The Invisible Hand of Internal Markets in Mutual Fund Families *

Luis Goncalves-Pinto † Juan Sotes-Paladino ‡

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Abstract

The internal markets of fund families can induce member funds to deviate excessively from their investment mandates. Theoretically, we show that fund managers who follow sufficiently different style benchmarks are likely to engage in risk-shifting by trading with one another at low cost inside their family. This benefits the managers and the family even in the absence of a family-level strategy. However, the excessive risks taken by the managers can be costly to fund investors. Empirically, we find support for the positive effect of intra-family style diversity on offsetting trades across funds and on deviations of funds' portfolios from their benchmarks.

Keywords: Mutual fund families, cross-trading, benchmarking, stock illiquidity.

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† Luis Goncalves-Pinto, National University of Singapore, Department of Finance, 15 Kent Ridge Drive, MRB BIZ1 Level 7-43, Singapore 119245; Tel. +65 6516-4620; Email: lgoncalv@nus.edu.sg

‡ Juan Sotes-Paladino, University of Melbourne, Department of Finance, Level 12, 198 Berkeley St, VIC 3010, Australia; Email: juan.sotes@unimelb.edu.au

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Abstract

The internal markets of fund families can induce member funds to deviate excessively from their investment mandates. Theoretically, we show that fund managers who follow sufficiently different style benchmarks are likely to engage in risk-shifting by trading with one another at low cost inside their family. This benefits the managers and the family even in the absence of a family-level strategy. However, the excessive risks taken by the managers can be costly to fund investors. Empirically, we find support for the positive effect of intra-family style diversity on offsetting trades across funds and on deviations of funds' portfolios from their benchmarks.

1 Introduction

Mutual fund families can potentially make up very large internal markets. The median family manages nearly $6 billion in assets and has 5 funds under its umbrella. Moreover, up to 35% of the portfolios of funds affiliated with the same family is invested in the same stocks. Funds in need of rebalancing their portfolios will thus likely search within their family first for counterparties to their trades, as trading in the internal market is less costly compared to trading with the external market.[1] In this paper, we argue both theoretically and empirically that the internal markets within fund families not only reduce transaction costs for their member funds but also increase the potential for misalignment between the investment policies of the funds and the mandates of their respective shareholders.

We model a family consisting of two funds that follow different benchmarks. Fund managers maximize expected utility of end-of-period compensation, which is positively related to the money flows of the fund investors. Building on the findings of Sirri and Tufano (1998) and Basak, Pavlova, and Shapiro (2007), we assume that investors' flows are a convex function of funds' past performance relative to the performance of their style benchmarks (DelGuercio and Tkac (2002)). In order to motivate trading in the internal market, we account for the empirically documented overlap in stock holdings inside a family by assuming that member funds share some of their portfolio holdings. In the model, the internal market offers an advantage over the external market only for trades in illiquid holdings. We then allow the two fund managers in our family to meet at the start of the investment period and decide whether it is in their mutual best interest to cross-trade some of their illiquid holdings. After this initial meeting, managers choose their funds' investment policies independently of each other.

[1] Chalmers, Edelen, and Kadlec (2013) estimate that the annual trading costs for equity funds are of first order relevance, averaging 1.44% of fund assets. In line with these estimates, a survey study conducted by the Bank for International Settlement (BIS (2003)) points to savings on transaction arising from "crossing of trades" as one of the main factors behind the trend towards consolidation among investment managers in the asset management industry.

The first outcome of our model is that style diversity alone can induce cross-trading within a fund family. As a result, trades in the same asset but in opposite directions can happen even when fund managers share the same information and have the same preferences. Moreover, the cross-trading in our model is not coordinated at the family-level but results from the optimal decentralized investment decision of the individual fund managers. The mechanism is as follows: (i) fund managers seek to beat their benchmarks to increase their personal compensation; (ii) to improve the chance of beating their benchmarks, managers need to deviate their portfolio composition away from the composition of their benchmarks; (iii) a manager following a risky benchmark deviates by taking safe bets, while a manager following a safe benchmark deviates by taking risky bets; (iv) when deviating at the same time, the first manager could be underweighting a risky illiquid asset that the second manager seeks to overweight in her portfolio, which creates the opportunity for cross-trading. The internal market within the mutual fund family facilitates these interfund trades, even without the need for a family-level strategy.

We show that the more disperse the styles that these funds follow, the higher the probability that they place opposite orders on the same asset, and the larger the expected magnitude of the internal trade. As a result, cross-trading increases monotonically with style dispersion and can be substantial in diverse enough families. Style diversity is then both a necessary condition for, and positively related to, the decentralized cross-trading in our model. In the empirical section of the paper we find support for this prediction.

Throughout the rest of the investment period, fund managers do not necessarily rebalance their portfolios towards their respective benchmark compositions. Hence, the initial cross-trade along with the subsequent trading alter the average portfolio liquidity of the family-affiliated funds relative to their benchmarks in a way that differs significantly from standalone funds (i.e., equivalent funds with no possibility of cross-trading). When following a low-liquidity style, funds increase liquidity relative to the benchmark more when they belong to a family. Conversely, funds following a high-liquidity style decrease portfolio liquidity more when affiliated with a family. Moreover, the deviation of funds' liquidity from the liquidity of the benchmark increases with style diversity within the family.

As if led by an "invisible hand" of internal markets, the decentralized cross-trading that maximizes each of the fund manager's utility also increases the benefits accruing to the family as a whole despite the absence of a family-level strategy.[2] It helps increase the value of future assets under management for the family, because it allows fund managers to take advantage of the relation between performance and future flows to a larger extent. We show that the benefits accruing to the family increase with the dispersion of styles within the family. These results provide an alternative rationale for fund families to offer a diverse menu of investment styles across their funds, as observed in practice.

However, there is also a dark side to the internal market in our model, as fund investors bear the burden of cross-trading in the form of delegation costs. Family-affiliated funds may appear to beat their standalone counterparts when evaluated by common performance measures such as the return-to-risk ratio. However, these measures fail to capture the option-like risk profile of fund returns that results from managers' dynamic policies in response to convex incentives. We compute utility from delegation to show that for the investors of at least one of the funds the net costs of delegation can approximate 0.4% per year. These investors would be better off by delegating their portfolios to a standalone fund instead, as cross-trading allows family-affiliated counterparts to take excessive risks. Overall, our results suggest that investors' decision to invest in family-affiliated versus standalone funds involves trading off the lower transaction costs versus the higher risk-shifting costs that result from the possibility of cross-trading.

We use a sample of U.S. domestic actively managed equity mutual funds to examine

[2] The "invisible hand" is an expression used by Adam Smith to describe his belief that individuals seeking their economic self-interest actually benefit society more than they would if they tried to benefit society directly.

empirically the novel predictions of our model. Specifically, we test the hypothesis that the style diversity offered by a family is positively related to (i) the level of intra-family offsetting trades, and (ii) the deviation of funds' portfolio liquidity relative to the liquidity of their style benchmarks, with the sign of the deviation depending on the benchmark liquidity. We measure intra-family style diversity by looking at the correlations of returns across all the benchmarks followed by the funds affiliated with the same family.[3]

We find that the diversity in styles offered by a mutual fund family is a first-order determinant of the offsetting trades within the family. Even after controlling for strategic cross-fund subsidization (Gaspar, Massa, and Matos (2006)), the extent of overlap in holdings, and the flow correlations across funds affiliated with the same family, a one standard deviation increase in style diversity is associated with a 25% increase in intra-family offsetting trades of illiquid stocks. As predicted by our model, this effect is present only *within* families: style diversity has no effect on the level of interfund trading for placebo families, which we create by randomly drawing comparable funds from different families. Second, we find that style diversity is positively associated with the deviation of liquidity between funds and their style benchmarks, and that the sign of this deviation depends on whether the benchmark has low or high average liquidity, as predicted by our model.

Our paper is related to the growing literature on cross-trading within asset management companies. In their seminal work, Gaspar, Massa, and Matos (2006) find that one way in which mutual fund families can transfer performance across member funds ('cross-fund subsidization'), to favor those funds with a higher expected contribution to family profits, is to have them cross-trade at below or above market prices. Chaudhuri, Ivkovic, and Trzcinka (2014) find evidence of a similar strategic performance re-allocation across the

[3] Our measure of intra-family style diversity is defined as the (negative of the) minimum of all the pairwise correlations of returns across the different benchmarks followed by the funds affiliated with the same family. The composition of these benchmark portfolios is outside of the control of the fund family. This way we avoid the endogeneity issues that would arise if pairwise correlations were computed using fund returns instead of benchmark returns.

different products offered by an institutional asset management company, with stronger effects occurring within illiquid investment styles. Casavecchia and Tiwari (2014) document a similar effect for brokers and other clients of the fund advisor, at the expense of the mutual fund clients. Eisele, Nefedova, and Parise (2014) provide transaction-level evidence of the cross-subsidization incentive hypothesized in Gaspar, Massa, and Matos (2006).[4]

We contribute to this literature in at least two ways. First, prior studies emphasize centralized decisions that favor some funds at the expense of others, whereas we study cross-trading that can happen without a centralized decision maker. Since actual mutual funds' trades are likely the outcome of both centralized and decentralized decisions, our results suggest that the exclusive focus of prior research on the centralized decisions of fund families may have understated the real costs to fund investors derived from interfund transactions. Second, most of this literature emphasizes agency costs stemming from cross-trades executed at 'transfer prices' that deviate from the prevailing market prices. In the U.S. context, these trades are clearly against SEC Rule 17(a)-7 of the Investment Act of 1940, which allows cross-trading as long as the transaction is effected at the "independent current market price of the securities" and is in the best interests of *both* the selling and the buying funds. The cross-trades in our model are executed at fair market prices and can improve the measured performance of both funds involved in the transfer. To the extent that investors in one or both funds are made worse off, these cross-trades still go against Rule 17(a)-7 but should arguably be harder to detect by regulatory authorities than in the cross-subsidization case in practice.

Our paper is also related to a more incipient theoretical research on the investment decisions of family-affiliated funds. Closest to ours is the paper by Binsbergen, Brandt, and Koijen (2008), who study the under-diversification and agency costs to an investor who

[4] Other empirical studies documenting family-level strategies within mutual fund complexes include Nanda, Wang, and Zheng (2004) and Bhattacharya, Lee, and Pool (2013).

delegates the administration of her savings to a fund family with multiple asset managers investing in different asset classes. The problem these authors analyze is different from ours in important respects. Asset classes are mutually exclusive in their framework, ruling out cross-trading by design. We show that in the presence of illiquidity and risk-shifting incentives, families can benefit from allowing some overlap in asset holdings across their different investment styles, which is consistent with the evidence.

The rest of the paper proceeds as follows. We set up our model in Section 2. We solve the model and discuss its main implications in Section 3. We provide empirical evidence consistent with the novel predictions of our model in Section 4. We conclude in Section 5.

2 Model Setup

Our goal is to study the asset allocation decision of mutual fund managers that seek to maximize the value of their compensation when (1) funds belong to a family organization, and (2) the securities managers trade may be not perfectly liquid. The choice of our theoretical framework attempts to capture the distinct features introduced by (1) and (2) to our problem without departing significantly—thus avoiding results that arise mechanically from a completely different setup—from prior literature. First, we follow the partial-equilibrium, dynamic approach in the analysis of family-affiliated asset management companies of Binsbergen, Brandt, and Koijen (2008). Second, we incorporate the concerns about future assets under management of open-end mutual funds as examined by Basak, Pavlova, and Shapiro (2007). Third, we motivate the introduction of a cross-trading "platform" within the mutual fund family by modeling asset illiquidity in the spirit of Longstaff (2001). We expand on each of these modeling choices bellow.

2.1 The Economy

We consider an economy in which investors (households) delegate the administration of their savings to mutual funds over a certain investment horizon $[0, T]$ (e.g., one calendar year). Mutual fund companies have access to financial markets consisting of three risky assets, with prices denoted by $S_i(t)$, for $i \in \{1, 2, C\}$:

$$dS_i(t) = \mu_i S_i(t)dt + \sigma_i S_i(t)dZ_i(t), \tag{1}$$

where μ_i and σ_i are constant, as are the correlation coefficients among the assets $0 \leq \rho_{kl} < 1$, for $k, l \in \{1, 2, C\}$, and $k \neq l$ (i.e. $E[dZ_k(t)dZ_l(t)] = \rho_{kl}dt$). Uncertainty is governed by the standard Brownian motion processes $Z_i(t)$, for $i \in \{1, 2, C\}$. Asset prices are assumed to start the investment period at the value $S_i(0) = s_i$.

The first two assets trade in perfectly liquid markets, whereas asset C trades in a *thin* market. We follow Longstaff (2001) in considering a market thin when its participants can only adopt trading strategies that are of *bounded variation*, i.e., the number of shares $\varphi_j(t)$ of asset C that can be bought or sold per unit of time is limited:

$$dN_C(t) = \varphi_j(t)dt, \tag{2}$$

where $-\infty < -\alpha \leq \varphi(t) \leq \alpha < +\infty$, for $\alpha > 0$, and $N_C^j(t)$ is the number of shares of the illiquid asset C in a fund's portfolio as of time t.

Equation (2) reflects a situation where traders' ability to buy or sell asset C is limited or restricted, so that building up or unwinding a large position in this security may take an extended period of time. In this way, traders behave as if accounting for the transitory price impact of their orders (see, e.g., Isaenko (2008)). This assumption represents a departure from the Black-Scholes-Merton complete financial market structure, and is key in our setup to motivate the convenience of cross-trading within a mutual fund family over trading in open, possibly thin, markets. Since the bulk of the transaction costs that mutual funds pay are in the form of price impact rather than in bid-ask spreads (see Edelen, Evans, and Kadlec (2013)), we choose this approach over the traditional proportional costs approach to model this friction in our setup.[5] As highlighted by Longstaff (2001), modeling illiquidity according to (2) has the convenient additional feature of leading to endogenous borrowing and short-selling constraints, a pervasive restriction observed in the mutual fund industry in practice (see, e.g., Almazan, Brown, Carlson, and Chapman (2004)).

Agents in our economy have constant relative risk aversion (CRRA) preferences over consumption of wealth at the terminal date T:

$$U_k(w) = \frac{w^{1-\gamma_k}}{1-\gamma_k}, \tag{3}$$

where $\gamma_k > 1$ and $k \in \{m, c, h\}$ denotes, alternatively, a fund manager m, a Chief Investment Officer (CIO) of the family organization c,[6] or a delegating household h. We further consider delegating investors' heterogeneous preferences for different investment styles by assuming that these investors are indexed by their relative risk aversion (RRA) coefficient γ_h in an interval $[\underline{\gamma}, \overline{\gamma}]$, for $\underline{\gamma} < \gamma_m < \overline{\gamma}$. We introduce fund managers and CIO and explain their objectives in subsection 2.4, after we introduce the mutual funds and the family organization in the next subsection.

[5] See, e.g., Constantinides (1986) and Dai and Yi (2009) for analyses of the impact of proportional transaction costs on the portfolio choice decisions of investors.

[6] In the asset management industry, a Chief Investment Officer is a board-level manager for an investment company. For most mutual fund families, CIOs have the responsibility for the investments and strategy of the overall group and oversee the team of investment professionals in charge of the individual funds' investments.

2.2 Investment Styles and Mutual Funds

We assume that investors' heterogeneity in appetite for risk translates into a preference for funds with different risk-return profiles, or 'investment styles' (e.g., large-cap value). Styles are identified by benchmark portfolios that invest in different, though not necessarily mutually exclusive, sets of assets. We consider two of such investment styles, L and S. Style L can be thought of as a conservative strategy focusing on liquid risky assets, such as well-known publicly traded large-cap ("L") stocks, while style S can be thought of as an aggressive strategy investing predominantly in illiquid risky assets, such as small-cap ("S") stocks. Consequently, we characterize style L by a portfolio of assets 1 and C, with a higher weight on the liquid asset 1. We characterize style S by a portfolio of assets 2 and C, with predominance of the illiquid asset C. Thus, only the illiquid asset C is held in common by both benchmark portfolios. This is without loss of generality, since the introduction of a liquid asset held in common by both benchmark portfolios—possibly, in larger proportion than the illiquid asset—would not lead to cross-trading and, as a result, would not qualitatively affect our result in later sections. In addition, the existence of a substantial overlap in illiquid stocks across different style benchmarks is empirically supported by the evidence we present in Section 4.

A style benchmark $Y_j(t)$ for $j \in \{1, 2\}$ is the value process of a (self-financing) traded portfolio holding $B^i_C(t)$ shares of asset C and investing $Y_j(t) - B^i_C(t)S_C(t)$ in asset j. We set $B^j_C(t) = y_j \beta^j_C(0)/s_C$, where $\beta^j_C(0)$ is the initial weight of asset C on benchmark j, for $j \in \{1, 2\}$. Benchmark 1 represents the relatively liquid investment style L, while benchmark 2 represents the relatively illiquid style S: $0 \leq \beta^1_C(0) < \beta^2_C(0) \leq 1$. Benchmark j's dynamics are given by:

$$dY_j(t) = \left[Y_j(t)\mu_j + B^j_C(t)S_C(t)(\mu_C - \mu_j)\right] dt + Y_j(t)\sigma_j dZ_j(t) + \\ + B^j_C(t)S_C(t)\left[\sigma_C dZ_C(t) - \sigma_j dZ_j(t)\right], \quad (4)$$

along with the initial condition $Y_j(0) = y_j$, $j \in \{1, 2\}$. Each benchmark portfolio represents a passive buy-and-hold strategy that keeps the *number of shares* of the illiquid asset as of time $t = 0$ constant over the investment period.[7]

Given each benchmark's weight in the illiquid asset C, we consider that investment style L (respectively, S) is catered to an investor with RRA coefficient γ_{h1} (γ_{h2}) if $\beta_C^1(0)$ ($\beta_C^2(0)$) equals the weight $\beta_{unc,C}^1(\gamma_{h1})$ ($\beta_{unc,C}^2(\gamma_{h2})$) of C in the optimal unconditional portfolio that this investor would choose under self-management and perfect liquidity for all assets. For $j \in \{1, 2\}$, this weight can be easily solved (see, e.g., Chen and Pennacchi (2009)) as:

$$\beta_{unc,C}^j(\gamma_{hj}) = \frac{\mu_C - \mu_j + \sigma_j^2 - \rho_{jc}\sigma_j\sigma_C}{\gamma_{hj}(\sigma_j^2 + \sigma_C^2 - 2\rho_{jc}\sigma_j\sigma_C)}. \tag{5}$$

Our analysis of the utility implications of family-affiliated fund strategies in Section 3.5 focuses on the investor with RRA coefficient γ_{hj}, $j \in \{1, 2\}$. Assuming that delegating investors self-select into the closest benchmark to their unconditionally efficient portfolio (5), we also examine the utility implications for investors in each *risk-appetite clientele*, i.e., investors whose RRA coefficients lie in a neighborhood of γ_{h1} or γ_{h2}.

We consider two types j of mutual funds, $j \in \{1, 2\}$. Fund 1 follows investment style L and is administered by portfolio manager $m1$, whereas fund 2 follows style S and is administered by portfolio manager $m2$. The value of fund j's self-financing portfolio, $F_j(t)$, is:

$$\begin{aligned} dF_j(t) = & \left[F_j(t)\mu_j + N_C^j(t)S_C(t)(\mu_C - \mu_j)\right] dt + F_j(t)\sigma_j dZ_j(t) + \\ & + N_C^j(t)S_C(t)\left[\sigma_C dZ_C(t) - \sigma_j dZ_j(t)\right] \end{aligned} \tag{6}$$

[7] A fixed-weight benchmark would instead be continuously rebalanced to hold the *relative weights* of the assets in the portfolios constant over the investment period. Since asset C is illiquid in our framework, it can be infinitely costly for a manager to keep the relative weight of this asset in her portfolio constant. Keeping the *number of shares* constant (a buy-and-hold strategy on asset C) instead is a more natural specification for a benchmark portfolio in our setup.

with initial value $F_j(0) = f_j$, for $j \in \{1, 2\}$. We constrain these portfolios to lie in the closed solvency region:

$$\mathscr{S} = \left\{ (S_j(t), S_C(t)) \in \mathbb{R}^2 : N_j(t) S_j(t) + N_C^j(t) S_C(t) \geq 0 \right\} \tag{7}$$

for all $t \in [0, T]$, where $N_j(t)$ denotes the number of shares of the liquid asset j that fund $j \in \{1, 2\}$ holds as of time t. Table 1 summarizes the main elements of the mutual fund structure introduced above.

[Insert Table 1 about here]

Due to the assumption of illiquidity in our setup, a fund's initial number of shares is not a variable of choice but an additional parameter in the model. We remove this degree of freedom in our setup by assuming that fund j's initial portfolio composition equals the composition of its benchmark: $n_C^j s_C / f_j = \beta_C^j(0)$ (i.e., $n_C^j = B_C^j(0)$ when $f_j = y_j$), where $n_C^j \geq 0$ is the initial number of shares of asset C in fund j's portfolio, for $j \in \{1, 2\}$. Remember that under illiquidity managers can adjust their portfolios only *gradually* over time. Hence, any other choice of n_C^j would arbitrarily impose a positive or negative benchmark-adjusted return on the fund portfolios right after the investment period starts. Our assumption for n_C^j avoids the equally arbitrary policies that managers would choose in response to this discretionary initial relative performance. Regardless, we explain in later sections that our qualitative results do not depend on this particular parameterization of funds' initial portfolio.

Manager's Compensation: We set fund managers' compensation to be proportional to the value of their assets under management and due at the investment horizon $t = T$.[8] Apart from the initial delegation of wealth, we assume that external cash inflows to or outflows from the funds occur only at the investment horizon and are a pre-specified function

[8] This compensation structure is in line with standard practice in the mutual fund industry.

of a fund's performance relative to its style benchmark. More precisely, we borrow from Basak, Pavlova, and Shapiro (2007) the following flow-performance relationship:

$$\phi_j(T) = \begin{cases} \phi_j^L & \text{if } R_j^F(T) - R_j^Y(T) < \eta_j \\ \phi_j^L + \psi_j \left[e^{R_j^F(T) - R_j^Y(T)} - e^{\eta_j} \right] & \text{if } R_j^F(T) - R_j^Y(T) \geq \eta_j, \end{cases} \tag{8}$$

where for $j \in \{1, 2\}$, $R_j^F(T) = \ln(F_j(T)/F_j(0))$ and $R_j^Y(T) = \ln(Y_j(T)/Y_j(0))$ denote the continuously-compounded return of fund j's portfolio and of benchmark j's portfolio, ϕ_j^L and ψ_j are positive constants, and $\eta_j \in \mathbb{R}$. We set $Y_j(0) = F_j(0)$ without loss of generality.

According to relationship (8), flows depart (arrive) at the constant rate $\phi_j(T) < 1$ ($\phi_j(T) > 1$) when fund j underperforms its benchmark by a margin greater than η_j, and arrive at the increasing rate $\psi_j\big(\exp(R_j^F(T) - R_j^Y(T)) - \exp(\eta_j)\big)$ otherwise. This flow relationship is meant to capture Sirri and Tufano (1998)'s empirical finding that fund investors' flows penalize very poor and moderately poor performance at a similar rate but reward good performance at an increasingly higher rate.[9]

Specification (8) can alternatively be interpreted as an explicit compensation contract according to which the fund family remunerates a fund manager with a fixed fee over assets under management plus a bonus conditional on meeting a given performance target. Such compensation structure has been shown to be optimal in delegated asset management contexts by, e.g., Maug and Naik (2011), Basak, Pavlova, and Shapiro (2008), Li and Tiwari (2009) and Dybvig, Farnsworth, and Carpenter (2010). Moreover, they are standard in practice in the mutual fund industry as reported by Ma, Tang, and Gomez (2015).

[9] We choose this flow-performance relation over Chevalier and Ellison (1997)'s empirical specification in order to capture the greater cash inflows to star performers in a fund family as found empirically by Nanda, Wang, and Zheng (2004). However, we do not consider the latter authors' documented 'spillover' effect to other funds in the same family of a star performer, as this would introduce strategic interactions between the portfolio decision problems of the fund managers. Such a problem is significantly harder to solve, but would likely result in even stronger cross-trading than in our simplified setup.

2.3 Family-Affiliated vs. Standalone Funds

Mutual funds 1 and 2 can be affiliated to a family (FA funds) or standalone (SA funds).[10] What makes a family different from just a portfolio of two standalone funds in our setup is the possibility of avoiding public markets at $t = 0$ by trading X shares of their common asset C across the two funds. In the U.S., SEC Rule 17(a)-7 of the Investment Act of 1940 allows cross-fund trading as long as the transaction is effected at the "independent current market price of the securities" and is in the best interests of *both* the selling and buying funds.[11] Although we recognize that cross-trading can happen at any point during the investment period $[0, T]$, we restrict it to occur only at the start of the period for tractability and interpret our results as a lower bound on the effects that can be expected in the real world. Two FA funds that decide to not cross-trade are indistinguishable from two SA funds in our model. This assumption allows us to distinguish our results from the effects arising from coordinated investment decisions at the overall family level, which have been thoroughly examined by prior literature.[12] We nonetheless briefly examine how centralized decisions affect our results in Section 3.4.

After cross-trading each FA fund is managed independently according to its own style. The dynamics of the funds' assets under management during $t \in (0, T]$ are still given by equation (6) but the funds' initial conditions change to:

$$N_C^1(0) = n_C^1 - X, \tag{9}$$

[10] A family is the prevalent organizational form in the U.S. mutual fund industry, see e.g., Gaspar, Massa, and Matos (2006). We abstract from looking into the reasons behind the emergence of families as an organizational form in the first place, or the factors determining families' optimal size, and take them as given instead.

[11] The latter condition was stipulated in a no-action letter (Federated Municipal Funds (November 20, 2006)) in which the SEC staff provided clarification on Rule 17(a)-7 with respect to an investment adviser's fiduciary duties in connection with Rule 17(a)-7 transactions. This condition prohibits transactions that are in the best interest of one fund but are otherwise neutral to the other fund.

[12] See the literature review in Section 1.

$$N_C^2(0) = n_C^2 + X. \qquad (10)$$

Thus, a positive value of X is interpreted as a purchase of asset C by fund 2 from fund 1, whereas a negative value represents the opposite transaction. We impose the condition that $-n_C^2 \leq X \leq n_C^1$ (no 'internal' short-selling). Equations (9) and (10) implicitly prevents cross-trading at 'transfer prices' in our setup, ruling out by assumption a situation in which one fund's performance is boosted by having it sell (buy) shares from the other fund at above-market (below-market) prices.[13] Funds 1 and 2 are standalone when $X = 0$.

2.4 Fund Managers' Problem

Family-affiliated mutual funds solve a two-stage recursive problem. Given the extent of cross-trading X at $t = 0$, in the second stage $t \in (0, T]$ fund j's manager solves the following problem:

$$V_j(F_j, Y_j, N_C^j, S_C, t) = \sup_{\varphi_j(t)} E_t \left[\frac{[\phi_j(T) F_j(T)]^{1-\gamma_{mj}}}{1 - \gamma_{mj}} \right], \qquad (11)$$

subject to the price process (1) for asset C, the dynamics of the assets under management (6), the benchmark process (4), and the initial conditions (9) and (10).

In the first stage of the problem, at $t = 0$, managers decide whether they trade with each other, and the number of shares of asset C to exchange if they do. Rational managers solving problem (11) will be willing to engage in cross-trading only if by doing so they can increase their indirect utility $V_j(f_j, y_j, n_C^j + x_j, s_C, 0)$, with $\{x_1(X), x_2(X)\} = \{-X, X\}$, relative to no cross-trading, $V_j(f_j, y_j, n_C^j, s_C, 0)$, $j \in \{1, 2\}$. Defining $\Delta V_j(X) \equiv V_j(f_j, y_j, n_C^j + x_j(X), s_C, 0) - V_j(f_j, y_j, n_C^j, s_C, 0)$, we thus assume that managers agree at the outset on the following constrained max-min rule to determine their time-0 cross-trading:

$$X = \arg\max_{X'} \left(\min\{\Delta V_1(X'), \Delta V_2(X')\} \right) \qquad s.t. \quad \min\{\Delta V_1(X'), \Delta V_2(X')\} > 0. \qquad (12)$$

[13] This type of strategies was first examined empirically by Gaspar, Massa, and Matos (2006).

According to this rule, FA fund managers will trade with each other only if (1) *both* managers' strictly benefit from so doing, and (2) the extent of cross-trading X is determined by the maximum improvement in utility achieved by the manager that benefits the least. This rule is consistent with a standard market adjustment whereby the "short side" of the market dominates, and excludes the possibility of side payments between managers that encourage otherwise sub-optimal participation in a cross trade.[14] Note that problem (12) does not necessarily have a solution, in which case managers will not trade with each other and will behave as SA funds throughout the entire investment period.

In case managers do decide to cross their trades, we assess the net impact on the overall family of the FA funds' decentralized cross-trading and investment policies by computing two performance measures. The first measure assumes that a Chief Investment Officer (CIO) runs the family company by deciding, for instance, the benchmarks that FA funds follow. We do not model this decision explicitly but, following Binsbergen, Brandt, and Koijen (2008), assume that the CIO's compensation is proportional to the family's end-of-period assets under management $W(T) \equiv \phi_1(T)F_1(T) + \phi_2(T)F_2(T)$. The CIO's derived utility, for each level of cross-trading X is:

$$V_c(X) = E_0 \left[\frac{W^*(T)^{1-\gamma_c}}{1-\gamma_c} \right], \tag{13}$$

where $W^*(T)$ is the terminal value of the family's AUM when the FA funds agree on the extent of cross-trading X and implement the optimal policies $\{\varphi_1^*(t), \varphi_2^*(t)\}$ during $t \in (0, T]$.[15]

Our second measure is the end-of-period (continuously-compounded) return of the family

[14] As is intuitive, Fig. 2 in Section 3 suggests that allowing for these type of side payments in our model should lead to *higher* levels of cross trading across all scenarios we consider.

[15] The CIO in our setting cares about the overall value of the family but has no role in the investment decision. Our setting could easily be modified to allow for the CIO to decide on the extent of cross-trading that maximizes the value of the family, in the spirit of the empirical findings of Gaspar, Massa, and Matos (2006). We prefer to focus on a previously unexplored type of cross-fund transactions in the rest of the paper, namely those that are determined at the individual fund level with no intervention of a centralized decision maker. We nevertheless briefly explore the CIO's problem in Subsection 3.4.

after flows or, equivalently, the expected growth of assets under management $R^*(T) \equiv \ln\big(W^*(T)/W(0)\big)$. Both $V_c(X)$ and $R^*(T)$ assume that the family benefits from managing a larger pool of assets, the only difference being that $V_c(X)$ accounts for higher-order moments in the distribution of total AUM growth rates. We examine both measures in Section 3 to determine whether managers' decentralized decisions are in the best interest of the family.

3 Model Solution

The assumption of imperfect liquidity in our model is a necessary condition to create cross-trading within fund families but prevents us from obtaining a closed-form solution to problem (11). Instead, we solve the model numerically using the Least-Squares Monte Carlo algorithm proposed in Longstaff and Schwartz (2001) and adopted in Longstaff (2001) to find the solution of a portfolio choice problem. Succinctly, this method involves replacing the conditional expectation function in (11) by its orthogonal projection on the space generated by a finite set of basis functions of the values of the state variables that are part of the managers' problem.[16] From this explicit functional approximation, we can solve for the optimal control variable $\varphi_j^*(t)$ for $t \in (0, T]$ for any starting value of $N_C^j(0)$ as given by the solution to manager j's Hamilton-Jacobi-Bellman equation. Because the control is constrained, this solution is as follows: if $\partial V_j/\partial N_C^j > 0$ then $\varphi_j^*(t) = \alpha$, and if $\partial V_j/\partial N_C^j < 0$ then $\varphi_j^*(t) = -\alpha$, whenever such amount of trading α is admissible, otherwise $\varphi_j^*(t) = 0$, for $j \in \{1, 2\}$.

Given the optimal trading strategies $\varphi_j^*(t)$ managers decide the extent of cross-trading at the start of the period according to the rule (12). Portfolio weights held in the risky illiquid asset C by fund j can then be easily retrieved, for each time $t \in (0, T]$, from the relation:

$$\omega_C^j(t) = \omega_C^j(0) + \int_0^t \frac{S_j(u)}{F_j(u)} \varphi_j^*(u) du \tag{14}$$

[16] We used up to the third order power polynomials of all the state variables (accounting for their interactions) and the first three powers of the utility function as basis functions.

where $\varphi_j^*(0) = 0$, $\omega_C^j(0) = N_C^j(0)s_C/f_j$, and the remainder $(1 - \omega_C^j(t))$ is invested in the liquid asset j that is specific to the investment style of fund $j \in \{1, 2\}$.

The numerical results presented throughout the rest of this Section are based on 100 time steps—the discretization period is 0.01 years—and 100,000 simulated paths for the state variables. Without loss of generality, we normalize the values of the funds' assets under management and of their corresponding benchmarks to unity at $t = 0$, i.e. $s_C = s_j = f_j = y_j = 1$, for $j \in \{1, 2\}$. We set the initial value of the total holdings of illiquid asset C within the family $(n_C^1 + n_C^2)s_C$ to one, so that $\beta_C^2(0) = 1 - \beta_C^1(0)$.

We consider a baseline and several alternative scenarios for the rest of the model parameters as detailed in Appendix A. In our baseline scenario we approximately match historical market data in the U.S. where available, and use calibrated values based on prior literature otherwise. The alternative scenarios allow us to check the robustness of our results to different parameterizations of the model and to derive testable predictions from comparative statics analyses. We calibrate the managers and the CIO in our model to exhibit "typical" levels of relative risk aversion as documented in the literature, and the family to offer investment styles catered to both more and less risk averse fund investors. To prevent non-observable differences in risk aversion between managers from driving our results, we further assume that managers have the same risk tolerance: $\gamma_{m1} = \gamma_{m2}$. We briefly discuss the case $\gamma_{m1} \neq \gamma_{m2}$ in Subsection 3.3.

3.1 Opposite Trades Induced by Relative Performance Concerns

As first pointed out theoretically and empirically by Basak, Pavlova, and Shapiro (2007) and Chen and Pennacchi (2009), under a flow-performance relationship like (8) a manager can deviate systematically from her benchmark in response to expected money flows. These deviations are unrelated to asset fundamentals, are time-varying, and can either overweight or underweight an asset in the manager's portfolio relative to the benchmark depending on the riskiness of the benchmark.[17]

Following this argument, when a family offers multiple investment styles some of its member funds can deviate from different benchmarks by simultaneously trading in common assets but in opposite directions. These trades need not be the result of opposite signals about the same security, but purely the consequence of performance concerns relative to the benchmarks characterizing their different investment styles. The average deviations of the portfolio weights of standalone (SA) funds 1 and 2 ($X = 0$) from their benchmarks depicted in Figure 1 illustrates this argument.

[Insert Figure 1 about here]

Indeed, the two SA funds in our baseline scenario will adopt opposite excess positions in the illiquid asset C in many situations over the investment period, with fund 1 overweighting and fund 2 underweighting this asset in their portfolios. Both managers share the same information and preferences in our model.[18] Thus, this opposite behavior is the result of managers' optimal response to their flow-performance relationship as characterized by Basak, Pavlova, and Shapiro (2007), with the additional constraint on trading imposed by asset illiquidity. Initially, the liquid benchmark 1 underexposes manager $m1$ to the illiquid asset C, to which $m1$ responds over the first fifth of the period by increasing asset C in the portfolio relative to the benchmark. The opposite is true for manager $m2$, who is initially overexposed to the illiquid asset C and attempts to reduce instead the weight in this asset relative to the benchmark.

[17] In line with this argument, Huang, Sialm, and Zhang (2011) find empirically that active mutual fund managers change their portfolio risk dynamically over time, increasing or decreasing it depending on their interim position relative to peers. Dai, Goncalves-Pinto, and Xu (2016) show that these effects weaken in the presence of liquidity restrictions, although managers' deviations from the benchmark can still remain significant.

[18] In particular, the symmetry in managers' risk preferences and their complete information about economic fundamentals means that, as direct traders, their portfolio decisions in perfectly liquid markets would be identical at each point in time. Thus, no trading between them could occur.

As each fund's performance relative to its respective benchmark varies over time, managers hedge against changes in expected flows by increasing or decreasing their excess exposure in asset C. Notably, average *changes* in the excess holdings of these two funds exhibit opposite signs during most of the period. For instance, between $t = 0.35$ and $t = 0.45$ manager 1 increases her excess position in C relative to the benchmark by more than 2%, while manager 2 decreases it by about the same proportion. Moreover, the correlation coefficient between the two funds' changes for the entire period in Figure 1 is -0.09. Since asset C is illiquid and thus costly to trade in external markets, Figure 1 suggests that there could be many instances in which trading with each other could be in the best interest of *both* SA funds.

3.2 Optimal Cross-Trading

If asset C were perfectly liquid managers would have no need to cross their opposite trades within the family because they could trade at zero cost in the open market. However, the restricted ability to buy or sell shares of asset C forces managers to pay a positive transaction cost, equal to the shadow price of illiquidity, when placing opposite and relatively large orders in the open market for this asset. Under SEC Rule 17(a)-7, both managers could then reduce these costs by 'crossing' their trades within the family.[19]

Figure 2 illustrates how benchmark concerns can give rise to substantial decentralized cross-trading between FA mutual funds in our model. When managing SA funds (NCT), both managers would decrease their indirect utility if fund 1 sought to enhance its profile as a style-L fund by *selling* shares of asset C to fund 2. By contrast, both fund managers could increase their utility if fund 1 *bought* shares of asset C from fund 2 instead. Specifically, manager $m1$ would agree to buy $|X| = 0.07$ shares of C from fund 2 as the resulting portfolio

[19] We assume that managers do not compete with each other within the fund family. See Taylor (2003) and Basak and Makarov (2014) for an analysis of the risk-shifting incentives induced by the strategic interaction among managers of the same family when their compensation is based on tournaments.

would maximize her indirect utility over all possible levels of cross-trading. Manager $m2$ would agree to the cross trade—and would be willing to sell even more shares of C—because the transaction allows her to improve her utility relative to the NCT case. That is, cross-trading in our setup is a mutually beneficial outcome arising from each manager's pursuit of her self-interest. Internal markets within the family can therefore improve both managers' utility. From Fig. 2 and our analysis of Table 2 below, it should be clear that this result is not unique to our assumption about funds' initial portfolio composition: even higher levels of optimal cross-trading can result from alternative values of the corresponding parameters.[20]

[Insert Figure 2 about here]

The purchase of 0.07 shares of asset C by fund 1 from fund 2 deviates these funds' initial portfolio composition from the benchmark. In particular, it makes the liquid fund 1 more illiquid, and vice versa for fund 2. The second row of Table 2 shows that managers' dynamic trading during the investment period does not fully revert, and may even increase, this initial deviation: relative to otherwise equivalent SA funds, fund 1's average holdings of asset C are 5.4% higher whereas fund 2's are 7.6% lower in our baseline scenario.

As illustrated by Figure 3, the end-of-period measured performance of the two FA funds (return-to-risk ratio (RRR) $E(R^j(T))/\sigma_j$ for funds $j = 1, 2$) under our baseline scenario seems to suggest no violation of SEC Rule 17(a)-7 regulating fund advisors' fiduciary duty in relation to cross-fund transactions.[21] While improving managers' utility, cross-trading also enhances the risk-return profiles of the funds involved as the optimal level of cross-trading $X = -0.07$ improves each fund's RRR over NCT (i.e., $X = 0$). Moreover, larger levels of cross-trading (e.g., $X = -0.20$) could improve the funds' RRR even further. To the extent

[20] Specifically, keeping the number of shares of asset C fixed at the family level, any initial split of C between the two funds that moves NCT to the right in Fig. 2 would result in a level of cross-trading $|X| > 0.07$. Table 2 indicates that alternative initial allocation to the left of NCT in Fig. 2 would in general be compatible with optimal cross-trading for different enough investment styles.

[21] See Section 2.3 for details on this rule.

that measured performance accurately reflects the benefits accruing to the fund investors, this situation is consistent with the requirement of SEC Rule 17(a)-7 that the cross trade is in the best interest of *both* the selling and the buying fund investors. However, a more rigorous analysis of the derived utility from delegation in subsection 3.5 reveals that this trade can still lead to large utility losses for the investors of at least one of the funds.

[Insert Figure 3 about here]

The qualitative results in our baseline case hold throughout alternative scenarios, with important nuances in some cases. Table 2 shows (rows 1 to 5) the extent of cross-trading, average illiquid asset holdings of FA funds relative to SA funds and changes in the RRR across our alternative parameterizations. Decentralized decisions by family-affiliated funds can lead to large cross-trading (e.g., 29% of each fund's initial AUM for $\mu_1 = \mu_2 = .085$) only as a consequence of managers' concerns relative to different investment styles. As cross-trading intensifies, so does the average deviation of each fund's portfolio from its style benchmark. We remind the reader that the parameter values that lead to high cross-trading also imply larger values of the distance $|\beta_C^2(0) - \beta_C^1(0)|$ between the style benchmarks' weights in the illiquid asset according to (5). Since larger values of this distance can be associated with greater style diversity, the results above suggest a positive relation between style diversity within a family, the extent of cross-trading and the differences in funds' average illiquidity relative to their benchmarks. We explore this relation more closely in the next subsection and derive novel testable implications for which we find empirical validation in Section 4.

[Insert Table 2 about here]

3.3 Style Diversity, Cross-Trading and Funds' Portfolio Liquidity

Our assumptions on the risk-appetite clienteles of mutual funds in Section 2.2 and on the family's total holdings of asset C allow us to identify style diversity equivalently with the distance $|\gamma_{h1} - \gamma_{h2}|$ between the RRA coefficients of investors 1 and 2. Indeed, by (5) a higher RRA coefficient γ_{h1} implies a lower weight $\beta_C^1(0)$ of benchmark 1 in asset C, which in turn implies a higher weight $\beta_C^2(0)$ of benchmark 2 and greater style diversity $|\beta_C^2(0) - \beta_C^1(0)|$.[22] Figure 4 plots the optimal level of cross-trading (Panel A) and the associated average excess holdings of the illiquid asset (Panel B) as a function of style diversity, where we keep the baseline assumption $\gamma_{h2} < \gamma_{m1} = \gamma_{m2} < \gamma_{h1}$.

[Insert Figure 4 about here]

Cross-trading increases monotonically with style diversity. As in Table 2, the possibility of cross-trading leads fund 1 to buy shares of C from fund 2. The optimal crossing goes from $|X| = 0.03$ for the lowest style diversity to $|X| = 0.42$ for the most dispersed styles within the family. The intuition is that high style diversity leads managers to follow more extreme benchmark compositions and exposes them to insufficient diversification, with manager $m1$ having too little and manager $m2$ too much exposure to asset C. Managers then require a larger rebalancing of their initial portfolios to achieve a more desired portfolio composition. Given that $m1$ demands more shares of C while $m2$ is willing to supply those shares, they can satisfy their need for rebalancing by trading with each other a large amount of the illiquid asset.[23] This positive relation between cross-trading (offsetting trades) and style diversity within a family is a main prediction of our model. We find empirical support for this prediction on a sample of U.S. actively managed mutual funds in Section 4.2.

Conversely, insufficient diversity leads to little or no cross-trading. This would be the case, for instance, if the liquid style L was catered to households with slightly larger RRA coefficient than the manager (e.g., $\gamma_{h1} = 3$). Thus, within-family diversity in investment styles

[22] Using (5) once again to back out the investor's 2 RRA coefficient γ_{h2}, we see that a higher risk aversion for $h1$ maps one-to-one onto a lower risk aversion for $h2$ in our model.

[23] The jump in optimal cross-trading when moving from 5 to 5.5 along the X-axis in Fig. 4 responds to the flat shape of the manager 1's CER curve in Fig. 2 for $X \in [-0.4, 0]$. The changes in the parameters considered under our alternative scenarios reduce the slope of this curve in this range of X (i.e., the curve "rotates" clockwise around NCT), substantially increasing the maximum benefits derived by $m1$ from cross-trading.

not only strengthens the extent of cross-trading in our model but is a necessary condition for managers to consider crossing their trades in the first place.

As diversity in the investment styles offered by a family increases, Panel B shows that so does each fund's average deviation from its respective benchmark in the direction of the other fund's benchmark. That is, *the FA fund that follows the more liquid style L (fund 1) increases its portfolio illiquidity more than an equivalent SA fund, while the converse—excess portfolio illiquidity falls more than for an equivalent SA portfolio—is true for the fund that follows the illiquid style S (fund 2).* As we show in Section 3.5, this relation between style diversity within a family and the illiquidity of a fund relative to the illiquidity of its benchmark has important implications on the derived utility of delegating investors. We confirm the empirical validity of this second prediction of our model in Section 4.3.

We note here that managers are less likely to trade in opposite directions over the investment period if they are both more (respectively, less) risk averse than the less (more) risk tolerant investor $h1$ ($h2$). In this case, when underperforming their respective benchmarks both managers would want to deviate by decreasing the weight of their portfolios in the relatively riskier and illiquid asset C (see Basak, Pavlova, and Shapiro (2007)). In this sense, no cross-trading could also be an optimal outcome. Since this situation reflects cases of "extreme"—either low or high—risk aversions for the managers, we concentrate on the more plausible case of intermediate levels of risk aversion for both managers in the rest of our analysis.

3.4 Decentralized Cross-Trading and Family Performance

Our model assigns no asset allocation role to a centralized decision maker or, as introduced in Section 2.4, a Chief Investment Officer (CIO) of the overall family.[24] In practice, CIOs of

[24] In this sense, our setup differs from Binsbergen, Brandt, and Koijen (2008), who assume the CIO's role is to allocate capital to the different investment styles. Although realistic in the context of, e.g., pension funds, this assumption does not necessarily hold in the context of open-end mutual funds for which the

mutual fund families may not have a direct say on the investment decisions of the affiliated funds but still have the responsibility for the strategy of the overall group. Under the family arrangement, it could be argued that the CIO would preclude cross-trading—by, e.g., offering a narrow set of investment styles—unless it satisfies not only the interests of the fund managers but also her own interest. Thus, our result so far can represent an equilibrium situation within the family only if the family CIO is also better off—or at least not worse off—after the internal trading.

Table 2 (row 6) shows that the CIO does benefit from the funds' cross-trading in our baseline scenario, making the trade consistent with the goals not only of fund managers but also of the manager of the family. Even though the after-flow assets of the overall family do not grow (row 7), the CIO increases her utility (certainty equivalent) substantially from allowing the direct trading between the funds.[25] Given that the CIO derives utility from the family's overall assets, this result implies that cross-trading allows for better diversification of the family's portfolio of funds. Intuitively, the possibility of cross-trading induces managers to take an overall exposure on all three assets that is closer, compared with the no-cross-trading scenario, to the CIO's desired exposure. Indeed, two equivalent SA funds would invest too little in one of the liquid assets (asset 2 in our baseline case), whereas the CIO prefers similar holdings in both liquid assets for diversification purposes.[26] Notably, the better diversification of the family's portfolio implies almost no loss in future AUM, as each fund's policy optimally exploits the positive and convex relation between performance and future fund flows.

The net benefits accruing to the CIO hold across all of our alternative scenarios, and increase significantly for large optimal cross-trading (e.g., for $\rho_{iC} = 0.6$). In the latter cases,

assets under management are decided by households instead. To reduce the layers of agency involved in our problem, we thus assume that the CIO does not make any investment decision (see Section 2.4).

[25] We describe the computation of agents' certainty equivalent (CE) in subsection 3.5.

[26] Since the liquid assets offer similar—the same, in our setup—risk-return tradeoff but are not perfectly correlated, a CIO investing in the three assets will invest similar weights in each of these assets.

the expected end-of-period AUM (after-flow returns) of the family organization exceed the sum of AUM of two otherwise equivalent SA funds (row 7 of Table 2). As if led by an "invisible hand" of internal markets, the decentralized cross-trading that maximizes the utility of each manager also increases the benefits accruing to the family and its CIO, *even though no family-coordinated decision* is made. This is the case even when the performance of one of the FA funds, as measured by RRR, does not improve relative to its SA counterpart (e.g., for $\mu_1, \mu_2 = 0.085$).

Since higher style diversity within the family leads to larger cross-trading in our model, the results above suggest that families can derive larger benefits from increasing the menu of investment styles (i.e., the style diversity) available to investors. We look into this prediction in Figure 5, which plots the CIO's certainty equivalent (CE) and the growth in AUM of the family as a function of style diversity.

[Insert Figure 5 about here]

As expected, the CIO's CE from running funds 1 and 2 under a family organization increases monotonically with style diversity, deriving high CE returns from allowing for cross-fund transactions relative to the no-cross-trading (NCT) scenario. The expected growth in the AUM of the family also increases monotonically with style diversity, from marginally negative values for low diversity (e.g., $\gamma_{h1} = 4$) to a few percentage points for large enough style dispersion. Altogether, these results imply that a centralized decision maker for a family of mutual funds (i) will not discourage internal trading across FA funds, and (ii) will offer a menu of investment styles that is as diverse as possible. The latter result seems to indicate that an optimal strategy for the family is to maximize the style diversity and encourage FA funds to follow more extreme benchmarks. However, we argue in the next subsection that such strategy can inflict high costs on delegating households. These costs should impose tight limits on the implementation of such strategy in practice.

Cross-Subsidization Hypothesis and Centralized vs. Decentralized Decisions. Gaspar, Massa, and Matos (2006) conjecture, and empirically verify, that the convexity of funds' flow-performance relationship can encourage fund families to 'play favourites' among affiliated funds in order to maximize the family's total amount of assets under management. In particular, they find that fund families can cross-subsidize some member funds over others within the family through interfund transactions at *below or above market prices.* Such behavior goes clearly against SEC Rule 17(a)-7 and should thus be illegal.[27]

As described above, a novel prediction of our model is that families can still increase the amount of assets under management without playing favourites by choosing to offer diverse enough styles. The affiliated funds following these styles will indirectly satisfy the family objective while engaging in *mutually beneficial* cross trades. This cross-trading is not decided by a centralized decision maker playing favorites among affiliated funds. It is instead decided by the decentralized optimal trading of the individual fund managers. As a result, no fund (manager) is "sacrificed" for the greater good of the family as documented by Gaspar, Massa, and Matos (2006).[28] Still, another 'invisible hand', one working in internal markets, ensures that the family also derives significant benefits from the decentralized cross-trading.

Notwithstanding the difference between the approach of these authors and our approach, a slight modification of our setup shows that when illiquidity costs are non-negligible, families can play favourites among affiliated funds by having them cross trade *even at fair market prices.* In Figure 6, we show the level of cross-trading that a CIO would choose if deciding to play favourites between funds 1 and 2 in our model. Clearly, because the CIO's derived utility is increasing in the number of shares of asset C sold from fund 2 to fund 1, the CIO

[27] Note that the 'non-market' feature of prices is key for this hypothesis to remain valid in perfectly liquid markets, since at fair market prices each fund would be just indifferent between cross-trading with another fund in the same family and trading in the public markets.

[28] See also Bhattacharya, Lee, and Pool (2013) and Casavecchia and Tiwari (2014). Although no fund manager is "sacrificed" for the benefit of the family in our model, we argue in Section 3.5 that the investors of at least one of the funds pay a "cost of family affiliation" arising exclusively from the possibility of cross-trading.

benefits by maximizing manager $m2$'s utility ($OM2$) rather than $m1$'s utility ($OM1$). At this level of cross-trading, the CIO enables the manager of the favoured fund 1 to reduce the costs of illiquidity by making the other fund in the family adopt a suboptimal investment policy. The end-of-period RRR of fund 1 is higher than that of a comparable SA fund (NCT), while the RRR of fund 2 is significantly lower. Relative to the no-cross-trading (NCT) scenario, the resulting funds' measured performance resembles a "cross-subsidization" of fund 1 at the expense of fund 2. Although such cross-trading would still violate the spirit of Rule 17(a)-7—both funds have to benefit from the trade according to this rule—this strategy would be arguably more difficult to detect in practice.

[Insert Figure 6 about here]

Figure 6 also shows the performance costs associated with centralized decision making. Under the 'playing favourites' strategy, in which case the CIO decides the level of cross-trading ($OM2$), the end-of-period performance of both funds, as measured by RRR, is lower than the performance attained under the decentralized optimum OCT. This result is consistent with the empirical findings of Kacperczyk and Seru (2012), who show that funds from decentralized families have higher performance than their centralized counterparts.

3.5 Delegation Costs of Cross-Trading

To the extent that lower transaction costs translate into higher after-fee risk-adjusted returns, investors should be better off by delegating their portfolios to family-affiliated (FA) funds compared to delegating to (otherwise identical) standalone (SA) funds. However, the availability of an internal market can also facilitate opportunistic trades that would otherwise be too costly to execute in the open market. When the incentives of the managers are not fully aligned with those of their delegating investors, cross-fund transactions can benefit both managers involved while at the same time impose costs on the funds' investors.

For instance, if at an interim point during the investment period manager $m1$ in our setup underperforms her relatively liquid benchmark, she may attempt to 'gamble for resurrection' by placing large bets on small illiquid stocks (asset C). Due to the assumed flow-performance relationship (8), $m1$ will enjoy large investors' inflows in the future if these bets pay off, and disproportionally lower outflows if these bets go sour. High transaction costs may deter a SA fund from gambling on illiquid stocks, but need not discourage a FA fund who can circumvent these costs by trading with a sibling fund with a similar but opposite intended order.

We assess the net effect to investors from portfolio delegation by examining their certainty equivalent (CE) rate of return. For an investment policy φ, this is the risk-free rate of return $CE(\varphi)$ that makes an agent indifferent between following the policy φ over the investment horizon T or alternatively earning this risk-free rate on the same initial investment over the same period. For an agent with CRRA coefficient γ and initial wealth z, $CE(\varphi)$ solves:

$$\frac{[CE(\varphi)z]^{1-\gamma}}{1-\gamma} = E\left[\frac{(Z^{\varphi}(T))^{1-\gamma}}{1-\gamma}\right], \tag{15}$$

where the superscript 'φ' denotes that the final wealth $Z(T)$ is attained under the investment policy φ.

We report the net effect of delegation to family-affiliated vs. standalone funds in Table 3.[29] These net effects arise only due to the potential cross-fund trades under the family arrangement, so they can equivalently be interpreted as *net effects of cross-trading.* As explained in Section 2.2, we consider two types of investors. First, the households $h1$ and $h2$ to which funds 1 and 2 are catered, in the sense that their benchmarks are the unconditional efficient portfolios that these investors would choose under self-management and perfect liquidity. Second, the alternative investors $h11$ and $h12$ in fund 1's clientele, and $h21$ and

[29] In all cases, investor's derived utility under delegation is obtained by plugging her managed fund's terminal wealth in utility function (3).

$h22$ in fund 2's clientele, with RRA coefficients as specified in Appendix A.

[Insert Table 3 about here]

Delegation costs of cross-trading can be substantial. Under our baseline case, investor $h1$ in fund 1 suffers significant costs (0.44% per year) from delegating to a FA fund relative to a SA fund. Except for those investors with similar or higher risk tolerance than $h2$ (e.g., $h21$), all other investors in a neighbourhood of $h1$ and of $h2$ also suffer the costs of family affiliation. In this case, the decentralized cross-trading effectively *cross subsidizes* some investors in fund 2 at the expense of other investors in fund 2 and of investors in fund 1. Thus, the relatively more risk tolerant investors in fund 2 enjoy the savings on illiquidity costs that the other family investors pay via the suboptimal investment policy that their funds adopt.

Our alternative scenarios show that the costs of delegation can be even larger, and up to 5.86% per year in some cases (i.e., for $\rho_{iC} = 0.6$). For large levels of cross-trading, manager's optimal policies can be such that *both investors $h1$ and $h2$ are worse off after cross-trading*, even though *the measured performance for both of their funds improves*—the RRR is higher for both funds at OCT relative to NCT, see Figure 6. This situation occurs because managers' dynamic policies in response to their convex incentives induces an option-like risk profile on their fund returns (Basak, Pavlova, and Shapiro (2007)). These policies expose fund investors to inadequate—either excessive or insufficient—risk, but this risk is not appropriately captured by conventional performance measures such as RRR (Goetzmann, Ingersoll, Spiegel, and Welch (2007)). Investors' decision to delegate to a family-affiliated vs. a standalone fund then *trades off saving on transaction costs vs. paying additional delegation costs*. In this sense, the extent of style diversity that a family could reach as described in subsection 3.4 should be limited by the costs that the resulting level of cross-trading imposes on its delegating investors.

To the extent that investors in one or in both funds are worse off after cross-trading, the cross-fund trades that we examine in this Section go against Rule 17(a)-7. However, these internal trades are executed at fair market prices. Moreover, both fund managers benefit and the RRR of both funds improves after the trades. Arguably, regulatory authorities should find such breach of fiduciary duty harder to detect in spite of the substantial negative effects accruing to delegating investors.

It is worth highlighting that our analysis in this section is by necessity limited to the particular problem we consider. In particular, our model leaves out potential benefits to investors from investing in a large and diverse family such as better allocation of managerial resources (Berk, van Binsbergen, and Liu (2014)) or lower fees (Khorana, Servaes, and Tufano (2009)). In industry equilibrium, we would expect these benefits to compensate at least some investors for the costs we identify.

4 Empirical Analysis

In this section, we test some of the novel implications of our model. First, we test the hypothesis that style diversity within a family is a first-order driver of interfund transactions, controlling for other variables that could explain interfund dealing such as commonality in holdings and correlation of flows across funds within a family. Second, we test the hypothesis that style diversity leads fund managers following high- and low-liquidity styles to deviate from their benchmarks in opposite directions. Specifically, a high (low) liquidity fund is likely to increase (decrease) portfolio illiquidity. To the best of our knowledge, the existing empirical evidence on mutual funds has not yet verified either of these two central implications of our model.

4.1 Data Sample, Variable Construction, and Descriptive Statistics

We obtain fund returns, investment objectives, fees, total net assets (TNA), and other fund characteristics from the Center for Research in Security Prices (CRSP) Survivor-Bias-Free Mutual Fund Database. We use the Wharton Research Data Services MFLINKS file to merge this database with the Thomson Financial Mutual Fund Holdings dataset, which contains information on stock positions of funds and identifies fund families (Wermers (2000)). We restrict our analysis to diversified domestic actively managed equity mutual funds.[30] We compute fund-level variables by aggregating across all the share classes. For instance, a fund's expense and turnover ratios are the TNA-weighted averages of the ratios of its different share classes. The age of the fund is equal to the age of its oldest share class, and the TNA of the fund is the sum of the TNAs of all its share classes.

Following Kacperczyk, Sialm, and Zheng (2008) and Glode (2011), we exclude funds that hold on average less than 80% or more than 105% of their net assets in equity. This is because reported fund objectives do not always accurately characterize a fund. We also exclude funds with TNA of less than $15 million as Elton, Gruber, and Blake (2001) show that the returns on such small funds tend to be biased upwardly in the CRSP database. In addition, we remove from our final sample observations associated with funds that at a given point in time have less than 18 months since inception, to minimize the effects of incubation bias (Evans (2010)). We also exclude funds that hold less than 10 stocks in their portfolios in a given quarter. We exclude fund families with less than two funds, as we need at least two funds to compute some of the pairwise measures used in our tests, which we describe in

[30] More specifically, and following existing literature, we include in our sample funds with AGG, GMC, GRI, GRO, ING, and SCG Strategic Insight codes, EIEI, G, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, and SCVE Lipper codes, and G, G-I, AGG, GCI, GRI, GRO, LTG, MCG, and SCG Wiesenberger codes. We exclude international, balanced, sector, bond, money market, and index funds.

more detail below. Our final sample covers the period 1999-2009 for a total of 443 families and 1,855 funds. The time period of our sample is limited below by the CRSP daily mutual fund returns data, which starts in 1999, and is limited above by the active share sample of Cremers and Petajisto (2009) and Petajisto (2013), which ends in 2009.[31] Due to the quarterly frequency of mutual fund holdings data, we run our tests at the quarterly level.

We construct a number of variables to help us perform our tests, some of which are computed at the family-level and others at the fund-level. We provide a detailed description of these variables in Appendix B.

First we describe our family-level variables. Two natural proxies for the style diversity offered by a fund family are the number of funds, which we denote as NFUNDS, and the total value of assets under management (FAMSIZE) of the family. However, it is possible that a small two-fund family offers more diverse (e.g., one very conservative and one very risky) investment styles compared to a large and relatively homogeneous—in terms of offered investment styles—multi-fund family. If this is the case, NFUNDS or FAMSIZE could fail to properly capture the extent of internal dispersion in fund styles. We construct an alternative measure, FAMDIVERS, to better reflect the style diversity offered by a fund family in our model. Specifically, for each family we compute all the pairwise correlations of returns across all the different benchmarks followed by the funds affiliated with that family. We take the minimum of all those pairwise correlations and denote that measure as FAMDIVERS.[32] Because a benchmark portfolio is outside of the family's control, we avoid in this way the endogeneity issues that would arise if pairwise correlations were computed on fund returns

[31] Even if our model predictions are borne in the data, we expect our empirical findings to weaken after the introduction of SEC rules 38a-1 and 206(4)-7 (introduction of chief compliance officer independent from fund management) and the amendments to rule 204-2 (advisers must maintain copies of their compliance policies and procedures and copies of any records documenting the adviser's annual review of those policies) in 2004, see Eisele, Nefedova, and Parise (2014).

[32] We take the negative of the minimum across all the pairwise correlations of benchmark returns within the family so that a decrease in that minimum correlation can be interpreted as an increase in style diversity within the family.

instead.

According to our model, style diversity within a fund family (i.e. FAMDIVERS) is an important driver of interfund transactions. In order to test this prediction we create a proxy for interfund trading, FAMOFFSET, that captures the dollar amount of all buy and sell trades of a particular stock that gets offset within a family in a given quarter, as a fraction of the intra-family trading volume. Similarly, we create a measure of offsetting trades of illiquid stocks only, FAMOFFSETILLIQ. We follow the standard in the literature and use changes in portfolio holdings between adjacent quarters to proxy for the trading of mutual funds. We control for other variables that could explain the extent to which trades get offset within fund families. In particular, one should expect offsetting trades to be more likely in families with more common holdings and lower flow correlations across their affiliated funds. We capture these two dimensions by creating the measures FAMCOMHOLD and FAMFLOWCORR, respectively. One possible concern with FAMCOMHOLD is that it might be mechanically related to the degree to which funds within the family follow the same style. To examine whether funds with different styles also hold many stocks in common, we compute two additional measures of cross-fund overlap in stock holdings: FAMCOMHOLDLIQ and FAMCOMHOLDILLIQ. In the calculation of both measures, we restrict our pairs of funds to follow distinct DGTW benchmarks. Moreover, FAMCOMHOLDLIQ includes only liquid portfolio holdings (i.e. stocks in the bottom quintile of the liquidity cost estimates of Hasbrouck (2009), in the cross-section of stocks held by mutual funds), while the calculation of FAMCOMHOLDILLIQ uses only illiquid portfolio holdings (i.e. stocks not in the bottom quintile of liquidity cost). The stocks we classify as liquid represent an average 43% of funds' equity portfolios, and their average liquidity cost is about one fourth the liquidity cost of the stocks we classify as illiquid.[33]

[33] More precisely, the average Hasbrouck's effective liquidity costs are 0.19% and 0.69% for the liquid and illiquid stocks in our sample.

Our testable predictions result from decentralized strategies at the level of the individual fund managers. However, Gaspar, Massa, and Matos (2006) document that families can also play strategies at a centralized level. In particular, they show that families can play favourites and maximize the amount of assets for the whole group by transferring performance from low-value funds to high-value funds ('cross-fund subsidization') via cross-trading. Gaspar et al. (2006) consider high-value funds to be young funds, small funds, and funds that charge higher fees. Because age and size are endogenous determinants of the flow-performance relationship according to Berk and Green (2004) and Huang, Wei, and Yan (2007), and this relationship is a key ingredient of our model, we distinguish high- and low-value funds based on their total fees only. More precisely, we assess the extent to which offsetting trades within fund families are driven by cross-subsidization by controlling for the dispersion of fees FAMFEEDISP across all the funds in a family-quarter combination.

Next, we describe the fund-level variables that we use to test the prediction that high-liquidity funds decrease their portfolio liquidity and vice-versa for low-liquidity funds. We create the measure FUNDILLIQDEV to capture the difference between the illiquidity of the fund's portfolio and the illiquidity of its benchmark.[34] The illiquidity of the fund's portfolio and the illiquidity of the benchmark are value-weighted averages of the illiquidity of their respective holdings.

We assign a benchmark to each fund-quarter according to the following procedure, which we explain in more detail in Appendix C. First, we obtain the fund's prospectus benchmark from Antti Petajisto's website.[35] To approximate the portfolio stock holdings of each prospectus benchmark, we assign to a fund-quarter the Daniel, Grinblatt, Titman, and Wer-

[34] Following Lou (2012), we use the liquidity cost estimates of Hasbrouck (2009) as our measure of illiquidity.

[35] http://www.petajisto.net/data.html. The list of official benchmarks that mutual funds disclose in their prospectuses in Antti Petajisto's website includes 5 indices from S&P, 12 indices from Russell, and 2 indices from Dow Jones / Wilshire. All the variables in this dataset are defined and the sample of funds is selected as in Petajisto (2013). The sample used in Petajisto (2013) covers the period 1980-2009.

mers (1997) (DGTW) benchmark that has a current quarter tracking error closest to the tracking error that Petajisto (2013) obtained when using the return series of the funds and their respective prospectus benchmarks. We believe that, even if the matching of DGTW benchmarks is made with error, there is no reason for a bias to exist in favour of our results.[36]

We identify control variables that may jointly affect FAMDIVERS and FUNDILLIQDEV when testing the hypothesis that style diversity is an important driver of the difference between fund and benchmark illiquidity. Specifically, we control for a number of fund characteristics, including the value of assets under management (FUNDSIZE), the expense ratio (FUNDEXPRATIO), the number of years since inception (FUNDAGE), the volatility of returns (FUNDRETVOL), and the average illiquidity of the benchmarks within the family (FAMBENCHILLIQ).

Table 4 provides descriptive statistics for the main variables described above. In Panel A we show the statistics for the family-level variables. The median family in our sample has about 5 funds under its umbrella (NFUNDS) and $5.7 billion in assets under management (FAMSIZE). The median ratio of the amount of offsetting trades to the total internal volume in a fund family is 1.6% when computing offsetting trades for all the stocks (FAMOFFSET) and 0.9% when computing offsetting trades for illiquid stocks only (FAMOFFSETILLIQ). The median value of common holdings within fund families in our sample is 0.354 (FAMCOMHOLD).

Funds that follow different styles also hold a significant amount of stocks in common. It is perhaps not surprising that the commonality of liquid stocks across the funds (FAMCOMHOLDLIQ) is larger compared to that of illiquid stocks. However, we also observe a significant degree of commonality of illiquid stocks across funds following different styles (FAMCOMHOLDILLIQ), which validates one of the central assumptions of our model.

[36] We adopt this indirect method to identify the funds' benchmarks because we do not have access to the index constituents of all the prospectus benchmarks reported in Petajisto (2013). We believe that this allows us to obtain a better match of stock characteristics between the fund and its benchmark.

[Insert Table 4 about here]

In Panel B of Table 4 we show summary statistics at the fund level, whereas in Panels D and E we report the correlations among the family-level and the fund-level variables, respectively. The Pearson correlations are reported above the diagonal, and the p-values are reported below the diagonal.

In Panel C, we provide descriptive statistics for placebo families that we form by randomly drawing funds from different families. The idea is to show that affiliation with a given family is what drives funds to offset trades when the style diversity across the funds in a given family is large. Therefore, when creating a placebo group of funds for a given family, we draw funds from all the other families making sure that they follow the same benchmark as in the actual family. This guarantees that we keep the level of diversity within the placebo family similar to that in the actual family. In Panel C of Table 4 we show that the difference in FAMDIVERS between actual and placebo families is statistically not significant (with a p-value of 0.238). However, actual and placebo families appear to differ in the other dimensions (e.g. FAMOFFSETILLIQ, FAMCOMHOLD, FAMFLOWCORR, and FAMFEEDISP), which is expected because the placebo families are intended to break the connections between the member funds.[37]

4.2 Style Diversity and Offsetting Trades in Fund Families

In order to test the hypothesis that style diversity within a family is a first-order driver of interfund transactions, we implement cross-sectional regressions using the following specifi-

[37] Panel C of Table 4 shows that the number of funds (i.e. NFUNDS) and the size (i.e. FAMSIZE) of the placebo families is smaller than those of the actual families. Even though these differences are statistically significant (with p-values of 0.008 and 0.009, respectively), they are not economically large. The difference of -0.056 for NFUNDS represents only 1.2% of the average number of funds in the actual family (i.e. the mean NFUNDS of 4.709 in Panel A of Table 4). The difference of -$353 million for FAMSIZE represents 6.1% of the average family size in the actual family (i.e. the mean FAMSIZE of $5,801 million in Panel A of Table 4). The reason for such differences is that, when creating placebo families by randomly drawing funds from other families, it is sometimes impossible to find a matching fund with the same benchmark.

cation:

$$\text{FAMOFFSET} = a_0 + a_1 \text{ FAMDIVERS} + a_2 \; Controls + \epsilon \tag{16}$$

where we control for other variables that could explain interfund dealing such as commonality in holdings (FAMCOMHOLD) and correlation of flows (FAMFLOWCORR) across funds belonging to the same family. We perform Fama and MacBeth (1973) regressions with heteroskedasticity-consistent standard errors and Newey and West (1987) correction using four lags. We present the results of this estimation in Table 5. In Panel A the dependent variable is the amount of offsetting trades across all the stocks traded within the family in a given quarter (FAMOFFSET), while in Panel B we replace the dependent variable in (16) with an offsetting measure that focuses on illiquid stocks only (i.e. FAMOFFSETILLIQ). The dependent variables are normalized using the total trading volume for a family-quarter-stock combination (see Appendix B for more details).

[Insert Table 5 about here]

As predicted, the coefficient for FAMDIVERS is positive and statistically significant at the 1% level in both Panels A and B. The economic magnitude of these results is also very strong. For instance, in Column (1) of Table 5 (Panel A), a coefficient of 0.0544 for FAMDIVERS indicates that a one-standard-deviation increase in FAMDIVERS (which is 0.124 in Table 4, Panel A) is associated with an increase in FAMOFFSET by 0.0067 (i.e., the product of 0.0544 by 0.124). This value of 0.0067 compares to an average FAMOFFSET in Table 4 (Panel A) of 0.015. Therefore, a one-standard-deviation increase in FAMDIVERS is associated with a 45% increase in average FAMOFFSET.

In Columns (2) to (4) of Table 5, we run univariate regressions of FAMOFFSET on other variables that could be associated with the degree of offsetting trades within fund families, such as commonality in holdings across the funds in the family (Column 2), the correlation of their money flows (Column 3), and the family-level incentive to cross-subsidize high-fee funds at the expense of low-fee funds (Column 3). The coefficients on FAMCOMHOLD, FAMFLOWCORR, and FAMFEEDISP are all significant at 1% level and have the expected sign: (1) the larger the extent of common holdings across the sibling funds, the more likely they are to eventually trade the same stocks in opposite directions (i.e., a positive sign on FAMCOMHOLD), (2) the lower the correlation of flows across sibling funds, the more they will be induced to trade in opposite directions (i.e., a negative sign on FAMFLOWCORR), and (3) the large the dispersion in fees charged by the funds within a family, the more likely it is that the family would want to transfer performance from low-fee funds to high-fee funds through cross-trading, as hypothesized by Gaspar, Massa, and Matos (2006) (i.e., a positive sign on FAMFEEDISP).

In Columns (5) to (7) and (9) of Table 5, we show that the effect of FAMDIVERS on FAMOFFSET in not explained away by any of FAMCOMHOLD, FAMFLOWCORR, or FAMFEEDISP, either taken individually or controlling simultaneously for all of them. The coefficient on FAMDIVERS remains statistically significant at 1% level, and economically large. In Column (9) of Table 5 (Panel A), a one-standard-deviation increase in FAMDIVERS is associated with a 21% increase in FAMOFFSET. In comparison, the economic significance of the remaining controls is as follows: (i) a one-standard-deviation increase in FAMCOMHOLD of 0.044, is associated with an increase in FAMOFFSET of 0.0011 (i.e., the product of 0.044 by 0.0250, the coefficient on FAMCOMHOLD), which is about 7.3% of the average FAMOFFSET; (ii) a one-standard-deviation increase in FAMFLOWCORR of 0.020, is associated with a decrease in FAMOFFSET of 0.000122, which is only 0.8% of the average FAMOFFSET; and (iii) a one-standard-deviation increase in FAMFEEDISP of 0.025, is associated with an increase in FAMOFFSET of 0.0001125, which is only 0.75% of the average FAMOFFSET. These results suggest that our measure of style diversity intra-family (FAMDIVERS) is of first-order importance in explaining FAMOFFSET.

When we restrict our analysis to the offsetting trades of illiquid stocks only (i.e., Panel B of Table 5), and after including all the control variables (i.e., Column (9)), a one-standard-deviation increase in FAMDIVERS is associated with a 25% increase in FAMOFFSETILLIQ (i.e., the product of 0.124 from Table 4 and the coefficient of 0.0182 for FAMDIVERS from Table 5 (Panel B), Column (9), divided by the average FAMOFFSETILLIQ of 0.009 from Table 4 (Panel A)).

In column (10) of Panels A and B of Table 5, we show that the relation between offsetting trades and style diversity that our model predicts is empirically stronger within fund families than outside of them. Following the approach in Gaspar, Massa, and Matos (2006), for each family in our sample we create a placebo family by randomly pairing each member fund with a fund that follows the same benchmark but does not belong in the same family. Except for those dimensions along which we would expect actual and placebo families to differ (e.g., FAMCOMHOLD, FAMFEEDISP), Panel C of Table 4 shows that the two types of families are comparable. For instance, placebo families are on average only 5% larger than actual families. We then run the multivariate regression of column (9) on the placebo families. In contrast to the actual families, we see that style diversity has no relation with the level of offsetting trades of either all stocks (Panel A) or of the relatively more illiquid stocks (Panel B) of the placebo families.

Overall, the results in Table 5 confirm our model's main prediction that the diversity in styles offered by a mutual fund family is a first-order determinant of, and is positively related to, the offsetting trades within the family. We have also performed the analysis of Table 5 using panel regressions with year-quarter fixed effects and standard errors clustered at the family and year-quarter levels, and the results are qualitatively unchanged.[38]

[38] For brevity, we have not tabulated the panel regressions, but the results are available upon request.

4.3 Style Diversity and Distortions in Funds' Portfolio Illiquidity

A second implication of our model is that higher style diversity within a family leads fund managers following high- and low-liquidity styles to deviate further away from their benchmarks in opposite directions. Specifically, the high-liquidity fund should increase portfolio illiquidity and conversely for the low-liquidity fund. Given the potentially negative consequences of this behavior on delegating investors' utility, as we emphasized in subsection 3.5, we test the validity of this prediction using the following specification:

$$\begin{aligned}\text{FUNDILLIQDEV} &= \alpha_0 + \alpha_1 \text{ DMEASURE} + \alpha_2 \text{ LOWBILLIQ} + \alpha_3 \text{ HIGHBILLIQ} + \\ &+ \alpha_4 \text{ DMEASURE}\times\text{LOWBILLIQ} + \alpha_5 \text{ DMEASURE}\times\text{HIGHBILLIQ} + \\ &+ \alpha_6 \; \textit{Controls} + \psi,\end{aligned} \tag{17}$$

where the dependent variable FUNDILLIQDEV, is the difference between the fund illiquidity and its benchmark illiquidity. This variable can take positive or negative values. DMEASURE is our family diversity measure as captured, alternatively by NFUNDS, FAMSIZE, or FAMDIVERS. The variable LOWBILLIQ (HIGHBILLIQ) is an indicator function that equals one if the fund benchmark ranks in the bottom (top) tercile of illiquidity across all the benchmarks in a given quarter. *Controls* is a vector of other determinants of FUNDILLIQDEV. In particular, we control for the age (in years) of the fund since inception (FUNDAGE) and the TNA of the fund (FUNDSIZE). These two variables are very skewed. We use a logarithmic transformation of those variables to deal with the skewness. We also include indicator variables DG and DGI, which equal one if the fund is in the Growth and in the Growth and Income categories, respectively, and equals zero otherwise, to control for the style of the funds. Our controls also include the past 12-month volatility of the fund's monthly returns, FUNDRETVOL, the fund's expense ratio, FUNDEXPRATIO, a dummy that equals one if the fund ranked in the bottom half across all the funds in the same investment category in the previous quarter, DLOSER, and the average illiquidity of the benchmarks within the fund's family, FAMBENCHILLIQ.

Our model implications relate specifically to the interactions between DMEASURE and the indicators LOWBILLIQ and HIGHBILLIQ, predicting a positive sign for the first and a negative sign for the second interaction terms. We are particularly interested in the interaction terms involving FAMDIVERS. We run Fama and MacBeth (1973) regressions with heteroskedasticity-consistent standard errors and Newey and West (1987) correction using four lags. We report the results of the estimation of this model in Panel A of Table 6.

[Insert Table 6 about here]

As predicted, the coefficients α_4 and α_5 on the interactions FAMDIVERS$\times$LOWBILLIQ and

FAMDIVERS$\times$HIGHBILLIQ are positive and negative, respectively, and statistically significant at 1% level (column (3)). The coefficients on NFUNDS and FAMSIZE and their interactions with LOWBILLIQ are also positive (columns (1) and (2)), consistent with the results for FAMDIVERS, although they show no or low statistical significance. Unlike the case of FAMDIVERS, the interactions of NFUNDS and FAMSIZE with HIGHBILLIQ are not statistically different from zero. Moreover, when we include all the alternative measures of style diversity in one single specification, as well as their multiple interactions with LOWBILLIQ and HIGHBILLIQ in column (4), only FAMDIVERS$\times$LOWBILLIQ and FAMDIVERS$\times$HIGHBILLIQ remain economically and statistically significant at the 1% level or better. These findings confirm the importance of style diversity in the choice of portfolio liquidity for family-affiliated funds, in agreement with our model.

To prove the incremental relevance of the decentralized cross-trading in our model, we seek to rule out the possibility that these findings are driven by family-coordinated trades between affiliated funds according to the cross-subsidization hypothesis. Specifically, we test the hypothesis that the deviations in funds' liquidity from their benchmarks' illiquidity is a consequence of the cross-subsidization of high-value (high-fee) funds at the expense of their low-value (low-fee) siblings within the family.

In Panel B of Table 6, we re-run the specification of column (3) in Panel A with two additional indicator variables, LOWFEE and HIGHFEE, their interactions with LOWBILLIQ and HIGHBILLIQ, as well as triple interactions involving FAMDIVERS. The variable LOWFEE (HIGHFEE) is an indicator that equals one if the fee charged by the fund is in the bottom (top) tercile of the fees charged across all the funds within a given family.

Our estimates indicate that we can reject this alternative explanation. If the effect we documented in column (3) of Panel A of Table 6 were indeed the result of a strategy played at the family-level, we would expect to observe (i) that deviations in funds' liquidity from their benchmarks are stronger for high- and low-value funds, both before and after controlling for FAMDIVERS, and (ii) that FAMDIVERS cannot explain deviations in funds' liquidity after controlling for high- and low-value fund effects. By contrast, the coefficients on LOWFEE and HIGHFEE, and their interactions with LOWBILLIQ, HIGHBILLIQ and FAMDIVERS are all statistically insignificant in columns (1) and (2). However, the coefficients on the interactions FAMDIVERS×LOWBILLIQ and FAMDIVERS×HIGHBILLIQ retain the sign and, and in the case of FAMDIVERS×LOWBILLIQ, statistical significance of column (3) in Panel A of Table 6. We conclude that our empirical findings cannot be attributed to the cross-subsidization hypothesis, lending further support to our model.

5 Conclusion

We propose a model of internal markets in fund families and explore the possibility that benchmark concerns generate opportunistic internal trades between family-affiliated funds. When the family offers a diverse enough menu of investment styles, and these styles represent portfolios with common holdings of illiquid assets, cross-trading can result as the optimal outcome of a decentralized strategy implemented at the individual fund-level. Fund managers have an incentive to distort their portfolios away from their style benchmarks in an attempt to attract investors' flows. When the styles that these funds follow are sufficiently different from one another, managers will likely trade common holdings in opposite directions. If such funds belong to the same family, they have access to an internal market, which they can use to cross those opposite trades at low cost, instead of having to deal with illiquid open markets. The ability that family-affiliated funds have to circumvent the costs of illiquidity by trading in the internal market, allows them to more aggressively change the excess liquidity of their portfolios relative to their respective benchmarks throughout the investment period. The overall family stands to benefit from this strategy nearly as much as if the cross-trading were centrally decided. However, the increased risk shifting that family-affiliated funds can perform due to the presence of internal markets, relative to equivalent standalone funds that have no access to such markets, creates additional delegation costs to fund investors who choose to invest under such a family arrangement. Lastly, we provide empirical evidence consistent with the novel implications of our model. In particular, we use a sample of U.S. actively managed equity mutual funds to test the hypothesis that style diversity within a fund family is positively associated with (i) the amount of intra-family offsetting trades, and (ii) the degree to which funds deviate the liquidity of their portfolios from the liquidity of their style benchmarks.

Our results have several implications. First, they draw attention to a novel delegation cost associated to family affiliation and to a subtle, although economically significant, potential breach of fiduciary duty of family-affiliated fund managers with respect to their shareholders. Second, they provide an alternative rationale for the diversity in investment styles within fund families that we observe in practice. Third, they relate differences in the performance of centralized versus decentralized mutual funds to the extent of cross-trading executed within a fund family. Finally, our results point to style diversity within fund families as a potential source of cross-sectional variation in the liquidity management by mutual funds.

Our model also has some limitations. In order to isolate the effects of decentralized intra-family trading on the choices of the individual funds, we abstract from decisions made at the family level. These include the choice of the number of funds and the menu of styles to offer by the family, which we take as exogenous in our model. This style diversity can lead to delegation costs to fund investors. The observed differences in style diversity across fund families could be explained as an equilibrium outcome. A model that would take into account differences in managerial skill, or in the determination of fund fees, could help offset some of these delegation costs of fund investors. We leave this extension for future research.

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Appendix

A Model Parameterization

In line with the median estimates of managers' risk aversion coefficients in Koijen (2014), we set $\gamma_{mj} = 2.5 = \gamma_c$ across all scenarios. We follow Basak, Pavlova, and Shapiro (2007) in calibrating funds' flow-performance relationship to match the estimates in Sirri and Tufano (1998) by setting $\phi_j^L = 0.97$, $\psi_j = 1.6$, and $\eta_j = -0.05$ for $j \in \{1, 2\}$.

Our baseline risk aversion coefficients for the investors $h1$ and $h2$ to which style L and S are catered according to (5) are $\gamma_{h1} = 5$ and $\gamma_{h2} = 1.5$. We consider alternative investors $h11$ and $h12$ in fund 1's clientele, and $h21$ and $h22$ in fund 2's clientele, with values $\gamma_{h11} = 1, \gamma_{h12} = 3, \gamma_{h21} = 3.5, \gamma_{h22} = 6.5$. In our comparative statics analysis of funds' investment styles, we allow for further heterogeneity in risk-preferences and the resulting benchmarks' compositions by letting γ_{hj} adopt values in $[\underline{\gamma}, \overline{\gamma}] = [1.01, 7.5]$, $j \in \{1, 2\}$.

We set market parameters to approximately match first- and second-order moments of the return distribution of the high (for the liquid assets 1 and 2) and low (for the illiquid asset C) quintiles of the size-sorted Fama-French value-weighted portfolios over the period 1927-2009.[39] The baseline expected returns and return volatilities are $\mu_1 = \mu_2 = 0.09$, $\mu_C = 0.18$, $\sigma_1 = \sigma_2 = 0.20$, and $\sigma_C = 0.37$. These values imply a higher reward-to-risk ratio μ/σ for the illiquid asset C relative to the liquid assets 1 and 2, which we assume as a non-negative premium for illiquidity.[40] Our alternative scenarios contemplate both a higher illiquidity premium as implied by $\mu_1 = \mu_2 = 0.085$ and a lower illiquidity premium as implied by $\mu_1 = \mu_2 = 0.095$. The baseline correlation coefficients are $\rho_{12} = \rho_{1C} = \rho_{2C} = 0.77$. Our alternative scenarios include the cases $\rho_{iC} \in \{0.6, 0.85\}$ $(i = 1, 2)$ and $\rho_{12} \in \{0.6, 0.9\}$.

We set the baseline illiquidity parameter $\alpha = 0.60$ to match the portfolio turnover in the mutual fund industry. Because α can be seen as a fund portfolio's maximum turnover rate over the investment period, we chose this value so that the optimal portfolio turnover of the funds in our model approximately matches, on average, the turnover rate of equity mutual funds over the period 1974-2009.[41] Our alternative scenarios contemplate both higher and lower asset illiquidity: $\alpha \in \{0.30, 0.90\}$.

[39] We downloaded these data from Ken French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[40] The historical average return for the large-cap Fama-French portfolio is closer to 11%. If we identify this portfolio with the purely liquid asset in our setup, the historical average implies a negative illiquidity premium that is difficult to reconcile with economic intuition. We therefore set $\mu_1 = \mu_2 = 0.09$ in our baseline case.

[41] See the 2009 *Investment Company Fact Book* published by the Investment Company Institute (ICI).

B Variable Definitions

Variable	Definition
DG	An indicator variable that equals one if the investment style of the fund is “Growth”, and equals zero otherwise.
DGI	An indicator variable that equals one if the investment style of the fund is “Growth and Income”, and equals zero otherwise.
DLOSER	An indicator variable that equals one if the performance of the funds ranks below the median across all the funds in the same style in a given quarter.
FAMBENCHILLIQ	The cross-sectional average illiquidity of the benchmarks followed by all the funds affiliated with the same family in a given quarter. The illiquidity of each benchmark is a value-weighted average of the liquidity cost estimates of Hasbrouck (2009) across all the stocks in the benchmark's portfolio.
FAMCOMHOLD	The measure of common holdings in Elton, Gruber, and Green (2007) but only for the funds affiliated with the same family. For any pair of funds (A, B), it is the sum of the minimum fraction of the portfolio held in any stock i between the two funds, i.e., $COM(A, B) = \sum_i \min(X_{Ai}, X_{Bi})$, where X_{Ai} (X_{Bi}) is the value of the portfolio of fund A (B) that is invested in stock i, as a fraction of the total identifiable amount of common stock held in the portfolio of fund A (B).
FAMCOMHOLDILLIQ	Similar to the measure FAMCOMHOLD above, but only for pairs of funds with different style benchmarks, and for illiquid stock holdings only (i.e., stocks ranked in quintiles 2 to 5 of the liquidity cost estimates of Hasbrouck (2009) in the cross-section of stocks held by mutual funds).
FAMCOMHOLDLIQ	Similar to the measure FAMCOMHOLDILLIQ described above, but only for pairs of funds with different style benchmarks, and for liquid stock holdings only (i.e., ranked in quintile 1 of the liquidity cost estimates of Hasbrouck (2009) in the cross-section of stocks held by mutual funds).
FAMDIVERS	The minimum pairwise correlation of DGTW benchmark returns across all the distinct pairs of benchmarks followed by the funds affiliated with the same family, using rolling windows of 6 months of daily DGTW benchmark returns.
FAMFEEDISP	The cross-sectional standard deviation of expense ratios across all the funds affiliated with the same family in a given quarter.
FAMFLOWCORR	The average pairwise correlation of monthly percentage flows across all funds in the same family, using rolling windows of 36 months and requiring a minimum of 20 observations. Monthly flows are computed as follows: $FLOW(t) = [TNA(t) - (1 + RET(t)) \times TNA(t-1)]/TNA(t-1)$, where $TNA(t)$ is the value of assets under management at month t, $TNA(t-1)$ is the value of assets at the end of month $t-1$, and $RET(t)$ is the return of the fund during month t.

FAMOFFSET	The dollar amount of offsetting buy and sell trades of a given stock (i.e., the minimum between positive holdings changes for that stock aggregated across all funds in the family, and the absolute value of negative holdings changes for that same stock aggregated across all funds in the family – changes in holdings being computed using adjacent quarters), normalized by the total dollar trading volume on that stock within the family (i.e., the sum of all positive and (the absolute value of) negative holdings changes for that stock across all funds in the family), averaged across all the stocks traded by the funds in the family for each quarter.
FAMOFFSETILLIQ	Similar to the measure FAMOFFSET but for illiquid stocks only (i.e., stocks ranked in quintiles 2 to 5 of the liquidity cost estimates of Hasbrouck (2009) in the cross-section of stocks held by mutual funds in a given quarter).
FAMSIZE	The sum of the quarter-end monthly TNAs of all the funds affiliated with the same family.
FUNDILLIQDEV	The difference between the illiquidity of the fund portfolio and the illiquidity of its benchmark portfolio (i.e., the value-weighted average of the liquidity cost estimates of Hasbrouck (2009) across all the stocks in the portfolio in a given quarter).
FUNDAGE	The number of years since the inception of the fund until the current quarter. This is equivalent to the age of the fund's oldest share class, for multi-share class funds.
FUNDEXPRATIO	The expense ratio of the fund, which is computed as the TNA-weighted average of the expense ratios across all its share classes, in the case of multi-share class funds.
FUNDRETVOL	The standard deviation of fund returns for the prior 12 months ending in the quarter prior to the quarter under consideration (i.e., from month $t-14$ to month $t-3$ relative to the last month t of the quarter under consideration).
FUNDSIZE	The TNA of the fund in a given quarter, which is the sum of the TNAs across all the fund's share classes in the case of multi-share class funds.
HIGHBILLIQ	An indicator variable that equals 1 if the value-weighted liquidity cost of the benchmark portfolio ranks in the top tercile across all the benchmarks in a given quarter, and equals zero otherwise.
HIGHFEE	An indicator variable that equals 1 if the expense ratio of the fund ranks in the top tercile across all the funds belonging to the same family in a given quarter, and equals zero otherwise.
LOGFAMSIZE	The logarithmic transformation of the variable FAMSIZE.
LOGNFUNDS	The logarithmic transformation of the variable NFUNDS.
LOWBILLIQ	An indicator variable that equals 1 if the value-weighted liquidity cost of the benchmark portfolio ranks in the bottom tercile across all the benchmarks in a given quarter, and equals zero otherwise.
LOWFEE	An indicator variable that equals 1 if the expense ratio of the fund ranks in the bottom tercile across all the funds belonging to the same family in a given quarter, and equals zero otherwise.
NFUNDS	The number of funds affiliated with the same fund family in a given quarter.

C Benchmark Assignment Methodology

We assign a benchmark to each fund-quarter according to the following procedure. First, we create the daily series of returns for each of the 125 DGTW benchmarks, following the methodology in Daniel, Grinblatt, Titman, and Wermers (1997). Some of the key steps of the methodology in Daniel, Grinblatt, Titman, and Wermers (1997) involve a triple sort of common stocks into buckets of size, book-to-market (B/M), and momentum (quintiles for each of these three dimensions), in the month of July of each year. Moreover, it requires availability of COMPUSTAT data for at least 2 years, a minimum of 6 months of returns in CRSP, size weights are constructed using the market value in June (using the NYSE size breakpoints), the B/M ratio uses the market cap in prior fiscal-year end (and are adjusted with industry averages, using the 49 Fama-French industry classification available in Ken French's webpage), and the momentum factor is the 12 month return with one month reversal gap. More details on the methodology are available in Russ Wermers' website: http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm.

Second, we compute the pairwise tracking errors (annualized) between the daily returns of the largest share class of each fund (following Petajisto (2013)) and all the 125 DGTW portfolios. Finally, we assign to a fund the DGTW benchmark that has a tracking error closest to the tracking error that Petajisto (2013) obtained when using the return series of the funds and their respective prospectus benchmarks. The list of official benchmarks that mutual funds disclose in their prospectuses is available in Antti Petajisto's website for the period between 1980 and 2009: http://www.petajisto.net/data.html. It includes 5 indices from S&P, 12 indices from Russell, and 2 indices from Dow Jones / Wilshire. All the variables in this dataset are defined and the sample of funds is selected as in Petajisto (2013). The sample used in Petajisto (2013) covers the period 1980-2009. Following Petajisto (2013), we use quarterly rolling windows of 6-month daily returns in the computation of such tracking errors.

D Tables and Figures

Table 1: Mutual Fund Structure in the Model

This table summarizes the main ingredients of our theory model, which consists of two mutual funds that follow two different investment styles. These investment styles are associated with different performance benchmarks and different sets of assets. Each fund holds two risky assets, one perfectly liquid, and the other illiquid. They both hold the illiquid asset. Each fund is managed by a different manager and caters its product to a different investor/household.

Mutual Fund	Investment Style	Benchmark	Invests in Assets	Specialized in Asset	Manager	Catered to Household
F_1	L	Y_1	1, C	1	$m1$	$h1$ (and $h11$, $h12$)
F_2	S	Y_2	2, C	C	$m2$	$h2$ (and $h21$, $h22$)

Table 2: Comparative Statics for Fund-Level and Family Outcomes

This table reports comparative statics on optimal cross-trading (OCT), differences in portfolio weights for asset C and in the return-to-risk ratio (RRR) between family-affiliated (FA) and standalone (SA) funds, the change from NCT to OCT in the certainty-equivalent (CE) rate of return for the CIO, and the difference in expected assets under management (AUM) for the family as a whole. The comparative statics are provided for different values of the return of the liquid assets (μ_1 and μ_2), the illiquidity of asset C (α), and the correlation between the illiquid asset C and the liquid assets (ρ_{iC}). The first column provides the results for the baseline case.

		$\mu_1 = \mu_2$		α		ρ_{iC}	
	Baseline	μ=8.5%	μ=9.5%	α=0.3	α=0.9	ρ_{iC}=0.6	ρ_{iC}=0.85
OCT	-0.07	-0.29	-0.05	-0.04	-0.29	-0.42	-0.01
$\Delta\omega_C^1$ from NCT to OCT (%)	5.48	25.41	3.9	3.59	22.85	33.64	0.79
$\Delta\omega_C^2$ from NCT to OCT (%)	-7.63	-29.9	-5.73	-4.25	-30.49	-44.35	-1.03
ΔRRR from NCT to OCT for fund 1 (%)	0.95	3.61	0.47	0.69	2.05	2.93	0.12
ΔRRR from NCT to OCT for fund 2 (%)	0.52	-0.71	0.62	0.32	0.68	4.07	0.02
ΔCE from NCT to OCT for CIO (bps)	25	257	17	6	270	586	1
ΔAUM from NCT to OCT for CIO (bps)	-2	233	-7	-5	206	483	-2

Table 3: Comparative Statics on Portfolio Delegation Costs

This table reports comparative statics on the costs accruing to the households from delegating to a family-affiliated fund compared to delegating to a standalone one. This is captured by the differences in certainty-equivalent (CE) rate of return (in basis points) between NCT and OCT for households 1 ($h1$) and 2 ($h2$), as well as their alternatives ($h11$, $h12$, $h21$, and $h22$). The comparative statics are provided for different values of the return of the liquid assets (μ_1 and μ_2), the illiquidity of asset C (α), and the correlation between the illiquid asset C and the liquid assets (ρ_{iC}). The first column provides the results for the baseline case.

		$\mu_1 = \mu_2$		α		ρ_{iC}	
	Baseline	μ=8.5%	μ=9.5%	α=0.3	α=0.9	ρ_{iC}=0.6	ρ_{iC}=0.85
ΔCE from NCT to OCT for h1	-44	-297	-30	-25	-289	-362	-8
ΔCE from NCT to OCT for h11	-15	-127	-11	-9	-123	-153	-3
ΔCE from NCT to OCT for h12	-75	-484	-53	-42	-483	-590	-12
ΔCE from NCT to OCT for h2	2	-26	1	2	-32	-100	2
ΔCE from NCT to OCT for h21	25	30	23	16	49	101	3
ΔCE from NCT to OCT for h22	-27	-146	-18	-17	-135	-197	-4

Table 4: Summary Statistics

This table provides summary statistics for the main variables used in this study. Panels A, C and D report the summary statistics for the variables calculated at the family-level (actual or placebo). Those family-level variables include (1) NFUNDS, which is the number of funds affiliated with the same family, (2) FAMSIZE is the sum of the assets under management across all the funds affiliated with the same family, (3) FAMOFFSET is the minimum between aggregate buy and sell trades of a given stock across the funds in a family, divided by the total trading volume of that stock in that family (i.e., the sum of the aggregate buy and sell trades for that stock), averaged across all the stocks traded in the family in a given quarter, (4) FAMOFFSETILLIQ is similar to FAMOFFSET, but restricting the calculations to illiquid stocks only (i.e., stocks not in the bottom quintile of liquidity cost across all the stocks held by mutual funds in a given quarter), (5) FAMCOMHOLD captures the extent of commonality in holdings across the funds in the same family, following Elton, Gruber, and Green (2007), (6) FAMFLOWCORR is the average pairwise correlation of monthly flows across all the funds in the family, using rolling windows of 36 months, (7) FAMDIVERS is the intra-family style diversity measure (-1 times the minimum of the pairwise correlations of returns across all the benchmarks in a given family), (8) FAMFEEDISP is the cross-sectional standard deviation of expense ratios across the funds in the family in a given quarter, (9) FAMBENCHILLIQ is the average illiquidity across the benchmarks within a family, (10) FAMCOMHOLDLIQ is similar to FAMCOMHOLD but applied only to funds with distinct benchmarks and to liquid stocks (i.e., stocks in the bottom quintile of liquidity cost across all the stocks held by mutual funds in a given quarter), and (11) FAMCOMHOLDILLIQ is similar to FAMCOMHOLDLIQ but applied to illiquid stocks (i.e., stocks not in the bottom quintile of liquidity cost). Panels B and E, report the summary statistics for the variables calculated at the fund-level, which include (1) FUNDILLIQDEV, which is the difference between the illiquidity of the fund and the illiquidity of its benchmark, (2) FUNDEXPRATIO is the fund's expense ratio, (3) FUNDAGE is the number of years since the inception of the fund, (4) FUNDSIZE is the fund's TNA, and (5) FUNDRETVOL is the monthly volatility of fund returns, for the prior 12 months. The 'placebo' families of Panel C are constructed as follows: for each family in our sample, we randomly pair each member fund with a fund that follows the same benchmark but does not belong in the same family (without replacement). Panels D and E report the correlations between family-level and fund-level variables, respectively. Pearson correlations are reported above the diagonal, and their respective p-values are reported below the diagonal.

PANEL A: Descriptive Statistics of Family-Level Variables

	Mean	Std	Skew	P5	P25	Median	P75	P95
NFUNDS	4.709	0.406	-0.880	3.823	4.552	4.748	5.019	5.207
FAMSIZE (in $ millions)	5,801	1,666	0.734	3,559	4,552	5,714	7,040	8,242
FAMOFFSET	0.015	0.004	-1.610	0.008	0.014	0.016	0.018	0.020
FAMOFFSETILLIQ	0.009	0.003	-0.662	0.006	0.007	0.009	0.010	0.013
FAMCOMHOLD	0.354	0.044	-0.505	0.271	0.338	0.354	0.391	0.415
FAMFLOWCORR	0.153	0.020	-0.817	0.122	0.145	0.155	0.168	0.174
FAMDIVERS	-0.689	0.124	0.951	-0.856	-0.763	-0.719	-0.655	-0.437
FAMFEEDISP (in %)	0.241	0.025	-1.170	0.208	0.225	0.245	0.259	0.274
FAMBENCHILLIQ (in %)	0.365	0.160	0.926	0.205	0.225	0.308	0.451	0.700
FAMCOMHOLDLIQ	0.205	0.040	-0.298	0.136	0.168	0.208	0.234	0.269
FAMCOMHOLDILLIQ	0.069	0.005	0.005	0.061	0.065	0.070	0.073	0.076

PANEL B: Descriptive Statistics of Fund-Level Variables

	Mean	Std	Skew	P5	P25	Median	P75	P95
FUNDILLIQDEV (in %)	-0.022	0.036	-1.929	-0.103	-0.025	-0.014	0.002	0.010
FUNDEXPRATIO	0.013	0.001	-0.438	0.012	0.012	0.013	0.014	0.014
FUNDAGE (in years)	11.080	1.672	0.318	9.448	9.787	10.674	12.409	14.437
FUNDSIZE (in $ millions)	1,272	386	2.436	815	1,013	1,223	1,441	1,682
FUNDRETVOL	0.051	0.019	0.218	0.027	0.032	0.052	0.069	0.077

Table 4: Continued

PANEL C: Descriptive Statistics of Family-Level Variables for Placebo Families									Diff. Between Actual and Placebo	
	Mean	Std	Skew	P5	P25	Median	P75	P95	Diff. in Means	p-value
NFUNDS	4.765	0.479	-0.910	3.894	4.509	4.826	5.151	5.342	-0.056	0.008
FAMSIZE	6,154	1,970	1.465	3,850	4,678	6,087	6,884	9,182	-353	0.009
FAMOFFSET	0.014	0.004	-1.027	0.006	0.012	0.015	0.017	0.020	0.001	0.050
FAMOFFSETILLIQ	0.007	0.002	-0.511	0.003	0.005	0.007	0.009	0.010	0.002	0.000
FAMCOMHOLD	0.155	0.022	-0.361	0.115	0.139	0.157	0.170	0.183	0.192	0.000
FAMFLOWCORR	0.054	0.049	4.264	0.009	0.026	0.046	0.067	0.088	0.099	0.000
FAMDIVERS	-0.690	0.125	0.979	-0.858	-0.766	-0.722	-0.653	-0.442	0.002	0.238
FAMFEEDISP	0.331	0.038	-0.907	0.269	0.309	0.342	0.363	0.375	-0.090	0.000

Table 4: Continued

PANEL D: Correlations of Family-Level Variables

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NFUNDS	(1)		0.6296	0.4858	0.3515	0.6794	-0.1103	0.2648	0.2074	-0.0801
FAMSIZE	(2)	<.0001		0.2722	0.2004	0.5298	-0.0040	0.1169	0.0474	-0.0521
FAMOFFSET	(3)	<.0001	<.0001		0.8354	0.3616	-0.0593	0.0774	0.0944	-0.0723
FAMOFFSETILLIQ	(4)	<.0001	<.0001	<.0001		0.2469	-0.0372	0.0959	0.0482	0.0227
FAMCOMHOLD	(5)	<.0001	<.0001	<.0001	<.0001		-0.0117	0.1739	0.1684	-0.0749
FAMFLOWCORR	(6)	<.0001	0.7320	<.0001	0.0025	0.3118		-0.0125	-0.1128	0.0224
FAMDIVERS	(7)	<.0001	<.0001	<.0001	<.0001	<.0001	0.2890		0.0901	0.3558
FAMFEEDISP	(8)	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001		-0.0400
FAMBENCHILLIQ	(9)	<.0001	<.0001	<.0001	0.0607	<.0001	0.0537	<.0001	0.0004	

PANEL E: Correlations of Fund-Level Variables

		(1)	(2)	(3)	(4)	(5)
FUNDILLIQDEV	(1)		0.0008	0.0243	0.0108	0.0318
FUNDEXPRATIO	(2)	0.8747		-0.1424	-0.1335	0.1062
FUNDAGE	(3)	<.0001	<.0001		0.2642	-0.0188
FUNDSIZE	(4)	0.0416	<.0001	<.0001		-0.0423
FUNDRETVOL	(5)	<.0001	<.0001	0.0004	<.0001	

Table 5: Style Diversity and Offsetting Trades in Mutual Fund Families

This table provides coefficient estimates obtained from Fama and MacBeth (1973) cross-sectional regressions. In Panel A, the dependent variable is FAMOFFSET (the minimum between buy and sell trades of a particular stock, aggregated across all the funds in a family, and then averaged across all the traded stocks in a given family-quarter). In Panel B, the dependent variable FAMOFFSETILLIQ only captures offsetting trades of illiquid stocks (i.e., stocks not in the bottom quintile of liquidity cost in the cross-section of stocks held by mutual funds in a given quarter). The control variables in both panels include our main independent variable of interest FAMDIVERS (the intra-family style diversity measure), FAMCOMHOLD (the extent of commonality in holdings across the funds within the family), FAMFLOWCORR (the average pairwise correlation of monthly flows across all the funds within the family), and FAMFEEDISP (the cross-sectional standard deviation of expense ratios across the funds within the family). For each family in our sample we create a 'placebo family' (column (10)) by randomly pairing each member fund with a fund that follows the same benchmark but does not belong in the same family. The standard errors (in parenthesis) are computed using the Newey and West (1987) correction. We denote by $***$, $**$, $*$ the significance at the 1%, 5%, and 10% levels, respectively.

PANEL A: Determinants of Offsetting Buy and Sell Trades within Fund Families

	Dependent Variable: FAMOFFSET									[Placebo Families]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
INTERCEPT	0.0552***	0.0052***	0.0160***	0.0112***	0.0257***	0.0551***	0.0508***	0.0051***	0.0249***	0.0020
	(0.0092)	(0.0003)	(0.0010)	(0.0008)	(0.0046)	(0.0090)	(0.0093)	(0.0006)	(0.0048)	(0.0028)
FAMDIVERS	0.0544***				0.0266***	0.0531***	0.0524***		0.0256***	-0.0013
	(0.0096)				(0.0051)	(0.0091)	(0.0096)		(0.0050)	(0.0037)
FAMCOMHOLD		0.0282***			0.0256***			0.0277***	0.0252***	0.0715***
		(0.0023)			(0.0023)			(0.0023)	(0.0023)	(0.0061)
FAMFLOWCORR			-0.0071***			-0.0063***		-0.0063***	-0.0061***	-0.0005
			(0.0020)			(0.0016)		(0.0016)	(0.0014)	(0.0012)
FAMFEEDISP				0.0152***			0.0120***	0.0050**	0.0043**	-0.0008
				(0.0019)			(0.0019)	(0.0020)	(0.0021)	(0.0010)
Observations	7,534	7,768	7,428	7,768	7,534	7,195	7,534	7,428	7,195	6,586
Adjusted R^2	0.0391***	0.1289***	0.0027	0.0067***	0.1359***	0.0401***	0.0428***	0.1292***	0.1356***	0.2725***
	(0.0075)	(0.0241)	(0.0026)	(0.0018)	(0.0251)	(0.0088)	(0.0071)	(0.0251)	(0.0259)	(0.0314)

Table 5: Continued

PANEL B: Determinants of Offsetting Buy and Sell Trades of Illiquid Assets within Fund Families										
	Dependent Variable: FAMOFFSETILLIQ									[Placebo Families]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
INTERCEPT	0.0324***	0.0042***	0.0097***	0.0077***	0.0183***	0.0322***	0.0308***	0.0045***	0.0184***	0.0045***
	(0.0044)	(0.0004)	(0.0006)	(0.0006)	(0.0027)	(0.0042)	(0.0045)	(0.0007)	(0.0027)	(0.0017)
FAMDIVERS	0.0317***				0.0185***	0.0310***	0.0311***		0.0182***	0.0035
	(0.0047)				(0.0032)	(0.0044)	(0.0047)		(0.0032)	(0.0021)
FAMCOMHOLD		0.0143***			0.0123***			0.0142***	0.0123***	0.0313***
		(0.0009)			(0.0011)			(0.0010)	(0.0012)	(0.0031)
FAMFLOWCORR			-0.0033**			-0.0027***		-0.0032***	-0.0030***	0.0000
			(0.0012)			(0.0009)		(0.0010)	(0.0009)	(0.0008)
FAMFEEDISP				0.0062***			0.0045***	0.0006	0.0005	-0.0008
				(0.0010)			(0.0011)	(0.0012)	(0.0012)	(0.0006)
Observations	6,636	6,856	6,567	6,856	6,636	6,348	6,636	6,567	6,348	6,438
Adjusted R^2	0.0388***	0.0941***	-0.0001	0.0015	0.1050***	0.0378***	0.0379***	0.0895***	0.1004***	0.1805***
	(0.0086)	(0.0187)	(0.0018)	(0.0014)	(0.0202)	(0.0090)	(0.0088)	(0.0193)	(0.0207)	(0.0289)

Table 6: Style Diversity and Deviations from Benchmark Illiquidity

This table provides coefficient estimates obtained from Fama and MacBeth (1973) cross-sectional regressions. The dependent variable is FUNDILLIQDEV, the difference between the illiquidity of a fund and the illiquidity of its benchmark. In Panel A, the main independent variables of interest are the log of NFUNDS (the number of funds affiliated with a given family), the log of FAMSIZE (the fund family's AUM), and the intra-family style diversity measure FAMDIVERS (-1 times the minimum of the pairwise correlations of returns across all the benchmarks in a given family). We include some extra indicators. The indicator LOWBILLIQ (HIGHBILLIQ) equals one if the fund benchmark ranks in the bottom (top) tercile of illiquidity across all benchmarks in a given quarter. We also include the interaction terms between these indicators and each of the proxies for style diversity, i.e., LOGNFUNDS, LOGFAMSIZE, and FAMDIVERS. In Panel B we test for the competing hypothesis of cross-fund subsidization (Gaspar, Massa, and Matos (2006)). Therefore, we include two additional indicators (LOWFEE and HIGHFEE), their multiple interactions with the indicators LOWBILLIQ and HIGHBILLIQ, as well as our proxy for style diversity within a fund family (FAMDIVERS). The indicator LOWFEE (HIGHFEE) equals one if the fees charged by the funds rank in the bottom (top) tercile of fees charged across all the funds affiliated with the same family in a given quarter. The remaining covariates in both panels are the log of FUNDAGE (the number of years since the inception of the fund), the log of FUNDSIZE (the fund's TNA), as well as DG (an indicator for the investment style "Growth"), DGI (an indicator for the investment style "Growth and Income"), FUNDRETVOL (the monthly return volatility of the fund for the past 12 months), FUNDEXPRATIO (the fund's expense ratio), DLOSER (an indicator that equals one if the fund ranked in the bottom half of performance across all the funds in the same investment style), and FAMBENCHILLIQ (the average illiquidity of the benchmarks within the family). The standard errors (in parenthesis) are computed using the Newey and West (1987) correction. We denote by ∗ ∗ ∗, ∗∗, ∗ the significance at the 1%, 5%, and 10% levels, respectively.

PANEL A: Deviation of Fund Illiquidity from Benchmark Illiquidity				
Dependent Variable:	FUNDILLIQDEV			
	(1)	(2)	(3)	(4)
INTERCEPT	0.0507***	0.0541***	0.0715**	0.1530***
	(0.0170)	(0.0175)	(0.0297)	(0.0432)
LOWBILLIQ	0.0420***	0.0340***	0.1115***	0.0877***
	(0.0106)	(0.0114)	(0.0177)	(0.0185)
HIGHBILLIQ	-0.1585***	-0.1324***	-0.3511***	-0.4733***
	(0.0373)	(0.0244)	(0.0645)	(0.1049)
LOGNFUNDS	-0.0013			-0.0062
	(0.0020)			(0.0077)
LOGNFUNDS x LOWBILLIQ	0.0046			-0.0033
	(0.0046)			(0.0033)
LOGNFUNDS x HIGHBILLIQ	0.0122			0.0546*
	(0.0218)			(0.0289)
LOGFAMSIZE		-0.0035**		-0.0048**
		(0.0013)		(0.0021)
LOGFAMSIZE x LOWBILLIQ		0.0023*		0.0009
		(0.0012)		(0.0013)
LOGFAMSIZE x HIGHBILLIQ		-0.0027		-0.0037
		(0.0017)		(0.0025)
FAMDIVERS			0.0368	0.1049***
			(0.0225)	(0.0338)
FAMDIVERS x LOWBILLIQ			0.0892***	0.0590***
			(0.0171)	(0.0181)
FAMDIVERS x HIGHBILLIQ			-0.3188***	-0.4336***
			(0.0837)	(0.1172)
Controls	Yes	Yes	Yes	Yes
Observations	33,254	33,254	33,254	33,254
Adjusted R^2	0.4768***	0.4672***	0.4897***	0.4991***
	(0.0244)	(0.0213)	(0.0221)	(0.0235)

Table 6: Continued

PANEL B: Alternative Hypothesis of Cross-Subsidization		
Dependent Variable:	FUNDILLIQDEV	
	(1)	(2)
INTERCEPT	0.0389**	0.0046
	(0.0183)	(0.0897)
LOWBILLIQ	0.0502***	0.1706**
	(0.0083)	(0.0639)
HIGHBILLIQ	-0.1450***	-0.1959*
	(0.0190)	(0.1042)
LOWFEE	0.0004	0.1505
	(0.0035)	(0.1510)
HIGHFEE	0.0007	0.0793
	(0.0050)	(0.0762)
LOWFEE x LOWBILLIQ	0.004	-0.055
	(0.0047)	(0.0425)
LOWFEE x HIGHBILLIQ	-0.0169	-0.2395
	(0.0130)	(0.2087)
HIGHFEE x LOWBILLIQ	0.0084	-0.0188
	(0.0082)	(0.0218)
HIGHFEE x HIGHBILLIQ	-0.0149*	-0.2519
	(0.0078)	(0.2024)
FAMDIVERS		-0.0676
		(0.1164)
FAMDIVERS x LOWBILLIQ		0.1702**
		(0.0775)
FAMDIVERS x HIGHBILLIQ		-0.1224
		(0.1449)
FAMDIVERS x LOWFEE		0.211
		(0.2066)
FAMDIVERS x HIGHFEE		0.1081
		(0.1070)
FAMDIVERS x LOWFEE x LOWBILLIQ		-0.0172
		(0.0114)
FAMDIVERS x LOWFEE x HIGHBILLIQ		-0.3297
		(0.2890)
FAMDIVERS x HIGHFEE x LOWBILLIQ		-0.0299
		(0.0304)
FAMDIVERS x HIGHFEE x HIGHBILLIQ		-0.3558
		(0.2892)
Controls	Yes	Yes
Observations	33,254	33,254
Adjusted R^2	0.4726***	0.4920***
	(0.0229)	(0.0229)

Figure 1: Average Deviations from the Benchmark

This plots the time-series of the cross-sectional average of the spread between the funds' portfolio weights on asset C and the weights of asset C in their respective benchmarks. The cross-section has 100,000 observations (the number of simulations we performed in our numerical analysis), while the time-series is divided in 100 time-steps, as represented by the length of the x-axis. The funds represented in this figure are standalone funds, which start off at time t=0 with portfolio compositions that exactly match those of their respective benchmarks (i.e., X=0), and are managed independently from that point onwards. The correlation between these two series is negative -0.09.

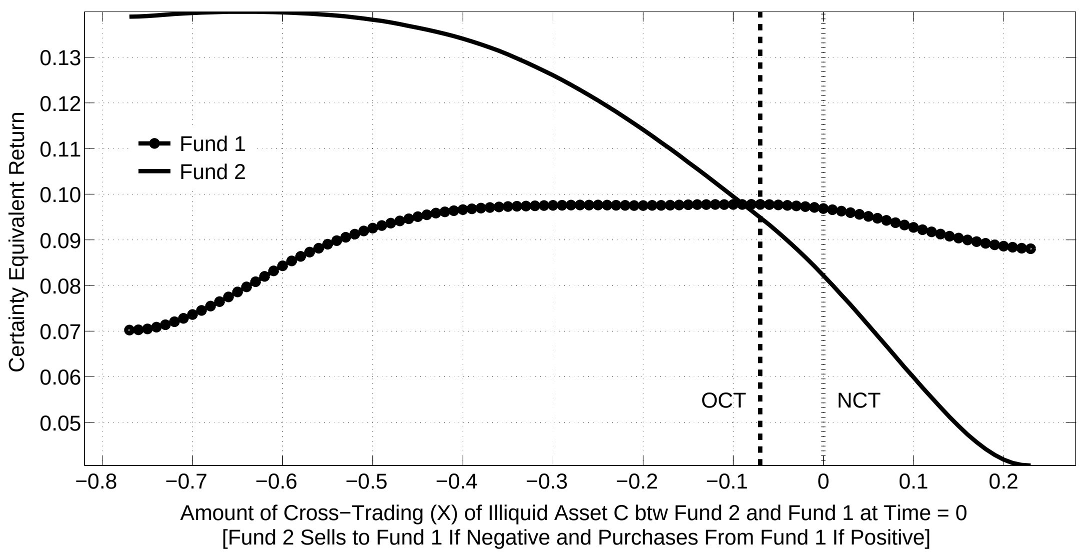

Figure 2: Optimal Cross-Trading

This plots the certainty equivalent (CE) rate of return each fund obtains for different levels of cross-trading. The vertical dotted line labelled as NCT represents the case in which both funds start off the investment period with portfolio compositions that exactly match those of their respective benchmarks. The vertical dashed line labelled as OCT identifies the level of cross-trading (X=-0.07) that improves the CE for both funds relative to NCT (i.e., X=0). The funds follow the constrained max-min rule proposed in (12) to agree on the optimal level of cross-trading (OCT).

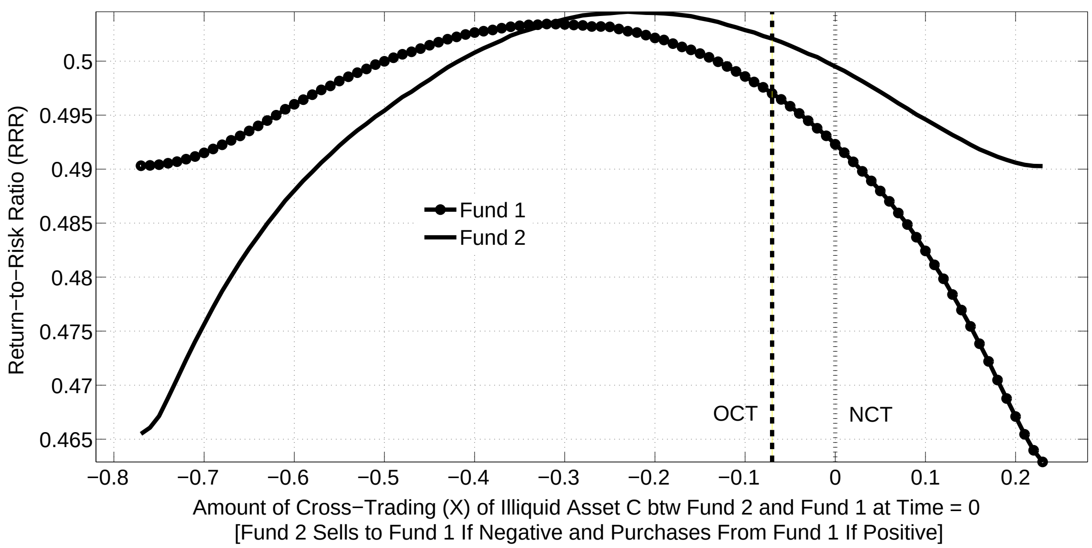

Figure 3: Funds' Return-to-Risk Ratio

This plots the return-to-risk ratio (RRR) that each fund obtains for different levels of cross-trading. The vertical dotted line labelled as NCT represents the case in which both funds start off the investment period with portfolio compositions that exactly match those of their respective benchmarks. The vertical dashed line labelled as OCT identifies the level of cross-trading (X=-0.07) that improves the CE for both funds relative to NCT (i.e., X=0). The funds follow the constrained max-min rule proposed in (12) to agree on the optimal level of cross-trading (OCT).

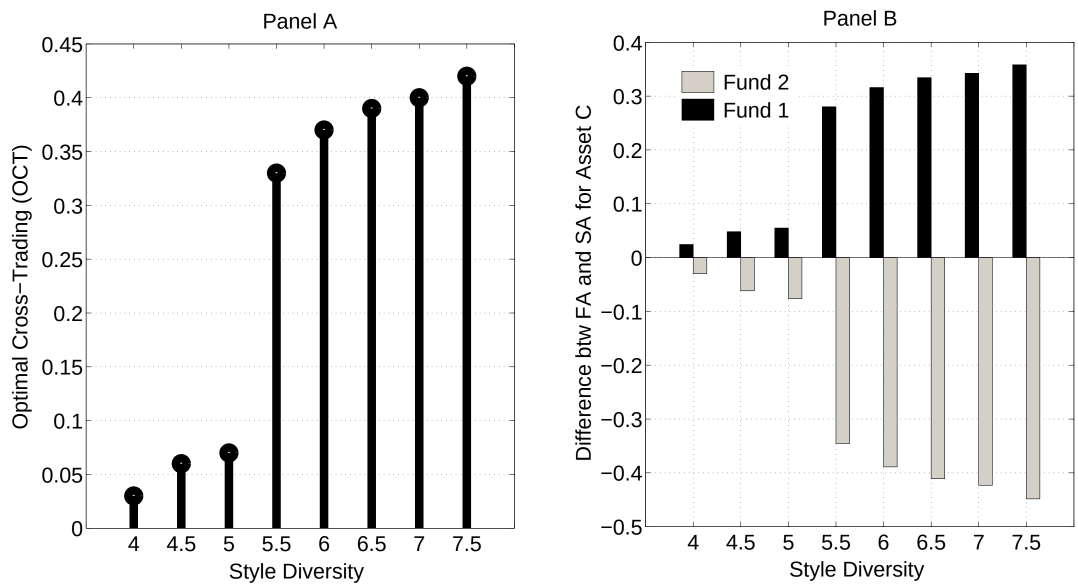

Figure 4: Style Diversity, Optimal Crossing, and Benchmark Deviations

Panel A reports the optimal level of cross-trading for different degrees of diversity within the fund family. Panel B plots the average excess holdings of illiquid asset C (comparing family-affiliated funds with their respective standalone versions) as a function of style diversity within the fund family. The style diversity in the x-axis is determined by the risk aversion parameter of investor $h1$ (γ_{h1}).

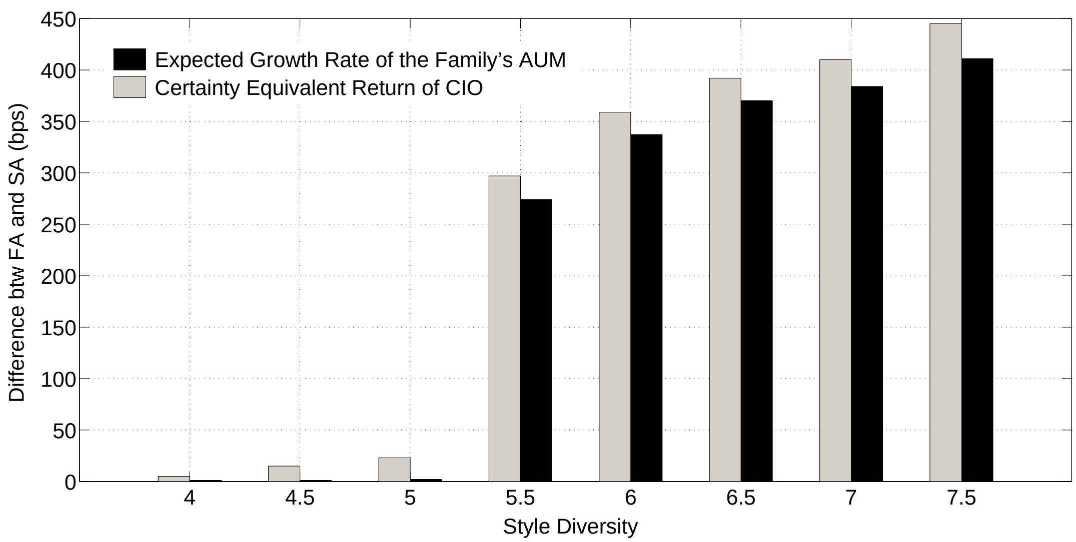

Figure 5: Certainty Equivalent Return to the Fund Family

This plots the certainty-equivalent (CE) rate of return for the CIO and the after-flow returns to the family (i.e., the expected growth rate of the assets under management of the fund family) as a function of style diversity. The style diversity in the x-axis is determined by the risk aversion parameter of investor $h1$ (γ_{h1}).

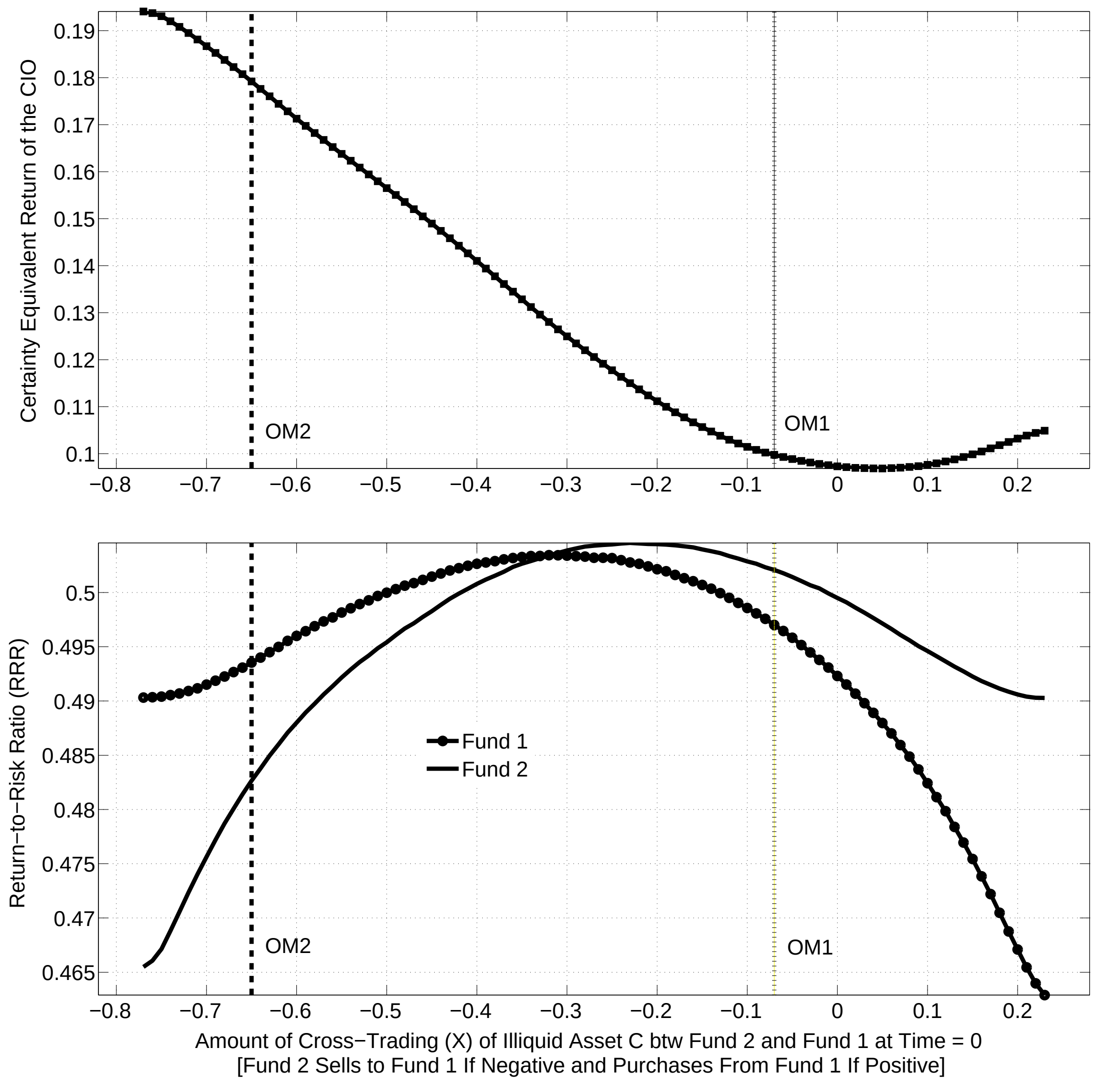

Figure 6: CER of the CIO and RRR of the Individual Funds

The top graph plots the certainty-equivalent (CE) rate of return that accrues to the CIO, and the bottom graph plots the return-to-risk ratio (RRR) of the individual funds, for different levels of cross-trading (X) between the two funds. The vertical dotted line labelled as OM1 identifies the amount of cross-trading between the two funds that would maximize the utility of fund manager 1, while the vertical dashed line labelled as OM2 indicates the amount of cross-trading that would maximize the utility of fund manager 2.