Co-Insurance in Mutual Fund Families *

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Abstract

We show that mutual funds coordinate trades with other funds in the same family to avoid the costs of asset fire sales. We find evidence of systematic offsetting trades within large families, especially when the selling funds are in distress, and when the traded stocks are illiquid. This type of co-insurance affects the behavior of investors and fund managers. It reduces the sensitivity of outflows to poor past performance, which induces more managerial risk-taking. It also diminishes the price impact of the widespread selling by distressed funds. Overall, despite its potential costs, co-insurance has a positive effect on fund performance.

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

JEL Classification: G11, G23, G30, G32.

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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 by brokers matching orders on their own trading desks. 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 study an additional source of off-exchange transactions, which has been largely under-explored: the internal markets of mutual fund families. Affiliation with a fund family provides mutual funds with access to a potentially very active off-exchange market, and this market can be an important source of liquidity for funds in the event of negative shocks. In particular, equity funds that are experiencing significant outflows may be forced to sell their stock holdings on the open-market at a fire sale discount (e.g., Coval and Stafford (2007)). However, funds affiliated with a family can, alternatively, sell these stocks internally at the prevailing market price.[2] This allows distressed funds to avoid fire sale costs, which they would otherwise incur if trading on the open-market. This could then be a benefit of particular importance to funds holding more illiquid assets. Moreover, the existence of an internal capital market, and the possibility of cross-trading, could have an impact on the incentives of fund managers and investors. If adopted on a sufficiently large scale, cross-trading could ultimately have implications for the asset prices displayed on the exchange. The purpose of this paper is to understand some of these effects.

The mechanism through which internal trades can provide liquidity to distressed funds plays an essential role in our analysis. Therefore, we start by showing that there is a systematic pattern in the way forced sales by one fund are offset by purchases of other funds in the same family. This form of co-insurance is then especially evident when the selling funds are also experiencing heavy redemption requests, when the stocks being traded are more illiquid, and when fund families tie together a large number of funds.

In order to differentiate between coordinated and non-coordinated trades, we use simulations to construct control-families. The goal is to replicate the structure of each family by randomly combining similar funds from all the remaining families in the sample. As a result, such control-families have

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

[2] 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 "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.

the same characteristics as the actual family of interest.[3] However, since the funds in the simulated families are drawn randomly from the other different families in the sample, their trades are unlikely to be coordinated, by construction. These simulated families then allow us to control for offsetting transactions that are unlikely to be the result of co-insurance.

Our tests consistently indicate that the degree of internal "absorption" of forced sales displayed by actual families is significantly larger than what one would expect in the absence of coordination.[4] This is especially the case within large families.[5] Therefore, throughout the paper, we use the number of funds affiliated with a family as a proxy of co-insurance. Alternatively, we compute the difference between the levels of absorption in the actual and in the simulated families, and use this difference to proxy for co-insurance.

We find that funds provide liquidity to one another by coordinating and crossing their trades within the internal markets of their fund families. However, it has been documented in Kempf and Ruenzi (2008) that funds of a family should not be viewed as coordinated entities, but as individualities that compete in a family tournament for investors' flows. We believe that there are at least two ways (not necessarily mutually-exclusive) to reconcile our hypothesis with the existence of tournaments within fund families. The existence of internal coordination may be the result of a group interest, and therefore a strategy encouraged by the family,[6] or it may be the result of an agreement established directly by the individual fund managers. In order to shed light on these potential explanations, we look at the characteristics of the funds involved in coordinated offsetting trades.

It has been shown that families can play favorites by transferring performance to funds that create high value to the fund complex, at the cost of their low-value siblings (Gaspar, Massa, and Matos (2006)). It could also be the case that our co-insurance argument holds primarily for funds that are more valuable to the family. These would be funds with good past performance that happen to be in transient distress, or funds that charge higher fees. Consistent with this idea, we show that funds that

[3] Mutual funds are matched first by the size of their assets under management, and then by portfolio holdings' characteristics. Besides matching on the standard characteristics of size, book-to-market, and momentum, as suggested in Daniel, Grinblatt, Titman, and Wermers (1997), we also match funds on the average liquidity cost of their portfolio holdings.

[4] We show that these results cannot be explained by the fact that funds belonging to the actual families have more common stock holdings than the funds in the simulated families. It has been documented in Elton, Gruber, and Green (2007) 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. We show that actual and simulated families are not statistically different from each other in terms of common holdings.

[5] 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, it should be more likely to find offsetting trades within large fund families, and 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.

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

are currently experiencing heavy outflows but which have a record of good past performance, as well as funds that charge 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 expect the burden of absorption to fall over funds with poor performance,[7] and funds that charge lower fees. We find supporting evidence of the former, but not of the latter.

We also show that funds are more likely to be internal absorbers of forced sales when it is relatively less costly for them to do so. These are funds holding more liquid assets, funds experiencing positive flows, and funds holding a large number of stocks in their portfolios.

Another potential explanation for the existence of coordination within fund families is that there exists an agreement among the individual managers. If that is the case, then fund managers would cooperate in the event of transient liquidity shortfalls, and would reciprocate in case of repeated interactions. We find supporting evidence for this argument. We show that a mutual fund is more likely to be an internal absorber of forced sales when it has also been in distress at some point in the recent past. We also find some (but weaker) evidence that a fund manager that is currently under distress is more likely to be helped if she was an absorber in the recent past.

These pieces of evidence are consistent with the idea that, repeated interactions among the fund managers can lead them to adopt a strategy of cooperation based on reciprocity. In other words, there seems to be an implicit agreement between funds affiliated with the same family, according to which one fund absorbs forced sales from the other fund, with the tacit understanding that, if the first fund happens to be in trouble, the second one will then come to its rescue.

We then show that fund managers are more likely to be involved in coordinated offsetting trades when they have been working at the same time for the same fund complex for a number of years. This suggests that fund managers are likely to develop social ties during the time they share when working for the same fund complex. As a result, they may be more willing to cooperate with one another.

We also look at the characteristics of the stocks being absorbed. We find evidence that absorption is larger for stocks that are less liquid, which are more costly to trade on the open market. We also find that stocks with relatively good past performance are more likely to be used in these offsetting transactions. This may be the case because such stocks could be preferred by the absorbing fund manager, as purchasing a good performing stock could be easier to justify before her fund's shareholders.

Taken together, all the findings described above are consistent with the existence of co-insurance within mutual fund families. What we do next is to try to understand the implications associated with such strategy. In particular, we focus on two main implications. First, we study whether the widespread adoption of co-insurance strategies affects stock prices displayed on the exchange. Sec-

[7] There is a convex shape for the response of fund flows to past performance, as documented in Chevalier and Ellison (1997) and Sirri and Tufano (1998), among others.

ond, we explore whether co-insurance can affect the behavior of investors and as a result distort the incentives of fund managers.

Regarding the asset-pricing effects of co-insurance, 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 price impact. In fact, the Financial Times reports that "[off-exchange trading venues] have grown popular with asset managers as they minimize the risk of the market moving against them when executing a large order."[8] Therefore, if forced sales by distressed funds are absorbed within the family, these trades should have no impact on the quoted prices of the traded stocks. Consistent with this conjecture, we show that the downward price pressure that could potentially be created by the forced selling of distressed funds is weak or not significant when these funds belong to co-insuring families. On the contrary, the price impact is shown to be strong when distressed funds are not co-insured by their families.[9]

In addition to the price impact costs that funds can avoid by the use of cross-dealings within their fund families, no brokerage commissions, no fees, and no other remuneration is paid in connection with cross-trades.[10] We measure trading costs using the proxy suggested in Bollen and Busse (2006), which is the difference between gross portfolio holding returns and net shareholder returns, after controlling for the expense ratio and cash holdings. We then show that there is a strong negative cross sectional relation between fund-level transaction cost estimates and the estimate of the extent to which a fund's forced sales are absorbed within the family.

Finally, we study whether co-insurance affects the behavior of fund investors and whether this in turn affects the incentives of fund managers. In particular, we explore whether co-insurance reduces the sensitivity of investors' outflows to poor past performance, and as a result it increases the risk-taking incentives of fund managers. We make such conjecture for the following reason. According to Chen, Goldstein, and Jiang (2010), following substantial investor redemptions, funds need to adjust their portfolios and execute costly trades, which can damage future fund returns. If mutual funds conduct most of these trades after the day of the redemptions, most of the costs are borne by those who stay invested with these funds. This increases the incentive for the remaining investors to also pull their money out of the funds, which then creates a "fund-run" effect. Naturally, illiquid funds are particularly susceptible to this effect. As a result, Chen, Goldstein, and Jiang (2010) find that the

[8] "US 'Dark Pool' Trades Up 50%" by Philip Stafford (Financial Times, 11/19/12).

[9] Coval and Stafford (2007), Khan, Kogan, and Serafeim (2011), and Lou (2012) show that mutual funds typically scale up and down their existing portfolio positions in response to investors' inflows and outflows, and that these "passive" (uninformed) trades can create price impact when they cluster in time across a significant number of funds.

[10] Internal coordination can also help prevent contagion effects of fire sales within the family. A recent study by Blocher (2011) measures the effects of capital flow contagion across portfolio managers linked through overlapping asset holdings. Such contagion effect is likely to happen within fund families, given the large degree of overlap in the portfolio holdings across funds within the same family, as documented in Elton, Gruber, and Green (2007).

generally convex shape of the flow-performance relationship (e.g., Chevalier and Ellison (1997), Sirri and Tufano (1998)) appears to be more pronounced for liquid funds than for illiquid funds.

We argue that our co-insurance hypothesis weakens the link between liquidity and the sensitivity of fund flows to past performance. In other words, if illiquid funds belonging to co-insuring families are insulated from fire sale costs, we expect a weaker sensitivity of outflows to poor past performance for such funds. We estimate the shape of the sensitivity of investors' flows to past performance of illiquid funds, and study the effect of being affiliated with co-insuring families. We find that the flow-performance relationship is more convex for co-insured illiquid funds than for their non-insured peers. As a result, and consistent with the argument used in Chevalier and Ellison (1997), managers of illiquid funds that are affiliated with co-insuring families are found to take more risks than managers affiliated with families that do not co-insure.

Hence, co-insurance can impose at least two distinct costs on family-affiliated funds. On the one hand, it can distort the portfolios of the co-insuring funds. On the other hand, it can induce the co-insured funds to take extra risks.[11] In order to establish whether co-insurance is a rational strategy from the point of view of the family and its affiliated funds, we try to assess the relative importance of its benefits relative to the costs. We analyze the performance of funds, in particular those funds holding more illiquid portfolios, as they are more relevant from the co-insurance standpoint. According to our hypothesis, illiquid funds can benefit from savings on asset fire sales costs and other trading costs, but their fund managers are more likely to take extra risks. Our results show that the overall net effect of co-insurance on the performance of distressed illiquid funds is positive. This suggests that the benefits of co-insurance outweigh the costs, and that this can be a rational strategy for families and their affiliated funds.

The research on risk-sharing strategies of mutual fund families is limited. 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 the form of direct investment.[12] They show that this action reduces the performance of the liquidity providers but improves the performance of the liquidity receivers, by possibly preventing them from engaging in asset fire sales. Our paper is different in many important respects. Their focus is on the unilateral provision of liquidity from affiliated funds of funds to their distressed investments. Our focus is instead on the internal trading of mutual fund families. In particular, we are interested in (i) how funds can exploit their ability to cross-trade with other siblings in order to co-insure each other, (ii) the consequences of such behavior on the incentives of investors and managers, and (ii) its effects on stock prices.

[11] It has been documented in Huang, Sialm, and Zhang (2011) that excessive risk-taking can be damaging to future fund performance.

[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.

The remainder of this paper is organized as follows. In Section II we describe the data we use in this study and the strategy we adopt in our empirical tests. Section III presents our results on trade coordination within fund families, and Section IV analyzes its asset pricing effects, 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 V.

II 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 2011 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 $100 million in 2011 dollars, at some point in time, using the CRSP value-weighted market index as deflator. We also require data on total net assets for each fund f and each month m ($TNA_{f,m}$) from CRSP not to be too different from that on Thomson-Reuters (TFN), [$0.75 < TNA^{CRSP}_{f,m}/TNA^{TFN}_{f,m} < 1.25$], and that changes in TNA are not too large, [$-0.5 < (TNA_{f,m} - TNA_{f,m-1})/TNA_{f,m-1} < 2$].

[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 replicate the proxy in Hasbrouck (2009) for trading cost estimates of U.S. equities until year 2011, and we only include stocks for which this measure is available.[15] Specifically, we replicate the Gibbs estimate of the effective bid-ask spreads computed from the Basic Market-Adjusted model, and use this 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 (2011 dollars), or with less than 36 months of return history. We also exclude reported fund holdings of less than $1,000 (2011 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-Reuters (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.

Throughout this paper, we will be interested in comparing the dynamics of the internal market of families with a large number of affiliated funds and that of families with a small number of funds. Our measure of large family is computed as follows. At the end of each quarter we rank families based on the 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 27, while in small families this number is roughly 4. The average size (TNA) of funds is $2.82 billion for large families and $820 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 larger for large families. Panel A of Table I also shows that funds affiliated with large families hold on average a larger number of stocks and charge higher fees than funds affiliated with small families.

The main purpose of this paper is to provide evidence of coordinated trades within families and to examine its implications. According to our working hypothesis, the benefits of co-insurance are more pronounced when distressed funds sell less liquid stocks. In other words, we should observe

[15] We extend the data on the estimates of liquidity costs that Joel Hasbrouck provides in his website, which only covers until year 2009: 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.

more absorption of asset fire sales by other funds in the family when the liquidity costs associated with such sales are larger. 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 effects. 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 cost. As described below, we take steps to mitigate the potential effects these relations can have on our results.

The relation between trade size and liquidity cost is evident in both Panels B and C of Table I. In particular, trade size increases monotonically with liquidity costs. For instance, in Panel B, we find that the average sale by a large-family fund is 4.9 basis points if the stock belongs to the lowest liquidity cost decile, and 11.3 basis points for the least liquid stocks (highest liquidity cost decile). The difference, 6.4 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 explains the differences in trade size observed for small and large families. For instance, the average buy for a large-family fund is 5.2 basis points for the most liquid stocks. At the same liquidity cost decile, the average fund in a small family buys 4.0 basis points of the company. On average, funds buy more than they sell. For instance, the 5.2 basis point average buy of a liquid company by large-family funds is matched with an average sale of 4.9 basis points of that 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 26.2 basis points of companies in the highest liquidity cost decile. By comparison, small families sell 16.7 basis points of such companies.

It is important to note that the sales described above are not necessarily induced by outflows. In the following section, we take a number of steps to separate the "forced," liquidity driven, asset fire sales, from other trades (e.g. 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 f'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 ($R_{f,m}$), assuming that all cash flows are re-invested at the end of the period, $flow_{f,m} = \frac{TNA_{f,m} - TNA_{f,m-1}(1+R_{f,m})}{TNA_{f,m-1}}$.

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 funds experiencing large outflows 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.[17]

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 s will be sold by fund f at quarter q due to outflows as: [18]

$$\text{AR}_{f,s,q} = \frac{\text{prob}[\text{sell}_{f,s,q}|\text{outflow}_{f,q}] - \text{prob}[\text{sell}_{f,s,q}|\text{no outflow}_{f,q}]}{\text{prob}[\text{sell}_{f,s,q}|\text{outflow}_{f,q}]} \tag{1}$$

In other words, $\text{AR}_{f,s,q}$ 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 $\widehat{\text{prob}}[\text{sell}_{f,s,q}|\text{outflow}_{f,q}]$ and $\widehat{\text{prob}}[\text{sell}_{f,s,q}|\text{no outflow}_{f,q}]$ as:

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

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

[17] For example, Alexander, Cici, and Gibson (2007) 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.

[18] 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 s will be sold due to outflows at quarter q by

$$\widehat{\text{AR}}_{s,q} = \frac{\sum_f \left(\widehat{\text{prob}}[\text{sell}_{f,s,q}|\text{outflow}_{f,q}] - \widehat{\text{prob}}[\text{sell}_{f,s,q}|\text{no outflow}_{f,q}]\right)}{\sum_f \widehat{\text{prob}}[\text{sell}_{f,s,q}|\text{outflow}_{f,q}]}$$

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

$$OIS^{[1]}_{f,s,q} = \%\ \text{Sell}_{f,s,q} \times \widehat{\text{AR}}_{s,q}$$

where $\%\ \text{Sell}_{f,s,q}$ represents the proportion of company s being sold by fund f at time q.[19]

Note that $OIS^{[1]}_{f,s,q}$ is scaled by the average increase in sale risk due to outflows across all funds. One alternative is to use the individual predicted probabilities, which gives our second measure of outflow-induced sales ($OIS^{[2]}_{f,s,q}$ henceforth):[20]

$$OIS^{[2]}_{f,s,q} = \%\ \text{Sell}_{f,s,q} \times \widehat{\text{AR}}_{f,s,q} \tag{2}$$

where $\widehat{\text{AR}}_{f,s,q} = \frac{\widehat{\text{prob}}[\text{sell}_{f,s,q}|\text{outflow}_{f,q}] - \widehat{\text{prob}}[\text{sell}_{f,s,q}|\text{no outflow}_{f,q}]}{\widehat{\text{prob}}[\text{sell}_{f,s,q}|\text{outflow}_{f,q}]}$.

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 surprisingly, 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 70% and 74%. 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 is indeed the case: when we restrict our sample to funds in the lowest flow decile, the correlations

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[19] Specifically, $\%\ \text{Sell}_{f,s,q} = \frac{\max(0, -\Delta H_{f,s,q})}{Shares_{s,q-1}}$, where $\Delta H_{f,s,q}$ represents the change in fund f's holdings of company s between quarters $q-1$ and q, and $\text{Shares}_{s,q-1}$ is the number of shares of company s outstanding at time $q-1$.

[20] And yet another alternative would be to compute the expected trade due to outflows similar to Lou (2012). First, one would run a regression like the following, $trade = \beta_0 + \beta_1 outflow + controls + \varepsilon$, and then use $\widehat{trade} = \widehat{\beta}_1 outflow$ as a measure of flow-induced trade, where $outflow = \max(0, -flow)$. For the purpose of our study, however, such measure is not ideal because of the low correlation that exists between the predicted sales and the actual sales. In fact, in many cases, a predicted sale corresponds to an actual buy.

increase from 74% to 83% for our first measure, and from 70% to 78% 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 total percentage of shares of company s bought across all the funds affiliated with family F and the total percentage of shares of that same company s sold by all the other funds (different from the buying funds, by construction) within that family F, given that there is at least one fund selling company s at quarter q:

$$A_{s,F,q} = \ln\left(1 + \%\,\mathit{Buy}_{s,F,q}\right) - \ln\left(1 + \%\,\mathit{Sell}_{s,F,q}\right) \tag{3}$$

where the variable $\%\mathit{Buy}_{s,F,q}$ is the proportion of the company s being bought by funds affiliated with family F at quarter-end q, and the variable $\%\mathit{Sell}_{s,F,q}$ is the proportion of the same company s being sold by all the other funds affiliated with the same family F. To compute the absorption of outflow-induced sales, we substitute the term $\%\mathit{Sell}_{s,F,q}$ by one of the outflow-induced selling 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 $A_{s,F,q}$. For instance, we can have $A_{s,F,q} > 0$ even under the hypothesis of no-coordination of trades, as long as some funds in the family are independently buying a large number of shares compared to the ones sold by their distressed siblings. The reasons for such behavior could include the existence of overlapping portfolios, differences in beliefs, or simply by pure 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 non-coordinated trades across affiliated funds. In that spirit, our main empirical strategy is to construct control-families by randomly combining funds from the remaining different families in the sample. The next section details the construction of these control-families.

D Simulated Families and Matched 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 with the same characteristics as F but with no coordination across its affiliated funds. We take the following approach to that effect. We simulate a series of control-families by randomly selecting funds from the entire remaining sample. We do that for each of the families that we classify as large.

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 also classify each stock based on a triple sort on size, book-to-market, and momentum, similar to Daniel, Grinblatt, Titman, and Wermers (1997).[21] 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 (style) of the fund over the previous three years.

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.

[21] 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 XI.

[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 control-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.

Our simulations proceed as follows:

1. For each quarter q:

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

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

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

2. The result is a simulated control-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.

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 control-family requires the sale of that same stock by both of these families. One of the problems with using just one sample of simulated families is that the simulated families 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 actual family (i.e. those that are sold by the actual family and the simulated family). With simulations we mitigate this problem by requiring that only some of the control-families be selling the stock. We impose different criteria for inclusion and found similar results. We settled for requiring that at least 1,000 control-families sold each particular stock.

In Table III we report the summary statistics for selected characteristics of our actual and simulated large families. We do that for the full sample (Panel A), and for illiquid funds only (Panel B). We classify funds as illiquid if the value-weighted average of the liquidity cost decile of their portfolio holdings belongs to the highest decile. It is important to note that, in general, the characteristics of our simulated families do not differ significantly from those of our actual families.

From Panel A of Table III, we find that a large family in our actual sample has close to 27 funds on average. Note that this number is slightly 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 that the average number of funds in the simulated samples is the same as the actual sample, which we impose by construction. 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 that exists between absorption and the number of funds, as we described before.

In the Column $S - A$ of Panel A in Table III, we compare the average characteristics of our 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 the same.

We find slightly higher turnover and holdings volatility for funds in the actual families compared to the simulated families. We also find a small difference in the risk-shifting measure and on the average value-weighted stock size quintile of the portfolio holdings.

The risk-shifting measure is similar to the one estimated in Huang, Sialm, and Zhang (2011). It captures the difference between the volatility of the funds' returns and the volatility of their portfolios, assuming the portfolios are not rebalanced within the quarter. We also show that actual large families do not have more overlap in holdings across their affiliated funds than the simulated families. We measure portfolio overlap within families of funds according to the measure suggested in Elton, Gruber, and Green (2007). The common percentage holdings of stock s between any two funds A and B is calculated as $\sum_s \min(X_{As}, X_{Bs})$, where X_{As} is the fraction of fund A's portfolio invested in stock s, and X_{Bs} is the fraction of fund B's portfolio invested in stock s. We then average across all pairs of funds affiliated with the same family.

We also present measures of return-gap as a proxy for the unobserved actions of fund managers within each quarter period, as defined in Kacperczyk, Sialm, and Zheng (2008). We use portfolio disclosures at the end of each quarter to make our inferences. This measure of return-gap proxies for the interim actions of managers that we miss by focusing only on quarterly portfolio disclosures. Note that actual and simulated families do not differ significantly in any of these dimensions.

In Table III, we also present the average style scores for funds in the actual and in the simulated large families, and well as the volatility of the funds' portfolio holdings. Note that the portfolio holdings characteristics of the actual families do not differ significantly from those of the simulated large families. The average size score for an actual large-family fund in Panel A is 4.77. Since scores range from one (smallest) to five (largest), this figure implies that most of the average fund's portfolio (in terms of value) consists of relatively large stocks.

Panel B of Table III repeats the analysis for illiquid funds only. Overall, we find similar characteristics when comparing the actual and simulated values.

Next, we compute the absorption measure, as defined in Section C above, for each one of these simulated families. Let $A^{[b]}_{s,F,q}$ denote the absorption measure of stock s at quarter q 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 $\Delta A_{s,F,q} = \frac{1}{B}\sum_b \left(A_{s,F,q} - A^{[b]}_{s,F,q}\right)$ where B denotes the number of simulations.

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

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

It is clear from Column (A) of Panel A in Table IV 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 -10.42 basis points and it is significant at the 1% 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 (Simulated (S)).

In 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 26% to 38%. 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 $P(S \geq OIS^{[i]})$, for $i = 1, 2$, is the steady decrease in p-values as liquidity costs increase. For instance, in Column $P(S \geq OIS^{[1]})$, p-values decrease from 22.2% to 7.2% 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 34.4% to 7.2% for the least liquid stocks. These differences are even more pronounced in Column $P(S \geq OIS^{[2]})$. First, p-values decrease from 11% to 2.9% as liquidity costs increase. Second, we only find higher levels of absorption of the most illiquid stocks in about 3% of the simulations. We interpret these patterns as evidence of co-insurance.

We rule out the possibility that the results regarding absorption could be driven by the fact that actual families exhibit a significantly larger degree of common holdings across their affiliated funds compared to the simulated families. In Column *Overlap* of Panel A in Table IV, we present p-values for the levels of overlapping holdings in actual large families relative to the simulated ones. The measure of common holdings that we use is similar to that suggested in Elton, Gruber, and Green (2007). Note that the probability that the measure of common holdings within our simulated families is greater or equal to the measure within our actual families is generally large, ranging from 25.7% to 36.8%. This means that we cannot infer that there is an abnormal level of common holdings in actual families, which could be a potential driver of our absorption results.

Finally, in Column *Trade Cost*, we provide an estimate of the costs incurred by the funds affiliated with our actual families and compare it with that of matched funds affiliated with our simulated families. The purpose of this exercise is to show that, if our co-insurance hypothesis holds, we should obtain smaller costs in our actual families than in the simulated families (where coordination is less likely to be present). We use the proxy for trading costs suggested in Bollen and Busse (2006), which is the difference between gross portfolio holding returns and net shareholder returns, after controlling for the expense ratio and cash holdings. In Table IV, Panel A, Column *Trade Cost*, we show that the empirical p-values of the actual trading costs (the probability that the trading costs in the simulated families is smaller than those in the actual families) are large across all the liquidity cost deciles, ranging from 14% to 42%. This suggests that, when looking at the full sample (Panel A), trading costs in the actual families are not significantly different from those in the simulated families.

Panel B of Table IV 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 (funds experiencing heavy outflows). In addition, the empirical p-values are much lower than their Panel A counterparts, ranging from 11.2% to 17.7%. Similarly to Panel A, we find lower empirical p-values when we use our proxies for outflow-induced sales. In fact, for outflow-induced sales, in particular $OIS^{[2]}$, for the least liquid stocks, we can reject the null hypothesis of no-coordination at the 5% level.

Note that, compared to Panel A of Table IV, the empirical p-values for the measure of common holdings are even larger in Panel B. However, the proportion of simulations with lower trading costs than the actual sample reduces significantly. We can reject the null hypothesis (at the 10% confidence level) that trading costs in the actual sample are the same as the simulated sample, in particular for stocks with large liquidity costs. This result strengthens our co-insurance argument. We find a negative relation between transaction cost estimates at the fund level, and the estimate of the extent to which forced sells by a distressed fund are absorbed internally.

The results we present above add to the findings in Nanda, Wang, and Zheng (2004). They show that "winner-picking" strategies can be used to create performance spillovers within fund 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.[24]

Next, 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 sales. 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 selling the stock, and the absorbing fund.

In Table V we report estimates of these quarterly probit regressions. We report the estimates for our three measures of asset fire sales. 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 overlap in 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 in offsetting trades have been working for the same family at the same time 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 our measures of outflow-induced sales we find a positive and significant coefficient at 5% level. The increase in the likelihood of absorption implied by the coefficients in Columns (1) to (3) range from 2.96 to 4.00 *percentage points*. We find no significant relationship between tenure overlap and the likelihood of absorption for the simulated

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

sample. Although the coefficients are positive for the simulated families, their magnitudes are small and they are not distinguishable from zero at conventional levels.[25]

We do not find that absorption is more likely when the stock being sold has performed well in the past. We find non-significant coefficients for the *Past Stk Performance* variable, which measures the performance of the stock over the prior 36 months. One could expect managers of absorbing funds to be more likely to buy past winners, regardless of whether they are asset fire sales or not.[26] However, we do not seem to be capturing that effect. The likelihood of absorption does not seem to be affected by the past performance of the stock being absorbed.

We also document that funds seem to be more likely to absorb sales by their distressed siblings if they have common holdings. On the one hand this is not surprising: funds with common holdings tend to trade similar stocks. But one of the ways we reconcile co-insurance with the presence of tournaments within families is that absorbing funds would belong to different styles (thus not competing for the same investors' flows), even though they hold similar holdings. The variable *Common Holdings* is the measure suggested in Elton, Gruber, and Green (2007). We find positive and significant coefficients for this variable in our actual sample.

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 in distress at some point during the prior three years. For the actual sample, we show in Table V 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 1.4 to 2.1 percentage points. We do not find 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. We also find such result for two out the three measures in 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

[25] 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.

[26] Grinblatt, Titman, and Wermers (1995) find that 77% of the mutual funds in their sample buy stocks that were past winners.

of forced sales are lower for poor performing funds. As a result, we should observe more absorption by such 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 of portfolios are lower for such funds. The coefficient on *Total Fees (%)* would capture this effect. For both the actual and the simulated samples, we do not seem to 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 do not find a positive coefficient for *Log(TNA)(q-1)*.

We include additional absorbing fund characteristics to control for their average propensity to take the other side of forced sales 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.

We also study some characteristics of distressed funds which we found to be associated with a higher probability of absorption. We start with additional evidence of the *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 variables *Sell* and $OIS^{[2]}_{f,s,q}$ these coefficients are significant at 10% and 5% levels, respectively, whereas for $OIS^{[1]}_{f,s,q}$ the coefficient is not significant. In contrast, no coefficient is found significant for the simulated sample. Taken together with our evidence on how prior distress affects the probability of absorption, these results can be interpreted as an indication of the existence of an implicit agreement among managers in the same family to co-insure one another, and to reciprocate.

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. We find a positive 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 10% level or better for all specifications when the actual sample is used. Average marginal effects range from 11.7 to 13.9 percentage points. We do not find a similar result for the average simulated family.

Similar positive 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 2.3 or 2.0 percentage points more likely to be absorbed by other funds in the family, for actual sales and outflow-induced sales ($OIS^{[1]}$), respectively. These estimates are significant at the 10% level or better.

In Table VI we report the Fama and MacBeth (1973) estimates of quarterly regressions in which the dependent variable is a proxy for the degree of internal absorption of distressed sales at the fund family level. In Panel A of Table VI, the dependent variable is a family's absorption of stock sales (either outflow induced or not) in excess of what would be observed across all the other funds in the same style affiliated with all the other families in the sample. In Panel B, we use as dependent variable the empirical p-values estimated in Table IV for the level of offsetting trades observed in the actual families. The smaller those p-values are the more likely it is that the level of offsetting trades observed in the actual families is due to coordination and not pure sampling variability. We would like to highlight the positive and significant coefficient associated with the variable that controls for the past performance of the stock being absorbed. This result could indicate that fund managers are willing to participate in coordinated offsetting transactions as long as the absorbing funds 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. Note, however, that in both panels of Table VI this result does not seem to hold when we focus on the sample with extreme flows, which is consistent with the results in Table V.

We have shown that co-insurance exists within fund families, and that fund managers in distress agree to reciprocate the internal support they receive in subsequent interactions. What we do next is to explore the effects of the widespread adoption of these co-insurance strategies in the mutual fund industry.

IV 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. We also study the net effects of co-insurance on the performance of the funds that are more likely to be affected.

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), Frazzini and Lamont (2008), Lou (2012), 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 are matched internally, we should observe no price impact to be associated with them. 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 having to sell at a 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 (2012) 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 s during the quarter q is defined as the difference between aggregate sales and purchases, $\textit{Pressure}^{[W]}_{s,q} = \sum_{f\in W} \%\ \textit{Sell}_{s,f,q} - \sum_{f} \%\ \textit{Buy}_{s,f,q}$, where the first summation is over all funds in a subset W, the second summation is over all funds in the sample, $\%\ \textit{Buy}_{s,f,q}$ is the proportion of company s being bought by fund f during quarter q, and $\%\ \textit{Sell}_{s,f,q}$ corresponds to one of the asset fire sales measures described in sub-section B of Section II above. We compute different measures of selling pressure for different subsets w. 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 of pressure. 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 coordinated-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 coordinated-family funds as $\textit{Relative Pressure}_{s,q} = \frac{\sum_{f \in \mathrm{CF}} \%\, \textit{Sell}_{s,f,q}}{\sum_{f} \%\, \textit{Sell}_{s,f,q}}$, where in the numerator the summation is over coordinated-family funds only ($f \in CF$). At the end of each quarter, we assign each stock to a *High Co-Insurance* or *Low Co-Insurance* 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 *High Co-Insurance* or *Low Co-Insurance* subsets, respectively. Note that this does not mean that only asset fire sales by coordinated families are included in the *High Co-Insurance* subset. What it means is that there are more asset fire sales by coordinated-family funds in the *High Co-Insurance* subset than in the *Low Co-Insurance* subset. Note also that each of these portfolios contains an equal amount of stocks at any given time.[27]

We use two proxies for the degree of coordination within a fund family. First, we proxy for it by using the number of funds affiliated with the family. Each quarter we rank families according to the number of funds under its umbrella, and we consider a family to fall in the high co-insurance category if it ranks on the top 5% in terms of number of affiliated funds. A rank below that would lead a family to be classified as exhibiting low co-insurance. The second proxy we use to classify families as more or less coordinated, is the empirical p-value they obtain from the distribution of the offsetting trades we described in Table IV. For each quarter, we classify a family as coordinated (high co-insurance) when the level of offsetting trades of that family is very large compared to the distribution of that measure for the simulated families for that quarter. If the empirical p-value is below 10%, the family is considered to be coordinated. If the p-value is larger than 10%, then the family falls in the non-coordinated category.

In Table VII we report abnormal returns for different calendar time portfolios. In Panel A of Table VII, we include all asset fire sales in the computation of the selling pressure. For the full sample, alphas range from -1 to 47 basis points per month. We find significant abnormal returns, at the 1% level, for four out of our six specifications. When we consider only families with at least 10 funds, alphas range from 73 to 118 basis points. In all of our six specifications we find significant alphas at the 1% level. These results are consistent with the findings of Coval and Stafford (2007) and Lou (2012).

In Panel B of Table VII, we include only events in which a larger proportion of the selling pressure comes from low co-insurance families. In several instances, we find higher magnitudes in Panel B than in Panel A, especially when we use the number of funds affiliated with the family as a proxy for coordination. We also find similar levels of significance as in Panel A. When we use the empirical

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

p-values as proxy for the level of internal coordination within a fund family, we find stronger results (Columns (4)-(6) in Panel B).

In Panel C, we include only events where a larger proportion of selling pressure is due to high co-insurance family funds. Note how the magnitudes of the alphas decrease significantly from Panel B to Panel C. Note also that we lose significance in many of the specifications. When we use the empirical p-values of absorption as proxy for family coordination, alphas are only significant for Column (4), at the 5% level or better. When we use our outflow induced sales variables, we find no abnormal returns.

In Panels B and C we consider only families with at least 10 funds.

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

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 can potentially attract a significant number of uninformed transactions, and as a result 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.[28] 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, 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.

[28] 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 pronounced for liquid 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 that belong to coordinated families. If investors understand such pattern, then we should observe a *more* convex flow-to-performance relationship for illiquid funds in coordinated families relative to their non-coordinated-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, and Yan (2007). To adjust returns for risk, 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 VIII. 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 coordinated and non-coordinated families. The first three columns of Table VIII 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 $Low_{f,q-1} = \min(Rank_{f,q-1}, 0.20)$, $Mid_{f,q-1} = \min(Rank_{f,q-1} - Low_{f,q-1}, 0.60)$, $High_{f,q-1} = Rank_{f,q-1} - Low_{f,q-1} - Mid_{f,q-1}$, and $Rank_{f,q-1}$ represents the performance percentile for fund f 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 15%, whereas the sensitivity of flows to high performance is much larger and close to 47%. A similar pattern is found in a sample that only includes liquid funds (Column *Liquid*). Although the sensitivity to high performance is relatively stable across specifications (ranging from 45% to 47%), the sensitivity to poor performance is higher for illiquid funds: 29% compared to 11% for liquid funds.

Our hypothesis predicts that the sensitivity to poor performance should be smaller for funds in co-insuring families. To test this hypothesis, we interact the performance variables with a dummy for co-insurance. We find a negative and highly significant coefficient for the interaction *Low* $\times$ *Co-Insurance* when we focus on illiquid funds. The coefficient of -28% implies that the sensitivity to low performance is *lower* for funds in families that rank on the top 5% in terms of the number of affiliated funds, which proxies for co-insurance. However, we do not find such effect for liquid funds. We find similar result when we use the empirical p-values of absorption as proxy for the level of coordination or co-insurance (the last three columns of Table VIII).

One interpretation of these results is that investors are aware of the co-insurance benefits that can be provided by families, which attenuates the strategic complementarity and "fund-run" effects documented in Chen, Goldstein, and Jiang (2010).[29] 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.

However, the results presented here may raise concerns regarding the fiduciary responsibility of mutual funds with respect to their shareholders, as internal absorption can be costly to the absorbing funds. 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. We address this question in more detail next.

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 investors, as it affects negatively the subsequent performance of mutual funds (Huang, Sialm, and Zhang (2011)).

We argue that if fund managers affiliated with co-insuring families are at least in part insulated from outflow-related liquidity shocks, that could give them the incentive to take more risks.

[29] The significance of our findings is strengthened once we account for what has been documented in Huang, Wei, and Yan (2007). They show 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. This means that, 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 larger families, we still find a significantly more convex flow-performance relationship for illiquid funds affiliated with large families.

In order to test this hypothesis, we use a number of different measures to capture the risk-taking behavior of fund managers. 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*$(m-36, m)$, which captures the change in holdings volatility over the past 36 months.

Our third measure, called *Risk-Shifting*, was developed in Huang, Sialm, and Zhang (2011). They measured changes in risk by looking at the difference between the current holdings volatility (i.e., based on the fund's most recently disclosed positions), $\sigma^H_{f,q}$, and the past realized volatility based on the fund's realized returns over the prior 36 months, $\sigma^R_{f,q}$. That is to say, *Risk-Shifting*$_{f,q} = \sigma^H_{f,q} - \sigma^R_{f,q}$. 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 co-insuring families than in other families. To that effect, we create dummy variables to indicate large changes in portfolio risk. To construct this variable, we first rank funds according to each of the risk-taking measures described above. We then assign a value of one if the fund belongs to the first decile (highest risk-taking), and a value of zero otherwise. In Table IX, we present the results of probit regressions in which this high risk-taking dummy serves as the dependent variable.

In Table IX, we include dummies for illiquid funds and for co-insurance proxies, as well as fund characteristics shown to affect the risk-taking measure in Huang, Sialm, and Zhang (2011). In Panels A and B, we use the number of funds in a family as a proxy for co-insurance. In particular, each quarter, we rank families according to the number of affiliated funds, and consider co-insuring families to be those on the top 5% of the ranking. In Panels C and D, we identify co-insurance as the cases in which the proportion of the simulated families with higher absorption than the actual family is less than 10%. We then 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(m-36)*, *Mid(m-36)*, *Winner(m-36)* are constructed analogously, except that we rank funds based on their performance over the past 36 months.

We find mixed coefficients for the *Co-Insurance* coefficient in Panel A. These results indicate a positive effect for loser funds in one out of three measures of risk-taking. In general, we do not find a significant effect of co-insurance on risk-taking for funds belonging to the *Mid* and *Winner* groups.

The only exceptions are for *Mid(m-36)* funds in the *Risk-Shifting* column, where we find an effect of -1.3%, significant at the 5% level, and for *Winner(m-36)* funds in the Δ*Holdings Volatility*$(m-36, m)$ column, where we find an effect of 2.6%, significant at the 5% level.

A more consistent pattern emerges when we control for both the co-insurance and the liquidity of the fund. From our results in the previous section, the convexity of the flow-to-performance relationship is larger for illiquid funds in coordinated families than for their non-coordinated peers. Therefore, we interact our dummy for co-insurance with the indicator for illiquid funds. Interestingly, across all specifications, we find a positive coefficient on *Illiquid* $\times$ *Co-Insurance*. 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 co-insuring families than in families that do not co-insure. If this is the case, we should expect more risk-taking in coordinated-family illiquid funds than in their non-coordinated illiquid peers. A positive and significant coefficient on *Illiquid* $\times$ *Co-Insurance* is consistent with this argument.[30]

These results also hold across Panels C and D, in which we use as proxy for co-insurance the empirical p-values of the absorption measure from Table IV.

What we do next is to try to understand whether or not the net effect of co-insurance on the performance of illiquid funds is positive. From what has been described in the previous sections, illiquid funds are the ones that can benefit the most from the co-insurance strategies implemented at the family level. This is because fire-sales costs are larger for more illiquid portfolios. However, we have shown that co-insurance can also change the way investors' flows react to the past performance of funds, which can lead fund managers to engage in additional risk-taking, deteriorating funds' subsequent performance and hurting investors. What we do in the next section is to study whether or not the net effect of co-insurance on the performance of illiquid funds is positive overall.

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 co-insuring family or not. According to our hypothesis, illiquid funds that belong to co-insuring families are (at least partially) insulated against liquidity shocks.

[30] Our results are consistent with the findings in Pollet and Wilson (2008), where it is shown that funds with many siblings diversify less rapidly as they grow, which can lead to more concentrated portfolios and larger risk taking. Our results are also consistent with the findings in Massa and Patgiri (2009), which show that family affiliation increases risk taking. All these results may ultimately be 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 (see Gervais, Lynch, and Musto (2005)).

Therefore, relative to peers of families that are not co-insuring, these funds should exhibit higher performance. This superior performance could however be offset by the extra incentives that managers of illiquid funds have to take additional risks, which can negatively affect subsequent performance, as shown in Huang, Sialm, and Zhang (2011).

In Table X, we report the Fama and MacBeth (1973) estimates obtained from monthly regressions of fund performance on several fund characteristics that have been shown to affect performance, as well as an indicator of whether the fund belongs to a co-insuring family. The main goal is to examine how the performance of illiquid funds is affected by their affiliation with a co-insuring family. There are two main mechanisms at play. On the one hand, illiquid funds benefit from being affiliated with a co-insuring family, as the internal absorption of asset fire sales prevents them from engaging in potentially very costly transactions with the open market. On the other hand, the sensitivity of outflows to poor past performance for these funds appears to be smaller when such funds belong to co-insuring funds. This can in turn lead them to take additional risks, which can deteriorate their subsequent performance. In this section we want to understand if the net effect of these two counteracting forces is positive to the funds, which would establish co-insurance as an optimal and rational strategy to implement at the family level.

In Panel A, we run regressions for the full sample. In Column (1), we present the estimates for our baseline regression specification. Note, for instance, that *Size* affects negatively the performance of funds, which is consistent with the argument in Berk and Green (2004) and the tests in Pollet and Wilson (2008). In Column (2), we include an indicator of whether or not the fund belongs to a co-insuring family. In Panel A, the *Co-Insurance* variable appears to positively affect the performance of funds, when we consider the full sample. In Columns (2) and (3), we proxy for co-insurance using the number of funds in a family. In Columns (4) and (5) we use instead the empirical p-values of the absorption of forced sales, as described in Table IV. Note that the interaction term *Illiquid* $\times$ *Co-Insurance* is not significant in Column (3) but it is significant at the 1% level in Column (5). This suggests that co-insurance at the family level has a net positive effect on the performance of illiquid funds.

In Panel B of Table X, we focus our attention to funds experiencing heavy outflows. In the interest of space, we only present the coefficient estimates for the *Co-Insurance* variable and the interaction *Illiquid* $\times$ *Co-Insurance*. Note that the coefficient associated with the interaction term is positive and significant at the 1% level, using either of our co-insurance proxies.

In Panel C, we try to distinguish between co-insurance and the cross-subsidization alternative proposed in Gaspar, Massa, and Matos (2006). We run our performance regressions separately for funds that charge high fees and funds that charge low fees. According to Gaspar, Massa, and Matos (2006), fund families are more likely to subsidize funds that charge large fees, as such funds are more valuable to the family. If we believe that cross-subsidization could be driving our co-insurance results, we should then see that illiquid funds that charge large fees are more likely to benefit from co-insurance. In Panel C, the estimates associated with the interaction term *Illiquid* $\times$ *Co-Insurance* are not significantly different from zero. Note that our co-insurance hypothesis and the cross-subsidization story of Gaspar, Massa, and Matos (2006) seem to be related. In Panel C, the coefficients associated with the *Co-Insurance* variable, are positive and significant for funds that charge large fees, but not significant for funds that charge low fees. But our co-insurance story applies in particular to funds that hold more illiquid portfolios, as the rebalancing of those portfolios is more costly. Therefore, forced sales by illiquid funds are more likely to be absorbed internally, as we have shown in Table IV.

The main takeaway of this Table X is that the co-insurance of illiquid funds results in a positive net effect in terms of performance for those funds.[31]

V Conclusion

In this paper, we document that mutual funds 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 coordinated-family funds. We then explore how risk-sharing strategies implemented at the family level can 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 co-insuring families. This can then encourage fund 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. We show that the net effect of co-insurance on performance is positive, in particular for funds that hold more illiquid portfolios.

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.

[31] Our findings complement those in Massa (2003), by showing how the organization of funds into families creates positive externalities across them. Other related work can be found in Chen, Hong, Huang, and Kubik (2004) and in Guedj and Papastaikoudi (2005). The latter documents that performance persists at the family level. We argue that some of that persistence might be due to co-insurance strategies adopted at the family level.

Note however that, such co-insurance strategies could constitute a violation of the fiduciary responsibility that the absorbing funds have with respect to their shareholders.[32]

We conjecture that, the incentive for trade coordination within fund families has likely become stronger in 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 total redemption rate of equity funds was 73%, of which 49.6% were exchange redemptions, and 23.4% were regular redemptions. In contrast, in the year 2011, the total redemption rate of equity funds was 30.1%, of which only 3.8% were exchange redemptions.[33] In the presence of a large amount of exchange redemptions, it is (mechanically) more likely that offsetting trades will be found within mutual fund families. As investors switch from one fund to another within the same family, they may induce these funds to submit simultaneous buy and sell trades that, by chance, and because of the existence of overlap in asset holdings across funds, offset each other in-house before being routed to other trading venues. However, we argue that, when the amount of exchange redemptions is small, more coordination effort is required on the part of the fund managers, in order to obtain the same degree of offsetting transactions. This is a question that could be explored further in future research.

[32] SEC Rule 17(a)-7 stipulates that cross-trade transactions need 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.

[33] 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.

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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 Families*) and small families (*Small Families*). 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 XI. In Panels B and C, we present the average size of buys and sales by liquidity cost deciles. *Sell (%)*, and *Buy (%)* 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 C 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 Families			Small Families		
	Mean	Median	Std Dev	Mean	Median	Std Dev
Number of Funds	27.027	24.000	8.805	4.206	3.000	3.229
TNA (mil)	2,822.162	2,477.844	1,984.558	820.910	459.185	1,050.833
Turnover	0.836	0.808	0.315	0.842	0.750	0.549
Number of Stocks	123.165	112.727	46.055	91.633	70.000	105.850
Total Fees	0.020	0.023	0.007	0.019	0.018	0.008
Fund-Stock-Quarter Obs		2,879,582			5,279,943	
Fund-Quarter Obs		24,662			57,387	

Panel B - Average Trades by Funds

	Funds in Large Families		Funds in Small Families	
	Sell (%)	Buy (%)	Sell (%)	Buy (%)
Low Liq Cost	0.0492	0.0518	0.0395	0.0403
Decile 2	0.0555	0.0593	0.0444	0.0460
Decile 3	0.0616	0.0660	0.0502	0.0523
Decile 4	0.0673	0.0721	0.0548	0.0572
Decile 5	0.0703	0.0764	0.0585	0.0616
Decile 6	0.0757	0.0818	0.0614	0.0655
Decile 7	0.0845	0.0903	0.0689	0.0737
Decile 8	0.0882	0.0955	0.0723	0.0776
Decile 9	0.0924	0.1040	0.0772	0.0825
High Liq Cost	0.1127	0.1170	0.0919	0.0967
High - Low	0.0635***	0.0652***	0.0525***	0.0564***

Panel C - Average Trades by Families

	Large Families		Small Families	
	Sell (%)	Buy (%)	Sell (%)	Buy (%)
Low Liq Cost	0.1103	0.1079	0.0417	0.0384
Decile 2	0.1299	0.1271	0.0525	0.0476
Decile 3	0.1441	0.1424	0.0627	0.0591
Decile 4	0.1573	0.1629	0.0740	0.0688
Decile 5	0.1716	0.1729	0.0818	0.0784
Decile 6	0.1818	0.1876	0.0934	0.0869
Decile 7	0.1950	0.2051	0.1063	0.1023
Decile 8	0.2108	0.2145	0.1103	0.1125
Decile 9	0.2230	0.2289	0.1257	0.1207
High Liq Cost	0.2624	0.2588	0.1670	0.1595
High - Low	0.1521***	0.1509***	0.1252***	0.1211***

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. *Log(ME)(q-1)* correspond to the logarithm of market equity in the previous quarter. *Ownership(q-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) (q-1)	Past Returns	Ownership(q-1)	Outflow	Outflow × Log(ME) (q-1)	Outflow × Past Returns	Outflow × Ownership(q-1)
Estimate	−5.1094***	0.3625***	0.2255***	1.0061***	0.2367***	0.0561***	−0.0589***	0.1683***
Std Error	(0.0730)	(0.0080)	(0.0169)	(0.0520)	(0.0762)	(0.0081)	(0.0175)	(0.0420)

Panel B - Correlations

	All Funds			Lowest Flow Decile		
	Sell	OIS[1]	OIS[2]	Sell	OIS[1]	OIS[2]
Sell	1.0000			1.0000		
OIS[1]	0.7358	1.0000		0.8326	1.0000	
OIS[2]	0.6952	0.8432	1.0000	0.7753	0.8556	1.0000

Table III: Comparison of Actual and Simulated Families

This table reports the summary statistics for the actual and the simulated samples 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 XI. 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 each measure in the actual and in the corresponding simulated family. The averages presented are across simulations. Standard errors are computed similarly. We also computed in Column *P(S ≥ A)* the proportion of the simulated families with measures above the one found for the actual family. 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)
Fund Characteristics				
Number of Funds	26.5354	26.5354	0.0000	1.0000
Log(TNA)	6.4191	6.3257	−0.0934	0.4701
4-Factor alpha (%)	−0.0726	−0.0784	−0.0058	0.4857
Turnover	0.8606	0.7639	−0.0967***	0.4043
Actual Vol	0.0464	0.0455	−0.0009***	0.4264
Risk-Shifting (%)	0.1855	0.2350	0.0495**	0.5697
Common Holdings	0.0218	0.0222	0.0004	0.4601
Return Gap	0.0250	0.0250	0.0000	0.4931
Holdings Characteristics				
VW Size	4.7740	4.7618	−0.0123***	0.7145
VW B/M	2.8250	2.8195	−0.0056	0.5371
VW Momentun	3.0236	3.0200	−0.0036	0.5337
VW Liquidity Cost (%)	0.2935	0.2907	−0.0027	0.4496
Holdings Vol	0.0484	0.0479	−0.0005	0.4756

Panel B - Illiquid Funds

	Actual (A)	Simulated (S)	S - A	P(S ≥ A)
Fund Characteristics				
Number of Funds	3.4538	4.0485	0.5947***	0.7693
Log(TNA)	6.2091	6.1660	−0.0428	0.5096
4-Factor alpha (%)	−0.0085	−0.0265	−0.0165	0.4787
Turnover	1.1202	1.0635	−0.0476	0.4676
Actual Vol	0.0687	0.0662	−0.0022*	0.4372
Risk-Shifting (%)	0.1285	0.1691	0.0380	0.5309
Return Gap	0.0269	0.0282	0.0015	0.5699
Holdings Characteristics				
VW Size	3.5611	3.5817	0.0205	0.7339
VW B/M	2.6066	2.6099	0.0028	0.6585
VW Momentun	3.1965	3.2318	0.0369	0.6903
VW Liquidity Cost (%)	0.3991	0.3949	−0.0044	0.4711
Holdings Vol	0.0689	0.0674	−0.0015	0.4350

Table IV: Absorption of Sales, Common Holdings, and Trade Cost

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- induced sales. A detailed description of each variable is included in Table XI. We first compute the absorption of sales using actual buys and sells *Actual (A)*. These represent the difference $\ln(1 + \%\,\text{Buy}) - \ln(1 + \%\,\text{Sell})$, where *% Buy* and *% Sell* represents the sum of all purchases and sales 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. We then compute measures of absorption using our two flow-induced sales measures as $\ln(1 + \%\,\text{Buy}) - \ln(1 + \text{OIS}^{[m]})$, where $\text{OIS}^{[m]}$, $m = 1, 2$ corresponds to our outflow induced sales measures defined in Table XI. Two additional empirical p-values are reported in the last two columns. In Column *Overlap*, we report the proportion of simulated families with more portfolio overlap than the actual family, whereas in Column *Trade Cost*, we report the proportion of simulations with lower trade costs than the actual family. In the last row, (*High - Low*) we compute the difference between the last and first liquidity cost deciles. 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				Overlap	Trade Cost
	Actual (A)	Simulated (S)	P(S ≥ A)	OIS[1]	P(S ≥ OIS[1])	OIS[2]	P(S ≥ OIS[2])	P(S ≥ A)	P(S < A)
Low Liq Cost	−0.0809	−0.0864	0.3811	0.0376	0.2220	0.0200	0.1098	0.3093	0.4189
Decile 2	−0.1092	−0.1054	0.3826	0.0421	0.2149	0.0228	0.1027	0.3678	0.4205
Decile 3	−0.1133	−0.1328	0.3747	0.0501	0.1820	0.0239	0.0973	0.3196	0.4173
Decile 4	−0.1290	−0.1482	0.3721	0.0416	0.1556	0.0201	0.0791	0.3219	0.3705
Decile 5	−0.1602	−0.1645	0.3800	0.0536	0.1256	0.0217	0.0745	0.2650	0.3701
Decile 6	−0.1532	−0.1739	0.2589	0.0493	0.1011	0.0218	0.0762	0.2600	0.3113
Decile 7	−0.1661	−0.2029	0.3683	0.0523	0.1004	0.0238	0.0617	0.2569	0.2298
Decile 8	−0.1842	−0.2030	0.3669	0.0386	0.0555	0.0163	0.0275	0.2663	0.1985
Decile 9	−0.1490	−0.2346	0.2967	0.0566	0.0799	0.0254	0.0607	0.2637	0.2044
High Liq Cost	−0.1843	−0.2762	0.3440	0.0744	0.0722	0.0124	0.0287	0.3328	0.1439
High - Low	−0.1042***	−0.1905***	−0.0377***	0.0369	−0.1521***	−0.0078**	−0.0822***	0.0183	−0.2772***

Panel B - Lowest Flow Decile

	All Sales			Flow Induced Sales				Overlap	Trade Cost
	Actual (A)	Simulated (S)	P(S ≥ A)	OIS[1]	P(S ≥ OIS[1])	OIS[2]	P(S ≥ OIS[2])	P(S ≥ A)	P(S < A)
Low Liq Cost	0.0314	−0.0100	0.1643	0.0471	0.1135	0.0274	0.0537	0.5157	0.1299
Decile 2	0.0696	−0.0086	0.1611	0.0873	0.1088	0.0414	0.0509	0.4318	0.1761
Decile 3	0.0822	−0.0259	0.1550	0.1052	0.0901	0.0502	0.0481	0.4896	0.1406
Decile 4	0.0860	−0.0300	0.1573	0.1165	0.0940	0.0515	0.0485	0.4938	0.0902
Decile 5	0.0766	−0.0389	0.1754	0.1076	0.0708	0.0512	0.0527	0.4528	0.1251
Decile 6	0.0700	−0.0238	0.1123	0.1009	0.0600	0.0484	0.0475	0.5065	0.0823
Decile 7	0.0704	−0.0637	0.1572	0.1061	0.0659	0.0577	0.0468	0.5405	0.0702
Decile 8	0.0934	−0.0330	0.1716	0.1153	0.0570	0.0365	0.0278	0.5309	0.0687
Decile 9	0.1430	−0.0429	0.1514	0.1877	0.0386	0.0592	0.0421	0.5871	0.0857
High Liq Cost	0.0291	−0.0638	0.1769	0.0614	0.0585	0.0285	0.0351	0.6284	0.0637
High - Low	−0.0017	−0.0531**	−0.0107	0.0099	−0.0754***	−0.0065	−0.0315***	0.1283***	−0.0723*

Table V: 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 three largest sales 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 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 each of the three largest sales of fund f. *3yr Manager Overlap* is a dummy equal to one if both managers have been working in the same fund family for at least three years. *Past Stk Performance* corresponds to the performance of the stock over the prior 36 months. *Common Holdings* corresponds to the measure of holdings overlap suggested in Elton, Gruber, and Green (2007). We risk-adjust stock returns using the four-factor model in Carhart (1997). 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 XI. 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 (1)	$\text{OIS}^{[1]}$ (2)	$\text{OIS}^{[2]}$ (3)	Sell (4)	$\text{OIS}^{[1]}$ (5)	$\text{OIS}^{[2]}$ (6)
3yr Manager Overlap	0.0400*	0.0296***	0.0355**	0.0003	0.0003	0.0004
	(0.0224)	(0.0080)	(0.0139)	(0.0003)	(0.0003)	(0.0002)
Past Stk Performance	−0.0076	0.0473	0.0484	0.1102	0.1240	0.2637***
	(0.1260)	(0.1152)	(0.1446)	(0.0805)	(0.0857)	(0.0970)
Common Holdings	0.0115**	0.0096**	0.0064*	0.0989	0.1023	0.1962***
	(0.0055)	(0.0042)	(0.0036)	(0.1572)	(0.1578)	(0.0538)
Absorbing Fund Characteristics						
Prior Distress	0.0162***	0.0141**	0.0205***	0.0006	0.0005	0.0747
	(0.0061)	(0.0071)	(0.0060)	(0.0011)	(0.0011)	(0.0706)
Fund Performance (q-1)	−0.0012***	−0.0014***	−0.0028**	−0.0006***	−0.0006***	−0.0021
	(0.0004)	(0.0005)	(0.0014)	(0.0002)	(0.0002)	(0.0015)
Total Fees (%)	0.0049	−0.0006	−0.0079	0.0007	0.0109	−0.0053
	(0.0035)	(0.0035)	(0.0086)	(0.0012)	(0.0100)	(0.0055)
Flow Decile	0.0070***	0.0077***	0.0129***	0.0059***	0.0059***	0.0043*
	(0.0018)	(0.0018)	(0.0024)	(0.0013)	(0.0013)	(0.0023)
Illiquid Fund	−0.0509***	−0.0422**	−0.0448***	< 0.0001	< 0.0001	< 0.0001
	(0.0136)	(0.0165)	(0.0078)	(< 0.0001)	(< 0.0001)	(< 0.0001)
Log(TNA) (q-1)	0.0001	−0.0020	0.0125**	0.0072***	0.0069***	0.0235
	(0.0048)	(0.0041)	(0.0059)	(0.0026)	(0.0023)	(0.0158)
N Stocks	0.0962***	0.1029***	0.1161***	0.0384***	0.0379***	0.0175
	(0.0078)	(0.0092)	(0.0127)	(0.0098)	(0.0097)	(0.0251)
Turnover	0.0043	−0.0041	0.0059	0.0243***	0.0252***	−0.0020
	(0.0076)	(0.0127)	(0.0090)	(0.0076)	(0.0077)	(0.0241)
Distressed Fund Characteristics						
Previously Absorbed	0.0174*	0.0124	0.0253**	< 0.0001	0.0001	0.0001
	(0.0100)	(0.0089)	(0.0109)	(< 0.0001)	(0.0001)	(0.0001)
Fund Performance (3yr)	0.1408**	0.1170**	0.1389*	−0.0156	−0.0153	−0.0039
	(0.0577)	(0.0471)	(0.0752)	(0.0180)	(0.0180)	(0.0119)
Total Fees (%)	0.0885***	0.0819***	0.0488***	−0.0002	−0.0002	−0.0003
	(0.0083)	(0.0076)	(0.0131)	(0.0005)	(0.0005)	(0.0008)
Illiquid Fund	0.0228**	0.0204*	0.0137	< 0.0001	< 0.0001	< 0.0001
	(0.0113)	(0.0104)	(0.0136)	(< 0.0001)	(< 0.0001)	(< 0.0001)
Turnover	0.0008	−0.0002	0.0152	−0.0017	−0.0012	0.0004
	(0.0097)	(0.0093)	(0.0179)	(0.0015)	(0.0016)	(0.0016)
Log(TNA) (q-1)	0.0028	0.0108**	0.0083*	−0.0001	−0.0001	−0.0000
	(0.0057)	(0.0047)	(0.0044)	(0.0001)	(0.0001)	(< 0.0001)

Table VI: Absorption Regressions

This table reports the Fama and MacBeth (1973) estimates of quarterly regressions in which the dependent variable is a measure of absorption of distressed sales. In Panel A, the dependent variable is the family's (excess) absorption of outflow induced sales. Only funds in large families are included. To compute the excess absorption of stock s by funds f affiliated with family F, we start by estimating the average proportion of company s being bought by all funds not affiliated with family F but in the same style as f. We then subtract this average from the actual buys of stock s by fund $f \in F$. We then sum these excess buys over all funds $f \in F$. Our measure of absorption is the (logarithm) of the ratio between these excess buys and the total sales of s by funds in F. In other words, family F's absorption of company s at time q is given by the (logarithm of the) ratio $(1 + \text{Excess \% Buy}(s, F, q))$ over $(1 + \text{\% Sell}(s, F, q))$. In Panel B, In Panel B, the dependent variable is (one minus) the empirical p-values calculated in Table IV, and all families with at least 10 funds are included. Specifically, the dependent variable is calculated as follows. For each quarter q, family F, and outflow induced sale of stock s, we compute the proportion of simulated families with less absorption than that observed for the actual family. We call this measure *P(Sim < Actual)*. We use different measures of sales in both panels. *Sale* 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(q-1)* and *B/M(q-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. *Flow(q-1)* represents the total inflow for the family over the previous quarter. *N Funds* $\times$ *Liq Cost* is the interaction between the number of funds in the family and the stock's liquidity cost (in %). Table XI 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.

Panel A: Dependent Variable = Excess Absorption

	All Funds						Lowest Flow Decile		
	Sell	OIS[1]	OIS[2]	Sell	OIS[1]	OIS[2]	Sell	OIS[1]	OIS[2]
N Funds × Liq Cost				0.3453***	0.3809***	0.3478***	0.4095***	0.5008***	0.5818***
				(0.0782)	(0.0611)	(0.1019)	(0.1296)	(0.1156)	(0.1094)
Number of Funds	0.1040***	0.1359***	0.1288***	0.0053	0.0283*	0.0246	0.1206*	0.0114	−0.0240
	(0.0280)	(0.0191)	(0.0247)	(0.0257)	(0.0160)	(0.0370)	(0.0724)	(0.0382)	(0.0583)
Stk Liquidity Cost (q-1)	0.0241	0.0688***	0.0689***	−1.1263***	−1.2066***	−1.0784***	−1.3894***	−1.6760***	−1.8818***
	(0.0157)	(0.0140)	(0.0215)	(0.2644)	(0.2008)	(0.3220)	(0.4267)	(0.3617)	(0.3609)
Market Cap (q-1)	0.0341***	0.0046***	−0.0052***	0.0337***	0.0041***	−0.0053***	0.0065	−0.0057**	−0.0056***
	(0.0024)	(0.0014)	(0.0015)	(0.0024)	(0.0014)	(0.0014)	(0.0044)	(0.0022)	(0.0020)
B/M(q-1)	−0.0260	−0.0367***	−0.0219*	−0.0287*	−0.0378***	−0.0238**	−0.0275*	−0.0099	−0.0215
	(0.0162)	(0.0069)	(0.0113)	(0.0166)	(0.0072)	(0.0111)	(0.0143)	(0.0158)	(0.0135)
Past Stk Returns	0.0304**	0.0267***	0.0328***	0.0298**	0.0272***	0.0277***	0.0182	0.0064	0.0278**
	(0.0120)	(0.0101)	(0.0105)	(0.0121)	(0.0101)	(0.0089)	(0.0138)	(0.0156)	(0.0126)
Avg TNA (q-1)	−0.0150***	0.0396***	0.0545***	−0.0148***	0.0398***	0.0525***	0.0330**	0.0554*	0.0575***
	(0.0043)	(0.0068)	(0.0140)	(0.0042)	(0.0070)	(0.0135)	(0.0144)	(0.0297)	(0.0167)
Avg Turnover (q-1)	−0.0251	0.0759***	0.0533	−0.0229	0.0770***	0.0621*	0.1552	0.2226**	0.1754**
	(0.0328)	(0.0170)	(0.0364)	(0.0329)	(0.0175)	(0.0332)	(0.1151)	(0.0929)	(0.0852)
Common Holdings (q-1)	−0.0891	−0.1436	−0.2794	0.0301	−0.0466	−0.1838	0.2844	0.2481	0.2272
	(0.0855)	(0.1081)	(0.1759)	(0.0731)	(0.0882)	(0.1253)	(0.3478)	(0.3720)	(0.4459)
Flow (q-1)	0.0214*	0.0035	−0.0033	0.0219**	0.0038	−0.0007	0.0281	−0.0447	−0.0391
	(0.0112)	(0.0071)	(0.0068)	(0.0110)	(0.0071)	(0.0068)	(0.0461)	(0.0282)	(0.0247)
Intercept	−0.6095***	−0.7929***	−0.7355***	−0.2845***	−0.4344***	−0.3919***	−0.8294**	−0.4433*	−0.3840*
	(0.1009)	(0.0798)	(0.0927)	(0.0990)	(0.0690)	(0.1363)	(0.3306)	(0.2391)	(0.2040)

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Table VI, Continued

Panel B: Dependent Variable = P(Sim < Actual)

	All Funds						Lowest Flow Decile		
	Sell	OIS[1]	OIS[2]	Sell	OIS[1]	OIS[2]	Sell	OIS[1]	OIS[2]
N Funds × Liq Cost				0.1454***	0.1524***	0.1828***	0.1333	0.3202**	0.2563
				(0.0528)	(0.0507)	(0.0698)	(0.0896)	(0.1336)	(0.1864)
Number of Funds	0.0435**	0.0673***	0.0224	0.0002	0.0231	−0.0343	0.1364	0.0848	0.1094
	(0.0198)	(0.0175)	(0.0429)	(0.0268)	(0.0274)	(0.0511)	(0.1244)	(0.1311)	(0.1745)
Stk Liquidity Cost (q-1)	0.0229	0.0471***	0.0787***	−0.4562***	−0.4561***	−0.5040**	−0.4236	−1.0545**	−0.7968
	(0.0167)	(0.0166)	(0.0187)	(0.1669)	(0.1664)	(0.2131)	(0.3011)	(0.4169)	(0.5894)
Market Cap (q-1)	0.0095***	0.0138***	0.0105***	0.0093***	0.0136***	0.0106***	0.0080**	0.0096***	0.0096
	(0.0027)	(0.0028)	(0.0035)	(0.0027)	(0.0028)	(0.0035)	(0.0033)	(0.0036)	(0.0081)
B/M (q-1)	−0.0308**	−0.0258***	−0.0191**	−0.0320**	−0.0267***	−0.0196**	−0.0025	0.0061	0.0293
	(0.0141)	(0.0085)	(0.0089)	(0.0144)	(0.0087)	(0.0086)	(0.0121)	(0.0115)	(0.0187)
Past Stk Returns	0.0161**	0.0109**	0.0024	0.0158**	0.0109**	−0.0006	0.0286***	0.0128	0.0133
	(0.0065)	(0.0054)	(0.0074)	(0.0066)	(0.0054)	(0.0067)	(0.0107)	(0.0086)	(0.0181)
Avg TNA (q-1)	−0.0257***	0.0133**	0.0362	−0.0253***	0.0135**	0.0348	−0.0246	−0.0550	0.0756*
	(0.0065)	(0.0066)	(0.0237)	(0.0064)	(0.0066)	(0.0234)	(0.0256)	(0.0612)	(0.0392)
Avg Turnover (q-1)	−0.0410	0.0932***	0.0809	−0.0408	0.0927***	0.0871	0.2953	0.2771	0.2922
	(0.0398)	(0.0323)	(0.0881)	(0.0403)	(0.0328)	(0.0869)	(0.1965)	(0.1836)	(0.2506)
Common Holdings (q-1)	−0.2067**	−0.1267	0.0384	−0.1623*	−0.0959	0.0770	−0.0196	0.0853	−0.0164
	(0.0911)	(0.0819)	(0.2012)	(0.0867)	(0.0840)	(0.1958)	(0.2848)	(0.3625)	(0.3059)
Flow (q-1)	0.0211***	0.0187***	0.0109	0.0212***	0.0190***	0.0130	−0.0631*	−0.0111	−0.1079
	(0.0063)	(0.0072)	(0.0087)	(0.0063)	(0.0072)	(0.0083)	(0.0367)	(0.0460)	(0.0886)
Intercept	0.3551***	−0.1032	−0.0420	0.4956***	0.0424	0.1390	−0.2141	0.1439	−0.8053
	(0.0962)	(0.0887)	(0.0919)	(0.1040)	(0.0877)	(0.1112)	(0.3680)	(0.3973)	(0.5140)

Table VII: Co-Insurance and the Price Pressure by Asset Fire Sales

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 calculating the difference between aggregate sells and buys for each stock. We compute two different measures of price pressure. The first, includes sales by both co-insured and not co-insured funds. 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) we 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 this measure of price pressure. In Columns (4)-(6) we only include funds affiliated with families with at least ten funds. Our second measure of pressure includes only sales by funds affiliated with families in which co-insurance is more likely. We use two proxies to identify co-insurance. The first consists of the top 5% families, in terms of number of funds (*Top 5% in N Funds*). The second corresponds to families (with at least 10 funds) with absorption levels higher than 90% of what we observe in the corresponding simulated families (*P(Sim $\geq$ Actual) $<$ 0.1*). Then, for each stock-quarter, we compute the proportion of the overall pressure induced by co-insured funds 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$^{[x]}$, $x = 1, 2$ 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 Families

	Full Sample			At Least Ten Funds		
	Sale	OIS$^{[1]}$	OIS$^{[2]}$	Sale	OIS$^{[1]}$	OIS$^{[2]}$
	(1)	(2)	(3)	(4)	(5)	(6)
3-Factor	0.4079***	−0.0176	0.4655***	1.1597***	0.7303***	0.8584***
	(0.1021)	(0.1055)	(0.1356)	(0.2987)	(0.2441)	(0.2548)
4-Factor	0.4370***	−0.0121	0.4369***	1.1748***	0.7684***	0.8426***
	(0.0951)	(0.1018)	(0.1334)	(0.2906)	(0.2362)	(0.2486)

Panel B: Low Co-Insurance, as Proxied by:

	Not Top 5% in N Funds			P(Sim $\geq$ Actual) $\geq$ 0.1		
	Sale	OIS$^{[1]}$	OIS$^{[2]}$	Sale	OIS$^{[1]}$	OIS$^{[2]}$
	(1)	(2)	(3)	(4)	(5)	(6)
3-Factor	0.6280***	−0.0834	0.6100***	1.1514***	0.8366***	0.8423***
	(0.1211)	(0.1329)	(0.1633)	(0.2974)	(0.2143)	(0.2655)
4-Factor	0.6073***	−0.0304	0.5798***	1.1680***	0.8716***	0.8255***
	(0.1172)	(0.1174)	(0.1681)	(0.2894)	(0.2083)	(0.2550)

Panel C: High Co-Insurance, as Proxied by:

	Top 5% in N Funds			P(Sim $\geq$ Actual) $<$ 0.1		
	Sale	OIS$^{[1]}$	OIS$^{[2]}$	Sale	OIS$^{[1]}$	OIS$^{[2]}$
	(1)	(2)	(3)	(4)	(5)	(6)
3-Factor	0.2141	−0.0039	0.3725**	0.9547**	0.2585	0.2837
	(0.1430)	(0.0945)	(0.1445)	(0.3831)	(0.5278)	(0.4557)
4-Factor	0.2630**	−0.0115	0.3440**	0.9727***	0.2990	0.3142
	(0.1315)	(0.0937)	(0.1422)	(0.3710)	(0.5046)	(0.4105)

Table VIII: Co-Insurance and the Flow-Performance Relationship

This table presents the effects of co-insurance 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 families in which co-insurance is more likely, their interactions, and controls. We use two proxies to measure co-insurance. The first corresponds to the top 5% families in terms of number of funds (*Top 5% N Funds*), whereas the second corresponds to families with higher absorption than at least 90% of their corresponding simulated families (*P(Sim ≥ Actual) < 10%*). Performance is corrected for risk using the four-factor model of Carhart (1997). We define $\text{Low}_{f,q-1} = \min(\text{Rank}_{f,q-1}, 0.20)$, $\text{Mid}_{f,q-1} = \min(\text{Rank}_{f,q-1} - \text{Low}_{f,q-1}, 0.60)$, $\text{High}_{f,q-1} = \text{Rank}_{f,q-1} - \text{Low}_{f,q-1} - \text{Mid}_{f,q-1}$, and $\text{Rank}_{f,q-1}$ represents the performance percentile of fund f in the previous quarter ($q-1$). A detailed description of all other variables are included in Table XI. 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.

	Co-Insurance = Top 5% N Funds			Co-Insurance = Top 5% N Funds			Co-Insurance = P(Sim ≥ Actual) < 10%		
	All	Illiquid	Liquid	All	Illiquid	Liquid	All	Illiquid	Liquid
Low × Co-Insurance				−0.0756**	−0.2787***	0.0012	0.0179	−0.0886***	0.0361*
				(0.0305)	(0.0654)	(0.0322)	(0.0190)	(0.0321)	(0.0206)
Mid × Co-Insurance				0.0131*	0.0071	0.0116	−0.0133**	−0.0013	−0.0098
				(0.0067)	(0.0172)	(0.0077)	(0.0066)	(0.0154)	(0.0072)
High × Co-Insurance				−0.0238	0.1105*	−0.0360	0.0972***	0.0894	0.1144
				(0.0416)	(0.0599)	(0.0668)	(0.0343)	(0.0596)	(0.0718)
Low Perf	0.1493***	0.2864***	0.1080***	0.1722***	0.3700***	0.1118***	0.0933***	0.1637***	0.0912***
	(0.0159)	(0.0291)	(0.0128)	(0.0194)	(0.0307)	(0.0138)	(0.0144)	(0.0342)	(0.0206)
Mid Perf	0.0943***	0.0677***	0.0967***	0.0900***	0.0624***	0.0927***	0.1057***	0.0711***	0.1072***
	(0.0073)	(0.0109)	(0.0057)	(0.0083)	(0.0120)	(0.0063)	(0.0073)	(0.0157)	(0.0057)
High Perf	0.4721***	0.4456***	0.4481***	0.4876***	0.4260***	0.4621***	0.3705***	0.3878***	0.3574***
	(0.0394)	(0.0366)	(0.0458)	(0.0355)	(0.0398)	(0.0456)	(0.0525)	(0.0680)	(0.0701)
Co-Insurance	0.0047**	−0.0009	0.0051***	0.0151***	0.0435***	0.0023	0.0056**	0.0063	0.0050**
	(0.0021)	(0.0033)	(0.0019)	(0.0046)	(0.0074)	(0.0052)	(0.0022)	(0.0038)	(0.0019)
Actual Vol	−0.1142	−0.2056	−0.2592	−0.1043	−0.1999	−0.2561	−0.4634**	−0.5962***	−0.2073
	(0.1814)	(0.1923)	(0.2442)	(0.1825)	(0.1979)	(0.2455)	(0.1836)	(0.2021)	(0.2477)
Total Flows	0.1637**	0.3262**	0.1905**	0.1624**	0.3025**	0.1898**	0.1571**	0.3247**	0.1841**
	(0.0690)	(0.1437)	(0.0776)	(0.0683)	(0.1386)	(0.0772)	(0.0665)	(0.1595)	(0.0742)
Log(Age)	−0.0215***	−0.0191***	−0.0208***	−0.0215***	−0.0185***	−0.0208***	−0.0209***	−0.0172***	−0.0214***
	(0.0025)	(0.0034)	(0.0024)	(0.0025)	(0.0034)	(0.0024)	(0.0026)	(0.0032)	(0.0025)
Log(TNA) (q-1)	−0.0063***	−0.0109***	−0.0040***	−0.0064***	−0.0111***	−0.0041***	−0.0060***	−0.0088***	−0.0041***
	(0.0009)	(0.0012)	(0.0008)	(0.0009)	(0.0012)	(0.0008)	(0.0010)	(0.0013)	(0.0008)
Total Fees	0.1029	−0.2691*	0.2058	0.1022	−0.2700	0.2054	0.1321	−0.1649	0.2372
	(0.1470)	(0.1540)	(0.1768)	(0.1486)	(0.1650)	(0.1763)	(0.1428)	(0.2085)	(0.1566)
Intercept	0.0466***	0.0781***	0.0378*	0.0428**	0.0661***	0.0378*	0.0629***	0.0901***	0.0365*
	(0.0174)	(0.0210)	(0.0208)	(0.0171)	(0.0204)	(0.0204)	(0.0165)	(0.0231)	(0.0203)

Table IX: Co-Insurance and Risk-Taking Behaviour

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-taking. We use three measures of risk-taking. 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 the logarithm of a fund's intended volatility and the logarithm of 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(m-36)*, *Mid(m-36)*, *Winner(m-36)*. All explanatory variables are described in Table XI. In Panels A and B, co-insurance is proxied by large families (in the top 5% in terms of number of funds.), whereas in Panels C and D we identify co-insurance when the proportion of the simulated families with higher absorption than the actual family is less than 10%. In Panels A and C, we present level regressions whereas in Panels B and D we present interaction terms between *Illiquid Fund* and *Co-Insurance*. 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, Co-Insurance = Top 5% N Funds

	Δ Holdings Volatility(q-1,q)			Δ Holdings Volatility(m-36,m)			Risk-Shifting		
	Loser(q-1)	Mid(q-1)	Winner(q-1)	Loser(m-36)	Mid(m-36)	Winner(m-36)	Loser(m-36)	Mid(m-36)	Winner(m-36)
Co-Insurance	0.0342***	−0.0006	0.0047	0.0050	−0.0027	0.0261**	−0.0020	−0.0129**	−0.0112
	(0.0103)	(0.0030)	(0.0125)	(0.0101)	(0.0040)	(0.0130)	(0.0130)	(0.0052)	(0.0133)
Illiquid Fund	0.0495***	0.0318***	0.0380***	0.0372**	0.0321***	0.0586***	0.0416**	0.0178***	0.0241
	(0.0150)	(0.0093)	(0.0117)	(0.0162)	(0.0084)	(0.0132)	(0.0205)	(0.0062)	(0.0155)
Industry Concentration	−0.0279	0.1864**	−0.0079	−0.0388	0.2101**	0.0462	−0.0216	0.3722***	−0.1770
	(0.1684)	(0.0892)	(0.2124)	(0.1574)	(0.1035)	(0.1853)	(0.1755)	(0.0822)	(0.2507)
N Stocks	−0.0646***	−0.0366***	−0.0506***	−0.0549***	−0.0391***	−0.0429***	−0.0282**	−0.0198***	−0.0302*
	(0.0131)	(0.0042)	(0.0106)	(0.0115)	(0.0037)	(0.0140)	(0.0131)	(0.0043)	(0.0158)
Log(TNA)	−0.0019	−0.0002	−0.0029	0.0032	< 0.0001	0.0021	0.0021	0.0014	−0.0092*
	(0.0046)	(0.0012)	(0.0051)	(0.0052)	(0.0013)	(0.0038)	(0.0058)	(0.0017)	(0.0047)
Turnover	0.0190***	0.0251***	0.0305***	0.0276***	0.0228***	0.0285***	0.0223***	0.0197***	−0.0190**
	(0.0057)	(0.0028)	(0.0063)	(0.0064)	(0.0027)	(0.0049)	(0.0081)	(0.0031)	(0.0081)

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Table IX, Continued

Panel B: Interactions, Co-Insurance = Top 5% N Funds

	Δ Holdings Volatility(q-1,q)			Δ Holdings Volatility(m-36,m)			Risk-Shifting		
	Loser(q-1)	Mid(q-1)	Winner(q-1)	Loser(m-36)	Mid(m-36)	Winner(m-36)	Loser(m-36)	Mid(m-36)	Winner(m-36)
Illiquid × Co-Insurance	0.0994***	0.0048	0.1510***	0.0665**	0.0094	0.1451**	0.1201***	0.0014	0.1099**
	(0.0381)	(0.0077)	(0.0474)	(0.0303)	(0.0078)	(0.0614)	(0.0416)	(0.0090)	(0.0428)
Co-Insurance	−0.0283	−0.0016	−0.0847*	−0.0516*	−0.0049	−0.0972*	−0.0660*	−0.0129**	−0.0615
	(0.0367)	(0.0035)	(0.0452)	(0.0291)	(0.0042)	(0.0577)	(0.0352)	(0.0058)	(0.0559)
Illiquid Fund	0.0400**	0.0301***	0.0094	0.0463***	0.0276***	0.0749***	0.0223	0.0164***	0.0702*
	(0.0169)	(0.0090)	(0.0225)	(0.0152)	(0.0087)	(0.0265)	(0.0283)	(0.0047)	(0.0426)
Industry Concentration	−0.0043	0.1850**	0.0171	−0.0374	0.2151**	0.0383	−0.0738	0.3744***	−0.2028
	(0.1753)	(0.0892)	(0.2141)	(0.1642)	(0.1042)	(0.1919)	(0.1774)	(0.0812)	(0.2621)
N Stocks	−0.0644***	−0.0364***	−0.0477***	−0.0544***	−0.0389***	−0.0429***	−0.0307**	−0.0199***	−0.0316**
	(0.0131)	(0.0042)	(0.0107)	(0.0117)	(0.0037)	(0.0146)	(0.0132)	(0.0043)	(0.0161)
Log(TNA)	−0.0022	−0.0002	−0.0033	0.0028	−0.0000	0.0016	0.0033	0.0014	−0.0095**
	(0.0047)	(0.0012)	(0.0052)	(0.0052)	(0.0013)	(0.0039)	(0.0061)	(0.0017)	(0.0048)
Turnover	0.0186***	0.0250***	0.0308***	0.0287***	0.0229***	0.0266***	0.0212**	0.0195***	−0.0191**
	(0.0059)	(0.0028)	(0.0064)	(0.0066)	(0.0027)	(0.0054)	(0.0086)	(0.0031)	(0.0083)

Panel C: Levels, Co-Insurance = P(Sim ≥ Actual) < 10%

	Δ Holdings Volatility(q-1,q)			Δ Holdings Volatility(m-36,m)			Risk-Shifting		
	Loser(q-1)	Mid(q-1)	Winner(q-1)	Loser(m-36)	Mid(m-36)	Winner(m-36)	Loser(m-36)	Mid(m-36)	Winner(m-36)
Co-Insurance	0.0150	−0.0007	0.0284**	0.0146	−0.0065	0.0336***	0.0375***	−0.0109*	0.0244***
	(0.0101)	(0.0056)	(0.0128)	(0.0122)	(0.0057)	(0.0098)	(0.0096)	(0.0056)	(0.0085)
Illiquid Fund	0.0435***	0.0290***	0.0752*	0.0343**	0.0290***	0.0495***	0.0333*	0.0147**	0.0222
	(0.0154)	(0.0092)	(0.0393)	(0.0171)	(0.0084)	(0.0132)	(0.0185)	(0.0058)	(0.0151)
Industry Concentration	−0.0668	0.1826**	0.6800	−0.1194	0.2042**	0.0337	−0.1297	0.3505***	−0.2229
	(0.1606)	(0.0882)	(0.7754)	(0.1560)	(0.1013)	(0.1698)	(0.1616)	(0.0766)	(0.2526)
N Stocks	−0.0589***	−0.0364***	−0.1051*	−0.0504***	−0.0389***	−0.0401***	−0.0288**	−0.0203***	−0.0314**
	(0.0124)	(0.0042)	(0.0554)	(0.0110)	(0.0037)	(0.0130)	(0.0133)	(0.0043)	(0.0148)
Log(TNA)	−0.0010	−0.0004	0.0073	0.0029	−0.0001	0.0019	−0.0013	0.0007	−0.0106**
	(0.0043)	(0.0012)	(0.0115)	(0.0048)	(0.0012)	(0.0032)	(0.0061)	(0.0016)	(0.0049)
Turnover	0.0165***	0.0249***	0.0291***	0.0244***	0.0228***	0.0239***	0.0189**	0.0192***	−0.0195**
	(0.0052)	(0.0028)	(0.0075)	(0.0062)	(0.0028)	(0.0041)	(0.0077)	(0.0031)	(0.0078)

Continued on next page

Table IX, Continued

Panel D: Interactions, Co-Insurance = P(Sim $\geq$ Actual) $<$ 10%

	Δ Holdings Volatility(q-1,q)			Δ Holdings Volatility(m-36,m)			Risk-Shifting		
	Loser(q-1)	Mid(q-1)	Winner(q-1)	Loser(m-36)	Mid(m-36)	Winner(m-36)	Loser(m-36)	Mid(m-36)	Winner(m-36)
Illiquid × Co-Insurance	0.1642***	0.0103	0.0940**	0.0523***	0.0102	−0.0002	0.0878***	0.0321*	0.0389
	(0.0461)	(0.0074)	(0.0420)	(0.0192)	(0.0127)	(0.0049)	(0.0309)	(0.0168)	(0.0276)
Co-Insurance	−0.1215***	0.0026	−0.0417	−0.0324	−0.0092	0.0420***	−0.0207	−0.0250	0.0093
	(0.0441)	(0.0097)	(0.0364)	(0.0246)	(0.0115)	(0.0108)	(0.0234)	(0.0177)	(0.0373)
Illiquid Fund	0.0426***	0.0313***	0.0620	0.0335*	0.0310***	0.0534***	0.0165	0.0163***	0.0417
	(0.0153)	(0.0092)	(0.0430)	(0.0172)	(0.0086)	(0.0134)	(0.0229)	(0.0059)	(0.0279)
Industry Concentration	−0.0880	0.1821**	0.6228	−0.1247	0.2085**	0.0018	−0.1284	0.3511***	−0.2384
	(0.1600)	(0.0887)	(0.7864)	(0.1661)	(0.1030)	(0.1686)	(0.1559)	(0.0766)	(0.2495)
N Stocks	−0.0592***	−0.0367***	−0.1050*	−0.0492***	−0.0392***	−0.0412***	−0.0271**	−0.0206***	−0.0325**
	(0.0125)	(0.0042)	(0.0552)	(0.0112)	(0.0037)	(0.0134)	(0.0131)	(0.0043)	(0.0149)
Log(TNA)	−0.0009	−0.0004	0.0074	0.0031	−0.0001	0.0020	−0.0013	0.0007	−0.0105**
	(0.0043)	(0.0012)	(0.0115)	(0.0048)	(0.0012)	(0.0032)	(0.0060)	(0.0016)	(0.0049)
Turnover	0.0161***	0.0249***	0.0290***	0.0238***	0.0229***	0.0240***	0.0189**	0.0193***	−0.0188**
	(0.0051)	(0.0028)	(0.0075)	(0.0064)	(0.0028)	(0.0042)	(0.0078)	(0.0031)	(0.0078)

Table X: The Effects of Co-Insurance on Fund Performance

This table reports the Fama and MacBeth (1973) estimates from monthly regressions of fund performance. We measure fund performance as monthly risk-adjusted returns using Carhart (1997) four factor model. We compute estimates for different samples. In Panel A, all funds are included. In Panel B, we include only funds in distress, i.e., in the lowest flow decile. In Panel C, we separate between high and low fee funds. High fee funds are those with total fees above the median of all funds affiliated with the same family. We use two proxies to identify co-insurance. The first consists of families on the top 5% in terms of number of funds (*Top 5% N Funds*). The second corresponds to families (with at least 10 funds) with absorption levels higher than 90% of what we observe in the corresponding simulated families (*P(Sim ≥ Actual) < 0.1*). *Annual Flow (m-1)* represents the total flow for the fund from m-12 to m-1. *Past Year Return (m-1)* correspond to the accumulated return from months m-12 to m-1. All other control variables are described in Table XI. 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 - Full Sample

		Top 5% N Funds		P(Sim ≥ Actual) < 10%	
	(1)	(2)	(3)	(4)	(5)
Illiquid × Co-Insurance			0.0219		0.1403***
			(0.0391)		(0.0380)
Co-Insurance		0.0444***	0.0412**	0.0775***	0.0621***
		(0.0162)	(0.0173)	(0.0227)	(0.0241)
Illiquid Fund	0.0510	0.0422	0.0372	0.0318	0.0120
	(0.0353)	(0.0358)	(0.0434)	(0.0371)	(0.0369)
3yr-Avg TNA	−0.0244***	−0.0260***	−0.0255***	−0.0211***	−0.0197***
	(0.0050)	(0.0049)	(0.0048)	(0.0052)	(0.0051)
Turnover (m-1)	−0.0117	−0.0105	−0.0088	−0.0215	−0.0215
	(0.0199)	(0.0197)	(0.0198)	(0.0201)	(0.0203)
Log(Age)	−0.0064	−0.0036	−0.0048	−0.0076	−0.0084
	(0.0093)	(0.0095)	(0.0093)	(0.0096)	(0.0094)
Total Fees (%)	−0.0433***	−0.0369***	−0.0369***	−0.0401***	−0.0410***
	(0.0078)	(0.0070)	(0.0071)	(0.0078)	(0.0080)
Annual Flow (m-1)	−0.0263***	−0.0251***	−0.0251***	−0.0243***	−0.0238***
	(0.0080)	(0.0079)	(0.0079)	(0.0081)	(0.0079)
Past Year Return (m-1)	0.0150***	0.0151***	0.0151***	0.0154***	0.0153***
	(0.0019)	(0.0019)	(0.0020)	(0.0020)	(0.0019)
Intercept	0.3244***	0.2795***	0.2807***	0.2770***	0.2854***
	(0.0912)	(0.0870)	(0.0876)	(0.0984)	(0.0988)

Panel B - Distressed Funds

	Top 5% N Funds		P(Sim ≥ Actual) < 10%	
	(1)	(2)	(3)	(4)
Illiquid × Co-Insurance		0.2313***		0.2876***
		(0.0840)		(0.1082)
Co-Insurance	0.1629**	0.1316*	0.1641***	0.0411
	(0.0682)	(0.0732)	(0.0602)	(0.0735)

Panel C - High and Low Fee Funds

	Top 5% N Funds				P(Sim ≥ Actual) < 10%			
	High Fees		Low Fees		High Fees		Low Fees	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Illiquid × Co-Insurance		−0.0932		0.1297		−0.0164		0.0715
		(0.0644)		(0.0817)		(0.0541)		(0.0567)
Co-Insurance	0.0772**	0.1032***	0.0058	−0.0154	0.1117**	0.0897**	0.0240	0.0155
	(0.0326)	(0.0319)	(0.0221)	(0.0155)	(0.0519)	(0.0453)	(0.0314)	(0.0282)

Table XI: 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 2011. 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 obtained from applying the methodology described in Hasbrouck (2009).

OIS$^{[x]}$, $x = 1, 2$	are our measures of outflow induced sales. They are defined by $OIS^{[1]}_{f,s,q} = \%\text{Sell}_{f,s,q} \times \widehat{\text{AR}}_{s,q}$, and $OIS^{[2]}_{f,s,q} = \%\text{Sell}_{f,s,q} \times \widehat{\text{AR}}_{f,s,q}$, respectively, where $\widehat{\text{AR}}_{s,q}$ and $\widehat{\text{AR}}_{f,s,q}$ are our two measures of the risk of being sold due to outflows.
3yr-Avg TNA	is the three-year average of the total net assets of a fund.
3yr Manager Overlap	is a dummy equal to 1 if two managers have been working for the same family for at least three years.
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.
Common Holdings	corresponds to the measure of common holdings in Elton, Gruber, and Green (2007). For each family, we compute the average common holdings of each stock s at each quarter q. To compute this average, we compute the minimum fraction of the portfolio held in stock s between any two funds f and j affiliated to the same family, or $\sum_s \min(w_{fs}, w_{js})$, where w_{fs} is the fraction of fund f's portfolio invested in stock s.
Flow Decile	corresponds to the flow decile of the fund, computed at the end of each quarter.
Fund Performance (q-1)	is the performance of an absorbing fund over the past quarter, in percentage points, adjusted for risk using the four-factor model of Carhart (1997).
Holdings Vol	for each fund f at the end of quarter q, we compute the volatility of its holdings as the squared root of $\sigma^2_{f,q} = w'_{f,q}\Sigma_q w_{f,q}$, where $w_{f,q}$ is the vector of portfolio weights and Σ is the variance-covariance matrix of individual assets.
Illiquid Fund	is an indicator variable that is equal to one when the value-weighted liquidity score of its portfolio holdings falls in the highest liquidity cost decile, and is equal to zero otherwise.
Industry Concentration	is a measure of how concentrated a portfolio in terms of industries, as suggested in Kacperczyk, Sialm, and Zheng (2005).
Large Family	is our proxy for large family. 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.
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(ME) (q-1)	is the logarithm of the market equity in the previous quarter (in millions of 2011 dollars).
Log(TNA) (q-1)	is the logarithm of the fund's TNA from CRSP in the end of the previous quarter (in millions of 2011 dollars).
Log(TNA)	is the logarithm of the fund's TNA from CRSP (in millions of 2011 dollars).
N Stocks	corresponds to the number of stocks in the fund.

Table XI Variable Definitions, Continued

Number of Funds	is the number of funds in a family.
Number of Stocks	is the average number of stocks held by funds in the family.
Outflow	is a dummy variable indicating whether a fund experienced a negative flow during that quarter.
Ownership(q-1)	represents the proportion of the company held by the fund in the previous quarter (in thousands).
Overlap	is the degree of common holdings across funds within a family, which is computed as suggested in Elton, Gruber, and Green (2007). This variable is equivalent to the *Common Holdings* measure defined above.
Past Returns	are the accumulated stock returns over the previous year.
Past Stk Performance	corresponds to the performance of the stock over the prior 36 months.
Past Year Return (m-1)	corresponds to the accumulated return of a fund from months $m-12$ to $m-1$.
Previously Absorbed	indicates whether a fund that is currently in distress (i.e. experiencing heavy redemptions) was itself an absorbing fund at some point during the past three years.
Prior Distress	indicates whether a fund that is currently absorbing forced sales within a family was itself in distress at some point during the past three years.
Return Gap	is the measure suggested in Kacperczyk, Sialm, and Zheng (2008), which captures the difference between the quarterly returns of a fund and the returns of its portfolio holdings as disclosed in the previous quarter, assuming a buy and hold strategy for the previously disclosed portfolio.
Risk-Shifting (%)	is the measure suggested in Huang, Sialm, and Zhang (2011).
Same Style	is a dummy equal to one if both funds belong to the same style group. Styles are defined based on 27 DGTW portfolios and liquidity deciles.
TNA (mil)	is the fund's TNA from CRSP (in millions of 2011 dollars).
Total Fees	is the sum of expense ratio and (1/7) $\times$ the maximum front load, as in Huang, Sialm, and Zhang (2011).
Total Flows	is the aggregate flow into each fund category in each fund-quarter.
Trade Cost	is the measure suggested in Bollen and Busse (2006), which is the difference between gross portfolio holding returns and net shareholder returns, after controlling for the expense ratio and cash holdings.
Turnover	is the turnover ratio from CRSP.
VW B/M	is a value-weighted measure of the book-to-market score of the holdings of the funds in the family. This measure is obtained from sorting stocks as suggested 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 measure is obtained from sorting stocks into five groups based on the liquidity cost estimates of Hasbrouck (2009), which we extend until year 2011.

Table XI Variable Definitions, Continued

VW Momentum	is a value-weighted measure of the momentum score of the holdings of the funds in the family. This measure is obtained from sorting stocks as suggested in Daniel, Grinblatt, Titman, and Wermers (1997).
VW Size	is a value-weighted measure of the size score of the holdings of the funds in the family. This measure is obtained from sorting stocks as suggested in Daniel, Grinblatt, Titman, and Wermers (1997).