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 target funds can avoid fire-sales, the cost of this insurance is borne by the investors in the AFoMF. The paper thus uncovers some of the hidden complexities of internal capital markets in mutual fund families.

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In many complex organizations, such as conglomerates or business groups, there exist internal capital markets that control the allocation of internal resources and provide an alternative to costly external financing. Mutual fund families, as they are a collection of legally independent units which are tied together by the sponsoring management company, face the same fundamental economic problem of the conglomerate, which is the tradeoff between the interests of the conglomerate and the interests of the units that make up the conglomerate. The considerations that go into solving this internal capital market problem, however, may be different. Though a vast literature analyzes the internal capital markets of conglomerates, there is little research on the internal capital markets of mutual fund families. How do internal capital markets of mutual fund families operate? Do these internal capital markets conflict with some shareholder objectives?

In this study, we address these two questions by examining the investments of affiliated funds of mutual funds (AFoMFs). AFoMFs are mutual funds that *only* invest in other mutual funds within the family. Instead of the investor or his financial advisor choosing which mutual funds of the family to invest in, AFoMFs do that for the investor. Virtually non-existent in the 1990s, these funds have become very popular. In 2007, which is the last year of our sample, of the 30 large families that made up 75% of the size of the mutual fund industry, 27 had AFoMFs.

AFoMFs are an ideal instrument for our study for two reasons. First, though cross-dealings among mutual funds in a family are severely constrained by Section 17 of the Investment Company Act of 1940, which prohibits lending and borrowing between individual funds,[1] AFoMFs can invest in other funds. Hence, families with an AFoMF could effectively side-step Section 17 by using the AFoMF as a channel through which money is allocated within the family. Second, as AFoMFs are mutual funds themselves, we have data on inflows and outflows from their own investors and, more importantly, inflows and outflows from their own investments (which happen to be the other mutual funds in the family). Therefore, we can directly test how AFoMFs invest, and whether their investment policy, which reveals how the internal capital markets operate, conflict with the objectives of the shareholders of the AFoMF.

What can AFoMFs do for their families that may not be in the interest of their own shareholders? The AFoMFs could direct capital to family funds that are facing large redemption redemption requests that may lead to costly fire sale losses. Though the provision of this insurance pool against temporary liquidity shocks to other family funds benefits the family, the cost of this insurance may be borne by the AFoMF investors.

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 ordinary mutual 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 flow from its family AFoMFs than any of the other nine deciles. This is our primary evidence showing that AFoMFs

[1] However, cross-trades are permitted via SEC Rule 17(a)-7, which is an exemption within Section 17. The use of cross trades is another potential way to pursue family objectives, and as such, it complements the channel we uncover in this paper.

offset severe liquidity shortfalls of funds in the family. Interestingly, though we scan through all the AFoMF prospectuses – relevant excerpts from a couple of them are shown in Appendix A – we find that none of them mention liquidity provision as an objective.

We perform a few additional tests to further confirm that what we find is not a spurious result, but rather evidence that AFoMFs are purposefully targeting distressed funds. First, we use the insight that if the results are due to liquidity provision by AFoMFs, the underlying liquidity position of the AFoMF should not matter. We find that AFoMFs provide liquidity to distressed funds even when the AFoMFs are cash poor. Second, if AFoMF activity reveals liquidity provision, it should be more prevalent in underlying funds that have more illiquid portfolio holdings because costly fire sales are more likely here. We find that AFoMFs favor distressed funds *less* if the distressed funds are more liquid. Third, if most funds in the same style are trying to sell at the same time, costly fire sales are more likely. We find that AFoMFs favor distressed funds *more* if funds in the same style as the distressed fund are also selling. Fourth, and finally, if our results reflect liquidity provision, the AFoMF should be providing liquidity for transient shortfalls rather than persistent shortfalls. Consistent with this argument, we find that AFoMFs help underlying funds to meet temporary liquidity needs but not persistent liquidity shortfalls.

Multivariate tests confirm the above main univariate tests. In these multivariate specifications, we control for other determinants of AFoMF flow, such as the underlying fund's previous performance, past AFoMF flow, the budget constraint AFoMFs face in the quarter, and various characteristics of the underlying fund including size and fees.

Why do AFoMFs provide liquidity to distressed mutual funds in their families? Thus far, our discussion is biased towards suggesting that they do so solely to help member funds avoid costly liquidity motivated trades. This explanation is motivated by prior research. Existing studies show that liquidity induced mutual fund trading is costly for several reasons. Edelen (1999) argues that these trades are uninformed and, as a result, lead to losses against informed traders in the order of approximately 140 basis points annually.[2] Coval and Stafford (2007) find that large redemptions induce fire sales that generate significant price impact in the markets. Zhang (2009) and Chen, Hanson, Hong, and Stein (2008) find that mutual and hedge funds prey on liquidity strapped mutual funds. Finally, since the cost of redemptions is borne by the remaining shareholders, especially for illiquid funds, Chen, Goldstein, and Jiang (2007) argue that withdrawal is the best response when investors expect that others will withdraw as well. This leads to a vicious cycle.

However, liquidity provision trades may not be aimed at helping other funds. An alternative explanation is that AFoMFs may have inside information, and so they may act as smart contrarian investors. This is conceivable since the AFoMF's know their own family and it is geographically near (see Lee (2010), Gervais, Lynch, and Musto (2005), Massa and Rehman (2008), Coval and Moskowitz (2001)). If AFoMFs provide liquidity to distressed mutual funds in their families 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

[2] In addition, several papers estimate mutual fund transaction cost. See, for instance, Blume and Edelen (2004), Bollen and Busse (2006), Chalmers, Edelen and Kadlec (1999), Christoffersen, Keim, Musto (2007), Edelen, Evans, and Kadlec (2007), Wermers (2000).

literature (e.g., Gruber (1996), Zheng (1999), and Sapp and Tiwari (2004)) to examine this alternate hypothesis. We find that AFoMFs lose by providing liquidity to the distressed funds.

Is liquidity provision a rational family strategy? To address this question, we test whether the sacrifice, which is the *cost* incurred by AFoMF shareholders from providing liquidity to distressed funds in the family, *benefits* the family. We first measure the benefit. We find that though liquidity shortfalls hurt fund performance, this hurt is ameliorated by liquidity provision from the AFoMFs. This amelioration is the fund's benefit. We then measure the cost. We 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 is the AFoMF's cost. Finally, we use a back of the envelope calculation to compare the cost and the benefit. We find that the benefit to distressed funds exceeds the AFoMF cost both in units of abnormal return and in dollars. Though we cannot draw definitive conclusions from quarterly data and a back of the envelope calculation, the results hint that the cross-subsidy may be rational for the family.

Our study is related to a small set of papers that examine mutual funds in the context of the family. The family's aim is to maximize the value of the complex, rather than that of an individual fund (e.g., Chevalier and Ellison (1997)). Evans (2010) mentions that families pursue this objective through various means, such as strategically setting fees, promoting the performance of some of their funds, increasing fund offerings, and the strategic choice of distribution channels. Nanda, Wang, and Zheng (2004) show that star funds in the family attract flows to other member funds as well, and so stars are encouraged. Gaspar, Massa, and Matos (2006) show that high value funds in the family may receive preferential IPO allocations and are likely supported by cross-trades from low value funds.[3] Evans (2010) argues that fund incubation is another family strategy to spuriously inflate family returns. Massa (2003) finds that non-performance-related fund characteristics, such as product differentiation, are also used to establish family reputation. In a new theoretical paper, Goncalves-Pinto and Sotes-Paladino (2010) model cross-trades as a way to smooth liquidity shocks in the family.

Finally, transferring performance from one fund to another inside the family may enhance family value even when the performance reduction in one fund exceeds the performance boost of the other because investors respond asymmetrically to performance: good performance is rewarded with additional flows, while investors fail to withdraw from bad performing funds (see, for instance, Sirri and Tufano (1998)).[4] We find, however, that the benefit of providing liquidity itself exceeds the AFoMF cost, which suggests that the cross-subsidy is rational for the family as a whole even before we take into account the amplifying effect of inflows.

Section I describes our data. Section II presents the tests of the liquidity provision hypothesis. Section III examines the sacrifice, which is the cost the AFoMF incurs in providing liquidity to distressed funds. Section IV examines the benefit to the family of this liquidity provision, and then does the cost-benefit analysis. Section V provides robustness results. Section VI concludes.

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[3] In their paper, high (low) value funds are defined as those with high (low) fees or high (poor) past returns that are more likely (not likely) to increase overall family profits.

[4] This asymmetry may be even more pronounced for AFoMFs. This is because AFoMFs are often included in 401(k) menus (often as the default choice), and so they are likely to be even less elastic to negative returns. According to a recent survey conducted by the Investment Company Institute, only 10% of 401(k) participants changed their asset allocation in response to the market turmoil in 2008 (http://conference.ici.org/faqs/faqs_401k).

I. Data and Descriptive Statistics

The data used in this study are drawn from the Morningstar Principia and the CRSP Survivor-Bias-Free Mutual Fund databases. First, we obtain the list of funds of mutual funds (FoMFs) from Morningstar Principia for the sample period October 2002 to January 2008. We compare the number of funds in our sample to the numbers reported in the 2008 ICI Fact Book.[5] 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 underlying fund's name, 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. To classify funds as 'affiliated,' we require that the FoMF and its holdings belong to the same family.[6] We restrict our FoMF sample to the affiliated funds. These are our AFoMFs. Finally, Morningstar contains basic information about the AFoMFs, which we also extract.

The length of the reporting period is a quarter in most cases, but it ranges from one month to over a year in some cases. In our analyses, we only include those fund reporting periods for which the two consecutive reporting dates are no more than three months apart. So our data allows us to compute flows quarterly for some AFoMFs and monthly for some AFoMFs. We divide the former by 3, which allows us to use monthly frequency for all our tests. In a

[5] See www.icifactbook.org/pdf/2008_factbook.pdf

[6] 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 largely due to the SEC's FoMF rule change in 2006. For hybrid funds, we only include the affiliated holdings in our sample. In addition, excluding these funds from our sample has no effect on our results.

robustness test, we run our tests again using the sub-sample of AFoMFs where we actually have monthly data.

We then hand-match each AFoMF and all of its mutual fund holdings to the corresponding funds in the CRSP mutual funds database by fund name. After identifying the CRSP fund number for each AFoMF and its portfolio funds, we draw information on monthly fund returns and assets under management (TNA), as well as fund characteristics (such as expense ratio, style, inception date, etc.) from the CRSP mutual funds database. Since AFoMFs are also mutual funds, these variables are available for both the AFoMFs and their fund holdings. In a few cases, (i) previous portfolio dates are missing, (ii) the underlying funds are not identified in the CRSP mutual funds database, or (iii) AFoMFs are not identified in the CRSP mutual funds database. Such observations are eliminated.

Throughout the paper, we work with fund-level data. Therefore, we combine each AFoMF's and ordinary fund's share classes into one series in the CRSP database. We first identify each share class based on fund names and 'crsp_portno'[7] reported in CRSP. We aggregate the share classes by calculating the TNA weighted average return, NAV, and expense ratio of the fund. For the TNA of the AFoMF, we use the sum of the TNAs across the different share classes. In the Morningstar database, the dollar value of each AFoMF holding (as well as the total number of shares held) is reported as the aggregate amount held across all share classes of the AFoMF; therefore, no adjustment is needed for Morningstar.

[Insert Table I about here]

[7] We use the CRSP portfolio number (crsp_portno) when available.

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 the characteristics of those families that offer unaffiliated funds of funds (UFoMFs) and families that offer no fund of funds products in Panels B and C, respectively. The table indicates that the number of funds of funds increases significantly during our sample period. AFoMFs are typically offered by larger families, large in terms of size (TNA) and large in number of mutual funds in the family. This makes sense because, as AFoMFs can only invest in family funds, their existence is meaningful only if their investment opportunity set is large. As a matter of fact, in 2007, of the 30 largest families that accounted for 75% of the size of the mutual fund 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[8] and, as a result, meeting large redemptions is very costly (see, for instance, Edelen (1999) and Coval and Stafford (2007)). We argue, however, that when a family has affiliated funds of funds, these AFoMFs may provide an insurance pool to offset temporary liquidity shocks of member funds.

We argue in two steps. First, we document that affiliated funds of funds invest a disproportionately large amount of money in distressed mutual funds, that is, in those funds that

[8] Other solutions to meet redemption requests, such as borrowing or short selling, are severely limited. Moreover, since funds are typically evaluated against a fully invested benchmark portfolio, they tend not to hold significant cash positions, and so they have to sell to meet severe redemption calls.

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 Flows and non-AFoMF Flows

Ordinary mutual funds in families that have AFoMFs have two groups of investors: AFoMFs 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 flow, respectively. We also refer to the latter as outsider or retail flow, interchangeably. 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. 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. 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 by the change in the number of shares held by AFoMF *i* in fund *j* multiplied by the net asset value (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 net asset value 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 and date $t\text{-}1$. Finally, we obtain the flow (investment) from other, non-AFoMF investors, by taking the difference between Equations 1 and 2:

$$Flow_{j,k,t}^{Outside} = Flow_{j,k,t}^{Total} - Flow_{j,k,t}^{AFoMF} \tag{3}$$

In the 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, a maintained position (zero flow), a position increase, or a 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 the current portfolio dates. It is important to recognize that AFoMFs make similar no trade decisions in several other funds in the family that may not be captured by this analysis. In particular, these are funds in which AFoMFs do not have an existing position and they choose not to obtain a position again in the current quarter. A concern is that ignoring these additional no trade funds affects our results because these funds may experience significant outflows and yet the AFoMFs do not go to their rescue. So ignoring these funds *biases us in favor* of our results. Therefore, in all our tests we include such funds.

Identifying these no trade funds is not straightforward. This is because AFoMFs must invest in accordance with their fund specific investment objectives set forth in the prospectus, and as a result, not all funds in the family belong to the AFoMFs' investment opportunity set. Investment restrictions are also likely to vary across the funds of funds. In our paper, to capture the no trade funds, we expand our holdings database to all ordinary funds that share a family with the AFoMFs and whose fund style is consistent with the investment objectives of the AFoMFs in the family. For these additional funds, AFoMF flow is zero, so non-AFoMF flow equals total flow. Since style category is probably not the only determinant of the AFoMF investment opportunity set, our definition is likely to be too generous.

Table II compares the mutual funds in the family held by AFoMFs with mutual funds in the family not held by AFoMFs. The latter are those funds that are eligible to be held by the AFoMFs based on style but are not held by the AFoMFs. The table illustrates that the two sets are different in a number of characteristics. In particular, funds held by AFoMFs tend to be larger and younger on average. The minimum expense ratio (i.e., the expense ratio of the lowest expense share class) is higher for funds held by AFoMFs.[9] Finally, the Sharpe ratio is slightly higher for funds held by AFoMFs, but the difference is not statistically significant.

[Insert Table II about here]

We start by sorting ordinary mutual funds into deciles according to the flows these funds face from their outside investors, as described in Equation 3 above. We follow the literature and

[9] While this could indicate investment in better managers who are able to extract more rent, it may also be simply due to differences in the proportion of low cost index funds in the two groups. Additionally, 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 the no trade funds (therefore, we use the minimum fee classes for comparison). Second, the fees CRSP reports for the constituent funds do not necessarily correspond to the actual fees AFoMFs pay to the constituents (e.g., due to quantity discounts or fee waivers and other arrangements between the AFoMF and the funds in its family).

define funds in decile 1 (i.e., funds that have flows below the 10^{th} flow percentile) as the 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 year. For each decile, we calculate the average flow from AFoMFs and the fraction of the AFoMF trades 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 retail investors. This implies that AFoMFs generally tend to prefer funds that outside investors favor during the quarter. If flows are the market's response to managerial talent, as Berk and Green (2004) hypothesize, 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 a low of 1.76 (significant at the 10% level) to 9.79. The heavy AFoMF investment in decile 1 funds described in Figure 1 constitutes our primary evidence on liquidity provision.

[Insert Figure 1 about here]

The figure also indicates that average AFoMF flow to distressed funds is about 0.6%. Is this economically significant in lessening distress? In decile 1, the average flow from outside investors is approximately -5.6%, which means that the 0.6% average AFoMF inflow represents more than 10% of the outflow. This is a very conservative estimate however, as our averages in Figure 1 include a generously defined set of maintained zero positions. When we concentrate on those funds that belong to the AFoMFs' portfolio at some point during the quarter (i.e., ignore maintained zero positions), average AFoMF flow to distressed funds is over 2% of the distressed fund's assets. To evaluate the role of AFoMF flow more rigorously, we calculate how much of the outside investor outflow is offset by AFoMF inflow as follows:

$$Flow_{i,t}^{Offset} = -\frac{Flow_{i,t}^{AFoMF}}{Flow_{i,t}^{outside}} \tag{4}$$

Using this formula, we find that the 2% AFoMF inflow offsets over 1/3 of the outflow by non-AFoMF investors in decile 1 on average.

Table III provides additional confirmation that AFoMFs provide liquidity to member funds in the family that experience severe liquidity problems. The table reports the proportion of position types in each decile. Column 4 in Table III, for instance, indicates that AFoMFs are more active in decile 1 than in the other deciles. Only 44.45% of the funds are not held by AFoMFs in decile 1, and this inactivity is the lowest amongst all the deciles. Column 7 in Table III tells us that AFoMFs also initiate a disproportionately large number of new positions in decile 1. The number here is 5.76%, and this new activity is the highest amongst all the deciles.

[Insert Table III about here]

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

$$Flow_{j,t}^{AFoMF} = \beta_0 + (\beta_1 + \beta_2 \cdot I_{j,t}) \cdot Flow_{j,t}^{Outside} + controls + \varepsilon_{j,t}, \tag{5}$$

where $Flow_j^{AFoMF}$ and $Flow_j^{Outside}$ are AFoMF flow and outside investor flow to underlying fund *j*, respectively, I_j is an indicator that takes the value of 1 when fund *j* is distressed (i.e. in the decile with the lowest outside investor flow) and 0 otherwise. The control variables are 1) the previous performance of fund *j*, measured by fund *j*'s Sharpe ratio in the previous year; 2) the flow AFoMFs receive from their own investors (budget constraint) as defined in Equation 6 below; 3) lagged AFoMF flow to underlying fund *j* ($Flow_{j,t-1}^{AFoMF}$); 4) lagged outside investor flow; 5) fund *j*'s expense ratio; and 6) fund *j*'s size measured by the logarithm of the assets under management in the previous quarter. 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. See, for example, Chevalier and Ellison (1997), Sirri and Tufano (1998), Busse (2001), and Del Guercio and Tkac (2002). Flow is also found to be persistent (see, for instance, Sirri and Tufano (1998)). Moreover, in our context, AFoMF flow is influenced by the fund of funds' budget constraint, and it may also be affected by the underlying fund's fees or size.

We estimate Equation 5 using both pooled regressions (using family fixed effects) and the Fama-MacBeth (1973) method. Table IV reports the results. Consistent with the univariate analyses above, the regression results 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 pooled coefficient estimates indicate that a 1% increase in outside investor outflow from distressed funds results in a 0.08% increase in inflows from family AFoMFs.

[Insert Table IV about here]

As reported in Table IV, the characteristics of the underlying fund and past flows also significantly affect fund of funds behavior. AFoMFs respond positively to past performance. This is consistent with Brav and Heaton (2002), who argue that since managerial ability is unobservable, the flow-performance relation is the result of rational learning. Moreover, several other papers (Ippolito (1992), Lynch and Musto (2003), and Berk and Green (2004), for instance) interpret flow response to performance as investors' updating about managerial ability and expected fund returns.

Finally, in columns 3 and 5 of the table, we also control for the cash position of the underlying fund as well as interact the cash position variable with extreme outside investor flow. It is the interaction variable that is important. In particular, for distressed funds, more cash on hand means that the fund can meet outflows better, and, consequently, requires less liquidity provision by the AFoMF. Cash positions are obtained from CRSP and are expressed as a percent of the fund's assets. Unfortunately, cash holdings are reported only at the annual frequency for most funds. Moreover, in many cases, the cash values are missing, which explains the lower sample size in these models. Our additional concern with the cash variables is that the underlying fund's cash holding is likely to be related to distress: funds with more volatile flows or a higher probability of large outflows are more likely to maintain more cash on hand. Nonetheless, the results in Table IV reveal that, consistent with the liquidity hypothesis, the coefficient on the interaction term is negative, indicating that AFoMF flows to distressed funds are lower when the funds have more cash.

B. Cash Rich and Cash Poor AFoMFs

In this section, we examine the insight that if the results are really due to liquidity provision, the underlying 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 inflow to AFoMFs from their own shareholders.[10] 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 quarters. Therefore, under the alternative, it matters whether the AFoMFs are cash rich or cash poor.

In Figure 1 above, average AFoMF flow is positive in each of the ten bins. The explanation for this lies in the growth of AFoMFs during our sample period (see, for instance, Table I). 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 above, we calculate the flow from investors to all AFoMFs in family *k*

[10] This may be a flight to quality if investors believe AFoMFs are a safer alternative, for instance.

as follows:

$$AFoMFflow_{k,t} = \frac{\sum_{i=1}^{n_k}(TNA_{i,t}^{AFoMF} - TNA_{i,t-1}^{AFoMF} \cdot (1 + r_{i,t}^{AFoMF}))}{\sum_{i=1}^{n_k} TNA_{i,t-1}^{AFoMF}} \qquad (6)$$

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 our fund quarters, investor flows to family AFoMFs are non-negative, that is, AFoMFs are generally cash rich. In comparison, approximately 51% of fund quarters feature non-negative 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 10th flow percentile for AFoMFs is -0.9% compared to -2.6% for ordinary mutual funds.[11]

To examine whether the tendency of AFoMFs to heavily invest in decile 1 funds is influenced by the AFoMF's own budget constraint, we sort each outside investor flow decile into further deciles based on the AFoMFs' own budget constraint (as defined in Equation 6 above). The purpose of this double sort is to investigate distress quarters in which AFoMFs are cash rich and quarters in which AFoMFs are cash poor. A family's AFoMFs are defined to be cash rich (poor) if they belong to the top (bottom) decile of investor flows to the family's AFoMFs. Figure 2 reports the results. The figure reveals that AFoMFs allocate a disproportionate amount of money to distressed funds even when they are cash poor: average fund of funds flow to decile 1

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

funds is statistically significantly larger than average fund of funds flow to any other decile in the top half of the figure. The bottom half of the figure documents the same behavior when funds of funds are cash rich. We compute p-values to test the equality of the mean AFoMF flow of decile 1 and that of each decile i={2,…,10}. All p-values show statistical significance in both groups.

[Insert Figure 2 about here]

To examine the relation between AFoMF flow and outside investor flow more formally for cash rich versus cash poor AFoMFs, we run the same multivariate regression given in Equation 5 separately for cash poor AFoMFs and cash rich AFoMFs. Recall that cash rich is defined as AFoMFs that belong to the top decile of investor flows to the family's AFoMFs, whereas cash poor are AFoMFs that belong to the bottom decile of investor flows to the family's AFoMFs, where investor flows are defined in Equation 6 above. The results are tabulated in Panel A of Table V. The results confirm that even cash poor AFoMFs rescue distressed funds.

[Insert Table V about here]

C. Fund Liquidity and AFoMF Investments

We now examine how the underlying fund's liquidity is related to AFoMF's behavior. If AFoMF activity reflects liquidity provision for the underlying fund, we expect the behavior to be more pronounced among member funds who find liquidating existing positions costly. To investigate this argument, we first need to rank underlying funds based on the cost they face when selling existing positions to meet redemption requests. In Panel A of Figure 3, we simply divide our sample of AFoMF holdings into two groups. Our 'liquid' group contains near cash holdings, which include money market funds and ETFs. Our 'illiquid' group contains all other holdings. Since fire sales are not much of an issue in liquid funds – an exception is the fire sales of some money market funds during the 2009 financial crisis – the liquidity provision hypothesis predicts little AFoMF help here. This is confirmed by the figure. We compute t-statistics and corresponding p-values to test the equality of the mean AFoMF flow of decile 1 and that of each decile $i=\{2,\ldots,10\}$. For the group of liquid holdings all of our t-statistics are negative, ranging from -2.19 to -0.44, indicating that average AFoMF investment is lowest in decile 1, although not always statistically different from the other deciles. In our illiquid group, all t-statistics are positive and significant, indicating that in this subsample, decile 1 investment is the highest.

[Insert Figure 3 about here]

In Panel B of Figure 3, we further subdivide the 'illiquid' group in Panel A into US equity funds and all other holdings (excluding money market funds and ETFs). Since US equity funds transact in one of the most liquid financial markets in the world, we expect AFoMFs to be less active in this group. The figure confirms that average AFoMF flow is much higher for distressed non-US funds than distressed US equity funds. We compute t-statistics and corresponding p-values for the equality of the mean AFoMF flow of decile 1 and that of each decile $i=\{2,\ldots,10\}$. For the subsample of funds that do not fall into the US equity category, all our t-statistics are positive and significant, ranging from 1.74 to 8.77. For US equity funds, the range is lower, 0.66 to 5.03, and not always significant.

To examine the relation between AFoMF flow and outside investor flow more formally for liquid versus illiquid funds, we run the same multivariate regression given in Equation 5 separately for liquid funds (money market funds and ETFs) and illiquid funds (everything else). The results are tabulated in the first few columns in Panel B of Table V. They confirm the univariate results observed in Panel A of Figure 3. We then estimate Equation 5 separately for US equity funds and non US funds (excluding money market funds and ETFs). The results are tabulated in the last few columns of Panel B of Table V. They confirm the univariate results observed in Panel B of Figure 3. In particular, the sum of the β_1 and β_2 coefficients is equal to -0.1045 in the pooled estimation and -0.0611 under the Fama-MacBeth method for the US equity group, while the corresponding coefficient estimates for the less liquid holdings sample equal -0.1408 and -0.1768, respectively. These numbers are statistically significant, and the corresponding differences (i.e., between -0.1045 and -0.1408 and between -0.0611 and -0.1768, respectively) are also statistically significant. Taken together, these results indicate that AFoMFs come to the rescue of distressed funds more so if the distressed funds operate in illiquid markets.

In the rest of our analyses, we exclude money market and ETF AFoMF holdings to avoid the possibility that they are over- or underrepresented in some of our subsamples below. However, including these underlying funds has no effect on our results.

D. Style-wide Liquidity Shocks

We now compare how AFoMFs respond to style-wide liquidity shocks which involve widespread investor outflows from a particular style. 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 long as other funds are there to buy.[12]

To differentiate between fund-specific and style-wide liquidity shocks, for each distressed fund, we calculate the proportion of other funds in its style that are experiencing negative flows. We have four classifications. In 'style distress 1,' we use a subsample of those fund quarters during which less than 25 percent of the funds in the mutual fund universe experience negative flows in each fund style. In 'style distress 2' ('style distress 3') at least 25 (50) percent but fewer than 50 (75) percent of the funds are facing outflows. Finally, in 'style distress 4,' includes those fund quarters during which the great majority of mutual funds (at least 75 percent) in each style category are experiencing fund withdrawals. Figure 4 plots average AFoMF flow for each outside investor flow decile for these four classifications. As can be seen, AFoMFs provide liquidity to distressed funds more in the 'style distress 3' and 'style distress 4' classifications, which are the classifications where liquidity shocks are more style-wide. We compute p-values for the equality of the mean AFoMF flow of decile 1 and that of each decile $i=\{2,\ldots,10\}$ in all four cases. The p-values show statistical significance, which corroborate our findings. In particular, for 'style distress 3' and 'style distress 4' (our style-wide liquidity shocks), AFoMF investment in decile 1 funds is significantly larger than AFoMF investment in essentially all of the other deciles. This is not the case however for the fund-specific liquidity shocks groups of 'style distress 1' and 'style distress 2'.

[12] This argument is motivated by Coval and Stafford (2007), who study domestic equity funds. Because US equity funds transact in one of the most liquid financial markets, Coval and Stafford argue that fire sale prices are a concern only when several funds experience large redemption requests at the same time. Since we focus on all AFoMF holdings, rather than only equity funds, price impact is a concern even when the underlying fund is experiencing an idiosyncratic outflow shock (see Section II.C above). Nonetheless, the fund's problem is further exacerbated when similar funds are also struggling.

[Insert Figure 4 about here]

Panel C of Table V examines the relation between AFoMF flow and outside investor flow more formally for style-wide versus fund-specific liquid shocks using the multivariate regression in Equation 5. The negative coefficients in the second row, which are the interaction term coefficients, become more negative as we go from 'style distress 1' to 'style distress 4'. The sum of the β_1 and β_2 coefficients are negative and statistically significant for each style distress group. Moreover, the difference between the sums decreases in a statistically significant way as we go from 'style distress 1' to 'style distress 4'. Our results thus indicate that AFoMFs come to the rescue of distressed funds more so if the distressed funds are experiencing style-wide liquidity shocks.

E. Transient Liquidity Shocks

Our next test is based on the insight that 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 has a bad manager rather than bad luck, and should probably not be helped.

To investigate this issue, we first do a simple univariate test. Figure 5 shows the results of this test. The top half of Figure 5 is just Figure 1 recreated. The bottom half of Figure 5 is Figure 1 with the ten deciles relabeled. In Figure 1, decile 1 (decile 10) had the least (most) flow from outside investors in a quarter. In the bottom half of Figure 5, decile 1 (decile 10) had the least (most) moving average flow from outside investors, where the moving average is taken over the last two quarters. This means that the top half of Figure 5 sorts by transient liquidity shocks, whereas the bottom half sorts by more persistent liquidity shocks. Comparing the two, we notice that AFoMFs only help distressed funds if the distressed funds' liquidity shock is transient. We compute t-statistics and p-values to test the equality of the mean AFoMF flow of decile 1 and that of each decile i={2,…,10}. Unlike for transient shocks, the t-statistics for persistent shocks are either negative or insignificant (ranging between -5.25 to 0.08), indicating that funds that fall into decile 1 persistently are not favored by AFoMFs.

[Insert Figure 5 about here]

As in the previous sections, a multivariate test replicates these results more formally. To incorporate the notion of persistence, we extend our regression specification in Equation 5 by an indicator variable ($I^{*}_{j,t-1}$) that takes the value of 1 if fund j is distressed in the previous reporting period as well and 0 otherwise:

$$Flow^{AFoMF}_{j,t} = \beta_0 + (\beta_1 + \beta_2 \cdot I_{j,t} + \beta_3 \cdot I^{*}_{j,t-1}) \cdot Flow^{Outside}_{j,t} + controls + \varepsilon_{j,t} \quad (7)$$

where all other variables are defined as in Equation 5 above. A preliminary look at our data reveals that persistent liquidity shocks are not rare. Our sample contains 2113 extreme outflow fund quarters, 659 of which involve funds that experience distress in the previous quarter as well.

Panel D of Table V reports the regression results. The estimates in the table reveal that liquidity provision by funds of funds is significantly dampened if the member fund faces severe redemption requests in the previous quarter as well. The estimated β_3 coefficient is 0.0462 and

0.0233 in the pooled and Fama-MacBeth regressions, respectively, and statistically significant. [13]

III. Is liquidity Provision Costly to AFoMFs?

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. A powerful alternative explanation is that AFoMFs favor distressed funds due to strategic/information based reasons. For example, AFoMFs may know more than outside investors because they share a family with the underlying funds. Or, 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 that they overreact to signals about these funds.

In this section, we examine and refute this alternative hypothesis. In an attempt to disentangle liquidity provision from this alternative explanation, we evaluate the investment performance of the AFoMF trades, especially those that involve distressed member funds. If AFoMF investment in distressed funds is opportunistic, these trades should deliver superior performance. Liquidity provision has the opposite prediction.

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

[13] As an additional test of the liquidity provision hypothesis, in unreported analyses we also examine the behavior of unaffiliated funds of funds (UFoMFs), which are funds that invest in other mutual funds not affiliated with the FoMFs' family. For UFoMFs, the liquidity provision story does not make sense. Indeed, we find that UFoMFs do not favor distressed funds. We do not use UFoMFs as a benchmark however, because UFoMFs face very different regulatory constraints (restrictions on investment size), which render them to be incomparable to 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 above.

the AFoMF bought or sold the underlying fund, respectively. Underlying funds that are bought comprise the positive flow portfolio, while those that are sold during the quarter 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 non-distressed funds (all other deciles). We rebalance our portfolios every quarter, that is, we form portfolios at the end of our first quarter, keep these funds in the appropriate portfolios for the next three months, then, at the end of the three months, we reallocate each holding to reflect the direction of the AFoMF trade during the second quarter. We examine the subsequent risk adjusted performance of each portfolio. For risk adjustment, we use the four- and seven-factor alphas. The four-factor model follows Carhart (1997) and is given by:

$$r_{p,t} = \alpha_p + \beta_{1,p} RMRF_t + \beta_{2,p} SMB_t + \beta_{3,p} HML_t + \beta_{4,p} UMD_t + \varepsilon_{p,t} \tag{8}$$

where r_p is the monthly excess return on a portfolio of funds; *RMRF* is the excess return on the market portfolio; and *SMB*, *HML*, and *UMD* are returns on zero-investment mimicking portfolios for common size, book-to-market, and momentum factors. We use Kenneth French's website to obtain monthly factor information. While the four-factor model is a standard approach for evaluating the abnormal performance of equity funds, the model may not capture the priced risks associated with non-equity funds. Therefore, we repeat our analyses using a seven factor model. We we use two bond-oriented factors (from David Hsieh's website), 1) the monthly change in the 10-year treasury yield (D10YR) and 2) the monthly change in the credit spread between the Moody's Baa yield and the 10 year treasury yield, and an international factor represented by the

MSCI market index return.

The results are shown in Table VI. Panels A and B are based on the four and seven factor models, respectively. Several interesting findings emerge from the table. First, positive flows directed to distressed funds significantly underperform in both models. The four (seven) factor model shows that the portfolio of distressed funds that AFoMFs buy exhibits a statistically significant negative monthly alpha of -0.0030 (-0.0033). This is in contrast with the performance of those AFoMF buys that involve non-distressed funds. The four (seven) factor model shows that the portfolio of non-distressed funds that AFoMFs buy exhibits a statistically significant positive monthly alpha of +0.0035 (+0.0040). Taken together, these findings indicate that investing in distressed funds is costly for the AFoMFs, but AFoMFs do appear to exhibit fund selection abilities in their other buy orders. All negative flow portfolios display negative alphas indicating that leaving these funds was the right choice; however, the coefficients here are not significantly different from zero.

[Insert Table VI about here]

The strategy of going long on the non-distressed buy portfolio and short on all other funds that AFoMFs sell delivers a statistically significantly positive monthly alpha of 0.0045 and 0.0049 under the four and seven factor models, respectively. The corresponding t-values are 2.12 and 2.56 respectively. While this is not a feasible strategy in practice since it involves shorting mutual funds, which is generally not permissible, the long-short portfolio result is used in the smart money literature as a test of whether investor flows predict performance. We also calculate the long-short portfolio results for going long on all positive flow and short on all negative flow portfolios. While the individual alphas are not statistically significant, the trading strategy does deliver a positive return equal to 0.0021 and 0.0016 for the two models, indicating that AFoMFs trade in the right direction on average.

Therefore, our findings indicate that despite providing costly liquidity to member funds in distress, AFoMFs do serve their investors by making up with their investments in the non-distressed portfolios. The results in Table VI are also consistent with Keswani and Stolin (2008) who show that institutional investors in the United Kingdom possess fund selection ability. As in Keswani and Stolin (2008), AFoMFs' smartness manifests itself in their buying decisions but not in their selling decisions.

Finally, how important are liquidity provision trades in the AFoMFs' portfolio? In Figure 1 (and throughout the paper), we express AFoMF investment in the constituent fund as a percent of the constituent's size. This means that we scale Equation 2 by $TNA_{j,t-1}$. We now reproduce the figure by expressing AFoMF flow as a percent of the family AFoMFs' assets instead (i.e., we scale Equation 2 by $\sum_i TNA_{i,t-1}^{AFoMF}$). The new scaling scheme produces a figure that is qualitatively identical to Figure 1 (not shown in the paper). The largest fraction of AFoMF resources, amounting roughly to 0.5% of the AFoMF assets, goes to distressed funds. Moreover, the pairwise difference between the average AFoMF investment in decile 1 and in any of the other nine deciles is also statistically significant.

IV. Is liquidity Provision Beneficial to the family?

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

Till now we had assumed that distress is costly; in particular, extreme outflows induce liquidity motivated trading that adversely affects a fund's performance. We now formally test this argument. To do this, we examine how extreme outflows from outsiders affect the performance of the fund. We also examine how AFoMF investment during these outflow periods is related to fund performance. 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 four and seven factor models above. We use the following regression specification:

$$\alpha_{j,t} = \beta_0 + \beta_1 \cdot I_{j,t} + \beta_2 \cdot I_{j,t} \cdot Flow_{j,t}^{AFoMF} + controls + \varepsilon_{j,t} \tag{10}$$

where α_j is the abnormal return of fund j, I_j is an indicator that takes the value of 1 if fund j is distressed (decile 1), and $Flow_j^{AFoMF}$ is the flow fund j receives from the AFoMFs in its family. The controls include the size of the underlying fund, the fees charged by the underlying fund, as well as the total flow received by fund j during the reporting period. The two main independent variables of interest are I_j, the indicator variable for liquidity shortfall, and $I_j \cdot Flow_j^{AFoMF}$, the interaction between the shortfall indicator variable and AFoMF flow.

Several issues need to be addressed before estimating model (10). First, flows in and of 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 10, 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 we focus on extreme outflows, and 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 10 above. 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 family fixed effects and the Fama-MacBeth method, respectively, to estimate the equation above.

We report the results in Table VII. We find that the estimated β_1 coefficient is significantly negative and equals -0.0008, implying that large redemptions hurt returns, and this is 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 hurt is ameliorated by liquidity provision from the AFoMFs. Our estimate of β_2 is 0.0524, which means that a 1% increase in AFoMF flow during fund distress reduces the negative impact of the distress by 5.2 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.

[Insert Table VII about here]

B. Is The Benefit Worth The Cost?

Thus far we have shown that liquidity provision is costly to the AFoMFs but benefits the underlying funds. Therefore, it represents a performance transfer from AFoMFs to ordinary mutual funds in the family. We now provide a simple back of the envelope calculation here to examine whether the benefit exceeds 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 nine deciles minus the weighted average performance of all ten 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. As above, we use the four and seven factor models to evaluate the performance of the individual decile portfolios. The results below are based on the seven factor results and are qualitatively identical to those of the four factor models.

We find that only the decile 1 portfolio features a significantly negative alpha; all other portfolios deliver insignificant or positive performance. To calculate our cost measure, we adopt three different weighting schemes to determine the weighted average performance of the deciles. Our lowest cost measure comes from equal weighting and equals 3.55 basis points a month. When we significance weight or flow weight the estimated alphas, the estimated cost becomes 6.02 and 7.11 basis points per month, respectively.

To be conservative, we take the highest estimated cost above, which we obtain by flow weighting the decile portfolios. This cost is 7.11 basis points per month. This is the performance AFoMFs in the average family give up to support distressed funds. $ 1.73 billion is the average aggregate TNA (assets under management) of family AFoMFs in our sample. 71.63 is the average number of families with AFoMFs. Multiplying these three numbers, we estimate that AFoMFs in this industry sacrifice approximately $88 million a month to provide liquidity to distressed funds.

On the benefit side, to be conservative, we use the lower of the two β_2 coefficients reported in Table VII, which equals 0.0481 (from the Fama-MacBeth estimation). We multiply this by the average AFoMF flow to decile 1, that is, by 0.0061 (see Figure 1). This is the benefit expressed in units of monthly abnormal return per ordinary mutual fund and equals 2.94 basis points. The average distressed fund has $1.44 billion under management. The average family has 3.54 distressed mutual funds a month. 71.63 is the average number of families with AFoMFs, as above. 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. So the benefit ($107 million a month) seems more than the cost ($88 million a month).

We should stress here that the above calculations are back of the envelope and crude. Formal statistical tests are impossible. Nevertheless, they do hint that the liquidity provision for temporary liquidity shocks may be rational for the family. Further, 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. Fund inflows are likely to increase the size of the ordinary distressed fund, but AFoMF fund outflows are less likely to affect the size of AFoMFs, due to the convex nature of the flow-performance relationship (see, for instance, Sirri and Tufano (1998)). This effect of flows is hard to quantify. Third, and finally, we overstate the AFoMF cost for two reasons. The first reason is that our calculations ignore the fact that in many cases, the AFoMF already has a position in the underlying distressed fund, and so part of the benefit is accruing to the AFoMF because the AFoMF help benefits the fund.[14] Second, diminishing returns to scale imply that redirecting the money AFoMFs spend on decile 1 investments to funds in the top 9 deciles would lower the average return on these funds.

[14] AFoMFs provide liquidity even in cases when they don't have a previous position (i.e., liquidity provision is not simply self serving). In section 3 for instance, we show that AFoMFs open more new positions in decile 1 funds than in any other flow decile.

V. Extensions and Robustness

A. Is Liquidity Provision a Star Creation Strategy?

Gaspar et al. (2006) argue that family strategies aimed at maximizing total revenue are often directed towards 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 et al. (2004), who show that star funds in the family attract flows to other member funds as well. Therefore, it is possible that AFoMFs are not providing liquidity to member funds in need, but rather, they are providing liquidity to high value funds, that is, their activity is another star creation strategy. To investigate this issue, we sort member funds into deciles based on past performance. We define past performance in several alternative ways, in each case, the look-back period ends on the previous portfolio date. Using alternative performance measures is important because the relevant metric is the measure the family uses to pinpoint its star funds, which is unobservable. We use 1) the Sharpe ratio; 2) cumulative return; and 3) style adjusted return to measure the underlying fund's performance in the past 3 months and 1 year. For the longer look-back horizon of 3 years, we also add the (more data intensive) four and seven factor alphas as measures of past performance.

We run the multivariate model in Equation 5 for each of the ten deciles under each performance metric. Table VIII summarizes the results for the three alternative performance measures of the 1 year look-back horizon by reporting the sum of the β_1 and β_2 coefficients from Equation 5 above, along with the t-statistic of the sum for each performance decile. The results based on the 1 year measures are representative of those of the other horizons. As defined above, the sum of the β_1 and β_2 coefficients indicates how AFoMF flow is related to fund outflow by outside investors during periods when the underlying fund is in distress. Columns 2, 3, and 4 of the table correspond to the summed coefficients for the Sharpe ratio, cumulative return, and style adjusted return specifications, respectively. In the table, performance decile 1 includes the worst performing funds, while performance decile 10 collects those member funds that exhibit the highest past performance. The estimation is based on pooled fixed effects regressions. The Fama-MacBeth results are qualitatively identical but are not tabulated in the paper.

[Insert Table VIII about here]

Independent on how we measure previous performance, the table reveals that liquidity provision does not merely involve high value funds in the family. Deciles below the median performance also feature significant estimates. It is true, however, that AFoMFs do not help the very worst performing funds (decile 1 and decile 2). This result is consistent with our finding in Section II above on persistent vs. transient illiquidity. Funds with the very worst performance or those that face persistent problems may be beyond repair. Helping them would be help for helping's sake, which is probably not a viable family strategy.

We also repeat the analyses for fund fees, as fees are an alternative criterion for high value funds in Gaspar et al. (2006). We sort funds into fee deciles and find that liquidity provision is prevalent in all fee deciles, although the highest fee decile features the largest coefficient estimate. These results are available from the authors but are not tabulated in the paper.

B. Is Liquidity Provision Driven by Side-by-Side Managers?

A mutual fund manager may manage multiple funds side-by-side in the same fund complex. We compare manager names across the family AFoMFs and their holdings to check for cases when an AFoMF and its portfolio fund are managed by the same person. Manager names are available in both CRSP and in Morningstar; we use Morningstar because it always identifies each manager when the fund is team managed. For team managed funds, we check each name individually. We find roughly 950 fund portfolio period observations for which at least one of the managers overlap (a little less than 5% of the sample).

Our univariate tests indicate that when we divide our sample into those fund portfolio reporting periods for which the underlying fund and the AFoMF share the same manager and those for which they do not, both subsamples feature overinvestment in decile 1 funds. We also reestimate Equation 5 by adding an indicator variable that takes the value of one when the fund of funds and the underlying fund are managed by the same manager and zero otherwise, and an interaction variable between this 'same manager' dummy and distress. Perhaps somewhat surprisingly, our results indicate that AFoMFs provide *less* liquidity to those underlying funds that share the manager with the AFoMF, though the coefficient estimate is not significant in the Fama-MacBeth estimation and is only marginally significant in the pooled regression. The result may be due to the greater scrutiny side-by-side funds may face. Moreover, a concern in these analyses is that the liquidity shocks of the underlying fund and those of the AFoMF are more likely to be correlated when the two are managed by the same person. As a cleaner test, we discard the ‘same manager’ observations and find that liquidity provision is not driven by side-by-side management.

VI. Conclusion

Using a hand-collected data set of affiliated funds of mutual funds (AFoMFs), which are mutual funds that only invest in funds in their own family, we explore the complexities of internal capital markets in mutual fund families. We document that AFoMFs offset severe liquidity 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.

There is one important question this paper does not answer. Why does the manager of the AFoMF sacrifice her fund’s investment performance to benefit the family? It must be that the AFoMF manager is either told to do so, or her compensation or career prospects are designed such that she gets rewarded not just for the investment performance of her own AFoMF but also for the total performance of the family. Alternatively, AFoMFs’ action may reflect an implicit contract equilibrium in which each manager shares inside information with the AFoMF to boost the AFoMF’s alpha with the tacit understanding that if their mutual fund is in trouble, the AFoMF will come to their help. The examination of this question is important for future research.

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Figure 1. Do AFoMFs Favor Distressed Funds?

This graph reports average AFoMF's 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

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

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. 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 net asset value of fund *j*. Finally, non-AFoMF or outside investor flow is expressed as follows:

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

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 $Flow_{j,k,t}^{Outside}$. Decile 1 collects the underlying funds that receive the lowest percentage flow (highest outflow) from outside investors, while Decile 10 includes funds with the highest outside investor flow. The dashed line in the graph indicates the breakpoint between negative and positive average non-AFoMF flow. In the graph below, the X-axis denotes outside investor flow deciles, while the Y-axis denotes average percentage flow from AFoMFs.

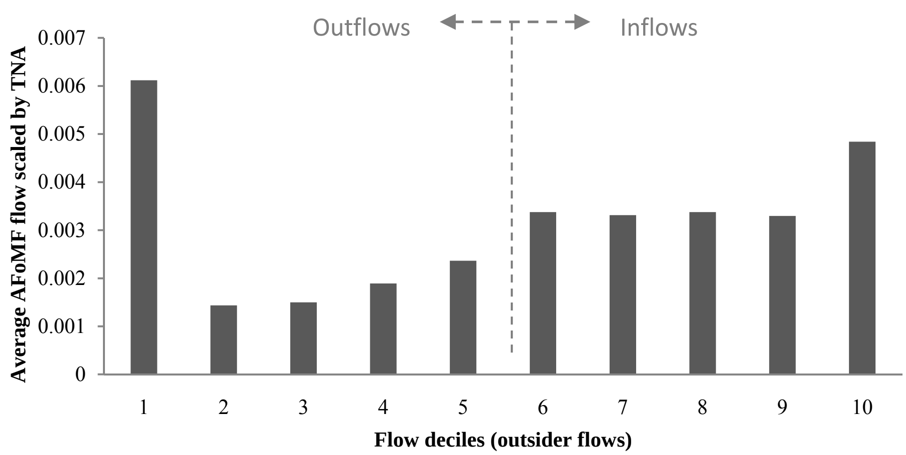


Figure 2. Do AFoMFs Favor Distressed Funds Even When the AFoMFs are Cash Poor?

The figure 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

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

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. 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 net asset value of fund *j*. Finally, non-AFoMF or outside investor flow is expressed as follows:

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

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 $Flow_{j,k,t}^{Outside}$. Decile 1 collects the underlying funds that receive the lowest percentage flow (highest outflow) from outside investors, while Decile 10 includes funds with the highest outside investor flow. The figure depicts two subsamples based on whether the AFoMF is constrained (cash poor) or unconstrained (cash rich). The constraints are measured by investors flow to AFoMFs. "Cash rich" refers to AFoMFs whose fund flow from investors is above the 90th percentile of AFoMF flows from investors, whereas "Cash Poor" AFoMFs receive flows from investors below the 10th percentile of AFoMF flows from investors.

(i) "Cash Poor" AFoMFs

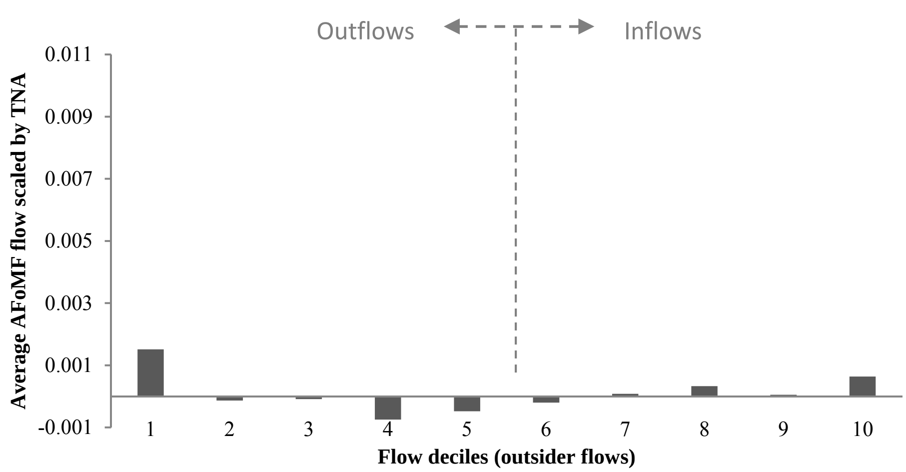


Figure 2 (*continued*)

(ii) "Cash Rich" AFoMFs

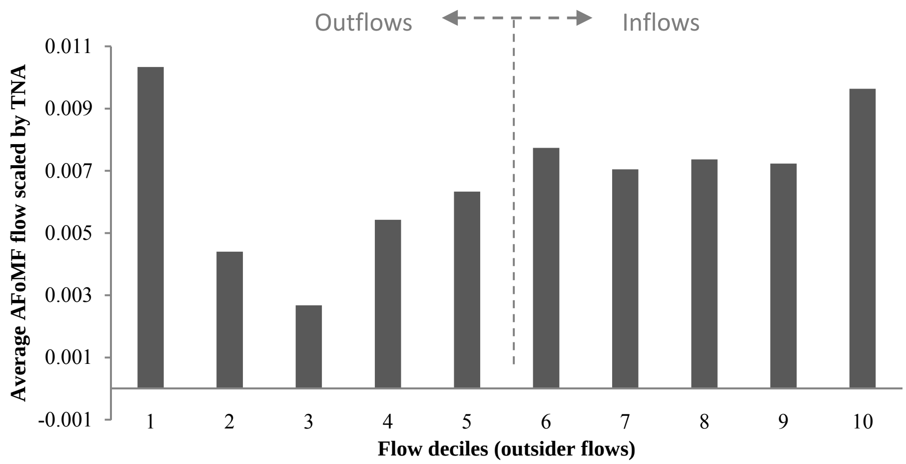


Figure 3. Do AFoMFs Favor Distressed Funds More When the Distressed Funds are in Illiquid Markets?

The figure 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

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

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. Flow from AFoMFs is determined by:

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

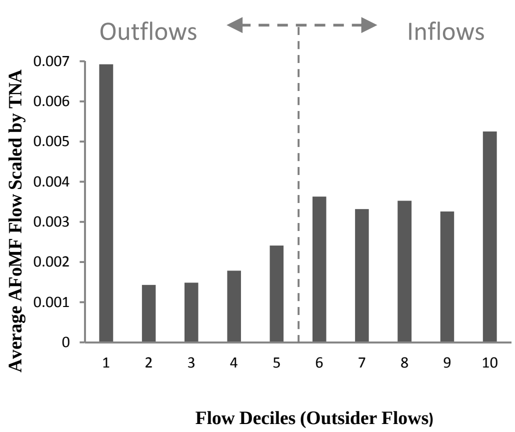
where $\Delta shares_{i,j}$ is the change in the number of shares held by AFoMF *i* in fund *j*, n_k is the number of AFoMFs in family *k*, and NAV_j is the net asset value of fund *j*. Finally, non-AFoMF or outside investor flow is expressed as follows:

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

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 $Flow_{j,k,t}^{Outside}$. Decile 1 collects the underlying funds that receive the lowest percentage flow (highest outflow) from outside investors, while Decile 10 includes funds with the highest outside investor flow. Panel A depicts average AFoMF flow to the underlying funds by outside investor flow decile for liquid and illiquid AFoMF holdings separately. Our liquid holdings group contains near cash holdings, which include money market funds and ETFs. Our illiquid group contains all other holdings. In Panel B, the illiquid subsample is further divided into U.S. equity funds and all other funds (excluding money market funds and ETFs).

<u>**Panel A**</u>

(i) Illiquid holdings



(ii) Liquid holdings

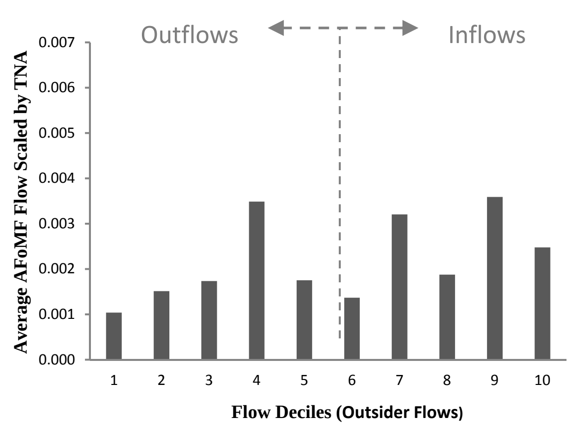
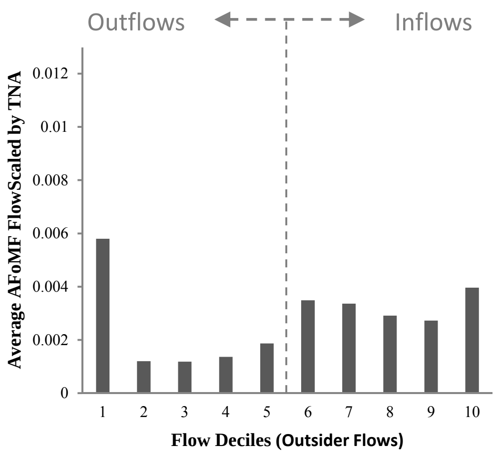


Figure 3 (*continued*)

Panel B

(i) US equity funds



(ii) All other funds

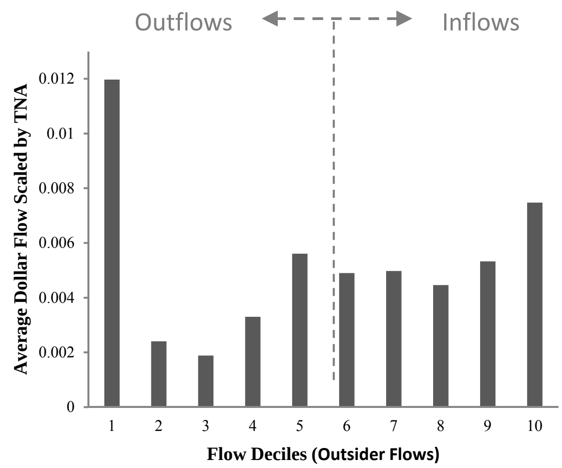


Figure 4. **Do AFoMFs Favor Distressed Funds More When the Distressed Funds Have Systematic Liquidity Shocks?**

The figure 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 total assets under management 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:

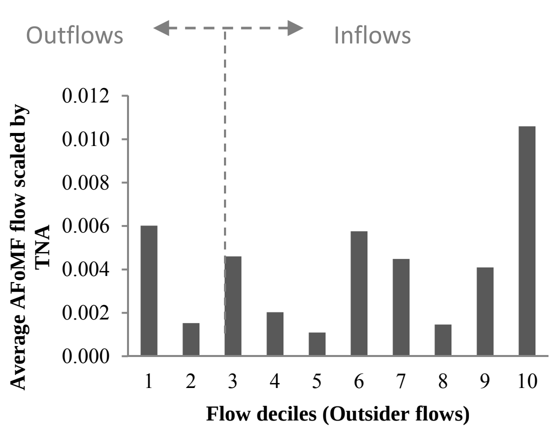
$$Flow^{AFoMF}_{j,k,t} = \sum_{i=1}^{n_k} \Delta shares_{i,j,t} \cdot NAV_{j,t}$$

where $\Delta shares_{i,j}$ is the change in the number of shares held by AFoMF *i* in fund *j*, n_k is the number of AFoMFs in family *k*, and NAV_j is the net asset value 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, while Decile 10 includes funds with the highest outside investor flow. The figure is depicted for four different subsamples to distinguish idiosyncratic liquidity events from systematic ones. In 'style distress 1,' we use a subsample of those fund quarters during which less than 25 percent of the funds in the mutual fund universe experience negative flows in each fund style. Similarly, in 'style distress 2' ('style distress 3') at least 25 (50) percent but fewer than 50 (75) percent of the funds are facing outflows. Finally, 'style distress 4,' includes those fund quarters during which the great majority of mutual funds (at least 75 percent) in each style category are experiencing fund withdrawals.

(i) Style Distress 1



(ii) Style Distress 2

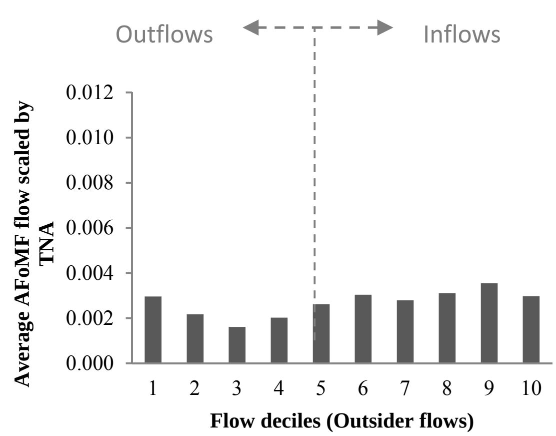
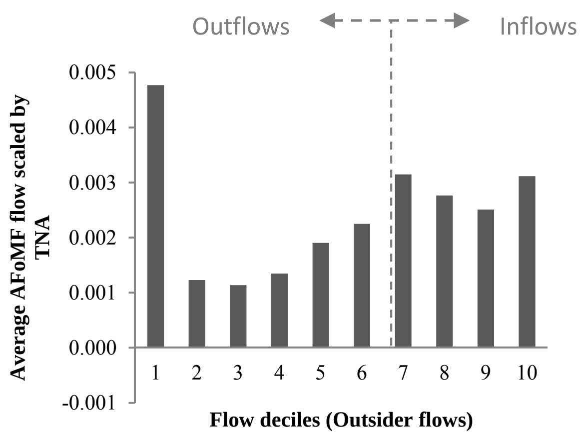


Figure 4 (*continued*)

(iii) Style Distress 3



(iv) Style Distress 4

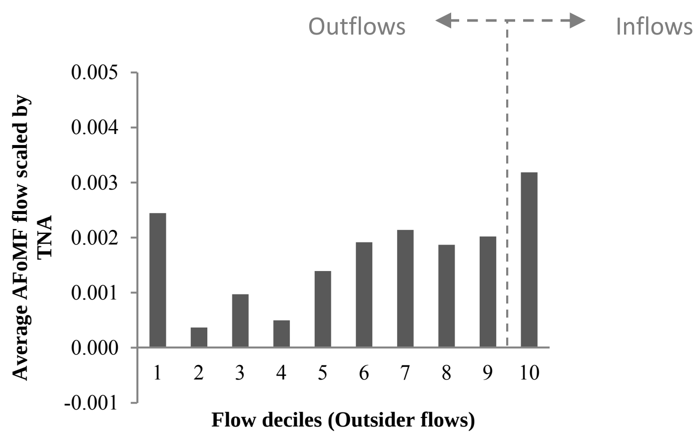
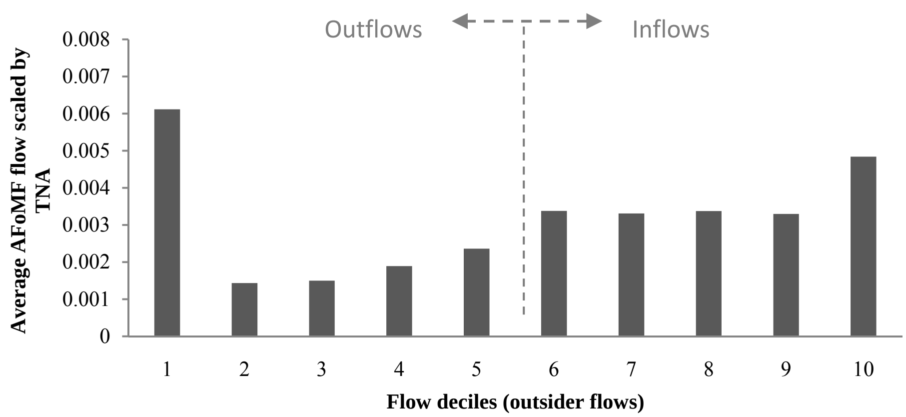


Figure 5. Do AFoMFs Provide Liquidity to Persistent Liquidity Shock?

The graphs below describe AFoMF liquidity provision to transient and persistent liquidity shocks. The top half of the figure is just Figure 1 recreated. The bottom half is Figure 1 with the ten deciles relabeled. In Figure 1, decile 1 (decile 10) has the least (most) flow from outside investors in a quarter. In the bottom half of the figure, decile 1 (decile 10) has the least (most) *moving average flow* from outside investors, where the moving average is taken over the last two quarters. This means that the top half sorts by transient liquidity shocks, whereas the bottom half sorts by more persistent liquidity shocks.

(i) Transient Liquidity Shock



(ii) Persistent Liquidity Shock

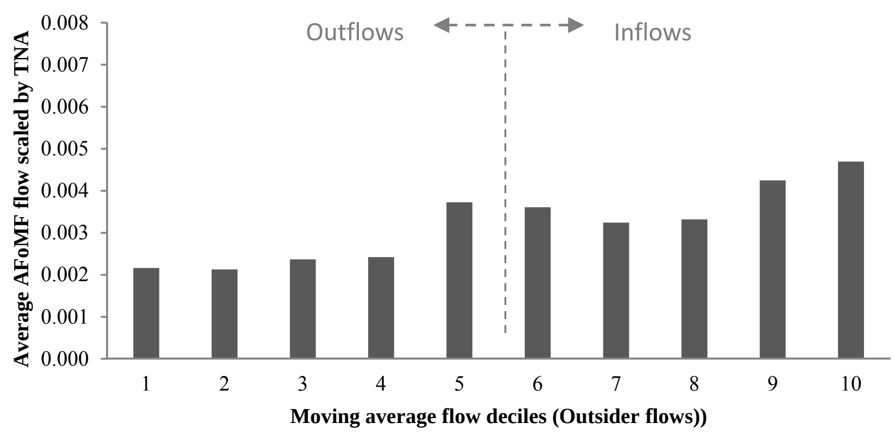


Table I. Descriptive Statistics of Fund Families

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), while 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 and 5) 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 Funds per 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%

Table I (*continued*)

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 Funds per 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

Table II. Comparison of Mutual Funds in Family Held by AFoMF and Mutual Funds in Family Not Held by AFoMF

This table compares funds in the family that are held by AFoMFs to those that are not held by AFoMFs though their style is consistent with the investment objectives of the AFoMFs in the family. Various fund characteristics are compared including outside investor flow, size (measured by total net assets under management), age, expense ratio, and previous performance (measured by Sharpe ratio). *P-value* indicates the significance of a *t*-test comparing the mean values of each fund statistic across the group of family funds held and not held by AFoMFs, respectively.

	Mutual Funds in Family Held by AFoMF	Mutual Funds in Family Not Held by AFoMF	P-value
Non-AFoMF flow	0.86%	2.34%	<0.0001
Flow from AFoMFs	1.12%	N/A	
Size in $ Billions (previous year TNA)	2.30	1.62	<0.0001
Size in $ Billions (excluding AFoMFs' stake)	2.08	1.62	<0.0001
Age (Years)	9.33	11.53	0.0023
Min. Expense	0.86%	0.84%	0.0004
Index funds	10.57%	17.81%	<0.0001
Previous year Sharpe ratio	0.24	0.22	0.6152
Number of fund portfolio periods	12,921	12,388	

Table III. 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 ordinary 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 total assets under management 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 net asset value of fund *j*. Finally, non-AFoMF or outside investor flow is expressed as follows:

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

All three flow measures are normalized by $TNA_{j,t-1}$. We sort our sample into deciles based on normalized $Flow_{j,k,t}^{Outside}$. Decile 1 collects the underlying funds that receive the lowest percentage flow (highest outflow) from outside investors, while 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 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).

Table III (*continued*)

Decile	N	Average Non-AFoMF Flow Scaled by TNA	% of Funds Not Held by AFoMF	Fraction of positions				
				Maintained	Eliminated	New Position	Reduced	Expanded
1 (largest outsider *out*flows)	2344	-0.0562	44.45%	3.11%	0.00%	5.76%	12.76%	33.93%
2	2360	-0.0200	46.03%	5.08%	0.00%	2.12%	14.73%	32.04%
3	2346	-0.0132	46.04%	3.88%	0.00%	1.79%	13.85%	34.44%
4	2369	-0.0082	46.43%	2.87%	0.04%	1.27%	13.59%	35.80%
5	2397	-0.0037	46.27%	3.34%	0.04%	0.88%	13.14%	36.34%
6	2399	0.0006	44.73%	3.54%	0.04%	0.71%	12.76%	38.22%
7	2398	0.0065	44.75%	2.92%	0.00%	1.25%	10.30%	40.78%
8	2387	0.0158	48.01%	2.39%	0.00%	1.05%	8.80%	39.76%
9	2381	0.0336	51.66%	2.81%	0.00%	1.68%	10.58%	33.26%
10 (largest outsider *in*flows)	2357	0.1309	63.17%	1.99%	0.00%	3.05%	6.83%	24.95%

Table IV. Do AFoMFs Favor Distressed Funds? (Multivariate Test)

The table lists 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* at time *t*, $Flow_{j,t}^{Outside}$ is the net flow by all other investors to fund *j* at time *t*, and $I_{j,t}$ is an indicator variable that equals one when mutual fund *j* is distress ed and 0 otherwise. The control variables are 1) the previous performance of fund *j*, measured by fund *j*'s Sharpe rati o in the previous year; 2) the flow AFoMFs receive from their own investors (budget constraint); 3) lagged AFoMF flow to underlying fund *j* ($Flow_{j,t-1}^{AFoMF}$); 4) lagged outside investor flow; 5) fund *j*'s expense ratio; and 6) fund *j*'s s ize measured by assets under management in the previous quarter. In columns 3 and 5 of the table, we also add the underlying fund's cash holding as reported in CRSP and an interaction variable between the cash holding and distres s ($I_{j,t}$) as additional controls. We estimate the above model by using both pooled regressions and the Fama-MacBet h (1973) method. Statistical significance at the 1, 5, 10 % level is denoted by 'a', 'b', 'c', respectively. The number of observations is denoted by N, and t-statistics are in parentheses.

Table IV *(continued)*

	Pooled (Fixed Effects)		Fama-MacBeth	
Outside Investor flow (β_1)	0.0143[a]	0.0122[a]	0.0071[c]	0.0024
	(6.71)	(5.43)	(2.03)	(0.42)
I*outside investor flow (β_2)	-0.0955[a]	-0.1015[a]	-0.0705[a]	-0.0731[a]
	(-18.99)	(-18.75)	(-4.79)	(-4.42)
Previous performance	0.0001	0.0001	0.0004[b]	0.0002
	(1.21)	(0.09)	(2.77)	(0.59)
Flow to AFoMF (budget constraint)	0.0109[a]	0.0113[a]	0.0242[a]	0.0258[a]
	(10.89)	(10.46)	(6.11)	(5.60)
Lag(Flow from AFoMF)	0.3182[a]	0.3047[a]	0.3444[a]	0.3361[a]
	(51.91)	(48.03)	(11.26)	(11.08)
Lag(Outside investor flow)	0.0068[a]	0.0074[a]	0.0103	0.0134
	(3.96)	(4.07)	(1.98)	(1.84)
AFoMF holding's exp ratio	-0.1731[a]	-0.1937[a]	-0.1347[a]	-0.1626[a]
	(-6.23)	(-6.56)	(-5.32)	(-5.69)
AFoMF holding's size	-0.0004[a]	-0.0004[a]	-0.0006[a]	-0.0007[a]
	(-7.08)	(-6.54)	(-7.29)	(-7.16)
AFoMF holding's cash position		0.0001[b]		0.0001[c]
		(2.81)		(2.47)
I*AFoMF holding's cash position		-0.0001[b]		-0.0000
		(-2.3)		(-1.06)
N	20997	19758	20997	19758
R-Sqr	0.2206	0.2142	0.1934	0.1944

Table V. Multivariate Tests

Panels A-C list 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* at time *t*, $Flow_{j,t}^{Outside}$ is the net flow by all other investors to fund *j* at time *t*, and $I_{j,t}$ is an indicator variable that equals one when mutual fund *j* is distressed and 0 otherwise. The control variables are 1) the previous performance of fund *j*, measure d by fund *j*'s Sharpe ratio in the previous year; 2) the flow AFoMFs receive from their own investors (budget constraint); 3) lagged AFoMF flow to underlying fund *j* ($Flow_{j,t-1}^{AFoMF}$); 4) lagged outside investor flow; 5) fund *j*'s expense ratio; and 6) fund *j*'s size measured by assets under management in the previous quarte r. In Panel A, we estimate the regression for constrained (cash poor) and unconstrained (cash rich) AFoMFs separately. We sort our sample into deciles based on fund flow to AFoMFs. "Cash rich" refers to the top decile, whereas "Cash Poor" is the bottom decile. In Panel B, we estimate the model for liquid and illiquid AFoMF holdings separately. Our liquid group contains near cash holdings, which include money market funds and ETFs. Our illiquid group contains all other holdings. Columns 2-5 of Panel B list the results. In columns 6-9 of Panel B, the illiquid subsample is further divided into U.S. equity funds and all other funds (excluding money market funds and ETFs). Panel C reports the model estimates for fund-specific vs. style-wide liquidity events. To distinguish firm-specific liquidity events from style-wide nes, we examine four scenarios. In 'style distress 1,' we use a subsample of those fund quarters during which less than 25 percent of the funds in the mutual fund universe experience negative flows in each fund style. Similarly, in 'style distress 2' ('style distress 3') at least 25 (50) percent but fewer than 50 (75) percent of the funds are facing outflows. Finally, in 'style distress 4,' includes those fund quarters during which the great majority of mutual funds (at least 75 percent) in each style category are experiencing fund withdrawals.
Panel D lists the results of:

$$Flow_{j,t}^{AFoMF} = \beta_0 + \ (\beta_1 + \beta_2 * I_{j,t} + \beta_3 * I_{j,t-1}^{*}) * Flow_{j,t}^{Outside} + Controls + \varepsilon_{j,t}$$

where $I^{*}_{j,t-1}$ is an indicator variable that equals one if mutual fund *j* is distressed in periods *t* and *t-1*, and 0 otherwise. We estimate the above models by using bot d pooled regressions and the Fama-MacBeth (1973) method. Statistical significance at the 1, 5, 10 % level is denoted by 'a', 'b', 'c', respectively. The number of observations is denoted by N, and t-statistics are in parentheses.

Table V (*continued*)

Panel A: Do AFoMFs Favor Distressed Funds When the AFoMFs are Cash Poor?

	Cash Poor AFoMFs		**Cash Rich AFoMFs**	
	Pooled (Fixed Effects)	**Fama-MacBeth**	**Pooled (Fixed Effects)**	**Fama-MacBeth**
Outside Investor flow (β_1)	0.0022	0.0046	0.0446[a]	-0.0385
	(0.46)	(0.75)	(3.77)	(-0.70)
I*outside investor flow (β_2)	-0.0698[a]	-0.0424[a]	-0.1390[a]	-0.0815[c]
	(-5.61)	(-3.13)	(-5.02)	(-1.79)
Previous performance	-0.0002	-0.0005	0.0015	0.0002
	(-0.60)	(-1.28)	(1.36)	(0.14)
Flow to AFoMF (budget constraint)	0.0689[a]	0.0738[a]	0.0054[a]	0.0083
	(4.25)	(5.39)	(2.75)	(1.53)
Lag(Flow from AFoMF)	0.1662[a]	0.2255[a]	0.4643[a]	0.5583[a]
	(9.19)	(3.85)	(20.11)	(5.34)
Lag(Outside investor flow)	0.0094[b]	0.0057	0.0221[a]	0.0420[b]
	(2.49)	(0.56)	(2.58)	(2.61)
AFoMF holding's exp ratio	-0.058	-0.024	-0.8018[a]	-1.0187[a]
	(-1.18)	(-0.47)	(-6.30)	(-4.86)
AFoMF holding's size	-0.0001	-0.0001	-0.0023[a]	-0.0029[b]
	(-0.29)	(-1.63)	(-7.71)	(-3.80)
N	1923	1923	1565	1565
R-Sqr	0.0684	0.1504	0.3058	0.3244

Table V (*continued*)

Panel B: Do AFoMFs Favor Distressed Funds When the Distressed Funds are Illiquid?

	Funds with Illiquid Assets		**Funds with Liquid Assets**		**US equity funds**		**Other AFoMF holdings**	
	Pooled (Fixed Effects)	**Fama-MacBeth**	**Pooled (Fixed Effects)**	**Fama-MacBeth**	**Pooled (Fixed Effects)**	**Fama-MacBeth**	**Pooled (Fixed Effects)**	**Fama-MacBeth**
Outside Investor flow (β_1)	0.0146[a]	0.0075	0.0106[b]	0.0050[a]	0.0165[a]	-0.0011	0.0121[a]	0.0171[a]
	(6.27)	(1.98)	(2.10)	(2.48)	(4.02)	(-0.11)	(4.60)	(2.48)
I*outside investor flow (β_2)	-0.1115[a]	-0.0823[a]	-0.0036	0.002	-0.1083[a]	-0.0632	-0.1157[a]	-0.1046[a]
	(-20.39)	(-4.28)	(-0.29)	(0.52)	(-11.10)	(-1.64)	(-18.75)	(-8.01)
Previous performance	0.0001[a]	0.0004[b]	0.0001	0.0003	-0.0002	0.0013[a]	0.0004	0.0001
	(0.02)	(2.60)	(0.24)	(1.83)	(-0.85)	(5.84)	(1.08)	(0.21)
Flow to AFoMF (budget constraint)	0.0113[a]	0.0229[a]	0.0056	0.0308[a]	0.0126[a]	0.0182[a]	0.0089[a]	0.0282[a]
	(10.74)	(6.89)	(1.62)	(4.68)	(7.25)	(5.01)	(7.01)	(5.71)
Lag(Flow from AFoMF)	0.3192[a]	0.3396[a]	0.2063[a]	0.5348[a]	0.3162[a]	0.3841[a]	0.2971[a]	0.3041[a]
	(50.24)	(10.98)	(8.39)	(3.33)	(31.95)	(8.96)	(35.64)	(7.31)
Lag(Outside investor flow)	0.0088[a]	0.0114[c]	-0.0025	0.0024	0.0172[a]	0.0048	0.0013	0.0199[b]
	(4.68)	(2.35)	(-0.61)	(0.64)	(5.23)	(0.84)	(0.62)	(3.81)
AFoMF holding's exp ratio	-0.1999[a]	-0.1705[a]	0.0328	0.103	-0.2399[a]	-0.0810	-0.1445[a]	-0.2855[b]
	(-6.61)	(-7.78)	(0.21)	(1.54)	(-4.81)	(-1.64)	(-3.74)	(-4.02)
AFoMF holding's size	-0.0004[a]	-0.0007[a]	-0.0003[c]	-0.0004[a]	-0.0007[a]	-0.0004[a]	-0.0002[b]	-0.0010[a]
	(-6.20)	(-7.11)	(-1.96)	(-7.77)	(-5.70)	(-7.94)	(-2.12)	(-6.01)
N	19241	19241	1756	1756	11230	11230	8011	8011
R-Sqr	0.2249	0.1927	0.2624	0.345	0.2244	0.2250	0.2453	0.2034

Table V (*continued*)

Panel C: Do AFoMFs Favor Distressed Funds When the Distressed Funds Have Style-Wide Liquidity Shocks?

	Style Distress 1		**Style Distress 2**		**Style Distress 3**		**Style Distress 4**	
	Pooled (Fixed Effects)	**Fama-MacBeth**	**Pooled (Fixed Effects)**	**Fama-MacBeth**	**Pooled (Fixed Effects)**	**Fama-MacBeth**	**Pooled (Fixed Effects)**	**Fama-MacBeth**
Outside Investor flow (β_1)	0.0172[a]	0.0270[b]	0.0199[a]	0.0008	0.0093[b]	-0.0014	0.0153	0.0028
	(3.56)	(3.19)	(4.44)	(0.08)	(1.98)	(-0.21)	(1.55)	(1.09)
I*outside investor flow (β_2)	-0.1199[a]	-0.0863[a]	-0.1185[a]	-0.0655	-0.1286[a]	-0.0875[a]	-0.1474[a]	-0.0841
	(-8.92)	(-6.17)	(-11.09)	(-1.68)	(-13.20)	(-4.31)	(-6.47)	(-1.37)
Previous performance	0.0001	0.0006[c]	0.0003	-0.0002	0.0001	0.0016	0.0001	0.0008
	(0.13)	(1.90)	(0.67)	(-0.25)	(0.38)	(1.59)	(0.10)	(0.65)
Flow to the AFoMF (budget constraint)	0.0114[a]	0.0226[a]	0.0147[a]	0.0257[a]	0.0095[a]	0.0374[a]	0.0102[b]	0.0370[b]
	(6.07)	(4.25)	(6.29)	(7.63)	(3.19)	(4.53)	(2.41)	(3.50)
Lag(Flow from AFoMF)	0.3376[a]	0.3272[a]	0.2679[a]	0.3385[a]	0.2747[a]	0.3245[a]	0.2051[a]	0.1929[a]
	(22.64)	(8.36)	(21.65)	(10.90)	(24.3)	(9.80)	(7.59)	(7.49)
Lag(Outside investor flow)	0.0187[a]	0.0184[a]	0.0048	0.0110	0.0045	0.0068	0.0040	0.0067[b]
	(4.62)	(4.26)	(1.34)	(1.03)	(1.21)	(1.46)	(0.51)	(2.71)
AFoMF holding's exp ratio	-0.1963[a]	-0.0792	-0.2213[a]	-0.1066	-0.1733[b]	0.0117	-0.4164[a]	-0.2580[a]
	(-2.61)	(-0.74)	(-3.43)	(-1.63)	(-2.39)	(0.17)	(-2.77)	(-6.80)
AFoMF holding's size	-0.0001	-0.0004[a]	-0.0003[a]	-0.0009[a]	-0.0004[a]	-0.0006[a]	-0.0005[c]	-0.0012[b]
	(-0.88)	(-4.81)	(-2.70)	(-7.73)	(-2.93)	(-3.61)	(-1.68)	(-2.70)
N	3518	3518	4906	4906	6513	6513	1365	1365
R-Sqr	0.3019	0.265	0.3314	0.2347	0.274	0.2247	0.3441	0.2502

Table V (*continued*)

Panel D: Do AFoMFs Favor Distressed Funds When the Distressed Funds Have Transient Liquidity Shocks?

	Pooled (Fixed Effects)	**Fama-MacBeth**
Outside Investor flow (β_1)	0.0119[a]	0.0055
	(5.11)	(1.23)
I_t*outside investor flow (β_2)	-0.1176[a]	-0.0851[b]
	(-18.59)	(-3.87)
I_{t-1}*outside investor flow (β_3)	0.0462[a]	0.0233[c]
	(4.67)	(2.17)
Previous performance	0.0002	0.0004[b]
	(0.02)	(2.63)
Flow to AFoMF (budget constraint)	0.0148[a]	0.0230[a]
	(15.52)	(6.79)
Lag(Flow from AFoMF)	0.3590[a]	0.3402[a]
	(57.71)	(11.1)
Lag(Outside investor flow)	0.0068[a]	0.0118[c]
	(3.56)	(2.13)
AFoMF holding's exp ratio	-0.1479[a]	-0.1685[a]
	(-5.83)	(-7.4)
AFoMF holding's size	-0.0005[a]	-0.0007[a]
	(-9.13)	(-7.24)
N	19232	19232
R-Sqr	0.1908	0.195

Table VI. Is Liquidity Provision by AFoMFs Costly for the AFoMFs?

This table reports the investment performance of the AFoMF trades. We form portfolios at the beginning of each quarter based on whether the AFoMF bought or sold the underlying fund, respectively. Underlying funds that are bought comprise the positive flow portfolio, while those that are sold during the quarter are placed in the negative flow portfolio. Within the positive and negative flow portfolios, two additional subgroups are created. The first group includes funds experiencing distress, and the second contains all non-distressed funds. For each group, we calculate the flow weighted return for each of the three months immediately following the end of each quarter and rebalance our portfolios every quarter. To evaluate performance, we estimate four- and seven-factor alphas. The four-factor model follows Carhart (1997) and is given by:

$$r_{p,t} = \alpha_p + \beta_{1,p}RMRF_t + \beta_{2,p}SMB_t + \beta_{3,p}HML + \beta_{4,p}UMD_t + \varepsilon_{p,t}$$

where r_p is the monthly excess return on a portfolio of funds; *RMRF* is the excess return on the market portfolio; and *SMB*, *HML*, and *UMD* are returns on zero-investment mimicking portfolios for common size, book-to-market, and momentum factors. In addition, the seven-factor model is given by:

$$r_{p,t} = \alpha_p + \beta_{1,p}RMRF_t + \beta_{2,p}SMB_t + \beta_{3,p}HML + \beta_{4,p}UMD_t + \beta_{5,p}D10YR_t + \beta_{6,p}DSPR_t + \beta_{7,p}MSCI_t + \varepsilon_{p,t}$$

where we use two bond-oriented factors (the monthly change in the 10-year treasury yield (D10YR) and the monthly change in the credit spread between the Moody's Baa yield and the 10 year treasury yield) and an international factor represented by the MSCI market index return. Panel A and Panel B list the four- and seven-factor results, respectively. Statistical significance at the 1, 5, 10 % level is denoted by [a], [b], [c], respectively.

Table VI (*continued*)

Panel A: Four-Factor Results

	Positive Flow Portfolios			Negative Flow Portfolios		
	All buys Portfolio	**Distressed fund portfolio**	**Portfolio of all other funds**	**All sells Portfolio**	**Distressed fund portfolio**	**Portfolio of all other funds**
Alpha	0.0011	-0.0030[c]	0.0035[a]	-0.0010	-0.0007	-0.0012
	(1.45)	(1.86)	(2.82)	(-0.59)	(-0.32)	(-0.71)
MKTX	0.6630[a]	0.6876[a]	0.5821[a]	0.8000[a]	1.0051[a]	0.8003[a]
	(16.25)	(9.28)	(8.03)	(8.50)	(8.95)	(8.66)
SMB	-0.0141	-0.0393	0.0288	-0.0549	0.0644	-0.0873
	(-0.35)	(-0.46)	(0.37)	(-0.64)	(0.44)	(-1.11)
HML	-0.0051	0.0127	-0.0360	0.1569	0.0146	0.1551
	(-0.09)	(0.14)	(-0.52)	(1.43)	(0.10)	(1.44)
MOM	-0.0917[a]	-0.1450[a]	-0.0573[b]	0.2083[a]	-0.1088[c]	0.2194[a]
	(-3.45)	(-3.21)	(-2.39)	(3.10)	(-1.74)	(3.29)
N	69	66	69	69	57	69
Rsqr	0.9259	0.7811	0.8763	0.8007	0.8327	0.8042

Table VI (*continued*)

Panel B: Seven Factor Results

	Positive Flow Portfolios			**Negative Flow Portfolios**		
	All buys Portfolio	**Distressed fund portfolio**	**Portfolio of all other funds**	**All sells Portfolio**	**Distressed fund portfolio**	**Portfolio of all other funds**
Alpha	0.0007	-0.0033[c]	0.0040[a]	-0.0009	-0.0004	-0.0012
	(0.96)	(-1.91)	(3.21)	(-0.62)	(-0.19)	(-0.86)
MKTX	0.6904[a]	0.6780[a]	0.6364[a]	0.7502[a]	0.9002[a]	0.7591[a]
	(16.46)	(9.57)	(11.75)	(11.09)	(10.22)	(11.56)
SMB	-0.0002	-0.0381	0.0109	-0.0517	0.1133	-0.0805
	(-0.00)	(-0.45)	(0.17)	(-0.64)	(0.99)	(-1.06)
HML	-0.0104	-0.0227	-0.0437	0.112	-0.0239	0.1066
	(-0.20)	(-0.24)	(-0.70)	(1.16)	(-0.18)	(1.12)
MOM	-0.0910[a]	-0.1232[b]	-0.0562[b]	0.2315[a]	-0.1013	0.2438[a]
	(-3.53)	(-2.64)	(-2.35)	(3.72)	(-1.66)	(4.02)
D10YR	-0.6484[c]	-1.1884[c]	-1.0670[a]	-1.6632[c]	0.4929	-1.9691[b]
	(-1.84)	(-1.71)	(-2.70)	(-1.94)	(0.59)	(-2.65)
DSPR	0.4731	-2.2515	0.0510	-3.9958[c]	-2.6050	-4.0064[c]
	(0.69)	(-1.34)	(0.05)	(-1.89)	(-1.11)	(-1.94)
MSCI	0.0049	0.0062	-0.0463[b]	0.0046	0.0388	0.0043
	(0.38)	(0.21)	(-2.36)	(0.17)	(1.17)	(0.16)
N	69	66	69	69	57	69
Rsqr	0.9293	0.7787	0.9003	0.8196	0.8387	0.8274

Table VII. Does Liquidity Provision by AFoMFs Benefit the Underlying Funds?

This table examines whether liquidity provision benefits the funds that get the 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 four- and seven-factor models, respectively. We use the following regression specification:

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

where α_j is the abnormal return of fund *j*, I_j is an indicator that takes the value of 1 if fund j is distressed (experiences large outflows from the outside investors), and $Flow_{j,t}^{AFoMF}$ is the flow fund j receives from the AFoMFs in its family. 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. Statistical significance at the 1, 5, 10 % level is denoted by [a], [b], [c], respectively.

Table VII *(continued)*

	Pooled (Fixed Effects)	**Fama-MacBeth**
I	-0.0008[a]	-0.0009[a]
	(-2.82)	(-3.3)
I*AFoMF Flow	0.0524[b]	0.0481[c]
	(2.31)	(1.74)
Total Flow	-0.0005	-0.0006
	(-0.6)	(-0.4)
Total Flow Squared	-0.0002	0.01
	(-0.36)	(1.07)
Fund Fees	0.1528[a]	0.0864[c]
	(6.05)	(1.72)
Fund Size	0.0000	0.0001
	(0.02)	(0.55)
Abnormal $Return_{t-1}$	0.1957[a]	0.1790[a]
	(39.51)	(5.38)
Abnormal $Return_{t-2}$	0.1632[a]	0.1459[a]
	(33.91)	(8.91)
Abnormal $Return_{t-3}$	0.0147[a]	0.0104
	(2.97)	(0.36)
Abnormal $Return_{t-4}$	-0.0018	-0.0049
	(-0.36)	(-0.27)
Abnormal $Return_{t-5}$	-0.0535[a]	-0.0566[c]
	(-11.22)	(-2.07)
Abnormal $Return_{t-6}$	-0.0199[a]	-0.0288
	(-3.99)	(-1.38)
N	20448	20448
R-sqr	0.1298	0.1460

Table VIII. Is Liquidity Provision a Star Creation Strategy?

This table examines whether liquidity provision by AFoMFs is another star creation strategy. To do so, we sort member funds into deciles based on past performance. We use three alternative performance measures: 1) Sharpe ratios; 2) cumulative returns; and 3) style adjusted returns calculated over the past 1 year return history of the underlying fund. For each group, we estimate the following regression specification:

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

where $Flow_{j,t}^{AFoMF}$ is the percentage flow from AFoMFs to underlying fund *j* at time *t*, $Flow_{j,t}^{Outside}$ is the net flow by all other investors to fund *j* at time *t*, and $I_{j,t}$ is an indicator variable that equals one when mutual fund *j* is distress ed and 0 otherwise. The control variables are 1) last year's performance of fund *j*; 2) the flow AFoMFs receive from their own investors (budget constraint); 3) lagged AFoMF flow to underlying fund *j* ($Flow_{j,t-1}^{AFoMF}$); 4) lagged outsid e investor flow; 5) fund *j*'s expense ratio; and 6) fund *j*'s size measured by assets under management in the previous quarter. We estimate the above model using the pooled regression method. For the sake of brevity, we report the su m of the β_1 and β_2 coefficients from the above equation, along with the t-statistic of the sum for each performance de cile. Statistical significance at the 1, 5, 10 % level is denoted by '[a]', '[b]', '[c]', respectively.

Deciles	$(\beta_1+\beta_2)$ (Past Sharpe ratio deciles)	$(\beta_1+\beta_2)$ (Past cumulative return deciles)	$(\beta_1+\beta_2)$ (Past style-adjusted return deciles)
1 (worst performance)	-0.0607	-0.0054	0.0055
	(-1.47)	(-0.28)	(0.37)
2	-0.0254	-0.0567	-0.1545[a]
	(-0.86)	(-1.33)	(-3.35)
3	-0.0924[b]	-0.1260[a]	-0.0980[b]
	(-2.08)	(-3.50)	(-2.24)
4	-0.1013[b]	-0.0546	-0.1011[b]
	(-2.50)	(-1.41)	(-2.06)
5	-0.0690	-0.1295[b]	-0.1164[a]
	(-1.55)	(-2.49)	(-2.75)
6	-0.0947[a]	-0.0806[b]	-0.0581[b]
	(-3.09)	(-2.33)	(-1.96)
7	-0.1018[a]	-0.1152[a]	-0.0470
	(-2.82)	(-3.60)	(-1.81)
8	-0.1043[a]	-0.1419[a]	-0.1876[a]
	(-3.01)	(-3.43)	(-4.37)
9	-0.1325[a]	-0.0812[b]	-0.0861[b]
	(-3.27)	(-2.55)	(-2.64)
10 (best performance)	-0.1038[a]	-0.0592[b]	-0.0315
	(-2.65)	(-2.07)	(-1.72)

Appendix A: Some Sample Prospectuses

1) Legg Mason Lifestyle Allocation Fund

Investment Objective: This fund seeks capital appreciation.

Principal Investment Strategy: The fund is a fund of funds- it invests in other mutual funds. The fund is managed as an asset allocation program and allocates its assets among Legg Mason-affiliated mutual funds. The fund organizes its investments in underlying funds into two main asset classes: the stock class (equity securities of all types) and the fixed income class (fixed income securities of all types). The fund seeks to maintain a Target Allocation [. . .] The fund may make tactical changes in its allocation within a specified range (the Target Range) around that Target Allocation, based on the portfolio managers' outlook for assets classes and market and economic trends. […]

Liquidity risk. Some securities held by an underlying fund may be difficult to sell, or illiquid, particularly during times of market turmoil. Illiquid securities may also be difficult to value. If an underlying fund is forced to sell an illiquid asset to meet redemption requests or other cash needs, the underlying fund may be forced to sell at a loss.

2) Mainstay Conservative Allocation Fund

Investment Objective: The fund seeks current income and, secondarily, long-term growth of capital.

Principal Investment Strategy: The fund is a "fund of funds," meaning that it seeks to achieve its investment objective by investing primarily in other MainStay Funds (the "Underlying Funds"). The Underlying Funds are described and offered for direct investment in separate prospectuses.

The Fund is designed for investors with a particular risk profile, and invests in a distinct mix of Underlying Funds.

The Fund seeks to achieve its investment objective by normally investing [. . .] in Underlying Fixed Income Funds and in Underlying Equity Funds. The Underlying Equity Funds may consist of approximately 5% (within the range of 0% to 15%) of international equity funds. The Subadvisor may change the asset class allocations, the portfolio of Underlying Funds, or the target weighting without prior approval from shareholders. The Subadvisor uses a two-step asset allocation process to create the Fund's portfolio. The first step is a strategic asset allocation to determine the percentage of the Fund's investable portfolio (meaning the Fund's assets available for investment, other than working cash balances) to be invested in Underlying Funds in two broad asset classes—equity and fixed income.

The second step in the portfolio's construction process involves the actual selection of Underlying Funds to represent the two broad asset classes indicated above and determination of target weightings among the Underlying Funds for each Fund's portfolio. A Fund may invest in any or all of the Underlying Funds within an asset class, but will not normally invest in every Underlying Fund at one time. Selection of individual Underlying Funds is based on several factors, including past performance, total portfolio characteristics, (e.g., size, style, credit quality and duration) and assessment of current holdings (e.g., valuation data, earnings growth, technical indicators and quality metrics). For cash management purposes, the Fund may hold a portion of its assets in U.S. government securities, cash or cash equivalents. The Fund also may invest in Underlying Funds that are money market funds. [. . .] In response to adverse market or other conditions, the Fund may, regardless of its normal asset class allocations, temporarily hold all or a portion of its assets in U.S. government securities, money market funds, cash, or cash equivalents.