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

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Abstract:

We investigate whether mutual fund families strategically allocate performance across their member funds favoring those more likely to generate higher fee income or future inflows. We find evidence of strategic cross-fund subsidization of 'high family value' funds (i.e. high fees or high past performers) at the expense of 'low value' funds in the order of 6 to 28 basis points of extra net-of-style performance per month, depending on the criteria. This over-performance is above the one that would exist between similar funds not part of the same family. We further document how this family strategy takes place by looking at preferential allocation of IPO deals and at the amount of opposite trades among 'high' and 'low value' funds belonging to the same fund complex (a practice that can encompass 'cross-trading'). Our findings complement the existing literature on distortions in delegated asset management by highlighting the role played by family affiliation.

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One of the most striking features of the US mutual funds industry is the prevalence of the fund family organization. Over 90% of equity mutual funds belong to a fund family with at least two funds and the top 50 fund families concentrate over 80% of all assets under management.[i] This implies that the great majority of fund managers (e.g. Fidelity Contrafund's portfolio manager) do not work directly for their fund investors, but rather for a mutual fund organization (e.g. Fidelity Investments).

Mutual fund families are a source of both potential value to investors and distortion to the incentives of the fund managers. Family affiliation may generate economies of scale and scope, both in terms of asset management, distribution externalities and better quality research. Moreover, the very existence of the family may, through brand-building and marketing, lower the search costs for the investors.[ii] At the same time, however, family affiliation distorts the incentives of fund managers, possibly inducing them to sacrifice their shareholders' interests if the overall family stands to benefit. The resulting divergence of interests (between the fund family and investors in the individual funds that belong to it) is a feature of the family form of organization whose empirical relevance has not to this date been sufficiently investigated.

We propose several reasons why families might engage in 'family strategies', in the form of performance transfer across funds. Our rationale is built on the observation that families' profits are a direct function of the fees charged and assets managed, that investors' inflows chase good past performers (in spite the fact that winners do not repeat themselves) and that the relation between inflows and past performance is convex (assets flow disproportionately to top performing funds).[iii]

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

The incentive to play family strategies is reinforced by the asymmetric relation between past performance and investors' flows. From a family perspective, this asymmetry 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 incentives 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 a 'star' performer fund has a positive 'spill-over' effect on the inflows of the other funds in a family, although there seems to be no negative effect from a poor performing fund [Nanda, Wang and Zheng (2003)].[iv] Naturally, cross-subsidization would hardly be in the interest of the end-investors in the 'low performing' fund .

In this paper we investigate empirically whether fund families actively pursue a family strategy of enhancing the performance of 'high value' funds, i.e. 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 - i.e. funds with high year-to-date performance likely to be well placed in fund rankings - at the expense of 'low-performing' funds; (3) enhancing the performance of young funds at the expense of old funds (given Chevalier and Ellison's (1997) finding that the convex flow-performance relation is more pronounced for younger funds). All these cross-subsidization policies can be optimal from the point of view of the management company but come at a cost to the investors in some of the funds.

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

Our first set of tests is based on examining whether the shocks of the fund investment style affecting some member funds of a family propagate to the other funds in the same family.[v] These tests follow closely a general methodology that Bertrand, Mehta and Mullainathan (2002) devise to quantify tunneling in business groups.[vi] We investigate how the returns of the funds belonging to a family behave differently from those of a mere grouping of stand-alone funds. In particular, we show that family affiliation affects the sensitivity of a given fund to the investment style shocks affecting other funds in the same family. We find that returns of individual funds belonging to a family are more positively sensitive to the investment styles of other 'low value' (i.e. 'low fee', 'low-performing' and old funds) funds in the same family than they are to those of other 'high value' (i.e. 'high fee', 'high-performing' and young funds) funds. This evidence suggests the existence of a co-coordinated family strategy geared to asymmetrically benefit the 'high value' funds at the expense of the 'low value' ones. This test, based on the differential sensitivity to external shocks in investment styles, is however only an indirect test, since it does not establish the existence of direct performance transfer from 'low' to 'high value' funds.

We therefore develop a set of direct tests, in which we investigate if the difference between the net-of-style returns of 'high value' funds (that is, their relative performance to other peer funds in the same style) and the net-of-style returns of ‘low value’ funds belonging to the same fund family exceeds the same difference for equivalent funds not belonging to the same family. These tests address directly the issue of whether the performance enhancement of ‘high value’ funds is directly associated to the underperformance of ‘low value funds’. The format of the test also allows us to address the question of whether cross-fund subsidization is indeed an in-family phenomenon or would have been present in the data regardless of family affiliation.

We find that ‘high value’ funds are favored inside fund families by 6 to 28 basis points of extra net-of-style performance per month (0.7%-3.3% per year) relative to ‘low value’ funds, depending on the criteria used (fees or past performance). Given the added power of these direct tests, we conclude that this difference in performance between high and low funds within families cannot be ascribed to chance.

We then investigate the sources of this aggregate effect of favoritism, studying when and where it takes place. We show that this behavior is prevalent at times when the styles of ‘low funds’ are doing relatively well, while it mostly disappears when these funds under-perform. We also find the level and intensity of cross-fund subsidization to be related to family characteristics, being prevalent in families that are large, that manage many funds and that are heterogeneous in terms of size of the funds they offer.

In the third part of our study, we explore the potential channels of strategic cross-fund subsidization. We look at two main mechanisms available to the fund families: *preferential allocation* and *opposite trades*. In the first case, the family concentrates its best deals on ‘high’ funds. In the second case, the family directly coordinates the trades of its funds such that ‘low value’ funds operate in the market to buffer the market impact of the ‘high value’ fund orders, or directly cross orders with the ‘high value’ funds without going to the open market (a practice commonly labeled as “cross-trading”).

We investigate preferential allocation by looking at whether there is evidence of favoritism at the allocations of ‘hot’ Initial Public Offerings (IPOs) to ‘high value’ funds. IPOs are 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 on which of their funds get the highest allocation at the offer date. Based on the reported holdings of mutual fund and a comprehensive sample of IPO issues for the 1992-2001 period, we find that fund families allocate relatively more under-priced (‘hotter’) IPOs to ‘high total fees’ and ‘high past performance’ funds. This evidence is highly suggestive of preferential treatment of ‘high’ 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 co-ordinates the trades of 'high' and 'low value' such that they place opposite orders, then any positive performance that the deal brings to 'high' 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 funds tend to exhibit larger net return differences between 'high' and 'low value' funds. These findings link the extent of strategic cross-fund subsidization to the actual trade strategies undertaken by mutual fund families and give extra credence to our indirect evidence based on the propagation of shocks and to our direct evidence based on net-of-style return differences.

Our work contributes to the literature on delegated asset management. The evidence we uncover, by illustrating a distortion in the behavior of mutual fund managers at the family level, is new in its nature and complements findings at the single mutual fund level. Besides the excessive risk-taking by mid-year losers (because of convex flow-performance relation alluded to before), previous research has uncovered other behavior such as marking-up or 'window-dressing' of disclosed portfolios by fund managers [Carhart, Kaniel, Musto and Reed (2002) and Lakonishok, Shleifer, Thaler and Vishny (1991)], 'herding' in portfolio holdings and commonality in trading behavior across funds [Grindblatt, Titman and Wermers (1995), Chevalier and Ellison (1999), Hong, Kubik and Stein (2003)]. We believe that future theoretical efforts should address the presence of these fund family 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 for the regulatory debate concerning cross-trades between investment vehicles 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 'low value' investors, this practice still entails a breach of fiduciary duty with respect to the assets each mutual fund manager is separately entrusted with (which requires the manager to execute transactions for clients in the most favorable way). The SEC routinely allows inter-fund cross-trading through exemptions provided under rule 17a-7 of the Investment Company Act of 1940.[vii] While the benefits of cross-trades are a debated issue (Willoughby (1998)), the potential for self-dealing has been less well analyzed. Some debate also has been sparked on the governance model of the industry as to how to give back priority to the interests of investors over those of the management company (which usually appoints the board of directors of a fund). Recent investigations into "market timing" and "late trading" in the fund industry illustrate other instances of this conflict of interest, where some investors and fund insiders' gains can at a loss to buy-and-hold investors (Financial Times, 2003).

Previous research on fund family strategies is scarce, with a few notable exceptions. Nanda, Wang and Zheng (2003) investigate whether fund families seek to generate 'star' performing 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 uneven way. Other evidence on fund family's strategies not coinciding with simple risk-adjusted performance maximization is uncovered by Massa (2003), who studies how industry structure affects fund behavior and the relation between performance, fund proliferation and the product differentiation. In particular, he shows that the degree of product differentiation negatively affects performance and positively affects fund proliferation.

The remainder of the paper is organized as follows. In section I, we present more formally our hypotheses. In Section II, we describe the data we use in this study. In section III, we describe our indirect tests of strategic cross-fund subsidization and their results. In section IV, we develop our direct tests of strategic cross-fund subsidization and present their results. In section V, we explore evidence on how strategic cross-fund subsidization takes place through trade strategies. Section VI presents a discussion of our results. A brief conclusion follows.

I. Hypotheses

The performance of a mutual fund is likely to be different for a fund member of a fund family as opposed to a stand-alone fund. A fund family typically exerts extensive control over how the mutual fund is run, not only because it appoints its portfolio manager, but also because it frequently shares research information or general investment strategies across all fund members. But fund families can go one step further: they have some scope for coordinating the investment strategies among the set of mutual funds under their control.

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. They constitute our two working hypothesis 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 co-ordinates actions across member funds to smooth their performance by supporting any fund whose performance is lagging behind;
- **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, independently 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 exists if the family as a whole stands to loose from a poorly performing member-fund. If that is the case, then mutual co-insurance, 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, empirical evidence casts some doubt on the fact that the family as a whole stands to loose much from a poorly performing member-fund. Nanda, Wang and Zheng (2003) indicate that, while a fund family with a top performing fund seems to benefit from a positive spill-over of extra flow 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 (we label these funds as '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' 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' ones.

- *H2-b: To 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. The 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, Wang and Zheng (2003)), where the existence of a top-performing fund in a family positively affects inflows to other funds of the same family.

- *H2-c: To 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.

Let us consider an example to illustrate our hypotheses. This example will accompany us throughout the paper to describe our methodology. Take a fictional fund family with only two funds, fund H and fund L. Fund H charges 'high' fees, while fund L charges 'low' fees.[viii] The fund family benefits if extra performance is directed towards 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 from L's lower investor flows. In this scenario, let us consider our three hypotheses. Under the null hypothesis of 'No Overall Family Strategy' (H0), we should not expect any coordinated strategy. Thus, the observed returns for the group of funds should approximate a collection of individually run funds in the same investment styles as H and L.

Under the 'Risk Sharing' (H1) hypothesis, fund H and fund L co-insure each other, depending on the needs of the funds. This co-insurance should make fund H sensitive to the shocks affecting fund L and vice-versa. How would this happen? When the performance of H is predicted to be poor – e.g., due to a negative shock to its investment style return - part of the predicted performance of fund L, which is itself a function of its investment style return, should be transferred to H. The transfer should work in the reverse direction when L is expected to perform poorly. Shocks are channeled symmetrically across the fund complex so that 'high value' and 'low value' funds should be equally sensitive to shocks affecting the other fund's investment styles.

Under our working hypothesis of ‘Strategic Cross-Fund Subsidization’ (H2), such symmetry is lost. If part of the performance of fund L is being transferred to fund H at all times, then we should expect fund H to be positively sensitive to fund L’s investment style shocks but less in the reverse direction. Under H2 we should thus find *asymmetric* sensitivity, that is, ‘high value’ funds should be more positively sensitive to shocks affecting the investment styles of the ‘low value’ funds than the ‘low value’ funds are to shocks affecting the investment styles of the ‘high value’ funds. This prediction will be the base for the Bertrand, Mehta and Mullainathan (2002) tests we conduct in section III. In section IV we will improve on these tests to account for several forms of tunneling, so we will come back to this hypothesis in more detail below.

Before we move on to test our hypotheses, we will 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 uses the information strategically 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 – e.g., 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’ funds not to exploit it or actually take the opposite side of the market (to smooth the price pressure of market orders of the ‘high’ 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 CRSP Survivor-Bias Free US Mutual Fund Database for the period January 1991 to July 2001, for which data on investment styles data (ICDI fund objective codes) and fund family membership (management company) is available. 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 US funds investing mostly in equities, that is, funds with the ICDI investment objective codes AG (‘Aggressive Growth’), GI (‘Growth Income’), LG (‘Long-term Growth’), IN (‘Income’) and BL (‘Balanced’). This dataset has been used extensively in the finance literature since Carhart (1997).

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 US 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.[ix] 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 highest TNA class in case a fund is found to have multiple classes. Our resulting base sample has approximately 68,000 fund-month observations.

Our objective is to investigate if 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 to shareholders of investing in a fund. It comprises the load fees (total of all maximum front, deferred and redemption fees) and the yearly management fees paid upfront the operating expenses (expense ratio). We assume for the purpose of the calculation that the average period an investor remains invested in the fund is seven years (Sirri and Tufano (1998)). Regarding performance, we follow Brown, Harlow and Starks (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 fund's inception) as a classification variable.

Table I presents summary statistics of these and other fund characteristics. Our average fund has assets of $1.6 Billion, charges 1.5% in total fees and is three and a half years old. The average family has 35 equity funds managing $47 Billion of assets. The volume of assets under management, as well as the number of funds, has steadily increased over time, with the top 50 families managing $1.9 Trillion of assets in 2000, distributed over more than 870 mutual funds.

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

(i) as 'high fees' a fund that is in the top quartile of funds in terms of total fees in its fund family (and conversely for 'low fee' funds),

(ii) as 'high performing' a fund that is in the top quartile of funds in terms of year-to-date return in its investment style (and conversely for 'low performing' funds),

(iii) as 'young' a fund that is in the bottom quartile of funds in terms of their age since initiation in its fund family (and conversely for 'old' funds).

Table II compares the characteristics of the resulting High and Low funds, in each classification. Note that for *Age*, a fund is classified as 'high' if it is a young fund. The families in our sample charge an average of 2.2% per year Total Fees 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 one year old.[x]

III. Indirect tests of strategic cross-fund subsidization

The first set of tests distinguishes 'Strategic Cross-Fund Subsidization' (hypothesis H2) from 'Risk Sharing' (H1) by analyzing the way return shocks propagate within fund families. The tests are indirect as they rely on the relation between exogenous return shocks and mutual fund observed returns. We follow closely a general methodology that Bertrand, Mehta and Mullainathan (2002) (BMM) devise to quantify tunneling for the case of business groups.[xi] In our context, the tests consist of examining whether the return shocks originating from the styles the mutual funds belong to propagate asymmetrically across the funds of the family. The asymmetry stems from the fact that we expect positive shocks to returns to be tunneled towards the 'high value' funds, even if they originate from the investment style of the 'low value' funds, but less in the reverse direction. We proxy for these style return shocks by the average return of the funds belonging to the investment style of 'high' or 'low value' funds. We assume these to be beyond the control of the fund family.

We adapt the main test of BMM (page 138) to our setting. The performance of each individual mutual fund is regressed on the shock of both its own investment style and the investment styles of the other funds in the family, grouped into 'high value' and 'low value' funds. For each classification criteria (fees, past performance or age), we estimate:

$$
\begin{aligned}
RET_{i,s,f,t} &= a + b(ST\_RET)_{s,t} + c_H \sum_{j \neq i} w_j (ST\_RET)^{High}_{j,f,t} + c_L \sum_{k \neq i} w_k (ST\_RET)^{Low}_{k,f,t} \\
&\quad + controls + time\_dummies + \varepsilon_{i,s,f,t}
\end{aligned} \tag{1}
$$

where RET is the raw return in month t of fund $i,$ belonging to family f and operating in investment style s, and ST_RET is the average raw return of the funds in same investment style s as fund i (ICDI fund objective code, i.e. the fund's self-declared style category). $(ST\_RET)^{High}$ represents the average style shocks affecting the 'high value' funds belonging to the same fund family f as fund i, where 'high' is defined according to the criteria under consideration (fees, past performance or age). The weights w_j correspond to the fraction of assets each fund j represents in the group of 'high value' funds. Similarly, $(ST\_RET)^{Low}$ represents the average style shocks affecting the 'low value' funds belonging to the same fund family f. The regressions are run with family-fixed effects to account for any fixed differences between fund families.[xii]

Based on the arguments put forward in the example in section I we can lay out testable predictions of each of the hypotheses. If no coordinated strategy is pursued at the family level (H0), then a typical fund's return should not be sensitive to shocks affecting the other fund's investment styles. Under 'risk sharing' (H1), instead, a typical fund should be symmetrically sensitive to shocks affecting the investment styles of the other funds (c_L=c_H). Finally, if 'high value' funds are being systematically channeled performance from 'low value' funds (H2), then we should observe that a typical fund is more (positively) sensitive to investment style shocks affecting 'low value' funds (c_L) of the same family, than it is to shocks affecting 'high value' funds (c_H). We summarize the testable restriction as follows:

- Under 'No Overall Family Strategy' (Hypothesis H0): $c_H = c_L = 0$
- Under 'Risk Sharing' (Hypothesis H1): $c_H = c_L$
- Under 'Strategic Cross-Subsidization' (Hypothesis H2): $c_H < c_L$

The results of estimating equation (1) using family-fixed effects can be found in Table III. The table shows, for each of our criteria of interest (fees, performance and age), the estimated sensitivity of a fund's return to shocks to its investment style (b) and to shocks in the investment style of 'High' (c_H) and 'Low' funds (c_L). Control variables, whose coefficients are not shown in the table, include time dummies, the size of the fund, the age of the fund, the size of the fund's family and the age of the fund's family.

These results provide evidence in favor of the strategic cross subsidization hypothesis (H2). Overall, a fund's sensitivity to its own style is high, with around 86% pass-through of the style shock to fund's return. More importantly, the typical fund is *more* sensitive to the investment styles of 'low value' funds than to the investment styles of 'high value' funds. For the case of fees, 11% of a shock to the styles of 'low fees' funds is passed to the typical fund, compared with 2% of a shock to the styles of 'high fees' funds (p-value of difference <0.001). In the case of Year-to-Date Returns, the difference is less pronounced (7.2% vs. 3.3%), but still significant at the 10% level. For Age, the results are again stronger, both economically and statistically (13.4% for old funds vs. 1.5% for young funds, p-value <0.001). These results are consistent with the conjectures that not only fund performance responds to shocks affecting other funds in the family, but does so in an asymmetric way consistent with our H2 hypothesis.

In short, the tests indicate that fund returns respond asymmetrically to shocks hitting 'high' and 'low value' funds belonging to the same mutual fund complex. This suggests that fund families are different from a mere collection of funds with no overall coordinated strategy.

IV. Direct tests of strategic cross-fund subsidization

The methodology we used in the previous section suffers from three main shortcomings. First, being based on the propagation of style shocks to the average fund, it does not provides a quantification of how much the over-performance relative to peer funds of 'high value' funds is directly associated to the under-performance of 'low value' funds. Second, the test does not address the question of whether the cross-fund subsidization pattern is indeed an *in-family phenomenon* or could be found to pre-exist for any combination of any 'high' and 'low value' mutual funds, irrespective of both funds being members of the same mutual fund complex or not. Third, the tests of section III are not able to address cross-fund subsidization *within styles* (that is between funds that belong to the same family *and* the same investment objective) but only *across styles.*

We start by describing our main tests. We directly quantify how much the performance of 'high fee' and 'high performing' funds are subsidized inside fund families at the cost of 'low fee' and 'low performing' funds, respectively. Then, in Section IV.B., we go more in detail investigating the sources of favoritism. In particular, in Section IV.B.1 we study the states of nature where subsidization is more prevalent, while in Section IV.B.2 we look at which family characteristics are more associated with the level of cross-fund subsidization.

A. Main tests

To present our main tests we return to the example we introduced in Section I. A direct test of whether fund L is transferring performance to fund H (hypothesis H2) asks whether the observed difference in return between the two funds systematically exceeds the one predicted by the corresponding difference in return 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 our hypotheses. 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. Under 'Strategic Cross-Fund Subsidization' (H2), we expect that on average fund H's net-of-style-return exceeds the 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 independently 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 independently 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 related to the recent empirical corporate finance literature critique to earlier findings concerning value-destroying cross-subsidization within diversified conglomerates (Chevalier (2000) and others).

Our improved test attempts to quantify the extra effect due to family affiliation. We implement this idea by using a 'matching' fund. This 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'). Let us now come back to our hypotheses. 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. That is, we expect that the net-of-style-return difference between H and L turn out to be greater than that of H and LM as many times as the reverse. So under H1 the average net-of-style-return difference between H and L should not differ from that between H and LM. However, 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 new 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' 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 criteria under consideration (fees, performance or age). We compute the net return difference for this 'matched pair'.[xiii]

Table IV 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. The results show that the net difference in performance is higher for funds belonging to the same family ('actual pairs') than for funds belonging to different families ('matched pairs'). It is always the case that the funds that are 'most valuable' to the family are benefited. 'Actual pairs' show an extra performance for the 'high value' funds that varies between 5 to 17 b.p. (basis points) per month. This extra performance is statistically significant.

Our main test consists of a multivariate regression where 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:

$$Net\_return_{i,t}^{High} - Net\_return_{j,t}^{Low} = a + \beta(Same\_family) + \gamma(Same\_style) + controls + \varepsilon_{i,s,f,t} \quad (2)$$

where Net_return^{High} is the net-of-style performance at time t of a fund i which is a 'high value' fund. Similarly, Net_return^{Low} is the net-of-style performance at time t of a fund j which is a 'low value' fund. The dummy variable *Same_family* takes the value 1 if fund i and j are members of the same fund family (i.e. an 'actual pair') and the value 0 otherwise (i.e. a 'matched pair'). The dummy variable *Same_style* takes the value 1 if fund i and j belong to the same investment style.

If 'high value' funds are being systematically channeled performance from '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 coefficient β 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-Subsidization' (Hypothesis H2): $\beta>0$

Table V presents the results of the multivariate regression analysis of equation (2), 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' 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.

These results show that cross-fund subsidization within the family contributes around 4 to 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 to 28 basis points for the funds valued highly in terms of performance (with *t-statistics* ranging from 5.7 to 6.5). This effect is in excess of the pre-existing difference between 'High' and 'Low' funds, given by the intercept term (at least in the case of fees). Note also that this impact occurs irrespectively 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 as found in indirect test presented in section III.

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 is always favoring the 'high value' funds (high fees and high past-performing funds).

B. Extended Tests

B.1. Does the level of 'Strategic Cross-Fund Subsidization' depend on styles' performances?

In this section, we explore more 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 the reverse.

Under our null hypothesis (H0), no coordinated strategy is pursued at the family level and we don't expect fund H and L to be systematically subsidized. Under 'Risk Sharing' (H1), we expect that fund H is subsidized when its investment style is under-performing with respect to that of fund L but that H subsidizes L when its investment style is over-performing. 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 over-performing and when it is under-performing 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 over-performing, but to offer less help to fund L when L's style is under-performing. The weaker form of H2 is consistent when the unconditional cross-subsidization we described before and it just qualifies it by defining the time when it takes place.

This more detailed test can also encompass another possibility: the fact that fund H and fund L belong to the same investment style. So far, all our tests have only looked at '*inter-style cross-fund* *subsidization*' because style shocks were needed to provide identification between observed and predicted shocks. But under our new method, 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 '*intra-style cross-fund subsidization*'.

We implement the test by estimating regressions of fund pairs in a similar way to equation (2) above. The specification differs from the previous one because the dummy *Same_family* has been split into three separate dummies: ($Same\_family|ST\_RET_{High}>ST\_RET_{Low}$) if the performance of the investment style of the 'high value' fund i out-performs that of the 'low value' fund j; ($Same\_family|ST\_RET_{High}<ST\_RET_{Low}$) if the performance of the investment style of the 'high value' fund i under-performs that of the 'low value' fund j ; and ($Same\_family|Same\_style$) if fund i and j belong to the same style. The specification is then:

$$
\begin{aligned}
Net\_return_{i,t}^{High} - Net\_return_{j,t}^{Low} = \\
& a + \beta_{+}(Same\_family \mid ST\_RET_{High} > ST\_RET_{Low}) \\
& + \beta_{-}(Same\_family \mid ST\_RET_{High} < ST\_RET_{Low}) \\
& + \beta_{0}(Same\_family \mid Same\_style) + \\
& + \gamma(Same\_style) + controls + \varepsilon_{i,s,f,t}
\end{aligned}
\tag{3}
$$

where Net_return^{High}, Net_return^{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' funds are only subsidized by 'low funds' when their performance is bad to start with ($\beta_{-} <0$) and get to help the 'low' 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-subsidization (H2) in its weaker form requires β_{+} to be lower than β_{-} in absolute terms for the case of 'inter-style' subsidization and β_{0} to be positive for the case of 'intra-style' subsidization. The hypothesis of strategic cross-subsidization in its strong form (that the 'high' funds are always helped, independently of how bad the 'low value' funds are performing) requires both the coefficients β_{+} and β_{-} to be positive. We can summarize our testable implications as follows:

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

- Under 'Strategic Cross-Subsidization' (Hypothesis H2): $\beta_{+} < or > 0$ *and* $\beta_{-} > 0$ but $|\beta_{+}| < |\beta_{-}|$ (for 'inter-style' subsidization) and $\beta_{0} > 0$ (for 'intra-style' subsidization)

Table VI presents the results of our extended tests. Results support the strategic cross-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 under-performing (54 b.p., *t-statistic* of 17.3). The difference between them is statistically significant. 'Intra-style cross-subsidization' is not significant. In the case of Year-to-date Returns, we see that our earlier result from Table V is mostly due to the help that low performing funds provide to high performing funds (60 b.p., *t-statistic* of 11.0). This is further confirmed by the hypothesis test showing that $|\beta_{-}| < \beta_{+}|$. 'Intra-style cross-subsidization' is relevant in this case (29 b.p., *t-statistic* of 3.6). Finally, as we have seen in the previous section, the results do not support the cross-subsidization of young by old funds.

B.2. Which family characteristics are associated with 'strategic cross-fund subsidization'?

Our findings that cross-fund subsidization is an empirically relevant phenomenon leads 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 family, family age and homogeneity of funds in 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-subsidization depends on the homogeneity of the funds in the complex. 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 deviate 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 in families where 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 VII. Each cell presents the same-family effect (the β coefficient of Table V) for the regression run on each family sub-group. 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-subsidization for High fees and High performance takes place within large families, with many funds (Panel A of Table VII) 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 would indicate 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 protect, presumably in an attempt to create flagship funds.

V. 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 two sections seem 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 promote 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 mutual fund activities are subject to.

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 where 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 where 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' fund orders) or eventually crosses buy and sell orders from 'high' and 'low' 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 where we can ex-post assume that the fund family had reliable information that a security would appreciate in value. One event, though, where we can explore whether fund families direct better trades to 'high' funds is the sizeable underpricing phenomenon in initial public offerings.[xiv]

Underwriters possess substantial information about the offer demand as a result of the book-building process, and 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 on 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, Prabhala and Puri (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.

Besides their overall apparent preferential treatment in IPOs, mutual fund families have some discretion on which of their member funds will receive shares of the most underpriced IPOs. Under our cross-fund subsidization hypothesis (H2), we expect that the more underpriced is the IPO (i.e. the 'hotter' is the IPO), the more these shares are allocated to 'high value' mutual funds.[xv]

To bring this test to the data, we collected all IPO deals from Securities Data Company's (SDC) database that took place between from 1992 and 2001. The SDC data allows us to compute 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 our sample of CRSP mutual funds and additional data from Spectrum/Thomson Financial database of Mutual Fund Holdings, which comes from N-SAR forms that mutual funds are required to file with the SEC on a semi-annual basis.[xvi] The merge procedure is described in more detail in the Appendix to this paper. We then compute each mutual fund's reported holdings of any IPO at the end of the quarter the issue took place. Similarly to Reuter (2002), our tests are based on whether a fund reported positive holdings of an IPO, which best approximates whether a fund was allocated IPO shares at the offer date.[xvii]

Table VIII 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%). Panel B performs our tests for preferential trade allocation. We compute the average and median first-day returns of all IPO issues for which 'high value' and 'low' mutual funds report positive holdings at quarter-end. 'High' and 'low' 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 fees' funds (1,751 deals average first-day return of 44.0%), as opposed to 'low fees' fund (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 IV, the evidence is much weaker for the 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 get 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 VIII shows that 'high value' funds were allocated higher amounts of underpricing during the sample period. This is especially true for good past performers. 'High fee' funds received \$2.2Bln of 'underpricing dollars', while 'low fee' funds received \$1.9Bln; 'high performance' funds received \$6.4Bln, while 'low performance' funds received \$1Bln. In addition, the contribution of this underpricing to funds' returns 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 0.47% to the return of 'high fee' funds 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 patterns in IPO allocations are consistent with a preferential treatment of 'high value' versus 'low value' funds. This further substantiates our earlier findings that fund families are strategically cross-subsidizing their most valuable funds.

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 its potential for conflicts of interest, are subject to special restrictions.[xviii]

We therefore explore whether trade strategies across fund members can work to enhance the performance of 'high' funds at the expense of 'low' funds, again using the Spectrum/Thomson Financial database of Mutual 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, *Opposite_ trades*$_{SUM}$, 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, *Opposite_ trades*$_{MIN}$, 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. However using quarterly changes in holdings as proxies for the transactions of a fund's portfolio is only a second-best choice determined by the lack of publicly available data on fund's actual trades.

We run regressions of fund pairs in a similar way to the direct test introduced in section IV.A. above, expanding specification (2) to include as additional explanatory variables a measure of opposite trades in securities held by the pair of funds:

$$
\begin{aligned}
Net\_return_{i,t}^{High} - Net\_return_{j,t}^{Low} = a + \beta(Same\_family) + \gamma(Same\_style) \\
+ \varsigma(Opposite\_trades) + \theta(Opposite\_trades \mid Same\_family) \\
+ controls + \varepsilon_{i,s,f,t}
\end{aligned}
\quad (4)
$$

where Net_return^{High}, Net_return^{Low} and the dummy variables *Same_family*, *Same_ style* are defined as before. *Opposite_ trades* refers to either of our two measures of opposite changes in holdings defined above; we present results for each separately. (*Opposite_ trades|Same_family*) is an interaction between either form of *Opposite_ trades* and the *Same_family* dummy variable.

Although this specification follows closely equation (2), 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 three 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 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 III to VII). This means that at least some of the measured return is not contemporaneous with the observed change in holdings.[xix]

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 (4).

Results are presented in Table IX. We find that the coefficients on ($Opposite\_trades|Same\_family$) are positive and statistically significant in the Total Fees and Year-to-Date Return criteria. This supports our prediction that opposite trades between two funds belonging to the same family seem to be potential mechanisms for '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 much 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 (θ>0).

These findings relate strategic cross-subsidization to trade strategies undertaken by fund families and, therefore, give extra credence to our indirect evidence from propagation of shocks (section III) and the direct tests on net-of-style performances (section IV).

VI. 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. Firstly, how feasible is the scale of cross-fund subsidization (performance redistribution) uncovered by our analysis? Secondly, how much does the typical fund family stand to gain from engaging in these cross-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' and 'low' value funds reported in section IV 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 25% of their funds (in terms of past performance) to outperform by 3% in a year the bottom 25% of funds in the family, they would have to shift 1.5% of the bottom 25% of the value of the asset under management per year. Such a scale of redistribution (around 25%*1.5%=0.375% of overall assets per year) is indeed economically significant if one takes into account that the universe of equity funds for the top 50 fund families we study had a total of $1 Trillion under management on average during the period we analyze.[xx]

To analyze how feasible is this level of cross-subsidization we are constrained by the amount and frequency of publicly disclosed information on mutual funds. The quarterly mutual fund holdings from SEC filings allowed us to explore two mechanisms of subsidization based on trades: preferential allocation of 'hot' IPOs and opposite trades across funds in same family. Data on mutual fund holdings have been used in the past to provide evidence for other distortions in fund managers' behavior (Lakonishok, Shleifer, Thaler and Vishny (1991) on 'window dressing', Wermers (1999) on 'herding', etc).

Our focus on coordinated trades across funds does not exclude a range of alternative ways by 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. Lack of available data prevents this several of this analyses.

How much of the performance redistribution from the bottom to the top 25% of the families' funds (estimated by us as 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 VIII shows that the overall dollar value of first-day IPO underpricing returns that went to 'high' past-performing funds is $6.4Bln versus $1Bln for 'low' funds over the full period of 1992 to 2001. Such a difference is spread over 10 years so if we take $0.54Bln per year this would approximately represent 0.22% [= $0.54Bln/($1,000Bln/ 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 assumed 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-subsidization that we study, using publicly available data on fund holdings, 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?

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' funds will more than compensate any outflows suffered by 'low' 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 make increase the assets managed by this set of funds by a net 4.2% per year.[xxi] Since fees are proportional to assets under management, a family's fee revenues grow by the same proportion per year. Over the course of the ten 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' 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' funds), while avoiding the ones they are likely to transfer performance from. However, there are three main obstacles to the implementation of this strategy. First, it would require investors to be able to trade in and out of funds of the same family very cheaply. Second, the cross-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 which funds the family considers of 'high value'. In summary, we expect that investors cannot profitably benefit from the existence of family strategies.

VII. 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' ones. 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; (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% to 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 where there exist more incentives to perform it. We demonstrate empirically a positive relationship between favoritism and (*i*) preferential treatment in the allocation of deals across funds (by showing that 'high value' funds are allocated more under-priced IPOs); and (*ii*) 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 mechanism contribute to the scale of performance redistribution uncovered by our analysis, what the typical fund family stand 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 it for mutual funds under rule 17a-7 of the Investment Company Act) differs from that of the US Department of Labor (which still prohibits it for actively managed ERISA plans). The claimed benefits of cross-trading in terms of trading cost savings should be weighted against the potential for 'self-dealing'. Our results provide relevant information for this assessment.

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Appendix: Merging CRSP and Spectrum Mutual Funds datasets

In this appendix we summarize our matching procedure for Spectrum/Thomson Financial database of Mutual Fund Holdings and the CRSP Survivor-Bias Free US Mutual Fund Database. CRSP and SPECTRUM use different identifiers of each mutual fund (CRSP: ICDI-NO; SPECTRUM: FundNumber).

We proceed as follows.[xxii] 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 found it to be reasonably consistent and hence we use it as the first step in generating the match between CRSP and SPECTRUM.[xxiii] Ticker data is available in SPECTRUM only for three 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, 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.[xxiv] A name-matching algorithm compares these two strings, with a match above 90 percent 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 performed 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 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 identified all fund names including the string 'index', which was useful to filter out index funds from our analysis.

Table I – Summary Statistics

This table presents summary statistics for the sample of mutual funds used in this study. Panel A presents a characterization of our sample composition, comparing it with (i) the overall CRSP Mutual Fund universe of equity funds and (ii) the subset of the former constituted by funds that belong to a fund family (defined as a management company with two or more mutual funds under management). Equity funds are defined as funds with ICDI investment objective codes AG ("Aggressive Growth"), GI ("Growth Income"), LG ("Long-term Growth"), IN ("Income") and BL ("Balanced"). Index funds and multiple share classes of the same fund are excluded. Figures presented are yearly averages for the sample period 1991-2001. Panel B presents summary statistics for some variables used in this study. The fund's monthly return (*Return*) is obtained from CRSP. 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 the 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. *Family Number of Funds* is the number of funds in a family. *Family Total TNA* is the sum of the family's assets under management. *Family Age* is the age of the oldest fund belonging to the family. The number of observations, N, represents fund-month combinations. Panel C presents similar statistics for a cross-section of three specific years (1991, 1996 and 2000).

Table I – Summary Statistics (cont.)

Panel A -Sample composition (yearly averages)

	All CRSP Equity funds	Funds belonging to fund families	Our Sample
Number of funds	1,777	1,624	598
Number of families	257	257	47
Total TNA under management	1,096,498	1,078,996	878,263

Panel B - Descriptive statistics

		N	Mean	Std.Dev.	Q1	Median	Q3
Fund	Return [a]	68,087	0.011	0.054	-0.018	0.013	0.040
	TNA	68,208	1,622	4,852	75	287	1,151
	Total Fees	76,416	0.015	0.008	0.009	0.014	0.020
	Year-to-Date Return [a]	65,668	0.009	0.024	-0.001	0.010	0.021
	Age	78,936	3.4	6.4	0.0	1.0	3.0
Family	Number of funds	78,936	34.9	29.1	11	27	55
	TNA	71,471	47,464	94,023	6,487	15,128	37,040
	Age	78,936	13.1	12.9	3.0	7.0	23.0

[a] Monthly returns

Panel C - Sample composition and descriptive statistics, selected years (1991, 1996, 2000)

		1991			1996			2000		
Number of funds			266			520			872	
Number of families			46			47			50	
Total TNA under management			181,121			755,974			1,868,464	
		Mean	Median	Std.Dev.	Mean	Median	Std.Dev.	Mean	Median	Std.Dev.
Fund	Return [a]	0.026	0.025	0.047	0.015	0.017	0.035	0.000	-0.008	0.074
	TNA	700	215	1,485	1,548	302	3,984	2,241	370	6,541
	Total Fees	0.012	0.012	0.007	0.014	0.013	0.007	0.015	0.015	0.008
	Year-to-Date Return [a]	0.036	0.031	0.021	0.016	0.015	0.011	0.001	0.002	0.024
	Age	8.5	5.0	9.5	3.3	2.0	6.1	3.3	2.0	5.5
Family	Number of funds	10.6	9.0	8.1	30.5	25.0	20.3	54.3	55	27.5
	TNA	9,140	3,742	13,175	36,651	11,020	64,284	80,798	31,833	134,063
	Age	20.1	23.0	10.7	12.3	5.0	12.6	13.2	7.0	12.9

[a] Monthly returns

Table II - Characteristics of High and Low Funds

This table presents summary averages for the different 'High' / 'Low' fund groups used in our study. 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, 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	*<.001*	0.010	0.010	*0.943*
	TNA	641	2,105	*<.001*	1,798	1,330	*<.001*	1,042	3,603	*<.001*
	Total Fees	0.022	0.009	*<.001*	0.014	0.016	*<.001*	0.015	0.013	*<.001*
	Year-to-Date Return [a]	0.008	0.010	*<.001*	0.020	-0.003	*<.001*	0.008	0.009	*0.113*
	Age	2.1	4.7	*<.001*	3.9	3.6	*<.001*	0.8	12.0	*<.001*

[a] Monthly returns

Table III – Indirect Tests of 'Strategic Cross-Fund Subsidization'

This table presents regression results of indirect 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, 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. For each classification, we run the following regression (equation (1) in the text):

$$RET_{i,s,f,t} = a + b(ST\_RET)_{s,t} + c_H \sum_{j \neq i} w_j (ST\_RET)^{High}_{j,f,t} + c_L \sum_{k \neq i} w_k (ST\_RET)^{Low}_{k,f,t} + controls + time\_dummies + \varepsilon_{i,s,f,t}$$

where RET is the fund i raw return in a given month t and ST_RET is the return of the style (ICDI investment objective code) s to which fund i belongs. The return of the style is the value-weighted average of returns for funds in that style. ST_RET^{High} is the average return of the style of 'high value' funds belonging to the same fund family f as fund i. The weights w_j correspond to fraction of assets each fund j represents in the group of 'High' funds. Similarly, ST_RET^{Low} represents the average return of the style of 'Low' funds belonging to the same fund family f. Control variables whose coefficients are not shown include the size of the fund, the age of the fund, the size of the fund's family and the age of the fund's family (all variables defined as in Table I). The table presents the p-value of the hypothesis test that the two coefficients C_H and C_L are equal. The number of observations, N, represents fund-month combinations. All regressions are run with family fixed-effects. T-statistics shown are obtained using heteroskedastic robust standard errors. The symbols ***,** and * denote significance at 1, 5 and 10% 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.	
Style return	0.860	89.69	***	0.860	89.56	***	0.877	69.94	***	0.877	69.96	***	0.845	73.51	***	0.845	73.32	***
Style return of "High" Funds (C_H)	0.023	2.33	**	0.022	2.25	***	0.033	2.52	**	0.033	2.59	***	0.012	0.70		0.015	0.85	
Style return of "Low" Funds (C_L)	0.112	9.45	***	0.112	9.43	***	0.073	5.58	***	0.072	5.52	***	0.135	8.84	***	0.134	8.72	***
Controls	no			yes			no			yes			no			yes		
Year Dummies	yes			yes			yes			yes			yes			yes		
P-value of test of $C_H = C_L$	*<0.001* ***			*<0.001* ***			*0.083* *			*0.094* *			*<0.001* ***			*<0.001* ***		
Mean Squared Error	0.00			0.00			0.00			0.00			0.00			0.00		
Adjusted R^2	0.71			0.71			0.72			0.72			0.71			0.71		
N	55,699			55,548			32,158			32,134			39,199			39,077		

Table IV – Univariate Analysis for Direct Tests

This table presents preliminary evidence of our direct 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, 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 1, 5 and 10% 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%***	*<.001****
Age	0.004%	-0.021%	*0.25*

Table V – Direct Tests of ‘Strategic Cross-Fund Subsidization’

This table presents regression results of the direct 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, 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 dataset to run our regressions. For each classification, the table shows the results of the following regression (equation (2) in the text):

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

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% 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	

Table VI – Extended Tests of 'Strategic Cross-Fund Subsidization'

This table presents regression results of extended tests of cross-fund subsidization. Please refer to Table V for a complete description of how pairs of 'High' and 'Low' funds are obtained. The table shows the results of the following specification (equation (3) in the text):

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

The left-hand side variable is the Difference in Net-of-Style Returns for each pair. The first variable in the right-hand side ($Same\_Family|ST\_RET_{High} > ST\_RET_{Low}$) 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 ($Same\_Family|ST\_RET_{High} < ST\_RET_{Low}$) 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 β+ and β– 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% 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 $\mid\beta_+\mid < \mid\beta_-\mid$	*.065 **			*.013 ***			*.001 ****			*.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 VII – Family Characteristics and Strategic Cross-Fund Subsidization

This table presents regression results of the direct tests of cross-fund subsidization, broken down across family characteristics. Each cell shows the β coefficient of the specification of Panel A of Table V for different family groups. Please refer to the caption of Table V 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 than the average of 27 funds or less than 27 funds), family age (more than the average of 13 years or less than 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% respectively, using heteroskedastic robust standard errors.

Panel A

	Families by Size		Families by # 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 yrs)	Young (<13 yrs)	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%**

Table VIII – 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 V 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 1992-2001 period, and calculate, for each IPO 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.

Panel A

All IPO issues, 1992-2001 (source: SDC)	N = 5,477	Value: $413.2 Bln.	Average 1st day return	14.5%
			Median 1st day return	6.3%
IPOs held at quarter-end by funds in the sample (source: Spectrum MF Holdings)	N = 2,657	Value: $26.7 Bln.	Average 1st day return	28.0%
			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 ($ Bln.)	$2.22Bln	$1.96Bln		$6.39Bln	$1.04Bln		$6.56Bln	$2.30Bln	
Percentage contribution of Underpricing to return of H or L fund (% of TNA)	0.474%	0.091%	*0.001* ***	0.288%	0.169%	*<0.001* ***	0.322%	0.144%	*0.004* ***

Table IX – 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 V for a complete description of how pairs of 'High' and 'Low' funds are obtained. For each classification (e.g. fees, performance, age), we run the following regression (equation (4) in the text):

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

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*. $Opposite\_trades_{SUM}$ denotes the sum, across the two funds 'High' and fund '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. $Opposite\_trades_{MIN}$ denotes the minimum, across the two funds 'High' and fund '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 (all variables defined as in Table I). 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% respectively.

Table IX – Opposite Trades and Strategic Cross-Fund Subsidization (cont.)

	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	*
Opp. Trades$_{SUM}$ (ς)	-0.0633	-6.46	***	-	-		-0.1690	-8.85	***	-	-		-0.0124	-1.46		-	-	
Opp. Trades$_{SUM}$ | Same Family (θ)	0.0234	1.97	**	-	-		0.0459	2.16	**	-	-		0.0307	2.93	***	-	-	
Opp. Trades$_{MIN}$ (ς)	-	-		-0.4978	-3.06	***	-	-		-1.9707	-5.34	***	-	-		-0.0659	-0.42	
Opp. 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		

[i] These figures refer to US domestic actively managed equity mutual funds on CRSP Survivor-Bias Free US Mutual Fund Database from 1991-2001.

[ii] Nonetheless, Chen, Hong, Huang and Kubik (2002) find evidence that fund size seems to erode fund performance, which they attribute to liquidity effects and potentially organizational diseconomies. Family size, however, does not seem to harm fund returns.

[iii] References include Brown, Harlow and Starks (1996), Chevalier and Ellison (1997), Sirri and Tufano (1998) and others.

[iv] Based on the finding by Khorana and Servaes (1999) that the launch of new funds is also related to past performance, we can think of an additional 'spill-over' effect of a fund family that produces good performing funds as it may capitalize on the brand name to open new funds.

[v] Throughout our study we use the expression 'investment styles' to mean the fund's stated investment objective (growth, income, balanced, sector, etc) and we implement it empirically by adopting ICDI fund objective from the CRSP Mutual Funds dataset. We thus chose 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).

[vi] Tunneling is usually defined as the diversion of profits from some business units in favor of others, for the benefit of controlling shareholders in a business group.

[vii] 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 to grant a class exemption that authorizes cross-trades involving passively managed ERISA plans, although it still prohibits them for actively managed accounts [http://www.dol.gov/ebsa/newsroom/pr121102.html]. Lobbying efforts by the Investment Company Institute can be found in http://www.ici.org/issues/mrkt/arc-oth/02_dol_cross_exempt.html#TopOfPage.

[viii] Similar examples are, naturally, valid for any of the two other dimensions: 'high performing' versus 'low performing' funds and 'young' versus 'old' funds.

[ix] The most frequent classes are: class 'A' with a front-end load and 12b-1 fee and no back-end load, class 'B' with a back-end load and a 12b-1 fee but no front-end, class 'C' with a back-end load (much smaller than B s) and a 12b-1 fee (generally greater than B s) but no front-end, a 'No-Load' class with no front-end back-end loads but a 12b-1 fee of 0.25% and 'Institutional class' with no load but generally with a large minimum initial purchase destined for institutional investors. See Zhao (2002) and Pozen (1998).

[x] One possible concern raised by our scheme is the possibility of overlap between the different sets of funds classified as High or Low under each classification. We find the amount of overlap to be low; for example, the correlation between the set of funds classified on the basis on fees and the set of funds classified on the basis of past performance is below 10%.

[xi] The analogy with BMM's application is that mutual funds, fund families and investment style shocks in our setting correspond, respectively, to business units, business groups and industry shocks in their paper. BMM classify business units in 'high' or 'low value' depending on the cash flow rights of the controlling shareholder of the group.

[xii] Given that a mechanical correlation exists if the fund itself is part of ST_RET, $(\text{ST\_RET})^{\text{High}}$, $(\text{ST\_RET})^{\text{Low}}$, we exclude fund i from any of these.

[xiii] 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 and the 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.

[xiv] See Ritter and Welch (2002) on the underpricing phenomenon in IPOs.

[xv] Interestingly, one high-profile SEC enforcement case involved 'hot IPO' allocations that favored Dreyfus Aggressive Growth Fund (DAG) at the cost of other funds. According to findings reported in SEC (2000), DAG fund was allocated disproportionate shares of over-subscribed IPOs. The SEC calculated that first-day returns from IPOs contributed by 51.3% of DAG's total return in the first 6 months (or 76% of its total return). DAG's outstanding performance allowed it to take the top ranking position in Morningstar in the first quarter of 1996 and #1 ranking in Lipper's capital appreciation category, drawing huge inflows, which made its assets increase from $ 2 million to $ 154 in one year.

[xvi] Although over 80 percent of funds report their portfolio holdings on a quarterly basis - Wermers (2000).

[xvii] 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 when holdings are reported should not be related to our 'high' versus 'low value' fund classifications. As Reuter (2002) we take positive holdings as best proxy available to us of whether fund was attributed shares at offer date.

[xviii] Indeed, Rule 17a-7 of the US Investment Company Act permits transactions between mutual funds subject to conditions to ensure 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 that a record is kept. Recently, the Department of Labor has also issued an exemption which permits cross trades of securities among ERISA index funds, but decided not to extend it to actively-managed funds.

[xix] An example illustrates our procedure. For an observation in February, fund pairs of High or Low value are constructed using classifications at the end of January. *Opposite_ Trades* is constructed using the observed change in holdings between end of December and 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 the end of February to the end of May, such that some of this return is no longer contemporaneous with the change in holdings.

[xx] 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 top and bottom 25% funds.

[xxi] 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 25th instead of 20th percentile as in their paper. Our estimates are of similar magnitude to Sirri and Tufano(1998) and R^2=15,5%:

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

(t-stat= 1.6) (t-stat= 2.4) (t-stat= 19.6)

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

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

[xxiii] 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 file 8, the Fund Ticker Information file. The fund ticker symbol here is also a five-character symbol.

[xxiv] Certain assumptions were made about the way the fund names were abbreviated in SPECTRUM based on observation For example, for in each name of the fund, the word fund is dropped in SPECTRUM, company is abbreviated as Co.