section IV, examine several alternative explanations for these findings in Section V, and conclude in Section VI.

I. A Family of Mutual Funds

We model n actively managed mutual funds in a family. The quality of management is an unobservable variable governing the success or failure of a fund. It is a linear combination of fund-specific skill and common family skill, which together form the composite skill $\boldsymbol{\theta}$. A fund's alpha is an increasing function of $\boldsymbol{\theta}$, and its realized abnormal return is its alpha plus noise. We calculate the conditional distribution of $\boldsymbol{\theta}$ for all funds in the family using abnormal fund returns as a continuous signal.

For simplicity, we abstract from managers' market-timing activity and focus only on stock selection. Funds' cumulative abnormal returns (CARs) $\mathbf{R}_t$ follow the process

$$d\mathbf{R}_t = \boldsymbol{\alpha}_t dt + \boldsymbol{\sigma}_t \mathbf{B} d\mathbf{W}_t, \tag{1}$$

where $d\mathbf{R}_t$ is an $n \times 1$ vector of excess fund returns above benchmarks over time interval dt, net of management fees; $\mathbf{R}_t$ represents the sum of abnormal returns over time, which corresponds to the concept of CARs commonly used in the event study literature; $\boldsymbol{\alpha}_t$ is an $n \times 1$ vector of fund alphas generated by active management; and $\boldsymbol{\sigma}_t \mathbf{B} d\mathbf{W}_t$ is the noise in abnormal returns. The $n \times n$ matrix $\boldsymbol{\sigma}_t$ represents the scale of funds' idiosyncratic risks. It has elements σ_{it} along the main diagonal, which are the instantaneous volatilities of abnormal returns, and zeros off the diagonal. The nonsingular square matrix $\mathbf{B}$ is the Cholesky factor of the correlation matrix $\mathbf{BB}'$, whose off-diagonal elements ρ_{ij} are the correlations of idiosyncratic shocks to abnormal returns. The $n \times 1$ vector $\mathbf{W}_t$ represents standard Brownian motions that are pairwise independent.

A fund's idiosyncratic risk σ_{it} is governed by the scale of its portfolio tilt, that is, the difference between its portfolio weights and the weights of a benchmark portfolio, which has exposure to systematic risks and zero alpha. A fund with no tilt has $\sigma_{it} = 0$. As a fund increases the scale of its tilt, with the expectation of increasing fund alpha, σ_{it} increases. If two funds i and j follow independent strategies and have orthogonal tilts, the idiosyncratic shocks are uncorrelated (i.e., $\rho_{ij} = 0$). For reasons noted above, however, we expect funds in a typical family to follow positively correlated strategies.[4]

As emphasized by Berk and Green (2004), there are diseconomies of scale in active portfolio management. We model fund alphas net of management fees by generalizing the specification of Dangl, Wu, and Zechner (2008) to allow for multiple funds:

$$\boldsymbol{\alpha}_t = \boldsymbol{\sigma}_t \boldsymbol{\theta} - \gamma \boldsymbol{\sigma}_t \boldsymbol{\sigma}_t \mathbf{A}_t - \mathbf{f}_t, \tag{2}$$

where $\boldsymbol{\theta}$, $\mathbf{A}_t$, and $\mathbf{f}_t$ are $n \times 1$ vectors of composite skill, asset size, and fees, respectively, and $\gamma > 0$ characterizes decreasing returns to scale.[5] The i^{th} element of the first term on the right-hand side of equation (2) is $\sigma_{it}\theta_i$, so that alpha increases linearly with composite skill for a given level of idiosyncratic risk. The i^{th} element of the second term is $-\gamma \sigma_{it}^2 A_{it}$. Thus, a fund's alpha decreases with its own size, and at a higher rate when a fund is more actively managed (i.e., when σ_{it} is high). Equation (2) captures the idea that diseconomies of scale are more severe for funds that are more actively managed. A passively managed fund, such as an index fund, suffers less from the price impact of trades because its trades contain little private information and because fund inflows are allocated to a broad set of securities. Equation (2) also implies that the marginal return from taking idiosyncratic risk decreases, especially for large funds. This deters funds from taking unlimited idiosyncratic risk.[6]

A fund's composite skill θ_i is a linear combination of two components, and is constant over time. For each fund i,

$$\theta_i = (1 - \beta_i)\theta_{fi} + \beta_i \theta_F, \tag{3}$$

where θ_{fi} is fund-specific skill, θ_F is family skill, and $\beta_i \in [0, 1]$ is the weight of family skill in composite skill. If a fund relies fully on family skill, $\beta_i = 1$. If it operates independently of family resources, $\beta_i = 0$. We expect individual funds to rely on common skill (i.e., $\beta_i > 0$). In this case, the fund's alpha increases directly with both θ_{fi} and θ_F.

[4] While we assume $\rho_{ij} > 0$ when we discuss the correlated-noise effect, our model allows for all $\rho_{ij} \in (-1, 1)$, $i \neq j$, such that $\mathbf{BB}'$ is nonsingular. A negative correlation arises when a fund family tries to hedge itself, or to accommodate different investor preferences, by offering funds pursuing opposite investment strategies.

[5] Chen et al. (2004) and Yan (2008) find that fund size erodes fund returns. Pástor, Stambaugh, and Taylor (2015) find evidence of industry-level decreasing returns in mutual fund management.

[6] Our performance evaluation method only requires $\boldsymbol{\alpha}$ to be linear in the latent variable $\boldsymbol{\theta}$. We specify $\boldsymbol{\alpha}$ explicitly. This allows us to derive equilibrium fund flows in closed form. See Dangl, Wu, and Zechner (2008) for a more detailed discussion of this specification.

II. Dynamics of Beliefs and Equilibrium Fund Flows

Information is symmetric but incomplete. Composite skill $\boldsymbol{\theta}$ and idiosyncratic shocks $d\mathbf{W}_t$ are not observable. Investors form beliefs about the conditional distribution of composite skill, using the returns of all funds in a family as signals. We now derive the optimal updating of beliefs and equilibrium fund flows.

A. Dynamics of Beliefs about Composite Skill

Substituting for $\boldsymbol{\alpha}_t$ using equation (2), the observable components in equation (1) form a signal $d\boldsymbol{\xi}_t$ of composite skill, which is

$$\begin{aligned} d\boldsymbol{\xi}_t &\equiv \boldsymbol{\sigma}_t^{-1}\left[d\mathbf{R}_t + (\gamma\boldsymbol{\sigma}_t\boldsymbol{\sigma}_t\mathbf{A}_t + \mathbf{f}_t)\,dt\right] \\ &= \boldsymbol{\theta}dt + \mathbf{B}d\mathbf{W}_t. \end{aligned} \tag{4}$$

The signal is centered on the drift $\boldsymbol{\theta}dt$ and has noise $\mathbf{B}d\mathbf{W}_t$ that is correlated across funds. At any time t , information is the history of fund returns represented by the filtration $\mathcal{F}_t \equiv \sigma\left\{\boldsymbol{\xi}_s\right\}_{s=0}^{t}$. Given a multivariate normal prior distribution with mean vector $\mathbf{m}_0$ and covariance matrix $\mathbf{V}_0$, the conditional distribution of composite skill is also multivariate normal.[7]

PROPOSITION 1: *The conditional mean vector $\mathbf{m}_t \equiv E(\boldsymbol{\theta}|\mathcal{F}_t)$ for $t \geq 0$ follows the process*

$$d\mathbf{m}_t = \mathbf{S}_t d\mathbf{W}_t^{\mathcal{F}}, \tag{5}$$

and the conditional covariance matrix $\mathbf{V}_t \equiv var(\boldsymbol{\theta}|\mathcal{F}_t)$ is

$$\boldsymbol{V}_t = \mathbf{B}\mathbf{Q}_t^{-1}\mathbf{B}', \tag{6}$$

where

$$\mathbf{S}_t = \mathbf{V}_t\left(\mathbf{B}\mathbf{B}'\right)^{-1}, \tag{7}$$

$$d\mathbf{W}_t^{\mathcal{F}} = \boldsymbol{\sigma}_t^{-1}\left[d\mathbf{R}_t - E\left(\boldsymbol{\alpha}_t|\mathcal{F}_t\right)dt\right], \tag{8}$$

$$\mathbf{Q}_0 = \mathbf{B}'\boldsymbol{V}_0^{-1}\mathbf{B}, \tag{9}$$

and the elements of the matrix $\mathbf{Q}_t$ are

$$Q_{ij}(t) = \begin{cases} Q_{ij}(0) + t, & i = j, \\ Q_{ij}(0), & i \neq j. \end{cases} \tag{10}$$

[7] Investor beliefs are conditional distributions of composite skill $\boldsymbol{\theta}$, which has the same dimension as the observation equation. A conditional distribution can be calculated numerically for individual components θ_{fi} and θ_F. Learning these components separately, which is not pursued in this paper, is important for hiring and firing decisions in fund families, and for investor responses to these decisions, but is not required to form expectations of fund alphas.

PROOF: See Appendix A. ■

The conditional mean $\mathbf{m}_t$ is a martingale, and follows the driftless process in equation (5). Although $\mathbf{m}_t$ converges to $\boldsymbol{\theta}$ as time goes to infinity, the true skill vector is unknown in finite time, and future innovations in $\mathbf{m}_t$ are unpredictable to investors. Equation (8) shows that $d\mathbf{W}_t^{\mathcal{F}}$, which drives the evolution of m_t, is a vector of unexpected abnormal returns standardized by volatility $\boldsymbol{\sigma}_t$. We refer to $d\mathbf{W}_t^{\mathcal{F}}$ simply as *unexpected performance*.

The matrix $\mathbf{S}_t$ in equation (5) characterizes the response of investors' beliefs to mutual fund performance. An element on the main diagonal of $\mathbf{S}_t$ is the sensitivity of a fund's conditional mean to its own unexpected performance. An off-diagonal element is the sensitivity to the unexpected performance of another fund. The sensitivities given in equation (7) increase with uncertainty about composite skill, which is described by matrix $\mathbf{V}_t$. Elements on and off the main diagonal of $\mathbf{V}_t$ are conditional variances and covariances of $\boldsymbol{\theta}$, respectively. Generally, if composite skill is known precisely, then $\mathbf{S}_t$ is small and beliefs are insensitive to unexpected performance. If instead little is known about the skill, then unexpected performance is an important signal and investors respond to it strongly. Equations (6) and (10) together demonstrate that elements of $\mathbf{V}_t$ decline as time passes, and converge to zero. Similarly, sensitivities of beliefs to unexpected performance converge to zero.[8]

B. Fund Flows in Equilibrium

We now investigate the dynamics of fund flows, in an environment mimicking that of Berk and Green (2004). Investors provide capital to mutual funds without transaction costs. They direct assets toward funds with positive expected alpha, net of fees, and pull assets from funds with negative expected net alpha. In equilibrium, the size of fund i is constantly adjusted to satisfy $\mathrm{E}(\alpha_{it}|\mathcal{F}_t) = 0$, meaning that the conditional expected alpha net of fees is zero. By substituting this equilibrium condition into equation (8), we see that

$$d\mathbf{W}_t^{\mathcal{F}} = \boldsymbol{\sigma}_t^{-1} d\mathbf{R}_t. \tag{11}$$

That is, in equilibrium, the unexpected performance is the vector of abnormal returns normalized by idiosyncratic volatilities. Since the expected alpha is zero, any nonzero abnormal return is a surprise under the investors' information set, and leads to a revision of beliefs and a response of fund flows.

[8] The elements of $\mathbf{V}_t$ in equation (6) are linear combinations of those of $\mathbf{Q}_t^{-1}$. Equation (10) shows that the elements along the main diagonal of $\mathbf{Q}_t$ increase linearly with t, which implies that elements of the inverse $\mathbf{Q}_t^{-1}$ converge to zero. In a previous version of the paper, we allow composite skill to change stochastically over time. Investors estimate the continuously changing $\boldsymbol{\theta}$, and the elements of both $\mathbf{V}_t$ and $\mathbf{S}_t$ are bounded away from zero. The main results are the same as in our current formulation.

Taking expectations on both sides of (2) and accounting for $\mathrm{E}(\alpha_{it}|\mathcal{F}_t) = 0$ yields the equilibrium fund size

$$A_{it} = \frac{1}{\gamma}\left(\frac{m_{it}}{\sigma_{it}} - \frac{f_{it}}{\sigma_{it}^2}\right). \tag{12}$$

A mutual fund family maximizes total fee income $\mathbf{f}'\mathbf{A}$, setting optimal fee ratios and idiosyncratic volatilities. The optimal quantities for fund i satisfy

$$\frac{f_{it}}{\sigma_{it}} = \frac{1}{2} m_{it}. \tag{13}$$

The ratio on the left-hand side is determined in equilibrium, but neither the fee nor the idiosyncratic volatility is unique. A fund may set a high fee, attract a low level of assets, and take large positions in mispriced assets. Alternatively, it may set a low fee, attract a large amount of inflows, and stick closely to a benchmark portfolio. Provided that the fund's fee and idiosyncratic risk satisfy equation (13), the total fee income is the same in either case. We follow Dangl, Wu, and Zechner (2008) and assume, without loss of generality, that the family sets constant fees, $\mathbf{f} = (f_i)$. Because $\sigma_{it} > 0$, equation (12) implies that a fund is viable (i.e., $A_{it} > 0$), and earns a positive fee, only if the estimated composite skill m_{it} is positive. Otherwise, the fund is either reorganized or closed.

Equations (12) and (13) determine the equilibrium size of a fund. For $m_{it} > 0$, fund size is a convex function of the estimate of the composite skill,

$$A_{it} = \frac{m_{it}^2}{4\gamma f_i},$$

and, using Ito's lemma and equation (5), the instantaneous growth rate of assets is

$$\begin{aligned} \frac{dA_{it}}{A_{it}} &= 2\frac{dm_{it}}{m_{it}} + \frac{(dm_{it})^2}{m_{it}^2} \\ &= \frac{1}{m_{it}^2}\mathbf{S}_{it}\mathbf{B}\mathbf{B}'\mathbf{S}_{it}' dt + 2\frac{1}{m_{it}}\mathbf{S}_{it} d\mathbf{W}_t^{\mathcal{F}}, \end{aligned} \tag{14}$$

where $\mathbf{S}_{it}$ is the i^{th} row of $\mathbf{S}_t$. By writing $\mathbf{S}_{it} d\mathbf{W}_t^{\mathcal{F}} = \sum_j s_{ijt} dW_{jt}^{\mathcal{F}}$, we see that one fund's asset growth rate responds to unexpected performance of all funds in the family. If $s_{ijt} > 0$, unexpectedly good performance by fund j increases the size of fund i. If $s_{ijt} < 0$, the relation is negative. The positive drift in $\frac{dA_{it}}{A_{it}}$ is due to the convex relation between the fund size A_{it} and the conditional mean of the composite skill m_{it}.

III. Sensitivities of Beliefs to Unexpected Performance

A. A Homogeneous Family

The basic insights from our model can be illustrated using a *homogeneous* family, which has $\beta_i = \beta \in [0, 1]$ and $\mathrm{var}\left(\theta_{fi}|\mathcal{F}_0\right) = v_f > 0$ for all i , $\rho_{ij} = \rho \in \left(\frac{-1}{n-1}, 1\right)$ for all $i \neq j$, and $\mathrm{var}\left(\theta_F|\mathcal{F}_0\right) = v_F$.[9] For simplicity, we also assume that the fund-specific skill is pairwise independent across funds, and is independent of the family skill, under the initial information set $\mathcal{F}_0$.[10] Under this structure, the matrix $\mathbf{V}_t$ has identical elements on the main diagonal, say, v_{nt}, and identical elements off the diagonal, say, $\overline{v}_{nt}$.[11] The matrix equation (6) is fully described by two equations, one for v_{nt} and the other for $\overline{v}_{nt}$. The initial (a priori) variance of composite skill of any fund is

$$v_{n0} = (1-\beta)^2\, v_f + \beta^2 v_F. \tag{15}$$

Although fund-specific skill is independent under $\mathcal{F}_0$, composite skill is correlated across funds, due to the common unobservable family skill. The a priori covariance of composite skill for any pair of funds is $\overline{v}_{n0} = v_{n0}\lambda$, where λ is the a priori correlation between each pair, given by

$$\lambda = \left(\left(\frac{1}{\beta} - 1\right)^2 \frac{v_f}{v_F} + 1\right)^{-1}. \tag{16}$$

It is evident that λ increases with β, and decreases with the ratio of initial variances v_f/v_F. A value $\lambda = 0$ indicates that either family skill is known precisely, $v_F = 0$, or managers of individual funds work independently, $\beta = 0$, while a value $\lambda = 1$ indicates that either fund skill is known precisely, $v_f = 0$, or member funds act in concert and rely entirely on family skill, $\beta = 1$.

Matrix $\mathbf{S}_t$ has the same structure as $\mathbf{V}_t$ in the homogeneous family. The matrix equation (7) contains two representative equations, one for the sensitivity of any fund to its own unexpected performance, and one for the sensitivity to the performance of any other fund. The dynamics of the conditional mean for each fund in equation (5) simplifies to

$$dm_{it} = s_{nt} dW_{it}^{\mathcal{F}} + \overline{s}_{nt} dX_{-i,t}^{\mathcal{F}}, \tag{17}$$

where

$$dX_{-it}^{\mathcal{F}} \equiv \frac{1}{n-1}\sum_{j\neq i} dW_{jt}^{\mathcal{F}}$$

is the average unexpected performance of the funds in the family excluding fund i, which we refer to as family performance; $dW_{it}^{\mathcal{F}}$ is the unexpected performance

[9] The condition $\frac{-1}{n-1} < \rho < 1$ ensures that the matrix $\mathbf{BB}'$ is nonsingular.

[10] θ_{fi} can be viewed as a component orthogonalized to θ_F under $\mathcal{F}_0$.

[11] The subscript n in v_{nt} and $\bar{v}_{nt}$ denotes the number of funds in a family, and the subscript t indicates time-dependence. The same notation scheme applies to s_{nt} and $\bar{s}_{nt}$ as well.

of fund i; and s_{nt} and $\bar{s}_{nt}/(n-1)$ are the diagonal and off-diagonal elements of $\mathbf{S}_t$, respectively. Accordingly, the dynamics of the fund growth rate (equation (14)) simplifies to

$$\frac{dA_{it}}{A_{it}} = \frac{\mu_{nt}}{m_{it}^2}dt + \frac{2s_{nt}}{m_{it}}dW_{it}^{\mathcal{F}} + \frac{2\bar{s}_{nt}}{m_{it}}dX_{-i,t}^{\mathcal{F}}, \tag{18}$$

where $\mu_{nt} \equiv s_{nt}^2 + 2\rho s_{nt}\bar{s}_{nt} + \frac{1+(n-2)\rho}{n-1}\bar{s}_{nt}^2$. Equations (17) and (18) have an obvious advantage over equations (5) and (14) in that the performance of the other funds is summarized in the single statistic $dX_{-it}^{\mathcal{F}}$.

In the following, we examine the dynamics of v_{nt}, $\bar{v}_{nt}$, and s_{nt}, $\bar{s}_{nt}$, and describe how common skill and correlated noise govern these dynamics. We first consider the case of a two-fund family. We then consider an n-fund family.

B. A Homogeneous Two-Fund Family

We obtain explicit solutions for the conditional variances, covariances, and sensitivities in a two-fund family, which are summarized in the following proposition.

PROPOSITION 2: *In a homogeneous family of two funds (n=2), the conditional variance and covariance of beliefs are*

$$v_{2t} = v_{20}\frac{1}{1+k(t)\,v_{20}t} \tag{19}$$

$$\bar{v}_{2t} = v_{2t}\frac{\lambda(1-\rho^2)+\rho(1-\lambda^2)v_{20}t}{1-\rho^2+(1-\lambda^2)v_{20}t}, \tag{20}$$

respectively, and the sensitivities of the conditional mean of beliefs to a fund's own unexpected performance and to the other fund's unexpected performance are

$$s_{2t} = v_{2t}\frac{1-\rho\lambda+(1-\lambda^2)v_{20}t}{1-\rho^2+(1-\lambda^2)v_{20}t}, \tag{21}$$

$$\bar{s}_{2t} = v_{2t}\frac{\lambda-\rho}{1-\rho^2+(1-\lambda^2)v_{20}t}, \tag{22}$$

respectively, where $k(t) = 1 + \frac{(\lambda-\rho)^2}{1-\rho^2+(1-\lambda^2)v_{20}t} \geq 1$. *Furthermore, we have*

$$\frac{\partial\bar{s}_{2t}}{\partial\lambda} > 0, \quad \frac{\partial\bar{s}_{2t}}{\partial\rho} < 0.$$

Holding the initial uncertainty v_{20} *constant, we also have*

$$\partial\bar{s}_{2t}/\partial\beta > 0.$$

PROOF: See Appendix B. ■

Equations (21) and (22) show that the responses of the optimal estimate of a fund's composite skill to both its own performance and the other fund's performance are stronger when the uncertainty about the skill, v_{2t}, is high. The direct sensitivity of the estimate to a fund's own performance, s_{2t}, is always positive, meaning that a fund's unexpected good performance always raises the optimal estimate of its own composite skill. However, the cross-sensitivity to the other fund's performance, $\bar{s}_{2t}$, is either positive or negative, depending on the difference between λ and ρ. It increases with the a priori correlation of composite skill, λ, and decreases with the correlation of noise in fund returns, ρ. Since λ increases with the weight of common skill β (see equation (16)), holding the initial uncertainty about the composite skill v_{20} constant, $\bar{s}_{2t}$ also increases with β.[12]

When unobservable shocks to fund returns are not correlated ($\rho = 0$), we have $\bar{s}_{2t} = v_{20}\lambda[(1 + v_{20}t)^2 - v_{20}^2 t^2 \lambda^2]^{-1}$. This measures the pure common-skill effect, and it is positive as long as $\lambda > 0$. Similarly, when managers do not share common skill ($\lambda = 0$), we have a measure of the pure correlated-noise effect, $\bar{s}_{2t} = -v_{20}\rho[(1 + v_{20}t)^2 - \rho^2]^{-1}$, which is positive if $\rho < 0$ and negative if $\rho > 0$. Between these two extreme cases, $\bar{s}_{2t}$ is a mixture of both effects. It is positive when $\lambda > \rho$, suggesting that the optimal estimate of one fund's skill rises with the performance of the second fund when the weight of common skill in a fund's composite skill is high and the correlation of noise in fund returns is low. Alternatively, when $\lambda < \rho$, the correlated-noise effect is dominant, and $\bar{s}_{2t} < 0$. Finally, when $\lambda = \rho$, the two effects offset each other, $\bar{s}_{2t} = 0$, which implies that the evaluation of a fund's composite skill is based entirely on its own performance, and we have $s_{2t} = v_{2t}$, as in the single-fund case of Dangl, Wu, and Zechner (2008).

The intuition for these results is clear. When the second fund performs well, it indicates two things that are relevant for the first fund. First, the unobservable family skill θ_F is high. This is good news if some family skill is shared by both funds. Second, the unobservable shock to the second fund's return is positive. This is bad news if unobservable shocks are correlated because it indicates that the performance of the first fund is partly attributable to good luck. If the two funds rely heavily on common resources and noise correlation is low, then the first effect dominates, leading to a positive spillover. If, in contrast, fund returns are driven by independent skill, and noise correlation is high, then the second effect dominates, leading to a negative spillover. When the two effects are equally strong, cross-fund learning is not possible. Therefore, the conditional mean of a fund's composite skill responds only to the fund's own performance.

[12] In general, when $v_F \neq v_f$, v_{20} is a function of β, which makes the total effect of β on $\bar{s}_{2t}$ difficult to sign. Numerical investigation suggests that the positive relation between $\bar{s}_{2t}$ and β is fairly robust. One exception occurs when $\rho < 0$, and v_F is far below v_f. In this case, $\bar{s}_{2t}$ is positive and may decrease as β increases, due to a negative relation between v_{20} and β.

The conditional variance of a fund's composite skill, $v_{2t} = v_{20}\,(1 + k(t)\,v_{20}t)^{-1}$, is high early in the fund's life, and decreases as investors learn from funds' track records. The rate of decrease is governed by λ and ρ through the function $k(t)$. Higher $k(t)$ implies faster convergence of v_{2t} to zero. It is evident that $k(t)$ is at its minimum, $k(t) = 1$, when $\lambda = \rho$. In this case, $v_{2t} = v_{20}\,(1 + v_{20}t)^{-1}$, which is independent of the correlations ρ and λ, and is identical to the conditional variance of a stand-alone fund. This is not surprising because there is no cross-fund learning in this scenario. Differentiation of $k(t)$ with respect to λ and ρ demonstrates that it increases as the distance $|\lambda - \rho|$ grows. Therefore, holding t constant, the conditional variance v_{2t} decreases with the gap between λ and ρ. This is because a bigger gap allows more effective cross-fund learning.

Denote the conditional correlation of the funds' composite skill by $\lambda(t)$, which equals $\bar{v}_{nt}/v_{nt}$. Equations (19) and (20) imply

$$\lambda(t) - \rho = \frac{(\lambda - \rho)(1 - \rho^2)}{1 - \rho^2 + (1 - \lambda^2)v_{20}t}, \tag{23}$$

which shows that $\lambda(t) - \rho$ has the same sign as $\lambda - \rho$. This explains why the sign of the cross-sensitivity $\bar{s}_{nt}$ depends only on the relative magnitude of ρ and the a priori correlation of skill λ.

C. A Homogeneous N-Fund Family

The returns of mutual funds in a family are a collection of signals. The unexpected performance of each fund may provide information about family skill and about the correlated noise in the performance of other funds. This suggests that the rate at which we learn about skill depends on family size. We investigate this idea here.

We calculate the representative elements of the covariance matrix $\mathbf{V}_t$ and sensitivity matrix $\mathbf{S}_t$ for a homogeneous family of n funds using equations (6), (7), and (10). There are five primitive parameters in our model: family size n, correlation of noise in fund returns ρ, weight of family skill in composite skill β, initial variance of fund-specific skill v_f, and initial variance of family skill v_F. We set the values of these parameters in our base case as follows. The number of funds in a family is n=10, close to the family size for an average fund in our sample (12.4), as summarized in Table I. The correlation of noise in fund returns is $\rho = 0.2$, approximately equal to our empirical estimate of pairwise correlation of idiosyncratic fund returns within families (0.19). We set $\beta = 1/2$, which means that fund-specific skill and family skill are equally important in generating alphas. The initial variances of fund-specific and family skill are $v_f = 0.32$ and $v_F = 0.16$, respectively. These values imply an initial variance of composite skill $v_{n0} = 0.12$, consistent with Dangl, Wu, and Zechner (2008), and an initial covariance $\overline{v}_{n0} = 0.04$. These values also imply an initial correlation of composite skill of $\lambda = 0.33$, which is higher than $\rho = 0.2$, and leads to dominance of the common-skill effect. This dominance is consistent with the positive spillover effect empirically observed for an average fund (see Section IV).

Figure 1 shows the evolution of the sensitivities of beliefs to both fund and family performance over 20 years beginning at fund inception. In general, the sensitivity to a fund's own performance, s_{2t} , is positive, and declines over time. The sensitivity to family performance, $\bar{s}_{2t}$, can be either positive or negative, and declines over time in absolute value, as investors develop more precise estimates of composite skill. Both sensitivities show a tendency of converging to zero in the limit.

Panels A and B of Figure 1 illustrate the influence of the weight of family skill in composite skill. Here, β varies from 0.3 to 0.7 while other parameter values are fixed at their base levels. Consistent with the two-fund results in Proposition 2, the sensitivities of optimal estimates to fund performance fall and the sensitivities to family performance rise as family skill becomes more important in alpha generation. When the reliance on family skill is low ($\beta = 0.3$), the sensitivity to family performance is negative, indicating the dominance of the correlated-noise effect.

Panels C and D illustrate the effects of changes in the correlation of noise in fund returns, ρ. It is clear that changes in ρ have opposite effects on the two sensitivities. As ρ increases from 0.05 to 0.40, the sensitivity of the optimal estimate of composite skill to fund performance increases, while the sensitivity to family performance decreases sharply: $\bar{s}_{n0}$ declines from about 0.2 to a value less than zero. This pattern is consistent with Proposition 2. It demonstrates that when ρ is high, the positive common-skill effect is largely offset, or even reversed, by the negative correlated-noise effect.

Panels E and F illustrate the effects of family size. As the number of funds in the family increases from 2 to 30, the sensitivity of beliefs to fund performance decreases, while the absolute value of the sensitivity to family performance increases.[13] This result is easy to understand. Family performance contains less noise and more information about family skill when it represents a large number of funds, so it generates a stronger response (either positive or negative) in large families. Panel F also suggests that the sensitivity to family performance declines faster over time in bigger families. This is because investors learn faster about family skill in the presence of a larger number of signals.

While the parameter values we use to draw Figure 1 are mainly illustrative, numerical experiments show that the general patterns are robust to a wide range of alternative parameterizations. To summarize, the cross-sensitivity $\bar{s}_{nt}$ can be either positive or negative. It increases with the weight of family skill, and decreases with the correlation of noise. Its absolute value is amplified by the number of funds in the family, and decreases over time. The direct sensitivity s_{nt} is always positive, and declines over time. It increases with the correlation of noise, and decreases with the weight of family skill and family size. Both sensitivities converge to zero as time goes to infinity.

[13] The common-skill effect is dominant and $\bar{s}_{nt} > 0$ in Panels E and F. When the correlated-noise effect is dominant instead, $\bar{s}_{nt} < 0$ and $|\bar{s}_{nt}|$ increases with family size n.

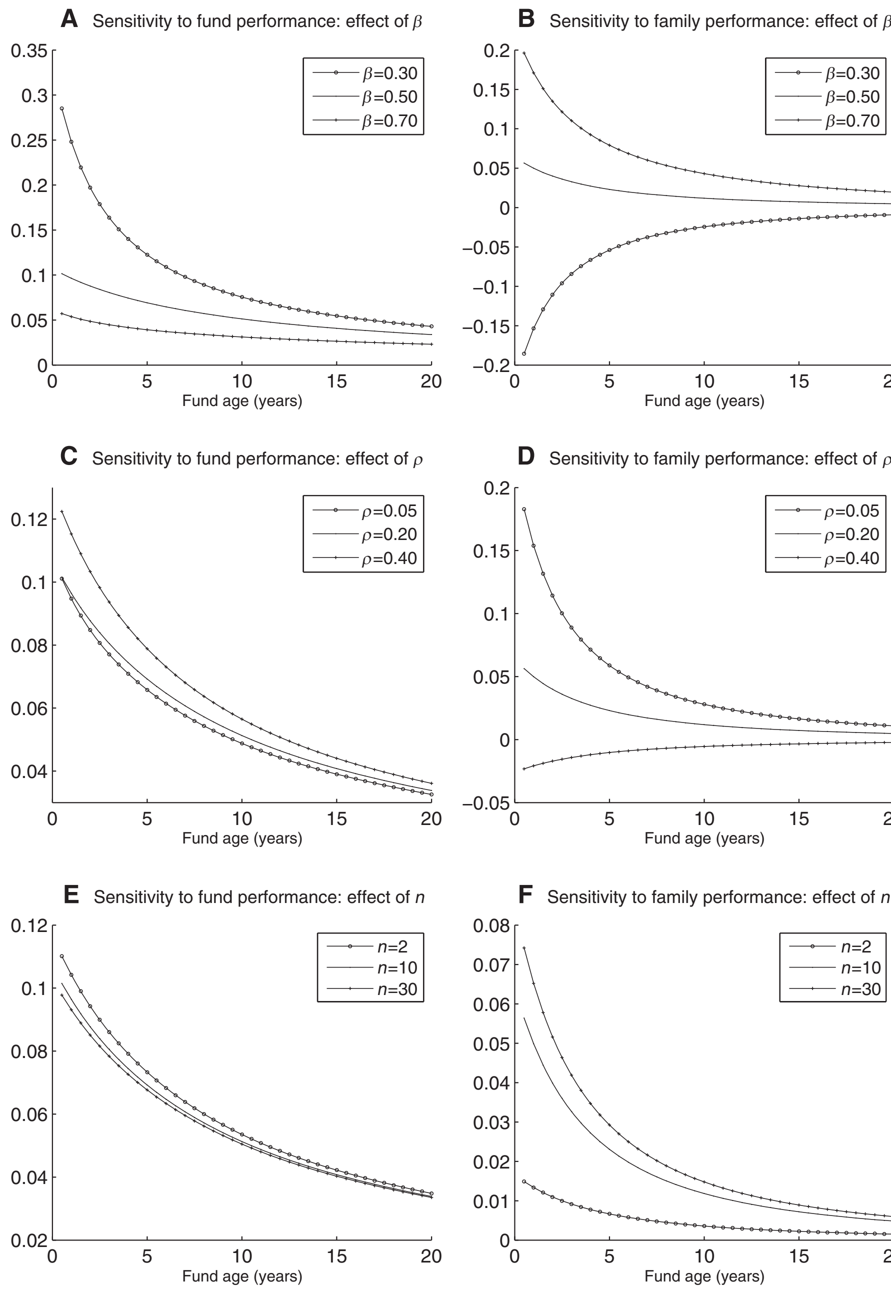

Figure 1. Sensitivities of beliefs over time. The left and right panels show sensitivities of the conditional skill estimate to fund performance and family performance, respectively. Panels A and B illustrate the effects of the weight of family skill in composite skill (β). Panels C and D illustrate the effects of the correlation of noise in fund returns (ρ). Panels E and F illustrate the effects of family size (n). In each panel, we vary the value of one parameter while fixing the values of all other parameters at the base levels ($n = 10$, $\beta = 0.5$, $\rho = 0.2$, $v_f = 0.32$, $v_F = 0.16$).

IV. Empirical Evidence

Our model generates predictions about the responses of mutual fund flows, measured as a percentage of fund assets, to unexpected performance, defined in (11). According to equation (18), the sensitivities of fund flows to fund and family performance are proportional to the direct sensitivity s_{nt} and cross-sensitivity $\bar{s}_{nt}$ of investor beliefs, respectively, and are inversely related to the equilibrium fund size governed by the conditional estimate of the composite skill, m_{it}. Therefore, our characterization of s_{nt} and $\bar{s}_{nt}$, presented in Section III, translates directly into predictions about the sensitivities of fund flows. Our model thus yields the following hypotheses about fund flows, which we test in this section:

H1: *Other things equal, greater use of common skill reduces the sensitivity of flows to fund performance, and increases the sensitivity to family performance.*

H2: *Other things equal, a higher correlation of noise in fund returns between one fund and other member funds increases the sensitivity of flows to fund performance, and reduces the sensitivity to family performance.*

H3: *Other things equal, a larger number of funds in the family reduces the sensitivity of flows to fund performance, and increases the absolute value of the sensitivity to family performance.*

H4: *Other things equal, as funds grow larger or older, the absolute values of fund flow sensitivities to both fund performance and family performance decrease.*

A. Sample

We construct a sample of actively managed domestic equity funds from the CRSP survivor-bias-free mutual fund database for the January 1999 to December 2011 period.[14] Our focus on domestic equity funds allows us to use the same asset pricing model to estimate the abnormal returns of all funds. The data are at the share class level. We use the MFLINKS database to aggregate observations to the fund level. A fund's total net asset value (TNA) is the sum across share classes, and its return and expense ratio are averages weighted by the lagged asset value of each class. Fund age is defined as the

[14] We select all funds in the following *Lipper* classes: Large-Cap Core, Large-Cap Growth, Large-Cap Value, Mid-Cap Core, Mid-Cap Growth, Mid-Cap Value, Small-Cap Core, Small-Cap Growth, Small-Cap Value, Multi-Cap Core, Multi-Cap Growth, and Multi-Cap Value. Information on the Lipper fund classification information begins in 1999. Furthermore, for most funds, the management company code, a data item we use to identify the fund family, is not available before 1999. We exclude index funds (identified either by the CRSP index fund flag, or the word "index" in the fund name), variable annuity funds, and exchange-traded funds(ETFs).

number of years since the inception of the oldest share class. Fund family is identified by the management company code.[15]

We exclude funds with fewer than 36 monthly return observations, and observations before a fund's TNA reaches five million dollars. Removing these observations mitigates incubation bias (Evans (2010)). To allow for cross-fund learning, funds must belong to a multifund family, which offers at least two actively managed domestic equity funds simultaneously for at least 36 months. Evans and Fahlenbrach (2012) show that some families offer multiple versions of the same fund, under different names, to different investors. The information provided by a pair of "twin" funds is identical, so we keep only the older one.[16] Our final sample consists of 2,053 funds from 328 fund families. For comparison, we also identify a sample of 276 stand-alone actively managed domestic equity funds, using otherwise the same criteria. These are funds belonging to a single-fund family for at least 36 months.

B. Empirical Measures

Table I reports summary statistics at the fund-month level for our sample of funds from multifund families. Variable definitions are detailed in Appendix C. Since large families have disproportionately more funds in the sample, these statistics are more reflective of the characteristics of large families than small families. For example, the number of funds simultaneously offered by a family, averaged across fund-months, is 12.44. This is larger than the size of a typical family, which manages on average 6.32 funds in a given month.

We define *Fund flow* as the difference between the monthly growth rate of TNA and the monthly return, expressed in percentage points. To mitigate the effects of extreme observations, potentially due to data errors or fund mergers, we exclude observations below the 1^{st} or above the 99^{th} percentile of the full sample.

Unexpected fund performance in our model, defined in equation (14), corresponds to the well-known Treynor and Black (1973) information ratio, which is the benchmark-adjusted return divided by its volatility. For this reason, we use the information ratio to measure performance. A nice feature of this ratio is that it explicitly accounts for the volatility of abnormal returns. We construct monthly series of information ratios using both the Fama-French three-factor model (Fama and French (1992)) and the Carhart (1997) four-factor model.

[15] For the quarters with a missing company code, we use the mapping between the company name and company code identified in other quarters. A few company names are associated with two different codes. We manually correct them to ensure consistency.

[16] Most twins identified in Evans and Fahlenbrach (2012) consist of one mutual fund and one separate account, which are not in our sample. Following a procedure similar to theirs, we identify 56 pairs of twin funds in our sample. Two funds are viewed as twins if their raw return correlation is above 0.95 and if they are in the same family, are managed by the same managers, and have a similar portfolio turnover rate (specifically, the absolute value of the difference between the two funds' turnover rates is less than 10% of their average turnover rate). Our results are largely the same without this filter.

Table I
Summary Statistics

This table presents summary statistics at the fund-month level, including mean, median, standard deviation, and number of observations. Our mutual fund sample consists of 2,053 domestic equity funds from 328 multifund families in the CRSP mutual fund database from January 1999 to December 2011. Total net asset (TNA), return, and expense ratio are aggregated across all share classes of the same fund. Fund age is the age of the oldest share class. Fund flow is the asset growth rate minus fund return, expressed in percentage points. Alpha is estimated by the Fama-French (1992) three-factor model and the Carhart (1997) four-factor model using rolling windows of 36 months. Fund performance is Alpha divided by idiosyncratic volatility (i.e., information ratio). Family performance is the average of fund performance excluding the fund under consideration. Correlation of idiosyncratic returns is the average pairwise correlation of the factor model residuals between one fund and the other funds in its family, estimated fund-by-fund using rolling windows of 36 months. Manager overlap rate is the average pairwise manager overlap rate between one fund and the other funds in its family, estimated fund-by-fund on a monthly basis. Number of funds within family is the total number of coexisting funds in a fund's family. Variable definitions are in Appendix C.

	Mean	Median	*SD*	*N*
Total net assets (million dollar), TNA	1,366.561	235.200	5,393.651	222,444
Fund age (year), Age	13.265	9.332	13.462	222,586
Monthly return (%)	0.410	0.837	5.786	221,001
Monthly fund flow (%), Fund Flow	0.277	−0.353	4.084	216,197
Annual expense ratio (%), Expense	1.276	1.233	0.424	220,172
Monthly alpha (three-factor, %), Alpha	−0.100	−0.100	0.402	142,622
Monthly alpha (four-factor, %), Alpha	−0.104	−0.100	0.385	142,622
Fund performance (three-factor): Perf	−0.093	−0.084	0.245	142,622
Fund performance (four-factor): Perf	−0.099	−0.091	0.256	142,622
Family performance (three-factor, %): FamPerf	−0.093	−0.092	0.161	142,351
Family performance (four-factor, %): FamPerf	−0.099	−0.096	0.168	142,351
Correlation of idiosyncratic returns (three-factor): Rho	0.191	0.160	0.217	141,140
Correlation of idiosyncratic returns (four-factor): Rho	0.185	0.156	0.207	141,140
Manager overlap rate: Beta	0.181	0.056	0.283	199,692
Number of funds within family: N	12.438	9.000	11.188	222,586
Log number of funds within family: Log(N)	2.181	2.197	0.836	222,586

Monthly factor returns and Treasury rates are obtained from the website of Professor Ken French. A fund's performance, *Perf*, is the ratio of its alpha to the standard deviation of its model residuals, each estimated using rolling windows of 36 months. During each rolling period, we require a fund to remain in the same family and to have at least 30 return observations. Both models estimate an average alpha of about −10 basis points per month. The finding of a negative average alpha is common in the mutual fund literature. One reason is that the benchmark returns do not account for transaction costs.

For a given fund and month, family performance (*FamPerf*) is the average of *Perf* across all funds in the family, *excluding* the fund itself. The correlation of idiosyncratic returns, *Rho*, is also measured at the fund level, using rolling windows of 36 months. It is calculated as the average of the pairwise correlations between a fund and each other fund in its family.[17] Across all fund-months, the average *Rho* calculated using the three- and four-factor models is 0.191 and 0.185, respectively.

For comparison, we calculate the correlations of idiosyncratic returns among the 276 funds in our sample of stand-alone funds using the same procedure. At the fund-month level, the average correlation estimated using the three- and four-factor models is 0.037 and 0.035, respectively. The large gap of about 15 percentage points between the within- and cross-family correlations is evidence of a strong family effect. It highlights the importance of correlated noise within families. Figure 2 plots monthly series of the average within- and cross-family correlations. The difference between the estimates from the three- and four-factor models is small, but the difference between the within- and cross-family correlations is large and stable over time.[18]

Another key parameter in our model is the weight of common skill in a fund's composite skill, β. Given the importance of manager skill in fund management, we construct an empirical measure of this weight using the overlap rate of managers across funds. Our objective is not to quantify common skill, but to capture the correlation of skill between funds. For each pair of funds, the manager overlap rate is defined as the ratio of the number of individuals managing both funds to the average number of managers of the two funds. A fund's β is then given by the average pairwise manager overlap rate between itself and other funds in the family. The idea of this measure is straightforward. Other things equal, two funds managed by the same individual or management team have a larger common component in their unobservable skill than if they were managed by different persons. This is true as long as manager skill contributes to fund performance, and varies across managers.[19] Funds may also use other family resources not captured by the manager overlap rate. However,

[17] By allowing *Rho* to be fund-specific instead of family-specific, we capture more information. Similarly, we also allow the empirical estimate of β to be fund-specific. Our approach can be reconciled with the assumption of a homogeneous family in the theoretical analysis in two ways. First, the family is viewed as homogeneous, but the subset of pairwise correlations we use to estimate this familywide parameter ρ changes from one fund to the next. Second, for each fund i in an N-fund family, we treat the other $N-1$ funds as an artificial fund. The average pairwise *Rho* between fund i and the $N-1$ funds is then an estimate of ρ for the resulting artificial two-fund family. We report the results under the restriction that both estimates of ρ and β are identical across member funds in the Internet Appendix, which may be found in the online version of this article on the *Journal of Finance* website.

[18] Elton, Gruber, and Green (2007) also document a higher correlation of mutual fund returns within than across families.

[19] For evidence of cross-sectional variation in mutual fund manager characteristics and performance, see Chevalier and Ellison (1999). Choi, Kahraman, and Mukherjee (2014) find that alphas of funds managed by the same managers are significantly correlated even after excluding common holdings.

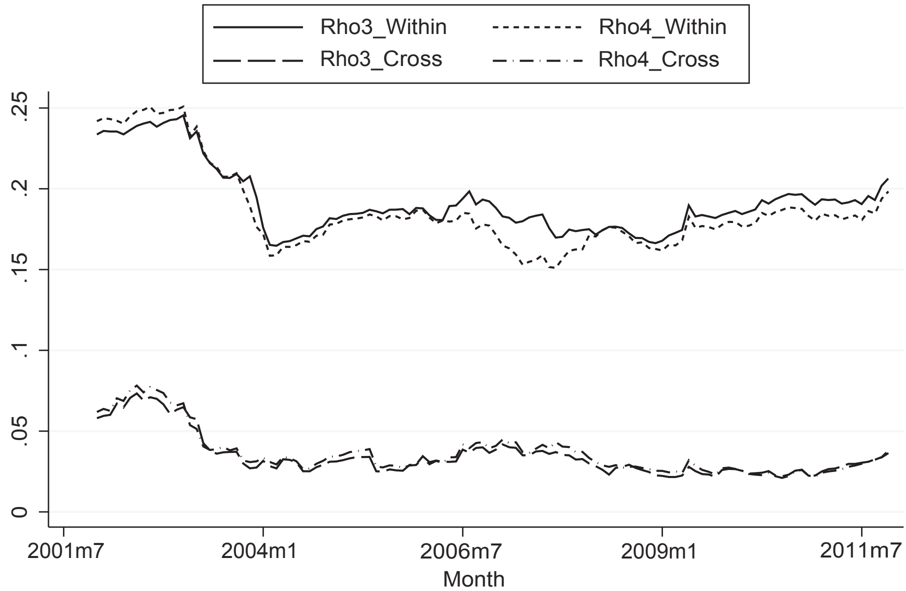

Figure 2. Correlation of idiosyncratic returns: within versus across families. *Rho*3*_Within* and *Rho*4*_Within* are average correlations of idiosyncratic returns within families, estimated using the Fama-French three-factor model and the Carhart four-factor model, respectively. For a given period, we first calculate for each fund its average correlation with other funds in its family, and then average it across all funds in the sample. *Rho*3*_Cross* and *Rho*4*_Cross* are the average correlations of idiosyncratic returns between 276 stand-alone funds, also first calculated pairwise at the fund level and then averaged across funds. Both idiosyncratic returns and correlations are estimated using rolling windows of 36 months.

the variation in those dimensions may be difficult for outside investors to observe. In contrast, mutual funds are required by regulation to fully disclose the names of fund managers. This information is available in fund prospectuses and many public websites. Therefore, our measure captures easily observable, and potentially the most important variation in β.

It is worth noting that funds managed by the same managers are likely to tilt their portfolios in similar directions, so shocks to their returns are more correlated. As a result, without controlling for the noise correlation ρ, the effect of the manager overlap rate on the sensitivity of fund flows to family performance is hard to interpret. Importantly, our empirical models jointly examine the impact of noise correlation and the manager overlap rate. Therefore, what we capture is the effects of variation in β, measured by the manager overlap rate, conditional on a given level of ρ. Our identification does not require the manager overlap rate to be uncorrelated with ρ.

We obtain manager data from Morningstar.[20] The database contains a unique code for each manager, and the start and end dates of each manager at each

[20] While the CRSP database contains an item recording the names of fund managers, it has important limitations. Almost all funds with more than three managers are recorded as

fund. Using CUSIP codes, ticker symbols and fund names, we link funds in Morningstar and CRSP, and obtain manager names for 90% of the fund-months in our CRSP sample. This allows us to calculate the average pairwise manager overlap rate for each fund, *Beta*, on a monthly basis. Table I shows an average manager overlap rate of 0.18 across all fund-months, and a standard deviation of 0.28.

To gauge the impact of the manager overlap rate on fund performance, we calculate the absolute value of the gap between *Perf* and *FamPerf*, and regress it on the manager overlap rate and the logarithm of the number of funds in the family, using the Fama-Macbeth approach (Fama and MacBeth (1973)). The t-statistic of the coefficient on the manager overlap rate, after Newey-West correction (Newey and West (1987)) for autocorrelation up to order three, is -14.10 under the three-factor model and -12.56 under the four-factor model. The point estimates imply that a one-standard-deviation increase in manager overlap rate reduces the absolute value of the performance gap by 0.10 and 0.09 standard deviations, respectively. This evidence suggests that fund performance is more correlated when the manager overlap rate is high.

C. Full-Sample Results

We use the Fama-MacBeth (1973) procedure to investigate the cross-sectional variation in investor responses to fund and family performance. Each month, fund flows are regressed on lagged *Perf* and *FamPerf*, a list of lagged fund characteristics, and the interaction terms between these two sets of variables. The fund characteristics include: manager overlap rate (*Beta*); correlation of idiosyncratic returns (*Rho*); family size (*Log*(*N*)); fund expense ratio (*Expense*); fund size (*Log*(*TNA*)); and fund age (*Log*(*Age*)). Hypotheses H1 to H4 are statements about the signs of the coefficients on the interaction terms. We also include the square of fund performance, $Perf^2$, as a regressor to account for the convexity of the flow-performance relation, reflected in the drift term of dA_{it}/A_{it} in equation (14). Fund age and fund size are highly correlated, so we investigate their effects both separately and jointly.

To account for potential variation in investor preferences for different types of funds over time, we subtract from each fund's monthly flow the contemporaneous mean of all funds in the same Lipper class. Our dependent variable is therefore the style-adjusted fund flow. To facilitate interpretation of the regression results, we also subtract from each fund characteristic its contemporaneous full-sample mean. Therefore, for a fund whose characteristics are at the average levels, the sensitivities of flows to fund and family performance are simply given by the coefficients on *Perf*, $Perf^2$ and *FamPerf*. All t-statistics are corrected for autocorrelation up to order three in the monthly coefficient estimates using the Newey-West (1987) procedure.

The first three columns of Table II report the results using the three-factor model to estimate *Perf*, *FamPerf*, and *Rho*, while the last three columns

"Team-Managed," in which case manager names are not reported. During the period from 2005 to 2011, CRSP designates 32% of funds as Team Managed, while Morningstar designates only 0.2%.

Table II

Responses of Fund Flows to Fund and Family Performance

We run Fama-MacBeth regressions of monthly style-adjusted fund flows on fund performance (*Perf*), its square (*Perf*^{2}), family performance (*FamPerf*), and other explanatory variables (all lagged by one month). *Beta* and *Rho* are, respectively, the average manager overlap rate and the average correlation of idiosyncratic returns of one fund with the other funds in the family. *Log(TNA)*, *Log(Age)*, and *Log(N)* are the natural logarithms of total net asset value, fund age, and number of funds in the family, respectively. *Expense* is the expense ratio. *Beta*, *Rho*, *Log(TNA)*, *Log(Age)*, *Log(N)*, and *Expense* are demeaned using contemporaneous sample means. Variable definitions are in Appendix C. The *t*-statistics (in parentheses) are Newey-West corrected for autocorrelation up to order three. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Three-Factor Model			Four-Factor Model		
	(1)	(2)	(3)	(4)	(5)	(6)
Perf	3.993***	4.227***	3.961***	3.840***	4.019***	3.795***
	(14.56)	(15.00)	(14.58)	(14.30)	(14.99)	(14.40)
Perf^2	3.083***	3.272***	2.944***	2.746***	2.852***	2.609***
	(7.39)	(7.52)	(7.04)	(7.39)	(7.77)	(7.29)
FamPerf	0.689***	0.589***	0.684***	0.780***	0.655***	0.780***
	(5.29)	(4.52)	(5.18)	(5.61)	(4.85)	(5.57)
Beta*Perf	−0.775**	−0.750**	−0.728**	−0.558*	−0.552*	−0.498*
	(−2.41)	(−2.34)	(−2.36)	(−1.87)	(−1.80)	(−1.69)
Beta*FamPerf	1.150***	1.008***	1.057***	1.180***	1.112***	1.163***
	(3.38)	(2.95)	(3.00)	(3.50)	(3.21)	(3.24)
Rho*Perf	1.363***	1.279***	1.375***	1.120***	1.042***	1.076***
	(4.08)	(4.08)	(4.27)	(3.30)	(3.13)	(3.21)
Rho*FamPerf	−1.123*	−1.170*	−1.153*	−1.190**	−1.267**	−1.252**
	(−1.77)	(−1.80)	(−1.77)	(−2.05)	(−2.04)	(−2.05)
Log(N)*Perf	−0.368***	−0.389***	−0.441***	−0.347***	−0.384***	−0.420***
	(−4.50)	(−4.36)	(−4.82)	(−4.45)	(−4.76)	(−4.91)
Log(N)*FamPerf	0.782***	0.762***	0.897***	0.825***	0.758***	0.907***
	(4.23)	(4.07)	(4.45)	(4.98)	(4.34)	(4.84)
Log(Age)*Perf	−1.073***		−1.175***	−1.040***		−1.140***
	(−7.94)		(−8.86)	(−8.99)		(−9.32)
Log(Age)*FamPerf	−0.286		−0.133	−0.330*		−0.219
	(−1.35)		(−0.57)	(−1.71)		(−1.01)
Log(TNA)*Perf		−0.090**	0.100***		−0.074**	0.107***
		(−2.27)	(2.66)		(−2.37)	(3.08)
Log(TNA)*FamPerf		−0.150**	−0.183**		−0.104	−0.125*
		(−2.38)	(−2.58)		(−1.62)	(−1.70)
Beta	−0.044	−0.102	−0.043	0.049	−0.002	0.066
	(−0.47)	(−0.99)	(−0.46)	(0.49)	(−0.02)	(0.66)
Rho	0.007	−0.030	0.019	−0.069	−0.095	−0.074
	(0.07)	(−0.31)	(0.18)	(−0.78)	(−1.06)	(−0.79)
Log(N)	0.003	0.022	−0.001	0.014	0.027	0.005
	(0.11)	(0.91)	(−0.05)	(0.60)	(1.07)	(0.21)
Log(Age)	−0.605***		−0.608***	−0.605***		−0.619***
	(−11.23)		(−11.28)	(−10.91)		(−11.10)
Log(TNA)		−0.102***	0.002		−0.091***	0.014
		(−7.32)	(0.16)		(−6.05)	(1.00)

(Continued)

Table II—*Continued*

	Three-Factor Model			Four-Factor Model		
	(1)	(2)	(3)	(4)	(5)	(6)
Expense	−0.601***	−0.549***	−0.604***	−0.566***	−0.509***	−0.562***
	(−14.45)	(−10.59)	(−12.03)	(−14.19)	(−10.60)	(−11.79)
Constant	0.276***	0.288***	0.276***	0.317***	0.325***	0.316***
	(4.99)	(4.97)	(5.04)	(5.57)	(5.54)	(5.61)
Observations	132,470	132,470	132,470	132,470	132,470	132,470
R^2	0.069	0.061	0.069	0.066	0.057	0.066

correspond to the four-factor model. The two sets of results are very similar, suggesting that the results are robust to the asset pricing model chosen for performance measurement. The estimated coefficients on *Perf*and *Perf*^{2} are positive and highly significant. The positive coefficient on *Perf*^{2} confirms the well-documented convex relation between flows and fund performance. The coefficient on family performance, *FamPerf*, is also positive, and significant at the 1% level. It follows that, for an average fund, investors respond positively to family performance, which means that the common-skill effect dominates the correlated-noise effect. The economic magnitude of the positive spillover effect is also significant. Take Model (6) as an example. For a fund whose manager overlap rate is at the mean level (*Beta* = 0), the sensitivity of fund flows to family performance (*FamPerf*) is 0.780. This implies that flows to the fund increase by 0.131 percentage points per month if family performance (excluding the fund's own performance) increases by one standard deviation (0.168 as shown in Table I).

Hypothesis H1 receives strong support from the data. Fund flows become more sensitive to family performance and less sensitive to fund performance as the manager overlap rate (*Beta*) increases. The coefficient on *Beta***FamPerf* is positive and statistically significant at the 1% level in each column, suggesting that investors rely more on family performance to learn about a member fund's composite skill when *Beta* is high, as our model predicts. The economic magnitude of this effect is significant as well. Consider again Model (6). The coefficient of 1.163 implies that the sensitivity to family performance increases from 0.780 to 1.109, a jump of 42%, if the manager overlap rate increases from the mean level by one standard deviation (0.283). At the same time, the coefficient on *Beta***Perf* is negative across all models, significant at either the 5% or 10% level, supporting the prediction that greater use of common skill reduces the sensitivity of fund flows to fund performance.

The predictions regarding the idiosyncratic return correlation (H2) also receive strong support. Fund flows are more sensitive to fund performance and less sensitive to family performance when a fund's idiosyncratic returns are more correlated with other funds in the family, as we hypothesize. The coefficient on *Rho***Perf* is positive and significant at the 1% level in each column, while the coefficient on *Rho***FamPerf* is significantly negative. Both effects are economically important. In Model (6), for example, the coefficient on *Rho*FamPerf* is −1.252. This implies that, other things equal, an increase of *Rho* by one standard deviation (0.207) from the sample mean reduces the sensitivity of fund flows to family performance by 33%, from 0.780 to 0.521. This suggests that the common-skill effect is significantly offset by the correlated-noise effect as the correlation of idiosyncratic fund returns increases.

The predictions regarding family size (H3) are strongly supported by the data. Fund flows become less sensitive to fund performance and more sensitive to family performance as the number of funds in families increases. The coefficients on *Log*(*N*)**Perf* and *Log*(*N*)**FamPerf* are negative and positive, respectively, and are significant at the 1% level in each column of the table. Because the performance of a large family is a relatively precise signal about family skill, it induces a strong response of fund flows. At the same time, family size reduces the response to fund performance.

Hypothesis H4 is also confirmed by the data. Fund flows are less sensitive to fund performance as a fund grows older. The coefficient on the interaction term *Log*(*Age*)**Perf* is always negative, and significant at the 1% level, consistent with the decline in uncertainty about composite skill as funds grows older, as our model predicts. The coefficient on *Log*(*TNA*)**Perf* is negative and significant when the variables involving fund age are not present, and turns significantly positive as they enter jointly. This is due to the strong positive correlation between fund age and fund size. The sensitivity of fund flows to family performance also declines with fund age and fund size, as Hypothesis H4 predicts, although these effects are often statistically insignificant.

The coefficients on *Log*(*TNA*) and *Log*(*Age*) are negative when these variables enter the regression separately, indicating that larger and older funds on average attract fewer inflows as a percentage of their asset sizes, independent of their performance. This is consistent with our model, in which the positive drift of fund size comes from the convex relation between the estimated composite skill and the equilibrium size. As the uncertainty declines over time, the drift becomes weaker.

To summarize, our results demonstrate that investors use both fund and family performance when they allocate money across mutual funds, and that they do so in a manner consistent with our model of rational learning. Each hypothesis (H1 to H4) receives strong empirical support. The response of fund flows to fund performance is strongest when funds are young and small, when the number of funds in the family is small, when the manager overlap rate is low, and when the correlation of idiosyncratic returns is high. The response to family performance is strongest when funds are young and small, when the family is large, when the manager overlap rate is high, and when the correlation of idiosyncratic returns is low.

D. Subsample Analysis

Our theory demonstrates that the cross-sensitivity of fund flows to family performance can be either positive or negative, depending on family characteristics. Table II shows that this cross-sensitivity is positive for the average fund in our sample. This raises an interesting question: While a negative cross-sensitivity is theoretically possible, is it empirically relevant? Extrapolations using the regression results in Table II suggest that a negative cross-sensitivity can exist if, for example, *Beta* is sufficiently low and *Rho* is sufficiently high. However, this result is more convincing if we can empirically identify a set of funds in which flows react negatively to family performance.

To address this question, we apply the Fama-MacBeth (1973) procedure separately to two subsamples. Sample 1 consists of funds for which the correlated-noise effect is likely to dominate the common-skill effect, while Sample 2 consists of funds with the opposite characteristics. According to our model, funds in Sample 1 should have a low common skill weight β, and a high correlation of noise ρ. Therefore, we include in this sample all funds with (1) a family-size adjusted manager overlap rate (*Beta*) below the contemporaneous sample median, (2) a family-size adjusted idiosyncratic return correlation (*Rho*) above the contemporaneous sample median,[21] and (3) a family size (*Log*(*N*)) below the contemporaneous sample median.[22] Approximately 10% of fund-month observations satisfy these criteria. If investors behave as our model predicts, fund flows should respond negatively to family performance in this sample.

In contrast, Sample 2 consists of funds with (1) an above-median family size-adjusted manager overlap rate, (2) a below-median family size-adjusted idiosyncratic return correlation, and (3) an above-median family size (*Log*(*N*)). Our model predicts that the common-skill effect strongly dominates the correlated-noise effect in this sample.

The results in Table III confirm these predictions. Panels A and B report the results from the three- and four-factor models, respectively. The results in these panels are very similar, and show striking differences between the two subsamples. In Sample 2, the sensitivity of flows to family performance is strongly positive, as our model predicts, and its economic magnitude is substantially bigger than that observed in the full sample. More interestingly, in Sample 1, the fund flow sensitivity to family performance is negative in each model of the two panels, significant at the 1% or 5% level. This confirms the dominance of the common-noise effect, and provides support for the empirical relevance of a novel prediction of our model.

[21] Both the manager overlap rate and idiosyncratic correlation are negatively correlated with the number of funds in the family. This is not a problem for our multivariate regressions, in which family size is controlled for, but may lead to an incorrect classification when we sort funds based on these variables. To adjust for family-size dependence, we first run cross-sectional regressions of these two variables on *Log*(*N*) on a monthly basis, and use the residuals from these regressions to classify funds.

[22] In theory, if the overall spillover effect is negative, it will be amplified by the number of funds in the family. However, the amplification effect may not be as large as for the positive spillover. As Bhattacharya, Lee, and Pool (2013) show, large families may provide liquidity support for members' funds with outflows through AFoMFs. This mitigates the negative spillover effect. For this reason, we include in Sample 1 funds from smaller families, which provide a cleaner environment.

Table III

Fund Flow Sensitivities: Two Subsamples

We run Fama-MacBeth regressions of monthly style-adjusted mutual fund flows on fund and family performance for two subsamples. Sample 1 consists of funds with a below-median family size-adjusted manager overlap rate (*Beta*), an above-median family size-adjusted idiosyncratic return correlation (*Rho*), and a below-mean family size (*Log*(*N*)). Sample 2 consists of funds with the opposite characteristics. *Perf* and *FamPerf* are fund performance and family performance (excluding the fund under consideration), respectively. *Log(TNA)*, *Log(Age)*, and *Log*(*N*) are the natural logarithms of total net asset value, fund age, and number of funds in the family, respectively. *Expense* is the expense ratio. *Log(TNA)*, *Log(Age)*, *Log*(*N*), and *Expense* are demeaned using contemporaneous full-sample means. All explanatory variables are lagged by one month. Variable definitions are in Appendix C. Panel A reports the results when *Perf* and *Rho* are estimated from the three-factor model, while Panel B reports results estimated using the four-factor model. The t-statistics (in parentheses) are Newey-West corrected for autocorrelation up to order three. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Sample 1			Sample 2		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Results from the Fama-French Three-Factor Model						
Perf	5.195***	4.961***	5.307***	3.852***	3.575***	4.215***
	(13.45)	(14.90)	(13.62)	(12.50)	(11.31)	(12.71)
Perf^2	3.097***	3.102***	3.347***	1.840***	1.751***	2.495***
	(3.65)	(4.22)	(3.81)	(3.99)	(3.87)	(5.00)
FamPerf	−0.623**	−0.506**	−0.701***	1.337**	0.857*	1.253**
	(−2.47)	(−1.98)	(−2.80)	(2.59)	(1.77)	(2.44)
Log(Age)*Perf		−1.446***			−1.192***	
		(−4.45)			(−3.82)	
Log(Age)*FamPerf		0.356			−0.447	
		(0.77)			(−1.02)	
Log(TNA)*Perf			0.047			−0.265**
			(0.35)			(−2.12)
Log(TNA)*FamPerf			−0.486***			−0.550***
			(−2.90)			(−3.53)
Log(Age)		−0.625***			−0.829***	
		(−5.96)			(−8.07)	
Log(TNA)			−0.027			−0.189***
			(−0.86)			(−4.35)
Expense		−0.471***	−0.338**		−0.783***	−0.657***
		(−3.87)	(−2.41)		(−7.68)	(−5.68)
Constant	0.284***	0.235***	0.314***	0.470***	0.362***	0.522***
	(4.50)	(4.00)	(4.97)	(5.04)	(5.07)	(4.93)
Observations	13,049	13,017	13,017	14,424	14,424	14,424
R^2	0.069	0.081	0.071	0.062	0.086	0.072
Panel B. Results from the Four-Factor Model (Fama-French Plus Momentum)						
Perf	5.107***	5.051***	5.369***	3.528***	3.306***	3.805***
	(14.04)	(14.91)	(15.15)	(12.65)	(11.85)	(13.20)
Perf^2	2.189***	2.634***	2.678***	1.191***	1.220***	1.513***
	(2.93)	(3.56)	(3.52)	(2.69)	(2.78)	(3.27)
FamPerf	−0.886***	−0.640**	−0.902***	1.273***	0.797**	0.936**
	(−3.75)	(−2.60)	(−3.56)	(3.46)	(2.34)	(2.52)

(*Continued*)

Table III—*Continued*

	Sample 1			Sample 2		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B. Results from the Four-Factor Model (Fama-French Plus Momentum)						
Log(Age)*Perf		−1.799***			−1.183***	
		(−5.48)			(−4.49)	
Log(Age)*FamPerf		1.116**			−0.148	
		(2.51)			(−0.27)	
Log(TNA)*Perf			0.002			−0.232***
			(0.01)			(−2.67)
Log(TNA)*FamPerf			−0.181			−0.234
			(−1.13)			(−1.33)
Log(Age)		−0.617***			−0.744***	
		(−6.00)			(−5.99)	
Log(TNA)			−0.031			−0.153***
			(−1.01)			(−3.35)
Expense		−0.502***	−0.406***		−0.808***	−0.698***
		(−4.41)	(−3.16)		(−8.84)	(−7.06)
Constant	0.366***	0.325***	0.394***	0.511***	0.395***	0.535***
	(6.26)	(5.90)	(6.76)	(5.94)	(6.14)	(5.59)
Observations	13,407	13,375	13,375	14,733	14,733	14,733
R^2	0.067	0.081	0.068	0.060	0.084	0.070

Models (2) and (3) allow the sensitivities to fund and family performance to vary with fund age and fund size. The results further confirm the significance of the negative spillover effect. Interestingly, while the coefficient on *Log*(*Age*)**FamPerf* is negative in Sample 2, as in the full sample, it is positive in Sample 1, and significant at the 5% level in Panel B. This suggests that fund age not only dampens the spillover effect when it is positive, but also mitigates it when it is negative. This provides further support for the hypothesis that the absolute value of flow sensitivity to family performance declines over time (H4). However, there is no evidence that fund size mitigates the negative spillover effect.

The contrasting results from these two subsamples demonstrate the economic importance of both the common-skill and common-noise effects. Either effect can be strong when the other counteracting effect is weak. In particular, the results from Sample 1 show that the dominance of the correlated-noise effect is not only theoretically possible, but also empirically evident for a sizable fraction of funds.

E. Robustness Checks

We conduct several robustness checks and report the results in an Internet Appendix. First, we use alpha instead of the information ratio to measure performance, and present the results for the full sample and the two subsamples, respectively. The patterns are largely the same as those in Tables II and

III, with one exception: the coefficients on *Rho*Alpha* and *Rho*FamAlpha* are either insignificant or marginally significant, although their signs are as expected. Our model suggests that a fund's abnormal return should be normalized by its volatility. In contrast to the information ratio, the alpha measure does not include such an adjustment. It is therefore not surprising that, using this alternative measure, we do not fully capture the effects of the idiosyncratic return correlation on the sensitivities of fund flows to performance.

Second, we use the five-factor model of Pástor and Stambaugh (2003) to measure performance and idiosyncratic return correlations. Traded liquidity, downloaded from the website of Professor Ľuboš Pástor, enters in this model as a risk factor, in addition to the four factors in the Carhart (1997) model. The addition of this risk factor is inconsequential to any of our regressions results.

Third, in our tests so far, we have estimated β and ρ at the fund level, and allow them to vary across funds in the same family. This allows us to capture more fund-specific information relevant for the strength of the spillover effect. As a further robustness check, we impose the restriction that *Beta* and *Rho* are identical across funds in a family, and estimate them as the averages of all pairwise manager overlap rates and idiosyncratic return correlations, respectively, on a monthly basis. The results under this approach are similar to those in Tables II and III, but the coefficients on *Beta*FamPerf* and *Rho*FamPerf* are less significant. This suggests that the strict homogeneity assumption in the estimation leads to a loss of relevant information.

V. Alternative Explanations

While the patterns of mutual fund flows are consistent with our model of optimal cross-fund learning within families, they may have other explanations. We consider four alternatives.

A. Star Family and Dog Family Effects

The positive spillover effects of family performance on flows to a member fund may arise because of the "star family" and "dog family" effects documented by Nanda, Wang, and Zheng (2004). When investors have limited attention or face search costs, the stellar or terrible performance of one fund can put the whole family in the spotlight, and lead investors to direct flows into or out of other member funds. To assess the importance of this mechanism in driving our results, we run our tests accounting for the star family and dog family effects.

Following Nanda, Wang, and Zheng (2004), a star (dog) fund is a fund in the top (bottom) 5% of the distribution of alphas, estimated over 36 months, of all funds in a Lipper class. A star (dog) family is a family that has at least one star (dog) fund under management. We create two dummy variables indicating whether a family is a star or dog family, respectively. Table IV reports the results after these variables are added to our regressions. Columns (1) and (4) confirm the power of a star documented by Nanda, Wang, and Zheng (2004). The significantly positive coefficient on the *Star Family* dummy suggests that

Table IV

Fund Flow Sensitivities: Controlling for Star Family and Dog Family Effects

We run Fama-MacBeth regressions of monthly style-adjusted fund flows on fund performance (*Perf*) and family performance (*FamPerf*), controlling for star family and dog family effects. *Star (Dog) Family* is a dummy variable indicating whether a family has at least one star (dog) fund under management. Other variables are the same as in Table II, and are defined in Appendix C. The t-statistics (in parentheses), omitted for the variables *Log(Age)*, *Log*(*N*), and *Expense* to save space, are Newey-West corrected (in parentheses) for autocorrelation up to order three. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Three-Factor Model			Four-Factor Model		
	(1)	(2)	(3)	(4)	(5)	(6)
Perf	3.289***	3.986***	4.200***	3.137***	3.832***	3.995***
	(17.70)	(14.37)	(14.78)	(17.68)	(14.45)	(15.15)
Star Family	0.142***	−0.004	0.032	0.139***	−0.011	0.023
	(3.24)	(−0.08)	(0.65)	(3.71)	(−0.25)	(0.52)
Dog Family	−0.175***	−0.149***	−0.164***	−0.143***	−0.111***	−0.128***
	(−5.24)	(−4.61)	(−4.77)	(−4.14)	(−3.21)	(−3.44)
Perf^2		3.127***	3.286***		2.773***	2.857***
		(7.35)	(7.40)		(7.63)	(7.93)
FamPerf		0.531***	0.362**		0.683***	0.489***
		(3.49)	(2.47)		(4.10)	(3.04)
Beta*Perf		−0.800**	−0.774**		−0.570*	−0.566*
		(−2.50)	(−2.44)		(−1.90)	(−1.84)
Beta*FamPerf		1.097***	0.962***		1.156***	1.092***
		(3.27)	(2.84)		(3.49)	(3.21)
Rho*Perf		1.366***	1.287***		1.114***	1.046***
		(4.12)	(4.15)		(3.28)	(3.17)
Rho*FamPerf		−1.069*	−1.145*		−1.144*	−1.251**
		(−1.69)	(−1.76)		(−1.97)	(−2.01)
Log(N)*Perf		−0.364***	−0.384***		−0.342***	−0.379***
		(−4.49)	(−4.36)		(−4.40)	(−4.71)
Log(N)*FamPerf		0.688***	0.622***		0.769***	0.657***
		(3.86)	(3.53)		(4.64)	(3.85)
Log(Age)*Perf		−1.068***			−1.035***	
		(−7.88)			(−8.95)	
Log(Age)*FamPerf		−0.284			−0.332*	
		(−1.35)			(−1.72)	
Log(TNA)*Perf			−0.082**			−0.068**
			(−2.06)			(−2.15)
Log(TNA)*FamPerf			−0.141**			−0.096
			(−2.27)			(−1.51)
Beta		−0.037	−0.095		0.061	0.011
Rho		0.021	−0.020		−0.063	−0.095
Log(N)	−0.051*	0.025	0.035	−0.066**	0.037	0.042
Log(Age)	−0.455***	−0.603***		−0.465***	−0.604***	
Log(TNA)	0.007		−0.102***	0.016		−0.091***
Expense	−0.569***	−0.578***	−0.526***	−0.535***	−0.556***	−0.498***
Constant	0.294***	0.296***	0.290***	0.296***	0.340***	0.331***
Observations	132,618	132,470	132,470	132,618	132,470	132,470
R^2	0.068	0.070	0.062	0.065	0.066	0.058

flows to all member funds increase when there is a star in the family. Unlike in their study, we also find that the detrimental effect of a dog fund is highly significant, suggesting that investors have become more alert to extremely poor performance since the time of their study.

The remaining four columns of Table IV report results of our baseline models augmented by the star and dog dummies. The coefficients on our variables are approximately the same as in Table II, but the coefficient on *Star Family* becomes insignificant. This suggests that our model of optimal learning explains the star phenomenon, but not vice versa. Interestingly, the *Dog Family* effect is largely unexplained by our model. It remains significant at the 1% level.

While star (dog) funds naturally attract investor attention, there are other mechanisms for positive spillovers. If many of its funds perform well, even if none are spectacular, a family can attract many new investors, who may then be rerouted to other member funds. Also, families often advertise more aggressively following good family performance, generating more interest in all member funds (Jain and Wu (2000)). However, like the star (dog) family effects, while these mechanisms may generate positive spillovers, they cannot explain why the spillover effect is negative when the correlation of idiosyncratic fund returns is high. In fact, they would suggest spillovers to be more positive among highly correlated funds because families can market one fund more easily based on the success of another fund when funds are similar.

B. Allocation by AFoMFs

The spillover effects within fund families may also be due to capital allocation by AFoMFs. Bhattacharya, Lee, and Pool (2013) document that many large fund families offer AFoMFs, which only invest in other mutual funds in the family. When one or more funds in a family perform well and attract large flows, an AFoMF may reallocate its investment from those funds to other member funds, either to mitigate the diseconomies of scale in fast-growing funds or to provide liquidity support to struggling funds. This creates a positive spillover from well-performing funds to poorly performing funds. On the other hand, an AFoMF may also reallocate investment from poorly performing funds to well-performing ones, either because it seeks high returns for its investors or because its flows are used as an incentive device to reward good performance. This leads to a negative spillover within a family. In either case, spillovers are generated by internal AFoMFs instead of outside investors.

As Bhattacharya, Lee, and Pool (2013, p. 177–198) note, "AFoMFs are typically offered by larger families, in terms of both size (TNA) and the number of funds offered. This makes sense because, as AFoMFs invest only in family funds, AFoMFs will not exist if their investment opportunity set is small."[23] Therefore, we expect the influence of AFoMFs on fund flows to appear mainly in large families. With this in mind, we repeat our tests using families with 10

[23] In their sample, families with AFoMFs offer on average 48 to 57 non-AFoMF funds, while families without AFoMFs offer on average 11 to 13.

or fewer funds. The results are reported in Table V. Although our sample size is reduced by 40%, the results are largely unchanged. The sensitivity of fund flows to family performance for an average fund decreases, as suggested by the coefficient on *FamPerf*, but the cross-sectional relations between flow sensitivities to both fund and family performance and fund characteristics, including the manager overlap rate, the correlation of idiosyncratic returns, family size, fund age, and fund size, are very similar to those in Table II. Since small families usually do not have an AFoMF, we conclude from these results that the cross-sectional patterns that we document cannot be attributed to activities of AFoMFs.

C. Cannibalization within Fund Families

One of our most novel findings is that good family performance has a negative effect on flows to a member fund when idiosyncratic returns are highly correlated. A potential explanation for this finding is cannibalization within families. A negative spillover occurs if investors search for alternative funds only within one family, and they reallocate money from poorly performing to well-performing ones. Such cannibalization is likely to be stronger among funds with high correlations, which are close substitutes for each other. Therefore, cannibalization may cause the overall spillover effect to be smaller, or even negative, when the return correlation is high.

One reason for investors being captive to a family is that mutual funds usually charge front- or back-end loads, which are one-time expenses paid by investors when they purchase or sell a fund. These load fees are often waived when investors switch between funds in the same family. This so-called "exchange privilege" makes a member fund a closer substitute for another member fund than for a nonmember fund. Another potential reason for investors being captive is that they invest through captive brokers, who are often compensated by sharing the load fees (Stoughton, Wu, and Zechner (2011), Christoffersen, Evans, and Musto (2013)).

Since cannibalization is most severe when there is a barrier between fund families created by load fees or captive brokers, we repeat our tests using a sample of families in which investors are least likely to be captive, that is, families with zero or low load fees. Moving into and out of such families is relatively easy. The lower load fees also make the use of captive brokers less likely. If cannibalization drives the negative relation between idiosyncratic correlation and spillovers, then this relation should be weaker in this low-load sample.

We calculate the average maximum front- and back-end loads across a family's member funds each month, and select for each month families with both averages below 1%.[24] We obtain a sample that is about one quarter of the size of our full sample, and report the estimated results in Table VI. Consistent

[24] Load fees vary across share classes, and typically decline with investment volume. We use the maximum of each load across share classes to calculate the loads at the fund level. Funds

Table V

Fund Flow Sensitivities: The Case of Small Families

We run Fama-MacBeth regressions of monthly style-adjusted fund flows on fund performance (*Perf*) and family performance (*FamPerf*), for families with no more than 10 funds. All explanatory variables are the same as in Table II, and are defined in Appendix C. The *t*-statistics (in parentheses), omitted for the variables *Log(Age)*, *Log(N)*, and *Expense* to save space, are Newey-West corrected for autocorrelation up to order three. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Three-Factor Model			Four-Factor Model		
	(1)	(2)	(3)	(4)	(5)	(6)
Perf	4.223***	4.385***	4.104***	4.024***	4.124***	3.882***
	(14.99)	(15.03)	(14.83)	(15.07)	(15.53)	(15.21)
$Perf^2$	3.503***	3.610***	3.242***	3.013***	2.959***	2.674***
	(7.33)	(7.12)	(6.75)	(7.81)	(7.87)	(7.43)
FamPerf	0.223	0.068	0.214	0.320**	0.144	0.319**
	(1.43)	(0.43)	(1.39)	(2.33)	(1.04)	(2.32)
Beta*Perf	−0.736**	−0.733**	−0.629*	−0.568*	−0.551*	−0.430
	(−2.11)	(−2.14)	(−1.91)	(−1.78)	(−1.66)	(−1.36)
Beta*FamPerf	0.969***	0.855**	0.872**	0.989***	0.959**	0.999**
	(2.82)	(2.41)	(2.43)	(2.80)	(2.58)	(2.62)
Rho*Perf	1.928***	1.897***	1.854***	1.740***	1.663***	1.595***
	(5.71)	(5.87)	(5.86)	(4.96)	(4.76)	(4.70)
Rho*FamPerf	−1.109*	−1.243*	−1.126*	−1.282**	−1.450**	−1.367**
	(−1.76)	(−1.92)	(−1.75)	(−2.21)	(−2.33)	(−2.26)
Log(N)*Perf	−0.386**	−0.585***	−0.555***	−0.417**	−0.628***	−0.581***
	(−2.18)	(−3.20)	(−2.94)	(−2.25)	(−3.25)	(−2.99)
Log(N)*FamPerf	0.537**	0.422*	0.713***	0.630***	0.430*	0.771***
	(2.37)	(1.84)	(2.96)	(2.89)	(1.96)	(3.34)
Log(Age)*Perf	−1.132***		−1.308***	−1.063***		−1.268***
	(−6.44)		(−7.81)	(−6.66)		(−8.04)
Log(Age)*FamPerf	−0.029		0.096	−0.049		0.049
	(−0.14)		(0.38)	(−0.25)		(0.21)
Log(TNA)*Perf		−0.036	0.192***		0.015	0.230***
		(−0.66)	(4.00)		(0.36)	(5.46)
Log(TNA)*FamPerf		−0.125*	−0.212**		−0.068	−0.145
		(−1.70)	(−2.42)		(−0.90)	(−1.61)
Beta	−0.151	−0.218**	−0.127	−0.084	−0.138	−0.037
Rho	0.027	0.001	0.018	−0.021	−0.057	−0.066
Log(N)	−0.179***	−0.275***	−0.218***	−0.183***	−0.288***	−0.224***
Log(Age)	−0.527***		−0.578***	−0.527***		−0.590***
Log(TNA)		−0.048***	0.047***		−0.033**	0.062***
Expense	−0.518***	−0.455***	−0.485***	−0.482***	−0.415***	−0.445***
Constant	0.217***	0.213***	0.208***	0.261***	0.251***	0.251***
Observations	83,085	83,085	83,085	83,085	83,085	83,085
R^2	0.064	0.059	0.066	0.061	0.055	0.062

Table VI

Fund Flow Sensitivities: Families with Less than 1% Maximum Load Fees

We run Fama-MacBeth regressions of monthly style-adjusted fund flows on fund performance (*Perf*) and family performance (*FamPerf*), for families charging on average zero or less than 1% front- and back-end load fees. All explanatory variables are the same as in Table II, and are defined in Appendix C. The t-statistics (in parentheses), omitted for the variables *Log(Age)*, *Log*(*N*), and *Expense* to save space, are Newey-West corrected for autocorrelation up to order three. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Three-Factor Model			Four-Factor Model		
	(1)	(2)	(3)	(4)	(5)	(6)
Perf	3.310***	3.527***	3.250***	3.250***	3.397***	3.167***
	(12.77)	(12.01)	(11.61)	(12.12)	(11.44)	(10.91)
Perf^2	2.359***	2.529***	2.424***	2.343***	2.426***	2.357***
	(4.84)	(4.55)	(4.38)	(4.97)	(4.60)	(4.55)
FamPerf	1.590***	1.081***	1.591***	1.973***	1.462***	1.972***
	(4.32)	(2.71)	(4.46)	(5.80)	(3.96)	(6.16)
Beta*Perf	−0.722	−0.803	−0.659	−0.752	−0.833	−0.644
	(−1.24)	(−1.40)	(−1.17)	(−1.35)	(−1.50)	(−1.18)
Beta*FamPerf	1.668***	0.914*	1.451***	2.159***	1.462**	2.019***
	(3.52)	(1.95)	(2.98)	(3.84)	(2.54)	(3.39)
Rho*Perf	1.416*	1.689**	1.419**	1.328**	1.606**	1.274**
	(1.91)	(2.29)	(2.01)	(2.01)	(2.37)	(2.01)
Rho*FamPerf	−2.332***	−2.160***	−2.111***	−2.907***	−2.665***	−2.793***
	(−2.98)	(−2.73)	(−2.68)	(−3.91)	(−3.43)	(−3.60)
Log(N)*Perf	−0.735***	−0.750***	−0.744***	−0.708***	−0.748***	−0.706***
	(−4.87)	(−4.37)	(−4.10)	(−4.29)	(−4.04)	(−3.53)
Log(N)*FamPerf	1.566***	1.265***	1.745***	1.998***	1.627***	2.098***
	(4.36)	(3.43)	(4.73)	(6.26)	(5.01)	(6.67)
Log(Age)*Perf	−1.063***		−1.137***	−1.066***		−1.108***
	(−4.23)		(−3.91)	(−4.82)		(−4.29)
Log(Age)*FamPerf	−0.177		0.028	−0.265		−0.156
	(−0.40)		(0.06)	(−0.66)		(−0.35)
Log(TNA)*Perf		−0.129*	0.029		−0.133*	0.015
		(−1.84)	(0.33)		(−1.94)	(0.18)
Log(TNA)*FamPerf		−0.280***	−0.269**		−0.193*	−0.169
		(−2.84)	(−2.33)		(−1.89)	(−1.42)
Beta	0.149	−0.050	0.154	0.238	0.046	0.264
Rho	−0.458***	−0.393**	−0.434***	−0.537***	−0.462**	−0.546***
Log(N)	−0.053	−0.097	−0.080	−0.052	−0.108	−0.090
Log(Age)	−0.718***		−0.743***	−0.751***		−0.786***
Log(TNA)		−0.072***	0.031		−0.061***	0.042*
Expense	−0.405***	−0.362***	−0.364***	−0.349***	−0.321***	−0.319***
Constant	0.379***	0.401***	0.374***	0.400***	0.419***	0.394***
Observations	32,550	32,550	32,550	32,550	32,550	32,550
R^2	0.047	0.041	0.049	0.044	0.037	0.045

with the idea that load fees intensify cannibalization that reduces positive spillovers, we find a much more positive spillover effect of family performance in this low-load sample. In five of the six models, the coefficients on *FamPerf* are more than twice the full-sample results in Table II.[25] At the same time, the cross-sectional patterns of flow sensitivities predicted by our model show up even more strongly. The estimated positive impacts of the manager overlap rate and family size on the spillover effect are generally bigger than those in Table II. More strikingly, the coefficient on the interaction term *Rho*FamPerf* is significantly negative at the 1% level in all models, and its magnitude is doubled in four of the six models, compared to the results in Table II. This suggests that the negative relation between idiosyncratic return correlation and the spillover effect is stronger when investments are less captive. Therefore, this negative relation is unlikely to be explained by cannibalization within families. These results demonstrate that the cross-sectional predictions of our model, derived under perfect capital mobility, receive even stronger support when there are fewer frictions in investors' capital allocation process.

D. Style Effects

The spillover effects we uncover may also reflect "style effects," arising because investors learn across funds with similar styles or because of competition among such funds. Both the manager overlap rate and idiosyncratic return correlation are positively related to the similarity of funds' investment styles.[26] This is because managers tend to manage funds with similar strategies, and factor models usually do not fully capture common return components for funds with similar styles. As a result, for a fund with high *Beta* or high *Rho*, good family performance may indicate that funds of similar styles are performing well. This can create a negative spillover through two channels: (i) a correlated-noise effect as we model, applied to funds in the same style instead of family, and (ii) stronger competition, as funds with similar styles are close substitutes. In addition, strong style performance may also generate a positive spillover, either through the common-skill effect we model or through investors chasing outperforming style. However, such positive within-style spillovers are unlikely to explain the positive within-family spillovers we find because all flows in our analysis are adjusted by contemporaneous style means.

To test the importance of the style effects discussed above, we add lagged style performance (*StyPerf*), measured by the average *Perf* of all funds belonging to a

without load data for any share class are treated as no-load funds. The average maximum front- and back-end loads are 2.8% and 2.0%, respectively, across all funds and months in our sample.

[25] Note that this coefficient measures the spillover effect for a fund whose characteristics are the full-sample means. The low-load families are generally smaller, with an average mean-adjusted $Log(N)$ of -0.5.

[26] Consistent with this statement, both the average manager overlap rate and the average idiosyncratic return correlation, adjusted for family size, are positively related to the concentration of investment styles in a family, measured by the Herfindahl index based on the number of funds in each *Lipper* fund class.

Table VII

Fund Flow Sensitivities: Controlling for Style Performance

We run Fama-MacBeth regressions of monthly style-adjusted fund flows on fund performance (*Perf*) and family performance (*FamPerf*), controlling for style performance (*StyPerf*), defined as the average *Perf* of all funds in the same Lipper class except the fund under consideration. All other explanatory variables are the same as in Table II, and are defined in Appendix C. The *t*-statistics (in parentheses), omitted for the variables *Log(Age)*, *Log(N)*, and *Expense* to save space, are Newey-West corrected for autocorrelation up to order three. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Three-Factor Model			Four-Factor Model		
	(1)	(2)	(3)	(4)	(5)	(6)
Perf	4.570***	4.801***	4.543***	4.383***	4.562***	4.339***
	(16.86)	(17.20)	(16.92)	(16.43)	(16.99)	(16.55)
Perf^2	3.141***	3.327***	3.000***	2.842***	2.946***	2.705***
	(7.56)	(7.61)	(7.14)	(7.70)	(7.96)	(7.49)
FamPerf	0.481***	0.386***	0.478***	0.611***	0.491***	0.614***
	(4.13)	(3.30)	(4.03)	(4.81)	(3.98)	(4.79)
StyPerf	−3.963***	−3.882***	−3.989***	−3.760***	−3.716***	−3.754***
	(−21.61)	(−21.88)	(−22.38)	(−22.73)	(−20.87)	(−23.16)
Beta*Perf	−0.895***	−0.859***	−0.835***	−0.641**	−0.625**	−0.570**
	(−2.94)	(−2.83)	(−2.86)	(−2.24)	(−2.13)	(−2.02)
Beta*FamPerf	1.021***	0.864**	0.910**	1.014***	0.918***	0.969***
	(3.02)	(2.55)	(2.61)	(3.07)	(2.72)	(2.77)
Rho*Perf	1.198***	1.118***	1.207***	0.961***	0.897***	0.927***
	(3.84)	(3.79)	(4.00)	(3.05)	(2.88)	(2.98)
Rho*FamPerf	−0.763	−0.802	−0.779	−0.770	−0.833	−0.817
	(−1.25)	(−1.29)	(−1.25)	(−1.41)	(−1.43)	(−1.43)
Log(N)*Perf	−0.338***	−0.369***	−0.421***	−0.312***	−0.359***	−0.395***
	(−4.38)	(−4.31)	(−4.81)	(−4.31)	(−4.72)	(−4.91)
Log(N)*FamPerf	0.624***	0.621***	0.753***	0.690***	0.646***	0.791***
	(3.56)	(3.49)	(3.93)	(4.28)	(3.81)	(4.37)
Log(Age)*Perf	−1.039***		−1.157***	−1.000***		−1.115***
	(−7.50)		(−8.58)	(−8.50)		(−9.16)
Log(Age)*FamPerf	−0.267		−0.094	−0.311		−0.173
	(−1.31)		(−0.41)	(−1.65)		(−0.81)
Log(TNA)*Perf		−0.072*	0.115***		−0.057*	0.121***
		(−1.85)	(3.12)		(−1.80)	(3.50)
Log(TNA)*FamPerf		−0.165***	−0.201***		−0.126**	−0.152**
		(−2.78)	(−2.98)		(−2.10)	(−2.20)
Beta	−0.097	−0.157	−0.097	−0.001	−0.055	0.014
Rho	0.114	0.080	0.131	0.033	0.012	0.033
Log(N)	−0.018	0.006	−0.020	−0.007	0.009	−0.015
Log(Age)	−0.618***		−0.618***	−0.614***		−0.625***
Log(TNA)		−0.108***	−0.001		−0.096***	0.011
Expense	−0.531***	−0.483***	−0.538***	−0.504***	−0.451***	−0.504***
Constant	−0.056***	−0.031	−0.059***	−0.025	−0.010	−0.027*
Observations	132,470	132,470	132,470	132,470	132,470	132,470
R^2	0.086	0.078	0.087	0.083	0.074	0.083

fund's Lipper class except the fund itself, as an additional explanatory variable. The results are reported in Table VII. Style performance has a very negative effect on a fund's inflows. One obvious reason is that flows are style-adjusted. As investors chase an outperforming style, a fund's flow relative to its style mean declines. However, results in the Internet Appendix show that unadjusted flows are also negatively affected by style performance, although the effect is only significant for the three-factor model. This suggests that, unlike family performance, style performance carries primarily a negative competition or common-noise effect.

Importantly, none of our previous results change noticeably after controlling for style performance, except the coefficients on *Rho*FamPerf* become statistically insignificant. The point estimates of this coefficient remain negative, ranging from -0.76 to -0.83, at about two-thirds their values in Table II. The weakened impact of *Rho* on family performance spillover effect after controlling for style performance is not surprising. Fund performance and style performance are positively correlated. This means that, as *Rho* increases, family performance becomes more correlated with style performance, and its incremental value in noise reduction decreases. The results for unadjusted flows, reported in the Internet Appendix, are very similar.

To summarize, while the alternative theories we consider may account for some aspects of mutual fund flows sensitivities, none of them can explain the rich cross-sectional patterns we empirically document. In contrast, our model of rational cross-fund learning provides an unifying explanation for all main patterns we report.

VI. Conclusion

The performance of a mutual fund depends on both its fund-specific characteristics and the quality of the common resources of its family. The use of family resources in the alpha-generating process introduces a common component in member funds' unobservable skill. It also induces a positive correlation of noise in idiosyncratic fund returns. These observations suggest rich possibilities of cross-fund learning within families. We develop a model that characterizes the optimal evaluation of a fund's composite skill in such an environment, and test whether mutual fund investors allocate money across funds in a manner that is consistent with rational cross-fund learning within families.

Our model highlights two potential impacts of one fund's performance on the optimal estimate of the skill of another fund in the family: a positive common-skill effect and a negative correlated-noise effect. The overall spillover depends on the relative strength of these two effects. Our theoretical analysis pins down the key variables that determine the sensitivities of beliefs about composite skill to both fund performance and family performance, including the number of funds in the family, the importance of common skill in alpha generation, the correlation of noise in fund returns, as well as fund size and fund age.

We empirically test our model predictions about mutual fund flows, and find strong support. Good family performance on average has a positive effect on fund flows to a member fund, suggesting the dominance of the common-skill effect. It has a stronger impact for funds in larger families, funds with a higher manager overlap rate, and funds with a lower correlation of idiosyncratic returns with other funds in their families. Interestingly, for the subsample of funds with a below-median manager overlap rate, an above-median correlation of idiosyncratic returns, and a below-median family size, the response of fund flows to family performance is significantly negative. This suggests the dominance of the correlated-noise effect in these funds. The sensitivity of flows to a fund's own performance decreases with fund age, the manager overlap rate, and family size, but increases with the correlation of idiosyncratic returns within families.

We have focused on the Berk and Green (2004) equilibrium of the mutual fund industry with no frictions in fund flows. As a result, there is no predictability in mutual fund returns. Family performance relevant for the optimal updating of beliefs is immediately reflected in fund flows. In practice, it is likely that transaction costs in reallocating money across funds cause temporary deviations from such an equilibrium. Family performance is then useful in predicting both fund returns and fund flows. This is a fruitful avenue for future research.

While we model the evaluation of mutual funds in a family, the basic insight of our theory is relevant in many other situations in which the performance of multiple units depends on both unobservable common fundamentals and correlated noise. For example, empirical studies show that many components of executive compensation, such as stock or options, depend on absolute performance rather than performance relative to peers (Murphy (1999)). Recent studies also find that forced CEO turnovers are negatively related to both peer-adjusted and absolute performance (Jenter and Kanaan (2014)). These findings contradict the simple model of relative performance evaluation. Accounting for both common-skill and correlated-noise effects may lead to a better understanding of these results. Our modeling framework may also be used to evaluate mutual funds or hedge funds with the same investment style, or stocks in the same industry or geographic region.

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Appendix A: Proof of Proposition 1

PROOF: We apply theorem 12.7 of Lipster and Shiryaev (2001), using (4) as the observation equation and $d\boldsymbol{\theta} = 0$ as the state equation, recognizing that composite skill is constant. The theorem gives equation (5) directly, where $\mathbf{S}_t$ is given in equation (7), and

$$d\mathbf{W}_t^{\mathcal{F}} = \left(d\boldsymbol{\xi}_t - \mathbf{m}_t dt\right). \tag{A1}$$

The vector $d\mathbf{W}_t^{\mathcal{F}}$ defined in equation (A1) is a set of correlated Brownian motions under $\mathcal{F}_t$ with correlation matrix $\mathbf{BB}'$, and is the innovation in the signal process $\boldsymbol{\xi}_t$. Taking the expectation of both sides of equation (2), we have

$$\mathbf{m}_t = \boldsymbol{\sigma}_t^{-1}[\mathrm{E}(\boldsymbol{\alpha}_t|\mathcal{F}_t) + \gamma\boldsymbol{\sigma}_t\boldsymbol{\sigma}_t\mathbf{A}_t + \mathbf{f}_t].$$

Substituting for $d\boldsymbol{\xi}_t$ using equation (4), equation (A1) becomes (8).

The theorem also gives

$$\frac{d\mathbf{V}_t}{dt} = -\mathbf{V}_t(\mathbf{BB}')^{-1}\mathbf{V}_t \tag{A2}$$

for the conditional variance, starting from a given prior variance $\mathbf{V}_0$. This is a matrix Ricatti equation. We substitute for $\mathbf{V}_t$ using equation (6), where $\mathbf{Q}_t$ is to be found. For any invertible $\mathbf{Q}_t$, $\frac{d\mathbf{Q}_t^{-1}}{dt} = -\mathbf{Q}_t^{-1}\frac{d\mathbf{Q}_t}{dt}\mathbf{Q}_t^{-1}$. Thus, equation (A2) is equivalent to $d\mathbf{Q}_t/dt = \mathbf{I}_{n\times n}$, where $\mathbf{I}_{n\times n}$ is an $n \times n$ identity matrix. A solution is equation (10), where the initial values $Q_{ij}(0)$ are elements of $\mathbf{Q}_0 = \mathbf{B}'\mathbf{V}_0^{-1}\mathbf{B}$. ■

Appendix B: Proof of Proposition 2

PROOF: In a homogeneous two-fund family,

$$\boldsymbol{V}_0 = v_{20}\begin{bmatrix} 1 & \lambda \\ \lambda & 1 \end{bmatrix},$$

$$\mathbf{B} = \begin{bmatrix} 1 & 0 \\ \rho & \sqrt{1-\rho^2} \end{bmatrix},$$

and

$$\mathbf{Q}_t = \frac{1}{v_{20}(1-\lambda^2)}\begin{bmatrix} 1 - 2\lambda\rho + \rho^2 + (1-\lambda^2)v_{20}t & \sqrt{1-\rho^2}\,(\rho-\lambda) \\ \sqrt{1-\rho^2}\,(\rho-\lambda) & 1-\rho^2+(1-\lambda^2)v_{20}t \end{bmatrix}.$$

We derive the elements of the matrices $\boldsymbol{V}_t$ and $\mathbf{S}_t$ by substituting for $\mathbf{B}$ and $\mathbf{Q}_t$ in equations (6) and (7), respectively. It is then apparent that the diagonal elements of each matrix equation are identical, and similarly for the off-diagonal elements.

The diagonal elements of equation (6) are

$$\begin{aligned} v_{2t} &= v_{20}\frac{1-\rho^2+(1-\lambda^2)v_{20}t}{[\rho+(1+\lambda)\,v_{20}t+1][1-\rho+(1-\lambda)\,v_{20}t]} \\ &= v_{20}\frac{1}{1+\frac{[\rho+(1+\lambda)v_{20}t+1]\,[1-\rho+(1-\lambda)v_{20}t]-[1-\rho^2+(1-\lambda^2)v_{20}t]}{1-\rho^2+(1-\lambda^2)v_{20}t}}, \end{aligned}$$

which is equivalent to equation (19) after some algebra and after substitution using the definition of $k(t)$. The off-diagonal elements of equation (6) are

$$\begin{aligned}\bar{v}_{2t} &= v_{20}\frac{\lambda(1-\rho^2)+\rho(1-\lambda^2)v_{20}t}{[\rho+(1+\lambda)v_{20}t+1][1-\rho+(1-\lambda)v_{20}t]}\\ &= v_{20}\frac{1-\rho^2+(1-\lambda^2)v_{20}t}{[\rho+(1+\lambda)v_{20}t+1][1-\rho+(1-\lambda)v_{20}t]}\frac{\lambda(1-\rho^2)+\rho(1-\lambda^2)v_{20}t}{1-\rho^2+(1-\lambda^2)v_{20}t},\end{aligned}$$

which is equivalent to equation (20).

The diagonal and off-diagonal elements of equation (7) are

$$s_{2t} = v_{20}\frac{1-\rho^2+(1-\lambda^2)v_{20}t}{[\rho+(1+\lambda)v_{20}t+1][1-\rho+(1-\lambda)v_{20}t]}\frac{1-\rho\lambda+(1-\lambda^2)v_{20}t}{1-\rho^2+(1-\lambda^2)v_{20}t}$$

and

$$\bar{s}_{2t} = v_{20}\frac{1-\rho^2+(1-\lambda^2)v_{20}t}{[\rho+(1+\lambda)v_{20}t+1][1-\rho+(1-\lambda)v_{20}t]}\frac{\lambda-\rho}{1-\rho^2+(1-\lambda^2)v_{20}t},$$

respectively. These are equivalent to equations (21) and (22), respectively.

Taking partial derivatives of $\bar{s}_{2t}$ with respect to λ and ρ, we have

$$\begin{aligned}\frac{\partial\bar{s}_{2t}}{\partial\lambda} &= v_{20}\frac{[(\lambda^2-2\lambda\rho+1)v_{20}t+2(1-\rho^2)]v_{20}t+1-\rho^2}{[1-\rho^2+(1-\lambda^2)v_{20}t+(1-\rho^2+(1-\lambda^2)v_{20}t+(\lambda-\rho)^2)v_{20}t]^2}\\ &> 0,\\ \frac{\partial\bar{s}_{2t}}{\partial\rho} &= -v_{20}\frac{[(1-\lambda^2)v_{20}t+2(1-\lambda^2)]v_{20}t+(\lambda-\rho)^2+(1-\lambda^2)}{[1-\rho^2+(1-\lambda^2)v_{20}t+(1-\rho^2+(1-\lambda^2)v_{20}t+(\lambda-\rho)^2)v_{20}t]^2}\\ &< 0.\end{aligned}$$

Holding v_{20} constant, $\frac{\partial\bar{s}_{2t}}{\partial\beta}$ and $\frac{\partial\bar{s}_{2t}}{\partial\lambda}$ have the same sign because λ increases monotonically in β (see equation (16)). Therefore, we also have $\frac{\partial\bar{s}_{2t}}{\partial\beta} > 0$. ■

Appendix C: Variable Definitions in Empirical Analysis

This appendix details the construction of variables for the empirical analysis. In the regressions, *Beta*, *Rho*, *Log*(*TNA*), *Log*(*Age*), *Log*(*N*), and *Expense* are adjusted by subtracting the contemporaneous full-sample means. The monthly fund flow is adjusted by subtracting the contemporaneous mean of all funds in the same Lipper class.

Fund Flow = Monthly growth rate of total net asset value minus monthly return (in %), truncated at the 1st and 99th percentiles.

Alpha = Monthly alpha (in %) estimated over rolling windows of 36 months, using various factor models (Fama-French, Carhart, and Pástor-Stambaugh). A minimum of 30 observations is required.

Perf = Monthly alpha estimated over rolling windows of 36 months, divided by monthly idiosyncratic volatility estimated over the same period.

$Perf^2$ = The square of *Perf*.

FamPerf = The average *Perf* of all funds in the same family *excluding* the fund under consideration.

FamAlpha = The average *Alpha* of all funds in a family *excluding* the fund under consideration.

StyPerf = The average *Perf* of all funds in the same Lipper fund class excluding the fund under consideration.

Beta = The average manager overlap rate of one fund with the other funds in its family. For each pair of funds, the overlap rate is defined as the number of managers common to both funds divided by the average number of managers of the two funds.

Rho = The average correlation of idiosyncratic returns between one fund and the other funds in its family, estimated fund-by-fund over a rolling window of 36 months. A minimum of 30 overlapping monthly return observations is required for each pair.

Star (Dog) Family = A dummy variable equal to one if a family has at least one fund in the top (bottom) 5% of the distribution of alphas in its Lipper fund class, and zero otherwise.

Log(TNA) = The natural log of total net asset value, aggregated across a fund's share classes.

Log(Age) = The natural log of fund age (in years), defined by a fund's oldest share class.

Log(N) = The natural log of the number of funds offered by a family.

Expense = Expense ratio (in %), value-weighted by assets in each share class.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.