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Favoritism in Mutual Fund Families? Evidence on Strategic Cross-Fund Subsidization

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ABSTRACT

We investigate whether mutual fund families strategically transfer performance across member funds to favor those more likely to increase overall family profits. We find that "high family value" funds (i.e., high fees or high past performers) overperform at the expense of "low value" funds. Such a performance gap is above the one existing between similar funds not affiliated with the same family. Better allocations of underpriced initial public offering deals and opposite trades across member funds partly explain why high value funds overperform. Our findings highlight how the family organization prevalent in the mutual fund industry generates distortions in delegated asset management.

ONE OF THE MOST STRIKING FEATURES of the U.S. mutual funds industry is the prevalence of the fund family organization. Virtually all mutual funds are affiliated with fund complexes and the top 50 fund families have steadily concentrated over 80% of all the equity assets under management.[1] This implies that most fund portfolio managers (e.g., Fidelity Contrafund's manager) do not work directly for their funds' shareholders, but rather for a mutual fund organization (e.g., Fidelity Investments).

Mutual fund families are potentially a source of value to investors but can also cause distortions to the incentives of fund managers. On the one hand, family affiliation offers the potential for economies of scale and scope, in terms of asset management, distribution externalities, and better research quality.[2] Moreover,

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[1] These figures are calculated based on U.S. domestic actively managed equity mutual funds in the CRSP Survivor-Bias Free U.S. Mutual Fund Database from 1991 to 2001. For the whole universe of U.S. equity funds, we find that over 98% of the assets (and over 90% in terms of the number of different equity mutual funds) are held by funds affiliated with fund complexes.

[2] Such potential economies are hard to document empirically. Chen et al. (2002) find evidence that overall family size does not seem to improve or harm fund returns. However, they find that fund size seems to erode fund performance, which they attribute to liquidity effects and potentially organizational diseconomies.

the very existence of the family may lower the search costs for investors, because of brand-building and marketing benefits. On the other hand, however, family affiliation may distort the incentives of fund managers, possibly inducing them to sacrifice the interest of fund shareholders if the overall family stands to benefit. Families are liable to coordinate actions across funds in the complex in order to enhance the performance of funds that are the most valuable to the family, even if this comes at the expense of the performance of other member funds. This family strategy of "favoritism" is the result of the divergence of interests between fund management companies and shareholders. To date, this feature of the family form of organization has not been the subject of sufficient empirical investigation.

We propose several reasons why families might engage in "cross-fund subsidization," that is, a family strategy of favoring some funds by transferring performance across member funds. The rationale for this strategy is built on the observations that families' profits are a direct function of fees charged and assets managed, that investors' inflows chase good past performers (in spite of the fact that winners do not repeat themselves), and that the relation between inflows and past performance is convex (new money flows disproportionately to top performing funds).[3]

Families can charge a different level of fees on each of its member funds, making different funds contribute unequally to the total family profit. The positive sensitivity of investor inflows to performance therefore provides an incentive for the fund family to improve the performance of some funds, namely the high fee funds, at the expense of others, the low fee funds. If new capital flows to high fee funds and/or current investors in low fee funds are induced to shift their investments toward high fee funds, then the family sees its profits increase (although investors of some funds do not necessarily stand to benefit).

The incentive to play strategic cross-fund subsidization also stems from the convex relation between past performance and investors' flows. From a family perspective, this convexity implies that the expected assets of a family are higher if it produces one top performing and one bad performing fund than if it produces two average performing funds. This creates the incentive to produce good performing funds even if it comes at a direct cost of generating bad performing ones. This effect is further amplified by the fact that investors seem first to pick a fund family and then the individual fund in which to invest (Massa (2003)). This makes a "star" performing fund have a positive spillover effect on the inflows of the other funds in the same family, even if there seems to be no negative effect from a poor performing fund (Nanda, Wang, and Zheng (2003)).[4] Naturally, cross-fund subsidization would hardly be in the interest of the end-investors in the low performing fund.

In this paper, we investigate empirically whether indeed fund families actively pursue a family strategy of enhancing the performance of "high value"

[3] References to these stylized facts are Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997), and Sirri and Tufano (1998).

[4] We can also think of an additional spillover effect: A fund family that produces good performing funds can capitalize on its brand name by opening new funds (Khorana and Servaes (1999)).

funds, that is, those more likely to generate fee income or new investor flows, at the expense of other "low value" funds belonging to the same family. In particular, we consider three types of cross-fund subsidization strategies: (1) enhancing the performance of high fee funds at the expense of low fee ones, (2) enhancing the performance of currently high performing funds—that is, funds with high year-to-date performance likely to be well placed in fund rankings—at the expense of low performing funds, and (3) enhancing the performance of young funds at the expense of old funds (based on Chevalier and Ellison's (1997) finding that the convex flow-performance relation is more pronounced for younger funds). All these cross-fund subsidization policies can be optimal from the point of view of the management company but come at a cost to investors in some of the funds.

We present considerable evidence consistent with the existence of performance reallocation across funds in a family using a two-pronged empirical approach. Our study covers all actively managed equity mutual funds of the top 50 families of U.S. equity mutual funds over the period from 1991 to 2001.

The first set of tests studies cross-fund subsidization by using observed fund returns. These tests focus on the existence of performance transfer from low value (i.e., low fee, low performing, and old funds) to high value funds (i.e., high fee, high past performing, and young funds) by investigating the difference between the net-of-style returns of high value funds and the net-of-style returns of low value funds. This difference tells us the performance gap that exists between the high value funds relative to other peer funds in the same investment style and the net-of-style performance of low value funds.[5] We then compare this performance gap with that observed on average for equivalent funds that do not belong to the same family. We show that the performance gap inside fund families is greater than for collections of equivalent funds. Our main result is that the high value funds are favored inside fund families by 6–28 basis points of extra net-of-style performance per month (0.7%–3.3% per year) relative to the low value funds, depending on the criteria used (fees or past performance). Our findings provide evidence in favor of the fact that this level of cross-fund subsidization is indeed an "in-family" phenomenon.

We then investigate the sources of this aggregate effect of favoritism, studying when and for which types of families it is more prevalent. We show that this behavior is more prevalent at times when the styles of low value funds are doing relatively well, while it is scaled down when the styles of these funds are underperforming. We also find the level of cross-fund subsidization to be related to family characteristics, being more common in families that are large, that manage many funds, and that are heterogeneous in terms of the size of the funds they offer.

[5] Throughout our study we use the expression "investment styles" to refer to the fund's stated investment objective (growth, income, balanced, sector, etc.) and we implement it empirically by adopting the ICDI fund objective from the CRSP Mutual Funds data set. We thus choose to rely on the traditional manager objective classifications used by the mutual fund industry rather than the return-based classifications of Brown and Goetzmann (1997).

The second part of our study investigates potential channels of strategic cross-fund subsidization. We look at two main mechanisms available to fund families: preferential allocation and opposite trades. In the first case, the family concentrates the best deals on high value funds. In the second case, the family directly coordinates the trades of its member funds such that the low value funds trade in the market to buffer the price pressure of orders by high value funds, or directly cross buy and sell orders with the high value funds without going to the open market ("cross-trading").

We investigate preferential allocation by looking at evidence of favoritism in the allocations of hot initial public offering (IPO) stocks to high value funds. IPOs offer a promising setting to test for preferential allocation as it is likely that mutual fund families have reliable information on each offer's potential for appreciation, as well as some discretion regarding which of their funds are allocated which IPOs at each offer date. Based on a data set containing the reported holdings of mutual funds and a comprehensive sample of IPO issues for the 1992 to 2001 period, we find that fund families allocate relatively more underpriced (hotter) IPOs to high fee and high past performance funds. This evidence is highly suggestive of preferential treatment of high value versus low value funds.

We also provide evidence concerning the use of opposite trades across funds belonging to the same family to carry out strategic cross-fund subsidization. If a fund family coordinates the trades of high value funds and low value funds such that they place opposite orders, then any positive performance that the deal brings to the high value funds should come as an adverse impact to low value funds. Based on quarterly changes in holdings reported by mutual funds, we build a proxy for symmetric transactions between any two funds. We test and find that fund families that engage more in opposite trades between their member funds tend to exhibit larger net return differences between high value and low value funds. These findings link the level of strategic cross-fund subsidization to the actual trade strategies undertaken by mutual fund families and give extra credence to our first set of tests.

Our work contributes to the literature on delegated asset management. The evidence we uncover illustrates a distortion in the behavior of mutual fund managers at the family level that is new in its nature and adds to several findings at the single-fund level. Besides the excessive risk-taking by mid-year losers (induced by the convex flow-performance relation referred to above), previous research has uncovered other behavior such as marking-up or window-dressing of disclosed portfolios by fund managers (Carhart et al. (2002) and Lakonishok et al. (1991)), herding in portfolio holdings, and commonality in trading behavior across funds (Grinblatt, Titman, and Wermers (1995), Chevalier and Ellison (1999), Hong, Kubik, and Stein (2003)). We believe that future theoretical efforts should address the presence of family-level strategies and, more generally, the implications of the family-based structure of the mutual fund industry for delegated asset management and its equilibrium effects on markets.

Our research findings have also an important normative dimension. Indeed, they are relevant to the regulatory debate concerning cross-trades between mutual funds under common management. Even if the likely aggregate effect of cross-fund subsidization is zero, as all gains accruing to investors in high value funds are borne by investors in low value funds, this practice can represent a breach of fiduciary duty with respect to the assets with which each mutual fund manager is separately entrusted. Indeed, fiduciary duty requires that managers execute transactions for clients in the most favorable way to the fund shareholders of each fund. The Securities and Exchange Commission (SEC) routinely allows interfund cross-trading through exemptions provided under rule 17a-7 of the Investment Company Act of 1940.[6] While the benefits of cross-trades are a debated issue (Willoughby (1998)), the potential for self-dealing has been less well analyzed. Considerable debate has been generated recently on the governance model of the industry on how to give priority once again to the interests of investors over those of management companies, following investigations concerning "market timing" and "late trading" (Financial Times (2003)).

Previous research on fund family strategies is scarce, with a few notable exceptions. Massa (1998) argues that market segmentation and fund proliferation can be seen as marketing strategies used by families to exploit investors' heterogeneity, showing the positive spillover that having a star fund provides to all the funds belonging to the same family. Khorana and Servaes (1999) empirically analyze the determinants of mutual fund starts, identifying several factors that induce the family to set up new funds, such as economies of scale and scope, the family's prior performance, and the overall level of funds invested. Mamaysky and Spiegel (2001) derive an equilibrium model of the mutual fund industry in which families generate funds to allow investors to overcome their hedging needs. Nanda et al. (2003) empirically investigate whether fund families seek to generate star funds by increasing the cross-fund return variance or the number of funds in the family. The authors find some evidence of this family-level behavior and conclude that investors do not seem to benefit from such strategies in terms of subsequent period returns. Guedj and Papastaikoudi (2004) report that performance persistence is more prevalent within big fund families, suggesting that families purposefully allocate resources across funds in an unequal way. Other evidence on fund family strategies not coinciding with simple risk-adjusted performance maximization is uncovered by Massa (2003), who studies how industry structure affects fund behavior and the relations among performance, fund proliferation, and product differentiation. In particular, the study shows that the degree of product differentiation negatively affects performance and positively affects fund proliferation.

The remainder of the paper is organized as follows. Section I more formally presents our hypotheses. Section II describes the data we use in this study. Section III describes our tests of strategic cross-fund subsidization and presents

[6] Rule 17a-7 of the Investment Company Act is an exemption from the general prohibited transaction provisions between an investment company and its investment adviser or his affiliates. Several lobbying efforts by the asset management industry have recently led the U.S. Department of Labor (DOL) also to grant a class exemption that authorizes cross-trades involving passively managed ERISA plans, although the DOL still prohibits these for actively managed accounts.

their results. Section IV explores evidence on how strategic cross-fund subsidization takes place. Section V presents a discussion of our results. A brief conclusion follows.

I. Hypotheses

We conjecture two major strategies that fund families, motivated by overall family profit-maximization, are likely to pursue. These strategies are similar to those frequently observed in other groups of connected firms such as business groups or conglomerates, and they constitute our two working hypotheses against a null of no family strategy being pursued.

- H0: No Overall Family Strategy—the fund family does not coordinate strategies of its member funds.
- H1: Risk Sharing—the fund family coordinates actions across member funds to smooth their performance by supporting any fund whose performance is lagging.
- H2: Strategic Cross-Fund Subsidization—the fund family coordinates actions so as to systematically boost the performance of the set of funds that have high family value at the expense of the set of low family value funds, independent of which set of funds is performing better or worse.

Under Risk Sharing (H1), a fund family pursues a coordinated strategy to smooth performance across its member funds. The incentive for this strategy exists if the family as a whole stands to lose from a poorly performing member fund. If that is the case, then mutual coinsurance, where funds subsidize other member funds in trouble, can be in the fund family's best interest. Although we investigate this hypothesis in the remainder of the paper, results from previous literature cast some doubt on the fact that the family as a whole stands to lose much from a poorly performing member fund. Nanda et al. (2003) indicate that while a fund family with a top-performing fund seems to benefit from a positive spillover of extra flows of new money to all its funds, there is no significant negative effect of having a poor performing fund.

Under Strategic Cross-Fund Subsidization (H2), a fund family pursues a coordinated strategy to enhance the performance of a set of funds at the expense of others. Families are motivated to pursue strategic cross-fund subsidization if different fund members contribute unequally to a fund family's joint utility. Member funds contributing more to the overall fund family's interests (high value funds) will receive performance transferred from others with lower contribution (low value funds). We focus on three alternative dimensions along which families may have an interest in pursuing strategic cross-fund subsidization.

- H2-a: Subsidization of high fee funds at the expense of low fee funds.
  Funds charging different levels of fees are perceived to be different from the family perspective as their contribution to the family overall profits differs—for a given level of assets under management, the higher the

fraction of high fees, the higher the family's profits. Differences in the level of fees may motivate the family to transfer performance across funds, propping up the performance of high fee funds at the expense of the low fee funds.

- H2-b: Subsidization of high performing funds at the expense of low performing funds.
  Investor inflows are unequally sensitive to the extra performance of current top performing funds versus low performing ones. This asymmetric response of investor flows has been documented by Chevalier and Ellison (1997) and Sirri and Tufano (1998), among others. Such a convex flow-performance relation implies that the gains (in terms of increased flows at the family level) from improving the performance of a moderately performing fund to a top ranking position more than offset the loss from having a moderate performer fall into a low end ranking position. Therefore, families have an incentive to subsidize top performing funds. This incentive is further reinforced by the existence of a spillover effect (Nanda et al. (2003)), where the existence of a top performing fund in a family positively affects inflows to other funds of the same family.

- H2-c: Subsidization of young funds at the expense of old funds.
  One final dimension in which funds are unequal from a fund family's point of view is the differential sensitivity to extra performance of young versus old funds. Chevalier and Ellison (1997) find that inflow sensitivity to good performance is more pronounced for funds with less established track records, as their immediate performance may be more informative to consumers trying to learn the ability of the fund's portfolio manager. This may induce mutual fund families to boost the performance of younger funds at the cost of older funds. The reduction in inflows to the old funds is smaller than the increase to the young funds and, therefore, the net effect at the overall family level is positive.

Before we move on to test our hypotheses, let us comment on how our hypotheses differ from the potential effects of information-sharing across mutual fund family members. First, if several funds belonging to the same family use investment research simultaneously and trade in the same direction, sharing of information may actually lead to risk enhancement at the overall family level. Alternatively, if the family strategically uses the information to coordinate the behavior of its member funds, then we fall into either one of our working hypotheses (H1 or H2). Let's assume that the family has some valuable but uncertain information—for example, inside information on a firm becoming a takeover target. The fund family may direct some funds to exploit this information and others to take an opposite position. This "hedging its bets" behavior would fall into our Risk Sharing (H1) hypothesis. If the information is very reliable, the family may allow its high value funds to benefit from it and instruct its low value funds to not exploit it or actually take the opposite side of the market (to smooth the price pressure of market orders of the high value funds).

Such family-level behavior falls into our Strategic Cross-Fund Subsidization (H2) hypothesis.

II. Data

The primary data source for our paper is the Center for Research in Security Prices (CRSP) Survivor-Bias Free U.S. Mutual Fund Database for the period January 1991 to July 2001. We extract data on mutual fund monthly returns, total assets under management, and annual fund characteristics (e.g., expense ratio, load fees, starting date of the fund) for U.S. funds investing mostly in equities, that is, funds with the Investment Company Data Inc. (ICDI) investment objective codes AG (Aggressive Growth), GI (Growth Income), LG (Long-term Growth), IN (Income), and BL (Balanced).

The sample we use in our study is obtained as follows. We limit our analysis to the set of funds that belong to the top 50 families of U.S. actively managed equity mutual funds, ranked by net equity assets under management in the end of 2000. These families manage on average 80% of the total assets in the universe of CRSP equity funds in our sample period. We eliminate multiple classes of the same fund to avoid multiple counting of returns. Although multiple share classes are listed as separate funds in CRSP, they have the same pool of securities, the same portfolio manager, and the same returns before expenses and loads.[7] We identify classes by matching the base sample with the Spectrum/Thomson Financial database of Mutual Fund Holdings (see the Appendix for a description of the matching procedure). We then keep the share class with the highest total net assets (TNA) in case a fund is found to have multiple classes.[8]

Our objective is to investigate whether mutual fund families enhance the performance of mutual funds that are most valuable to the family. In line with the hypotheses stated above, we use three main criteria throughout our analysis to define the "value" of a fund to a mutual fund family: Fees, performance, and age.

Our proxy for the level of fees is Total Fees, defined as Expense Ratio + (Total Load/Average Number of Years of Investment for the investor). This is a measure of the total yearly cost charged to shareholders of a fund. It comprises the load fees (front, deferred, and redemption fees) and the yearly management fees

[7] Frequently, funds are sold through multiple share classes (e.g., "A," "B," "C," "No-Load," "Institutional") which can offer a different mix of front-end loads, back-end loads, and 12b-1 fees. More details can be found in Zhao (2002) and Pozen (1998).

[8] We choose to treat multiple fund share classes by taking the highest TNA class as this is the most representative class. Indeed, the highest TNA class represents over 90% of assets across all share classes and funds with multiple share classes became prevalent only in the later part of the 1990s. In unreported tests, we test the accuracy of our choice. We find that a classification based on the highest TNA class delivers a classification of the funds along our dimensions of interest (year-to-date returns, fees, and age) that is correlated almost perfectly with the classification based on the weighed average of the TNAs of the different classes. Moreover, we also find that the results of cross-fund subsidization we develop in Section III are robust if we implement an alternative share class treatment to take the TNA-weighted average of all fund share classes. Results are available from the authors upon request.

plus 12b-1 fees (expense ratio). Following Sirri and Tufano (1998), we assume that the average period an investor remains invested in the fund is 7 years. Regarding performance, we follow Brown et al. (1996), Chevalier and Ellison (1997), and others and use Year-to-Date Return (the return of the fund since January of the current year), removing funds with less than 6 months of return history. We are motivated by the fact that influential fund listing providers such as Morningstar, and much of the financial press, usually produce top ranking tables that report fund performance in terms of year-to-date. Finally, the literature points out that the flow-performance relation is stronger for younger funds (e.g., Chevalier and Ellison (1997)). Hence, we use Age (the number of years since the fund's inception) as a classification variable.

In our sample of actively managed equity funds, the volume of assets under management, as well as the number of funds, has steadily increased over time. On average, over the full sample period, the top 50 fund families manage $878 billion in assets (representing 80% of the total TNA of all CRSP equity funds) distributed over 598 funds. The corresponding figures for 2,000 are $1.9 trillion, distributed over more than 870 mutual funds. The average fund in the sample period has assets worth $1.6 billion, charges 1.5% in total fees, and is 3.5 years old. The average family has 35 equity funds managing $47 billion of assets and is 13 years old.

In order to implement our tests, we classify funds as having high value or low value to the family to which they belong. Our general rule is that a fund is classified as a high (low) value fund for a given criteria, that is, fees, performance, age, if the fund is above (below) the 75^{th} (25^{th}) percentile of the relevant peer group of funds for that criteria. More specifically, we classify as:

1. high fees a fund that is in the top quartile of funds in terms of Total Fees in its fund family (conversely for low fee funds),
2. high performing a fund that is in the top quartile of funds in terms of Year-to-Date Return in its investment style (conversely for low performing funds),
3. young a fund that is in the bottom quartile of funds in terms of its Age since initiation in its fund family (conversely for old funds).

Table I compares the characteristics of the resulting high value and low value funds, in each classification. Note that for Age, a fund is classified as high value if it is a young fund. The families in our sample charge an average of 2.2% per year on their high fees funds while they charge only 0.9% for a low fees fund (all differences mentioned are significant at the 1% level). The mean high year-to-date return funds yielded 2% per month on average since the start of the year, compared with a performance of −0.3% for low year-to-date return funds. Finally, the average old fund is 12 years old, while the average young fund is slightly less than 1 year old.[9]

[9] One possible concern raised by our scheme is the possibility of overlap between the different sets of funds classified as high value or low value under each classification. However, we find that the correlations among a fund's ranking percentile in the fees, year-to-date returns, and age classifications are very close to zero.

Table I

Characteristics of High and Low Funds

This table presents summary averages for the different "high value"/"low value" fund groups used in our study. Our sample is composed of all actively managed equity funds of the top 50 fund families in the CRSP Mutual Funds database, and the sample period is from 1991 to 2001. Every month, we partition funds into quartiles with respect to a variable of interest (e.g., Total Fees). A fund is classified as High (Low) if the fund's value for that variable is above (below) the 75th (25th) percentile for the relevant peer group of funds. For Total Fees and Age, the comparison peer group is all funds in the same fund family (e.g., Fidelity). For Year-to-Date Return, the comparison peer group is all funds in the same style, defined by its ICDI investment objective code (e.g., Aggressive Growth funds). Note that for the Age criteria, a High value fund is a young fund, while a Low value fund is an old fund. The fund's monthly return (Return) is obtained from CRSP Mutual Funds. Total Net Assets (TNA) is the closing market value, in millions of dollars, of all securities owned by a fund, plus all assets minus all liabilities. Total Fees is a measure of total yearly cost to shareholders of investing in a fund, and is defined as Expense Ratio + (Total Load/average number of years of investment). Total Load is the total of all maximum front, deferred, and redemption fees applied to a fund, while Expense Ratio is the (yearly) percentage of total investment shareholders pay for the mutual funds operating expenses. We assume for the purposes of the calculation that the average number of years a shareholder remains invested is seven (Sirri and Tufano (1998)). Year-to-Date Return is the return of the fund since January of the current year (in monthly equivalent returns). Age is the number of years since a fund's inception to the current date. For each variable of interest, each line presents the sample-wide mean of each variable for High funds, the mean for Low funds, and the p-value of the hypothesis test that the two means are equal.

	Total Fees			Year-to-Date Return			Age		
	High Funds	Low Funds	p-Val. Diff.	High Funds	Low Funds	p-Val. Diff.	High Funds	Low Funds	p-Val. Diff.
Fund return[a]	0.011	0.011	0.999	0.014	0.007	<0.001	0.010	0.010	0.943
TNA	641	2,105	<0.001	1,798	1,330	<0.001	1,042	3,603	<0.001
Total fees	0.022	0.009	<0.001	0.014	0.016	<0.001	0.015	0.013	<0.001
Year-to-date return[a]	0.008	0.010	<0.001	0.020	−0.003	<0.001	0.008	0.009	0.113
Age	2.1	4.7	<0.001	3.9	3.6	<0.001	0.8	12.0	<0.001

[a]Monthly returns.

III. Main Tests of Strategic Cross-Fund Subsidization

A. Our Methodology

Let us start by considering an example of a fictional fund family with only two funds, fund H and fund L, where fund H charges high fees and fund L charges low fees.[10] The fund family benefits if extra performance is directed toward fund H, because the extra benefits that accrue in terms of higher fees from H's higher investor inflows (due to its improved performance) more than offset the costs arising to the fund family from L's lower investor flows.

[10] Naturally, similar examples are valid for any of the two other dimensions: high performing versus low performing funds and young versus old funds.

A direct test of whether fund L is transferring performance to fund H (hypothesis H2) is to ask whether the observed difference in returns between the two funds systematically exceeds the one predicted by the corresponding difference in returns of their investment styles. This same difference can be expressed, by a simple reorganization of terms, as the difference between fund H's net-of-style return (H's observed return minus its corresponding investment style return) and fund L's net-of-style return.

We can then state the testable implications for the hypotheses laid out in Section I. If there is no overall family strategy (H0), then there is no reason to expect that the net-of-style returns of fund H and L will differ. Under Risk Sharing (H1), such a difference should also not exist as on average fund H is subsidized by fund L as many times as it subsidizes L, because H and L coinsure each other, depending which of the funds is more in need. Under our working hypothesis of Strategic Cross-Fund Subsidization (H2), however, we expect that on average fund H's net-of-style return exceeds L's net-of-style return.

This reasoning overlooks one important caveat: The wedge between fund H and fund L's net-of-style return can exist in the data independent of whether H and L are under the control of the same fund family or not. If, for example, a difference exists on average between any high fee and low fee funds independent of whether they belong to the same fund family, then such difference cannot be ascribed to a cross-Fund subsidization strategy. This type of selection bias is similar to the one uncovered by the recent corporate finance literature studying value-destroying cross-subsidization within diversified conglomerates (Chevalier (2000) and others).

The test should therefore quantify the extra effect due to family affiliation. We implement this idea by using a "matching" fund, that is, a fund that does not belong to the same family and that can be used as a good replacement for fund L. We call this fund LM (standing for "L matched"). Under No Overall Family Strategy (H0), the difference between H and L should not differ from that between H and LM. Under Risk Sharing (H1), we expect that fund H is as many times subsidized by fund L as L is by H. Hence the net-of-style return difference between H and L should be greater than that between H and LM as many times as the reverse is true. The average net-of-style return difference between H and L should therefore not differ from that between H and LM. Under Strategic Cross-Fund Subsidization (H2), H should be helped at the expense of L and therefore the average net-of-style return difference between H and L should be greater than that between H and LM.

We implement this methodology as follows. Tests are conducted by taking fund pairs composed of one high value and one low value fund from the same fund family. We calculate the net-of-style return of each fund and then we take the difference in net returns between the high value and low value funds. We label this as the net return difference for the "actual pair." Then, for each pair, the low value fund is matched with a very similar fund, that is, a fund that is in the same investment style and in the same sample decile in terms of the

Table II

Univariate Analysis

This table presents preliminary evidence concerning cross-fund subsidization. Every month, we partition funds into quartiles with respect to a variable of interest (e.g., Total Fees). A fund is classified as High (Low) if the fund's value for that variable is above (below) the 75th (25th) percentile for the relevant peer group of funds. For Total Fees and Age, the comparison peer group is all funds in the same family. For Year-to-Date Return, the comparison peer group is all funds in the same style (ICDI investment objective code). Note that for the Age criteria, a High value fund is a young fund, while a Low value fund is an old fund. We then construct, for each classification, two sets of High/Low pairs of funds as follows. In the first set, each High fund is matched with all Low funds belonging to the same family. We call these pairs, constructed within the same family, "Actual" pairs. In the second set, each Low fund in every Actual pair is replaced by a matching control fund taken from the remaining sample of funds. The matching control fund is selected randomly from the set of funds of the same style and belonging to the same decile of the variable of interest as the Low fund it replaces (Total Fees, Year-to-Date Return, or Age). We call these pairs "Matched" pairs. For each fund in the pair, we calculate the Net-of-Style Return (defined as the fund's monthly return minus the return for its style) and subsequently the Difference in Net-of-Style Returns, the difference between the Net-of-Style Return of High fund i and Low fund j within each pair. The first column of the table shows, for each classification variable, the mean Difference in Net-of-Style Returns for Actual Pairs, along with the significance symbols of the test that the mean is zero. The second column shows the mean Difference in Net-of-Style Returns for Matched pairs, along with the significance symbols of the test that the mean is zero. The third column shows the p-value of the t-statistic of the test that the two means are equal. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Net Difference in Performance for Pairs of High and Low Funds		
	Actual Pairs	Matched Pairs	p-Value of Difference
Total fees	0.052%***	0.000%	0.03**
Year-to-date return	0.665%***	0.492%***	<0.001***
Age	0.004%	−0.021%	0.25

criteria under consideration (fees, performance, or age). We compute the net return difference for this "matched pair."[11]

B. Results

Table II presents univariate statistics. The table shows the mean net-of-style performance differences for our criteria (fees, performance, and age), along with tests of the difference of means between the two types of pairs. Results show that the net difference in performance is higher for funds belonging to the same

[11] This methodology effectively "resamples" the low value funds, while keeping the set of high value funds fixed. An alternative strategy is to resample both the low value and high value funds simultaneously. We find this "double resampling" to be extremely demanding computationally, so we settle for resampling the low value funds only. The preliminary results we obtain, which are available upon request, indicate that our findings are stronger if we use double resampling.

family (actual pairs) than for funds belonging to different families (matched pairs). Actual pairs show an extra performance for the high value funds that varies between 5 and 17 b.p. (basis points) per month, respectively, for high fees and high past performance, which is statistically significant. These results provide a first indication of cross-fund subsidization inside fund families and we find no equivalent results of favoritism toward young funds.

Our main test consists of a multivariate regression in which we stack all the actual and matched pairs into a column vector and test whether the actual pair and matched pair net return differences are significantly different. This is done by running the following specification:

$$\text{Net\_return}_{i,t}^{\text{High}} - \text{Net\_return}_{j,t}^{\text{Low}} = a + \beta(\text{Same\_family}) + \gamma(\text{Same\_style}) + \text{controls} + \varepsilon_{i,s,f,t}, \tag{1}$$

where $\text{Net\_return}^{\text{High}}$ is the net-of-style performance at time t of a high value fund i. This is calculated by subtracting from the raw return in month t of each high value fund the value-weighted average return of the funds in the same investment style (i.e., the same ICDI fund objective code). Similarly, $\text{Net\_return}^{\text{Low}}$ is the net-of-style performance at time t of a low value fund j. The dummy variable Same_family takes the value of one if funds i and j are members of the same fund family (i.e., an actual pair) and the value of zero otherwise (i.e., a matched pair). The dummy variable Same_style takes the value of one if funds i and j belong to the same investment style.

If the performance of high value funds is boosted at the expense of that of low value funds (H2), we should observe that actual pair net return differences are significantly greater than those of matched pairs. If this is the case, we expect the β coefficient to be significantly positive. Under Risk Sharing (H1) or if no coordinated strategy is pursued at the family level (H0), then the actual pair net return differences should not be significantly different from those of matched pairs. Let us summarize our testable implications.

- Under No Overall Family Strategy (Hypothesis H0): $\beta = 0$
- Under Risk Sharing (Hypothesis H1): $\beta = 0$
- Under Strategic Cross-fund Subsidization (Hypothesis H2): $\beta > 0$

Table III presents the results of the multivariate regression analysis of equation (1), for each of our criteria of interest (fees, performance, and age). All specifications include controls for family, time, and style effects. We also present specifications with additional control variables (whose coefficients are not shown), which include, for both the high value and the low value funds in each pair, the size of the funds, the age of the funds, the size of the funds' families, and the age of the funds' families.

These results show that cross-fund subsidization within the family contributes around 4–6 basis points of extra net-of-style performance for the funds valued highly in terms of fees (with t-statistics ranging from 1.8 to 2.4) and 21–28 basis points for the funds valued highly in terms of performance (with

Table III

Tests of Strategic Cross-Fund Subsidization

This table presents regression results of the tests of cross-fund subsidization. Every month, we partition funds into quartiles with respect to a variable of interest (e.g., Total Fees). A fund is classified as High (Low) if the fund's value for that variable is above (below) the 75th (25th) percentile for the relevant peer group of funds. For Total Fees and Age, the comparison peer group is all funds in the same family. For Year-to-Date Return, the comparison peer group is all funds in the same style (ICDI investment objective code). Note that for the Age criteria, a High value fund is a young fund, while a Low value fund is an old fund. We then construct, for each classification, two sets of High/Low pairs of funds as follows. In the first set, each High fund is matched with all Low funds belonging to the same family. We call these pairs, constructed within the same family, "Actual" pairs. In the second set, each Low fund in every Actual pair is replaced by a matching control fund taken from the remaining sample of funds. The matching control fund is selected randomly from the set of funds of the same style and belonging to the same decile of the variable of interest as the Low fund it replaces (Total Fees, Year-to-Date Return, or Age). We call these pairs "Matched" pairs. For each fund in the pair, we calculate the Net-of-Style Return (defined as the fund's monthly return minus the return for its style) and subsequently the Difference in Net-of-Style Returns, the difference between the Net-of-Style Return of High fund i and Low fund j within each pair. Both sets of pairs are added together in the same data set to run our regressions. For each classification, the table shows the results of the following regression (equation (1) in the text):

$$\text{Net\_return}^{\text{High}}_{i,t} - \text{Net\_return}^{\text{Low}}_{j,t} = a + \beta(\text{Same\_family}) + \gamma(\text{Same\_style}) + \text{controls} + \varepsilon_{i,s,f,t}.$$

The left-hand side variable is the Difference in Net-of-Style Returns for each pair. Same-Family is a dummy variable that takes a value of 1 if the two funds in the pair belong to the same fund family, and 0 otherwise. Same-style is a dummy variable that takes a value of 1 if the two funds in the pair belong to the same style, and 0 otherwise. Control variables whose coefficients are not shown include, for both the High and the Low funds in each pair, the size of the funds, the age of the funds, the size of the funds' families and the age of the funds' families. t-statistics shown are obtained using heteroskedastic-robust standard errors. The symbols ***,**, and * denote significance at 1%, 5%, and 10% levels, respectively.

	Total Fees				Year-to-Date Return				Age			
	(1)		(2)		(3)		(4)		(5)		(6)	
	Coeff.	t-Stat.	Coeff.	t-Stat.	Coeff.	t-Stat.	Coeff.	t-Stat.	Coeff.	t-Stat.	Coeff.	t-Stat.
Intercept	0.0012	2.01*	0.0019	2.78*	−0.0007	−0.65	−0.0006	−0.48	−0.0014	−1.81*	−0.0009	−0.93
Same family (β)	0.0004	1.75*	0.0006	2.44**	0.0021	5.68***	0.0028	6.49***	−0.0004	1.95*	−0.0003	−1.33
Same style (γ)	−0.0003	−1.06	−0.0003	−1.06	0.0011	2.42**	0.0011	2.46**	−0.0001	−0.20	−0.0001	−0.24
Controls	no		yes		no		yes		no		yes	
Year dummies	yes		yes		yes		yes		yes		yes	
Family dummies	yes		yes		yes		yes		yes		yes	
Style dummies	yes		yes		yes		yes		yes		yes	
Mean squared error	0.00		0.00		0.00		0.00		0.00		0.00	
Adjusted R^2	0.01		0.01		0.03		0.03		0.01		0.01	
N	160,007		159,164		86,602		86,271		176,203		175,212	

t-statistics ranging from 5.7 to 6.5). This effect is in excess of the preexisting difference between high value and low value funds, given by the intercept term (at least in the case of fees). Note also that this impact occurs irrespective of the pair having the same style. The coefficient for funds classified by age groups is not significant or slightly negative, not supporting cross-fund subsidization to young funds.[12]

We conclude that there exists a difference in performance between high and low funds within the family that is not determined by chance, and that this difference favors the high value funds (high fees and high past-performing funds).[13]

C. Does the Level of Strategic Cross-Fund Subsidization Depend on How the Investment Styles of the Funds Are Performing?

In this section, we explore in more detail the types of cross-fund subsidization strategies. Getting back to our working example, we can treat separately the cases in which fund H is more in need of help—because H has been severely hit by a negative shock—and the opposite case in which fund L is more in need of help. One simple way to proxy for these cases is to identify whether H's investment style is outperforming L's investment style or whether the reverse is true.

Under our null hypothesis (H0), we don't expect fund H or L to be systematically subsidized. Under Risk Sharing (H1), we expect that fund H is subsidized when its investment style is underperforming with respect to the style of fund L but that H subsidizes L when its investment style is overperforming. Under Cross-Fund Subsidization (H2), fund H should be subsidized by fund L at all times—that is, both when H's investment style is overperforming and when it is underperforming L's investment style. A strong form of H2 would posit that the difference between actual pair and matched pair net return differences is always positive. We can also posit a weaker form of H2 that only requires fund H to be "more helped" by fund L when L's style is overperforming, but to offer less help to fund L when L's style is underperforming.

[12] In unreported regressions, we run our tests using "gross-of-expenses" returns (calculated as the CRSP fund monthly returns plus 1/12 of the annual expense ratio). Using gross-of-expenses returns we pick up the real change in a fund's net asset value before expenses are deducted, so this measures the full performance transfer from low value to high family value funds that families engage in, before any effects from the setting of fees. In tests similar to the ones implemented in Table III, we conclude that high fees and high past performing funds are subsidized by up to 10 and 31 b.p. in terms of full net asset value before expenses are deducted, at the cost of low fees and low performing funds, respectively. Note also that these results alleviate concerns that fee-setting strategies on the part of fund families could play a role in our findings. Results are available from the authors upon request.

[13] A previous version of this paper includes additional tests based on the methodology of Bertrand, Mehta, and Mullainathan (2002) devised to quantify "tunneling" in business groups. These tests examine whether the shocks of the fund investment style affecting some member funds of a family are geared asymmetrically to the benefit of high value funds in the family. The results of these tests are also consistent with our H2 hypothesis of strategic cross-fund subsidization.

This more detailed test can also encompass another possibility: the fact that funds H and L belong to the same investment style. So, we can also test whether actual pair and matched pair return differences are significantly different for funds belonging to the same style. We label this case as intrastyle cross-fund subsidization.

We implement the test by estimating regressions of fund pairs in a similar way to equation (1) above. The specification differs from the previous one because the dummy Same_family has been split into three separate dummies: (Same_family | $\text{ST\_RET}_{\text{High}} > \text{ST\_RET}_{\text{Low}}$) if the performance of the investment style of the high value fund i outperforms that of the low value fund j; (Same_family | $\text{ST\_RET}_{\text{High}} < \text{ST\_RET}_{\text{Low}}$) if the performance of the investment style of the high value fund i underperforms that of the low value fund j; and, (Same_family | Same_style) if funds i and j belong to the same style. The specification is then

$$\begin{aligned}
&\text{Net_return}_{i,t}^{\text{High}} - \text{Net_return}_{j,t}^{\text{Low}} \\
&\quad = a + \beta_{+}(\text{Same_family} \mid \text{ST_RET}_{\text{High}} > \text{ST_RET}_{\text{Low}}) \\
&\qquad + \beta_{-}(\text{Same_family} \mid \text{ST_RET}_{\text{High}} < \text{ST_RET}_{\text{Low}}) \\
&\qquad + \beta_{0}(\text{Same_family} \mid \text{Same_style}) \\
&\qquad + \gamma(\text{Same_style}) + \text{controls} + \varepsilon_{i,s,f,t} \qquad (2)
\end{aligned}$$

where $\text{Net\_return}^{\text{High}}$, $\text{Net\_return}^{\text{Low}}$, and the dummy variable Same_family are defined as before.

Under our null hypothesis (H0), no coordinated subsidization is pursued at the family level. This implies that β_{+}, β_{-}, and β_0 should be equal to zero. Under the hypothesis of Risk Sharing (H1), high value funds are only subsidized by low value funds when their performance is bad to start with ($\beta_{-} > 0$), but get to help the low value funds in the reverse case ($\beta_{+} < 0$) by equal amounts ($|\beta_{+}| = |\beta_{-}|$). This implies that, on average, β_{+} should be equal to β_{-} in absolute terms.

The hypothesis of strategic cross-fund subsidization (H2) in its weaker form requires that β_{+} be lower than β_{-} in absolute terms for the case of interstyle subsidization (H is more helped by fund L than the reverse) and that β_0 be positive for the case of intrastyle subsidization. The hypothesis of strategic cross-fund subsidization in its strong form (wherein high value funds are always helped, independent of how bad the low value funds are performing) requires that both the coefficients β_{+} and β_{-} be positive. We can summarize our testable implications as follows:

- Under No Overall Family Strategy (Hypothesis H0): $\beta_{+} = 0, \beta_{-} = 0$, and $\beta_0 = 0$.
- Under Risk Sharing (Hypothesis H1): $\beta_{+} < 0$ and $\beta_{-} > 0$, $|\beta_{+}| = |\beta_{-}|$, and $\beta_0 = 0$.

- Under Strategic Cross-Fund Subsidization (Hypothesis H2): $\beta_+ <$ or > 0 and $\beta_- > 0$, but $|\beta_+| < |\beta_-|$ (for interstyle subsidization) and $\beta_0 > 0$ (for intrastyle subsidization).

Table IV presents the results of these extended tests. Results support the strategic cross-fund subsidization hypothesis in its weak form, although with some variations across the different classifications. In the case of fees, high value funds are helped relatively more when their style is not performing well (the extent of help being 67 b.p., t-statistic of 21.3) than they help the low value ones when the style of the latter is underperforming (-54 b.p., t-statistic of -17.3). The difference between them is statistically significant (p-value of 1.3%). Intrastyle cross-fund subsidization is not significant. In the case of year-to-date returns, we see that our earlier result from Table III is mostly due to the help that low performing funds provide to high performing funds (60 b.p., t-statistic of 11). This is further confirmed by the test that $|\beta_-| < \beta_+|$ (with a p-value less than 1%). Intrastyle cross-fund subsidization is relevant in this case (29 b.p., t-statistic of 3.6). Finally, as we see in the previous section, the results do not support the cross-fund subsidization of young at the cost of old funds.

D. Which Family Characteristics Are Associated with Strategic Cross-Fund Subsidization?

Our findings that cross-fund subsidization is an empirically relevant phenomenon lead naturally to the question of what kind of families engage more in this practice.

We look at four dimensions: family size, number of funds in the family, family age, and homogeneity of funds in the fund complex. On the first two, we expect cross-fund subsidization to be positively related to the size of the family. As the family grows bigger, it must increasingly decide to allocate the best trading opportunities to some of its constituent funds. At the same time, having many funds provides the family with a margin of maneuver that allows it to buffer the market impact of market orders of each fund. On the third dimension, we expect to find more subsidization in young families with relatively short track records, because flow-performance incentives are higher. Finally, the ability to engage in cross-fund subsidization depends on the homogeneity in terms of the size of the funds in the family. While small funds should be more sensitive to subsidization—that is, it is easier to affect their performance—they are not good “helpers”—that is, their performance suffers relatively more if they are used to deviating performance to other funds in the family. Therefore, we should not find cross-fund subsidization in very homogeneous families (families with only small or only large funds), but rather in families in which there is a wide dispersion of fund sizes.

We run our direct tests for different subsets of families according to different characteristics. Results are reported in Table V. Each cell presents the

Table IV

Extended Tests of Strategic Cross-Fund Subsidization

This table presents regression results of extended tests of cross-fund subsidization. Please refer to Table III for a complete description of how pairs of "High" and "Low" funds are obtained. The table shows the results of the following specification (equation (2) in the text):

$$\text{Net\_return}_{i,t}^{\text{High}} - \text{Net\_return}_{j,t}^{\text{Low}} = a + \beta_+(\text{Same\_family} \mid \text{ST\_RET}_{\text{High}} > \text{ST\_RET}_{\text{Low}}) + \beta_-(\text{Same\_family} \mid \text{ST\_RET}_{\text{High}} < \text{ST\_RET}_{\text{Low}})$$
$$+ \beta_0(\text{Same\_family} \mid \text{Same\_style}) + \gamma(\text{Same\_style}) + \text{controls} + \varepsilon_{i,s,f,t}.$$

The left-hand side variable is the Difference in Net-of-Style Returns for each pair. The first variable in the right-hand side (Same_Family | $\text{ST\_RET}_{\text{High}} > \text{ST\_RET}_{\text{Low}}$) is a dummy variable that takes a value of 1 if the two funds in the pair belong to the same fund family and the style of the High fund is currently performing better than the style of the Low fund. The second variable (Same_Family | $\text{ST\_RET}_{\text{High}} < \text{ST\_RET}_{\text{Low}}$) takes a value of 1 if the two funds belong to the same fund family and the style of the Low fund is currently performing better than the style of the High fund. (Same_Family | Same_Style) takes a value of 1 if the two funds belong to the same fund family and the same style. Other variables are defined as before. The table presents also the p-value of the hypothesis test that the two coefficients $\beta+$ and $\beta-$ are equal. The number of observations, N, represents pair-month combinations. t-statistics shown are obtained using heteroskedastic-robust standard errors. Symbols ***,**, and * denote significance at 1%, 5%, and 10% levels, respectively.

	Total Fees				Year-to-Date Return				Age			
	(1)		(2)		(3)		(4)		(5)		(6)	
	Coeff.	t-Stat.	Coeff.	t-Stat.	Coeff.	t-Stat.	Coeff.	t-Stat.	Coeff.	t-Stat.	Coeff.	t-Stat.
Intercept	0.0009	1.49	0.0016	2.31**	−0.0010	−0.86	−0.0008	−0.71	−0.0013	−1.61	−0.0008	−0.86
Same family (β_+)	−0.0055	−18.67***	−0.0054	−17.30***	−0.0012	−2.53**	−0.0005	−0.85	−0.0045	−15.05***	−0.0054	−15.26***
Same family (β_-)	0.0064	21.58***	0.0067	21.27***	0.0053	10.70***	0.0060	11.02***	0.0050	16.96***	0.0042	12.12***
Same Style & family (β_0)	0.0001	1.16	0.0008	1.63	0.0022	2.85***	0.0029	3.60***	0.0007	1.66*	−0.0003	−0.62
Same style (γ)	−0.0004	−0.86	−0.0004	−0.90	0.0010	1.48	0.0011	1.55	−0.0003	−0.74	−0.0002	−0.56
Controls	no		yes		no		yes		no		yes	
Year dummies	yes		yes		yes		yes		yes		yes	
Family dummies	yes		yes		yes		yes		yes		yes	
Style dummies	yes		yes		yes		yes		yes		yes	
P-value of test that $\lvert\beta_+\rvert < \lvert\beta_-\rvert$	0.065*		0.013**		0.001***		0.001***		0.31		0.063*	
Mean squared error	0.00		0.00		0.00		0.00		0.00		0.00	
Adjusted R^2	0.02		0.02		0.03		0.04		0.01		0.01	
N	160,007		159,164		86,602		86,271		176,203		175,212	

Table V

Family Characteristics and Strategic Cross-Fund Subsidization

This table presents regression results of the tests of cross-fund subsidization, broken down across family characteristics. Each cell shows the β coefficient of the specification of Panel A of Table III for different family groups. Please refer to the caption of Table III for a complete description of the variables and how the pairs of "High" and "Low" funds are constructed. Families are divided into groups according to size (top 25 families versus bottom 25), number of funds in the family (more or less than the average of 27 funds), family age (more or less than the average of 13 years), and dispersion of fund size within the family (above and below the average). Dispersion of fund size within the family is calculated as the coefficient of variation of the TNA of funds within the same family. The symbols ***, **, and * denote significance of the β parameter at 1%, 5%, and 10% levels, respectively, using heteroskedastic-robust standard errors.

Panel A

	Families by Size		Families by Number of Funds	
	Top 25	Next 25	Above Average	Below Average
Total fees	0.07**	0.07	0.12***	−0.08**
Year-to-date return	0.29***	0.16*	0.34***	0.09*
Age	−0.06**	0.04	−0.09***	0.09**

Panel B

	Families by Age		Families by Size Heterogeneity	
	Old (>13 Years)	Young (<13 Years)	Above Average	Below Average
Total fees	−0.05	0.09***	0.11**	−0.05
Year-to-date return	0.29	0.18***	0.33***	0.10
Age	0.25***	−0.14***	−0.05	−0.09**

Note: Values expressed are in percent.

same-family effect (the β coefficient of Table III) for the regression run on each family subgroup. Families are divided into groups according to the criteria we identified: family size in terms of equity TNA (top 25 families versus bottom 25), number of funds in the family, family age, and dispersion of fund size within the family (coefficient of variation of the TNA of funds within the same family).

Results show that most of cross-fund subsidization for high fees and high performance funds takes place within large families, with many funds (Panel A of Table V), and with a great heterogeneity in fund size (Panel B). As before, results are contradictory concerning the subsidization of young funds. It is interesting to note, however, that the respective β coefficient is statistically significant and positive for old families and statistically significant and negative for young families. This indicates that the established track record of old families allows them to help young funds, while in mostly young families it's the relatively older funds that the family wants to favor, presumably in an attempt to create flagship funds.

IV. Evidence on How Strategic Cross-Fund Subsidization Takes Place

If fund families are strategically cross-subsidizing their most valuable funds, as the body of evidence in the last section seems to suggest, then a question arises: How does cross-fund subsidization take place? In this section we explore preliminary evidence on the possible ways mutual fund families increase the performance of their most valuable funds. However, we should make clear from the start that we can only provide evidence that is limited by the level of information disclosure to which mutual fund activities are subject.

We look at two ways fund families can coordinate actions among their funds to favor high value funds: Preferential allocation and opposite trades. The first entails a strategy whereby the family concentrates its best deals on high value funds and excludes low value funds from taking advantage of these. The second entails a strategy whereby the family arranges for the low value funds to take a market position that is symmetric to that of the high value funds (e.g., to buffer the market impact of the high value fund orders) or eventually crosses buy and sell orders from high value and low value funds without going to the open market, a practice commonly labeled as "cross-trading."

A. Preferential Allocations in IPOs

We first investigate preferential trade allocation. Although preferential trade allocation is an intuitive notion, it may somehow be short of empirical value as there are few instances in which we can ex post assume that the fund family had reliable information that a security would appreciate in value. One event, however, does allow us to explore whether fund families direct better trades to high value funds: the sizeable underpricing phenomenon in IPOs.[14]

Underwriters possess substantial information about the offer demand as a result of the book-building process. Moreover, underwriters have considerable latitude on how IPO shares are allocated. In principle, underwriters can favor preferred investors by allocating them more shares in hot issues that are expected to trade up in the aftermarket (Agarwal, Prabhala, and Puri (2002)). In the past, securities regulators have charged some underwriters with the practice of "spinning" hot IPOs to favored executives to win or keep investment banking business (*Wall Street Journal* (2003)). Mutual fund families are also likely to receive preferential treatment in IPOs. Agarwal et al. (2002) suggest that institutional allocation in underpriced issues is in excess of that explained by book-building theories alone. Additionally, Reuter (2002) finds that allocations of underpriced IPOs to mutual fund families seem to be related to the level of brokerage commissions they have paid the underwriters in the months surrounding the IPO.

Mutual fund families also have some discretion over which of their member funds will receive shares of the most underpriced (hotter) IPOs. There have been some news reports on favoritism in IPO allocations (*Wall Street Journal* (2004))

[14] See Ritter and Welch (2002) for an overview of the underpricing phenomenon in IPOs.

and also several SEC enforcement cases.[15] Under our cross-fund subsidization hypothesis (H2), we expect that the hotter an IPO is, the more these shares are allocated to high value mutual funds.

To test this hypothesis, we collect all IPO deals from the Securities Data Company's (SDC) database that took place between 1992 and 2001. The SDC data allows us to compute the first-day return of each IPO issue (defined as the percentage increase from the offer price to the first-day closing price). We merge this information with both our sample of CRSP mutual funds and data on mutual fund common stock holdings from the Spectrum/Thomson Financial database that contains the N-SAR filings that mutual funds are required to submit to the SEC on a semi-annual basis.[16] The data merge procedure is described in more detail in the Appendix to this paper. We then identify each mutual fund's reported holdings of any IPO stock at the end of the quarter the issue took place. Similarly to Reuter (2002), our tests are based on positive reported holdings of an IPO, which best approximates whether a fund was allocated IPO shares at the offer date.[17]

Table VI presents results on IPO allocations across funds. Panel A shows that the 2,657 IPO issues for which mutual funds reported holdings at quarter-end of the time of the issue earned significantly higher first-day returns on average (28%) than the full SDC sample (14.5%). This indicates that mutual funds as a group receive more underpriced issues. Panel B performs our tests of preferential trade allocation. We compute the average and median first-day returns of all IPO issues for which high value and low value mutual funds report positive holdings at quarter-end. High value and low value funds are defined according to our criteria of analysis: fees, performance, and age. A comparison of the average and median IPO first-day returns indicates that fund families allocate relatively more underpriced IPOs to high fee funds (1,751 deals average first-day return of 44.0%), as opposed to low fee funds (1,277 deals, 30.6%). The same pattern applies to high past performance funds (1,666 deals, 50.5%) versus low past performance ones (1,061 deals, 37.2%). Interestingly, and in line with findings in Section III, the evidence is much weaker with regards to the

[15] One high-profile SEC enforcement case involved hot IPO allocations that favored Dreyfus Aggressive Growth Fund (DAG) at the cost of other Dreyfus funds. According to findings reported in SEC (2000), the DAG fund was allocated disproportionate shares of oversubscribed IPOs. The SEC calculated that first-day returns from IPOs contributed 51.3% of DAG's total returns in the first 6 months (or 76% of its total returns). DAG's outstanding performance allowed it to take the top ranking position in Morningstar in the first quarter of 1996 and the #1 ranking in Lipper's capital appreciation category, drawing huge inflows, which made its assets increase from $2 million to $154 million in 1 year. *Wall Street Journal* (2004) lists other cases and the recent settlement between the SEC and Massachusetts Financial Services for this company to change its trading practices to minimize the chances that IPOs will distort funds performance.

[16] In practice, most funds voluntarily report funds holdings in prospectuses at a higher frequency. Wermers (2000) finds that over 80% of funds report their portfolio holdings on a quarterly basis in the Spectrum/Thompson Financial data set.

[17] We don't expect trading between the time of the IPO and the time a fund reports its holdings to bias our results. The reason is that the amount of "flipping" or buying of IPO shares between the offer date and the quarter-end at which holdings are reported should not be related to our high versus low value fund classifications. As in Reuter (2002), we take positive holdings as the best proxy available of whether a fund was attributed shares at the offer date.

Table VI

IPO Allocations across High and Low Funds

This table presents an investigation of how IPO allocations differ across "High" and "Low" funds. Please refer to Table III for a complete description of how pairs of High and Low funds are obtained. We obtain data for IPOs from the Securities Data Corporation Platinum database for the 1992 to 2001 period, and calculate the equally weighted average and median first-day return (defined as the percentage price increase from the offer price to the first day closing price). We match these IPOs with the Spectrum Mutual Funds holdings data for the funds in our sample. The table presents, for the different High and Low groups in each classification variable (e.g., fees, performance, age), the time-series and cross-section average of the number of IPOs, as well as the average and median first-day IPO returns. The next-to-last row shows the average total dollar amount of underpricing (the first-day price increase times number of shares held) allocated to each group. The last row shows the contribution of underpricing to fund returns, defined as the average ratio between the dollar amount of underpricing and the fund's previous quarter TNA, for all funds that had positive holdings in any IPO. Note that for the Age criteria, a High value fund is a young fund, while a Low value fund is an old fund. The table also shows the p-value of the hypothesis test that the figures are equal for High and Low funds. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A

All IPO issues, 1992–2001	$N = 5{,}477$	Value: \$413.2 billion	Average 1st-day return	14.5%
(source: SDC)			Median 1st-day return	6.3%
IPOs held at quarter-end by funds in the sample	$N = 2{,}657$	Value: \$26.7 billion	Average 1st-day return	28.0%
(source: Spectrum MF Holdings)			Median 1st-day return	12.5%

Panel B

	Total Fees			Year-to-Date Return			Age		
	IPOs Held by High Funds	IPOs Held by Low Funds	p-Value Diff.	IPOs Held by High Funds	IPOs Held by Low Funds	p-Value Diff.	IPOs Held by High Funds	IPOs Held by Low Funds	p-Value Diff.
N	1,751	1,277		1,666	1,061		2,249	872	
Average 1st-day return	44.0%	30.6%	<0.001***	50.5%	37.2%	<0.001***	43.8%	44.7%	0.72
Median 1st-day return	20.8%	13.5%	<0.001***	20.0%	19.4%	<0.001***	19.2%	17.6%	0.40
Dollar amount of underpricing going to H or L funds (\$ billion)	\$2.22	\$1.96		\$6.39	\$1.04		\$6.56	\$2.30	
Percentage contribution of underpricing to returns of H or L funds (% of TNA)	0.474%	0.091%	0.001***	0.288%	0.169%	<0.001***	0.322%	0.144%	0.004***

preferential treatment of young funds as first-day returns are not statistically different between young (43.8%) and old funds (44.7%), although they still are allocated a higher number of IPOs (2,249 versus 872 deals).

To better understand the magnitude of these findings, we calculate the dollar amount of the average underpricing (first-day price appreciation times number of shares) received by each group of funds, as well as its relative contribution to their fund returns. Table VI shows that high value funds were allocated higher amounts of "underpricing dollars" during the sample period. This is especially true for good past performers. High fee funds received \$2.2 billion of underpricing dollars, while low fee funds received \$1.9 billion; high performance funds received \$6.4 billion, while low performance funds received \$1 billion. In addition, the contribution of this underpricing to boost a funds' TNA was systematically higher for high value rather than low value funds. Within the set of funds that had IPO shares in their portfolios, underpricing contributed on average 0.47% to the return of high fee funds (estimated by taking the ratio of underpricing dollars to the TNA of the funds receiving the IPO stock) and 0.29% to the return of high performance funds, but only 0.09% and 0.17% to low fee and low performance funds, respectively.

We conclude that these patterns in IPO allocations are consistent with a preferential treatment of high value versus low value funds. It may be argued that funds might not sell off the IPO issue 1 day after the offer date, but hold on to it for a longer period. There is some concern that the patterns of post-IPO returns may reverse over a longer time horizon. To address this issue, we replicate our tests using 1-month and 3-month returns of IPO deals and find similar patterns to those reported above using first-day returns. Results are available from the authors upon request.

B. Opposite Trades and Cross-Fund Strategic Subsidization

Opposite trades are coordinated trade strategies that occur when a purchase of a particular security made by one mutual fund coincides with a parallel sale order from another mutual fund belonging to the same family. Cross-trading is included in this general category but requires additionally that buy and sell orders be matched one with the other, effectively constituting a transfer of securities from one fund to the other. Any positive performance the deal brings to one party should negatively affect the other. Cross-trades are feasible between mutual funds but, due to their potential for conflicts of interest, are subject to special restrictions.[18]

We therefore explore whether trade strategies across fund members can contribute to enhance the performance of high value funds at the expense of low value funds, again using the Spectrum/Thomson Financial database of Mutual

[18] Indeed, Rule 17a-7 of the U.S. Investment Company Act permits transactions between mutual funds subject to conditions of fair valuation of assets ("independent current market price," usually last sale market price), fair treatment of both parties (the traded asset fits the investment guidelines of the funds and no special fee or other remuneration is paid in connection with the transaction), and adequate record-keeping. Recently, the DOL has also issued an exemption which permits cross-trades of securities among Employee Retirement Income Security Act (ERISA) index funds, but does not extend it to actively managed funds.

Fund Holdings. Opposite trades (i.e., opposite buy and sell orders) imply that strategic cross-fund subsidization should be positively related to the opposite changes in holdings of high value and low value funds. We compute two measures of opposite trades between any pair of high value and low value funds as follows. The first measure, $\text{Opposite\_trades}_{\text{SUM}}$, is the sum, across both funds in the pair, of the dollar value of the securities for which we observe quarterly changes in the opposite direction in the number of shares held. The second measure, $\text{Opposite\_trades}_{\text{MIN}}$, is the minimum, across both funds in the pair, of the dollar value of the changes in holdings for the securities for which we observe quarterly changes in the opposite direction. Both measures are normalized by the total portfolio value of the pair of funds. Using quarterly changes in holdings as proxies for the transactions of a fund's portfolio is, however, only a second-best choice determined by the lack of publicly available data on a fund's actual trades.

We run regressions of fund pairs in a similar way to the direct test introduced in Section III above, expanding specification equation (1) to include as additional explanatory variables measures of opposite trades in securities held by the pair of funds:

$$
\begin{aligned}
&\text{Net\_return}_{i,t}^{\text{High}} - \text{Net\_return}_{j,t}^{\text{Low}} \\
&\quad = a + \beta(\text{Same\_family}) + \gamma(\text{Same\_style}) + \varsigma(\text{Opposite\_trades}) \\
&\qquad + \theta(\text{Opposite\_trades} \mid \text{Same\_family}) + \text{controls} + \varepsilon_{i,s,f,t}
\end{aligned} \tag{3}
$$

where $\text{Net\_return}^{\text{High}}$, $\text{Net\_return}^{\text{Low}}$, and the dummy variables Same_family and Same_style are defined as before. Opposite_trades refers to either of our two measures of opposite changes in holdings defined above ($\text{Opposite\_trades}_{\text{SUM}}$ and $\text{Opposite\_trades}_{\text{MIN}}$); we present results for each separately. (Opposite_trades | Same_family) is an interaction between the Opposite_trades measure and the Same_family dummy variable.

Although this specification closely follows equation (1), the fact that holdings are observed only at a quarterly frequency leads us to adjust our estimation procedure in several important ways. First, we assume that the effect of trades is spread evenly across the 3 months of the quarter, such that in each month we can use the current quarter's change in holdings as a proxy for trading activity. Second, to ensure the strategy we are studying is implementable, we classify each fund as high value or low value at the beginning of each month, but we measure returns after the end of the month. Third, we use 3-month net returns (instead of monthly returns as in Tables II–V). This means that at least some of the measured return is not contemporaneous with the observed change in holdings.[19]

[19] An example illustrates our procedure. For an observation in February, fund pairs of "high value" or "low value" are constructed using classifications at the end of January. Opposite_trades is constructed using the observed change in holdings between the end of December and the end of March. This change in holdings is a proxy for the trade activity during the month of February, under the assumption that trade activity is spread over the quarter. The 3-month return difference of the pair is measured from February to May, such that some of this return is no longer contemporaneous with the change in holdings.

We test whether the existence of opposite trades affects differently the net return differences between actual pairs and matched pairs. If such trades are a potential mechanism for cross-fund subsidization (H2), then they should enhance the wedge between high value and low value net-of-style returns of two funds that are members of the same family. We therefore test whether the coefficient θ is significantly positive in specification (3).

Results are presented in Table VII. We find that the coefficient on (Opposite_trades | Same_family) is positive and statistically significant in the Total Fees and in the Year-to-Date Return criteria. This supports our prediction that opposite trades between two funds belonging to the same family contribute to cross-fund subsidization (H2), increasing the difference between high value and low value net-of-style returns in actual pairs as opposed to that of matched pairs. The negative sign on the coefficient of Opposite_trades indicates that this type of trade (which is a function of how similar the portfolios of the two funds are) contributes to reduce the net-of-style performance differences between any two funds in a pair. Trades inside the family are different as stated by the working hypothesis ($\theta > 0$).

These findings relate strategic cross-fund subsidization to trade strategies undertaken by fund families and, therefore, give extra credence to our tests based on net-of-style performances (Section III).

V. Discussion

Our results provide strong evidence that mutual fund family organizations often play favorites with their funds. We now put this analysis in perspective, addressing the following three major questions. First, how feasible is the scale of cross-fund subsidization (performance redistribution) uncovered by our analysis? Second, how much does the typical fund family stand to gain from engaging in these cross-fund subsidization strategies? Finally, what are the implications of our findings for the individual investor?

A. How Feasible Is the Scale of Cross-Fund Subsidization We Uncover?

The performance gap between high value and low value funds reported in Section III averages between 6 (fees) and 28 (past performance) basis point per month, or between 0.7% and 3.3% per year. For the purposes of the following discussion we will work with the highest of these figures, a scale of redistribution that should be harder to attain. In order for the fund management companies to cause the top quarter of their funds (in terms of past performance) to outperform by 3% in a year the bottom quarter of funds in the family, they would have to shift 1.5% of the value of the bottom quarter of funds per year. Such a scale of redistribution (around $25\% * 1.5\% = 0.375\%$ per year of the overall assets under management by a typical family) is indeed economically significant if one takes into account that the universe of equity funds for the top 50 fund families

Table VII

Opposite Trades and Strategic Cross-Fund Subsidization

This table presents regression results of the relationship between common holdings and cross-fund subsidization. Quarterly fund holdings are obtained from Spectrum-Mutual funds database. Please refer to Table III for a complete description of how pairs of "High" and "Low" funds are obtained. For each classification (e.g., fees, performance, and age), we run the following regression (equation (3) in the text):

$$\text{Net\_return}_{i,t}^{\text{High}} - \text{Net\_return}_{j,t}^{\text{Low}} = \alpha + \beta(\text{Same\_family}) + \gamma(\text{Same\_style}) + \varsigma(\text{Opposite\_trades}) + \theta(\text{Opposite\_trades} \mid \text{Same\_family}) + \text{controls} + \varepsilon_{i,s,f,t}.$$

The left-hand side variable is the Difference in Net-of-Style Returns for each pair. Same_family is a dummy variable that takes a value of 1 if the two funds in the pair belong to the same fund family, and 0 otherwise. Same-style is a dummy variable that takes a value of 1 if the two funds in the pair belong to the same style, and 0 otherwise. For each classification, we present two different versions of Opposite_trades. Opposite_trades$_{\text{SUM}}$ denotes the sum, across the two funds High and Low in a given quarter, of the percentage of stocks (in dollar value) for which there were opposite (of symmetric sign) changes in holdings with respect to the total stock holdings (in dollar value) of both funds. Opposite_trades$_{\text{MIN}}$ denotes the minimum, across the two funds High and Low in a given quarter, of the percentage of stocks (in dollar value) for which there were opposite (of symmetric sign) changes in holdings with respect to the total stock holdings (in dollar value) of both funds. (Opposite_trades | Same_family) denotes an interaction variable obtained by multiplying the corresponding version of Opposite_trades with the Same_family dummy. Control variables whose coefficients are not shown include, for both the High and the Low funds in each pair, the size of the funds, the age of the funds, the size of the funds' families, and the age of the funds' families. Time dummies, family dummies, and style dummies are also included in the regression. To ensure the strategy we study is implementable, the timing of measurement of the variable is as follows. The classification of funds is done at the beginning of each month (we discard the month of January, because its classification is the final classification of the previous year). Opposite_trades is calculated using the corresponding quarter change in holdings. Difference in Net-of-Style Returns is calculated after the end of the month, using compounded 3-month returns. The number of observations, N, represents pair-month combinations. t-statistics shown are obtained using heteroskedastic-robust standard errors. The symbols ***,**, and * denote significance at 1%, 5%, and 10% levels, respectively.

	Total Fees				Year-to-Date Return				Age			
	(1)		(2)		(3)		(4)		(5)		(6)	
	Coeff.	t-Stat.	Coeff.	t-Stat.	Coeff.	t-Stat.	Coeff.	t-Stat.	Coeff.	t-Stat.	Coeff.	t-Stat.
Intercept	0.0001	0.33	0.0004	0.20	0.0427	16.66***	0.0424	16.50***	0.0154	5.52***	0.0154	5.51***
Same family (β)	0.0001	0.83	0.0001	1.23	0.0058	6.23***	0.0056	6.13***	−0.0003	−0.42	−0.0003	−0.37*
Opposite_trades$_{\text{SUM}}$ (ς)	−0.0633	−6.46***	–	–	−0.1690	−8.85***	–	–	−0.0124	−1.46	–	–

Opposite_trades$_{SUM}$ | Same family (θ)	0.0234	1.97**	–	–	0.0459	2.16**	–	–	0.0307	2.93***	–	–
Opposite_trades$_{MIN}$ (ς)	–	–	−0.4978	−3.06***	–	–	−1.9707	−5.34***	–	–	−0.0659	−0.42
Opposite_trades$_{MIN}$ | Same family (θ)	–	–	0.3754	1.97**	–	–	0.7637	1.88*	–	–	0.5045	2.72***
Same style (γ)	0.0001	0.83	0.0006	0.78	0.0034	3.73***	0.0033	3.60***	0.0011	1.76	0.0011	1.72
Controls	yes		yes		yes		yes		yes		yes	
Year dummies	yes		yes		yes		yes		yes		yes	
Family dummies	yes		yes		yes		yes		yes		yes	
Style dummies	yes		yes		yes		yes		yes		yes	
Mean squared error	0.01		0.01		0.01		0.01		0.01		0.01	
Adjusted R^2	0.03		0.03		0.09		0.08		0.02		0.02	
N	92,117		92,117		58,123		58,123		97,552		97,552	

we study had a total of $1 trillion under management on average during the period we analyze.[20]

To analyze how feasible is this level of cross-fund subsidization, we are constrained by the amount and frequency of publicly disclosed information on mutual funds. The mechanisms of subsidization we explore, preferential allocation and opposite trades, use quarterly mutual fund holdings from SEC filings, which have been used in the past to provide evidence for other distortions in fund managers' behavior (Lakonishok et al. (1991) on window dressing, Wermers (1999) on herding, etc). Our focus on these two strategies does not exclude a range of alternative ways through which the performance of high value funds can be boosted, at the expense of low value funds. For example, families may strategically allocate the best managerial talent to the best performing funds (Guedj and Papastaikoudi (2004)), or implement selective brokerage execution of trade orders across funds.

How much of the performance redistribution from the bottom to the top quarter of the families' funds (estimated by us to be 1.5% of asset value of these funds per year) can therefore be explained by the preferential allocation of IPOs and opposite trades across these funds?

- In terms of preferential allocation, Table VI shows that the overall dollar value of first-day IPO underpricing returns that went to high past-performing funds is $6.4 billion versus $1 billion for low past-performing funds over the full period of 1992 to 2001. Such a difference is spread over 10 years; so if we take $0.54 billion per year this would approximately represent 0.22% [=$0.54 billion/($1,000 billion/4)] per year as a percentage of asset value.
- In terms of opposite trades, if we were to assume these transactions were made at an average off-market price 5% away from the market, and we were to assume that opposite trades constitute only 1% of the funds' portfolios per quarter, then up to 0.05% of asset value would be redistributed per quarter. This would imply a 0.2% cross-fund subsidization of asset value of these funds per year.

These back-of-the-envelope calculations reveal that the mechanisms of cross-fund subsidization that we analyze in this study—the ones for which we have fund holdings data to explore, but are merely two out of several potential mechanisms that come to mind—are able to explain roughly one-quarter of the observed amount of favoritism (=0.42%/1.5%).

B. How Much Do Fund Families Benefit Out of Favoritism?

Fund families should engage in cross-fund subsidization if this practice allows them to influence their revenue stream in a meaningful way. Using the results in this paper, how much does the typical fund family stand to gain from this practice?

[20] The scale of the redistribution can be higher or lower than 1.5% depending on the relative size of the assets under management of the family's top- and bottom-quarter funds.

Let us take as an example the transfer of performance from low to high performing funds. This enables the family to take advantage of the convex shape of the flow-performance relation prevalent in the fund industry, as new inflows to high value funds will more than compensate any outflows suffered by low value funds. Based on the flow-performance regression specification of Sirri and Tufano (1998), we find that a redistribution of 1.5% performance from the bottom to the top ranking quarter of the families' funds would increase the assets managed by this set of funds by a net 4.2% per year.[21] Since fees are proportional to assets under management, a family's fee revenues grow by this same proportion per year. Over the course of the 10 years studied in our analysis, this could increase the value of the fund management company by more than half.

C. What Are the Implications for the End-Investor?

The first implication deals with overall investor welfare. If families have the ability to shift performance from low value to high value funds, investors in high value funds will gain and investors in low value funds will lose. But can investors on the aggregate be worse off? It is impossible to draw any welfare conclusion without also determining the benefits generated by the fund family organization. These can take the form of economies of scale and scope (namely, in areas such as research, trading, and execution, and investor search and distribution costs). If the fund families pass on these savings to consumers, it could be the case that these more than compensate any value-destruction coming from firms pursuing cross-fund subsidization.

Another implication is whether investors, once aware of the existence of the family strategies we document here, can actively profit from them. For example, they may, in each period, invest in funds that families are expected to favor (the high value funds), while avoiding the ones from which the families are likely to transfer performance. However, there are three main obstacles to the implementation of this strategy. First, it would require that investors be able to trade in and out of funds of the same family very cheaply. Second, the cross-fund subsidization we uncover is defined in terms of net-of-style performance; therefore, investors would still bear the risk that the whole style underperforms. Finally, it is doubtful that the average investor would always be able to actively select

[21] This calculation is done in two steps. First, we calculate that a 1.5% increase in annual net-of-style performance will translate into a 5% jump in a fund's ranking within its investment style. Second, we estimate the flow-performance relation as in Sirri and Tufano (1998, Table II) with the difference that High/Low stands for top/bottom 25$^{\text{th}}$ instead of 20$^{\text{th}}$ percentile as in their paper. Our estimates are of similar magnitude to Sirri and Tufano (1998) and $R^2 = 15.5\%$ (t-statistics of the slope coefficients are 1.6, 2.4, and 19.6):

$$\begin{aligned}\text{Flow}_{i,t} &= 0.12 + 0.17.\text{LOWPERFORM}_{i,t-1} + 0.12.\text{MIDPERFORM}_{i,t-1}\\ &\quad + 1.01.\text{HIGHPERFORM}_{i,t-1} + \text{Controls}\end{aligned}$$

Hence, a 5% increase in a fund's ranking for a high value fund would produce an inflow of 5.05% in terms of assets, while a 5% drop in a fund's ranking for a low value fund would produce an outflow of −0.85% of assets of the second fund. The set of high value and low value funds as a group would experience a net 4.2% growth in asset value.

which funds the family considers of high value. In summary, we expect that investors cannot profitably benefit from the existence of family strategies.

VI. Conclusion

In this paper, we argue why the maximization of a fund family's profits may not necessarily coincide with the maximization of the risk-adjusted returns for its individual mutual funds. We identify funds of high value (i.e., those more likely to generate fee income or extra investor inflows) and low value to a family, and argue that fund management companies have incentives to cross-subsidize the performance of high value funds at the expense of the low value funds. We consider three types of cross-fund subsidization: (1) enhancing the performance of high fee funds at the expense of low fee ones, (2) enhancing the performance of currently high performing funds at the expense of low performing funds, and (3) enhancing the performance of young funds at the expense of old funds.

We show that fund families actively pursue a direct family strategy of enhancing the performance of high value funds to the detriment of other low value funds in the order of 6 to 28 basis points of extra net-of-style performance per month, or 0.7%–3.3% per year, depending on the classification criteria used (fees or past performance). We further show evidence that this practice occurs in the fund families for which there exist greater incentives to perform it. We also demonstrate empirically a positive relation between both favoritism and preferential treatment in the allocation of deals across funds (by showing that high value funds are allocated more under-priced IPOs) and the amount of opposite sign trades among funds belonging to the same fund complex, a practice that can encompass cross-trading. We finish by discussing how much these mechanisms contribute to the scale of performance redistribution uncovered by our analysis, what the typical fund family stands to gain from engaging in it, and the implications of our findings for the individual investor.

Our results on family-level strategic behavior contribute to the literature on delegated asset management and shift the focus from fund-specific individual incentives to family strategies. Further empirical research may study other instances of coordinated behavior across funds that are part of the same fund complex. Theoretical efforts can also address the presence of these fund family strategies and investigate its consequences for delegated asset management and its equilibrium effects on markets.

Our results also provide important normative insights. They are relevant for the regulatory debate concerning cross-trades between mutual fund managers, where the SEC's position (which allows cross-trades among mutual funds under rule 17a-7 of the Investment Company Act) differs from that of the U.S. DOL (which still prohibits cross-trades for actively managed ERISA plans). The claimed benefits of cross-trading in terms of trading cost savings should be weighed against the potential for "self-dealing." Our results provide relevant information for this assessment.

Appendix: Merging CRSP and Spectrum Mutual Funds Data Sets

In this appendix we summarize our matching procedure for the Spectrum/Thomson Financial Database of Mutual Fund Holdings and the CRSP Survivor-Bias Free U.S. Mutual Fund Database. CRSP and Spectrum use different identifiers of each mutual fund (CRSP: ICDI_no; Spectrum: Fund Number).

We proceed as follows.[22] First, we perform a merge based on the ticker code. The ticker is the five-digit code that is used to represent a stock or a mutual fund (it is an unofficial way of identifying a fund and there are no guarantees about it being unique). We find that it is reasonably consistent and hence we use it as the first step in generating the match between CRSP and Spectrum.[23] Ticker data is available in Spectrum only for 3 years, 1999, 2000, and 2001. The 1999 ticker matches are then extrapolated back for the prior years. The reliability of the ticker merge weakens as we move back in time as tickers of some funds change, funds die, and their tickers can be reused.

A second step involves the name of the fund. Unfortunately, the CRSP database uses a 50-character text field for the fund's name, while Spectrum uses a 25-character field. Names are abbreviated differently in the two databases. We use a name recognition code written in Delphi to match the two strings of text. Fund names from the two databases are arranged side-by-side and each fund name is compared with all fund names in the other database.[24] A name-matching algorithm compares these two strings, with a match above 90% being accepted. If there is a conflict in the merge between the name and the ticker merge, we consider the ticker merge as valid. Finally, for all the other cases as well as the ones that seemed to be dubious, we perform an "eye match." That is, funds are manually compared against each other.

The merge procedure is also useful in two other aspects. First, while CRSP Mutual Funds identifies different classes of the same mutual funds as distinct funds, Spectrum has a single record for them. This is also described in Wermers (2000). Thus, the merger procedure allowed us to identify multiple share classes of the same fund. Second, we identify all fund names with the string "index," which is useful to filter out index funds from our analysis.

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[22] The procedure is similar to the one proposed by Wermers (2000).

[23] The ticker in CRSP comes from the annual summary data file. The column called ticker has the Nasdaq ticker symbol as a five-character field. In Spectrum, the ticker comes from the Fund Ticker Information file. The fund ticker symbol here is also a five-character symbol.

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