The Journal of FINANCE
The Journal of THE AMERICAN FINANCE ASSOCIATION

THE JOURNAL OF FINANCE • VOL. LXVIII, NO. 1 • FEBRUARY 2013

Conflicting Family Values in Mutual Fund Families

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ABSTRACT

We analyze the investment behavior of affiliated funds of mutual funds (AFoMFs), which are mutual funds that can only invest in other funds in the family, and are offered by most large families. Though never mentioned in any prospectus, we discover that AFoMFs provide an insurance pool against temporary liquidity shocks to other funds in the family. We show that, though the family benefits because funds can avoid fire sales, the cost of this insurance is borne by the investors in the AFoMFs. The paper thus uncovers some of the hidden complexities of fiduciary responsibility in mutual fund families.

A MAJOR REASON FOR the existence of conglomerates or business groups is to create internal capital markets to promote the efficiency of the group. One of many efficiency measures that internal capital markets can offer is an insurance pool, which provides temporary liquidity to the members of the group in the event of adverse shocks.[1]

If mutual fund families, which are a collection of legally independent entities tied together by the sponsoring management company, are regarded as groups, it seems reasonable to assume that there would be a group interest.[2] If so, it seems natural to ask whether insurance pools could exist in these families where cash-rich mutual funds direct capital to family funds that are facing

*Bhattacharya and Pool are with Indiana University Kelley School of Business, and Lee is with A. B. Freeman School of Business, Tulane University. For useful comments and discussions, we thank the Editor (Cam Harvey), the Associate Editor, an anonymous referee, Sudheer Chava, Nishant Dass, Nandini Gupta, Cam Harvey, Mike Hemler, Ravi Jagannathan, Sreenivas Kamma, Juhani Linnainmaa, Pedro Matos, Toby Muhlhofer, Vikram Nanda, Vallapuzha Sandhya, Paul Schultz, Amit Seru, Ashish Tiwari, Charles Trzcinka, Jay Wang, Scott Weisbenner, Deniz Yavuz, and Scott Yonker. Seminar comments at Bocconi University, Boston College, Catholic University of Milan, Chicago Booth School of Business, HKUST, Georgia Tech, University of Houston, University of Illinois at Chicago, University of Illinois at Urbana-Champaign, National Taiwan University, University of North Carolina, Northwestern University, Mannheim University, Texas Christian University, University of Venice, the 2010 State of Indiana Conference, the 2011 Spring Meeting of the Q-Group, the 2011 Fidelity Quant Meeting, the 2011 FIRS Conference, and the ICI and AIM Investment Center Conference at the University of Texas at Austin vastly improved the paper.

[1] A large theoretical literature, beginning with Levy and Sarnat (1970), analyzes co-insurance as the financial rationale for mergers. Gopalan, Nanda, and Seru (2009) document insurance pools in Indian business groups.

[2] Chevalier and Ellison (1997) argue that the mutual fund family's aim is to maximize the value of the complex, rather than that of an individual fund.

large redemption requests, as these redemptions could lead to large fire sale losses. By law, they cannot. This is because, although the provision of such an insurance pool against temporary liquidity shocks benefits the family, the cost is borne by the shareholders of the fund providing this "free" insurance. A mutual fund, however, owes a fiduciary responsibility only to its own shareholders, and not to its family.[3] Nevertheless, several papers suggest that group interest comes before fiduciary responsibilities in certain cases.[4]

In this study, we ask whether insurance pools exist in mutual fund families. We examine this question by analyzing the investments of affiliated funds of mutual funds (AFoMFs). AFoMFs are mutual funds that invest only in other mutual funds within the family. Instead of investors or their financial advisors choosing which mutual funds of the family to invest in, AFoMFs do so for investors.[5] Virtually nonexistent in the 1990s, these funds have become very popular. In 2007, which is the last year of our sample, 27 of the 30 large families that made up around 75% of the industry's assets[6] had AFoMFs.

To determine whether AFoMFs provide liquidity to member funds in need, we divide total fund flow to each ordinary mutual fund into AFoMF flow and non-AFoMF (or outside investor) flow. The flows are normalized by the underlying fund's value. We find that, when we sort each family fund into deciles based on the flow from its outside investors, the lowest decile (i.e., the group of distressed funds/funds experiencing the largest withdrawals from their outside investors) has a statistically significantly higher average inflow from its family AFoMFs than any of the other nine deciles. This is our primary evidence showing that AFoMFs offset severe liquidity shortfalls of funds in the family. Interestingly,

[3] Section 17 of the Investment Company Act of 1940 substantially restricts lending/borrowing/investment between individual funds in a family. These restrictions were originally designed to "prevent fund of funds arrangements that have been used in the past to enable investors in an acquiring fund to control the assets of an acquired fund and use those assets to enrich themselves at the expense of acquired fund shareholders." There are some exceptions. One is the legalization of certain fund of funds structures over time, which we claim is exploited to provide an insurance pool. Another exception is that cross-trades at market prices are permitted via SEC Rule 17(a)-7. The use of cross-trades at favorable prices (or funds acquiring unwanted positions) is another potential way to pursue family objectives.

[4] Evans (2010) mentions that families pursue their own objectives by strategically setting fees, promoting the performance of some of their funds, increasing fund offerings (Massa (2003)), and strategically choosing distribution channels. Gaspar, Massa, and Matos (2006) show that high-fee or high-performance funds receive preferential IPO allocations and are likely supported through cross-trades by low-fee or poor-performance funds. Evans (2010) argues that fund incubation is another family strategy to spuriously inflate family returns. Goncalves-Pinto and Sotes-Paladino (2010) theoretically model cross-trading as a way to smooth liquidity shocks in the family. Casavecchia and Tiwari (2011) document the cost cross-trading imposes on client portfolios. Sandhya (2010) studies target date funds and finds that, when these funds are structured as funds of funds, they often invest in high fee or low-performance funds.

[5] In 1996, Congress added Section 12(d)(1)(G) to Section 17. It allowes an AFoMF to legally invest in other funds in its own family. This exception to Section 17 was granted so that mutual fund families could compete with investment advisors to provide their clients the best investments within their family. AFoMFs, being mutual funds, still have a fiduciary responsibility to their own shareholders and not to their family.

[6] See http://www.ici.org, 2010 Investment Company Institute Fact Book.

though we scan the AFoMF prospectuses—relevant excerpts from a couple of them are provided in the Internet Appendix[7]—we find that none of them mention liquidity provision as an objective.

We perform several additional tests to confirm that what we find is not a spurious result but rather evidence that AFoMFs are purposefully providing liquidity to distressed funds. First, if AFoMFs provide liquidity to distressed funds, this liquidity support should not exist for funds that rarely need this support. We find that AFoMFs do not favor distressed funds that are money market funds, Treasury funds, or exchange-traded funds (ETFs). Second, the liquidity position of the AFoMF should not matter. We find that AFoMFs provide liquidity to distressed funds even when the AFoMFs are cash poor. Third, if the AFoMFs are providing an insurance function, they should be providing liquidity for transient liquidity shortfalls rather than persistent shortfalls. We find that AFoMFs do not help underlying funds that have persistent liquidity shortfalls. Fourth, if fund flows to distressed funds represent insurance, it should not be provided by unaffiliated funds of mutual funds (UFoMFs), which are funds of funds that can only invest outside the family. We find that UFoMFs do not provide liquidity to distressed funds. Fifth, as fire sale costs are higher for less liquid funds than for more liquid funds, the temporary liquidity provision should be more for less liquid funds. We find that AFoMFs provide greater insurance to less liquid distressed funds than to more liquid U.S. equity funds. Finally, if most funds in the same style are trying to sell at the same time, costly fire sales are more likely, in which case temporary liquidity provision by AFoMFs should be more likely. We find that AFoMFs favor distressed funds more if other funds in the distressed fund's style are also selling.

Multivariate tests confirm the above main univariate tests. In these tests, we control for measures of the underlying fund's liquidity, the AFoMF's liquidity, and various characteristics of the underlying fund, such as size, fund fees, and past performance.

Why do AFoMFs favor distressed mutual funds in their families? Thus far, our discussion is biased toward suggesting that they do so solely to help member funds avoid costly liquidity-driven trades. This explanation is motivated by prior research. Existing studies show that liquidity-induced mutual fund trading is indeed costly. Edelen (1999) argues that these trades are uninformed and as a result lead to losses against informed traders on the order of approximately 140 basis points annually. Moreover, Coval and Stafford (2007) find that large redemptions induce fire sales that generate a significant price impact in the markets.[8]

However, AFoMF investment in distressed funds may not be aimed at helping these funds. An alternative explanation, given to us by fund managers,

[7] The Internet Appendix is located on the *Journal of Finance* website at http://www.afajof.org/supplements.asp.

[8] Zhang (2009) and Chen et al. (2008) find that other funds prey on liquidity-strapped mutual funds. Also, since the cost of redemptions is borne by the remaining shareholders, Chen, Goldstein, and Jiang (2010) argue that withdrawal is the best response when investors expect that others will withdraw. This leads to a vicious cycle.

is that many AFoMFs are asset allocation or target date funds that maintain target weights in various asset classes. This implies a mechanical injection of inflows into any distressed fund whose asset class value has fallen below the target. To check this possibility, we construct a variable that measures the current deviation from the target weight. We find that liquidity provision, though diminished by the addition of this control variable, remains. A second explanation is that temporary liquidity provision is given only to the top-performing or high-fee mutual funds, and so it is just a strategy to protect these funds. We find that liquidity provision exists for all types of funds except the extreme losers. A third explanation is that liquidity provision to another fund occurs only if the manager of an AFoMF manages the other fund as well. We find that this is not the case.

A final alternative explanation is that AFoMFs may have inside information that others do not, and so they act as smart contrarian investors. This is conceivable since AFoMFs are geographically close to their own family (e.g., Coval and Moskowitz (2001), Gervais, Lynch, and Musto (2005), Massa and Rehman (2008), Lee (2011)). If AFoMFs invest in distressed mutual funds because they have superior information and believe that these distressed funds are undervalued, AFoMFs should profit by going against the crowd. We follow the smart money literature (e.g., Gruber (1996), Zheng (1999), and Sapp and Tiwari (2004)) to examine this alternative hypothesis. We find that AFoMFs lose by providing liquidity to distressed funds.

Finally, to address whether liquidity provision is a rational family strategy, we test whether the sacrifice, which is the *cost* incurred by AFoMF shareholders from these investments, *benefits* the family. We first measure the benefit. We find that, though liquidity shortfalls hurt fund performance, this effect is ameliorated by AFoMFs' inflow. This amelioration is a fund's benefit. We next find that, if the AFoMF invested in the distressed portfolio the same way it invested in the other portfolios, its performance would have improved. This improvement sacrifice is the AFoMF's cost. We find that the benefit to distressed funds exceeds the cost to AFoMFs. Though we cannot draw definitive conclusions from our low-frequency data and a back-of-the-envelope calculation, the results suggest that the cross-subsidy may be rational for the family.

Section I describes our data. Section II presents tests of the liquidity provision hypothesis. Section III refutes the alternative hypotheses. Section IV estimates the cost and benefit of liquidity provision, and provides a cost-benefit comparison for the whole family. Section V provides robustness results. Section VI concludes.

I. Data and Descriptive Statistics

The data used in this study are drawn from the Morningstar Principia and CRSP Survivor-Bias-Free Mutual Fund databases. We first obtain the list of funds of mutual funds (FoMFs) from Morningstar Principia for the October 2002 to January 2008 period. We compare the number of funds in our sample to the number reported in the 2008 ICI Fact Book.[9] The comparison shows that our sample covers more than 90% of the FoMF universe. The Morningstar database contains periodic reports about the exact portfolio composition of each FoMF, including each portfolio weight, the corresponding market value, the number of shares it holds in each underlying fund at the end of the current reporting period, as well as the number of shares it held in the previous reporting period.[10] To classify funds as "affiliated" ("unaffiliated"), we require that the FoMF and its holdings belong (do not belong) to the same family.[11]

We next hand-match each FoMF and all of its mutual fund holdings to the corresponding funds in CRSP by fund name. After identifying the CRSP fund number for each FoMF and its portfolio funds, we obtain information on monthly fund returns and total net assets (TNAs), as well as fund characteristics (such as expense ratio, style, inception date, etc.) from the CRSP mutual funds database. Since FoMFs are also mutual funds, these variables are available for both the FoMFs and their fund holdings. In a few cases, previous portfolio dates are missing or the FoMF or the portfolio funds are not identified in CRSP. Such observations are eliminated.

Throughout the paper, we work with fund-level data. Accordingly, we combine each fund's share classes into one series in the CRSP database. We aggregate the share classes by calculating the TNA value weighted average return, net asset value (NAV), and expense ratio of the fund. For the TNA of the FoMF and the underlying funds, we sum the TNAs across the different share classes. In the Morningstar database, the dollar value of each FoMF holding (as well as the total number of shares held) is reported as the aggregate amount held across all share classes of the FoMF, and thus no adjustment is needed for Morningstar.

Table I provides information about our sample. Panel A reports the number of families that offer AFoMFs, the average size of these families, the average number of AFoMFs offered, and how the AFoMFs' size compares to the aggregate size of the family. For comparison, we present similar data for those families that offer UFoMFs and families that offer no fund of funds products in Panels B and C, respectively. We notice that AFoMF assets account for about 10% of family assets in 2007; the rapid growth came from pension plans adopting this new type of fund in the 2000s, often as the Qualified Default Investment Alternative. AFoMFs are typically offered by larger families, in terms of both size (TNA) and the number of funds offered. This

[9] See http//:www.icifactbook.org/pdf/2008_factbook.pdf.

[10] The length of the reporting period is a quarter in most cases, but it ranges from 1 month to over a year in some cases. In our analyses, we include only those fund reporting periods for which the two consecutive reporting dates are no more than 3 months apart. So our data allow us to compute flows quarterly for some FoMFs and monthly for other FoMFs. We divide the former by three, which normalizes all units to be monthly.

[11] In a few cases, a given fund of funds appears to be both affiliated and unaffiliated. We mark these as "hybrid" FoMFs. These funds typically emerge toward the end of our sample period due to the SEC's rule change in 2006. For hybrid funds, we only include the affiliated holdings. Excluding these funds has no effect on our results.

Table I

Descriptive Statistics of Fund Families

This table provides summary statistics of mutual fund families in our sample. Panel A describes fund families that offer AFoMFs. For comparison, Panel B lists the characteristics of those mutual fund families that offer unaffiliated FoMFs (UFoMFs), whereas Panel C lists summary statistics of families with no fund of funds products. The summary statistics are (1) the number of families in each group; (2) the total number of fund families in the mutual fund universe; (3) the average size of the assets under management by each fund family; (4) the average number of ordinary mutual funds; (5) the average number of FoMFs available in each family; and (6) the average proportion of assets under management by the aggregate FoMF relative to the size of the corresponding fund family.

Panel A: AFoMFs

Year	Number of Families with AFoMFs	Total Number of Fund Families	Average Size of Family with AFoMFs (in $ Billions)	Average Number of Ordinary Family with AFoMFs	Average Number of AFoMFs per Family with AFoMFs	Average Size of Aggregate AFoMFs Relative to the Size of Family with AFoMFs
2002	63	651	57.7	48	4	6.10%
2003	66	645	64.6	48	4	7.00%
2004	76	616	68.3	50	4	9.00%
2005	80	626	74.5	52	5	11.00%
2006	84	613	82.7	52	6	11.90%
2007	86	620	113.6	57	6	10.50%

Panel B: UFoMFs

Year	Number of Families with UFoMFs	Total Number of Fund Families	Average Size of Family with UFoMFs (in $ Billions)	Average Number of Ordinary Family with UFoMFs	Average Number of UFoMFs per Family with UFoMFs	Average Size of Aggregate UFoMFs Relative to the Size of Family with UFoMFs
2002	23	651	4.9	14	5	25%
2003	23	645	2.3	10	4	44%
2004	27	616	2.8	11	4	49%
2005	34	626	2.7	11	4	45%
2006	42	613	8.4	15	5	29%
2007	47	620	48.9	25	6	14%

Panel C: Others

Year	Number of Families without FoMFs	Total Number of Fund Families	Average Size of Family without FoMFs (in $ Billions)	Average Number of Ordinary Funds per Family without FoMFs
2002	565	651	9.2	11
2003	556	645	10.8	11
2004	513	616	12.6	12
2005	512	626	13.8	12
2006	487	613	16.7	12
2007	487	620	20.2	13

makes sense because, as AFoMFs invest only in family funds, AFoMFs will not exist if their investment opportunity set is small. In 2007, of the 30 largest families that accounted for 75% of the size of the industry, 27 offered AFoMFs.

II. Liquidity Provision by AFoMFs

The extant literature argues that, when mutual funds experience large outflows, the only option they are often left with is to sell existing portfolio positions,[12] and as a result meeting large redemptions is very costly. We show that, when a family has AFoMFs, these AFoMFs may provide an insurance pool to offset temporary liquidity shocks of member funds.

We proceed in two steps. First, we document that AFoMFs invest a disproportionately large amount of money in funds that are experiencing extreme outflows from their outside investors. Second, we provide several subsample results to show that this behavior is consistent with liquidity provision.

A. AFoMF and Non-AFoMF Flows

Ordinary mutual funds in families that have AFoMFs have two groups of investors: AFoMF and non-AFoMF investors. To examine how the investment behavior of AFoMFs is related to the investment/redemption decisions of the non-AFoMF investors, we decompose total flow to each ordinary fund into AFoMF flow and non-AFoMF (outsider) flow. The standard measure of total net dollar flow to each ordinary mutual fund j in family k during portfolio period t is given as follows:

$$Flow_{j,k,t}^{Total} = TNA_{j,t} - TNA_{j,t-1} \cdot (1 + r_{j,t}), \tag{1}$$

where TNA_j is the total assets under management of the j^{th} fund and r_j is the net-of-fees return for the relevant time period. Equation (1) assumes that cash flows arrive at the end of the reporting period.[13] To calculate the investment (flow) mutual fund j receives from AFoMFs during the portfolio period, we first determine the dollar change in each AFoMF's position in fund j. This is expressed as the change in the number of shares held by AFoMF i in fund j multiplied by the average NAV of fund j. Note that NAV is just the price per share of fund j. We then aggregate this dollar change across all AFoMFs in the family that are investing in fund j:

$$Flow_{j,k,t}^{AFoMF} = \sum_{i=1}^{n_k} \Delta shares_{i,j,t} \cdot NAV_{j,t}, \tag{2}$$

where n_k is the number of AFoMFs in family k that are investing in fund j, NAV is fund j's average NAV in the portfolio period, and $\Delta shares$ is the change in the number of shares of fund j held by AFoMF i between date t–1 and date t.

[12] Other solutions to meet redemption requests, such as borrowing or short selling, are severely limited. Moreover, funds tend not to hold significant cash positions. Several papers estimate mutual fund transaction costs. See, for instance, Blume and Edelen (2004), Bollen and Busse (2006), Christoffersen, Keim, and Musto (2007), and Edelen, Evans, and Kadlec (2007).

[13] For robustness, we also adopt a flow measure that assumes that flows arrive at the beginning of the period instead. All results are robust to this alternative specification.

Finally, we obtain the flow (investment) from outsiders by taking the difference between equations (1) and (2):

$$Flow_{j,k,t}^{Outside} = Flow_{j,k,t}^{Total} - Flow_{j,k,t}^{AFoMF}. \quad (3)$$

In all our analyses, we divide the three flow measures above by $TNA_{j,t-1}$.

In addition to quantifying the magnitude of the AFoMF flow to each underlying fund (equation (2)), we classify each AFoMF flow as a new position, liquidation, maintained position (zero flow), position increase, or position decrease. Maintained positions are existing positions that remain the same over the portfolio period, that is, the fund of funds engages in no trade in the underlying fund between the previous and current portfolio dates. It is important to recognize that there are also funds in the family in which AFoMFs do not have an existing position and choose not to acquire positions. We call these no-trade funds.

It is very important for our research design to answer why AFoMFs do not invest in these no-trade funds. Are they outside the investment opportunity set of the AFoMF, or are they in the investment opportunity set but the AFoMF chooses not to trade in them? In other words, what is the investment opportunity set of the AFoMF? For the purpose of our study, we define the investment opportunity set of an AFoMF as all funds in the family whose fund styles are consistent with the investment objectives of the AFoMF. Since style category is probably not the only determinant of the AFoMF investment opportunity set, our definition is imprecise. For robustness, we redefine the investment opportunity set of the AFoMF in two extreme ways. The first way—the investment opportunity set of the AFoMF consists of all funds that they trade at least once in our sample period—is the most conservative definition and biases us toward our results. The second way—the investment opportunity set of the AFoMF consists of all funds in the family—is the most liberal definition and biases us against our results. All our results are robust to both of these extreme definitions (see the Internet Appendix).

In results tabulated in the Internet Appendix, we find that the funds held by AFoMFs tend to be larger and younger on average than funds not held by AFoMFs. The Sharpe ratio, the seven-factor alpha, and the flow-performance sensitivities, however, are not statistically significantly different across the two groups. The minimum expense ratio (i.e., the expense ratio of the lowest expense share class) is higher for funds held by AFoMFs[14] and the fraction of index funds held is lower. Note that, if AFoMFs were really following an asset allocation strategy, they should be investing more in low-cost index funds.

[14] While this could indicate investment in better managers, it may also be due to differences in the proportion of low-cost index funds in the two groups. In addition, it is important to note that, throughout the paper, the fee variables have to be interpreted with caution. First, we do not know which share class AFoMFs would invest in should they invest in no-trade funds (however, as a legal matter, it is almost certain that the AFoMF pays the lowest fee class; therefore, we use these for comparison). Second, the fees CRSP reports for each fund do not necessarily correspond to the actual fees paid (e.g., due to waivers).

We begin our formal analysis by sorting ordinary mutual funds in each family into deciles according to the flows these funds face from their outside investors, as described in equation (3). Following the literature, funds in decile 1 (i.e., funds that have flows below the 10^{th} flow percentile) are distressed funds. These are funds that experience severe redemption requests. Since aggregate flows may vary across different time periods, we reset our decile breakpoints each portfolio period. For each decile, we calculate the average flow from AFoMFs (scaled by TNA) and the fraction of the AFoMF positions that are new positions, liquidations, maintained positive positions, position increases, position decreases, or maintained zero positions.

Figure 1 depicts average flow from AFoMFs by outside investor flow decile. The dashed line in the graph indicates the breakpoint between negative and positive average outsider flows: bins to the left (right) of the line contain those ordinary mutual funds that are experiencing a negative (positive) flow, on average, from their outside investors. The figure reveals a generally positive correlation between the investment behavior of AFoMFs and that of outside investors. This implies that AFoMFs generally tend to prefer funds that outside investors favor during the portfolio period. If flows are the market's response to managerial talent, it seems that AFoMFs and outside investors make very similar assessments on how ordinary funds rank with respect to each other. The only exception, however, is decile 1. While outside investors are fleeing funds in decile 1, AFoMFs invest statistically significantly more in these distressed funds than in any of the other flow groups. The t-statistics we compute to test the equality of the mean AFoMF flow of decile 1 and that of each decile $i = \{2,\ldots,10\}$ range from 1.76 to 9.79 with corresponding p-values that are statistically significant. The large AFoMF investment in decile 1 funds described in Figure 1 constitutes our primary evidence on liquidity provision.

The figure also indicates that average AFoMF flow to distressed funds is a little over 0.6%. In decile 1, the average flow from outside investors is approximately –5.6%, which means that the average AFoMF inflow represents more than 10% of the outflow. This is a very conservative estimate as our averages in Figure 1 include a generously defined investment opportunity set. When we concentrate on those funds that belong to AFoMFs' portfolio at some point during the reporting period (i.e., exclude no-trade funds), the average AFoMF inflow offsets over one-third of the outflow by outside investors in decile 1. Figure 1 also suggests that AFoMFs are not following contrarian or momentum strategies. If they followed a contrarian (momentum) strategy, AFoMF flow would be negatively (positively) correlated with outsider flows. Figure 1 instead shows a U-shaped function.

Table II provides additional confirmation that AFoMFs provide liquidity to distressed member funds in the family. The table reports the proportion of position types in each decile and, in parentheses, the average AFoMF flow scaled by the TNA of the fund. Column 4, for instance, indicates that AFoMFs are more active in decile 1 than in most of the other deciles. Of the funds in decile 1, only 48.24% are not held by AFoMFs. The other deciles have higher nonparticipation rates, the highest being decile 10, where 64.55% of the funds are not

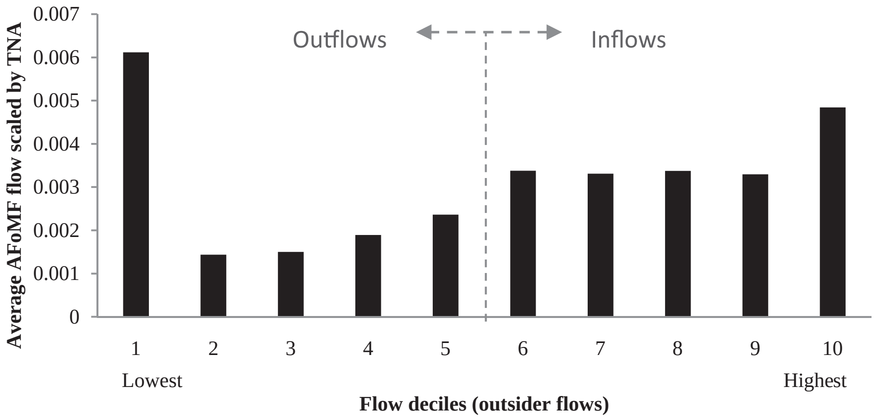

Figure 1. Do AFoMFs favor distressed funds? This graph reports average AFoMF flow to the underlying funds by outside investor flow deciles. We divide total flow to ordinary mutual fund j in family k into AFoMF flow and non-AFoMF flow, that is, net flow by all other investors. Total dollar flow is estimated by

$$Flow^{Total}_{j,k,t} = TNA_{j,t} - TNA_{j,t-1} \cdot (1 + r_{j,t}),$$

where TNA_j is the TNA of the j^{th} fund and r_j is the net-of-fees return for the relevant time period. Flow from AFoMFs is determined by

$$Flow^{AFoMF}_{j,k,t} = \sum_{i=1}^{n_k} \Delta shares_{i,j,t} \cdot NAV_{j,t},$$

where $\Delta shares_{i,j}$ is the change in the number of shares held by AFoMF i in fund j during the reporting period, n_k is the number of AFoMFs in family k, and NAV_j is the average NAV of fund j. Finally, non-AFoMF or outside investor flow is expressed as follows:

$$Flow^{Outside}_{j,k,t} = Flow^{Total}_{j,k,t} - Flow^{AFoMF}_{j,k,t}.$$

All three flow measures are normalized by $TNA_{j,t-1}$. Outside investor flow deciles are determined by sorting our sample into deciles based on normalized $Flow^{Outside}_{j,k,t}$. Decile 1 collects the underlying funds that receive the lowest percentage flow (highest outflow) from outside investors, whereas decile 10 includes funds with the highest outside investor flow (highest inflow). The dashed line in the graph indicates the breakpoint between negative and positive average non-AFoMF flow. In the graph, the X-axis denotes outside investor flow deciles, whereas the Y-axis denotes average percentage flow from AFoMF.

traded by AFoMFs. Column 7 tells us that AFoMFs also initiate a disproportionately large number of new positions in decile 1. The number here is 5.37%, and this new activity is the highest among all the deciles. The numbers in parentheses give us qualitatively similar results if we use the average AFoMF flow for each category. For example, AFoMFs initiate new positions in decile 1 distressed funds by providing them liquidity as much as 5.3% of their NAV, and this number is much higher than what they provide to initiate new positions in the other deciles.[15]

[15] Since the outflow from outsiders is 5.58% in decile 1, it would seem that, with a 5.3% liquidity provision to initiate new positions in decile 1, the AFoMFs are replenishing all the liquidity

To examine the relation between AFoMF flow and outside investor flow more formally, we run the following multivariate regression:

$$Flow_{j,t}^{AFoMF} = \beta_0 + (\beta_1 + \beta_2 \cdot I_{j,t}) \cdot Flow_{j,t}^{Outside} + controls + \varepsilon_{j,t}, \qquad (4)$$

where $Flow_j^{AFoMF}$ and $Flow_j^{Outside}$ are AFoMF flow and outside investor flow to underlying fund j during the current reporting period, respectively, and I_j is an indicator that takes the value of one if fund j is distressed and zero otherwise. The control variables are (1) measures of AFoMF liquidity represented by the contemporaneous and lagged flow AFoMFs receive from their own investors and the percentage of AFoMF assets held in cash; (2) measures of fund j's liquidity represented by lagged AFoMF flow ($Flow_{j,t-1}^{AFoMF}$) and lagged outside investor flow to underlying fund j, fund j's cash holdings, and an interaction variable between the cash holdings and distress ($I_{j,t}$); and (3) additional characteristics of fund j including previous performance measured by fund j's Sharpe ratio in the previous year, fund j's expense ratio, and fund j's size measured by average TNA in the 3 months immediately preceding the current portfolio period. The control variables are motivated by previous research. Existing studies find a strong relation between mutual fund performance and the subsequent flow of investor capital into or out of a fund (Chevalier and Ellison (1997), Sirri and Tufano (1998), and Del Guercio and Tkac (2002)). Flow is also found to be persistent; moreover, in our context, AFoMF flow is likely to be influenced by the liquidity of the fund and the AFoMF.

We estimate equation (4) using the Fama–MacBeth (1973) method. Table III reports the results. Consistent with the univariate analyses above, the regression results (the β_1 coefficient) indicate a generally positive and significant relation between AFoMF flow and outside investor flow. For distressed funds, however, this relation is significantly negative, and is represented by the sum of the β_1 and β_2 coefficients, which are the coefficients in the first two rows. The coefficient estimates indicate that a 1% decrease in outside investor flow from distressed funds results in a 0.04% to 0.08% increase in flows from family AFoMFs.

B. AFoMF and Non-AFoMF Flows—Various Subgroups

In this section, we examine the insight that, if the results are really due to liquidity provision by AFoMFs, the results should be different for different subgroups of funds. For each subgroup, we first present univariate results that repeat the analysis conducted to obtain Figure 1. We then provide a multivariate formal test by running the multivariate regression given in equation (4) for each subsample.

First, if AFoMF activity reflects liquidity provision for the underlying fund, we expect the behavior not to exist for funds that rarely need liquidity support.

shortfalls in decile 1 funds. This would not be a legitimate conclusion because new positions constitute only about 5% of AFoMF flows to decile 1.

Table II
Do AFoMFs Favor Distressed Funds? (Univariate Test)

This table examines how AFoMFs' mutual fund holdings change conditional on outside investor flow to the holding. First, we divide total flow to mutual fund j in family k into AFoMF flow and non-AFoMF flow, that is, the net flow by all other investors. Total dollar flow is estimated by

$$Flow_{j,k,t}^{Total} = TNA_{j,t} - TNA_{j,t-1} \cdot (1 + r_{j,t}),$$

where TNA_j is the TNA of the j^{th} fund and r_j is the net-of-fees return for the relevant time period. Flow from AFoMFs is determined by

$$Flow_{j,k,t}^{AFoMF} = \sum_{i=1}^{n_k} \Delta shares_{i,j,t} \cdot NAV_{j,t},$$

where $\Delta shares_{i,j}$ is the change in the number of shares held by AFoMF i in fund j, n_k is the number of AFoMFs in family k, and NAV_j is the average NAV of fund j. Finally, non-AFoMF or outside investor flow is expressed as the difference between total dollar flow and flow from AFoMFs. All three flow measures are normalized by $TNA_{j,t-1}$. We sort our sample into deciles based on normalized outsider flow. Decile 1 collects the underlying funds that receive the lowest percentage flow (highest outflow) from outside investors, whereas decile 10 includes funds with the highest outside investor flow. For each outside investor flow decile, the table reports the average fraction of the AFoMF positions in the AFoMFs' investment opportunity set that are maintained (no change in position), eliminated (complete liquidation of the current position), new positions (complete new buy), reduced (decrease in the current position), or expanded (increase in the current position). Reported proportions are based on the total number of funds in the AFoMF's investment opportunity set (i.e., all family funds whose investment objectives are consistent with the investment objectives of the AFoMFs in the family). The number in parentheses reports the average AFoMF flow in each category (as a fraction of the portfolio fund's TNA).

			Fraction of Positions (Average AFoMF Flow Scaled by TNA)					
Decile	N	Average Non-AFoFM Flow	Not Held by AFoFM	Maintained	Eliminated	New Position	Reduced	Expanded
1 (largest outsider *out* flows)	2,439	–0.0558	48.24%(0)	2.91%(0)	0% (0)	5.37%(0.053)	12.67%(–0.0060)	30.81%(0.0155)
2	2,451	–0.0202	51.7%(0)	4.77%(0)	0% (0)	2.12%(0.018)	12.65%(–0.0036)	28.76%(0.0057)
3	2,453	–0.0131	50.8%(0)	3.91%(0)	0% (0)	1.96%(0.0126)	14.02%(–0.00280)	29.31%(0.0049)
4	2,449	–0.0082	48.35%(0)	2.82%(0)	0.04% (–0.0017)	0.98%(0.0112)	12.21%(–0.0040)	35.6%(0.0065)
5	2,448	–0.0037	48.43%(0)	3.43%(0)	0.04% (–0.0009)	0.82%(0.0121)	12.87%(–0.0044)	34.42%(0.0079)
6	2,457	0.0008	45.42%(0)	3.42%(0)	0% (0)	0.85%(0.023)	12.29%(–0.0037)	38.01%(0.0089)
7	2,452	0.0068	45.19%(0)	2.41%(0)	0.04% (–0.0014)	1.14%(0.0115)	10.52%(–0.0037)	40.70%(0.0095)
8	2,450	0.0161	49.18%(0)	2.82%(0)	0% (0)	1.14%(0.0252)	9.10%(–0.0037)	37.76%(0.0098)
9	2,454	0.0341	53.3%(0)	2.77%(0)	0% (0)	1.55%(0.0193)	9.74%(–0.0042)	32.64%(0.0112)
10 (largest outsider *in* flows)	2,440	0.1309	64.55%(0)	1.68%(0)	0% (0)	2.95%(0.0419)	6.64%(–0.0063)	24.18%(0.0192)

Table III

Do AFoMFs Favor Distressed Funds?

The table presents the results of the following regression specification:

$$Flow_{j,t}^{AFoMF} = \beta_0 + (\beta_1 + \beta_2 * I_{j,t}) * Flow_{j,t}^{Outside} + controls + \varepsilon_{j,t},$$

where $Flow_{j,t}^{AFoMF}$ is the percentage flow from AFoMFs to underlying fund j during portfolio period t, $Flow_{j,t}^{Outside}$ is the net flow by other investors to fund j, and $I_{j,t}$ is an indicator that equals one when mutual fund j is distressed (defined as a fund in the bottom decile, when funds are ranked into deciles based on their outside flows, $Flow_{j,t}^{Outside}$) and zero otherwise. The control variables are (1) three measures of AFoMF liquidity given by the contemporaneous and lagged flow AFoMFs receive from their own investors and the percentage of AFoMF assets held in cash; (2) measures of fund j's liquidity proxied by lagged AFoMF flow ($Flow_{j,t-1}^{AFoMF}$) and lagged outside investor flow, fund j's cash holdings, and the interaction variable between cash holding and distress ($I_{j,t}$); and (3) additional characteristics of fund j including previous performance measured by fund j's Sharpe ratio in the previous year, fund j's expense ratio, and fund j's size measured by the assets under management in the previous portfolio period. We estimate the above model using the Fama–MacBeth (1973) method. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. The number of observations is denoted by N, and p-values are in parentheses.

	(1)	(2)	(3)	(4)
Outside investor flow (β_1)	0.0098*	0.0096*	0.0061	0.0191
	(0.0696)	(0.0908)	(0.1541)	(0.1139)
I*Outside investor flow (β_2)	–0.0504***	–0.0650***	–0.0632***	–0.0527***
	(0.0001)	(0.0026)	(0.0019)	(0.0039)
Measures of AFoMF liquidity:				
Flow to AFoMF (Budget constraint)	0.0687***	0.0536***	0.0556***	0.6664
	(0.0010)	(0.0095)	(0.0036)	–0.2184
Lag (Flow to AFoMF)	–0.0072	0.0036	–0.0049	–0.4803
	(0.2048)	(0.7082)	(0.3259)	(0.2699)
AFoMF's cash position				–0.1789
				(0.2542)
Measures of fund j's liquidity:				
Lag (Flow from AFoMF)	0.3940***	0.3914***	0.3953***	0.5928**
	(< 0.0001)	(< 0.0001)	(< 0.0001)	(0.0370)
Lag (Outside investor flow)	0.0084**	0.0088**	0.0079**	–0.0032
	(0.0413)	(0.0164)	(0.0410)	(0.6575)
Fund j's cash position		0.0006	0.0074***	0.0025
		(0.9259)	(0.0018)	(0.6267)
I*Fund j's cash position			–0.0037	0.0894
			(0.7221)	(0.3808)
Other fund characteristics:				
Fund j's pervious performance	–0.0003	0.0001	0.0002	–0.0010
	(0.4638)	(0.9602)	(0.7198)	(0.3423)
Fund j's exp ratio	–0.0771**	–0.0710**	–0.0634*	–0.0779
	(0.0427)	(0.0465)	(0.0684)	(0.1075)
Fund j's size	–0.0006***	–0.0006***	–0.0006***	–0.0004***
	(< 0.0001)	(< 0.0001)	(< 0.0001)	(< 0.0001)
N	20,623	19,500	19,500	13,202
Adj. R^2	0.3065	0.2973	0.2989	0.3594

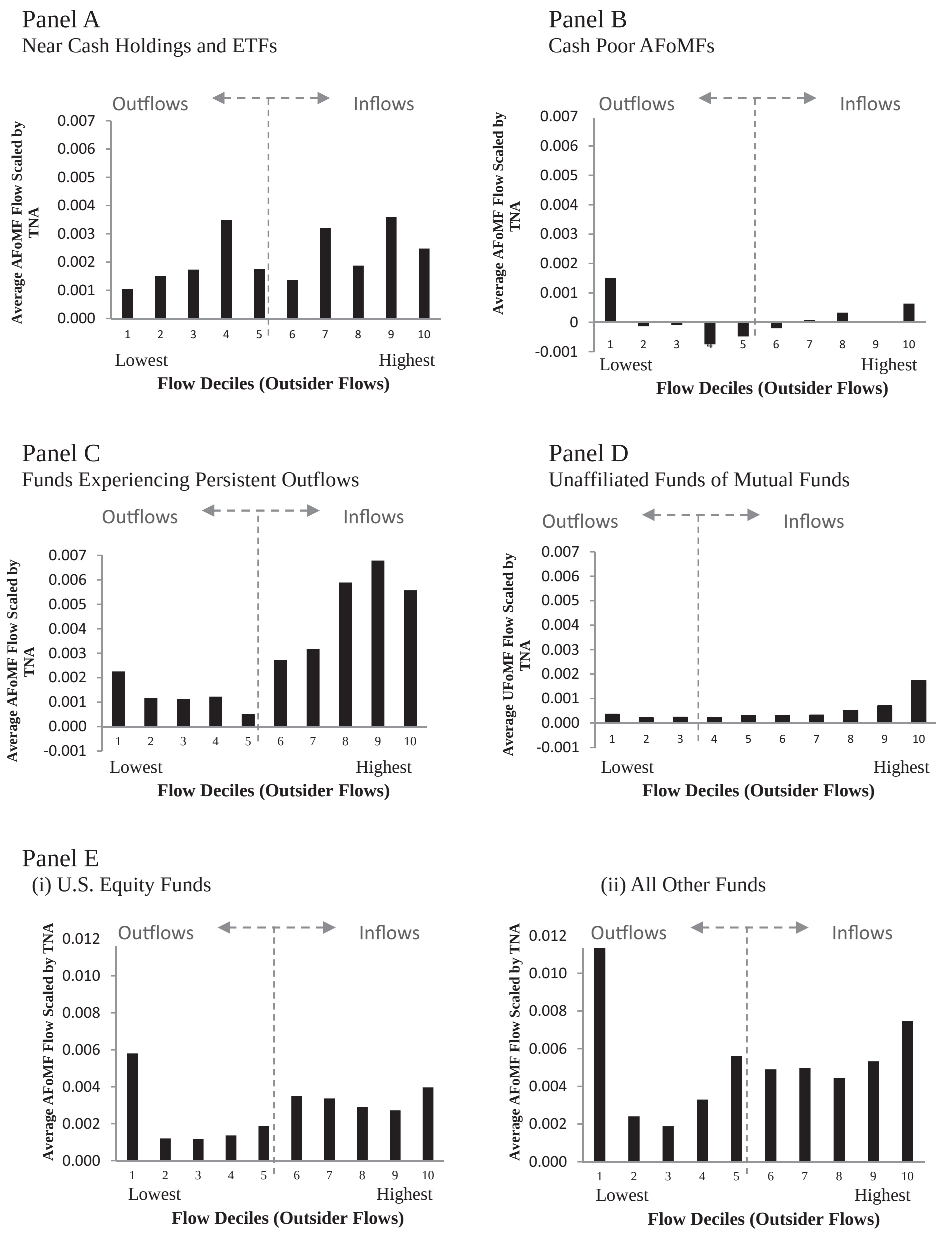

Figure 2. Subsample characteristics of liquidity provision. The figure reports average AFoMF flow to the underlying funds by outside investor flow deciles. We calculate total flow, AFoMF flow, and non-AFoMF flow using the formulas described in Figure 1. Decile 1 collects the underlying funds that receive the lowest percentage flow (highest outflow) from outside investors, whereas decile 10 includes funds with the highest outside investor flow. The figure depicts subsample results based on the following characteristics. In Panel A, we calculate the average AFoMF flow by outside investor flow decile for underlying funds that fall into the categories of ETFs, money market funds, or Treasury funds. We then remove these funds from our sample for the

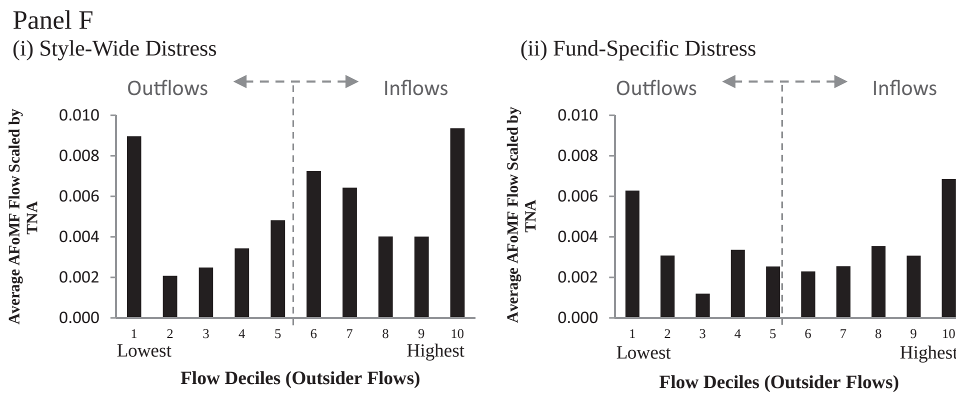

Figure 2. Continued.
rest of the analysis. In Panel B, we restrict our sample to cash-poor AFoMFs. To denote AFoMFs as cash poor, we sort our sample into deciles based on investor flow to AFoMFs. "Cash Poor" is the bottom decile. In Panel C, we restrict our sample to funds whose distress is persistent (defined as mutual funds in the bottom decile, when funds are ranked into deciles based on their outsider flows in the year immediately proceeding the current portfolio period). In Panel D, we restrict our sample to unaffiliated funds of mutual funds (UFoMFs). In Panel E, we restrict our sample to U.S. equity funds and then the rest. In Panel F, we restrict our sample to style-wide distress funds and then fund-specific distress funds. A style-wide distress fund is a mutual fund that is in a style that is suffering a style-wide liquidity event. Every month we calculate for every fund j in style s the ratio of $Flow_{j,t}^{Outside}$ to its cash holding, and average this ratio for all funds in a particular style s. We then sort these style averages into deciles. Style s is said to be experiencing a style-wide (fund-specific) liquidity event if it falls in the lowest (highest) decile.

Since fire sales are not much of an issue for near-cash funds (money market funds or Treasury funds)—an exception is the fire sales of some money market funds during the 2008 and 2009 financial crisis—and not an issue at all for ETFs, the liquidity provision hypothesis predicts little AFoMF help here. Panel A of Figure 2 reports our univariate results for these funds. As shown, there is no spike in the lowest flow decile: AFoMFs provide little liquidity to the distressed near-cash fund or ETFs.

In Column 1 of Table IV, we run our multivariate regression for near-cash funds (money market funds and Treasury funds) and ETF holdings. As can be seen, the β_2 coefficient is insignificant. This is consistent with the interpretation that there is no liquidity provision by AFoMFs for distressed funds that do not need liquidity support.

Second, if the results are really due to liquidity provision, the liquidity position of AFoMFs should not matter. Alternatively, an innocuous correlation could be at work. In particular, the distress of ordinary funds may simply coincide with significant inflows to AFoMFs from their own shareholders. Since AFoMFs have to invest the money they receive from their investors, such correlation would also result in high AFoMF inflow in high outside investor outflow periods. Therefore, under this alternative explanation, it matters whether the AFoMFs are cash rich or cash poor.

Table IV

Do AFoMFs Favor Particular Types of Distressed Funds?

Columns 1 to 4 present the regression specification in Column 3 of Table III for various subgroups. In Column 1, we estimate the regression for near-cash holdings (money market funds and Treasury holdings) and ETFs. We remove these funds from our sample for the rest of the analysis. In Column 2, we estimate the regression for cash-poor AFoMFs. To denote AFoMFs as cash poor, we sort our sample into deciles based on fund flow to AFoMFs. "Cash Poor" is the bottom decile. Column 3 estimates the model for funds whose distress is persistent (defined as mutual funds in the bottom decile, when funds are ranked into deciles based on their outside flows in the previous year). Column 4 reports results for the unaffiliated funds of mutual funds. In Column 5, $I^{*}_{j,t} = I^{ILLIQ}{}_{j,t}$ is an indicator variable that equals one if mutual fund j is not a U.S. equity fund. In Column 6, $I^{*}_{j,t} = I^{SYST}{}_{j,t}$ is an indicator variable that equals one if mutual fund j is in a style that is experiencing a style-wide liquidity event. Every month, we calculate for every fund j in style s the ratio of $Flow^{Outside}_{j,t}$ to its cash holdings and average this ratio for all funds in a particular style s. We then sort these style averages into deciles. A style is said to suffer a style-wide liquidity event if it falls in the lowest decile. We estimate the model using the Fama–MacBeth (1973) method. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. The number of observations is denoted by N, and p-values are in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Outside investor flow (β_1)	0.0086	–0.0091	0.0528*	0.0042***	0.0083	0.0061
	(0.6966)	(0.6047)	(0.0809)	(0.0004)	(0.1383)	(0.1887)
I^{*}Outside investor flow (β_2)	–0.0274	–0.0339*	–0.0792**	0.0065	–0.0517**	–0.0377**
	(0.4667)	(0.0933)	(0.0423)	(0.2358)	(0.0110)	(0.0476)
I^{ILLIQ*} I^{*}Outside investor flow (β_3)					–0.0300*	
					(0.0773)	
I^{SYST*} I^{*}Outside investor flow (β_3)						–0.0592*
						(0.0623)
Measures of AFoMF liquidity:						
Flow to AFoMF (Budget constraint)	0.0356	–0.1677	0.0448*	0.0035	0.0451***	0.0446***
	(0.1839)	(0.5274)	(0.0543)	(0.2963)	($<$0.0001)	(0.0002)
Lag (Flow to AFoMF)	0.0637	0.0099	0.0057	0.0023	–0.0036	–0.0020
	(0.1333)	(0.8947)	(0.6353)	(0.1253)	(0.5536)	(0.7395)
Measures of fund j's liquidity:						
Lag (Flow from AFoMF)	0.2793***	0.9387	0.4369***	0.1661**	0.3938***	0.3521***
	(0.0030)	(0.2673)	(0.0003)	(0.0122)	($<$0.0001)	($<$0.0001)
Lag (Outside investor flow)	–0.0231	–0.0179	–0.0109	–0.0024**	0.0088**	0.0078*
	(0.2020)	(0.3490)	(0.4042)	(0.0447)	(0.0373)	(0.0632)
Fund j's cash position	0.0099	0.0216	0.0155	–0.0000	0.0074***	0.0083***
	(0.1788)	(0.1809)	(0.3427)	(0.9434)	(0.0025)	(0.0007)
I^{*}Fund j's cash position	–0.0484	–0.0192	–0.0405	0.0032	–0.0108	0.0094
	(0.1880)	(0.7794)	(0.2848)	(0.3040)	(0.3739)	(0.4810)
Other fund characteristics:						
Fund j's pervious performance	0.0071	0.0018	0.0017	0.0001	0.0000	0.0002
	(0.1136)	(0.1830)	(0.2347)	(0.5032)	(0.9357)	(0.6228)
Fund j's exp ratio	–0.0672	–0.1942	0.0032	–0.0201	–0.0946**	–0.0799**
	(0.5292)	(0.1393)	(0.9785)	(0.2833)	(0.0202)	(0.0360)
Fund j's size	–0.0009	0.0004	–0.0010**	–0.0001***	–0.0006***	–0.0005***
	(0.2579)	(0.2304)	(0.0433)	(0.0033)	($<$0.0001)	($<$0.0001)
N	1,139	1,806	1,754	4,286	18,361	18,302
Adj. R^2	0.3987	0.2242	0.4516	0.3810	0.3205	0.3447

In Figure 1, average AFoMF flow is positive in each of the 10 bins. This is because AFoMFs grew significantly during our sample period. Since AFoMFs are also mutual funds, their portfolio allocation decisions are related to their budget constraints, that is, to the investment/redemption decisions of their own investors. Analogous to equation (1), we calculate the flow to all AFoMFs in family k as follows:

$$AFoMFflow_{k,t} = \frac{\sum_{i=1}^{n_k} \left(TNA_{i,t}^{AFoMF} - TNA_{i,t-1}^{AFoMF} \cdot \left(1 + r_{i,t}^{AFoMF}\right)\right)}{\sum_{i=1}^{n_k} TNA_{i,t-1}^{AFoMF}}, \tag{5}$$

where TNA_i^{AFoMF} is AFoMF i's total assets under management and r^{AFoMF} is the net-of-fees return of the AFoMF for the relevant time period. In our sample, in over 75% of the observations, investor flows to family AFoMFs are nonnegative, that is, AFoMFs are generally cash rich. In contrast, approximately 51% of fund portfolio periods feature nonnegative investor flows among ordinary mutual funds. In addition, even when AFoMFs face outflows, the magnitude of the flow is much less severe. In our sample, the 10$^{\text{th}}$ flow percentile for AFoMFs is –0.9% compared to –2.6% for ordinary mutual funds.[16]

To examine whether the tendency of AFoMFs to heavily invest in decile 1 funds is influenced by an AFoMF's own budget constraint, we sort each outside investor flow decile into further deciles based on the AFoMFs' own flow from equation (5). The purpose of this double sort is to investigate distress periods in which AFoMFs are cash poor. A family's AFoMFs are defined to be cash poor if they belong to the bottom decile of investor flows to the family's AFoMFs. Panel B of Figure 2 reports the results. The figure reveals that AFoMFs allocate a disproportionate amount of money to distressed funds even when the AFoMFs are cash poor: their average flow to decile 1 funds is statistically significantly larger than average flow to any other decile. Column 2 of Table IV is our multivariate formal test of Figure 2, Panel B. The test is run only for cash-poor AFoMFs. The table shows that the β_2 coefficient is negative and significant at the 10% level, implying that there is liquidity provision even by cash-poor AFoMFs.[17]

Third, if the results are really due to liquidity provision, AFoMFs should provide liquidity for transient shortfalls rather than persistent shortfalls. This is because persistent shortfalls signal that the underlying fund's troubles are deeper than just bad luck. Such a fund is not likely to be helped, because it is bad marketing for any fund to invest in an imploding fund—the plug needs to be pulled due to unbearable losses.

To investigate this issue, we define a persistently distressed fund as one whose outside investor flows for the previous year are in the lowest decile. Panel C of Figure 2 reproduces Figure 1 for the subsample of persistently distressed funds. The graph shows no spike in the lowest decile. The multivariate results are summarized in Column 3 of Table IV. Though individually statistically significant, the sum of the β_1 and β_2 coefficients is statistically insignificant (p-value of 0.3754). This is consistent with the interpretation that there is no

[16] In our analyses, we aggregate all AFoMFs of a given family into a single entity. This probably is also contributing to our observing smaller outflows for AFoMFs.

[17] The results hold for all deciles, cash poor to cash rich. The p-values are more significant for the cash-rich deciles.

liquidity provision by AFoMFs for distressed funds whose liquidity shortfalls are persistent.[18]

Fourth, if the results are really due to liquidity provision, UFoMFs should not provide liquidity support. As UFoMFs are funds that can invest only in mutual funds not affiliated with their families, the liquidity provision story does not make sense for them. Panel D of Figure 2 graphs the average UFoMF flow by outside investor flow deciles. As can be seen, there is no spike in the lowest decile: UFoMFs do not provide liquidity to their portfolio funds. Column 4 of Table IV is a multivariate formal test of Figure 2, Panel D. The test is run only for UFoMFs. Consistent with our univariate result, the β_2 coefficient is statistically insignificant. We should interpret this test with caution, however, because UFoMFs face very different regulatory constraints (restrictions on investment size) than AFoMFs. More importantly, the investment opportunity set of UFoMFs is nearly the entire mutual fund universe, which is impossible to accommodate in some of our test designs described earlier. This restricts us to define the investment opportunity set of UFoMFs as the set of mutual funds in which they invest in our sample.

Fifth, if AFoMF activity reflects liquidity provision for the underlying fund, we expect the behavior to exist more for funds that are less liquid because fire sales caused by extreme redemptions are more costly for these funds. As U.S. equity markets are among the most liquid markets in the world, we remove all near-cash and ETF holdings, and split the remaining sample into two subgroups: U.S. equity funds and the rest. The univariate results in Panel E of Figure 2 show that the spike in the lowest decile is higher for all other funds ((ii) in Panel E of Figure 2) than for U.S. equity funds ((i) in Panel E of Figure 2). More liquidity support by AFoMFs exists for less liquid distressed funds. Mean investment is also higher across all deciles for non-U.S. funds, indicating that a multivariate comparison is warranted.

In Column 5 of Table IV, we reestimate equation (4) with one additional variable. This variable is an interaction term between three variables: I, which, as before, is an indicator that takes the value of one when fund j is distressed and zero otherwise; I^{ILLIQ}, which is an indicator that takes the value of zero if fund j is a U.S. equity fund and one if it is not; and outside investor flow in fund j during the portfolio period. The column shows that the β_3 coefficient on this interaction variable is negative and significant. This is consistent with the interpretation that, though there is liquidity provision by AFoMFs for distressed funds, it is stronger for less liquid funds that need this support more.

Sixth, as it is more costly for ordinary mutual funds to engage in liquidity trades when the redemption requests they face are style-wide (because a single fund experiencing a fund-specific shock can easily sell its existing positions as

[18] We also redefine persistent distress in terms of returns. A persistently distressed fund is a fund whose style-adjusted performance is below the 10th percentile of its distribution. We find that AFoMFs provide no liquidity support to such funds.

long as other funds are there to buy),[19] it follows that liquidity provision by AFoMFs should be stronger if the distress is style-wide.

We label mutual fund j as a style-wide distress fund if many funds in its style category are also suffering from a liquidity event. In every reporting period, we calculate for every fund j in its style s the ratio of $Flow_{j,t}^{Outside}$ to its cash holdings. We then average this ratio for all funds in style s and sort these style averages into deciles. Style s is said to suffer a style-wide liquidity event if it falls in the lowest decile.

Panel F of Figure 2 shows that the spike in the lowest decile is higher when the fund is experiencing a style-wide distress ((i) in Panel F of Figure 2) than when it is suffering from a fund-specific distress ((ii) in Panel F of Figure 2). The corresponding multivariate result is reported in Column 6 of Table IV. We again augment equation (4) with one additional variable. This variable is an interaction term between three variables: I, which, as before, is an indicator that takes the value of one when fund j is distressed and zero otherwise; I^{SYST}, which is an indicator that takes the value of one if fund j is experiencing a style-wide liquidity shock and zero otherwise; and outside investor flow in fund j during the portfolio period. In Column 6, the β_3 coefficient on this indicator variable is negative and significant. This suggests that AFoMFs provide more liquidity support to funds that are experiencing a style-wide shock.

III. Possibility of Other Interpretations

A. Is It Asset Allocation?

Thus far, our results are consistent with the argument that AFoMFs provide liquidity to distressed family funds to help these funds avoid costly liquidity trades, which is our null hypothesis. However, AFoMF investment in distressed funds may not be aimed at helping these funds. An alternative explanation, as suggested to us by several fund managers, is that many AFoMFs are asset allocation or target date funds that maintain target weights in various asset classes. This implies a mechanical injection of inflows into any distressed fund whose asset class value has fallen below the target.

To check for this possibility, we construct an “asset allocation” variable defined as the difference between the weight the AFoMFs of the family place in the asset class of fund j at the beginning of the current portfolio period and their target weight. The manager knows the target weight, but we do not. We assume the target weight is the average of the weight over time in an asset class for the whole sample period.

We next run the same multivariate regression given in equation (4) with this additional indicator variable. Column 1 of Table V gives the results. The table shows that the coefficient on this variable is indeed negative, implying that

[19] This argument is motivated by Coval and Stafford (2007), who study domestic equity funds. Since we focus on all AFoMF holdings, rather than only equity funds, price impact is a concern even when the fund is experiencing a fund-specific shock. Nonetheless, the fund’s problem is further exacerbated when similar funds are also struggling.

Table V
Is It Liquidity Provision or Rebalancing Due to Asset Allocation Targets?

Columns 1 and 2 list the results of the regression specification in Column 3 of Table III with two additional control variables to measure the role of asset allocation. Asset allocation is defined as the difference between the weight in the asset class of fund j by the AFoMFs of a family at the beginning of the current portfolio period from the average weight over the whole sample. I^{TGT} is an indicator variable that equals one when at least 50% of the AFoMFs in fund j's family are target date or asset allocation funds, as indicated by the funds' name. We estimate the above model using the Fama–MacBeth (1973) method. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. The number of observations is denoted by N, and p-values are in parentheses.

	(1)	(2)
Outside Investor flow (β_1)	0.0033	0.0027
	(0.5756)	(0.6523)
I^*Outside investor flow (β_2)	–0.0501**	–0.0467**
	(0.0168)	(0.0313)
Measures of AFoMF liquidity:		
Flow to AFoMF (Budget constraint)	0.0573***	0.0636***
	(<0.0001)	(<0.0001)
Lag (Flow to AFoMF)	–0.0096	–0.0128**
	(0.1755)	(0.0458)
Measures of fund j's liquidity:		
Lag (Flow from AFoMF)	0.3696***	0.3682***
	(<0.0001)	(<0.0001)
Lag (Outside investor flow)	0.0067	0.0067
	(0.1097)	(0.1049)
Fund j's cash position	0.0058	0.0075*
	(0.2041)	(0.0795)
I^*Fund j's cash position	0.0234	0.0290
	(0.5704)	(0.4754)
Other fund characteristics:		
Fund j's pervious performance	0.0002	0.0002
	(0.6496)	(0.6926)
Fund j's exp ratio	–0.0882**	–0.0914**
	(0.0298)	(0.0168)
Fund j's size	–0.0006***	–0.0006***
	(0.0006)	(0.0007)
Asset allocation	–0.0004	–0.0001
	(0.1428)	(0.7252)
I^{TGT*}Asset allocation		–0.0019**
		(0.0297)
N	17,486	17,486
Adj. R^2	0.3893	0.3952

AFoMFs invest in (take money out of) funds whose asset class weight falls below (rises above) the target weight. This supports the asset allocation hypothesis. However, the β_2 coefficient continues to remain negative and significant. This is consistent with the interpretation that AFoMFs' preference for distressed funds cannot be fully explained by asset allocation.

Using the name of the AFoMF for identification, we notice that approximately 32% of our AFoMFs are target date funds and about 19% are other asset allocation funds. We now define an indicator variable I^{TGT} that equals one when at least 50% of the AFoMFs in fund *j*'s family are target date or asset allocation funds. We interact this indicator variable with our asset allocation variable. Column 2 of Table V gives the results. The column shows that the coefficient on the asset allocation variable is insignificant, but the coefficient on the interaction variable is negative and significant. This suggests that asset allocation mainly occurs for these special types of funds, and hence that our asset allocation measure is valid. However, the β_2 coefficient continues to remain negative and significant.

B. Is It a Cross-Subsidy to Favored Funds?

Gaspar, Massa, and Matos (2006) argue that family strategies aimed at maximizing total revenue are often directed toward helping high-value funds. They define high-value funds as those funds that either exhibit good previous performance or charge high fees. The argument for supporting funds that have performed well in the past is based on Nanda, Wang, and Zheng (2004), who show that star funds in the family attract flows to other member funds as well. Therefore, it is possible that our findings simply describe another star protection strategy. To investigate this possibility, we sort member funds into deciles based on past performance. For measures of past performance, we use their (1) Sharpe ratio, (2) cumulative return, and (3) style-adjusted return in the past 3 months, 1 year, and 3 years. For the longer look-back horizon of 3 years, we also add the four- and seven-factor alphas as alternative measures.

Using the Fama–MacBeth (1973) methodology, we run the multivariate model in equation (4) for each of the 10 deciles under each performance metric. The results using pooled regressions are provided in the Internet Appendix. Independent of how we measure previous performance, we find that liquidity provision does not merely involve high-value funds in the family. Except for the very worst performing funds (deciles 1 and 2), the other distressed funds are also provided liquidity. This result is consistent with our finding in Section II on persistent versus transient illiquidity: funds with bad performance or with persistent liquidity problems are not helped.

We also repeat the analyses for fund fees, as fees are an alternative criterion for high-value funds in Gaspar, Massa, and Matos (2006). We find that liquidity provision is prevalent in all fee deciles. These results are tabulated in the Internet Appendix.

A mutual fund manager may manage multiple funds side-by-side in the same fund complex, and may cross-subsidize the various funds. We compare manager names across the family AFoMFs and their holdings to check for cases in which an AFoMF and its portfolio funds share the same manager. For team-managed funds, we check each name individually. We find that at least one of the managers overlaps in approximately 5% of the sample. We then divide our sample into those reporting periods for which the underlying fund and the AFoMF share the same manager and those reporting periods for which they do not. We find overinvestment in distressed funds in both subsamples.

C. Is It Inside Information?

A powerful alternative explanation is that AFoMFs favor distressed funds due to information-based reasons. For example, AFoMFs may know more about the funds than outside investors because they are in the same family. Alternatively, they may use extreme outflow by retail investors as a contrarian signal to buy if retail investors consistently make mistakes when evaluating a certain group of funds, or if retail investors overreact to signals about these funds.[20]

We follow the smart money literature (see, for instance, Gruber (1996), Zheng (1999), or Sapp and Tiwari (2004)) and form portfolios at the beginning of each quarter based on whether the AFoMF bought or sold the underlying fund. Underlying funds that are bought comprise the positive flow portfolio, whereas those that are sold are placed in the negative flow portfolio. Within the positive and negative flow portfolios, we create two additional subgroups. The first group includes funds experiencing distress (decile 1), and the second contains all nondistressed funds (all other deciles). We rebalance our portfolios every 3 months. We examine the subsequent risk-adjusted performance of each portfolio. For risk adjustment, we use the Fung and Hsieh (2004) seven-factor model. The results are provided in the Internet Appendix. We find that AFoMF positive flows directed to distressed funds significantly underperform. This is in contrast with the positive performance of those AFoMF buys that involve nondistressed funds. These findings indicate that investing in distressed funds is not based on inside information because it is costly for the AFoMFs, but AFoMFs do appear to exhibit fund selection abilities in their other fund trades. The Internet Appendix also gives the results using the Carhart (1997) four-factor model.

IV. A Cost-Benefit Analysis

A. Is Liquidity Provision Beneficial to Funds Experiencing Severe Liquidity Shortfalls?

We examine how extreme outflows from outsiders affect the performance of the fund, and whether AFoMF inflows during these extreme outflow periods make any difference. In other words, is liquidity provision beneficial to the underlying funds? Our test is similar to the design in Edelen (1999). We measure performance by fund alphas (abnormal return) obtained from the seven-factor

[20] Frazzini and Lamont (2008), Ben-Rephael, Kandel, and Wohl (2011, 2012), and Edelen, Marcus, and Tehranian (2010) suggest that a counter-tilting strategy may be profitable.

model above. We use the following regression specification:

$$\alpha_{j,t} = \beta_0 + \beta_1 \cdot I_{j,t} + \beta_2 \cdot I_{j,t} \cdot Flow_{j,t}^{AFoMF} + controls + \varepsilon_{j,t}, \tag{6}$$

where α_j is the abnormal monthly return of fund j, $Flow_{j,t}^{AFoMF}$ is the flow fund j receives from the AFoMFs in its family, and I_j is an indicator that takes the value of one if fund j is distressed (defined as earlier). We control for the past abnormal returns of fund j, the size of fund j, the fees charged by the fund, as well as the total flow received by fund j during the reporting period. We instrument AFoMF and total flow using lagged AFoMF and total flow, respectively.

Several issues need to be addressed before estimating equation (6), which are carefully considered by Edelen (1999). First, flows themselves should have no impact on abnormal fund performance; they will have an effect on performance only if they induce additional trading. Therefore, in models such as equation (6), the flow measures are only a proxy; a better right-hand-side variable is the actual amount of trading caused by the flow, which is not observable. Flows are bad proxies because they are often only weakly related to the amount of trading. In our case, this issue is less of a concern because extreme outflows are likely to induce sales.

The second concern is reverse causality. It emerges because flows are measured at a low frequency (monthly or quarterly). For instance, our specification is biased if the fund's performance in the early part of the portfolio period determines AFoMF flows in the later part. Moreover, flows may also be smart (Gruber (1996)), that is, they predict rather than influence returns. We follow Edelen (1999) to address these issues. In particular, we use lagged flows as instruments for our AFoMF and total flow variables, and include lagged abnormal returns as additional controls in equation (6). We estimate the lagged flow instruments (fitted value of the flow) for each fund individually using its time-series of total and AFoMF flows. In addition to the problems associated with generated regressors, the errors of the model are likely to be cross-correlated; so we use the Fama–MacBeth (1973) method to estimate equation (6).

We report the results in Table VI. We find that the estimated β_1 coefficient is significantly negative and equal to –0.0009, implying that large redemptions hurt returns, probably due to costly liquidity-motivated trades that have to be undertaken to meet these redemptions. We find that β_2 is positive and statistically significant, implying that, though liquidity shortfalls hurt returns, this effect is ameliorated by liquidity provision from the AFoMFs. Our estimate of β_2 is 0.0481, which means that a 1% increase in AFoMF flow during fund distress reduces the negative impact of the distress by 4.8 basis points. This is direct evidence in favor of the hypothesis that AFoMFs that fund liquidity shortfalls improve the investment performance of the mutual funds that receive such liquidity. So the sacrifice of the AFoMFs benefits the family.

Table VI

Does Liquidity Provision by AFoMFs Benefit the Underlying Funds?

This table examines whether liquidity provision benefits the funds that get liquidity from the AFoMFs. To do so, we examine how AFoMF investment affects the abnormal performance of the distressed funds. We define abnormal performance as the alpha of the underlying fund estimated using the seven-factor model. We use the following regression specification:

$$\alpha_{j,t} = \beta_0 + \beta_1 * I_{j,t} + \beta_2 * I_{j,t} * Flow_{j,t}^{AFoMF} + controls + \varepsilon_{j,t},$$

where α_j is the abnormal monthly return of fund j, $Flow_{j,t}^{AFoMF}$ is the flow fund j receives from the AFoMFs in its family, and I_j is an indicator that takes the value of one if fund j is distressed (defined as a mutual fund in the bottom decile, when funds are ranked into deciles based on their outside flows, $Flow_{j,t}^{Outside}$). We control for the past abnormal returns of fund j, the size of fund j, the fees charged by the fund, as well as the total flow received by fund j during the reporting period. We instrument AFoMF and total flow using lagged AFoMF and total flow, respectively. The Fama–MacBeth (1973) method is used for the estimation. Statistical significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively. The number of observations is denoted by N, and p-values are in parentheses.

	(1)
I	–0.0009***
	(0.0036)
I*AFoMF flow	0.0481*
	(0.0972)
Total flow	–0.0006
	(0.6934)
Total flow squared	0.0100
	(0.2964)
Fund fees	0.0864*
	(0.0996)
Fund size	0.0001
	(0.5884)
Abnormal Return$_{t-1}$	0.1790***
	(< 0.0001)
Abnormal Return$_{t-2}$	0.1459***
	(< 0.0001)
Abnormal Return$_{t-3}$	0.0104
	(0.7226)
Abnormal Return$_{t-4}$	–0.0049
	(0.7899)
Abnormal Return$_{t-5}$	–0.0566*
	(0.0516)
Abnormal Return$_{t-6}$	–0.0288
	(0.1828)
N	20,448
R^2	0.1460

B. *Is the Benefit Worth the Cost?*

What is the cost to the AFoMF of providing liquidity to distressed funds? We form hypothetical portfolios for each of the outside investor flow deciles. Each hypothetical portfolio consists of all funds that fall into the decile during the portfolio period weighted in proportion to the size of the AFoMF investment in these funds. We rebalance the portfolios after each reporting period. The cost to the AFoMF is the weighted average performance of the top 9 deciles minus the weighted average performance of all 10 deciles. The assumption here is that, if the AFoMF invested in the distressed portfolio in the same way as it invested in the other portfolios, the difference would be zero. We use the seven-factor model to evaluate the performance of the individual decile portfolios.

We find that only the decile 1 portfolio has a significantly negative alpha; all other portfolios deliver insignificant or positive performance. To calculate cost, we adopt two different weighting schemes. Our lower cost comes from equal weighting and equals 3.55 basis points a month. When we flow-weight the estimated alphas, the estimated cost becomes 7.11 basis points per month. To be conservative, we take the higher estimated cost above, 7.11 basis points per month. This is the performance AFoMFs in the average family give up to support distressed funds. The average aggregate TNA of family AFoMFs in our sample is \$1.73 billion. On average, 71.63 families have AFoMFs during our sample period. Multiplying these three numbers, we estimate that AFoMFs lose about \$88 million a month to provide liquidity.

On the benefit side, the β_2 coefficient reported in Table VI is 0.0481. We multiply this by the average AFoMF flow to decile 1, that is, by 0.0061 (see Figure 1) to get 2.94 basis points monthly abnormal return per ordinary mutual fund. The average distressed fund has \$1.44 billion under management. The average family has 3.54 distressed mutual funds a month. On average, 71.63 families have AFoMFs. Multiplying these four numbers, we estimate ordinary mutual funds in this industry save approximately \$107 million per month in liquidation costs due to AFoMF help. This suggests that the benefit exceeds the cost.

We should stress here that the above calculations are back of the envelope and crude. Formal statistical tests are impossible. Nevertheless, the results do imply that liquidity provision for temporary liquidity shocks may be rational for the family. Furthermore, these calculations overstate costs and understate benefits. First, we ignore fund fees. For instance, though AFoMF expense ratios are lower than the expense ratio of ordinary funds, these are fees on fees, and for affiliated funds both fee layers accrue to the family. It is not clear how to determine the double layer fee, that is, how the fees AFoMFs actually pay to ordinary funds are related to the expense ratio of these funds reported in CRSP (because of, for instance, the prevalence of waivers and quantity discounts). Second, we ignore the potential flow consequences of the performance transfer from AFoMFs to distressed mutual funds. Better performance is likely to increase the size of the ordinary distressed fund, but lower AFoMF performance is less likely to affect the size of AFoMFs, due to the convex nature of the flow-performance relationship. Finally, we overstate the AFoMF cost, because our calculations ignore the fact that in many cases the AFoMFs already have a position in the underlying distressed fund, and so part of the benefit of mitigating fire sales is accruing to the AFoMFs.[21]

V. Robustness

First, we verify our results using pooled regressions with time and family fixed effects. These results are tabulated in the Internet Appendix. Second, our main data correspond to the 2002 to 2007 period. We hand-collect information for 2008 and 2009 to examine whether there is any change in the behavior of the AFoMFs during the financial crisis. In the Internet Appendix, we reproduce Table III for the 2008 and 2009 crisis period. We confirm that β_2 is still negative and statistically significant. This is consistent with the interpretation that AFoMFs are providing liquidity for distressed funds even during the crisis. However, the liquidity provision is less than before (the magnitude of the β_2 coefficient is now less than half of the magnitude we uncovered previously), as expected.

Third, we redefine the investment opportunity set of the AFoMF in two extreme ways as discussed in Section II.A earlier. The Internet Appendix shows that the results remain for these extreme cases. Fourth, low-frequency data may mask significant trading during the portfolio period. We run our tests again using the subsample of AFoMFs for which we actually have monthly data. As can be seen in the Internet Appendix, the results continue to go through. Fifth, since part of the AFoMF flow may come from mechanical/automatic dividend reinvestments, our estimate of the strategic AFoMF inflow may be upward-biased. To address this issue, we run our tests again using dividend-adjusted flow. The Internet Appendix shows that our results remain.

Finally, throughout the paper we express AFoMF investment as a percent of the underlying fund's size (i.e., scale by $TNA_{j,t-1}$). Though this measures the importance of liquidity provision to the fund, it does not measure its importance to the AFoMF. Moreover, it could be the case that we are artificially getting a U-shape in Figure 1 because the lowest and highest deciles are populated by smaller funds. To check this possibility, in the Internet Appendix we reproduce Figure 1 by expressing AFoMF flow as a percent of the family AFoMFs' assets instead (i.e., we scale equation (2) by $\sum_i TNA^{AFoMF}_{i,t-1}$). We find that the largest fraction of AFoMF resources, amounting roughly to 0.5% of the AFoMF assets, goes to the distressed fund decile. The pairwise difference with other deciles is statistically significant.

VI. Conclusion

Using a data set of AFoMFs, which are mutual funds that only invest in funds in their own families, we document that AFoMFs offset severe liquidity

[21] AFoMFs provide liquidity even in cases in which they do not have a previous position (i.e., liquidity provision is not simply self-serving). In Section III, we show that AFoMFs open more new positions in decile 1 funds than in any other flow decile.

shortfalls of other funds in their fund complex. We show that, though this action reduces their own investment performance, this sacrifice does benefit the family. It improves the investment performance of the mutual funds that receive such liquidity because it prevents them from doing fire sales. Finally, we show that the benefit exceeds the AFoMF cost, which suggests that the cross-subsidy is rational for the family as a whole.

The managers of target funds are happy because they are benefiting from the liquidity provision. Family headquarters is happy because the family has a net benefit. The manager of the AFoMF may be happy with an appropriate compensation scheme that is also tied to family performance. So the only group that may be unhappy about providing free insurance is AFoMF investors. But they may be unaware that this insurance is being provided.

Initial submission: November 28, 2010; Final version received: August 13, 2012
Editor: Campbell Harvey

REFERENCES

Ben-Rephael, Azi, Shmuel Kandel, and Avi Wohl, 2011, The price pressure of aggregate mutual fund flows, *Journal of Financial and Quantitative Analysis* 46, 585–603.

Ben-Rephael, Azi, Shmuel Kandel, and Avi Wohl, 2012, Measuring investor sentiment with mutual fund flows, *Journal of Financial Economics*, forthcoming.

Blume, Marshall, and Roger Edelen, 2004, S&P 500 indexers, tracking error and liquidity, *Journal of Portfolio Management* 30, 37–46.

Bollen, Nicolas P. B., and Jeffrey A. Busse, 2006, Tick size and institutional trading costs: Evidence from mutual funds, *Journal of Financial and Quantitative Analysis* 41, 915–937.

Carhart, Mark, 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Casavecchia, Lorenzo, and Ashish Tiwari, 2011, Cross-trading and the cost of conflict of interest of mutual fund advisers, Working paper, University of Iowa.

Chen, Joseph, Samuel Hanson, Harrison G. Hong, and Jeremy C. Stein, 2008, Do hedge funds profit from mutual fund distress? NBER Working Paper No. W13786.

Chen, Qi, Itay Goldstein, and Wei Jiang, 2010, Payoff complementarities and financial fragility: Evidence from mutual fund outflows, *Journal of Financial Economics* 97, 239–262.

Chevalier, Judith, and Glenn Ellison, 1997, Risk taking by mutual funds as a response to incentives, *Journal of Political Economy* 105, 1167–1200.

Christoffersen, Susan, Donald Keim, and David Musto, 2007, Valuable information and costly liquidity: Evidence from individual mutual fund trades, Working paper, University of Pennsylvania.

Coval, Joshua, and Tobias Moskowitz, 2001, The geography of investment: Informed trading and asset prices, *Journal of Political Economy* 109, 811–841.

Coval, Joshua, and Erik Stafford, 2007, Asset fire sales (and purchases) in equity markets, *Journal of Financial Economics* 86, 479–512.

Del Guercio, Diane, and Paula A. Tkac, 2002, The determinants of the flow of funds of managed portfolios: Mutual funds versus pension funds, *Journal of Financial and Quantitative Analysis* 37, 523–557.

Edelen, Roger, 1999, Investor flows and the assessed performance of open-end mutual funds, *Journal of Financial Economics* 53, 439–466.

Edelen, Roger, Richard Evans, and Gregory B. Kadlec, 2007, Scale effects in mutual fund performance: The role of trading costs, Working paper, University of California.

Edelen, Roger, Alan J. Marcus, and Hassan Tehranian, 2010, Relative sentiment and stock returns, *Financial Analyst Journal* 66, 20–32.

Evans, Richard B., 2010, Mutual fund incubation, *Journal of Finance* 65, 1581–1611.

Fama, Eugene, and James MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Frazzini, Andrea, and Owen Lamont, 2008, Dumb money: Mutual fund flows and the cross-section of stock returns, *Journal of Financial Economics* 88, 299–322.

Fung, William, and David A. Hsieh, 2004, Hedge fund benchmarks: A risk based approach, *Financial Analysts Journal* 60, 65–80.

Gaspar, Jose-Miguel, Massimo Massa, and Pedro Matos, 2006, Favoritism in mutual fund families? Evidence on strategic cross-fund subsidization, *Journal of Finance* 61, 73–104.

Gervais, Simon, Anthony Lynch, and David Musto, 2005, Delegated monitoring of fund managers: An economic rationale, *Review of Financial Studies* 18, 1139–1169.

Goncalves-Pinto, Luis, and Juan Sotes-Paladino, 2010, The value of cross-trading to mutual fund families in illiquid markets: A portfolio choice approach, Working paper, University of Southern California.

Gopalan, Radhakrishnan, Vikram Nanda, and Amit Seru, 2009, Affiliated firms and financial support: Evidence from Indian business groups, *Journal of Financial Economics* 86, 759–795.

Gruber, Martin, 1996, Another puzzle: The growth in actively managed mutual funds, *Journal of Finance* 51, 783–810.

Lee, Jung Hoon, 2011, Do funds of funds add any value? Working paper, Indiana University.

Levy, Haim, and Marshall Sarnat, 1970, Diversification, portfolio analysis and the uneasy case for conglomerate mergers, *Journal of Finance* 25, 795–802.

Massa, Massimo, 2003, How do family strategies affect fund performance? When performance-maximization is not the only game in town, *Journal of Financial Economics* 67, 249–304.

Massa, Massimo, and Zahid Rehman, 2008, Information flows within financial conglomerates: Evidence from the bank-mutual funds relationship, *Journal of Financial Economics* 89, 288–306.

Nanda, Vikram, Z. Jay Wang, and Lu Zheng, 2004, Family values and the star phenomenon: Strategies of mutual fund families, *Review of Financial Studies* 17, 667–698.

Sandhya, Vallapuzha, 2010, Agency problems in target-date funds, Working paper, Georgia State University.

Sapp, Travis, and Ashish Tiwari, 2004, Does stock return momentum explain the "smart money" effect? *Journal of Finance* 59, 2605–2622.

Sirri, Erik, and Peter Tufano, 1998, Costly search and mutual fund flows, *Journal of Finance* 53, 1589–1622.

Zhang, Hanjiang, 2009, Asset fire sales, liquidity provision, and mutual fund performance, Working paper, University of Texas.

Zheng, Lu, 1999, Is money smart? A study of mutual fund investors' fund selection ability, *Journal of Finance* 54, 901–933.