Predation versus Cooperation in Mutual Fund Families

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Abstract

In this paper we investigate how mutual funds react to the distress of another fund in the same fund family. We test three alternative hypotheses: (1) funds help the distressed fund, (2) funds front-run the distressed fund improving their relative performance in the fund family and, (3) the family coordinates and benefits from front-running the distressed fund. Our results suggest that fund managers front-run their distressed siblings and that this is the outcome of a coordinated strategy. As a consequence, funds in the same family exhibit abnormal returns, while the distressed fund pays a higher cost of distress.

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1 Introduction

Most mutual funds today are organized in mutual fund families. Mutual fund families are business groups of legally independent entities. Therefore, the only objective of each member in the family should be the maximization of investor wealth.

Despite their legal independence, recent literature suggests that mutual funds inside a family are not acting independently. On the one hand, significant amounts of potentially private information flows inside business groups can lead to correlated actions (see Massa and Rehman (2008)). On the other hand, the interests of the family can be put in front of the interest of the individual funds. Gaspar, Massa, and Matos (2006), for example, show that a mutual fund family can enforce strategies that maximize family's instead of its investors' wealth by cross-trading among funds or by allocating potentially underpriced IPOs to the most valuable funds.

This paper empirically investigates how private information flows inside mutual fund families and family objectives affect the behavior of mutual fund families when one of their funds faces a severe distress in the form of investor redemptions. In particular, we ask whether other funds in the family (siblings) cooperate and provide liquidity to the distressed fund or whether the siblings front-run a distressed fund.

Both of these trading strategies affect investors' wealth as they reallocate performance across different funds in the same family. Cooperation diminishes the distress cost for a fund, potentially at the expense of other funds in the family. The consequences of front-running are theoretically investigated in Brunnermeier and Pedersen (2005) in the seminal paper "Predatory Trading". Their model shows how an informed trader can profit from selling contemporaneously with a distressed fund[1] and buying when the price reverts. An informed trader (i.e., a fund sibling) sells the same position in

[1] In Brunnermeier and Pedersen (2005) the "pray" is a trader who is forced to sell, e.g., a hedge fund that has to meet a margin call. In our paper, a distressed mutual fund is forced to sell because of investors' redemptions.

advance to avoid holding the fire sale stock in the portfolio when the price drops. This pushes further down the price of the fire sale stock, increasing the cost of distress for the distressed fund. Ultimately, when the distressed fund is done selling, the informed trader buys back the position enjoying the reversal of the price to its fundamental value.

Drawing on the existing literature, we test three alternative hypotheses: siblings cooperate with the distressed fund by buying fire sale stocks[2] to reduce the price impact for the distressed fund (H1), siblings front-run[3] the distressed fund in an uncoordinated manner to improve their performance (H2), or siblings front-run their distressed siblings under a family-coordinated strategy (H3). In our tests we pay particular attention to large fund families, since they are more likely to promote any of the above-mentioned strategies due to larger internal capital markets (Schmidt and Goncalves-Pinto (2012)), a more competitive environment (Kempf and Ruenzi (2008)), more concentrated holdings (Pollet and Wilson (2008)) and a higher motivation to generate star funds (Nanda, Wang, and Zheng (2004)).

Our empirical findings indicate that distressed funds in large families suffer more than distressed funds in small families[4], ruling out the cooperation hypothesis since a high number of siblings endangers the performance of a distressed fund. At the same time, mutual funds in large families outperform their peers on average by 0.26% per quarter, when there is at least one family member in distress. These abnormal returns

[2]Fire sale stocks are the positions a fund is forced to sell to meet investors' redemptions, see Coval and Stafford (2007).

[3]"Front-running" is the practice of trading ahead of large orders in order to profit or to avoid losses from the price impact, exploiting downward sloping demand curves for stocks (Coval and Stafford (2007)). When based on the analysis of public available information, front-running is not forbidden, it is however illegal when based on private information.

[4]This result is interesting also because Chen, Hong, Huan, and Kubik (2004) show that belonging to a large family is beneficial for the performance of a fund. We find that this is true on average, however this relation reverts when a fund enters into distress

are earned at the expense of distressed funds, which, consistently with the predation hypotheses, suffer more the higher is the portfolio overlap with their siblings. In small families there is a weak positive correlation between the portfolio overlap and the performance of the distressed fund which may suggest cooperation in small families. Finally, we find that the outperformance is clustered in high-fee siblings. We interpret this result as the evidence for a coordinated strategy at a family level (H3).

Overall, our findings suggest that funds front-run their distressed siblings, and that this strategy is coordinated and optimal for the whole family (H3). Anecdotal evidence in support of our results comes from the recent law suit between a former fund manager Roseanne Ott and her investment management company, Fred Alger Management Inc[5]. The asset manager complained that she was obliged to disclose her trades before execution to other portfolio managers inside the family, who were using this information to trade ahead of her. She claimed that her fund was suffering, while the other asset managers were improving their performance at the expense of her fund.

There are three main motives that may influence a fund family to tolerate or promote a predatory trading strategy. Firstly, families may wish to improve the performance of the best funds in order to attract new inflows. Secondly, distressed funds are more likely to be shut down. Thirdly, directing flows into funds generating high fees increases the overall profit for the family. According to Chevalier and Ellison (1997), the shape of the flow-performance relationship serves as an implicit incentive contract for mutual funds. Mutual funds earn their fees based on their assets under management and this creates incentives for them to attract new assets. In the same vein mutual fund complexes desire to attract flows to the family to collect more fees. Sirri and Tufano (1998) show that an improvement in the return of a well-performing fund attracts new inflows disproportionally, while the outflows of the worst performing

[5]"Alger Faces Lawsuit on Firing", Wall Street Journal, July 6, 2011

funds are less affected by a further drop in performance. Thus, shifting performance from a distressed fund to a top-performing fund can be optimal for a mutual fund family seeking to maximize its assets under management. Furthermore, Nanda, Wang, and Zheng (2004) show empirically that a star fund (i.e., a fund within the 5% top funds in a month based on average return) attracts higher inflows to all funds in the family, while a low-performing fund does not affect inflows to other funds in the family.

Our paper contributes to the existing finance literature in a number of ways. First, we show that front-running pumps up the returns of siblings, while further depressing the performance of the distressed funds. This trading practice results from a coordination of trades that must be the result of private information sharing and constitutes an "agency problem". Even though a fund manager has no formal obligation to the investors of other funds in the same family, most fund complexes take strategic decisions at a centralized level, e.g., the marketing strategy is usually defined by the top management with the intent to attract attention to the family as a whole rather than to a specific fund (see Gallaher, Kaniel, and Starks (2008)). Often the ads promise a better "care" to clients choosing one family over the other. However, front-running endangers the performance of the investors of the distressed funds, while improving the performance of investors in high-fee funds. Second, we empirically test Brunnermeier and Pedersen (2005) predatory trading model in a framework that allows us to clearly identify the funds that are forced to sell together with the funds that are likely to have access to the information about the fire sale[6] Their theoretical model shows how an informed trader can profit from selling contemporaneously with a distressed fund[7] and buying when price reverts. An informed trader (i.e., a fund

[6]On this topic Chen, Hanson, Hong, and Stein (2008). find results that are consistent with hedge funds front-running distressed mutual funds.

[7]In Brunnermeier and Pedersen (2005) the "pray" is a trader who is forced to sell, e.g., a hedge fund that has to meet a margin call. In our paper, a distressed mutual fund is forced to sell because

sibling) sells the same positions in advance to avoid holding the fire sale stock in the portfolio when the price drops. This pushes further down the price of the fire sale stocks, increasing the cost of distress for the distressed fund. Ultimately, when the distressed fund is done selling, the informed trader buys back the position enjoying the reversal of the price to its fundamental value. Finally, we show that the organizational structure and, more specifically, the size of a fund family has a major impact on the strategies a fund is going to implement: we find the evidence for predatory trading only in large families.

The paper proceeds as follows. Section 2 develops our working hypotheses, while section 3 describes our data sources. In section 4 our results are described and discussed. Section 5 rules out alternative explanations for our results and include additional robustness checks. Section 6 concludes.

2 Hypotheses development

In this section we postulate a set of hypotheses and formulate our empirical predictions on the strategy a fund family, or individual funds inside a family, could pursue when at least one of its members faces a severe outflow of investor money. Our null hypothesis suggests, that funds in the family do not have access to any privileged information about the position a distressed mutual fund is planning to sell in the market, and a fund entering into distress does not trigger any particular strategy by the siblings. Hence, the behavior and the performance of funds inside the family should not be significantly different from funds outside the fund family during the liquidity shock of the affiliated fund.

of investors' redemptions.

H0: No information sharing and no strategic interaction

a. *Returns of siblings are not affected by the distress of a family member;*

b. *The distressed fund is not affected by family characteristics.*

The existing literature suggests that H0 is not likely to be true. Massa and Rehman (2008), for example, show that there exist significant amounts of private information flows inside financial business groups. Gaspar, Massa, and Matos (2006) find evidence that mutual fund families pursue coordinated strategies to maximize profits on the family level. Drawing on insights offered by academic literature, we propose three alternative hypotheses.

Bhattacharya, Lee, and Pool (2012) find that funds of mutual funds, quite common in large families, cooperate with some of the funds experiencing high redemptions through investing in their shares. This study suggests that in large mutual fund families there is a higher likelihood of cooperation among family members. Therefore, our hypothesis H1 investigates an overall cooperation strategy inside mutual fund families aiming to help members experiencing a severe liquidity shock. The liquidity provision is thereby particularly prevalent among large mutual funds due to the bigger internal capital market.

This hypothesis predicts that funds in large families pay a lower cost of distress. Furthermore, it predicts that the fire sale stocks of funds belonging to large fund families face less price pressure. There is, however, no clear prediction concerning the performance of the liquidity providers. On the one hand, Bhattacharya, Lee, and Pool (2012) find that liquidity provision negatively affects the performance of funds of mutual funds. On the other hand, there is an extensive literature documenting the profitability of liquidity providing strategies at a stock level (see, for instance, Da, Gao, and Jagannathan (2011)).

H1: Cooperation

a. *Distressed funds in large mutual fund families pay a lower cost of distress;*

b. *Fire sale stocks held primarily by funds belonging to large fund families face less demand pressure.*

The second empirical prediction is equivalent to Schmidt and Goncalves-Pinto (2012). However, the authors are not testing the first part of the hypothesis which, in our opinion, is crucial. Observing that fire sale stocks mainly held by distressed funds in large fund families face less demand pressure measured over a quarterly horizon does not necessarily imply that other fund family members are providing liquidity to the distressed fund. It is also consistent with the idea of "Predatory Trading" put forward in the seminal paper by Brunnermeier and Pedersen (2005). Brunnermeier and Pedersen (2005) show that an optimal strategy of an informed trader can be to front-run the distressed trader. The informed trader thereby tries to sell holdings in potential fire sale stocks before or simultaneously with the distressed trader. After the distressed trader has liquidated all his positions in the stock, he buys back its position at a lower price and profits from the reversal back to fundamental value. At a quarterly horizon such a behavior can look like liquidity provision if prices are already pushed back to fundamental value by the non-distressed traders.

Such a behavior is thereby more likely in large fund families. Kempf and Ruenzi (2008) find that in large fund families competition among fund members is much more intense. We maintain that more competition makes predation more likely. Therefore, in our next hypothesis we conjecture that mutual funds in the same family are predating their distressed siblings. This hypothesis has clear predictions concerning the performance of a distressed fund and the performance of siblings. The performance effect on siblings is positive, because they limit their losses through the front-running and profit from the reversal back to fundamental value. Since we conjecture that predatory trading is more likely in large families, we would expect distressed funds in large families to report more negative performance than distressed funds in small families.

Most mutual funds are not allowed to engage in short-selling. For this reason, to front-run the distressed fund, other funds in the family need a portfolio overlap with the distressed fund[8]. We, therefore, suggest that the negative impact of predatory behavior on the performance of a distressed fund increases with the portfolio overlap of other funds in the family with the distressed fund.

H2: Predatory Trading and Family Tournaments

a. *Siblings profit from the distress of a family member;*

b. *Distressed funds in large families are more likely to be predated due to tournament behavior;*

c. *The negative performance of distressed funds is increasing in the portfolio overlap with other funds in the family.*

In hypothesis H2 we implied that funds are acting individually. This seems to be in contrast with studies like Gaspar, Massa, and Matos (2006) and Bhattacharya, Lee, and Pool (2012), which find evidence of overall family coordination in large mutual fund families. A predatory trading behavior, nevertheless, can be inconsistent with an overall family strategy. Nanda, Wang, and Zheng (2004) indicate that a poor performing fund does not have a significant effect on the rest of the family, whereas a top-performer has positive spill-over effects on all the funds in the family. Hence, through predation, a family has a possibility to create a top-performing fund with

[8]Chen, Desai, and Krishnamurthy (2012) report that in 2009 only 7% of equity mutual funds used short sales. However, for these funds an overlap in stock holdings is not a necessary condition to predate.

positive effects on all other funds. Moreover, boosting the returns of valuable sibling funds at the expense of distressed funds makes particularly sense if we take into account the findings of Sirri and Tufano (1998), showing that an improvement in the return of a good fund disproportionally attracts new inflows, while on the contrary, the outflows of the worst performing funds are less affected by a further drop in performance.

Consistent with Gaspar, Massa, and Matos (2006) a family thereby favors the most valuable funds, i.e., funds with high fees, to maximize family profits. Along these lines, we conjecture in our last hypothesis that families coordinate the predation of distressed funds. The predictions of this hypothesis coincide with the predictions of H2, except that the positive performance effect on siblings is concentrated among high-fee funds.

H3: Coordinated Predatory Trading

a. *High-fee siblings profit from the distress of a family member;*

b. *Distressed funds in large families are more likely to be predated;*

c. *The negative performance of distressed funds increases in the portfolio overlap with other funds in the family.*

3 Data

For our empirical analysis we merge mutual fund data from the CRSP Survivor Bias Free US Mutual Fund Database with mutual fund holdings data from CDA/Spectrum. Our sample period spans the time period from 1990 to 2010. We focus on the time after 1990 when the number of merged funds increases significantly. From the CRSP mutual fund database we obtain data on monthly returns, the fund family name and several characteristics commonly used in the literature like fund size and expense ratio. All our analysis is done on a quarterly frequency. Therefore, we cumulate the returns in CRSP to get quarterly returns. The CDA/Spectrum database provides us with mutual fund stock holdings on a quarterly reporting frequency. After merging the two databases we apply several filters to the data.

First, holdings in the CDA/Spectrum database are most complete for domestic open-end equity mutual funds. Therefore, we only include funds with investment objectives “Aggresive Growth”, “Growth” and “Growth & Income” in the Spectrum Database. Second, the CRSP mutual fund database often includes several share classes of one fund. All the share classes however are managed by the same manager and the same portfolio is underlying them. To avoid double counting we eliminate duplicates and aggregate the fund level variables across different share classes. Third, the focus of our analysis is on mutual fund families. Hence, we require that a fund reports its management company. Furthermore, we exclude families with less than two family members. The last filter we impose concerns the number of return observation. In our empirical analysis our dependent variables are raw returns as well as risk-adjusted returns. For the risk adjustment we thereby have to run time-series regressions on a fund level. To ensure reliable estimates we require a fund to have at least a 3-year return history.

Table 1 shows the descriptive statistics of our final dataset. Our final sample includes a total of 1651 distinct mutual funds organized in 259 distinct mutual fund families. We have around 75000 quarterly observations and on average around 1000 mutual funds per quarter. Other characteristics reported in Table 1 include the quarterly net return, fees, the number of funds, quarterly flows, size and familysize. Following the literature flows are computed as follows:

$$FLOW_{it} = \frac{TNA_{it} - (1+ret_{it})TNA_{it-1}}{TNA_{it-1}}.$$

To mitigate the influence of outliers, we follow Coval and Stafford (2007) and exclude observation with $FLOW_{it} > 2$ and $FLOW_{it} < -0.7$. The $FLOW_{it}$ variable is important in our analysis because we use it to define a fund in distress. The mean quarterly flow in our sample period is 2% and the median is slightly negative. While prior studies also report median flows which are significantly lower than mean flows, they usually report positive median flows. We conjecture that the decrease in median flows is due to the financial crisis since 2007, which led to heavy outflows in the mutual fund sector.

4 Empirical Results

4.1 Cooperation versus Predatory Trading

Are severe liquidity shocks of one fund in a mutual fund family absorbed by other fund members (hypothesis H1) or do other funds in the family trade on their private information to gain from the forced liquidations of other funds in the family (hypotheses H2 and H3)? In this section we test the cooperation hypothesis (H1) against the predatory trading hypotheses (H2 and H3). The most straightforward way to do so is to examine the performance of distressed funds.

The cooperation hypothesis (H1) suggests that liquidity shocks of one fund are absorbed by other funds in the family and the capability to absorb liquidity shocks increases with the number of siblings in the fund family. Schmidt and Goncalves-Pinto (2012) suggest that a higher number of siblings increases the size of the internal capital market and decreases the cost of providing liquidity for a single fund as the costs are split among more parties. Hence, H1 predicts that the underperformance of a distressed fund in a large fund family is lower than the underperformance of a distressed fund in a small family keeping all else equal. On the contrary, the predation hypotheses (H2 and H3) predict that the performance of distressed funds in large families is suffering since the additional selling of the siblings pushes further down the price of the fire sale stocks.

Therefore, the first step of our analysis is to define a fund in distress and whether a fund belongs to a large or a small family. These definitions are arbitrary to some extent. To make our results the least susceptible to data mining we follow the previous literature and repeat our results using different cut-off points. Similar to Bhattacharya, Lee, and Pool (2012), we classify a fund as "distressed" when its flows are below -10%, which corresponds roughly to the 10th percentile of the distribution of flows[9]. Similar to Kempf and Ruenzi (2008) we classify a mutual fund family as large when it has more than 20 members, which corresponds to the 75th percentile of the distribution of families by the number of funds.

Using our definition of distress we keep only distressed funds[10] in our sample and run the following Fama and MacBeth (1973) cross-sectional regressions of (risk-adjusted) returns on the large dummy and other control variables:

$$Return_{i,t} = a + \beta Large + controls + \varepsilon_{i,t},$$

where the control variables are lagged size, lagged flows and lagged returns of a fund as well as the fund's age. The dependent variable in our regressions is either raw returns or risk-adjusted returns[11]. To compute risk-adjusted returns, we run monthly time-series regression of mutual fund excess returns on the three Fama and French (1993) factors and the Carhart (1997) momentum factor using the past three years of data. The risk-adjusted return in month t is then defined as the constant of the

[9] The results stay qualitatively the same using other thresholds

[10] Note that keeping only distressed funds in the sample does not have an impact on our results. Keeping all funds in the sample and using a dummy equal to 1, when a fund is in distress yields the same result. Restricting the sample to distressed funds is however more convenient in terms of the results interpretation

[11] Using other risk-adjustments like 1-factor or 3-factor models does not change the results

time-series regression plus the residual.

Columns 1 and 3 of Table 2 suggest a significant and negative impact of family size on the (risk-adjusted) performance of the distressed fund. Belonging to a large family decreases the (risk-adjusted) returns during the distress quarter by 1% (0.8%). This result is in stark contrast to the cooperation hypothesis (H1) and favors the predatory trading hypotheses H2 and H3. In columns 2 and 4 of Table 2 we include other control variables. The higher dollar volume of stock liquidations of funds with more assets under management (AUM) impacts prices more. Therefore, the returns of such funds during the distress are significantly worse than for small funds. In line with this conjecture, the coefficient on lagged size is significantly negative. The negative and significant coefficient can also be due to the size-performance relationship in mutual fund returns documented by Chen, Hong, Huan, and Kubik (2004).

Other controls include the lagged return of a fund, the lagged flow and the expense ratio. The coefficients reported for these controls are in line with previous research. Carhart (1997) documents that funds with high expense ratios report lower net returns to their investors suggesting that managers cannot compensate higher expense ratios with higher returns. Finally, the coefficient of the $Flow$ is negative, since higher flows in the previous period lead to lower returns in the next. This is because flows increase the size of a fund, which makes it harder to employ the assets profitably due to decreasing returns to scale. Overall, the control variables do not affect the magnitude of the *Large* dummy significantly and they are similar to previous research.

In columns 5 to 8 we replace the *Large* dummy with the dollar size of the family, *FamilySize*. The number of siblings and the AUM of the mutual fund family are highly correlated. Therefore, using *Large* and the AUM of the fund family should yield similar results. As expected, the results are qualitatively the same. Even more interestingly, *FamilySize* is in general regarded as a positive predictor of mutual fund performance due to increasing returns to scale in research and administrative tasks (see Chen, Hong, Huan, and Kubik (2004) and Nanda, Wang, and Zheng (2004)).

However, this relation reverts when a fund enters into a distress situation. In fact, we find that belonging to a large family hurts the performance of a distressed fund consistently with siblings exploiting the forced liquidation exercising further downward pressure on the stock price.

We interpret the evidence from Table 2 as evidence for predatory trading. There is however another possible explanation. Pollet and Wilson (2008) find that funds in larger mutual fund families run more concentrated portfolios. They do so, because fund families want to offer for marketing purposes a large range of different products. To offer different products the portfolios of funds have to be different, which means that there is less scope for diversification for the individual fund. This suggests that the performance funds in large families is more heavily hit by outflows as they have to liquidate larger positions in a stock for a given fund size. To exclude this explanation we make two other tests. First, the predatory trading hypothesis predicts that the negative performance of the distressed funds in large families should increase in the portfolio overlap with other funds in the family. Second, the predatory trading hypothesis predicts that the siblings should earn more when one of their siblings is in distress.

4.2 Portfolio overlaps and the performance of distressed funds in large fund families

A necessary condition for a mutual fund to front-run another mutual fund is to have a portfolio overlap with the distressed fund, since most mutual funds cannot take short positions. Thus, to sell ahead of a distressed fund they need to have an existing position. Therefore, we compute for every family its dollar overlap with the positions the distressed fund was selling during the quarter. In particular we compute:

$$Overlap_t = \frac{\sum_{i=1}^{N}\sum_{j=1}^{M} shares_{i,j,t-1} * price_{j,t-1} * I_{distress_{j,t}}}{\sum_{i=1}^{N}\sum_{j=1}^{M} shares_{i,j,t-1} * price_{j,t-1}}$$

The overlap is computed over all funds i in a family which are **not** in distress and $I_{distress_{j,t}}$ is an indicator equal to one when a distressed fund inside the family is selling stock j during quarter t. Hence, the overlap variable specifies the fraction of the affiliated funds aggregated portfolio invested in the positions of the distressed funds at time $t-1$. In Table 3 we rerun the regression from Table 2 including the overlap and an interaction term of our large variable and the overlap. Table 3 shows that the negative effect of a large family on the performance of the distressed fund only occurs in large families with a positive overlap in the holdings of the distressed fund. Furthermore, column 3 of Table 3 suggests that a high overlap with other funds is positively related to performance given a fund belongs to a small mutual fund family. This can be interpreted as weak evidence for liquidity provision in small mutual fund families.

4.3 Distress in the family and mutual fund returns

To examine the relation between a distress situation in the family and the performance of affiliated funds we run the following Fama and MacBeth (1973) regression after excluding the distressed funds[12] from the sample:

$$Return_{i,t} = a + \beta Distress\_Family + controls + \varepsilon_{i,t}$$

where the control variables are lagged size, lagged flows and lagged returns of a fund, as well as the age. Our dependent variables are again either raw returns or risk-adjusted returns.

[12] We show in the robustness section that this does not affect the results

While we conjecture in hypotheses H2 and H3 that the returns of the affiliated funds are increasing in the number of siblings in the family, in our first test we avoid to take any prior assumption. We first look at the effect of distress in the family on the returns of the affiliated funds unconditionally on the size of the family. Table 4 suggests that there is a positive and statistically significant effect of the *Distress_Family* on the returns of the affiliated mutual funds. The coefficient on *Distress_Family* suggests that having at least a distressed fund in the family increases the quarterly four-factor alpha of the affiliated funds by 0.10%. Hence, even if we do not condition on the number of siblings in the family, funds affiliated with a distressed fund on average profit from the distress of its siblings (this is due to the fact that most funds in our sample belong to large families). This result is consistent with fund siblings selling fire sale stocks before the distressed fund, avoiding the negative effect on their performance when distressed fund is selling, and buying them back to profit from the price reversal[13].

In Table 5 we include an interaction of the *Large* dummy and the *Distress_Family* dummy into the regression. The results suggest that the positive return effect of the *Distress_Family* dummy is concentrated in large mutual fund families. The unconditional *Distress_Family* dummy is insignificant and the interaction term suggests that one distressed fund in a large family increases the quarterly excess returns (4-factor alphas) of the other funds in the family by 0.52% (0.26%). This result corroborates our results from the previous sections. Funds in large mutual fund families predate each other and this allow them to realize significant profits.

Overall, our results suggest a form of predatory trading inside large fund families. So far we are however not able to distinguish between hypotheses H2 and H3. Hence, we are not able to say whether this behavior is due to individual actions of mutual

[13] For the whole strategy to be possible, asset managers have to be informed in advance on which positions the distressed fund is going to liquidate. In the whole analysis we are assuming that information is "less asymmetric" for asset managers within the family.

funds in the family or a coordinated action pursued by the management of a fund complex. In the next section we try to disentangle between these two possibilities.

4.4 Family Tournaments or Coordinated Predatory Trading?

In the last sections, we showed that siblings in large families use private information to predate distressed funds within their own family. However, we did not enter into details on how this strategy is organized. In this section we test whether predatory trading is an uncoordinated behavior by individual asset managers, in the context of a competitive environment within the fund family (H2) against the presence of a coordinated strategy promoted at a family level (H3). Asset managers sharing the same trading room are likely to have lower barriers to private information compared to outsiders. In a competitive environment they can use this information to exploit each other's distress to outperform. This, according to hypothesis H2, will lead to family tournaments in which individual funds are willing to improve their relative performance compared to the siblings, for instance because the best performing funds will get bigger bonuses or better resource allocation. This idea is in line with Kempf and Ruenzi (2008) who show that funds compete to be the relative best performers in their family. The aforementioned behavior does not require any family coordination. The entire predatory trading strategy could, however, be coordinated at a family level (H3). A few arguments suggest that this strategy is potentially beneficial for the whole family. First, the convexity of the flow-performance relation (Chevalier and Ellison (1997), Sirri and Tufano (1998)) suggests that the inflows arising to the siblings due to the outperformance will more than compensate the outflows from the distressed fund. Second, according to our talks with professional asset managers the choice to shut down a distressed fund has no major negative implications for a large family, and,therefore, it appears to be optimal to sacrifice its performance in favor of the siblings[14]. Third, predatory trading may give to a fund family a way to reallocate performance from distressed funds to its most valuable funds. We construct our test on the basis of this last consideration. Considering that in order to improve its ability to generate wealth, a family might like to reallocate performance to its high-fee funds, we investigate whether the outperformance is stronger in these funds or whether it is randomly allocated. In the former case the result would be consistent with a coordinated strategy (H3), in the latter - with family tournaments (H2). We define a fund as "high-fee" whenever its quarterly fees (computed as in Gaspar, Massa, and Matos (2006)) are above a family's median and run the following Fama and MacBeth (1973) regression

$$Return_{i,t} = a + \beta(Distress\_Family * High\_Fees) + controls + \varepsilon_{i,t}.$$

We find positive and significant beta coefficient for high-fee funds in large families (see Table 7). Coherently with our previous results we do not find any outperformance of high-fee funds in small families. Interestingly, the whole outperformance seems to be clustered in high-fee funds from large families with an average excess return of 0.58% and a risk-adjusted return of 0.53%. This result indicates that the performance shifting is economically important at a family level and suggests a coordinated strategy (H3). This result is not surprising if we consider previous research. Gaspar, Massa, and Matos (2006) and Bhattacharya, Lee, and Pool (2012) suggest that fund families are prone to boosting the performance of high-fee funds or past good performers. Moreover, Nanda, Wang, and Zheng (2004) show how mutual fund families organize their structure to increase the probability of generating high performers. However, the most interesting and original result that emerges from our analysis is that family coordinated strategies increase the performance of investors in the high-fee funds at

[14] We run probit regression of the probability of a fund to be shut down in quarter $t+1$ conditionally on being in distress at time t plus controls. The probability of being shut down is positive and significant.

the expense of other investors holding shares of funds in the same mutual fund family.

5 Alternative explanations and Robustness checks

In this section we discuss and address other possible explanations for our results.

5.1 Truncated return distributions

One may be concerned that by excluding distressed funds in estimating the outperformance of the siblings we truncate the return distributions, and by doing so we shift up the average performance of the affiliated funds compared to families where none of the funds is in distress. In this case the positive and significant coefficient of the *Distress_Family* dummy only captures the mechanical effect of truncating the return distribution for some families. To exclude this possibility we rerun our regressions leaving in the sample only funds which have positive flows (see Table 8). In this way we tilt the distribution of the returns upward in the same way for distressed and not distressed families. We find that running the regression from Table 4 using only funds with positive flows makes our result even stronger. Hence, good performers[15] from distressed families are performing better than good performers that are not connected with a distressed fund. Therefore, we can exclude this type of mechanical relation between the *Distress_Family* dummy and mutual fund returns.

5.2 Contrarian trading and return dispersion in large mutual fund families

An alternative explanation for our results could potentially be a larger return dispersion inside large mutual fund families. Nanda, Wang, and Zheng (2004) suggest that it can be rational for a fund family to choose a strategy yielding returns with

[15]Here under "good performers" we mean funds with positive flows.

zero or even negative correlation among funds. In this way the family maximizes the odds that one of their funds is reporting very high returns. Under this scenario the significant relation between *Distress_Family* and returns would be driven by the ex-ante family policy.

To address this concern we first replicate our results including the variable cs_σ, which is the average cross-sectional standard deviation of fund alphas within the same family using the previous 12 months of data. If larger dispersion in investment styles or contrarian strategies are the drivers of our result, we should expect the variables *Distress_Family* or *Distress_Family&Large* to be subsumed by cs_σ. We see from Table 9 that this is not the case.

5.3 Sub-sample Results

Another concern we address is that our result might be driven by a specific time period. Therefore, we split our sample in two subsamples (1990-1999 and 2000-2010) and replicate our regressions. Statistical significance of the coefficients diminishes, but the results remain qualitatively similar.

5.4 Investment styles

In Table 4 we compare the average performance of siblings in large families and unconnected funds for each one of the main investment categories in equity ("Aggressive Growth", "Growth", "Growth and Income") using a t-test. The difference in the performance is very strong among "Aggressive Growth" and "Growth" funds while it is in the same direction but weaker in the class of "Growth and Income" funds. This result suggests that the successful timing of fire sale stocks from family members is mostly driven by growth funds

5.5 Stock-level evidence

Finally, we replicate our analysis at a stock level. To do so we compute the Coval and Stafford (2007) measure conditionally on a stock to be sold mostly by funds belonging to small or large families. This measure calculates the impact of aggregate buying/selling induced by fund flows on stock prices. A low value indicates a downward pressure on a stock (i.e., a fire sale), a high value indicates an upward pressure. The formula we use is the following:

$$PRESSURE_{i,q} = \frac{\sum_j (max(0, \Delta Holdings_{j,i,q}) | flow_{j,q} > Percentile(90th)) - \sum_j (max(0, -\Delta Holdings_{j,i,q}) | flow_{j,q} < Percentile(10th))}{AvgVolume_{i,q-4:q-2}}$$

where the subscripts indicate a change in the holdings of a stock i, by a fund j, in a quarter q. Fire sale stocks are defined as those with pressure below the first decile.

In particular, we compute two versions of the numerator: one, including only funds belonging to small families, and one only with funds belonging to large families. We divide the numerator by the average trading volume in the stock and we keep stocks in the first decile.

We then compute the average 4-factor return for the fire sale stocks for the three months of the distress quarters. What we see from Table 10 is that stocks sold by distressed funds in large families suffer more in the first month of distress compared to those sold by distressed funds in small families. In the second month the difference is not statistically significant. While in the third month the returns revert and stocks sold by distressed funds in large families outperform. This result is compatible with predatory trading in large families. Interestingly, if we compare the quarterly performance they look very similar, this happens because stocks sold by funds from large companies suffer more at first but reverts even more afterwards. However, the distress of a fund might occur at any time of a quarter, this fact increases the variability of our findings and can potentially bias this result.

6 Conclusion

In this paper, we study the response of fund siblings to the distress of a member in their own family. In testing our research question we pay particular attention to large groups, since they seem to have the necessary requirements to promote organized strategies (e.g., large internal capital markets and more funds with similar holdings). We test and discuss three hypotheses: siblings help the distressed fund, siblings sacrifice the performance of the distress fund in order to improve their own, and mutual fund families coordinate a predation strategy to increase the overall benefit of the group.

Our major empirical findings are supportive of the third hypothesis. Siblings outperform when there are distressed funds in the same family and funds pay a higher cost of distress when they have an big number of siblings. This last result sheds new light on the analysis of Chen, Hong, Huan, and Kubik (2004) who show that in general the size of a family has a positive effect on its performance. We find that this result reverts when a fund enters into distress. This evidence indicates that informed siblings sell high and buy low, acquiring fire sale stocks before the distressed fund unloads them into the market (forcing it to sell at a lower price). This trading strategy uses private information to time the fire selling of a family member. Moreover, consistently with the predation hypothesis, the cost of distress increases with the portfolio overlap. This adds further support to the finding that siblings are trading in the same direction as the distressed fund (if cooperation is the preferred strategy, they should trade in the opposite direction). The fact that high-fee funds outperform is coherent with a coordinated strategy encouraged at a family level.

Our results indicate that there is a sharing of private information within mutual fund groups and that this information is used to reallocate performance from distressed funds to high-fee funds. This has positive implications for the investors holding shares of the high-fee funds, but negative effects for the investors holding shares of the distressed funds, even considering that a greater underperformance can trigger more redemptions.

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Table 1: Descriptive Statistics

This table presents the summary statistics for the sample of equity mutual funds over the period 1990 to 2010.

	Mean	Median	SD
Number of distinct mutual funds	1651		
Number of fund-quarter observations	74611		
Number of distinct families	259		
Number of mutual funds per quarter	1011.24	1034.00	239.04
Investor return (in % per quarter)	1.45	1.90	10.54
Age in months	156.55	124.00	115.50
Annual expense ratio	1.21	1.15	0.55
Front-load fee in %	1.02	0.00	1.58
Back-load fee in %	0.24	0.00	0.55
Total load in %	1.39	1.35	0.63
Siblings	21.71	12.00	29.38
Flow (in % per quarter)	2.19	-0.24	15.47
Size (in million USD)	1401.94	226.09	5126.02
Familysize (in million USD)	36959.92	3869.60	96773.79

Table 2: Are distressed funds in large families suffering more?

This table presents Fama-MacBeth cross-sectional regressions of excess and 4-factor abnormal fund returns on fund/family characteristics and controls. The independent variables: ***Large***, a dummy which takes the value of one if a family has more than 20 equity funds; ***Lag***(***FamilySize***), the natural log of the lagged assets under management of the family; ***Age***, the log of the age (in months) of the mutual fund; ***Lag***(***Size***), the natural log of the lagged fund's total assets under management; ***Lag***(***Ret***) fund return in the previous quarter; ***Lag***(***Flow***), one quarter lagged net quarterly flow in the mutual fund, ***Lag***(***FamilySize***), the natural log of the lagged assets under management of the family; ***Exp_ratio***, the expense an investor has to pay.The frequency of the returns is quarterly. **Only** distressed funds are included. The data in the sample is from 1990 to 2010.

	Excess returns		4-factor alpha		Excess returns		4-factor alpha	
Large	**-0.0102*****	**-0.00915*****	**-0.00897*****	**-0.00626*****				
	(-3.341)	(-3.018)	(-4.516)	(-2.737)				
Lag(FamilySize)					**-0.00254*****	**-0.00184*****	**-0.00185*****	**-0.00120*****
					(-4.827)	(-3.316)	(-5.038)	(-2.909)
Age		-0.00180		-0.000296		-0.00103		4.32e-05
		(-0.902)		(-0.186)		(-0.511)		(0.0270)
Lag(Size)		-0.00208**		-0.000953		-0.00142		-0.000525
		(-2.477)		(-1.594)		(-1.632)		(-0.833)
Lag(Ret)		0.0185		-0.0218		0.0224		-0.0199
		(0.444)		(-0.801)		(0.542)		(-0.736)
Lag(Flow)		-0.0179**		-0.00964*		-0.0190**		-0.00962*
		(-2.486)		(-1.992)		(-2.574)		(-1.963)
Exp_ratio		-0.559**		-0.647***		-0.601***		-0.665***
		(-2.489)		(-3.399)		(-2.680)		(-3.486)
Constant	0.00694	0.0277**	-0.00755***	0.00404	0.0249**	0.0343**	0.00424	0.00870
	(0.683)	(2.283)	(-5.605)	(0.540)	(2.142)	(2.628)	(1.480)	(1.128)
R^2	0.043	0.247	0.036	0.193	0.049	0.248	0.041	0.193

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3: Are distressed funds suffering more if they have a portfolio overlap with their siblings?

This table presents Fama-MacBeth cross sectional regressions of excess and 4-factor abnormal returns on fund characteristics and controls. **Only** distressed funds are included. The independent variables are *Large*, a dummy that takes value 1 if the family has more than 20 funds, *Overlap*, the intersection between the stocks the distressed fund is selling and the holdings of the siblings in quarter q-1, $Flow$, the net quarterly flow in the mutual fund, Ret_{t-1}, the fund return in the previous quarter, *Age*, the age of the mutual fund, $Family\_size_{t-1}$, the natural log of the assets under management at the family level and $Size_{t-1}$, the natural log of the total assets under management. The frequency of the returns is quarterly. The data sample is from 1990 to 2010.

	Ex. returns	4-factor alpha	Ex. returns	4-factor alpha
Large	-0.00286	-0.00332	0.000345	-0.00195
	(-0.900)	(-1.159)	(0.103)	(-0.620)
Large&Overlap	-0.0425***	-0.0277**	-0.0580***	-0.0319**
	(-2.901)	(-2.342)	(-3.659)	(-2.170)
Overlap	0.0103	0.00778	0.0120**	0.00592
	(1.324)	(1.462)	(2.088)	(1.308)
$Size_{t-1}$			-0.00168**	-0.000636
			(-2.473)	(-1.247)
Ret_{t-1}			0.0346	-0.00842
			(0.805)	(-0.217)
$Flow_{t-1}$			-0.0192***	-0.0158***
			(-3.006)	(-2.813)
Exp. Ratio			-0.451**	-0.497***
			(-2.167)	(-2.730)
Constant	0.00381	-0.00948***	0.0126	-0.00190
	(0.387)	(-4.999)	(1.542)	(-0.588)
R^2	0.062	0.050	0.237	0.197

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Are funds earning more when they have a distressed sibling?

This table presents Fama-MacBeth cross-sectional regressions of excess and 4-factor abnormal fund returns on family characteristics and controls. The independent variables: *DistressFamily*, a dummy which takes the value of one if a fund belongs to a family with at least one fund in distress (a fund with 10% or more ouflows in a quarter), $Lag(Ret)$, fund return in the previous quarter, $Lag(Flow)$, one quarter lagged net quarterly flow in the mutual fund, *Age*, the log of the age (in months) of the mutual fund, $Lag(FamilySize)$, the natural log of the lagged assets under management of the family and $Lag(Size)$, the natural log of the lagged fund's total assets under management. Distressed funds are not included. The frequency of the returns is quarterly. The data in the sample is from 1990 to 2010.

	Excess returns		4-factor alpha	
DistressFamily	**0.00213****	**0.00112***	**0.00213*****	**0.00102****
	(2.634)	(1.943)	(3.839)	(2.192)
Age		0.000351		0.000111
		(0.503)		(0.280)
Lag(Ret)		0.0986*		0.0395*
		(1.780)		(1.711)
Lag(Flow)		0.00455		0.00380
		(1.101)		(1.666)
Lag(Size)		-0.00111***		-0.000596***
		(-3.651)		(-3.411)
Lag(FamilySize)		0.000947***		0.000821***
		(4.664)		(5.351)
Constant	0.0153	0.00688	-0.00240**	-0.00925***
	(1.519)	(0.594)	(-2.484)	(-2.879)
R^2	0.005	0.159	0.005	0.063

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Are funds in large families earning more when they have a distressed sibling?

This table presents Fama-MacBeth cross-sectional regressions of excess and 4-factor abnormal fund returns on family characteristics and controls. The independent variables: *DistressFamily*, a dummy which takes the value of one if a fund belongs to a family with at least one fund in distress (a fund with 10% or more ouflows in a quarter), *Large*, a dummy which takes value one if the family has more than 20 funds, $Lag(Ret)$, fund return in the previous quarter, $Lag(Flow)$, one quarter lagged net quarterly flow in the mutual fund, *AgeFamily*, the log of the age (in months) of the mutual fund family and $Lag(Size)$, the natural log of the lagged fund's total assets under management. The frequency of the returns is quarterly. Distressed funds are not included. The data in the sample is from 1990 to 2010.

	Excess returns		4-factor alpha	
DistressFamily	-2.63e-05	0.000165	0.000659	0.000476
	(-0.0327)	(0.220)	(1.178)	(0.897)
DistressFamily_&Large	**0.00546*** **	**0.00515*** **	**0.00269** **	**0.00261** **
	(3.026)	(3.289)	(2.387)	(2.326)
Large	-0.00103	-0.00136	0.000638	0.000408
	(-0.786)	(-1.279)	(0.775)	(0.504)
Lag(Flow)		0.00462		0.00413*
		(1.098)		(1.849)
Lag(Size)		-0.000655**		-0.000295*
		(-2.599)		(-1.990)
AgeFamily		0.00131**		0.00110**
		(2.296)		(2.605)
Lag(Ret)		0.0994*		0.0396*
		(1.793)		(1.725)
Constant	0.0155	0.00630	-0.00241**	-0.00988***
	(1.541)	(0.566)	(-2.441)	(-2.788)
R^2	0.011	0.158	0.010	0.063

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Is the result driven by a particular category of funds?

This table shows t-tests on abnormal returns computed with Carhart 4-factor model. The three equity categories of investment from Thompson Reuters are included (Investment objectives 2,3 and 4). In "mean alpha siblings" the average of the alphas of siblings from large distress families is computed while in "mean alpha others" that of all the other funds (unconnected and connected to small distress families). Distressed funds are not included, the period is 1990-2010.

Inv. Obj.	**mean alpha siblings**	**mean alpha others**	**others-siblings**	**t-stat**
Aggressive Growth (2)	.0041132	-.003238	-.0073512	-5.9261
Growth (3)	-.0000562	-.0025588	-.0025026	-5.2229
Growth and Income (4)	-.002267	-.002853	-.000586	-1.2608

Table 7: Is the outperformance stronger for high-fee funds?

This table presents Fama-MacBeth cross-sectional regressions of excess and 4-factor abnormal fund returns on family characteristics and controls. The independent variables: *High_Fees*, a dummy variable, which takes the value of one if the fund fees are above the family's median; *DistressFamily*, a dummy which takes the value of one if a fund belongs to a family with at least one fund in distress (a fund with 10% or more ouflows in a quarter); $Lag(Ret)$, fund return in the previous quarter; $Lag(Flow)$, one quarter lagged net quarterly flow in the mutual fund; *AgeFamily*, the log of the age (in months) of the mutual fund family and $Lag(Size)$, the natural log of the lagged fund's total assets under management. The frequency of the returns is quarterly. Distressed funds are not included. The data in the sample is from 1990 to 2010.

	Excess return	4-factor alpha	Excess return	4-factor alpha
Funds x Family	**Small**	**Small**	**Large**	**Large**
DistressFamily_&HighFees	**5.06e-06**	**2.85e-05**	**0.00582*****	**0.00534*****
	(0.00481)	(0.0318)	(3.124)	(3.062)
DistressFamily	0.000175	0.000526	0.00287**	0.000686
	(0.226)	(1.019)	(2.084)	(0.555)
HighFees	0.00126	3.12e-05	-8.05e-05	-0.00155
	(1.408)	(0.0673)	(-0.0629)	(-1.197)
Lag(Ret)	0.0942	0.0323	0.108**	0.0582**
	(1.666)	(1.431)	(2.012)	(2.058)
Lag(Flow)	0.00692	0.00750***	-0.00254	-0.00768
	(1.599)	(2.870)	(-0.450)	(-1.452)
Lag(Size)	-0.000431**	-0.000169	-0.000303	-9.64e-05
	(-2.113)	(-1.020)	(-0.779)	(-0.370)
Constant	0.0121	-0.00344*	0.00984	-0.00560
	(1.289)	(-1.667)	(1.062)	(-1.480)
R^2	0.162	0.062	0.184	0.102

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 8: Conditioning on funds with positive flows

This table replicates table 2 including only funds with flow>0 in order to compare good performers connected to a distressed fund to good performers in unconnected families

	Excess returns		4-factor alpha	
DistressFamily	**0.00499*** **	**0.00211*** **	**0.00416*** **	**0.00162** **
	(5.708)	(2.802)	(6.559)	(2.520)
Age		0.00242***		0.00157***
		(3.735)		(3.306)
Lag(Ret)		0.124**		0.0514**
		(2.200)		(2.187)
Lag(Flow)		-0.00780**		-0.00386
		(-2.042)		(-1.503)
Lag(Size)		-0.00223***		-0.00150***
		(-5.743)		(-6.224)
Lag(FamilySize)		0.00183***		0.00162***
		(7.659)		(7.912)
Constant	0.0211**	0.000248	0.000564	-0.0156***
	(2.078)	(0.0223)	(0.565)	(-4.466)
R^2	0.008	0.172	0.007	0.079

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 9: Are the results explained by larger cross sectional dispersion in fund returns in large families?

This table replicates table 3 including the variable *CS_σ* that is the average cross sectional dispersion of the returns of the funds in the family during the previous 12 months

	Excess returns		4-factor alpha	
DistressFamily	-0.000425	5.65e-05	5.83e-05	0.000160
	(-0.630)	(0.0760)	(0.109)	(0.292)
DistressFamily_&Large	0.00504**	0.00512***	0.00274**	0.00265**
	(2.480)	(2.973)	(2.363)	(2.325)
Large	-0.00117	-0.00153	0.000720	0.000550
	(-0.895)	(-1.402)	(0.845)	(0.673)
CS_σ	0.0813	0.0572	0.0352	0.0221
	(1.522)	(1.610)	(1.139)	(0.845)
Lag(Flow)		0.00585		0.00402*
		(1.416)		(1.827)
Lag(Size)		-0.000620**		-0.000275*
		(-2.372)		(-1.762)
AgeFamily		0.00123*		0.00113**
		(1.853)		(2.376)
Lag(Ret)		0.0965*		0.0367
		(1.702)		(1.563)
Constant	0.0129	0.00409	-0.00378***	-0.0111***
	(1.428)	(0.374)	(-3.622)	(-2.986)
R^2	0.021	0.167	0.016	0.068

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 10: How are the prices of fire sale stocks changing within the distress quarter? This table shows t-tests on average 4 factor alpha returns within a distress quarter depending whether the fire sale has been originated mostly by distressed funds in small (dummy variable ***Large*** equal zero) or in large families (dummy variable ***Large*** equal zero). Fire sale stocks are computed coherently with Coval and Stafford (2007). The data sample goes from 1990 to 2010

	Large	Obs	Mean	Std. Err.	Std. Dev.	[95%	Conf. Interval]
Month 1							
	0	21072	-.005859	.0010497	.1523756	-.0079164	-.0038015
	1	18909	-.009205	.0010436	.1435003	-.0112505	-.0071596
diff = mean(0) - mean(1)						t-stat	**2.2533**
Month 2							
	0	21045	.0059499	.0009827	.1425648	.0040237	.0078761
	1	18891	.0046032	.0009615	.1321582	.0027185	.0064879
diff = mean(0) - mean(1)						t-stat	**0.9755**
Month 3							
	0	20801	.0009204	.0009662	.1393496	-.0009734	.0028142
	1	18695	.0046667	.0009528	.1302797	.002799	.0065343
diff = mean(0) - mean(1)						t-stat	**-2.7509**