Co-Insurance in Mutual Fund Families

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August 28, 2012

Abstract

We argue that cross-trading within mutual fund families can decrease the costs associated with asset fire sales. This in turn creates an incentive for fund families to coordinate internal trades in order to support member funds that are in distress. We find evidence that forced sales by funds experiencing large outflows tend to be absorbed by other funds in the family. We show how this is more likely to be observed in families with a large number of funds, and we provide evidence of reciprocity among funds engaging in this type of co-insurance. Consistent with internal coordination, we document that the stock price reaction arising from the widespread selling by distressed funds is weak or insignificant when such funds belong to large families. We then study how co-insurance affects the behavior of investors and fund managers. Consistent with our hypothesis, we show that affiliation with large families significantly reduces the sensitivity of outflows to poor past performance, especially for funds holding more illiquid portfolios. As a result, we find that fund managers of illiquid funds affiliated with large families take on more risk than their small-family peers.

Keywords: Mutual Fund Families, Internal Capital Markets, Asset Fire Sales, Price Impact, Liquidity, Co-Insurance, Risk-Taking Incentives.

JEL Classification: G11, G23, G30, G32.

I Introduction

Nearly one-third of all U.S. equity flow was traded away from exchanges during the first quarter of 2012. Approximately 20% of all trades were executed internally by brokers matching orders on their own trading desks (cross-trading). Dark pools accounted for an additional 13%. By comparison, the combined internalized and dark pool figures totaled only 15% in 2008.[1] Given the significant and rapidly growing amount of trading taking place away from traditional exchanges, it is important to understand how off-exchange markets affect stock prices and whether they affect the incentives governing the investment management industry.

In this paper, we focus on an important and largely unexplored source of off-exchange trades: the internal markets of mutual fund families. We argue that funds affiliated with large families are likely to coordinate trades in order to provide liquidity to their siblings in the event of liquidity shocks. The rationale for such behavior is as follows. Equity funds experiencing significant outflows may be forced to sell their stock holdings in the open-market at an asset fire sale discount (e.g., Coval and Stafford (2007)). We postulate that funds belonging to large families can, alternatively, sell these stocks internally at the prevailing market price. This allows distressed funds to avoid asset fire sale costs they would otherwise incur in the open-market. By absorbing asset fire sales, affiliated funds essentially co-insure one another against liquidity shocks. In other words, these coordinated trades can mitigate the costs associated with investors' heavy share redemptions – a benefit of particular importance to funds holding more illiquid assets.

The existence of an internal capital market and the possibility of co-insurance thus affect the effective price at which mutual fund managers can trade their assets. As a result, it is likely to also have an impact on the behavior of both managers and investors. If adopted on a sufficiently large scale, this in turn can ultimately affect asset prices in the open market. The purpose of this paper is to understand some of these effects.

We provide evidence consistent with the coordination of some trades taking place in the internal markets of mutual fund families, and then study the circumstances under which coordination is more likely to occur. Finally, we analyze its effects on stock prices and on the behavior of managers and investors.

Although co-insurance can greatly benefit distressed funds in need of liquidity, it may come at a cost for those funds that serve as counterparty for these forced transactions. We argue, however,

[1] These estimates were obtained from Tabb Group, a financial markets' research and strategic advisory firm focused on capital markets.

that the absorption costs incurred by individual funds decrease as the number of funds in the family increases. Consistent with this prediction, we find the level of co-insurance to be more pronounced in families with a larger number of funds.[2]

Ideally, differentiating between coordinated and uncoordinated trades would involve comparing the actual levels of absorption observed in the data with those observed in a sample of (otherwise identical) families with uncoordinated trades across affiliated funds. In that spirit, our main empirical strategy is to construct pseudo (comparable) families by randomly combining funds from different families. In particular, we replicate the structure of each one of our large families by randomly drawing similar funds from the remaining families in the sample. Because these pseudo-families consist of funds from different families, their trades should not be coordinated by construction. We then use such families to benchmark the levels of absorption found in the actual sample. Our tests consistently indicate that the degree of absorption displayed by actual families are significantly higher than what one would expect in the absence of coordination.

Our next step is to look at the characteristics of the funds involved in co-insurance. We look at three characteristics that can affect the level of co-insurance: the value of the distressed funds to the family, the absorption costs incurred by the absorbing funds, and reciprocity.

We show that the funds more likely to have their forced sales absorbed tend to be relatively more valuable to the family. In particular, these are funds with higher fees, good past performance, and less liquid assets. On the other hand, funds are more likely to absorb when it is relatively less costly for them to do so. For instance, we show that these are larger funds in size, with poorer past performance, holding more liquid assets, and experiencing larger inflows.

We also look at reciprocity as a potential driver of co-insurance. We find that funds that have previously absorbed stocks of distressed siblings are more likely to have their own stocks absorbed when they are themselves in distress. One explanation for this finding is that co-insurance arises from the adoption of a strategy of co-operation based on reciprocity, or “tit-for-tat.” Interestingly, we also find that a fund is more likely to absorb sales from a distressed sibling if the managers of these two funds have been working together for the same fund complex for a number of years.

[2] SEC Rule 35(d)-1 requires that an investment company with a name that suggests that it focuses its portfolio holdings in a particular type of investment, or in investments in a particular industry, should invest at least 80% of its assets in the type of investment suggested by its name. As a result, not only it should be more likely to find offsetting trades within large fund families, but it should also be easier to absorb large block trades within large families without having to deviate from compliance with the SEC Rule 35(d)-1. This rule is commonly referred to as a style-drift restriction.

Finally, we look at the characteristics of the stocks begin absorbed. We find strong evidence that stocks are more likely to be absorbed if they are less liquid (more costly to trade on the open market) and with relatively good past performance, which might be preferred by the absorbing manager.

Taken together, our findings are consistent with our co-insurance hypothesis. Our next goal is to look at the consequences of co-insurance.

If co-insurance is indeed more pronounced in larger families, their fund managers and investors may exhibit a different behavior than their small-family peers. On the one hand, co-insurance mitigates the detrimental effects of asset fire sales, which may affect how investors react to performance. In fact, we show that the relationship between fund flows and past performance is more convex for funds in larger families, in particular if they hold more illiquid assets. On the other hand, and given the investors' response to fund performance, co-insurance can induce managers to take on more risk. Our findings support this prediction: managers of more illiquid funds which are affiliated with large families are more prone to risk-shifting.

We also highlight the importance of the off-exchange stock market that is the mutual fund industry. Perhaps not surprisingly, the existence of internal capital markets inside mutual fund families may alter the way their trades affect prices in the open market. For instance, if asset fire sales by distressed funds are absorbed internally, these trades should have no impact on quoted prices of the traded stocks. In fact, we document a weak or null effect on stock prices when a large portion of asset fire sales comes from funds associated with large families (where absorption is more pronounced). Conversely, the price pressure is shown to be strong when forced selling is originated mostly by small-family funds.

Our main hypothesis is that funds in large families coordinate trades in order to provide liquidity to one another. This is possible because funds are allowed to trade with other siblings within their fund complex, essentially bypassing the open market. Cross-trading is the process of matching buy and sell orders electronically for execution, without first routing the order to an exchange or other displayed market. It can represent a significant source of savings in transaction costs for mutual funds.[3] It may also, however, create an incentive for internal coordination of trades, which might violate the fiduciary responsibility that the absorbing funds have to their shareholders.

The U.S. Securities and Exchange Commission (SEC) allows interfund cross-trading through exemptions provided under Rule 17(a)-7 of the Investment Company Act of 1940. A number of conditions need to be satisfied. One of such conditions is that the transaction needs to be effected at the

[3] Examples of crossing platforms include Liquidnet, Pipeline, ITG's Posit, Goldman Sachs' SIGMA X, or BlackRock's Aladdin. No brokerage commission, fee or other remuneration is paid in connection with these transactions.

"independent current market price of the securities," which is usually taken to be the average of the highest current independent bid and lowest current independent offer.[4] Note that such price calculations could leave out the information on volume and liquidity level of the securities involved in the interfund transactions. Assuming a large rate of internal participation, this could mean that funds are able to buy or sell large share blocks at the prevailing price by trading within the fund family, instead of having to break such trade down into smaller orders so as to be able to deal with the open-market.

The ability to cross trade with other affiliated funds then allows fund managers to potentially execute large orders in a short period of time. This would be most beneficial to those funds experiencing large outflows, as they are forced to sell large amounts of stocks to cover redemptions. If these funds can sell those shares internally, bypassing the open market, they can avoid asset fire sale discounts. Of course, this is only possible if other funds in the family are willing to take the other side of the trade. Here we need to make an important distinction between coordinated and uncoordinated trades, which is the central theme of this paper.

Consider the case of a fund j that is being forced to sell stock i. It could be that other funds in the same family decide (independently) to buy stock i at the same time. Although part of these trades would be executed internally, there is no *a priori* coordination. In other words, this would be an example of an uncoordinated cross-trade that happens to benefit fund j. The crucial element here is that fund j did not know in advance it would be able to place those sales internally. On the contrary, our hypothesis of co-insurance implies that fund j expects other funds in the family to absorb its forced sales, even if it implies some distortion of their optimal portfolios.

At a first glance, our hypothesis of co-insurance may seem at odds with the findings of Kempf and Ruenzi (2008). These authors show that funds of a family should not be viewed as coordinated entities, but as individualities that also compete in a family tournament for investors' flows. There are at least two ways to reconcile our hypothesis with the existence of tournaments.

First, co-insurance can be encouraged by the family. Prior literature found evidence of selective allocation of resources within families. In Gaspar, Massa, and Matos (2006) it is shown that families tend to transfer performance to funds that create high value to the fund complex, at the cost of their low-value siblings.[5] It could be the case that a similar argument holds for funds with good past performance (which happen to be in transient distress), or funds that charge higher fees. Consistent with

[4] The SEC Rule 17(a)-7 also stipulates that the transaction needs to be in the best interest of both the selling and buying funds. The concern is that if the buying fund participates in such a transaction, it may be foregoing an opportunity to make a better investment in a different security in the marketplace.

[5] Cohen and Schmidt (2009) provide another example in which funds distort allocations to benefit the family as a whole.

this idea, we show that both distressed funds with a record of good past performance and funds with higher fees are more likely to have their forced sales absorbed within the fund complex. Similarly, if co-insurance is encouraged at the family level, we should also expect the burden of absorption to fall on funds with lower performance (given the convex shape of the response of fund flows to past performance) and with lower fees. We find supporting evidence of the former, but not of the latter.

Another possibility is that there is collusion among managers, who would cooperate in the event of transient liquidity shortfalls for their mutual benefit. We find evidence consistent with collusion. First, as mentioned above, a mutual fund is more likely to be an absorber of forced selling when it has also been in distress at some point in the recent past. In addition, we show that a fund manager under distress is more likely to be helped when she herself was an absorber in the recent past. We also find that fund managers are more likely to be involved in co-insurance when they have been working for the same fund complex for at least a number of years. One explanation for this result is that fund managers may develop social ties during the period of time they work for their common management company. As a result, they may be more willing to cooperate with each other.

We argue that one of the key reasons why so much U.S. equity trading is now making its way outside of traditional exchanges, is the desire to prevent market impact. Consistent with this conjecture, our results indicate price pressure to be less significant for traded securities that are mostly held in common by distressed funds that belong to coordinated families. Conversely, the effect is stronger when most of the forced selling comes from their non-coordinated peers.[6]

The ability to co-insure against liquidity shortfalls may however decrease the likelihood that liquidity shortfalls will happen in the first place. The reason is related to the differences in the flow to performance sensitivities uncovered by Chen, Goldstein, and Jiang (2010). Following substantial outflows, funds need to adjust their portfolios and conduct costly and unprofitable trades, which damage future returns. If mutual funds conduct most of the resulting trades after the day of redemption, most of the costs are borne by the remaining investors. This increases the incentive for the remaining investors to pull their money out of the funds, which creates a "fund-run" effect. Illiquid funds are particularly susceptible to this effect. As a result, Chen, Goldstein, and Jiang (2010) find that the generally convex shape of the flow-performance relationship (e.g., Chevalier and Ellison (1997), Sirri and Tufano (1998)) appears to be more robust for liquid funds than for their illiquid peers. Our hypothesis of co-insurance, however, weakens the link between liquidity and the sensitivity of fund

[6] Flow-driven trading has been shown to trigger price impact. Specifically, Coval and Stafford (2007), Khan, Kogan, and Serafeim (2011), and Lou (2011) show that mutual funds typically scale up and down their existing portfolio positions in response to inflows and outflows from investors and that these "passive" trades create price impact.

flows to past performance. If illiquid funds in large families are insulated from asset fire sale costs, we should *not* expect a higher sensitivity of flows to poor past performance for these funds. Consistent with this argument, we estimate the shape of the sensitivity of investors' flows to past performance of illiquid funds affiliated with large families, which we find to be relatively more convex than that of their small family counterparts. As a result, and consistent with the argument used in Chevalier and Ellison (1997), managers of more illiquid funds are found to take more risks than their small-family peers.

This paper contributes to the literature on mutual funds in a number of ways. First, we emphasize the possibility of co-insurance within mutual fund families, which has been largely overlooked. In doing so, we highlight the fact that the characteristics and organizational form of fund families can be fundamental determinants of their strategic behavior, which can have important implications for asset prices. Secondly, we investigate the implications of potential conflicts of interest that may exist between individual fund managers and fund families, and how those conflicts can reduce the efficiency of the internal capital markets in the mutual fund industry. Finally, we highlight the importance of understanding the implications of such an important off-exchange market as the internal market of mutual fund families.

We conjecture that the incentive for trade coordination within fund families has likely become stronger over the recent past. According to the Investment Company Institute, the amount of exchange redemptions in equity funds has been steadily decreasing over the past 25 years. In year 1987, the redemption rate of equity funds was the highest of the past 25 years, having reached the value of 73%, of which 49.6% were exchange redemptions, and 23.4% were regular redemptions. In contrast, in the year 2011, the redemption rate of equity funds was 30.1%, of which only 3.8% were exchange redemptions.[7]

The remainder of the paper is organized as follows. In Section II we present a brief review of the literature related to this paper. Section III describes the data we use in this study and the strategy we adopt in our empirical tests. Section IV presents our results on trade coordination within fund families, and Section V analyzes its asset pricing implications, its implications for the relation between fund flows and past performance, and its effect on fund managers' risk-taking behavior and performance. A brief conclusion follows in Section VI.

[7] See the 2012 Investment Company Fact Book, 52nd Edition. Exchange redemptions are the dollar value of mutual fund shares switched out of funds and into other funds in the same fund group. Regular redemptions are the dollar value of shareholder liquidation of mutual fund shares.

II Related Literature

Our results complement those in Gaspar, Massa, and Matos (2006) where it is shown that fund families selectively allocate performance across member funds in order to favor those that are more likely to generate higher fee income or future flows into the family. Also related is the work by Pollet and Wilson (2008) who show that funds with many siblings diversify less rapidly as they grow (which may lead to more concentrated portfolios and larger risk taking). Our findings also complement those in Massa (2003) by showing how the organization of funds into families creates positive externalities across them.

We also add to the findings in Nanda, Wang, and Zheng (2004), which show that "winner-picking" strategies can be used to create performance spill-overs within the families. We instead explore the "socialistic" side of the mutual fund family organization and show that strategies aimed at smoothing outflows of funds that are more sensitive to underperformance can be an important instrument to help families achieve the maximization of the value of their net assets under management.[8]

Our results are consistent with those in Massa and Patgiri (2009), which show that family affiliation increases risk taking. What we find is also consistent with the findings in Chen, Hong, Huang, and Kubik (2004), who provide evidence that the performance of a fund is related to the family it belongs to. Guedj and Papastaikoudi (2005) show that performance persists at the family level, and we argue that some of that persistence may be due to co-insurance strategies implemented at the family level.

This paper is also closely related to the extensive literature on mutual fund herding and on the price impact of institutional flows. Examples of work on this issue are Wermers (1999), Coval and Stafford (2007), Frazzini and Lamont (2008), and Lou (2011).

Our work is also related to the research done by Almazan, Brown, Carlson, and Chapman (2004), which shows that fund managers in large families are less constrained by the investors than managers in small families, because the family is supposed to function as a delegated monitor.[9] Moreover, Huang, Wei, and Yan (2007) documents that fund investors are subject to lower participation costs when investing in funds that belong to large families, which may also reduce the transaction costs associated with switching from one fund to another. We believe that such evidence strengthens the significance of our findings. Specifically, even though we should expect outflows to be more sensitive to underperformance, due to the fact that it is easier for investors to substitute between funds within

[8] This "socialistic" view of internal capital markets finds theoretical support on e.g. Bernardo, Luo, and Wang (2006).

[9] See also Gervais, Lynch, and Musto (2005).

larger families, we still find a significantly more convex flow-performance relationship for illiquid funds affiliated with large families, compared to their matched counterparts from small families.

Our work also adds to the debate on the costs and benefits of dark pools of liquidity. A recent theoretical paper by Zhu (2012) shows that dark pools are more attractive to uninformed traders and can therefore improve price discovery on the exchange.[10] Similarly, our results suggest that mutual funds may contribute to the improvement of price discovery on the exchange by coordinating liquidity-motivated trades with their siblings within the fund family before having to deal with the open market. Coordination in internal capital markets of mutual fund families can then help prevent asset fire sales and contagion within the family. A recent study by Blocher (2011) measures the effects of capital flow contagion across portfolio managers linked through overlapping asset holdings. This contagion effect is something very likely to happen within fund families, given the large degree of overlap in the portfolio holdings of funds within families, as documented in Elton, Gruber, and Green (2007).[11]

The research on risk-sharing strategies of mutual fund families is almost non-existent. Closest to ours is a recent paper by Bhattacharya, Lee, and Pool (2012), which investigates how affiliated funds of mutual funds provide liquidity to other funds within the family, in particular when these later funds are experiencing heavy redemption requests from their outside investors.[12] They show that this action reduces the performance of the liquidity providers but improves the performance of the liquidity receivers, by allegedly preventing them from engaging in asset fire sales.

Our paper differs from theirs in many important respects, however. Their focus is on the unilateral provision of liquidity from affiliated funds of funds to their distressed investments. In other words, they study how these affiliated funds can provide liquidity in the form of direct investment. Instead, our focus is on the internal market of mutual fund families. In particular, we are interested in (i) how large-family funds can exploit their ability to cross-trade with other siblings in order to co-insure each

[10] This research is also related with the effect of mutual fund ownership on stock price volatility. Recent papers by Anton and Polk (2010) and Greenwood and Thesmar (2011) show that the concentration of ownership of a financial asset can create stock price fragility via the correlation of the trading needs of its owners. We believe that our results can shed some light on this issue. In particular, the internal absorption of forced transaction within mutual fund families could reduce the fragility of stocks and their volatility on the exchanges.

[11] Elton, Gruber, and Green (2007) find evidence that mutual fund returns are more closely correlated within than between fund families, due primarily to common stock holdings. They show that, depending on the objective group being considered, as much as 34% of total net assets (TNA) consist of stocks held in common by funds in the same objective. For funds with different objectives, the median percent of the portfolio held in the same securities is 17% inside the family compared to 8% outside the family.

[12] Funds of funds are mutual funds that primarily invest in shares of other mutual funds. Affiliated funds of mutual funds are funds that can only invest in other funds in the family.

other, (ii) the consequences of such behavior on the incentives of managers and investors, and (ii) its effects on stock prices.

III Data and Empirical Strategy

In this section we describe our data sources, the construction of our measures of absorption of asset fire sales, and the empirical strategy we develop to identify coordinated trades.

A Data Sources

We employ data from several sources in our analysis. We start with all the funds in the CRSP Survivorship-Bias Free U.S. Mutual Fund Database that can be matched to the mutual fund holdings data from the Thomson-Reuters Mutual Fund Holdings Database.[13] We restrict our sample coverage to the period between 1995 and 2009 because information about the fund families is scarce before 1995.

We focus our analysis on actively-managed domestic equity mutual funds. We use the Lipper classification in CRSP to identify these funds.[14] All stock-level information is obtained from CRSP and only common stocks traded on NYSE, NASDAQ, and AMEX stock markets are included. We require funds to hold at least ten CRSP stocks.

For funds with multiple share classes, we compute fund-level variables by aggregating across the different share classes, using each class TNA as weight. We exclude funds indicated in CRSP as being subject to restricted sales.

We limit our sample to funds whose assets under management reach at least \$100 million in 2009 dollars, using the CRSP value-weighted market index as deflator. We also require that data on total net assets for each fund j and each month t ($TNA_{j,t}$) from CRSP to not be too different from that on Thomson-Reuters (TFN), [$0.75 < TNA_{j,t}^{CRSP}/TNA_{j,t}^{TFN} < 1.25$], and that changes in TNA are not too large, [$-0.5 < (TNA_{j,t} - TNA_{j,t-1})/TNA_{j,t-1} < 2$].

[13] We use the MFLINKS table from WRDS, which follows the procedures in Wermers (2000).

[14] Specifically, we include the following types of funds: Balanced, Capital Appreciation, Equity Income, Flexible Portfolio, Growth and/or Income, Long/Short Equity, Mid, Small, or Micro Cap. If the Lipper classification is missing, we use Weiscat and Strategic Insight to identify the types of funds described above. We exclude all index funds identified either by their classification or their names.

We look at liquidity costs in many of our tests. We resort to Hasbrouck (2009) for trading cost estimates of U.S. equities, and we only include stocks for which this measure is available.[15] Specifically, we use the Gibbs estimate of the effective bid-ask spreads computed from the Basic Market-Adjusted model as our measure of liquidity cost.

We exclude stocks with market capitalization below the first NYSE decile throughout our sample, with median price below $5 (2009 dollars), or with less than 36 months of return history. We also exclude reported fund holdings of less than $1,000 (2009 dollars), or holdings that represent more than 10% of the ownership of the underlying company.[16] In order to further mitigate potential issues with the Thompson database, we also exclude cases in which any fund buys or sells more than 5% of the value of the underlying company.

Our final sample only includes funds with fund family information. We use the management company name from both CRSP and Thomson (TFN) to identify mutual fund families. We manually check for consistency across these two sources and across different sample periods. Whenever inconsistencies are found, we use the 13-F filings to identify the management company. We then assign a unique identifier to each family.

We are primarily interested in the internal market of families with a large number of funds, which we will call *large families*. Our measure of large family is computed as follows. At the end of each quarter we rank families based on their number of funds. We then classify families in the top 5% of the distribution as large. All the other mutual fund families are considered small.

In Table I, we provide information about our final sample. Panel A reports an average number of funds per large family of close to 30, while in small families this number is roughly three. The average size (TNA) of funds is $965 million for large families and $537 million for small families. Therefore, the average fund in a large family is itself larger than the average fund in a small family. We will discuss how that affects our empirical strategy in the next section. In terms of fund portfolio turnover, the large and small family sub-samples are similar, on average, although the median is higher for large families.

As described in the next section, we look at the characteristics of stocks held by the fund to create proxies for its style, in a manner similar to Daniel, Grinblatt, Titman, and Wermers (1997) (DGTW). We look at four stock characteristics: market cap, book-to-market, momentum, and liquidity cost.

[15] We would like to thank Joel Hasbrouck for providing the data on the estimates of liquidity costs in his website: http://people.stern.nyu.edu/jhasbrou/Research/GibbsCurrent/gibbsCurrentIndex.html

[16] If a fund elects to be diversified, the Investment Company Act requires that, with respect to at least 75 percent of the portfolio, no more than five percent may be invested in the securities of any one issuer and no investment may represent more than 10 percent of the outstanding voting securities of any issuer.

We follow DGTW and classify each stock based on a triple sort on size, book-to-market, and momentum.[17] For each one of these characteristics, we assign scores to each stock, ranging from one to five. These scores correspond to the stock's quintile in the triple sort. For our fourth characteristic, liquidity, we assign each stock to a liquidity cost decile and compute its score independently of the other characteristics. Liquidity scores thus range from one (most liquid) to ten (least liquid).

We then value-weight the scores of each stock held by the fund to compute the corresponding fund-level scores. For each of the four stock characteristics, our final measure is the average score of the fund over the previous three years. Panel A of Table I presents the average scores for funds in small and large families. The average size score for a large-family fund is 4.2. Since scores range from one (smallest) to five (largest), this figure implies that most of the fund's portfolio (in terms of value) consists of relatively large stocks. The corresponding score for a small-family fund is lower, about 4.0, but not statistically different from that of large families. A similar picture emerges for the other three characteristics. In particular, the average liquidity cost scores for large- and small-family funds are 3.8 and 3.9, respectively. Since liquidity scores range from one to ten, this number implies that funds hold primarily liquid stocks.

The main purpose of this paper is to provide evidence of coordinated trades within families and to examine its implications. According to our hypothesis, the benefits of co-insurance are more pronounced when distressed funds sell less liquid stocks. In other words, we should observe more absorption of asset fire sales by other funds in the family when the liquidity costs associated with such sales are higher. As detailed in the next section, it will be important to have a sense of how the purchases and sales of stocks vary across family sizes and liquidity costs. To that effect, we report in Panel B of Table I the average trade size (at the fund level) for different family sizes and liquidity cost deciles. Similarly, we report trade averages at the family level in Panel C.

Our measures of trade size are the proportions of the company being bought or sold. One advantage of using this measure is that we can easily aggregate trades across funds to compute the overall proportion of the company being traded. This will facilitate the interpretation of our measures of absorption and their asset-pricing implications. One disadvantage of such measure is that it is directly related to the size of the company, which is in turn related to its liquidity costs. As described below, we take steps to mitigate the potential effects these relations can have on our results.

[17] Specifically, each July we sort stocks into five groups based on each firm's market equity on the last day of June. The firms within each size group are then sorted into five groups based on their book-to-market ratio. Last, the firms in each of the nine size and book-to-market portfolios are sorted into five groups based on their preceding 12-month returns. All measures are computed following Daniel, Grinblatt, Titman, and Wermers (1997) and are described in Table VII.

The relation between trade size and liquidity cost is evident in both Panels B and C – trade size decreases monotonically with liquidity costs. For instance, in Panel B, we find that the average sale by a large-family fund is 4.8 basis points if the stock belongs to the lowest liquidity cost decile, and 10.0 basis points for the least liquid stocks. The difference, 5.2 basis points, is statistically significant at conventional levels. We find a similar pattern for both buys and sells, both at the fund and family levels, regardless of family size.

As mentioned above, funds in large families tend to be larger themselves. This accounts for the differences in trade size observed by comparing small and large families. For instance, the average buy for a large-family fund is 5.1 basis points for the most liquid stocks. At the same liquidity cost decile, the average fund in a small family buys 3.9 basis points of the company. On average, funds buy more than they sell. For instance, the 5.1 basis point average buy of liquid stocks by large-family funds described above is matched by an average sale of 4.8 basis points of the company. This pattern is observed throughout most of the table.

Finally, we report average trade sizes at the family level in Panel C. By definition, larger families have more funds. Therefore, once trades are aggregated, a much larger proportion of the company tends to be traded by the average large family relative to the average small family. For instance, large families sell on average 22.4 basis points of companies in the highest liquidity cost decile. By comparison, small families sell 17.0 basis points of such companies.

Panel C also reports the differences between the trades of companies in the highest and lowest liquidity cost deciles (*High - Low*). When we concentrate on large families, the average buy size increases more rapidly than the average sell size as we move from more to less liquid stocks. However, we do not observe such pattern for small families. Although only suggestive at this point, this pattern is consistent with our hypothesis. If coordinated trades increase with family size and liquidity cost, we should observe purchases increase over sales as stocks become less liquid. We show in the next section how we separate co-insurance from other alternative hypotheses.

It is important to note that the sales described above are not necessarily induced by outflows (i.e., not asset fire sales). We take a number of steps to separate these "forced," liquidity driven, asset fire sales from other trades (which might be driven by information).

B Flow-Induced Selling

In this section, we describe how we compute our measures of flow-induced selling. We start by computing fund j's flows following prior literature (e.g. Chevalier and Ellison (1997), Sirri and

Tufano (1998)). Specifically, we calculate monthly flows as the growth rate of TNA after adjusting for the appreciation of the fund's assets ($R_{j,t}$), assuming that all cash flows are re-invested at the end of the period, $flow_{j,t} = \frac{TNA_{j,t} - TNA_{j,t-1}(1+R_{j,t})}{TNA_{j,t-1}}$.

We use different measures to proxy for outflow-induced sales. The first is the actual proportion of the company being sold by funds in the lowest flow decile (large outflows), similar to the one used by Coval and Stafford (2007). This measure has the advantage of being easy to compute and easy to interpret. One disadvantage is that it assumes that *all* sales by distressed funds are asset fire sales. It is not necessarily the case that every sale by a distressed fund is an asset fire sale. In other words, the probability of an asset fire sale can be different for different stocks.[18]

To overcome this problem, we propose a way to estimate the proportion of actual sales more likely to be the result of outflows. The idea is to scale an actual sale by its attributable risk of being outflow-induced. We define the (attributable) risk that each stock i will be sold by fund j at time t due to outflows as: [19]

$$\text{AR}_{j,i,t} = \frac{\text{prob}[\text{sell}_{j,i,t}|\text{outflow}_{j,t}] - \text{prob}[\text{sell}_{j,i,t}|\text{no outflow}_{j,t}]}{\text{prob}[\text{sell}_{j,i,t}|\text{outflow}_{j,t}]} \tag{1}$$

In other words, $\text{AR}_{j,i,t}$ represents the increase in risk of a share being sold as a result of the occurrence of an outflow. Larger values of AR can be interpreted as indication of higher risk of outflow-induced sales. We therefore use estimates of AR to scale the actual sales we observe in the data. We construct two estimates of AR. In both cases, we first estimate a Logit model and then compute the predicted probabilities $\widehat{\text{prob}}[\text{sell}_{j,i,t}|\text{outflow}_{j,t}]$ and $\widehat{\text{prob}}[\text{sell}_{j,i,t}|\text{no outflow}_{j,t}]$ as:

$$\begin{aligned} \widehat{\text{prob}}[\text{sell}_{j,i,t}|\text{outflow}_{j,t}] &\propto \exp\left(\widehat{\alpha} + \widehat{\beta}\text{outflow}_{j,t} + \widehat{\gamma}\text{controls}\right) \quad \text{and} \\ \widehat{\text{prob}}[\text{sell}_{j,i,t}|\text{no outflow}_{j,t}] &\propto \exp\left(\widehat{\alpha} + \widehat{\gamma}\text{controls}\right) \end{aligned}$$

where $\widehat{\alpha}$, $\widehat{\beta}$, and $\widehat{\gamma}$ are ML estimates from the Logit model.

[18] Alexander, Cici, and Gibson (2007) show that the reason behind the decision to trade matters when assessing trade performance. They look at purchases of stock by funds when funds are experiencing outflows as a signal that such funds have information that such stock is undervalued.

[19] The concept of attributable risk is commonly used in the Epidemiology literature (e.g., Gefeller (1992) and Lloyd (1996)). It is typically defined as $\frac{RR-1}{RR}$, where $RR = \frac{\text{prob[Event}|[Exposure]}{\text{prob[Event|Non-exposure]}}$. In our context, the "event" is the sale of a stock and the "exposure" is the occurrence of an outflow.

We estimate the attributable risk that a stock i will be sold due to outflows at time t by

$$\widehat{\text{AR}}_{i,t} = \frac{\sum_j \left(\widehat{\text{prob}}[\text{sell}_{j,i,t}|\text{outflow}_{j,t}] - \widehat{\text{prob}}[\text{sell}_{j,i,t}|\text{no outflow}_{j,t}] \right)}{\sum_j \widehat{\text{prob}}[\text{sell}_{j,i,t}|\text{outflow}_{j,t}]}$$

where the summation is over all funds in the sample. We use this estimate to scale the actual sales of stock i by each fund j at time t and create our first measure of outflow-induced sales (denoted $OIS^{[1]}_{j,i,t}$ henceforth) as

$$OIS^{[1]}_{j,i,t} = \%\ \text{Sold}_{j,f,t} \times \widehat{\text{AR}}_{i,t}$$

where $\%\ \text{Sold}_{j,f,t}$ represents the proportion of company i being sold by fund j at time t.[20]

Note that $OIS^{[1]}_{j,i,t}$ is scaled by the average increase in sale risk due to outflow across all funds. One alternative is to use the individual predicted probabilities, which gives our second measure of outflow-induced sales ($OIS^{[2]}_{j,i,t}$ henceforth):[21]

$$OIS^{[2]}_{j,i,t} = \%\ \text{Sold}_{j,f,t} \times \widehat{\text{AR}}_{j,i,t} \tag{2}$$

where $\widehat{\text{AR}}_{j,i,t} = \frac{\widehat{\text{prob}}[\text{sell}_{j,i,t}|\text{outflow}_{j,t}] - \widehat{\text{prob}}[\text{sell}_{j,i,t}|\text{no outflow}_{j,t}]}{\widehat{\text{prob}}[\text{sell}_{j,i,t}|\text{outflow}_{j,t}]}$.

Panel A of Table II presents the Logit estimates used in the construction of the outflow-induced sales measures, as well as the correlations of outflow-induced sales with the actual sales. Perhaps not surprising, the estimates in Panel A indicate a higher likelihood of sale when a fund experiences an outflow. Conditional on outflows, funds tend to sell larger companies, companies with lower past returns, and companies for which funds have a larger ownership. These are the estimates we use when computing the predicted probabilities discussed above.

In Panel B of Table II, we present the correlations between the measures of outflow-induced sales and the actual sales. Overall, these correlations are high, ranging between 71% and 73%. Since our measures scale actual sales by the attributable risk of outflows, we should expect them to be more correlated with the actual sales when we focus only on those funds experiencing large outflows. This

[20] Specifically, $\%\ \text{Sold}_{j,f,t} = \frac{\max(0, -\Delta H_{j,i,t})}{\text{Shares}_{i,t-1}}$, where $\Delta H_{j,i,t}$ represents the changes in fund j's holdings of company i between quarters $t-1$ and t, and $\text{Shares}_{i,t-1}$ is the number of shares of company i outstanding at time $t-1$.

[21] And yet another alternative would be to compute the expected trade due to outflows similarly to Lou (2011). First, one would run a regression like the following, $\text{trade} = \beta_0 + \beta_1 \text{outflow} + \text{controls} + \varepsilon$, and then use $\widehat{\text{trade}} = \widehat{\beta}_1 \text{outflow}$ as a measure of flow-induced trade, where $\text{outflow} = \max(0, -flow)$. For the purpose of our study, however, such measure is not ideal because of the low correlation that exists between $\widehat{\text{trade}}$ and actual sales.

is indeed the case: when we restrict our sample to funds in the lowest flow decile, the correlations increase from 73% to 82% for our first measure, and from 71% to 77% for our second measure of outflow-induced sales.

C Absorption of Flow-Induced Selling

Our hypothesis of co-insurance states that asset fire sales by distressed funds will likely be "absorbed" by other funds in the family. In this section, we describe the construction of our absorption measure. Specifically, we define absorption as the log ratio of the number of shares of company i bought by any fund $k \neq j$ within family f and the number of shares of the same company i sold by any fund j within the same family f:

$$A_{i,f,t} = \ln \left(1 + \% \text{ Bought}_{i,f,t}\right) - \ln \left(1 + \% \text{ Sold}_{i,f,t}\right) \tag{3}$$

where the variable $\%\text{Bought}_{i,f,t}$ is the proportion of the company i being bought by all funds $k \neq j$ in family f at quarter-end t, and the variable $\%\text{Sold}_{i,f,t}$ is the proportion of the same company i being sold by funds j affiliated with family f. To compute the absorption of outflow-induced sales, we substitute the $\%\text{Sold}_{i,f,t}$ by one of the outflow-induced sale measures described in Section B above.

It is important to note that it is difficult to infer co-insurance from either the level or the sign of $A_{i,f,t}$. For instance, we can have $A_{i,f,t} > 0$ even under the hypothesis of no coordination of trades – as long as some funds in the family are independently buying more shares than the ones sold by their distressed siblings. The reasons for such behavior include the existence of overlapping portfolios, differences in beliefs, or simply by chance. Similarly, finding higher levels of (absolute) absorption for larger families does not constitute a test of our hypothesis. This is because, mechanically, the probability of an offsetting trade increases with the number of funds in the family. Even if buys and sells are random, we should expect a higher proportion of offsetting trades in a family with hundreds of funds than in a family with only a few funds.

Ideally, a test of co-insurance would involve comparing the actual levels of absorption observed in the data with those observed in a sample of (otherwise identical) families with uncoordinated trades across affiliated funds. In that spirit, our main empirical strategy is to construct pseudo, comparable, families by randomly combining funds from different families. The next section details the construction of these pseudo (comparable) families.

D Simulated Families and Comparable Funds

As explained above, examining only the level of our absorption measures is not ideal. In this section, we propose to compare the actual level of absorption for each family with those of a control group. Intuitively, for each family f we would like to construct a control "family" (or pseudo-family) with the same characteristics as f but with uncoordinated trades across its funds. We take two approaches to that effect. The first is to simulate a series of control or pseudo-families by randomly selecting funds from the entire (remaining) sample. We do that for each of the families that we classify as large. The second approach we use is to create one control or pseudo-family for each large family by selecting the closest comparable funds from small families only. We discuss later the advantages and disadvantages of each approach.

The first step we take to construct these control families is to classify each fund in our sample based on their size and the type of stocks they typically hold (i.e., their style). To that effect, at the end of each quarter, we rank all funds based on their TNA and assign each fund to a TNA quintile. We then use each fund's value-weighted measures of size, book-to-market, and momentum to assign each fund to one of the different styles, similar to Daniel, Grinblatt, Titman, and Wermers (1997). Each fund is then assigned to one of $27 \times 5 = 135$ categories or TNA-style groups. For the remainder of the paper, we use the term "style" to indicate one of these 135 categories.[22]

The idea behind our simulations is simple: by randomly selecting funds from different families we can ideally eliminate the possibility of coordination.[23] This allows us to evaluate the degree of trade coordination within mutual fund families and to explore its implications. Each large fund family f is replicated by randomly drawing mutual funds in the same style as each of its funds from the rest of our sample. The pool of potential matching candidates comes from both small and large families. These large families do not include the family from which we pick the fund to be matched.

Our simulations proceed as follows:

1. For each quarter t:

[22] Daniel, Grinblatt, Titman, and Wermers (1997) construct their 125 style groups based solely on holdings characteristics. Since we further require funds to be similar in size (TNA) using the 125 style portfolios in Daniel, Grinblatt, Titman, and Wermers (1997) proved impractical, as many groups would have just one or two funds.

[23] In practice, when constructing pseudo-families for the family f, we allow for the possibility that the funds sampled also belong to one same family (some other family $g \neq f$). This means that we could potentially pick up coordinated trades between these funds. Since our results are based on the differences between actual and simulated families, the possibility of coordination even in simulated families goes against us.

(a) For a given family f, count the number of actual funds in each of the 135 styles. Let $N(f, t, y)$ represent the number of funds belonging to family f that are assigned to style y at the end of quarter t.

(b) Using the entire sample of funds that do not belong to family f, randomly select $N(f, t, y)$ distinct funds of style y at the end of quarter t.

(c) Repeat this process for each style y of family f.

2. The result is a simulated pseudo-family $\bar{f}_1$ containing the same number of funds as the actual family f and with the same distribution of funds by style.

We repeat this process 5,000 times to construct, for each family f, a sequence of simulated families $\{\bar{f}_b\}$ for $b \in [1 : 1 : 5,000]$. Note that, by construction, there should be little or no coordination of trades within each of these simulated families.

Our second approach involves the use of comparable funds from small families only. The advantage of this approach is that it more closely replicates the size of each comparable fund. In addition, it allows us to look at how funds in large families behave differently than funds in small families. Specifically, for each fund $j \in f$, we find among all small-family funds with the same style as j the one with closest TNA. This process leaves us with one comparable pseudo-family for each large family in our sample.

Note that absorption is a family-stock-quarter measure. As a result, comparing the absorption of a stock by an actual family to that of a pseudo-family requires the sale of that same stock by both these families . One of the problems with using just one sample of comparable funds is that the comparable funds do not necessarily sell the same stock as in the actual family at the same time. As a result, we can only compare a subset of stocks held by the large family (i.e. those that are sold by the actual family and the family of comparables). With simulations we mitigate this problem by requiring that only some of the pseudo-families be selling the stock. We impose different criteria for inclusion and found similar results. We settled for requiring that at least 1,000 pseudo-families sold each particular stock.

In Table II we report the summary statistics for selected characteristics of our actual, simulated, and comparable large families. We do that for the full sample (Panel A), and for illiquid funds only (Panel B). We classify funds as illiquid if they belong to the highest liquidity cost decile. It is important to note that, in general, the characteristics of our simulated and comparable large families do not differ significantly from those of our actual large families.

From Panel A of Table II, we find that a large family in our actual sample has close to 25 funds on average. Note that this number is smaller than the one found on Table I. This is because (i) we only include fund-styles for which we can find at least ten other candidate funds, and (ii) funds in less populated styles are concentrated on the largest families. As a result, removing these funds mitigates the effect of outliers in the number of funds. Note also that the average number of funds in the simulated and comparable samples are smaller relative to the actual sample. This is because there were cases in which we could not find distinct funds belonging to other families (simulated) or to small families (comparables). It is important to note that in all our tests, the computation of absorption measures includes only funds that could be matched. In other words, we *only* compare absorption of families with the same number of funds. Otherwise, our results would be influenced by the mechanical relation between absorption and number of funds described above.

In the column $S - A$ of Panel A we compare the average characteristics of actual and simulated samples. For each characteristic, we compute the difference between the simulation average and the corresponding actual value. We use the time series of estimates to make inference. In the column $P(S \geq A)$ we report the average proportion of simulations in which the simulated value was above the actual value. Thus, this number can be interpreted as an empirical p-value for the difference $S - A$. From Column $P(S \geq A)$, we can see that we cannot reject the hypothesis that the actual and simulated characteristics are different (the exception is the number of funds, as discussed above).

Panel A also compares the characteristics of the actual and comparable families. As we describe above, funds in larger families tend to be larger themselves. As a result, we find a significant difference in the size of actual and comparable funds (the former includes only small-family funds). We also find slightly higher turnover for funds in the actual family and a small difference in the average value-weighted stock size quintile.

Panel B of Table II repeats the analysis for illiquid funds only. Overall, we find similar characteristics when comparing the actual and simulated values. For the comparable sample, we find higher turnover, risk-shifting, liquidity cost, and holdings volatility for the actual family.

Next, we compute the absorption measure, defined in Section C above, for each one of these simulated families. Let $A_{i,f,t}^{[b]}$ denote the absorption measure of stock i at time t by the $b-th$ simulated family with the same characteristics as family f. We then create a measure of excess absorption using these simulated families as $\Delta A_{i,f,t} = \frac{1}{B}\sum_b \left(A_{i,f,t} - A_{i,f,t}^{[b]}\right)$ where B denotes the number of simulations.

Intuitively, higher values of $\Delta A_{i,f,t}$ indicate that families are absorbing more sales than we would expect from similar families with no coordination. We can draw inferences by comparing the actual absorption against the entire distribution of absorption across simulated families. Define $\text{Prob}\left(A^{\text{sim}}_{i,f,t} \geq A_{i,f,t}\right) = \frac{1}{B}\sum_b I\left(A^{[b]}_{i,f,t} \geq A_{i,f,t}\right)$, where $I\left(A^{[b]}_{i,f,t} \geq A_{i,f,t}\right)$ is an indicator function which is equal to one if $A^{[b]}_{i,f,t} \geq A_{i,f,t}$. We interpret $\text{Prob}\left(A^{\text{sim}}_{i,f,t} \geq A_{i,f,t}\right)$ as an empirical p-value. Lower values of $\text{Prob}\left(A^{\text{sim}}_{i,f,t} \geq A_{i,f,t}\right)$ indicate a higher probability that the absorption we actually observe is more than we would expect in the absence of coordination.

IV Co-Insurance

The purpose of this section is to provide evidence that mutual fund families coordinate actions across member funds in order to support affiliated funds that experience temporary liquidity shocks. As discussed above, our empirical approach to measure the absorption of asset fire sales is to compare the offsetting trades observed in large families to those one would observe if coordination was absent. In general, we predict a higher level of absorption of asset fire sales relative to that found for the control groups. In addition, our hypothesis implies that such differences should be more pronounced for less liquid stocks and for funds experiencing large outflows.

A Evidence of Co-Insurance

The first column of Panel A of Table III, titled *All Buys (A)*, shows how the average absorption of *any* sale varies with liquidity costs. To understand how these measures are constructed, note first that absorption is a family-stock-time measure. In other words, our unit of observation is a triple (i, f, t) corresponding to a family f, trading a stock i during the quarter t. Since the focus is on how absorption varies across a stock characteristic (liquidity), we first average absorption across large families to create the measure $A_{i,t} = (1/N)\sum_f A_{i,f,t}$, where N is the number of large families. We then average across stocks in the same liquidity cost decile by computing $A_{d,t} = (1/N_d)\sum_{i \in d} A_{i,t}$, where the summation is over all stocks belonging to liquidity cost decile d. The figures presented in the first column of Table III correspond to time series averages of $A_{d,t}$.

It is clear from Column (A) that, at least unconditionally, absorption decreases monotonically with liquidity costs, which is the opposite of what our hypothesis predicts. In particular, we present in the last row of Panel A the difference between the absorption of high and low liquidity cost stocks. This difference is -8.22 basis points and it is significant at the 5% level. As explained before, this pattern is not surprising given the strong relation between size and liquidity. Note also that, regardless of liquidity levels, not all sales are absorbed on average – all the coefficients are negative. Similar patterns are observed for the simulated sample (Column *Simulated (S)*).

In the third column ($P(S \geq A)$), we compare the estimates of absorption observed in the data with their distributions from the simulated families. We estimate the probability that the simulated absorption is greater than the actual one. Intuitively, lower values of $P(S \geq A)$ indicate a lower proportion of simulations with higher absorption levels than what is observed in the data. We interpret this value as an empirical p-value.

When we look at all sales, the probability that offsetting trades occurring within our simulated families is greater or equal to those occurring within our actual families is generally large, ranging from 28% to 41%. This means that we cannot infer that there is an abnormal level of offsetting trades in actual families. Note, however, that our hypothesis does not make predictions about the absorption of all sales, but only about asset fire or flow-induced sales. Therefore, the large p-values found in column $P(S \geq A)$ do not necessarily contradict our hypothesis. To test whether this pattern persists when asset fire sales are considered, we repeat the analysis using our two proxies for outflow-induced sales.

The first thing to notice in Columns $P(S \geq OIS^{[i]}), m = 1, 2$, is the monotonic decrease in p-values as liquidity costs increase. For instance, in Column $P(S \geq OIS^{[1]})$, p-values decrease from 23% to 8% as we move from the most to the least liquid stocks. This is in line with our prediction that absorption is more pronounced for less liquid stocks. Note also how the p-values decrease relative to those found in Column $P(S \geq A)$. Although we cannot reject the null of no coordination at high levels of significance, the proportion of simulations with higher absorption decreases from 35% to 8% for the least liquid stocks. These differences are even more pronounced in Column $P(S \geq OIS^{[2]})$. First, p-values decrease from 12% to 4% as liquidity costs increase. Second, we only find higher levels of absorption of illiquid stocks in about 4% of the simulations. We interpret these patterns as evidence of co-insurance.

Panel B of Table III repeats the analysis above but only for funds in the lowest flow decile. In other words, we look at the log ratio of buys (by any fund) of stocks sold by funds experiencing extreme outflows. Note that the estimates in Column (A) are now positive, in contrast to their corresponding figures in Panel A. This is simply because we only look at a subset of all sales, i.e., those by distressed funds. More importantly, note how absorption increases with liquidity costs for the actual sample but not for the simulated sample. This is exactly what we would expect in the presence of co-insurance. In addition, the empirical p-values are much lower than their Panel A counterparts, ranging from 13% to 21%. Similarly to Panel A, we find lower empirical p-values when we use our proxies for outflow-induced sales. In fact, for both measures of outflow-induced sales for the least liquid stocks, we can reject the null hypothesis of no coordination at the 5% level.

In Table IV, we report the results of absorption using our families of comparable funds (replicated families using similar funds from small families only). Note that, relative to the comparable families, our actual large families seem to experience a significantly larger amount of purchases per amount of sales of a particular stock, in particular if the selling funds are experiencing extreme outflows and the selling is more likely induced by such outflows. These results confirm what we document in Table III, that there is coordination of trades within large families, in particular when funds within the family are being forced to sell due to heavy redemption requests, and when the liquidity of the assets of the funds involved in these transactions is low.

In the next sub-section we present the characteristics of funds and families that engage in (excess) absorption of outflow-induced sales, as well as the characteristics of their stock holdings.

B Characteristics of Absorbing and Co-Insured Funds

In this sub-section, we study the characteristics of the funds involved in coordinated trading within fund families. We are interested in the following related questions. First, which distressed funds are more likely to have their sales absorbed. Second, which funds are more likely to absorb asset fire sales. Finally, we are also interested in studying which stocks are more likely to be absorbed.

To answer these questions, we take the following approach. First, we look at the largest sale by distressed funds. Note that for our two proxies of outflow-induced sales, these can be interpreted as the largest outflow-induced sale. Everything else constant, these are the sales most likely to be absorbed in the presence of co-insurance. We then examine whether other funds in the family are buying such stock and create a dummy variable, which we use as the dependent variable in a probit model. The advantage of this approach is that we can examine how the probability of absorption is simultaneously related to the characteristics of the stock being sold, the distressed fund, and the absorbing fund.

In Table VI we report estimates of these quarterly probit regressions. Only large families are included. We report the estimates for our three measures of asset fire sale. We run the same regressions for the actual families and for their simulated counterparts. The idea is to test whether the relations found for the actual families are more likely to be attributed to coordination.

We start by examining whether the tenure of fund managers is related to the probability of absorption. We create a dummy variable that indicates whether the managers of the two funds involved have been working on the same family for three years or more (*3yr Manager Overlap*). The idea is that a positive coefficient on *3yr Manager Overlap* indicates a higher probability of absorption if managers have known each other for at least three years. We do find evidence of such effect for the actual sample – for all our measures of asset fire sales we find a positive and significant coefficient at 5% level. Unconditionally, the probability of absorption is about 13%. The increase in the likelihood of absorption implied by the coefficients in Columns (1) to (3) range from 2.0 to 2.2 *percentage points*. We find no significant relationships between tenure and absorption for the simulated sample. Although the coefficients are positive, they are not distinguishable from zero at conventional levels.[24]

We find that absorption is more likely when the stock being sold has performed well in the past. We find a positive and significant coefficient for the *Past Stk Performance* variable, which measures the performance of the stock over the prior 36 months. The average marginal effects range from 64 to 90 basis points and are significant at the 5% level or better. One potential explanation for this is that managers of absorbing funds are more likely to buy past winners, regardless of whether they are asset fire sales or not. We do not, however, find a similar effect for the simulated sample. The significant coefficient for the actual sample may thus be capturing an additional effect. It could be that absorbing fund managers are willing to participate in such offsetting transactions as long as they get to purchase an asset that has performed well in the past. This may be a way for the absorbing fund manager to more easily justify such trades before her shareholders.

Funds are more likely to absorb sales by distressed funds if both have similar styles. On the one hand this is not surprising: funds with similar styles tend to trade similar stocks. But one of the ways we reconcile co-insurance with the presence of tournaments is that absorbing funds would belong to different styles (thus not competing for the same investors' flows). The variable *Same Style* is an indicator of whether both funds belong to the same style. We find positive and significant coefficients for both our actual and simulated samples. As a result, we are unable to differentiate between these two explanations.

We now discuss how the characteristics of absorbing funds affect the probability of absorption. We create a variable called *Prior Distress* to indicate whether the (potentially) absorbing fund was itself distressed at some point during the prior three years. For the actual sample, we show in Table VI that a fund that has been in distress in the recent past is more likely to subsequently absorb asset fire sales originated by its siblings. Estimates range from 3.7 to 4.9 percentage points. We do not find

[24] It is important to note that differences in the magnitudes of the estimates for the actual and simulated samples have to be interpreted with care. This is because of potential differences in the distributions of dependent and independent variables across these two samples. For this reason, we will focus on comparing the significance of the estimates instead.

such relationship for the simulated sample. This result is consistent with a tit-for-tat explanation for co-insurance.

Poor performing funds are more likely to participate in the absorption of outflow-induced sales by other funds in the family. The variable *Fund Performance (q-1)* represents the performance of the absorbing fund during the previous quarter, adjusted for risk by the four-factor model of Carhart (1997). We find negative and significant coefficients for all our measures of outflow-induced sales in the actual sample, but we do not find such result for the simulated families. One explanation consistent with this result relies on the convexity of the response of fund flows to past performance, as documented in Chevalier and Ellison (1997) and Sirri and Tufano (1998). Since flows are less sensitive to poor performance, one can argue that the costs associated with absorption are lower for poor performing funds. As a result, we should observe more absorption by these funds.

If co-insurance is encouraged by the family, we would expect funds with lower fees to absorb more. This is because the costs (to the family) of potential distortions in their portfolio are lower for such funds. The coefficient on *Total Fees (%)* captures this effect. For the actual sample, we do not find a significant relationship between (absorbing funds') fees and absorption. We therefore do not find evidence consistent with this prediction.

Similarly, larger funds would arguably bear lower costs from absorbing asset fire sales. This is because, everything else constant, the absorbed stock would represent a lower proportion of their overall portfolio. For the actual sample we find a positive coefficient for *Log(TNA)(t-1)*. In all specifications, these coefficients are significant at the 1% level. This result must be interpreted with care: an alternative explanation consistent with our results is simply that larger funds buy more stocks. Interestingly, however, we only find a positive coefficient for the simulated sample in one specification, with a 5% level of significance.

We include additional absorbing fund characteristics to control for their average propensity to take the other side of forced sales of assets within the family. These include inflows, the number of stock holdings, and turnover. Perhaps not surprisingly, we find that funds experiencing inflows are more likely to buy stocks, as are funds with a larger number of stocks. Turnover does not seem to significantly affect the probability of absorption: the coefficient on *Turnover* is only positive and significant for one out of six specifications.

We now study some characteristics of distressed funds which we found to be associated with a higher probability of absorption. We start with additional evidence of a tit-for-tat strategy. We create the dummy variable *Previously Absorbed* to indicate whether the distressed fund absorbed stocks at some point during the previous three years. Intuitively, a positive coefficient on this variable indicates a higher probability of absorption for those funds which absorbed stocks in the past. We find a positive coefficient for all specifications when we use the actual sample. For the asset fire sale proxies *Sell* and $OIS^{[1]}_{j,i,t}$ these coefficients are significant at the 5% level, whereas for $OIS^{[2]}_{j,i,t}$ the coefficient is significant at the 10% level. Magnitudes range from 3.9 to 6.3 percentage points. In contrast, only one coefficient is found significant for the simulated sample, at the 10% level. Taken together with our evidence on how prior distress affects the probability of absorption, these results can be interpreted as an indication of collusion among managers in the same family to co-insure one another.

Interestingly, funds that are helped within the family are more likely to be funds which, although in distress now, have displayed good performance in the past. One explanation for this result relies once more on the idea that co-insurance is encouraged at the family level. This means that funds that are experiencing transient distress are more likely to have their sales absorbed. In fact, we find a strong relation between prior performance and absorption. The coefficient on *Fund Performance (3yr)*, i.e., the accumulated performance of the fund adjusted for risk by the four factor model, is positive and significant at 5% level or better for all specifications when the actual sample is used. Average marginal effects range from 12.3 to 23 percentage points. We do not find a similar result for the average simulated family.

Similar patterns are observed when we look at more illiquid funds (*Illiquid Fund*) or funds with higher fees (*Total Fees (%)*). Our result on fees is consistent with the cross-fund subsidization argument of Gaspar, Massa, and Matos (2006) – from a family perspective, funds with higher fees are more valuable. We also find that asset fire sales by illiquid funds are more likely to be absorbed by other funds in the family. These are the funds that benefit the most from co-insurance. This is because it is more costly for such funds to trade their assets, and such funds are more likely to experience fund runs, as documented in Chen, Goldstein, and Jiang (2010). We find that asset fire sales by illiquid funds are 5.7 to 5.9 percentage points more likely to be absorbed by other funds in the family. These estimates are significant at the 5% level.

V Implications of Co-Insurance

In this section, we explore how co-insurance can affect the stock price reaction to asset fire sales and how it can help distort the incentives of the fund managers affiliated with coordinated families.

A Price Reaction to Aggregate Flow-Induced Selling

Aggregate mutual fund trades have been shown to impact stock prices. For instance, Coval and Stafford (2007), Lou (2011), and Jotikasthira, Lundblad, and Ramadorai (2011), among others, argue that aggregate mutual fund trades that occur in response to flows can lead to significant stock price movements. In this section, we study how the internal markets of mutual fund families can affect the stock price response to flow-motivated trades.

Our hypothesis of co-insurance predicts that asset fire sales by distressed funds will be absorbed by other funds in the family. Since these cross-trades will be matched internally, we should observe no price impact. The absence of price impact is, in fact, what links internal trades to co-insurance – distressed funds can bypass the open-market and sell their assets to other funds in the family, thereby avoiding an asset fire sale discount.

In the spirit of Coval and Stafford (2007), we examine the price impact of asset fire sales by identifying instances where a stock happens to be sold by many distressed funds. Because these are liquidity motivated sales, as opposed to informed ones, we should observe a temporary price drop following such events. To capture the magnitude of this effect, we follow Lou (2011) and construct a calendar time portfolio in which we buy stocks with the most selling-pressure and sell stocks with the least pressure. Portfolios are then held for 36 months. This will be a profitable strategy if asset fire sales induce a temporary price decrease. To measure profitability, we construct measures of abnormal returns. These correspond to the intercept of two different models of expected returns: the three-factor model of Fama and French (1993), and the four-factor model of Carhart (1997).

Specifically, at the end of each quarter we assign each stock to a selling pressure decile. The selling pressure for stock i during the quarter t is defined as the difference between aggregate sales and purchases, $\text{Pressure}_{i,t}^{[S]} = \sum_{j \in S} \% \text{ Sold}_{i,j,t} - \sum_j \% \text{ Bought}_{i,j,t}$, where the first summation is over all funds in a subset S, the second summation is over all funds in the sample, $\% \text{ Bought}_{i,j,t}$ is the proportion of company i being bought by fund j during quarter t, and $\% \text{ Sold}_{i,j,t}$ corresponds to one of the asset fire sales measures described in sub-section B of Section III. We compute different measures of selling pressure for different subsets S. We then assign each stock to a selling pressure decile. Calendar time portfolios are formed by buying stocks in the highest selling pressure decile and selling stocks in the lowest decile. Portfolios are rebalanced quarterly and positions are held for three years.

Our hypothesis predicts that when a higher proportion of the selling pressure comes from asset fire sales by large-family funds then it is associated with a smaller price impact. This is because, according to our hypothesis, these sales are being absorbed by other funds in the family, as opposed to being offered in the open market. To test this prediction, we construct a measure of the relative selling pressure exerted by large-family funds as $\textit{Relative Pressure}_{i,t} = \frac{\sum_{j \in \text{Large}} \% \text{ Sold}_{i,j,t}}{\sum_j \% \text{ Sold}_{i,j,t}}$, where in the numerator the summation is over large-family funds only. At the end of each quarter, we assign each stock to a *Large* or *Small* portfolio depending on whether its relative pressure measure is above or below the median. We then construct two distinct calendar time portfolios – including only stocks in the *Large* or *Small* subsets, respectively. Note that this does not mean that only asset fire sales by large families are included in the *Large* subset. What it means is that there are more asset fire sales by large-family funds in the *Large* subset than in the *Small* subset. Note also that each of these portfolios contains an equal amount of stocks at any given time.[25]

In Table VIII we report abnormal returns for different calendar time portfolios, both equal- and value-weighted. In Panel A of Table VIII, we include all asset fire sales in the computation of the selling pressure. For equal-weighted returns, alphas range from 37 to 68 basis points per month. We find significant abnormal returns, at the 5% level or better, for four out of our six specifications. For value-weighted portfolios, alphas range from 28 to 69 basis points. In four out of six specifications we find significant alphas at the 1% level or better. These results are consistent with the findings of Coval and Stafford (2007) and Lou (2011).

In Panel B of Table VIII, we include only events in which a larger proportion of the selling pressure comes from small families. In general, we find higher magnitudes in Panel B than in Panel A, although these differences are not statistically significant.

In Panel C, we include only events where a larger proportion of selling pressure is due to large-family funds. For equal-weighted returns, we lose significance in all but one specification. The four-factor alpha for *Sales* is 59 basis points and significant at the 5% level. When we use other variables, we find no abnormal returns. For value-weighted portfolios, we find smaller magnitudes in all six specifications, compared to their corresponding estimates in Panel B. While in Panel B these estimates range from 36 to 81 basis points, they fall between 29 and 56 basis points in Panel C. We also find weaker statistical significance relative to Panel B.

Overall, these findings are consistent with our hypothesis. When we include in the computation of the selling pressure measure more sales that are likely to be absorbed internally by other large family funds, we find a weaker effect on stock prices.

[25] We only include events in which there is at least one asset fire sale by both a large-family and a small-family fund. We also only consider events in which at least 10 funds sell the stock.

This then suggests that, coordination in the internal capital markets of fund families can mitigate the impact that forced transactions can impose on asset prices. As a result, allowing for cross dealings within fund families, which can potentially attract a significant number of uninformed transactions, may help improve the quality of prices on the stock exchanges. This is consistent with the argument used in Zhu (2012).

B Response of Fund Flows to Past Performance

The finding that the flow-performance relationship seems to be convex for the average fund is consistent with investors being reluctant to redeem shares of losing funds. One explanation for such behavior is the existence of economic or psychological costs associated with the redemption of fund shares. Chen, Goldstein, and Jiang (2010) argue, however, that flow-performance sensitivities are not the same for all types of funds. In particular, conditional on poor past performance, funds that hold illiquid assets experience more outflows than other funds.[26] This difference in sensitivities can be interpreted as investors paying closer attention to the poor performance of illiquid funds. One explanation for this behavior is related to the larger performance consequences of asset fire sales by illiquid funds. Because these are less liquid stocks, asset fire sales of illiquid assets are especially detrimental to the performance of the fund. If investors believe that these effects offset the psychological or economic costs mentioned above, we should observe a less convex flow-to-performance relationship for illiquid funds.

The argument above relies on the existence of larger asset fire sale costs for illiquid funds, which adversely affect performance. However, our hypothesis predicts that these costs are mitigated for distressed funds in large families. If investors understand such pattern, then we should observe a *more* convex flow-to-performance relationship for illiquid funds in larger families relative to their small-family counterparts. In other words, investors in illiquid funds should be less sensitive to withdrawals by other investors (weaker strategic complementarities). This is because the damage created by forced transactions of illiquid assets is partially absorbed by the other funds in the family.

In order to test this hypothesis, we estimate the sensitivity of fund flows to past fund performance using piecewise linear regressions, similar to those used in Sirri and Tufano (1998) and Huang, Wei,

[26] More precisely, Chen, Goldstein, and Jiang (2010) show that illiquid funds start to experience negative net flows at an average monthly relative performance of -0.8%, over the previous six months, while the threshold for liquid funds is -1.6%. In addition, the magnitude of negative net flows for illiquid funds appears to become significantly higher when the funds' average monthly relative performance, over the previous six months, falls below -2.7%. As a result, the generally convex shape of the flow-to-performance relationship, as so documented by Chevalier and Ellison (1997), and Sirri and Tufano (1998), appears to be more robust for liquid funds.

and Yan (2007). To risk-adjust returns, we use the four-factor model of Carhart (1997), estimated using the prior 36 months of returns. At the end of each quarter, we run cross-sectional regressions to estimate the sensitivity of flows to performance. We control for many other factors that could potentially affect the level of flows, as in Huang, Wei, and Yan (2007). The results are displayed in Table IX. In this Table, we report the means and t-statistics from the time series of coefficient estimates, in the spirit of Fama and MacBeth (1973). Because we relate quarterly flows to past performance measured over the preceding 12 months, the cross-sectional flow-performance sensitivity estimated in each quarter is likely to be autocorrelated. To account for this problem, standard errors are corrected using 12 lags, following Newey and West (1987).

In order to test whether co-insurance strategies at the family level affect the sensitivity of the fund flows to past performance, we focus our analysis on the comparison between liquid and illiquid funds, similar to Chen, Goldstein, and Jiang (2010), for our large and small families. The first three columns of Table IX report our baseline specification. The main variables of interest are the performance levels. Following Huang, Wei, and Yan (2007), we first rank the performance of funds into percentiles. We then define $\text{Low}_{j,t-1} = \min(\text{Rank}_{j,t-1}, 0.20)$, $\text{Mid}_{j,t-1} = \min(\text{Rank}_{j,t-1} - \text{Low}_{j,t-1}, 0.60)$, $\text{High}_{j,t-1} = \text{Rank}_{j,t-1} - \text{Low}_{j,t-1} - \text{Mid}_{j,t-1}$, and $\text{Rank}_{j,t-1}$ represents the performance percentile for fund j in the previous quarter.

Our results are consistent with Chen, Goldstein, and Jiang (2010). We find a convex flow-to-performance sensitivity for the entire sample (Column *All*). The sensitivity of flows to poor performance is around 13.6%, whereas the sensitivity of funds to high performance is much larger and close to 45.9%. A similar pattern is found in a sample only including liquid funds (Column *Liquid*). Although the sensitivity to high performance is relatively stable across specifications (ranging from 47.1% to 47.3%), the sensitivity to poor performance is higher for illiquid funds: 24.9% compared to 9.7% for liquid funds.

Our hypothesis predicts that the differences in the sensitivity to poor performance should be smaller for funds in large families. To test this hypothesis, we interact the performance variables with a dummy for large family. We find a negative and highly significant coefficient for the interaction *Low* $\times$ *Large* when we focus on illiquid funds. The coefficient of -26.2% implies that the sensitivity to low performance is *lower* for funds in large families. However, we do not find such effect for liquid funds.

One interpretation of these results is that investors are aware of the co-insurance benefits that can be provided by large families, which attenuates the strategic complementarity and "fund-run" effects documented in Chen, Goldstein, and Jiang (2010). Along the same lines, our results seem to suggest that internal capital markets can be used strategically by fund families in order to mitigate the damaging effects of redemptions and the ownership costs associated with the lack of liquidity of a fund's portfolio holdings. This also suggests that coordination within large fund families can help ameliorate the fund-run effect identified in Chen, Goldstein, and Jiang (2010).

However, the results presented here may raise concerns regarding the fiduciary responsibility of fund families with respect to their investors. In addition, the reduced sensitivity of flows to poor past performance for illiquid funds can lead to changes in the incentives of the managers of these funds that are affiliated with large families. We address this question in more detail below.

C Risk-Taking by Co-Insured Fund Managers

In this sub-section, we analyze whether co-insurance strategies implemented at the family level affect the behavior of their affiliated fund managers. The convexity of the response of fund flows to past performance, and the limited liability associated with it, can implicitly encourage fund managers to take excessive risks (e.g., Chevalier and Ellison (1997) and Basak, Pavlova, and Shapiro (2007)). This asset substitution incentive can be costly for mutual fund investors, as shown in Huang, Sialm, and Zhang (2011).

We argue that if large-family fund managers are at least in part insulated from outflow-related liquidity shocks, they may have the incentive to take more risks.

We use different measures of risk-shifting. Our first measure, denoted Δ*Holdings Volatility*$(q-1, q)$, corresponds to the changes in the volatility of holdings from quarter $q-1$ to quarter q. This measure is intended to capture short-term changes in the volatility of holdings. We look at a longer horizon in our second measure, Δ*Holdings Volatility*$(t-36, t)$, which captures the change in holdings volatility over the past three years.

Our final measure, *Risk-Shifting*, was developed in Huang, Sialm, and Zhang (2011). These authors measure changes in risk by looking at the difference between the current holdings volatility (i.e., based on the fund's most recently disclosed positions), $\sigma^H_{f,t}$, and the past realized volatility based on the fund's realized returns $\sigma^R_{f,t}$ over the prior 36 months. That is to say, *Risk-Shifting*$_{f,t} = \sigma^H_{f,t} - \sigma^R_{f,t}$. This measure is positive if the most recently disclosed holdings exhibit a higher volatility than the actual fund holdings over the prior 36 months and is negative otherwise. Thus, a positive risk-shifting measure indicates that a mutual fund increases the portfolio risk, which is achievable either by holding assets with higher risk levels or by concentrating its portfolio more.

Our goal is to show that sharp increases in risk are more likely in large families than in small families. To that effect, we create dummy variables to indicate large changes in risk. To construct this variable, we first rank funds according to each of the risk-shifting measures described above. We then assign a value of one if the fund belongs to the first decile (highest risk-shifting), and a value of zero otherwise. In Table X, we present the results of probit regressions in which this high risk-shifting dummy serves as dependent variable.

In Panel A of Table X, we include dummies for large families and illiquid funds, as well as fund characteristics shown to affect the risk-shifting measure in Huang, Sialm, and Zhang (2011). We run separate regressions for different levels of performance. In particular, we classify funds based on their performance over the previous quarter (adjusting for risk using the four-factor model). Funds in the first column (*Loser(q-1)*) are those falling on the first quintile of performance, whereas *Winner(q-1)* contains all funds in the fifth performance quintile. All other funds are assigned to the *Mid(q-1)* group. The columns *Loser(t-36)*, *Mid(t-36)*, *Winner(t-36)* are constructed analogously, except that we rank funds based on their performance over the past 36 months.

We find mixed coefficients for the *Large Family* coefficient in Panel A. These results indicate a positive effect for loser funds in two out of three measures of risk-shifting. In general, we do not find a significant effect of large families on risk-shifting for funds belonging to the *Mid* and *Winner* groups. The only exception is for *Mid(q-1)* funds in the Δ*Holdings Volatility*$(q-1, q)$ column, where we find a small marginal effect of 0.5%, significant at the 10% level.

A more consistent pattern emerges when we control for both the size of the family and the liquidity of the fund. From our results above, the largest differences in convexity of the flow-to-performance relationship occur for illiquid funds in large families compared to their small-family peers. Therefore, we interact our dummy for large family with the indicator for illiquid funds. Interestingly, across all specifications, we find a positive coefficient on *Illiquid* $\times$ *Large*. In general, these coefficients are significant for the *Loser* and *Winner* groups. This is in line with the findings in Brown, Harlow, and Starks (1996). The convexity in the flow-to-performance relationship induces loser funds to take on more risk. According to our hypothesis, this convexity is more pronounced for illiquid funds in large families than in small families. If this is the case, we should expect more risk-shifting in large-family illiquid funds than in small-family illiquid funds. A positive and significant coefficient on *Illiquid* $\times$ *Large* is consistent with this argument.

We then conclude that the convex shape of the implicit payoff structure of illiquid funds in coordinated families can ultimately induce managers to take extra risks.

D Net Performance Implications of Co-Insurance for Illiquid Funds

As we documented in the previous sections, the benefits of co-insurance seem particularly pronounced for illiquid funds. In this sub-section we examine whether the performance of these funds can be related to whether they belong to a large or small family. According to our hypothesis, illiquid funds that belong to large families are co-insured against liquidity shocks. Therefore, relative to their small-family peers, these funds should exhibit higher performance.

In Table XI, we report the Fama and MacBeth (1973) estimates obtained from quantile regressions of funds' risk-adjusted performance on several fund characteristics. The goal is to examine how the performance of illiquid funds is affected by their affiliation to a large family at different points of the distribution. We concentrate on the 20th, 50th, and 80th percentiles. Intuitively, these correspond to "poor", "average", and "high" performing funds.

In Panel A, we run different regressions for illiquid and liquid funds. For liquid funds, affiliation to a large family is related to lower performance at the 20th performance percentile. The coefficient on *Large Family* indicates that this decrease in performance is about 10.5 basis points, significant at the 1% level. This effect is consistent with our prior results on the likelihood of absorption. In Table VI we showed that both poor performing and liquid funds are more likely to absorb asset fire sales. If absorption has a negative effect on performance, this effect should be more pronounced for these types of funds, which is what we find in Panel A of Table XI. For the median liquid fund, large family association does not seem to be related to performance. When we look at the 80th percentile, however, affiliation to a large family has a positive effect on performance. This is consistent with the cross-fund subsidization argument of Gaspar, Massa, and Matos (2006), in which the best performing funds will be subsidized by the other funds in the family.

A different picture emerges when we focus on illiquid funds. For these funds, affiliation to a large family has a positive effect on performance in all quantile regressions in Panel A. In particular, the performance of illiquid funds in the lowest quantile we examine is 47.5 basis points higher in large families. One explanation for this result is co-insurance: We showed in Table VI that illiquid funds are more likely to have their sales absorbed. Since these funds can avoid asset fire sales costs, their performance is better relative to similar funds in smaller families.

We find similar patterns in Panel B, in which all funds are included in the estimation. For all quantile regressions, the interaction term *Illiquid* $\times$ *Large* is positive and significant at 1% level.

The main takeaway of this table is that the co-insurance of illiquid funds in large families results in a positive net effect in terms of performance for those funds.

VI Conclusion

In this paper, we document that funds affiliated with large enough families tend to coordinate actions in order to absorb trades executed by their distressed siblings. We provide evidence consistent with tit-for-tat behavior among funds affiliated with the same family, and we show that coordination is more likely to happen when forced transactions involve more illiquid assets. Our argument is that the aggregate adoption of such strategies by mutual fund families mitigates the damaging effects of asset fire sales. As a result, we show how the stock price reaction to such sales is less pronounced for large-family funds. We then explore how risk-sharing strategies implemented at the family level help distort the incentives of the individual fund managers. We show that the convexity of the relation between flows and past performance in illiquid funds is preserved within large families. As a result, co-insurance strategies at the family level can encourage individual managers of illiquid funds to take extra risks.

Overall, our findings highlight the importance of the benefits of co-insurance relative to its costs in the context of the mutual fund industry. These results contribute to our understanding of the incentives behind the form and organization of mutual fund families. As such, they highlight a new dimension to be taken into consideration in the investment decisions of practitioners, and can help inform policymakers on potential regulatory needs.

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Table I: Summary Statistics

This table reports the summary statistics for the main variables employed in this study. In Panel A, we report the mean, median, and standard deviation for each of those variables. In each case, we compute summary statistics separately for the large families (*Large Fams*) and small families (*Small Fams*). Fund-level statistics were computed as follows. First, for each quarter, we average across all funds within a family. Then, we take averages, at each quarter, for each sample separately. The table presents these time-series statistics. A detailed description of each variable is included in Table VII. In Panels B and C, we present the average size of buys and sales by liquidity cost deciles. *Sells (%)*, and *Buys (%)* represent the proportion of the company being sold and bought, respectively (in %). These are time series averages and were computed by first averaging trades of each stock across funds within each family (conditional on a trade occurring). Then, for Panel B, we average these trades across large and small families to compute fund-level averages for each stock-quarter. For Panel C, we sum the trades of all funds in each family instead, to compute family-level averages for each stock-quarter. Finally, we average across stocks within each liquidity cost decile at the end of each quarter. This panel presents times series averages of these numbers. In the last row, (*High - Low*) we compute the difference between the last and first decile. Standard-errors, shown in parentheses, are corrected for serial-dependence with four lags. Throughout the table, $*$, $**$, and $***$ represent significance at the 10%, 5%, and 1% level, respectively.

Panel A - Fund-Level Statistics

	Large Fams			Small Fams		
	Mean	Median	Std Dev	Mean	Median	Std Dev
Number of Funds	29.752	24.000	17.447	3.356	2.000	3.680
TNA (mil)	965.089	677.533	901.707	536.513	220.152	1,002.045
Turnover	1.894	1.840	0.536	1.816	1.407	2.553
VW Size	4.177	4.235	0.279	3.950	4.000	1.047
VW B/M	2.739	2.750	0.172	2.809	3.000	0.510
VW Momentun	3.088	3.064	0.224	3.075	3.000	0.520
VW Liquidity Decile	3.809	3.812	0.467	3.893	4.000	1.140

Panel B - Average Trades by Funds

	Funds in Large Fams		Funds in Small Fams	
	Sales (%)	Buys (%)	Sales (%)	Buys (%)
Low Liq Cost	0.0480	0.0505	0.0381	0.0389
Decile 2	0.0537	0.0570	0.0427	0.0448
Decile 3	0.0595	0.0654	0.0487	0.0517
Decile 4	0.0636	0.0687	0.0514	0.0542
Decile 5	0.0676	0.0749	0.0550	0.0587
Decile 6	0.0733	0.0785	0.0585	0.0622
Decile 7	0.0785	0.0856	0.0623	0.0675
Decile 8	0.0818	0.0924	0.0672	0.0710
Decile 9	0.0873	0.1012	0.0713	0.0782
High Liq Cost	0.1000	0.1125	0.0846	0.0897
High - Low	0.0521***	0.0620***	0.0465***	0.0508***

Panel C - Average Trades by Families

	Large Fams		Small Fams	
	Sales (%)	Buys (%)	Sales (%)	Buys (%)
Low Liq Cost	0.1172	0.1092	0.0437	0.0415
Decile 2	0.1402	0.1334	0.0548	0.0530
Decile 3	0.1496	0.1496	0.0687	0.0657
Decile 4	0.1612	0.1671	0.0766	0.0728
Decile 5	0.1766	0.1805	0.0852	0.0814
Decile 6	0.1786	0.1914	0.0943	0.0913
Decile 7	0.1876	0.2066	0.1038	0.1027
Decile 8	0.1941	0.2164	0.1152	0.1135
Decile 9	0.2078	0.2326	0.1284	0.1228
High Liq Cost	0.2237	0.2770	0.1695	0.1655
High - Low	0.1065***	0.1678***	0.1258***	0.1240***

Table II: Estimating Flow Induced Sales

This table presents Fama and MacBeth (1973) estimates from the quarterly logit regressions used in the construction of the outflow induced measures $OIS^{[1]}$ and $OIS^{[2]}$ (Panel A), as well as their correlation with actual sales (Panel B). At the end of each quarter, we assign a value of one to the dependent variable if fund f sold a stock s it previously held, and zero otherwise. Our main explanatory variables of interest are the level and interactions of *Outflow*, which is a dummy indicating whether the fund experienced an outflow during that quarter. *Ownership(t-1)* represents the proportion of the company held by the fund in the previous quarter. *Past Returns* are the accumulated stock returns over the previous year. Standard-errors, shown in parentheses, are corrected for serial-dependence with four lags. Throughout the table, $*$, $**$, and $***$ represent significance at the 10%, 5%, and 1% level, respectively.

Panel A - Logit Results

	Intercept	Log(ME) (t-1)	Past Returns	Ownership(t-1)	Outflow	Outflow × Log(ME) (t-1)	Outflow × Past Returns	Outflow × Ownership(t-1)
Estimate	−5.089***	0.350***	0.250***	1.222***	0.267***	0.051***	−0.058***	0.131***
Std Error	(0.075)	(0.008)	(0.019)	(0.068)	(0.083)	(0.009)	(0.020)	(0.049)

Panel B - Correlations

	All Funds			Lowest Flow Decile		
	Sell	$OIS^{[1]}$	$OIS^{[2]}$	Sell	$OIS^{[1]}$	$OIS^{[2]}$
Sell	1.000			1.000		
$OIS^{[1]}$	0.729	1.000		0.819	1.000	
$OIS^{[2]}$	0.709	0.843	1.000	0.772	0.864	1.000

Table III: Comparison of Actual, Simulated, and Comparable Families

This table reports the summary statistics for the actual, simulated, and comparable sample of large families. In Panel A, we include all funds in the sample. In Panel B only illiquid funds are included. Statistics for the actual sample (*Actual (A)*) were computed as follows. For the fund characteristics, at the end of each quarter we average across all funds within a family. Then, we take averages for each sample separately. The table presents these time- series statistics. A detailed description of each variable is included in Table VII. To compute the holdings characteristics, we first value-weighted each of the stock level measure to create fund- quarter averages. We then proceed as described above. For the sample of simulated families, we compute the measures described above for each simulated family. To compute the averages in Column *S-A*, we start by computing the difference between the each measure in the actual and corresponding simulated family. The averages presented are across simulations. Standard errors are computed similarly. We also computed in Column $P(S \geq A)$ the proportion of the simulated families with measures above the one found for the actual family. Statistics for the families of comparable funds (*Comparable (C)*) were computed analogously to the actual sample. For each measure, we computed the difference between the comparable and actual family. We then average these differences across families for each quarter and use the time series of averages to test whether the difference *C - A* is significant. Standard-errors, shown in parentheses, are corrected for serial-dependence with four lags. Throughout the table, $*$, $**$, and $***$ represent significance at the 10%, 5%, and 1% level, respectively.

Panel A - Full Sample

	Actual (A)	Simulated (S)	S - A	P(S ≥ A)	Comparable (C)	C - A
Fund Characteristics						
Number of Funds	24.8809	22.3799	−2.5011***	0.0000	23.7751	−1.1059***
Log(TNA)	6.4881	6.3233	−0.1648***	0.3272	6.4593	−0.0288**
4-Factor alpha (%)	−0.0625	−0.0719	−0.0094	0.4760	−0.0754	−0.0107
PS alpha (%)	−0.0619	−0.0706	−0.0091	0.4704	−0.0718	−0.0105
Turnover	1.8990	1.6529	−0.2461***	0.3251	1.8193	−0.0797***
Actual Vol	0.0438	0.0438	−0.0000	0.4967	0.0436	−0.0002
Risk-Shifting (%)	0.2623	0.2341	−0.0282*	0.4514	0.2398	−0.0228
Holdings Characteristics						
VW Size	4.4985	4.4672	−0.0313***	0.2886	4.5428	0.0443***
VW B/M	2.7902	2.7891	−0.0012	0.4460	2.8009	0.0107
VW Momentun	3.0435	3.0417	−0.0018	0.4335	3.0314	−0.0121
VW Liquidity Cost (%)	0.3148	0.3138	−0.0010	0.4672	0.3131	−0.0017
Holdings Vol	0.0464	0.0461	−0.0003	0.4687	0.0460	−0.0004

Panel B - Illiquid Funds

	Actual (A)	Simulated (S)	S - A	P(S ≥ A)	Comparable (C)	C - A
Fund Characteristics						
Number of Funds	2.9923	2.7771	−0.2152***	0.0318	2.8748	−0.1175***
Log(TNA)	5.9139	5.8731	−0.0484	0.4813	5.8578	−0.0645
4-Factor alpha (%)	−0.0198	−0.0362	−0.0114	0.4960	−0.0538	−0.0286
PS alpha (%)	−0.0353	−0.0418	0.0041	0.4918	−0.0534	−0.0110
Turnover	1.7271	1.5313	−0.1900**	0.4189	1.3426	−0.3801***
Actual Vol	0.0597	0.0584	−0.0020	0.4276	0.0587	−0.0017
Risk-Shifting (%)	0.1782	−0.0910	−0.2517***	0.4040	−0.0953	−0.2571***
Holdings Characteristics						
VW Size	2.7845	2.7176	−0.0669***	0.1338	2.7636	−0.0209
VW B/M	2.6146	2.5734	−0.0400	0.2948	2.5350	−0.0777
VW Momentun	3.2196	3.3097	0.1025***	0.3367	3.3007	0.0913**
VW Liquidity Cost (%)	0.4311	0.4105	−0.0247***	0.2755	0.3876	−0.0471***
Holdings Vol	0.0621	0.0577	−0.0047***	0.3709	0.0581	−0.0043***

Table IV: Absorption of Sales by Liquidity Cost Deciles and Simulated Families

This table reports our absorption of sales measures. In Panel A, we include all funds in the sample. In Panel B only funds in the lowest flow decile are included in each quarter. We compute the absorption using both the actual sales and our measures of flow- induces sales. A detailed description of each variable is included in Table VII. We first compute the absorption of sales using all buys *All Buys (A)*. These represent the difference $\ln(1 + \text{Buys}) - \ln(1 + \text{Sells})$, where *Buys* and *Sells* represents the sum of all buys and sells of a given stock by all funds in the family. In Column (A) we compute averages by liquidity cost decile. To compute these measures, we first average the absorption of each stock across all families in a given quarter, and then across all stocks in that liquidity decile. The numbers reported correspond to the time series average of these measures. We also compute our measure of absorption for each simulated family analogously. The column *Simulated (S)* contains the average across simulations, while the column *P(S ≥ A)* contains the proportion of simulations with higher measures of absorption than the actual family. In Column *Excess Buys*, we control for the average quantity of stock being bought by similar funds. Our measure of absorption is then $\ln(1 + \%\text{ Bought} - \text{E}[\%\text{ Bought}]) - \ln(1 + \%\text{ Sold})$, where E[% Bought] represents the average quantity of that stock being bought by all other funds in the same style. We compute measures of absorption using our two flow- induced sales measures as $\ln(1 + \%\text{ Bought}) - \ln(1 + \text{OIS}^{[m]})$, where $\text{OIS}^{[m]}$, $m = 1, 2$ corresponds to our outflow induced sales measures defined in Table VII. In the last row, (*High - Low*) we compute the difference between the last and first decile. Standard-errors, shown in parentheses, are corrected for serial-dependence with four lags. Throughout the table, $*$, $**$, and $***$ represent significance at the 10%, 5%, and 1% level, respectively.

Panel A - Full Sample

	All Sales				Flow Induced Sales			
	All Buys (A)	Simulated (S)	P(S ≥ A)	Excess Buys	$\text{OIS}^{[1]}$	$\text{P(S} \geq \text{OIS}^{[1]})$	$\text{OIS}^{[2]}$	$\text{P(S} \geq \text{OIS}^{[2]})$
Low Liq Cost	−0.0762	−0.0677	0.4091	−0.1043	0.0213	0.2319	0.0085	0.1166
Decile 2	−0.1195	−0.0787	0.4068	−0.1375	0.0270	0.2200	0.0118	0.1088
Decile 3	−0.1221	−0.0988	0.4000	−0.1279	0.0315	0.1893	0.0097	0.1018
Decile 4	−0.1345	−0.1098	0.4029	−0.1407	0.0258	0.1665	0.0106	0.0871
Decile 5	−0.1582	−0.1300	0.4112	−0.1655	0.0345	0.1289	0.0128	0.0776
Decile 6	−0.1248	−0.1275	0.2776	−0.1324	0.0472	0.1055	0.0118	0.0814
Decile 7	−0.1240	−0.1510	0.3958	−0.1340	0.0424	0.1075	0.0181	0.0686
Decile 8	−0.1346	−0.1581	0.3824	−0.1441	0.0525	0.0580	0.0161	0.0273
Decile 9	−0.1102	−0.1767	0.3063	−0.1215	0.0629	0.0824	0.0217	0.0680
High Liq Cost	−0.1580	−0.2019	0.3479	−0.1748	0.0678	0.0803	0.0145	0.0363
High - Low	−0.0822**	−0.1352***	−0.0623***	−0.0711	0.0462***	−0.1545***	0.0058	−0.0817***

Panel B - Lowest Flow Decile

	All Sales				Flow Induced Sales			
	All Buys (A)	Simulated (S)	P(S ≥ A)	Excess Buys	$\text{OIS}^{[1]}$	$\text{P(S} \geq \text{OIS}^{[1]})$	$\text{OIS}^{[2]}$	$\text{P(S} \geq \text{OIS}^{[2]})$
Low Liq Cost	0.0574	−0.0141	0.2026	0.0404	0.0853	0.1187	0.0453	0.0637
Decile 2	0.0949	−0.0075	0.1897	0.0699	0.1072	0.1121	0.0498	0.0620
Decile 3	0.1438	−0.0285	0.1873	0.1298	0.1875	0.0930	0.0582	0.0543
Decile 4	0.1490	−0.0245	0.1937	0.1320	0.1826	0.1015	0.0588	0.0582
Decile 5	0.1160	−0.0591	0.1886	0.1010	0.1197	0.0652	0.0572	0.0531
Decile 6	0.1183	−0.0376	0.1325	0.1041	0.1577	0.0586	0.0769	0.0577
Decile 7	0.2325	−0.0451	0.1668	0.1983	0.2301	0.0651	0.0911	0.0427
Decile 8	0.1783	−0.0550	0.2031	0.1583	0.2114	0.0627	0.0585	0.0388
Decile 9	0.1703	−0.1106	0.1565	0.1464	0.2397	0.0311	0.0860	0.0216
High Liq Cost	0.1118	−0.0316	0.1689	0.0978	0.1771	0.0425	0.0615	0.0377
High - Low	0.0570*	−0.0201	−0.0431***	0.0607**	0.0956***	−0.0901***	0.0157	−0.0341***

Table V: Absorption of Sales and Families of Comparable Funds

This table reports our absorption of sales measures for actual and comparable families. In Panel A, we include all funds in the sample. In Panel B only funds in the lowest flow decile are included in each quarter. For both the actual (*Actual (A)*) and comparable (*Comparable (C)*) families, we compute absorption as the difference $\ln(1 + \text{Buys}) - \ln(1 + \text{Sells})$, where *Buys* and *Sells* represent the sum of all buys and sells of a given stock by funds in the family, respectively. We compute the absorption using both the actual sales and our measures $\text{OIS}^{[m]}$, $m = 1, 2$ of flow-induces sales. A detailed description of each variable is included in Table VII. Statistics for the families of comparable funds (*Comparable (C)*) were computed analogously to the actual sample. For each measure, we computed the difference between the comparable and the actual family. We then average these differences across families for each quarter and use the time series of averages to test whether the difference *C - A* is significant. In the last row, (*High - Low*) we compute the difference between the last and first decile. Standard-errors, shown in parentheses, are corrected for serial-dependence with four lags. Throughout the table, $*$, $**$, and $***$ represent significance at the 10%, 5%, and 1% level, respectively.

Panel A - Full Sample

	All Sales			Flow Induced ($\text{OIS}^{[1]}$)			Flow Induced ($\text{OIS}^{[2]}$)		
	Actual (A)	Comparable (C)	(A) - (C)	Actual (A)	Comparable (C)	(A) - (C)	Actual (A)	Comparable (C)	(A) - (C)
Low Liq Cost	−0.0254	−0.0246	0.0073	0.0087	−0.0034	0.0122***	0.0023	−0.0003	0.0026***
Decile 2	−0.0372	−0.0367	0.0003	0.0104	−0.0031	0.0134***	0.0047	−0.0001	0.0048***
Decile 3	−0.0427	−0.0413	−0.0013	0.0117	−0.0039	0.0155***	0.0028	−0.0010	0.0038***
Decile 4	−0.0478	−0.0501	0.0021	0.0131	−0.0057	0.0205***	0.0044	−0.0011	0.0057***
Decile 5	−0.0673	−0.0585	−0.0084	0.0125	−0.0046	0.0172***	0.0038	−0.0012	0.0049***
Decile 6	−0.0408	−0.0619	0.0219***	0.0171	−0.0059	0.0233***	0.0053	−0.0008	0.0061***
Decile 7	−0.0456	−0.0684	0.0228**	0.0203	−0.0049	0.0276***	0.0075	−0.0016	0.0096***
Decile 8	−0.0486	−0.0674	0.0188**	0.0226	−0.0064	0.0289***	0.0057	−0.0015	0.0073***
Decile 9	−0.0217	−0.0800	0.0579***	0.0279	−0.0108	0.0388***	0.0080	−0.0021	0.0102***
High Liq Cost	−0.0621	−0.0641	0.0387	0.0265	−0.0112	0.0375***	0.0107	−0.0010	0.0118**
High - Low	−0.0371*	−0.0400***	0.0310	0.0176**	−0.0077***	0.0251***	0.0084	−0.0007	0.0091

Panel B - Lowest Flow Decile

	All Sales			Flow Induced ($\text{OIS}^{[1]}$)			Flow Induced ($\text{OIS}^{[2]}$)		
	Actual (A)	Comparable (C)	(A) - (C)	Actual (A)	Comparable (C)	(A) - (C)	Actual (A)	Comparable (C)	(A) - (C)
Low Liq Cost	0.0231	−0.0076	0.0598***	0.0327	−0.0031	0.0513***	0.0170	−0.0000	0.0219**
Decile 2	0.0278	−0.0048	0.0327***	0.0353	0.0019	0.0335***	0.0105	0.0025	0.0080**
Decile 3	0.0304	−0.0064	0.0369***	0.0598	0.0046	0.0552***	0.0159	0.0040	0.0119*
Decile 4	0.0575	−0.0220	0.0796*	0.0696	−0.0081	0.0778**	0.0151	−0.0010	0.0161***
Decile 5	0.0183	−0.0214	0.0397***	0.0331	−0.0019	0.0386***	0.0177	0.0013	0.0173***
Decile 6	0.0284	−0.0097	0.0381**	0.0457	−0.0032	0.0489***	0.0209	−0.0003	0.0212***
Decile 7	0.1179	−0.0318	0.1499***	0.0844	−0.0075	0.0919***	0.0369	−0.0024	0.0393**
Decile 8	0.0171	−0.0322	0.0493*	0.0348	−0.0086	0.0474***	0.0148	−0.0006	0.0163*
Decile 9	0.0647	−0.0876	0.1521**	0.0889	−0.0328	0.1216**	0.0180	−0.0014	0.0194**
High Liq Cost	0.0406	−0.0198	0.0958**	0.0647	−0.0058	0.0723**	0.0179	−0.0005	0.0232
High - Low	0.0219	−0.0133**	0.0486*	0.0395*	−0.0033	0.0340	0.0041	−0.0005	0.0063

Table VI: Probability of Absorption

This table reports the Fama and MacBeth (1973) estimates of quarterly probit regressions in which the dependent variable is an indicator equal to one when an outflow induced sale by a distressed fund is absorbed by another fund in the same family. Only funds in large families are included. To identify outflow induced sales, we concentrate on sales by funds in the lowest flow decile (distressed). For each distressed fund f we identify its largest sale according to each one of the variables *Sale*, $\text{OIS}^{[1]}$, and $\text{OIS}^{[2]}$. We then look at the buys of all other funds $j \neq f$ in the same family as f. If fund j is absorbing the largest sale of fund f, we assign a value of one to the dependent variable (and zero otherwise). Therefore, for each quarter, the unit of analysis is a triple $(j, f, s(f))$, where $s(f)$ represents the largest sale of fund f. *Past Stk Performance* corresponds to the performance of the stock over the prior 36 months. We risk-adjust stock returns using the four-factor model in Carhart (1997). *3yr Manager Overlap* is a dummy equal to one if both managers have been working at the same family for at least three years. For ease of exposition, we separate fund j's characteristics (placed under *Absorbing Fund Characteristics*) from those of fund f, which are under *Distressed Fund Characteristics*. *Prior Distress* indicates whether the absorbing fund was itself distressed at some point during the past three years. *Previously Absorbed* is a dummy indicating whether the fund absorbed stocks from affiliated distressed funds at some point during the past three years. *Fund Performance (q-1)* is the performance of the absorbing fund over the previous quarter, also adjusted by the four-factor model (in %). *Fund Performance (3yr)* is the performance of the distressed fund over the prior three years, also adjusted by the four-factor model. All other variables are individually described in Table VII. Standard-errors, shown in parentheses, are corrected for serial- dependence with four lags. Throughout the table, $*$, $**$, and $***$ represent significance at the 10%, 5%, and 1% level, respectively.

	Actual Sample			Simulated Sample		
	Sell	$\text{OIS}^{[1]}$	$\text{OIS}^{[2]}$	Sell	$\text{OIS}^{[1]}$	$\text{OIS}^{[2]}$
3yr Manager Overlap	0.0209**	0.0200**	0.0224**	0.0094	0.0106	0.0080
	(0.0101)	(0.0099)	(0.0089)	(0.0151)	(0.0198)	(0.0221)
Past Stk Performance	0.0064***	0.0065**	0.0090**	0.0337	0.0431	0.0285
	(0.0024)	(0.0026)	(0.0043)	(0.0502)	(0.0512)	(0.0366)
Same Style	0.0435***	0.0448***	0.0541***	0.0301***	0.0535***	0.0460***
	(0.0121)	(0.0126)	(0.0100)	(0.0094)	(0.0184)	(0.0103)
Absorbing Fund Characteristics						
Prior Distress	0.0494***	0.0484***	0.0373***	0.0054	−0.0053	0.0092
	(0.0073)	(0.0075)	(0.0072)	(0.0053)	(0.0086)	(0.0101)
Fund Performance (q-1)	−0.0011***	−0.0011***	−0.0011***	−0.0007	0.0006	−0.0007
	(0.0003)	(0.0003)	(0.0003)	(0.0007)	(0.0006)	(0.0006)
Total Fees (%)	0.0011	0.0017	−0.0002	0.0170***	0.0137**	−0.0073
	(0.0034)	(0.0036)	(0.0038)	(0.0053)	(0.0066)	(0.0090)
Flow Decile	0.0060***	0.0059***	0.0042***	0.0006*	0.0013***	−0.0002
	(0.0015)	(0.0016)	(0.0012)	(0.0004)	(0.0005)	(0.0008)
Illiquid Fund	−0.0920***	−0.0920***	−0.0727***	0.0141*	0.0101	−0.0111
	(0.0108)	(0.0109)	(0.0066)	(0.0077)	(0.0129)	(0.0078)
Log(TNA) (t-1)	0.0192***	0.0194***	0.0128***	−0.0013	−0.0044	0.0092**
	(0.0030)	(0.0031)	(0.0022)	(0.0039)	(0.0068)	(0.0046)
N Stocks	0.0925***	0.0933***	0.0906***	0.0534***	0.0677***	0.0380***
	(0.0056)	(0.0051)	(0.0054)	(0.0085)	(0.0185)	(0.0108)
Turnover	0.0008	0.0011	0.0033	−0.0060	0.0074	0.0144***
	(0.0020)	(0.0021)	(0.0021)	(0.0055)	(0.0075)	(0.0051)
Distressed Fund Characteristics						
Previously Absorbed	0.0387**	0.0418**	0.0630*	0.1801*	0.1353	0.1598
	(0.0189)	(0.0187)	(0.0329)	(0.0932)	(0.1389)	(0.1519)
Fund Performance (3yr)	0.1240***	0.1231***	0.2307**	−0.6499	−1.9989	0.2826
	(0.0302)	(0.0296)	(0.0921)	(0.8931)	(1.5677)	(0.5491)
Total Fees (%)	0.0488**	0.0486**	0.0702*	−0.4114	−0.3899	0.0327
	(0.0194)	(0.0199)	(0.0384)	(0.4025)	(0.4301)	(0.0200)
Illiquid Fund	0.0594**	0.0572**	0.0564**	−0.0400	0.0539	−0.0205
	(0.0236)	(0.0229)	(0.0276)	(0.0401)	(0.0594)	(0.0547)
Turnover	−0.0066**	−0.0066**	−0.0165*	−0.0036	−0.1438	−0.0558
	(0.0027)	(0.0028)	(0.0098)	(0.0603)	(0.0919)	(0.0578)
Log(TNA) (t-1)	0.0051	0.0048	−0.0071	0.0041	−0.0458	0.0024
	(0.0053)	(0.0052)	(0.0135)	(0.0175)	(0.0579)	(0.0207)

Table VII: Absorption Regressions

This table reports the Fama and MacBeth (1973) estimates of quarterly regressions in which the dependent variable is the family (excess) absorption of outflow induced sales. Only funds in large families are included. To compute the excess absorption of stock i by funds k affiliated with family f, we start by estimating the average proportion of company i being bought by all funds z not affiliated with family f but in the same style as k. We then subtract this average from the actual buys of stock i by fund $k \in f$. We then sum these excess buys over all funds $k \in f$. Our measure of absorption is the (logarithm) of the ratio between these excess buys and the total sales of i by funds in f. In other words, family f's absorption of company i at time t is given by the (logarithm of the) ratio $(1 + \text{Excess \% Bought}(i, f, t))$ over $(1 + \text{\% Sold}(i, f, t))$. We use different measures of sales. *Sell* corresponds to the actual sales. OIS$^{[1]}$ and OIS$^{[2]}$ are our proxies for outflow induced sales. For each of these measures, we compute the absorption of sales by any fund within the family (*All Funds*), as well as the absorption of sales only by funds in the lowest flow decile in that quarter (*Lowest Flow Decile*). *Market Cap(t-1)* and *B/M(t-1)* represent the company's market capitalization and book-to-market ratio at the end of the previous quarter. *Past Stk Returns* are the accumulated stock returns over the previous year. *N Funds* $\times$ *Liq Cost* is the interaction between the number of funds in the family and the stock's liquidity cost (in %). Table VII contains a detailed description of all controls. Standard-errors, shown in parentheses, are corrected for serial-dependence with four lags. Throughout the table, $*$, $**$, and $***$ represent significance at the 10%, 5%, and 1% level, respectively.

	All Funds						Lowest Flow Decile		
	Sell	OIS$^{[1]}$	OIS$^{[2]}$	Sell	OIS$^{[1]}$	OIS$^{[2]}$	Sell	OIS$^{[1]}$	OIS$^{[2]}$
N Funds × Liq Cost				0.260***	0.331***	0.338***	0.419***	0.663***	0.189
				(0.067)	(0.053)	(0.052)	(0.142)	(0.234)	(0.204)
Number of Funds	0.090***	0.150***	0.154***	0.022	0.066***	0.070***	0.024	0.005	0.054
	(0.022)	(0.022)	(0.026)	(0.024)	(0.023)	(0.025)	(0.028)	(0.044)	(0.061)
Stk Liquidity Cost (t-1)	0.061***	0.101***	0.090***	−0.853***	−1.067***	−1.100***	−1.401***	−2.308***	−0.473
	(0.022)	(0.016)	(0.015)	(0.222)	(0.179)	(0.171)	(0.514)	(0.859)	(0.738)
Market Cap(t-1)	0.030***	−0.002	−0.012***	0.030***	−0.002	−0.012***	0.013**	−0.003	−0.017**
	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.005)	(0.005)	(0.007)
B/M(t-1)	−0.005	−0.057***	−0.035***	−0.006	−0.057***	−0.037***	0.031	0.090	0.129
	(0.016)	(0.012)	(0.012)	(0.017)	(0.012)	(0.013)	(0.076)	(0.078)	(0.089)
Past Stk Returns	0.068***	0.048***	0.051***	0.067***	0.048***	0.050***	0.015	0.009	0.059**
	(0.014)	(0.011)	(0.014)	(0.014)	(0.011)	(0.014)	(0.059)	(0.024)	(0.027)
Avg TNA(t-1)	−0.019***	0.048***	0.051***	−0.020***	0.047***	0.051***	0.029***	0.062***	0.133**
	(0.005)	(0.008)	(0.007)	(0.005)	(0.008)	(0.007)	(0.010)	(0.020)	(0.067)
Avg Turnover (t-1)	0.050**	0.096***	0.077**	0.050**	0.095***	0.075**	0.198***	0.108*	−0.292
	(0.020)	(0.027)	(0.030)	(0.019)	(0.027)	(0.030)	(0.051)	(0.058)	(0.302)
Intercept	−0.582***	−0.906***	−0.822***	−0.338***	−0.605***	−0.519***	−0.658***	−0.518**	−0.621***
	(0.116)	(0.097)	(0.101)	(0.119)	(0.092)	(0.094)	(0.168)	(0.206)	(0.209)

Table VIII: Price Pressure by Asset Fire Sales of Large and Small Families

This table reports calendar time returns of portfolios constructed by buying stocks in the highest decile of asset fire sale induced price pressure and selling stocks in the lowest price pressure decile. Specifically, at the end of each quarter we compute a measure of asset fire sale-induced price pressure by computing the difference between aggregate sells and buys for each stock. We compute two different measures of price pressure. The first, includes sales by all funds in the sample. We use this measure to rank all stocks into deciles. We then construct monthly calendar time portfolios in which at the end of each quarter buy companies in highest decile of pressure and sell companies in the lowest pressure decile. The risk-adjusted monthly returns from this portfolio are presented in Panel A (in percentages). In Columns (1)-(3), we include all funds in our computation of price pressure. In Columns (4)-(6) we only include sales of funds in the lowest flow decile. Each column corresponds to portfolios constructed using one of our three measures of asset sales. Our second measure of pressure includes only sales by funds in large families. For each stock-quarter, we compute the proportion of the overall pressure induced by funds in large families by dividing the price pressure measure described above by this second measure. We then split the sample by considering only events in which that proportion is lower than its median (Panel B), and higher than its median (Panel C). The numbers represent monthly alphas from either a three- or four-factor model. All numbers are expressed as percentages. OIS$^{[m]}$, $m = 1, 2$ correspond to our measures of outflow induced sales. Standard-errors, shown in parentheses, are corrected for serial-dependence with 12 lags. Throughout the table, $*$, $**$, and $***$ represent significance at the 10%, 5%, and 1% level, respectively.

Panel A - All

	Equal-Weighted			Value-Weighted		
	Sell	OIS$^{[1]}$	OIS$^{[2]}$	Sell	OIS$^{[1]}$	OIS$^{[2]}$
	(1)	(2)	(3)	(4)	(5)	(6)
3-Factor	0.368	0.473	0.616**	0.641***	0.510***	0.276
	(0.269)	(0.261)	(0.251)	(0.177)	(0.178)	(0.243)
4-Factor	0.585**	0.679***	0.665***	0.691***	0.552***	0.339
	(0.237)	(0.235)	(0.251)	(0.166)	(0.167)	(0.219)

Panel B - Small

	Equal-Weighted			Value-Weighted		
	Sell	OIS$^{[1]}$	OIS$^{[2]}$	Sell	OIS$^{[1]}$	OIS$^{[2]}$
	(1)	(2)	(3)	(4)	(5)	(6)
3-Factor	0.326	0.487	0.795***	0.806***	0.592***	0.364
	(0.275)	(0.262)	(0.287)	(0.166)	(0.160)	(0.255)
4-Factor	0.549**	0.698***	0.818***	0.831***	0.617***	0.395
	(0.252)	(0.246)	(0.286)	(0.163)	(0.156)	(0.237)

Panel C - Large

	Equal-Weighted			Value-Weighted		
	Sell	OIS$^{[1]}$	OIS$^{[2]}$	Sell	OIS$^{[1]}$	OIS$^{[2]}$
	(1)	(2)	(3)	(4)	(5)	(6)
3-Factor	0.389	0.341	0.267	0.426**	0.489**	0.291
	(0.274)	(0.420)	(0.421)	(0.215)	(0.245)	(0.256)
4-Factor	0.585**	0.509	0.346	0.503**	0.558**	0.353
	(0.235)	(0.371)	(0.403)	(0.197)	(0.215)	(0.232)

Table IX: Flow-Performance in Large and Small Families

This table presents the effects of family size on the flow-to-performance sensitivity. Each quarter, a piecewise linear regression is performed by regressing quarterly flows on funds' fractional performance rankings over the low, medium, and high performance ranges, our indicator for large families, their interactions, and controls. A detailed description of each variable is included in Table VII. We estimate the flow-to-performance sensitivities for three different samples. The first, contains all funds in our sample (*All*). The second contains only illiquid funds (*Illiquid*), while the third contains only liquid funds (*Liquid*). The table presents the time-series average coefficients and standard- errors (in parentheses) corrected for serial-dependence with 12 lags. $*$, $**$, and $***$ represent significance at the 10%, 5%, and 1% level, respectively.

Past Peformance = 4-Factor Alpha

	All	Illiquid	Liquid	All	Illiquid	Liquid
Low × Large				−0.0754**	−0.4370**	−0.0313
				(0.0329)	(0.1707)	(0.0421)
Mid × Large				−0.0010	0.0167	−0.0011
				(0.0067)	(0.0160)	(0.0079)
High × Large				−0.1326***	−0.0915	−0.0838
				(0.0355)	(0.0611)	(0.0768)
Low Perf	0.1260***	0.2009***	0.0926***	0.1452***	0.3141***	0.1020***
	(0.0254)	(0.0577)	(0.0198)	(0.0308)	(0.0372)	(0.0279)
Mid Perf	0.0987***	0.0950***	0.0982***	0.0983***	0.0898***	0.0980***
	(0.0080)	(0.0149)	(0.0060)	(0.0089)	(0.0155)	(0.0065)
High Perf	0.4696***	0.4682***	0.4825***	0.5102***	0.4883***	0.5142***
	(0.0420)	(0.0336)	(0.0591)	(0.0389)	(0.0395)	(0.0572)
Large Family	0.0015	−0.0026	0.0032	0.0178***	0.0696**	0.0114
	(0.0033)	(0.0046)	(0.0030)	(0.0067)	(0.0345)	(0.0072)
Actual Vol	0.0484	0.0747	−0.1344	0.0500	0.0866	−0.1261
	(0.1884)	(0.2129)	(0.2426)	(0.1894)	(0.2220)	(0.2405)
Total Flows	0.1009	0.3244	0.1197*	0.1015	0.3212	0.1196*
	(0.0653)	(0.1998)	(0.0663)	(0.0657)	(0.2000)	(0.0663)
Log(Age)	−0.0210***	−0.0215***	−0.0210***	−0.0210***	−0.0224***	−0.0210***
	(0.0025)	(0.0038)	(0.0022)	(0.0025)	(0.0036)	(0.0022)
Log(TNA) (t-1)	−0.0055***	−0.0122***	−0.0040***	−0.0055***	−0.0115***	−0.0040***
	(0.0010)	(0.0011)	(0.0009)	(0.0010)	(0.0011)	(0.0009)
Total Fees	0.2255	−0.0524	0.3395*	0.2194	−0.0328	0.3368*
	(0.1770)	(0.2347)	(0.1945)	(0.1794)	(0.2393)	(0.1988)
Intercept	0.0367**	0.0816***	0.0360**	0.0326*	0.0602***	0.0334*
	(0.0160)	(0.0197)	(0.0183)	(0.0171)	(0.0217)	(0.0195)

Table X: Risk-Shifting

This table reports the Fama and MacBeth (1973) estimates of quarterly probit regressions in which the dependent variable is an indicator equal to one for funds in the largest decile of risk- shifting. We use three measures of risk-shifting. The first two, under Δ *Holdings Volatility* are the change in the volatility of holdings over the previous quarter and over the previous 36 months. The third measure, *Risk-Shifting* is the holdings-based risk shifting measure defined as the difference between a fund's intended volatility and its realized volatility, as defined in Huang, Sialm, and Zhang (2011). We first sort funds based on prior performance. We risk-adjust fund returns using the four-factor model in Carhart (1997). We measure prior performance over two different horizons. First, funds are sorted into quintiles based on their performance over the previous quarter and then assigned to three groups, *Loser(q-1)*, *Mid(q-1)*, *Winner(q-1)*, corresponding to quintiles one, two to four, and five, respectively. We follow a similar procedure to assign funds to groups based on their prior 36-month performance, *Loser(t-36)*, *Mid(t-36)*, *Winner(t-36)*. All explanatory variables are described in Table VII. In Panel A we present level regressions whereas in Panel B interaction terms between *Illiquid Fund* and *Large Family* are included. Standard-errors, shown in parentheses, are corrected for serial-dependence with four lags. Throughout the table, ∗, ∗∗, and ∗ ∗ ∗ represent significance at the 10%, 5%, and 1% level, respectively.

Panel A: Levels

	Δ Holdings Volatility(q-1,q)			Δ Holdings Volatility(t-36,t)			Risk-Shifting		
	Loser(q-1)	Mid(q-1)	Winner(q-1)	Loser(t-36)	Mid(t-36)	Winner(t-36)	Loser(t-36)	Mid(t-36)	Winner(t-36)
Large Family	0.0485***	0.0054*	0.0049	−0.0581***	−0.0001	0.0064	0.0095*	0.0003	−0.0100
	(0.0127)	(0.0032)	(0.0109)	(0.0221)	(0.0036)	(0.0133)	(0.0050)	(0.0041)	(0.0090)
Illiquid Fund	0.0530***	0.0345***	0.0418**	0.0531**	0.0365***	0.0473***	0.0219**	−0.0110	0.0165**
	(0.0176)	(0.0090)	(0.0163)	(0.0264)	(0.0092)	(0.0130)	(0.0109)	(0.0071)	(0.0076)
Industry Concentration	−0.0516	0.1380***	0.2256	−0.0202	0.1389**	0.0551	−0.3955***	0.1448***	−0.1712
	(0.1481)	(0.0460)	(0.1609)	(0.1326)	(0.0580)	(0.1157)	(0.1046)	(0.0417)	(0.1101)
N Stocks	−0.0586***	−0.0429***	−0.0538***	−0.0685***	−0.0432***	−0.0586***	−0.0302***	0.0060*	−0.0342***
	(0.0119)	(0.0040)	(0.0092)	(0.0093)	(0.0037)	(0.0116)	(0.0086)	(0.0031)	(0.0131)
Log(TNA)	−0.0003	−0.0005	0.0013	−0.0018	0.0007	0.0017	0.0025	−0.0087***	−0.0032
	(0.0033)	(0.0011)	(0.0044)	(0.0043)	(0.0012)	(0.0035)	(0.0048)	(0.0011)	(0.0026)
Turnover	0.0061*	0.0079***	0.0099**	0.0076**	0.0083***	0.0088*	0.0008	0.0069***	−0.0021
	(0.0035)	(0.0023)	(0.0042)	(0.0035)	(0.0026)	(0.0046)	(0.0011)	(0.0025)	(0.0058)

Panel B: Interactions

	Δ Holdings Volatility(q-1,q)	Δ Holdings Volatility(t-36,t)	Risk-Shifting

Continued on next page

Table X, Continued

	Loser(q-1)	Mid(q-1)	Winner(q-1)	Loser(t-36)	Mid(t-36)	Winner(t-36)	Loser(t-36)	Mid(t-36)	Winner(t-36)
Illiquid × Large	0.1174**	0.0068	0.2351***	0.1033**	0.0057	0.1412**	0.0646***	0.0282***	0.0615*
	(0.0493)	(0.0079)	(0.0712)	(0.0409)	(0.0076)	(0.0715)	(0.0235)	(0.0092)	(0.0319)
Large Family	0.0072	0.0029	−0.1729**	−0.1098***	−0.0025	−0.0957	−0.0184	−0.0053	−0.0519
	(0.0631)	(0.0038)	(0.0764)	(0.0341)	(0.0041)	(0.0777)	(0.0148)	(0.0046)	(0.0344)
Illiquid Fund	0.0811	0.0322***	0.0103	0.0323	0.0339***	0.0490*	0.0090	−0.0180**	0.0295**
	(0.0551)	(0.0086)	(0.0246)	(0.0299)	(0.0091)	(0.0290)	(0.0145)	(0.0077)	(0.0120)
Industry Concentration	−0.0805	0.1386***	0.2145	−0.0375	0.1393**	0.0713	−0.3902***	0.1422***	−0.1468
	(0.1520)	(0.0463)	(0.1597)	(0.1420)	(0.0575)	(0.1168)	(0.1015)	(0.0408)	(0.1281)
N Stocks	−0.0597***	−0.0429***	−0.0531***	−0.0683***	−0.0432***	−0.0606***	−0.0305***	0.0061**	−0.0350**
	(0.0116)	(0.0040)	(0.0088)	(0.0101)	(0.0037)	(0.0117)	(0.0090)	(0.0031)	(0.0135)
Log(TNA)	−0.0005	−0.0006	0.0013	−0.0017	0.0006	0.0019	0.0023	−0.0088***	−0.0031
	(0.0035)	(0.0011)	(0.0043)	(0.0046)	(0.0012)	(0.0035)	(0.0050)	(0.0011)	(0.0028)
Turnover	0.0059*	0.0079***	0.0099**	0.0075**	0.0083***	0.0091**	0.0004	0.0068***	−0.0024
	(0.0036)	(0.0023)	(0.0041)	(0.0035)	(0.0026)	(0.0043)	(0.0011)	(0.0024)	(0.0060)

Table XI: Fund Performance – Quantile Regressions

This table reports the Fama and MacBeth (1973) estimates from monthly quantile regressions of fund performance. We measure fund performance as monthly returns risk-adjusted using Carhart's four factor model. We concentrate on the 20%, 50%, and 80% quantiles, which we associate with low, mid, and high performance. In Panel A we include all funds, whereas in Panel B we separate between liquid and illiquid funds. *Annual Flow (t-1)* represents the total inflow for the fund from t-12 to t-1. *Past Year Return (t-1)* correspond to the accumulated return from months t-12 to t-1. All other control variables are described in Table VII. Standard-errors, shown in parentheses, are corrected for serial-dependence with 12 lags. Throughout the table, $*$, $**$, and $***$ represent significance at the 10%, 5%, and 1% level, respectively.

Panel A - All Funds

	20%	50%	80%	20%	50%	80%
Illiquid × Large				0.6379***	0.2418***	0.1959***
				(0.0825)	(0.0283)	(0.0376)
Illiquid Fund	−0.2903***	0.1593***	0.4378***	−0.4588***	0.0912*	0.3915***
	(0.0505)	(0.0460)	(0.0634)	(0.0590)	(0.0479)	(0.0664)
Log(TNA) (t-1)	0.0214***	−0.0197***	−0.0598***	0.0199***	−0.0186***	−0.0601***
	(0.0067)	(0.0051)	(0.0095)	(0.0060)	(0.0050)	(0.0095)
Large Family	−0.0057	0.0436***	0.1464***	−0.1160***	0.0025	0.1144***
	(0.0261)	(0.0132)	(0.0195)	(0.0228)	(0.0112)	(0.0184)
Turnover (t-1)	−0.0560***	−0.0035	0.0354***	−0.0516***	−0.0026	0.0348***
	(0.0123)	(0.0070)	(0.0079)	(0.0127)	(0.0073)	(0.0077)
Log(Age)	−0.0170	−0.0079	−0.0097	−0.0134	−0.0089	−0.0084
	(0.0160)	(0.0057)	(0.0082)	(0.0143)	(0.0059)	(0.0082)
Total Fees (%)	−0.0519***	−0.0263***	0.0002	−0.0475***	−0.0270***	0.0009
	(0.0099)	(0.0075)	(0.0081)	(0.0099)	(0.0070)	(0.0084)
Annual Flow (t-1)	−0.0227*	−0.0206	−0.0193	−0.0261*	−0.0204	−0.0192
	(0.0129)	(0.0127)	(0.0151)	(0.0154)	(0.0127)	(0.0145)
Past Year Return (t-1)	0.0142***	0.0162***	0.0205***	0.0142***	0.0162***	0.0204***
	(0.0030)	(0.0018)	(0.0023)	(0.0030)	(0.0018)	(0.0023)
Intercept	−0.6593***	0.3184***	1.2836***	−0.6355***	0.3252***	1.2912***
	(0.0982)	(0.0784)	(0.1358)	(0.0943)	(0.0775)	(0.1355)

Panel B - By Liquidity

	Liquid Funds			Illiquid Funds		
	20%	50%	80%	20%	50%	80%
Log(TNA) (t-1)	0.0233***	−0.0134***	−0.0520***	0.0371**	−0.0426***	−0.1065***
	(0.0065)	(0.0047)	(0.0101)	(0.0155)	(0.0104)	(0.0119)
Large Family	−0.1045***	−0.0009	0.1143***	0.4747***	0.2705***	0.3390***
	(0.0211)	(0.0111)	(0.0190)	(0.0714)	(0.0282)	(0.0408)
Turnover (t-1)	−0.0516***	−0.0032	0.0294***	−0.0558**	−0.0085	0.0353***
	(0.0124)	(0.0075)	(0.0079)	(0.0225)	(0.0122)	(0.0124)
Log(Age)	−0.0057	−0.0068	−0.0132	−0.0750***	−0.0309	0.0102
	(0.0152)	(0.0054)	(0.0104)	(0.0260)	(0.0227)	(0.0320)
Total Fees (%)	−0.0531***	−0.0305***	−0.0009	−0.0569***	−0.0216	0.0138
	(0.0104)	(0.0074)	(0.0087)	(0.0213)	(0.0131)	(0.0237)
Annual Flow (t-1)	−0.0098	−0.0160	−0.0263	−0.0498	−0.0584***	−0.0472**
	(0.0068)	(0.0128)	(0.0162)	(0.0367)	(0.0185)	(0.0215)
Past Year Return (t-1)	0.0128***	0.0154***	0.0209***	0.0194***	0.0183***	0.0157***
	(0.0033)	(0.0021)	(0.0024)	(0.0030)	(0.0027)	(0.0036)
Intercept	−0.6409***	0.3273***	1.2840***	−1.0848***	0.5386***	1.8370***
	(0.1021)	(0.0832)	(0.1400)	(0.1511)	(0.1330)	(0.2043)

Table XII: Variable Definitions

The sample consists of all the actively-managed domestic equity mutual funds from CRSP that can be matched to the mutual fund holdings data from Thomson-Reuters, for the period between 1995 and 2009. The stock-level information is obtained from CRSP. It only includes common stock traded on NYSE, NASDAQ, and AMEX. The liquidity cost estimates for U.S. equities are those in Hasbrouck (2009).

OIS$^{[m]}$, $m = 1, 2$	are our measures of outflow induced sales. They are defined by $OIS^{[1]}_{j,i,t} = \%\ \text{Sold}_{j,i,t} \times \widehat{\text{AR}}_{i,t}$, and $OIS^{[2]}_{j,i,t} = \%\ \text{Sold}_{j,i,t} \times \widehat{\text{AR}}_{j,i,t}$, respectively, where $\widehat{\text{AR}}_{i,t}$ and $\widehat{\text{AR}}_{j,i,t}$ are our two measure of attributable risk of being sold due to outflows.
4-Factor alpha (%)	is the intercept of the four-factor model of Carhart (1997).
Actual Vol	is the realized volatility of a mutual fund estimated as the standard deviation of a fund's actual return over the prior 36 months.
Holdings Vol	for each fund f at the end of quarter t, we compute the volatility of its holdings as the squared root of $\sigma^2_{f,t} = w'_{f,t}\Sigma_t w_{f,t}$, where $w_{f,t}$ is the vector of portfolio weights and Σ is the variance-covariance matrix of individual assets.
Log(Age)	is the fund's age measured by the natural logarithm of (1+*age*), where *age* is the distance between the current date and the fund's inception date.
Log(TNA)	is the logarithm of the fund's TNA from CRSP (in millions of 2009 dollars).
Number of Funds	is the number of funds in a family.
Ownership(t-1)	represents the proportion of the company held by the fund in the previous quarter (in thousands).
PS alpha (%)	is the intercept of a five-factor model, in which we add the liquidity factor of Pastor and Stambaugh (2003) to the four-factor model of Carhart (1997)
TNA (mil)	is the fund's TNA from CRSP (in millions of 2009 dollars).
Total Flows	is the aggregate flow into each fund category in each fund-quarter.
Turnover	is the turnover ratio from CRSP.
VW B/M	is a value-weighted measure of book-to-market for the holdings of the funds in the family, averaged over the past 3 years. This measured is obtained from a triple-sort style classification similar to that proposed in Daniel, Grinblatt, Titman, and Wermers (1997).
VW Liquidity Cost	is a value-weighted measure of liquidity for the holdings of the funds in the family, averaged over the past 3 years. This measured is obtained from sorting stocks into five groups based on the liquidity cost estimates of Hasbrouck (2009).
VW Momentun	is a value-weighted measure of momentum for the holdings of the funds in the family, averaged over the past 3 years. This measured is obtained from a triple-sort style classification similar to that proposed in Daniel, Grinblatt, Titman, and Wermers (1997).
VW Size	is a value-weighted measure of size for the holdings of the funds in the family, averaged over the past 3 years. This measured is obtained from a triple-sort style classification similar to that proposed in Daniel, Grinblatt, Titman, and Wermers (1997).