Payoff Complementarities and Financial Fragility: Evidence from Mutual Fund Outflows[1]

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Abstract

It is often argued that strategic complementarities generate financial fragility. Finding empirical evidence, however, has been a challenge. We derive empirical implications from a global-game model and test them using data on mutual fund outflows. Consistent with the theory, we find that conditional on low past performance, funds with illiquid assets (where complementarities are stronger) are subject to more outflows than funds with liquid assets. Moreover, this pattern disappears in funds that are held primarily by large/institutional investors (who can internalize the externalities). We provide evidence that are inconsistent with the alternative explanations based on information conveyed by past performance or on clientele effects.

1 Introduction

Various economic theories link financial fragility to strategic complementarities. In banks, depositors' incentive to withdraw their deposits increases when they expect other depositors to do the same. This is because the withdrawal by others will deplete the bank's resources and harm depositors who stay in the bank. As a result of this complementarity, bank runs that are based on self-fulfilling beliefs might occur in equilibrium (see Diamond and Dybvig (1983)). A similar phenomenon may occur in currency markets, where the ability of the government to defend the exchange rate regime decreases in the number of speculators who attack the regime, and this might lead to an equilibrium with self-fulfilling currency attacks (see Morris and Shin (1998)).

Finding empirical evidence in support of the above theories has been a challenge. There are two obstacles. First, there is limited data on the behavior of depositors/speculators in settings that exhibit strategic complementarities. Second, theoretical models of financial fragility and strategic complementarities usually have multiple equilibria, and thus do not generate clear empirical predictions. The usual view has been that these models impose no restrictions on the data, and thus cannot be tested (see Gorton (1988)).

In this paper we provide a unique empirical study on the link between strategic complementarities and financial fragility. To overcome the first obstacle, we use data on mutual fund outflows. Based on previous literature (e.g., Edelen (1999), Johnson (2004)), we argue that the payoff structure faced by mutual-fund investors generates strategic complementarities. The basic argument goes as follows. Open-end mutual funds allow investors to redeem their shares at the funds' daily close Net Asset Values (NAV) at any given day. Following substantial outflows, funds need to adjust their portfolios and conduct unprofitable trades, which damage the future returns and hurt the remaining shareholders of the funds. As a result, the expectation that other investors will withdraw their money increases the incentive of each individual investor to do the same thing. We discuss the institutional details more fully in Section 2.[1] The advantage of using mutual-fund data,

[1] The case for strategic complementarities in mutual fund outflows is illustrated particularly well by the case of Putnam Investment Management. Following federal investigation for improper trades in late 2003, this fund family saw massive redemptions. Shareholders who kept their money in the funds suffered big losses. Interestingly, it has

of course, is that this data is rich and wide. The availability of information on funds' underlying assets and investor clientele enables us to test sharp empirical predictions on the relation between payoff complementarities and financial fragility.

To overcome the second obstacle, we rely on recent developments in the theoretical literature on strategic complementarities. The framework of global games enables us to obtain a unique equilibrium in a model of strategic complementarities. This framework is based on the realistic assumption that investors do not have common knowledge, but rather receive private noisy signals, on some fundamental variable that affects their optimal choice. The global game literature was pioneered by Carlsson and Van Damme (1993). It has been applied in recent years to study different finance-related issues, such as currency crises (Morris and Shin (1998), Corsetti, Dasgupta, Morris, and Shin (2004)), bank runs (Goldstein and Pauzner (2005), Rochet and Vives (2004)), contagion of financial crises (Dasgupta (2004), Goldstein and Pauzner (2004)), and stock-market liquidity (Morris and Shin (2004), Plantin (2006)).

Our empirical approach is based on the idea that strategic complementarities in mutual fund outflows are stronger when the fund's assets are more illiquid. This is because funds with illiquid assets should experience more costly adjustments to the existing portfolio. Importantly, such strategic complementarities arise only when the fund's past performance is relatively poor. Funds with strong past performance tend to attract more inflows (e.g., Chevalier and Ellison (1997), Sirri and Tufano (1998)), which offset the outflows and help avoid the resulting damage. Using a global-game model in the context of mutual funds, our main prediction is then that, conditional on low past performance, funds with illiquid assets will be subject to more outflows than funds with liquid assets. Essentially, the strong strategic complementarities in funds with illiquid assets amplify the effect that poor performance has on investors' redemptions. This is because the negative externality imposed by withdrawing shareholders on remaining shareholders in these funds increases the tendency to withdraw. We derive a second prediction from extending the model to include large investors (in the spirit of Corsetti, Dasgupta, Morris, and Shin (2004)). Large investors are more

been estimated by Tufano (2005) that the direct losses due to the improper trades were \$4.4 million, while those due to the unusually high level of redemptions were \$48.5 million. This example is also discussed in more detail in Section 5.3.

likely to internalize the effect that their actions have on the fund's assets. Thus, the presence of large investors pushes towards an equilibrium with less outflows driven by self-fulfilling beliefs. The resulting prediction is that the effect of illiquidity on outflows is stronger in funds that are held primarily by small investors than in funds that are held primarily by large investors.

Using data on net outflows from U.S. equity mutual funds from 1995 to 2005, we find strong support for our two predictions. When faced with a comparable level of low performance, funds holding illiquid assets (henceforth: illiquid funds) experience more outflows than funds holding liquid assets (henceforth: liquid funds). Essentially, outflows from the illiquid funds are more sensitive to bad performance than outflows from the liquid funds. These results are first obtained when we sort funds' liquidity with a dummy variable, where illiquid funds include funds that invest in small-cap and mid-cap stocks and most funds that invest in equity of a single foreign country. We then obtain similar results on a smaller sample of domestic equity funds, where we use finer measures of assets' liquidity – namely, trading volume, and a measure of price impact based on Amihud (2002). Moreover, we find that these results hold strongly for funds that are primarily held by small or retail investors, but not for funds that are primarily held by large or institutional investors.

There are two main alternative explanations that might be generating the relation between illiquidity and outflows. We analyze them and provide evidence to rule them out. The first alternative explanation is reminiscent to the empirical literature that attributes banking failures to bad fundamentals (see e.g., Gorton (1988), Calomiris and Mason (1997), Schumacher (2000), Martinez-Peria and Schmukler (2001), and Calomiris and Mason (2003)). In our context, it is possible that illiquid funds see more outflows upon bad performance because their performance is more persistent, and so, even without considering the outflows by other shareholders, bad performance increases the incentive to redeem. We rule out this explanation by showing that performance in illiquid funds is no more persistent than in liquid funds. Thus, unlike the conclusion in some of the above papers, differences in fundamentals cannot account for the difference in outflows. The second alternative explanation is based on differences in clientele. Suppose that investors in illiquid funds are more tuned to the market than investors in liquid funds, and thus they redeem more after bad performance. We address this point by considering only the behavior of institutional investors in retail-oriented funds.[2] We show that within this group of funds, institutional investors' redemptions are more sensitive to bad performance in illiquid funds than in liquid funds. Thus, to the extent that institutional investors in illiquid funds are similar to those in liquid funds, our results are not driven by the clientele effect.

Finally, we provide two additional pieces of evidence that support our story. First, our story relies on the idea that outflows in illiquid funds cause more damage to future performance. We confirm this premise in the data. Indeed, fund return is more adversely affected by outflows when the underlying assets are illiquid. This result holds when we use conventional return measures, and holds even more strongly when we use the "return gap" measure from Kacperczyk, Sialm, and Zheng (2006). The latter, defined as the difference between the fund return and the return of the fund's underlying assets, focuses on the effect that the fund's forced trading has on its return. Second, given that outflows are much costlier for illiquid funds, one would expect illiquid funds to take measures to either reduce the amount of outflows or minimize their impact on fund performance. Such measures include setting a redemption fee and holding more cash reserves. Indeed, we find that illiquid funds are more likely to take each one of these measures. Of course, these measures can only partially mitigate, but cannot completely eliminate, the damaging effect of self-fulfilling outflows caused by payoff complementarities.

Overall, our paper makes three main contributions. We will list them from the more specific to the more general. The first contribution is to the mutual fund literature. Our results shed new light on the behavior of mutual fund outflows. The literature that studies mutual fund flows is large, a partial list including papers by Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997), Sirri and Tufano (1998), and Zheng (1999). Our results that payoff complementarities among fund investors magnify outflows imply that investors' redemption decisions are affected by what they believe other investors will do. Also, not knowing what other investors will do, mutual fund investors are subject to a strategic risk due to the externalities from other investors' redemptions.

[2] We focus on retail-oriented funds because, as we argued above, we expect to see complementarities-based outflows mostly in these funds.

This brings a new dimension to the literature on fund flows, which thus far did not consider the interaction among fund investors.

The second contribution is to show that payoff complementarities increase financial fragility. To the best of our knowledge, our paper is the first to provide explicit empirical analysis on the relation between the strength of strategic complementarities and the level of financial fragility. In our case, fearing redemption by others, mutual fund investors may rush to redeem their shares, which, in turn, harms the performance of the mutual fund.[3] These results demonstrate the vulnerability of mutual funds and other open-end financial institutions. The fact that open-end funds offer demandable claims is responsible for the strategic complementarities and their destabilizing consequences. Beyond the funds and their investors, this has important implications for the workings of financial markets. Financial fragility prevents open-end funds from conducting various kinds of profitable arbitrage activities (see Stein (2005)) and thus promotes mispricing and other related phenomena. Our results also suggest that this fragility is tightly linked to the level of liquidity of the fund's underlying assets, and that funds that invest in highly illiquid assets may be better off operating in closed-end form. This idea underlies the model of Cherkes, Sagi, and Stanton (2006).[4]

Our third contribution is to conduct empirical analysis to test predictions from a model with strategic complementarities. Such models posed a challenge for empiricists for a long time (see, for example, Manski (1993), Glaeser, Sacerdote, and Scheinkman (2003), and recently Matvos and Ostrovsky (2006)). The usual approach of testing directly whether agents choose the same action

[3] It should be noted that while our results indicate that forces of self-fulfilling beliefs amplify the amount of outflows from mutual funds, these forces do not usually generate full-fledged runs. As we explain later in the paper, we believe this is related to the fact that most mutual-fund investors do not review their portfolios very often. Thus, our results apply to the marginal investor making decisions at a given time, not to the average investor. In general, there are very few examples of full-fledged runs in mutual funds; one of them occurred recently in open-end real-estate mutual funds in Germany (see Bannier, Fecht, and Tyrell (2006)). The fact that these mutual funds held real estate, which is probably the most illiquid asset held by open-end funds, is arguably the reason for their collapse.

[4] A complete evaluation of this issue should, of course, consider the reasons that lead financial institutions to offer demandable claims to begin with. Two such reasons are the provision of liquidity insurance (see Diamond and Dybvig (1983)) and the role of demandable claims in monitoring (see Fama and Jensen (1983), Calomiris and Kahn (1991), Diamond and Rajan (2001), and Stein (2005)).

chosen by others cannot credibly identify the effects of strategic complementarities because this approach is prone to a missing variable problem, that is, agents may act alike because they are subject to some common shocks unobserved by the econometrician. Another issue is that these games have multiple equilibria and thus the equilibrium predictions are hard to test. We show in this paper that applying a global-game technique proves to be very useful for empirical analysis. Generally speaking, the prediction coming out of a global-game framework is that the equilibrium outcome monotonically depends on the level of complementarities. It is also affected by whether the players are small or large. Then, finding proxies in the data for the level of complementarities and for the relative size of the players, one can identify the causality implied by the predictions of the model. We believe that this identification strategy can help in empirical analysis of other settings with strategic complementarities.

The remainder of the paper is organized as follows. In Section 2, we describe the institutional details that support the design of our study. Section 3 presents a stylized global-game model for investors' redemption decisions. In Section 4, we describe the data used for our empirical study. In Section 5, we test our hypotheses regarding the effect of funds' liquidity and investor base on outflows. Section 6 describes the potential alternative explanations and provides evidence to rule them out. In Section 7, we provide robustness checks and extensions. Section 8 concludes.

2 Institutional background

Investors in a mutual fund can redeem their shares on each business day at the daily-close net asset value (NAV) of the fund shares. The redemption right makes mutual funds attractive to investors because it provides them with ready access to their money when they need it. Further, the redemption right can serve as an important monitoring device to discipline and motivate fund managers whose compensation and status are often associated with the size of the assets under management. Our analysis is based on the premise that redemptions impose costs on mutual funds – in particular on illiquid mutual funds – and that these costs are not fully reflected by the price investors get when they redeem their shares. Instead, a significant portion of these costs is borne by the remaining shareholders. This premise is consistent with evidence in several papers in the mutual-fund literature, for example, Chordia (1996), Edelen (1999), Greene and Hodges (2002), Johnson (2004), Coval and Stafford (2006), and Christoffersen, Keim, and Musto (2007). It generates strategic complementarities in the redemption decision. We now discuss the institutional details that support it.

There are two types of costs imposed on mutual funds by investors' redemptions that give rise to payoff complementarities among fund investors. First, there are the direct transaction costs resulting from the trades that funds make in response to outflows. These direct costs include commissions, bid-ask spreads and price impact. Edelen (1999) estimates that for every dollar of outflow, approximately \$0.76 goes to a marginal increase in the fund's trading volume. Direct transaction costs on these trades can be substantial for mutual funds. For example, Jones and Lipson (2001) find that for their sample of institutional investors that trade on the NYSE and the AMEX, the average one-way transaction cost is 85 basis points. Further, these transaction costs are significantly higher for thinly-traded illiquid stocks. Hasbrouck (2006) reports that the effective trading cost for a thinly-traded stock is at the order of about 25 cents on a \$5 stock. Second, fund flows may generate indirect costs by forcing fund managers to alter their optimal portfolios or to execute non-information based trades, which in a competitive securities market, have negative expected abnormal returns (Grossman and Stiglitz (1980), Kyle (1985)). These costs are again more pronounced for funds holding illiquid stocks because portfolio changes are more costly with such stocks and because these stocks exhibit more asymmetric information (Easley, kiefer, O'Hara, and Paperman (1996), Easley, Hvidkjaer, and O'Hara (2002)).[5]

As we noted above, these costs are not generally reflected in the price investors get when they redeem their shares (NAV). This happens for two reasons. First, the NAV at which investors can

[5] In addition to the costs mentioned here, mutual-fund outflows have two other effects on fund value that are not directly related to our story. First, flow-driven trades trigger realizations of capital gains and losses which affect the tax liabilities of investors. This channel, however, does not affect all remaining shareholders negatively. Instead, the effect depends on the tax status of each individual investor. Moreover, the strength of this effect is unrelated to the illiquidity of the fund's underlying assets. Second, investors who trade in funds' shares may impose a cost on other shareholders due to stale fund share prices (Chalmers, Edelen, and Kadlec (2001); Zitzewitz (2003), Avramov and Wermers (2006)). This effect, however, can be due to trades in both inflows and outflows, so there is no reason to expect systematic complementarities in the outflow redemption decisions.

buy and sell is calculated using the same-day market close prices of the underlying securities (this is determined at 4:00pm and reported to the NASD by 6:00pm). In most funds, investors can submit their redemption orders until just before 4:00pm of a trading day. Because it takes time for the orders (especially those from the omnibus accounts at the brokerage firms) to be aggregated, mutual funds usually do not know the final size of daily flows until the next day. As a result, the trades made by mutual funds in response to redemptions happen after redeeming investors are being paid. Second, in some cases, even if mutual funds know the size of flows, they still may prefer to conduct the resulting trades at a later date. This depends on their assessment of optimal trading strategies in light of investment opportunities and trading costs.

As a result of these features of the institutional environment, remaining shareholders end up bearing most of the cost imposed by redeeming shareholders. Concerned about this effect, the Securities and Exchange Commission adopted a new rule in 2005 formalizing the redemption fees (not to exceed 2% of the amount redeemed) that mutual funds can levy and retain in the funds. In theory, the redemption fee could eliminate the payoff complementarity.[6] However, in reality the rule is far from perfect. First, usually redemption fees are only assessed when the holding period falls short of some threshold length. Second, so far many funds choose not to implement the rule, either because of the competition (to offer ordinary investors the liquidity service), or because of insufficient information regarding individual redemptions from the omnibus accounts.[7] Another measure funds can take is to build cash position as a buffer. However, cash reserves are costly since they dilute fund returns, and have limited capacity to handle large flows. We discuss these policy issues more in Section 7.3.

Overall, the direct and indirect costs that result from investors' redemptions can be substantial. Edelen (1999) estimates that they contribute to a significant negative abnormal fund return of

[6]Note that redemption fees are different from back-end load fees in that they are retained in the fund for the remaining shareholders. Back-end load fees are paid to the brokers, and thus do not eliminate the payoff complementarities.

[7]The new rule requires funds to enter into written agreements with intermediaries (such as broker-dealers and retirement plan administrators) that hold shares on behalf of other investors, under which the intermediaries must agree to provide funds with certain shareholder identity and transaction information at the request of the fund and carry out certain instructions from the fund.

up to -1.4% annually. He shows that the under-performance of the mutual funds in his sample disappears after accounting for the trades that are driven by redemptions. Similarly, Wermers (2000) estimates that the total expenses and transaction costs of mutual funds amount to 1.6% annually. Further, Christoffersen, Keim, and Musto (2007) document that outflows are more costly than inflows, reflecting the greater urgency to sell following outflows than to buy following inflows. Importantly, as shown by Coval and Stafford (2006), the costs are higher when the fund holds illiquid assets.

3 Model

3.1 The basic setup: liquidity and outflows

In this section, we present a stylized model of strategic complementarities in mutual fund outflows. Using the global-game methodology, we derive empirical implications that we then take to the data.

There are three periods 0, 1 and 2. At $t = 0$, each investor from a continuum $[0, 1]$ invests one share in a mutual fund; the total amount of investment is normalized to 1. The fund generates returns at $t = 1$ and $t = 2$. At $t = 1$, the gross return of the fund, R_1, is realized and becomes common knowledge. At this time, investors decide whether to withdraw their money from the fund (by redeeming their shares) or not. We assume that only a fraction $\overline{N} \in (0, 1)$ of all investors make a choice between withdrawing and not withdrawing. As we discuss below, this is consistent with empirical evidence that many investors do not actively review their portfolios (see Johnson (2006) and Agnew, Pierluigi, and Sunden (2003)). Moreover, this assumption helps to simplify the model by ruling out the possibility that the fund goes bankrupt. Investors that withdraw at $t = 1$ receive the current value per share R_1, which they can then invest in outside assets that yield a gross return of 1 during period $t = 2$. Thus, overall, withdrawing from the fund provides a final payoff of R_1 by $t = 2$.

To capture the fact that redemptions impose a negative externality on the investors who stay in the fund, we assume that in order to pay investors who withdraw at $t = 1$, the fund needs to sell assets. Due to illiquidity, generated by transaction costs or by asymmetric information, the fund cannot sell assets at the NAV on date $t = 1$. Instead, in order to get R_1 in cash, the fund needs to sell $R_1 \cdot (1 + \lambda)$ worth of assets, where $\lambda > 0$ is the level of illiquidity of the fund's assets. Thus, absent any inflows to the fund, if proportion N withdraws at $t = 1$, the payoff at $t = 2$ for the remaining shareholders is:[8]

$$\frac{1 - (1 + \lambda) N}{1 - N} R_1 R_2 (\theta) . \tag{1}$$

Here, $R_2 (\theta)$ is the gross return at $t = 2$ absent any outflows. It is an increasing function of the variable θ, which is realized at $t = 1$. We will refer to the variable θ as the fundamental of the fund. It captures the ability of the fund to generate high future return, and is related to the skill of the fund manager and/or to the strength of the investment strategy that the fund has picked. For simplicity, we assume that θ is drawn from the uniform distribution on the real line. For now, to keep the exposition simple, we say that $R_2 (\theta)$ is independent of R_1. Later, we discuss the possibility of performance persistence – i.e., the possibility that $R_2 (\theta)$ and R_1 are positively correlated – and explain why it does not change our results. Finally, to avoid the possibility of bankruptcy, we assume that $\overline{N} < \frac{1}{1+\lambda}$.

The above setup generates strategic complementarities among investors in their decision to redeem their shares. Specifically, as N increases, the expected payoff from remaining with the fund till $t = 2$ decreases, since the outflows cause damage to the value of the remaining portfolio. These complementarities will be a destabilizing force on fund outflows as they create the potential for the realization of outflows based on self-fulfilling beliefs only. This basic idea is very similar to the bank-run model of Diamond and Dybvig (1983) and to other models of coordination failures. In the mutual fund context, however, there is an additional force that mitigates the coordination problem to some extent. This is represented by the new money that flows into the fund and enables the fund to pay withdrawers without having to sell assets. It is empirically well known that funds receive more inflows when their past performance is better. To simplify the exposition, we take this to be exogenous for now. In particular, we denote the amount of inflows as $I (R_1)$, where $I (.)$

[8] For simplicity, it is assumed here that redeeming shareholders do not bear any portion of the liquidity cost. The important thing is that remaining shareholders bear a disproportionate amount of the cost. This is motivated by the institutional details discussed in the previous section.

is an increasing function.[9] Later, we discuss how this feature can be endogenized.

Now, faced by withdrawals of N and inflows of $I(R_1)$, the fund will need to sell only $(1+\lambda) \cdot \max\{0, (N - I(R_1))\}$ assets, where the max term represents the fact that if inflows are greater than outflows, the fund does not need to sell any assets. Thus, investors waiting till $t = 2$ will receive:[10]

$$\frac{1-(1+\lambda)\max\{0,(N-I(R_1))\}}{1-\max\{0,(N-I(R_1))\}} R_1 R_2(\theta). \tag{2}$$

To summarize, investors need to decide between withdrawing in $t = 1$, in which case they get R_1, and waiting till $t = 2$, in which case they get the amount in (2). We can see that the $t = 2$ payoff is increasing in the fundamental θ and decreasing in the proportion N of investors who withdraw early, as long as N is above $I(R_1)$.

Solving the model entails finding the equilibrium level of N. Clearly, this will depend on the realization of the fundamental θ. The complication arises because investors' optimal actions also depend on the actions of other investors, and this generates the potential for multiple equilibria. We define two threshold levels of θ: $\underline{\theta}$ and $\overline{\theta}(R_1)$. The threshold $\underline{\theta}$ is defined such that if investors know that θ is below $\underline{\theta}$, they choose to withdraw at $t = 1$, no matter what they believe other investors are going to do. Thus,

$$R_2(\underline{\theta}) = 1. \tag{3}$$

Similarly, the threshold $\overline{\theta}$ is defined such that if investors know that θ is above $\overline{\theta}$, they choose to stay in the fund till $t = 2$, no matter what they believe other investors are going to do. Thus,

$$R_2\left(\overline{\theta}\right) = \frac{1-\max\left\{0,\left(\overline{N}-I(R_1)\right)\right\}}{1-(1+\lambda)\max\left\{0,\left(\overline{N}-I(R_1)\right)\right\}}, \tag{4}$$

which defines $\overline{\theta}$ as a function of R_1, i.e., $\overline{\theta}(R_1)$.

[9] In practice, in addition to strategic outflows that are modelled here, there are also outflows driven by investors' liquidity needs. I can be thought of as inflows net of these exogenous liquidity-based outflows.

[10] Here, we assume that when the mutual fund receives positive net inflows, there are no externalities associated with the need to buy new assets at a price above the current value of fund shares. This assumption is reasonable given that typically there is less urgency in buying new securities in response to inflows than in selling securities in response to outflows.

Define $\overline{R_1}$ such that $I\left(\overline{R_1}\right) = \overline{N}$, where I is the level of inflows. We can see that

$$\begin{aligned} \overline{\theta}(R_1) &> \underline{\theta} \quad if \quad R_1 < \overline{R_1}, \\ \overline{\theta}(R_1) &= \underline{\theta} \quad if \quad R_1 \geq \overline{R_1}. \end{aligned} \tag{5}$$

Suppose that the realization of θ is common knowledge in $t = 1$. In this case, in equilibrium, all investors withdraw in $t = 1$ when $\theta < \underline{\theta}$, whereas all of them wait till $t = 2$ when $\theta > \overline{\theta}(R_1)$. When θ is between $\underline{\theta}$ and $\overline{\theta}(R_1)$ (which is possible when $R_1 < \overline{R_1}$), there are two equilibria: In one equilibrium, all investors withdraw at $t = 1$, whereas in the other equilibrium, they all wait till $t = 2$.

To overcome the problem of multiplicity, we apply the techniques developed in the literature on global games. This literature started with the seminal contribution of Carlsson and Van Damme (1993), who showed that the introduction of non-common knowledge into models of strategic complementarities generates unique equilibrium. Thus, following this literature, we assume that the realization of θ in period 1 is not common knowledge. Instead, we make the more realistic assumption that at $t = 1$, investors receive noisy signals about θ. In particular, suppose that each investor i receives a signal $\theta_i = \theta + \sigma\varepsilon_i$, where $\sigma > 0$ is a parameter that captures the size of noise, and ε_i is an idiosyncratic noise term that is drawn from the distribution function $g(\cdot)$ (the cumulative distribution function is $G(\cdot)$). One way to think about this information structure is that all investors see some common information about the realization of θ – for example, they observe the rating that the fund received from Morningstar – but have slightly different interpretations of it, generating the different assessments captured by the θ_i's.

As is shown in many applications of the theory of global games, under the information structure assumed here, there is a unique equilibrium, in which there is a cutoff signal θ^*, such that investors withdraw in $t = 1$ if and only if they receive a signal below θ^* (clearly, θ^* is between $\underline{\theta}$ and $\overline{\theta}$). For the economy of space, we do not prove this uniqueness result here, and refer the reader to the review article by Morris and Shin (2003) and to the many papers cited in this review.

The level of the threshold signal θ^* captures the propensity of outflows in equilibrium. Our empirical predictions will center on the behavior of θ^*. Thus, we now turn to characterize this threshold signal. First, we know that, in equilibrium, investors who observe a signal above (below)

θ^* choose to wait till $t = 2$ (withdraw in $t = 1$). Then, by continuity, an investor who observes θ^* is indifferent between withdrawing and remaining in the fund. This implies that,

$$\int_{-\infty}^{\infty} \frac{1-(1+\lambda)\max\left\{0,\left(G\left(\frac{\theta^*-\theta}{\sigma}\right)\overline{N}-I(R_1)\right)\right\}}{1-\max\left\{0,\left(G\left(\frac{\theta^*-\theta}{\sigma}\right)\overline{N}-I(R_1)\right)\right\}} R_2(\theta)\frac{1}{\sigma}g\left(\frac{\theta^*-\theta}{\sigma}\right)d\theta = 1. \tag{6}$$

Here, conditional on the signal θ^*, the posterior density over θ is $\frac{1}{\sigma}g\left(\frac{\theta^*-\theta}{\sigma}\right)$. Then, given the state θ, the proportion of investors (out of $\overline{N}$) who receive a signal below θ^* is $G\left(\frac{\theta^*-\theta}{\sigma}\right)$. Thus, the amount of withdrawals $N(\theta,\theta^*)$ is equal to $G\left(\frac{\theta^*-\theta}{\sigma}\right)\overline{N}$. Denoting $G\left(\frac{\theta^*-\theta}{\sigma}\right) = \alpha$ and changing the variable of integration, we get the following equation that implicitly characterizes θ^*:

$$\int_{0}^{1} \frac{1-(1+\lambda)\max\left\{0,\left(\alpha\overline{N}-I(R_1)\right)\right\}}{1-\max\left\{0,\left(\alpha\overline{N}-I(R_1)\right)\right\}} \cdot R_2\left(\theta^*-G^{-1}(\alpha)\sigma\right)d\alpha = 1. \tag{7}$$

This equation provides the basis for our first hypothesis. To gain more intuition for this equation, it is useful to rewrite it for the limit case as information converges to common knowledge, i.e., as σ approaches 0:

$$R_2(\theta^*) = \frac{1}{\int_0^1 \frac{1-(1+\lambda)\max\left\{0,\left(\alpha\overline{N}-I(R_1)\right)\right\}}{1-\max\left\{0,\left(\alpha\overline{N}-I(R_1)\right)\right\}}d\alpha}. \tag{8}$$

The solution for θ^* here has a very intuitive interpretation. Essentially, the investor who observes θ^* is indifferent between the two possible actions under the belief that the fundamental is θ^* and that the proportion of other investors who withdraw early (out of $\overline{N}$) will be drawn from a uniform distribution between 0 and 1.

We now turn to develop our first hypothesis based on the expression in (7). In doing so, we need to separate the case where $R_1 \geq \overline{R_1}$ from that where $R_1 < \overline{R_1}$. When $R_1 \geq \overline{R_1}$, the threshold signal θ^* is constant in λ. Intuitively, when past performance is high, the fund receives sufficient inflows. Then, when investors withdraw their money, they do not impose a negative externality on the investors who stay in the fund, as the fund can pay the withdrawers using money from new inflows. As a result, investors withdraw only when it is efficient to do so, i.e., when their signals indicate that the fundamental underlying the fund's assets is so low that the assets of the fund are expected to pay less than the outside opportunity of 1 (i.e., when $R_2(\theta)$ is expected to be below 1).

When $R_1 < \overline{R_1}$, the threshold signal θ^* is increasing in λ and decreasing in R_1. In this range, investors who withdraw their money early impose a negative externality on those who stay. This force generates self-fulfilling outflows such that investors withdraw just because they believe other investors are going to withdraw. Self-fulfilling outflows become more prominent as the externality imposed by withdrawing investors is greater. This is the case when λ is greater and when R_1 is smaller so that the damage caused by withdrawals to the fund's assets is more severe. This discussion leads to our first and main hypothesis.

Hypothesis 1: *Conditional on low past performance, funds that hold illiquid assets will experience more outflows than funds that hold liquid assets.*

We conclude this subsection by discussing the role of two assumptions made above for expositional simplicity. The first one is the assumption that $R_2(\theta)$ is independent of R_1, i.e., that there is no persistence in performance. The second one is that the stream of inflows $I(R_1)$ is exogenously positively affected by the past return R_1. As it turns out, these two points can be addressed together. That is, by relaxing the first assumption, we can endogenize the second one, and leave the prediction of the model intact.

Suppose that there is some persistence in returns due, for example, to managerial skill. As before, there is common knowledge about R_1. In addition, investors in the fund, who decide whether to redeem their shares or not, observe noisy signals θ_i about the fundamental that affects the fund's return. Thus, from each investor's point of view, the expected R_2 is an increasing function of R_1 and of θ_i. Now, suppose that outside investors, who decide whether to invest new money in the fund observe the past return R_1, but do not have private information about θ. This assumption captures the idea that insiders have superior information about the fund's expected return, since they have been following the fund more closely in the past (see Plantin (2006) for a similar assumption). In such a model, for every R_1, insiders' decision on whether to redeem or not will still be characterized by a threshold signal θ^*, below which they redeem, and above which they do not. As before, this threshold will be increasing in λ. It will also be decreasing in R_1, which does not change our prediction. Interestingly, the decision of outsiders on whether to invest new money in the fund will depend on R_1, so that the increasing function $I(R_1)$ will be endogenous. This is because a high R_1 will indicate a higher likelihood of a high R_2, and this will attract more inflows. The only important difference in the extended model will be that the inflow decision will also depend on the liquidity of the fund's assets. For every R_1, outside investors will be less inclined to invest new money in illiquid funds since they know that these funds are more likely to be subject to large outflows. This, however, will only strengthen our result by increasing the payoff complementarity among inside investors in illiquid funds and thus increasing the amount of outflows in these funds.

3.2 Extension: the role of large investors

We now extend the model to study the effect of the type of investors holding shares in the fund. So far, we analyzed a situation where there are many small investors. This corresponds to a fund that is held by retail investors. Another prominent type of investors in mutual funds is institutional investors, who are often characterized by having large positions. As it turns out, introducing investors with large positions into the model has a substantial effect on the nature of the game, and this will lead to our second hypothesis.

The exercise we conduct is similar to that in Corsetti, Dasgupta, Morris, and Shin (2004). Specifically, we introduce one large investor into the model of the previous subsection. Specifically, assume that out of the assets that might be withdrawn from the fund, $\overline{N}$, proportion β is controlled by one large investor, and proportion $(1-\beta)$ is controlled by a continuum of small investors. We take the large investor to represent an institutional investor, while the small investors represent retail investors. We assume that, just like the retail investors, the institutional investor also gets a noisy signal on the fundamental θ. Conditional on θ, the signal of the institutional investor is independent of the signals of the retail investors. For simplicity, the amount of noise σ is the same for all investors. As before, investors need to decide at $t=1$ whether to redeem their shares or not. The large investor either redeems proportion β or does not redeem at all. This is because it is never optimal for him to redeem only part of his position, as he can always increase the return on the part he keeps in the fund by keeping more.

The results in Corsetti, Dasgupta, Morris, and Shin (2004) establish that there is again a unique equilibrium in the game. This equilibrium is characterized by two thresholds: retail investors redeem if and only if their signals fall below θ^R, and the institutional investor redeems if and only if his signal is below θ^I. Let us characterize these threshold signals. As before, a retail investor that observed θ^R is indifferent between redeeming and not redeeming:

$$\int_{-\infty}^{\infty}\left[\begin{array}{c} G\left(\frac{\theta^I-\theta}{\sigma}\right)\cdot\frac{1-(1+\lambda)\max\left\{0,\left(\left(G\left(\frac{\theta^R-\theta}{\sigma}\right)(1-\beta)+\beta\right)\overline{N}-I(R_1)\right)\right\}}{1-\max\left\{0,\left(\left(G\left(\frac{\theta^R-\theta}{\sigma}\right)(1-\beta)+\beta\right)\overline{N}-I(R_1)\right)\right\}} \\ +\left(1-G\left(\frac{\theta^I-\theta}{\sigma}\right)\right)\cdot\frac{1-(1+\lambda)\max\left\{0,\left(G\left(\frac{\theta^R-\theta}{\sigma}\right)(1-\beta)\overline{N}-I(R_1)\right)\right\}}{1-\max\left\{0,\left(G\left(\frac{\theta^R-\theta}{\sigma}\right)(1-\beta)\overline{N}-I(R_1)\right)\right\}}\end{array}\right]\cdot R_2(\theta)\frac{1}{\sigma}g\left(\frac{\theta^R-\theta}{\sigma}\right)d\theta=1. \tag{9}$$

Here, conditional on the signal θ^R, the posterior density over θ is $\frac{1}{\sigma}g\left(\frac{\theta^R-\theta}{\sigma}\right)$. Then, given the state θ, the proportion of retail investors (out of $(1-\beta)\overline{N}$) who receive a signal below θ^R and redeem is $G\left(\frac{\theta^R-\theta}{\sigma}\right)$. The amount of withdrawals now depends on the behavior of the institutional investor. Conditional on θ, with probability $G\left(\frac{\theta^I-\theta}{\sigma}\right)$ he receives a signal below θ^I and withdraws, in which case the amount of withdrawals is $\left(G\left(\frac{\theta^R-\theta}{\sigma}\right)(1-\beta)+\beta\right)\overline{N}$. With probability $\left(1-G\left(\frac{\theta^I-\theta}{\sigma}\right)\right)$, he does not withdraw, in which case the amount of withdrawals is $G\left(\frac{\theta^R-\theta}{\sigma}\right)(1-\beta)\overline{N}$. The institutional investor is indifferent at signal θ^I:

$$\int_{-\infty}^{\infty}\left[\frac{1-(1+\lambda)\max\left\{0,\left(G\left(\frac{\theta^R-\theta}{\sigma}\right)(1-\beta)\overline{N}-I(R_1)\right)\right\}}{1-\max\left\{0,\left(G\left(\frac{\theta^R-\theta}{\sigma}\right)(1-\beta)\overline{N}-I(R_1)\right)\right\}}\right]\cdot R_2(\theta)\frac{1}{\sigma}g\left(\frac{\theta^I-\theta}{\sigma}\right)d\theta=1. \tag{10}$$

Essentially, from his point of view, he knows that if he does not withdraw, the amount of withdrawals conditional on θ is $G\left(\frac{\theta^R-\theta}{\sigma}\right)(1-\beta)\overline{N}$.

After changing variables of integration in a similar way to what we did in the previous subsection, we obtain the following two equations:

$$\int_{-\infty}^{\infty}\left[\begin{array}{c} G\left(\frac{\theta^I-\theta^R+G^{-1}(\alpha)\sigma}{\sigma}\right)\cdot\frac{1-(1+\lambda)\max\left\{0,\left((\alpha(1-\beta)+\beta)\overline{N}-I(R_1)\right)\right\}}{1-\max\left\{0,\left((\alpha(1-\beta)+\beta)\overline{N}-I(R_1)\right)\right\}} \\ +\left(1-G\left(\frac{\theta^I-\theta^R+G^{-1}(\alpha)\sigma}{\sigma}\right)\right)\cdot\frac{1-(1+\lambda)\max\left\{0,\left(\alpha(1-\beta)\overline{N}-I(R_1)\right)\right\}}{1-\max\left\{0,\left(\alpha(1-\beta)\overline{N}-I(R_1)\right)\right\}}\end{array}\right]\cdot R_2\left(\theta^R-G^{-1}(\alpha)\sigma\right)d\alpha=1. \tag{11}$$

$$\int_{-\infty}^{\infty}\left[\frac{1-(1+\lambda)\max\left\{0,\left(G\left(\frac{\theta^R-\theta^I+G^{-1}(\alpha)\sigma}{\sigma}\right)(1-\beta)\overline{N}-I(R_1)\right)\right\}}{1-\max\left\{0,\left(G\left(\frac{\theta^R-\theta^I+G^{-1}(\alpha)\sigma}{\sigma}\right)(1-\beta)\overline{N}-I(R_1)\right)\right\}}\right]\cdot R_2\left(\theta^I-G^{-1}(\alpha)\sigma\right)d\alpha=1. \tag{12}$$

As before, we analyze the solution for the case where $\sigma \to 0$. It is easy to see that in this case θ^I and θ^R converge to the same value, which we will denote as θ^{**}. Why? Suppose that this was not the case, and assume that $\theta^R > \theta^I$. Then, when observing θ^R the retail investors know that the institutional investor is not going to withdraw, so they expect a uniform distribution of withdrawals between 0 and $(1-\beta)\overline{N}$. Similarly, when observing θ^I the institutional investor knows that the retail investors are going to withdraw, so he expects withdrawals to be $(1-\beta)\overline{N}$, i.e., he expects more withdrawals than the retail investors expect when they observe θ^R. Thus, the only way to make the retail investors indifferent at signal θ^R and the institutional investor indifferent at signal θ^I is to say that $\theta^I > \theta^R$, but this contradicts the above assumption that $\theta^R > \theta^I$. Similarly, one can establish that there cannot be an equilibrium where θ^I and θ^R do not converge to the same value and $\theta^I > \theta^R$.

Thus, effectively, there is one threshold signal θ^{**} that characterizes the solution to the game and determines the propensity of outflows. Another variable that is important for the solution is $\frac{\theta^R - \theta^I}{\sigma}$,[11] which from now on we will denote as x. Then, the solution to the model boils down to solving the following two equations for θ^{**} and x (here, the first equation is for the retail investors and the second one is for the institutional investor):

$$R_2(\theta^{**}) = \frac{1}{\int_0^1 \left[\begin{array}{c} G\left(G^{-1}(\alpha) - x\right) \cdot \frac{1-(1+\lambda)\max\left\{0,\left((\alpha(1-\beta)+\beta)\overline{N} - I(R_1)\right)\right\}}{1-\max\left\{0,\left((\alpha(1-\beta)+\beta)\overline{N} - I(R_1)\right)\right\}} \\ +\left(1 - G\left(G^{-1}(\alpha) - x\right)\right) \cdot \frac{1-(1+\lambda)\max\left\{0,\left((\alpha(1-\beta)+\beta)\overline{N} - I(R_1)\right)\right\}}{1-\max\left\{0,\left((\alpha(1-\beta)+\beta)\overline{N} - I(R_1)\right)\right\}} \end{array} \right] d\alpha}. \tag{13}$$

$$R_2(\theta^{**}) = \frac{1}{\int_0^1 \left[\frac{1-(1+\lambda)\max\left\{0,\left(G(G^{-1}(\alpha)+x)(1-\beta)\overline{N} - I(R_1)\right)\right\}}{1-\max\left\{0,\left(G(G^{-1}(\alpha)+x)(1-\beta)\overline{N} - I(R_1)\right)\right\}} \right] d\alpha}. \tag{14}$$

To derive our hypothesis, we wish to compare θ^{**}, which is characterized by the above two equations, with θ^*, which is characterized by (8). Using (14), we can derive an upper bound on θ^{**} by setting $G\left(G^{-1}(\alpha) + x\right) = 1$. We will denote the upper bound as θ^{UB}.

$$R_2(\theta^{**}) < \frac{1}{\int_0^1 \left[\frac{1-(1+\lambda)\max\left\{0,\left((1-\beta)\overline{N} - I(R_1)\right)\right\}}{1-\max\left\{0,\left((1-\beta)\overline{N} - I(R_1)\right)\right\}} \right] d\alpha} \equiv R_2\left(\theta^{UB}\right). \tag{15}$$

[11] Note that from the argument above, both the numerator and the denominator approach 0, and the fraction is well defined.

Analyzing (15), we can see that θ^{UB} is decreasing in β. Moreover, it is clearly below θ^* when $\beta = 1$. Thus, given continuity, there exists a $\beta^* < 1$, such that when $1 > \beta > \beta^*$, $\theta^{**} < \theta^*$. In words, when the institutional investor is large enough, funds that have an institutional investor will experience less outflows than funds with only retail investors. By the same token, for funds with an institutional investor, the effect of illiquidity on outflows (after bad performance) will be weaker. Importantly, to keep things simple, our theoretical analysis followed directly the one in Corsetti, Dasgupta, Morris, and Shin (2004), and looked at the effect of introducing one large investor. But, the basic insight (as it is explained below) would be the same if we looked at the more empirically relevant question of what happens when we increase the total proportion that is held by large investors. This leads us to our second hypothesis.

Hypothesis 2: *The pattern predicted in Hypothesis 1 is less prominent in funds that are held mostly by institutional investors than in funds that are held mostly by retail investors.*

Let us clarify the intuition behind this hypothesis. Because large investors hold larger proportions of the fund's shares, they are less affected by the actions of other investors. They at least know that by not withdrawing they guarantee that their shares will not contribute to the overall damage caused by withdrawals to the fund's assets. Thus, the negative externality imposed by withdrawals is weaker for large investors, and they are less likely to withdraw. Moreover, knowing that the fund is held by some large investors, other investors will also be less likely to withdraw. This is because the large investors inject strategic stability and thus reduce the inclination of all shareholders to withdraw. Overall, funds with more institutional investors will be less subject to the self-fulfilling outflows described in this paper. It is important to note that the presence of a large investor pushes towards the outcome that is efficient for investors. This is also the case in Corsetti, Dasgupta, Morris, and Shin (2004). There, the efficient outcome is a currency attack, so the large investor injects fragility, rather than stability.

4 Data

Our empirical analysis focuses on 3,185 equity funds from the CRSP Mutual Fund database from 1995-2005.[12] A fund is defined as an equity fund if at least 50% of its portfolio are in equity in all years from 1995-2005. To ensure that our flow measure captures investors' desired action, we include only fund-year observations when the funds are open to new and existing shareholders. We exclude retirement shares because they are issued for defined-contribution plans (such as 401(k) and 403(b) plans) whose participants are usually limited in their investment choice set of funds or families and in the frequency they can reallocate their funds within the choice set.

We use CRSP S&P style code and area code to identify the types of assets each fund invests in and create a dummy variable *Illiq* based on these codes. *Illiq* equals one if these codes indicate that the fund invests primarily in one of the following categories: small-cap equities (domestic or international), mid-cap equities (domestic or international), or single-country assets excluding U.S., U.K., Japan, and Canada. We cross check these classifications for consistency with the CRSP Mutual Funds asset class code and category code. Since these codes are available only after 2002, for data before 2002, we extrapolate the classification by matching both the fund's names and tickers. For funds that deceased before 2002, we manually classify them based on the description of their investment area/style in the Morningstar database. Our results are qualitatively similar if we exclude mid-cap funds or funds investing in developed single-country markets. For the subsample of domestic equity funds, we are able to construct finer and continuous liquidity measures using the holdings data information (details in Section 7.1).

We rely on CRSP data and hand-collected data to create a dummy variable *Inst* to denote whether a fund share is an institutional share or a retail share. For the post-2002 period, CRSP assigns each fund share a dummy for institutional share and a dummy for retail share. The two dummies are not mutually exclusive. Therefore, we set *Inst* to be one for a fund share if the CRSP institutional share dummy is one *and* the CRSP retail share dummy is zero,[13] and we then

[12] The intuition and prediction of our theoretical model also apply to bond funds. However, we do not have available data to measure the liquidity of bond funds.

[13] The double criteria serve to exclude fund shares that are open to both institutional investors and individuals with high balances. For example, some funds (such as the Vanguard Admiral fund series) offer individuals with large

extrapolate the *Inst* dummy to the earlier period by matching the fund share's unique ID in CRSP (ICDI code). The remaining sample is then manually classified according to the Morningstar rule where a fund share is considered an institutional one if its name carries one of the following suffixes: I (including various abbreviations of "institutional" such as "Inst", "Instl", etc.), X, Y, and Z. A fund share is considered retail if it carries one of the following suffix: A, B, C, D, S, and T. Fund shares with the word "Retirement" (or its various abbreviations such as "Ret") or with a suffix of R, K, and J in their names are classified as retirement shares and are excluded from our analysis for reasons stated earlier. Other fund shares, those carrying other suffix (mainly M and N) or no suffix, are classified as institutional if the amount of minimum initial purchase requirement is greater than or equal to $\$50,000$ (a standard practice adopted by the mutual fund literature).[14] According to the 2005 Investment Company Fact Book, institutional shareholders in mutual funds include financial institutions such as banks and insurance companies, business corporations (excluding retirement plans that are considered employee assets), nonprofit organizations (including state and local governments), and others. In addition to the dummy variables for institutional and retail shares, we use the minimum initial purchase requirement of a fund share as an alternative measure for the size of the typical investors of a fund.

Our main analysis of fund flows is conducted at the fund-share level. This is mainly because some key variables are fund-share specific (rather than fund specific), such as institutional shares, minimum initial purchase, expenses and loads. Some sensitivity analysis is repeated at the fund level where we aggregate fund-share data that belong to the same fund. Analysis about fund policy is conducted at the fund level. The definitions and summary statistics of the main variables are reported in Table 1. All regressions allow year fixed effects and all standard errors adjust for clustering at the fund level. Our final sample includes $639,596$ fund share-month observations with $7,777$ unique fund shares in $3,185$ unique funds.

[Insert Table 1 here]

balances access to fund shares that charge lower expenses. Such fund shares are not classified as institution shares in our coding.

[14] The minimum initial purchase information is available from the Morningstar, but not from the CRSP database.

5 Hypothesis Testing

5.1 Hypothesis 1: The effect of liquidity

5.1.1 Overview

As discussed in Section 3, our first hypothesis is that conditional on poor performance, funds that invest primarily in illiquid assets (i.e., illiquid funds) will experience more outflows because investors take into account the negative externality of other investors' redemptions. The resulting empirical observation should be that illiquid funds have a higher sensitivity of outflows to performance when performance is relatively poor. The reason is that different funds have different performance thresholds, below which they start seeing net outflows and complementarities start affecting the redemption decision. On average, as we go down the performance rank, we are gradually hitting the threshold for more and more funds. Then, because complementarities are stronger for illiquid funds than for liquid funds, a decrease in performance in illiquid funds has a larger effect on outflows. In illiquid funds the complementarities that come with the reduced performance amplify outflows.

Most of our analysis will be on explaining the sensitivity of flows to performance in linear regressions. Before we turn to the regression analysis, it is useful to consider a semiparametric approach, where the relation between flow and performance is not restricted to be linear. This will offer a diagnostic view of the relation between fund flow and past performance. This analysis is important in light of the vast evidence of a non-linear relationship between flow and performance (see Chevalier and Ellison (1997)). The drawback is, of course, that significance levels are much lower in this type of analysis. The results are presented in Figure 1.

[Insert Figure 1 here]

In Figure 1, the vertical axis is the percentage net flow into the fund share in month t and the horizontal axis is the fund share's past return performance, measured by the monthly *Alpha* from the one-factor market model averaged over months $t-7$ to $t-1$.[15] The net flow ($Flow$) is measured

[15] All *Alpha* values are calculated from the return of the month under consideration, and *Beta* estimates using monthly return data of the previous 36 months (or as many as the data allows). The value is set to be missing if there are less than 12 observations in the estimation.

following the standard practice in the literature:

$$Flow_t = \frac{TNA_t - TNA_{t-1}\,(1 + Ret_t)}{TNA_{t-1}}, \tag{16}$$

where TNA is the total net assets managed by the fund share, and Ret is the raw return. About 45% of the fund share-month observations see negative net flows.

Figure 1 plots, separately for the sample of liquid funds and the sample of illiquid funds, the estimated nonparametric functions $f(\cdot)$ in the following semiparametric specification:

$$Flow_{i,t} = f\,(Alpha_{i,t-1}) + \beta X_{i,t} + \varepsilon_{i,t}, \tag{17}$$

where X is a vector of control variables including: fund size ($Size$, in log million dollars), fund age (Age, years since inception, in logs), expenses in percentage points ($Expense$), and total sales load ($Load$, the sum of front-end and back-end loads). These variables are shown in prior literature to affect mutual funds' flow-to-performance sensitivity. The estimation of (17) applies the method introduced by Robinson (1988).[16] The method first estimates $\widehat{\beta}$ by differencing out $Alpha$ on both sides of the equation, and then estimates the following relation using the nonparametric kernel method[17]:

$$Flow_{i,t} - \widehat{\beta} X_{i,t} = f\,(Alpha_{i,t-1}) + \varepsilon'_{i,t}. \tag{18}$$

The intercept in (18) is identified by setting $\widehat{f}\,(Alpha = 0) = \widehat{E}\,(Flow|Alpha = 0)$, where the $\widehat{E}$ (the empirical analog to expectation) operation is taken on observations within the kernel centered on $Alpha = 0$. Thus, the intercept represents the net flow for each type of funds when they achieve market performance.

The thick solid (dotted) line in Figure 1 represents the plot of $f\,(\cdot)$ for the liquid (illiquid) funds, and the corresponding thin lines represent the 10% confidence intervals. Figure 1 reveals two features that are consistent with investors' behavior under complementarities in redemption

[16] Chevalier and Ellison (1997) apply the same method in estimating the nonparametric relation between past performance and fund flows/management turnover.

[17] Specifically, $\widehat{\beta}$ is estimated using the regular linear regression method on $y - \widehat{m}_y = (X - \widehat{m}_X)\beta + v$, where $\widehat{m}_y$ ($\widehat{m}_X$) are the kernel-weighted average value of all observations within a neighborhood centered on $Alpha_{i,t-1}$. See Robinson (1988) for details. The choice of kernel function follows the best practice of Silverman (1986).

decisions.. First, while the flow-to-performance sensitivities for liquid and illiquid funds are more or less comparable in the positive *Alpha* region, illiquid funds experience noticeably more sensitive flows when performance is below par, with the magnitude significantly higher for illiquid funds when the average monthly *Alpha* in the past six months falls below -2.7% (about 4.4% of the observations fall below this point).[18] Second, redemptions on average occur at a higher past performance level for illiquid funds than for liquid ones. Illiquid funds on average start to experience negative net flows when the monthly *Alpha* falls below -0.8%; the threshold point for liquid funds is -1.6%.

Another interesting feature in Figure 1 that is not directly related to the main theme of our paper is at the top end of the performance chart. Previous literature documents a convex relation between net flows and performance at the top end (Chevalier and Ellison (1997), Sirri and Tufano (1998)). Figure 1 shows that the phenomenon is present only for liquid funds (which represent about three-quarters of all data observations). The lack of convexity for illiquid funds shown in Figure 1 suggests that illiquid funds face greater diseconomies of scale, both because of the unfavorable price impact from trading and because of the limited positions that managers with superior information can take on. This is related to the analysis of Berk and Green (2004).

5.1.2 Regression analysis

For a summary estimate of the effect of liquidity on the flow-performance sensitivity, we conduct the following regression and report the results in Table 2:

$$Flow_{i,t} = \beta_0 Perf_{i,t-1} + \beta_1 Illiq_i \cdot Perf_{i,t-1} + \beta_2 Illiq_i + \beta_3 Control_{i,t} + \beta_4 Control_{i,t} \cdot Perf_{i,t-1} + \varepsilon_{i,t}. \tag{19}$$

[Insert Table 2 here]

In (19), $Perf_{i,t-1}$ is a lagged performance measure. In Table 2 columns (1) to (3), we use three common performance measures: *Alpha* from a one-factor market model (*Alpha*1), *Alpha* from a

[18] The significance is based on the point-wise standard errors from kernel-based nonparametric method. The non-parametric method allows flexible specification in the shape of the function, at the expense of much wider confidence intervals.

four-factor (the Fama-French three factors plus the momentum factor) model ($Alpha4$), and return in excess of the category return ($RetExCat$) where category is defined by the CRSP S&P style code. All measures are monthly average excess returns, in percentage points, during the six-month period ending in the month before $Flow$ is calculated.[19] Control variables ($Control$) include: lagged flow ($Flow(-1)$), size of the funds in log million dollars ($Size$), fund age in log years (Age), fund expense in percentage points ($Expense$), sum of front-end and back-end load charges in percentage points ($Load$), and the dummy variable for institutional shares ($Inst$). The control variables enter both directly, and interactively with the performance measure.

Columns (1) to (3) of Table 2 show that fund flows are highly responsive to past performance, a relation well documented in prior literature. Specifically, in our sample, one percentage point increase in lagged monthly average $Alpha1$ leads to an increased net inflow in the magnitude of 0.70% of the fund's total net assets. The flow responses to $Alpha4$ and $RetExCat$ are also significant (at 0.50% and 0.77%, respectively). Because we are mostly interested in the pattern of fund outflows, in Columns (4) to (6) we focus on the subsample where funds underperform the benchmark returns. Consistent with prior literature, we see that investors are more responsive to good performance than to bad performance: the coefficients on $Perf$ in columns (4) to (6) of Table 2 are significantly lower than their counterparts in the full sample. Interestingly, the responsiveness to poor performance differs quite significantly across the three performance measures. When using $Alpha1$, one percentage point of sub-benchmark performance leads to 0.27% of reduced flows (significant at less than 1%). The response is 0.09% using the two other measures (insignificant at the 10% level). Since we are analyzing how investors behave as a function of the behavior of other investors, the appropriate performance measure for our analysis is the one that investors use and are overall more responsive to, rather than a measure that does a better job in performance attribution. Thus, we will mostly focus on $Alpha1$ for the rest of the paper.

The focus of our analysis is the coefficients for $Illiq \cdot Perf$. Table 2 shows that all coefficients for $Illiq \cdot Perf$ are positive, and all except for one of them are significant at less than the 5% level. The

[19] We settled on the six-month lag after we regressed flows on lagged individual monthly returns up to a year. We find that the effects of the recent six months' returns on current flows are monotonically decreasing, and the effects weaken substantially when the returns are lagged further.

most important result for our hypothesis is that flows are more sensitive to poor performance in illiquid funds than in liquid funds as indicated by the positive coefficients on $Illiq \cdot Perf$ in columns (4) to (6). Specifically, the estimated coefficient for $Illiq \cdot Alpha1$ is 0.14 for the negative $Alpha1$ subsample. Thus, when $Alpha1$ is negative, the flow-performance sensitivity in illiquid funds is 52% higher than that in liquid funds (0.41% vs. 0.27%). For the full sample, the sensitivity is 19% higher for the illiquid funds (0.83% vs. 0.70%). This result provides support for our first hypothesis that outflows in illiquid funds are more sensitive to bad performance than in liquid funds.

5.2 Hypothesis 2: The effect of investor composition

Hypothesis 2 of our model predicts that the effect of complementarities on investors' response to poor performance is less pronounced when there are fewer, larger shareholders (such as institutional investors). The idea is that fewer and larger shareholders are more likely to internalize the payoff externalities and avoid outflows that damage funds' assets. As a result, we expect the effect of illiquidity on flow-performance sensitivity to be smaller in funds that are held mostly by large investors. To test this hypothesis, we use the percentage of a mutual fund's assets held by large investors as an instrument to identify the extent of the internalization of the redemption cost. We use two proxies for the presence of large investors. One is based on whether a share is an institutional share ($Inst$), and the other is based on whether it has a high minimum initial purchase requirement ($MinPur250K$). For the latter, we use $\$250,000$ as the cutoff, but the results are very similar if we use a lower ($\$100,000$) or a higher ($\$500,000$) cutoff. We consider a fund to be held primarily by large investors ("institutional-oriented fund") if more than 75% of the fund assets are issued to institutional shares, or to fund shares with minimum initial purchase requirement of $\$250,000$ or higher. Conversely, a fund is considered to be held primarily by small investors ("retail-oriented fund") if less than 25% of the fund assets are in fund shares that are issued to large investors. Table 3 repeats the analysis of column (4) of Table 2 on subsamples partitioned by the composition of investors.

[Insert Table 3 here]

Table 3 shows that the effect of asset liquidity on the flow-to-poor-performance sensitivity is only present among retail-oriented funds. Using the percentage of institutional shares to classify the clientele of the fund, the coefficient for $Illiq \cdot Alpha1$ is 0.20 ($t = 2.91$) for funds held primarily by small investors and 0.02 ($t = 0.18$) for funds primarily held by large investors. This indicates that flows are more sensitive to poor performance in illiquid funds only when there is a lack of large-investor mass in the shareholder base. Similar results prevail when we use the minimum initial purchase requirement as the proxy for large investors. These results are consistent with the second hypothesis of the model.

5.3 Summary and discussion

Overall, we find that investors' flows are significantly more sensitive to poor performance for funds that invest in illiquid securities than for funds that invest in liquid securities. Further, the liquidity effect on fund outflows is only present in funds that are primarily open to small/retail investors. As discussed above, this is consistent with behavior that is based on payoff complementarities among investors in their redemption decisions. Such behavior contributes to financial fragility of the type highlighted in the bank-run literature.

Despite the analogy to the bank-run literature, it is important to emphasize a key difference. This is that our evidence does not apply to the behavior of the average mutual-fund investor, but rather to that of the marginal mutual-fund investor. Indeed, in our full sample, the 1st, 5th, and 25th percentile values of monthly net flows are -23.2%, -6.2%, and -1.3%, respectively. This indicates that even after very bad performance, funds do not in general experience massive outflows within a short period of time (one month). This is probably because the majority of mutual fund investors do not frequently monitor the fund managers or rebalance their portfolios. Johnson (2006) indicates that about 93% of the investors in a mutual fund family do not have redemption transactions within one year after opening their accounts. Agnew, Pierluigi, and Sunden (2003) show that 87% of the 401(k) participants from a large brokerage house do not conduct any trade in a year. Thus, the key to our model is that for the marginal investors who are making the decision at a given point in time, the incentive to redeem is monotonically increasing in the magnitude of redemption by other investors in the same fund. Our empirical results are consistent with these predictions.

While massive outflows within a short period of time are rare for mutual funds, they do happen from time to time. Putnam's recent experience offers an illustrative example of the effect of strategic complementarities in mutual funds and their large potential damage. On October 23, 2003, Putnam Investments went under federal investigation for improper trades, including market timing activities and excessive short-term trading. Over the next month the fund family saw a net redemption of 8.1% of its total assets, followed by another 4.2% net outflow in the following month. A monthly net redemption rate of about $1-2\%$ continued for another three years during which the whole fund family lost more than 40% of its assets. By and large, the "run" on the Putnam funds seems to be driven by strategic complementarities, rather than by "fundamentals." Given that the portfolio managers were replaced immediately after the start of the investigation (on October 24, 2003) and that the Putnam funds were expected to be under close scrutiny, there was no reason to believe that the returns from Putnam funds going forward would be lower than from other funds had all investors chosen to stay. Indeed, in his special report to the SEC, Tufano (2005) estimates that the damage to investors caused directly by the abusive trading behavior of the managers was $4.4 million during the seven years before the allegation. On the other hand, the damage from the unusual magnitude of redemptions was estimated to be $48.5 million. Therefore, the fear of investors that other investors will redeem became self-fulfilling and resulted in a huge loss to most shareholders.[20]

6 Alternative Explanations

We interpret our result that outflows are more sensitive to bad performance in illiquid funds than in liquid funds as evidence that strategic complementarities amplify outflows and increase financial fragility. We use the fact that this holds in retail-oriented funds but not in institutional-oriented funds to strengthen our conclusion. In this section we examine two main alternative explanations

[20]In 2005, Putnam agreed to compensate shareholders for the cost stemming from the redemption following the public allegation.

for our results, and present evidence to refute them. The first explanation is based on information that past returns convey about future returns and the second one on different clienteles investing in the two types of funds.

6.1 Information

The fact that investors are more sensitive to bad performance in illiquid funds than in liquid funds may be due to higher return persistence in illiquid funds, for reasons other than the effect of redemptions. This can reflect either higher persistence in the performance of the underlying assets or in managerial performance. If indeed illiquid funds show more persistence, then following bad performance, investors would want to flee out of illiquid funds more than out of liquid funds, even without considering the effect of other investors' redemptions. This explanation is reminiscent of the empirical banking-crises literature (Gorton (1988), Calomiris and Mason (1997), Schumacher (2000), Martinez-Peria and Schmukler (2001), and Calomiris and Mason (2003)) that argues that withdrawals from banks are driven by the expectation that bad fundamentals will lead to future bad performance.

We first note that this mechanism is unlikely to be driving our results because it does not explain the results of Table 3. We further conduct a sharper test by examining whether funds investing in illiquid assets display more return persistence, especially when the past performance is poor. This is necessary for the mechanism mentioned here to explain the results of Table 2. Table 4 presents a formal comparison between liquid and illiquid funds. To isolate the effect of information about fundamentals from that of the damage caused by other redemptions, we exclude all observations that experience more than 5% outflows during the past month (about 6.3% of the sample).[21] For each month, we sort funds into quintiles based on their three performance measures ($Alpha1$, $Alpha4$, and $RETEXCAT$, all defined in Table 1) during the past six months. Then, we report the average performance over all funds in each quintile in the current month. We conduct the analysis separately for liquid and illiquid funds.

[21] According to our model, large redemptions per se will cause some return persistence, an effect we will analyze in a later section of this paper. This effect is different from the information story we discuss here.

[Insert Table 4 here]

In interpreting the results, we focus on $Alpha1$, which is the performance measure we focused on thus far in the paper. Our conclusion is that information conveyed in past performance about future performance cannot explain the results in our paper. First, one way to think about return persistence, as proposed in previous literature, is to compare the current return of the highest quintile – formed on the basis of past return – with that of the lowest quintile. This measure ($Q5-Q1$) is reported in Table 4 for liquid and illiquid funds. As we see in the table, while ($Q5-Q1$) is slightly higher for illiquid funds, the difference is far from being statistically significant ($t-$statistic $= -0.28$). Second, for our purposes it is perhaps more important to compare only the funds with the worst performance, as they experience most of the outflows and thus are the subject of our paper. We can see in the table that illiquid funds with the worst past performance (bottom quintile) do not underperform the liquid funds with the worst past performance. In fact, the performance of the former is actually slightly higher (but the difference is also not statistically significant). Overall, the lack of incremental return persistence among illiquid funds is consistent with evidence in the asset pricing literature on illiquid stocks. (See for example, Avramov, Chordia, and Goyal (2006) who show that illiquid stocks display stronger return reversal at the monthly frequency.)

Related to the information effect is the potentially different implication that bad performance in illiquid and liquid funds has on investors, which could lead to difference in redemptions. One might argue, that some investors become more risk averse after incurring a loss in their mutual fund investment because of the wealth effect. As a result, they are more likely to withdraw money from illiquid funds because these are more risky. This idea is inconsistent with the results in Table 3. In particular, if changes in risk tolerance are in play then it is not clear why they are more important in retail-oriented funds than in institutional-oriented funds. Moreover, the wealth effect is not expected to be that big to generate such changes in risk tolerance. In their analysis of two decades of panel data from the Panel Study of Income Dynamics (PSID), Brunnermeier and Nagel (2005) find that wealth shocks do not have economically significant effects on household asset allocation.

6.2 Different clienteles

Another possible mechanism for the differences in the sensitivity of outflows to poor performance between liquid and illiquid funds is that these funds are held by different clienteles. For example, if illiquid funds were held by institutional investors, who are more tuned to the market and redeem more after bad performance, while liquid funds were held by retail investors, our result could be generated by a clientele effect. A brief look at the data indicates that this mechanism does not generate our results. According to our data, liquid funds are more likely than illiquid funds to be held by institutions. Moreover, Table 3 indicates that institutions are on average slightly more sensitive to poor performance than retail investors (although they do not chase after good performance as much). These two facts alone would generate the opposite result to what we find in the paper.

A sharper test to address the clientele issue is to see whether our results hold when we isolate the observations belonging to the relatively more sophisticated clientele – namely, that of large/institutional investors. Thus, we repeat the analysis in Table 3 only for shares held by large/institutional investors. For this, we use two different measures: whether the share belongs to an institutional class and whether the minimum initial purchase is at least $\$250,000$. We report the results in Table 5.

We can see from the table that our previous results are not driven by the clientele effect. That is, the results in Table 5 – obtained only from the behavior of large/institutional shares – are very similar to those in Table 3 – obtained from the behavior of all shares. Specifically, we can see that among retail-oriented funds – where we expect strategic complementarities to affect outflows – institutional investors are more sensitive to bad performance in illiquid funds than in liquid funds. The difference in sensitivity of flow to performance between illiquid and liquid funds is 0.34% or 0.50%, depending on the measure that we use for large/institutional investors, both significant at less than the 10% level. Thus, to the extent that institutional investors in illiquid funds are similar to those in liquid funds, Table 5 indicates that differences in clientele are not driving our results.

[Insert Table 5 here]

7 Extensions

7.1 Liquidity measures based on fund holdings

Our *Illiq* variable is based on funds' investment style (e.g., small-cap or single-country). One potential concern is that differences in flow-to-poor performance sensitivities are caused by unobservable fund characteristics unrelated to the liquidity of their assets. To confirm that our earlier findings are related to the liquidity of the fund assets, we retrieve from the Thomson Financial database the detailed holding data for the subsample of domestic equity funds, and calculate finer measures of the liquidity of the funds' underlying assets ($Liq\_Holding$). Specifically, for each stock held by a fund, we calculate two measures to capture the underlying stock's liquidity: the dollar trading volume ($Trade\_Vol$, in logs), and the liquidity measure developed in Amihud (2002) ($Amihud$).[22] The liquidity measure of a fund is then calculated as the value-weighted average liquidity measure of the fund's underlying securities. To ensure the accuracy of these measures, we exclude funds where less than 75% of the underlying securities are matched to the CRSP database.[23]

The trading volume is the average daily dollar value of the trading volume over the quarter ending on the holding data report date. For stocks with high trading volumes, it is easier to execute large trades without a significant adverse price impact. Thus, the (value-weighted) average trading volume of a fund's underlying assets captures the ability of the fund to accommodate outflows without hurting the value for the remaining shareholders. The Amihud liquidity measure is constructed as an inverse price-impact measure (i.e., how much trading volume can a stock absorb for one unit of price change). For each stock, it is calculated as the annual average of $0.001\sqrt{\$Trading\ Volume}/|Return|$ (using daily data). We download this measure for all CRSP stocks from Joel Hasbrouck's web site.[24] The correlation coefficient between the trading volume

[22] See discussions in recent papers by Acharya and Pedersen (2005) and Spiegel and Wang (2006) on the performance of the two measures in capturing return premium due to illiquidity.

[23] It is reasonable to assume that stocks not covered by CRSP tend to have small market cap. Therefore, the total value weights of the missing stocks are likely to be lower than 25%. Thus, the error of the measure due to missing stocks should not impose a major cost on our estimation.

[24] We are grateful to Joel Hasbrouck for providing the Amihud measure data for individual stocks on his website. The measure we adopt is named "L2" by Hasbrouck.

and the Amihud measure is 0.78, and their correlation coefficients with the dummy variable for illiquid funds are -0.46 and -0.59, respectively.

For each holding liquidity measure, we conduct the same tests as in Tables 2 and 3. The results are reported in Table 6. Columns (1) and (3) show that the coefficients on $Liq\_Holding * Perf$ are all significant with the expected signs, indicating less outflow for liquid funds than for illiquid funds for a given poor performance. When we focus on the subsample of fund shares in institutional oriented funds (Columns (2) and (4)), the effect is reduced to near zero in magnitude and becomes insignificant for both measures.

[Insert Table 6 here]

In untabulated results, we find that when we include the dummy $Illiq$ with either $Trade\_Vol$ or $Amihud$, the dummy variable becomes statistically insignificant at conventional levels while the holding-based liquidity measures remain highly significant. This result indicates that the dummy variable is indeed a coarser proxy of funds' liquidity compared to holding-data-based measures (and therefore loses its significance in the presence of a finer measure of liquidity). In another sensitivity check (untabulated), we re-estimate the regression in Table 6 for the subsample of illiquid funds. We find similar results. For example, the coefficient for $Trade\_Vol$ is still significantly negative at less than the 1% level. Together, these results indicate that our main results in Tables 2 and 3 are not driven by some unobservable characteristics of small-cap/single-country funds that are orthogonal to the liquidity aspect of these funds.

7.2 Outflows, liquidity, and fund performance

Our model implies that large outflows should damage future fund performance in illiquid funds more than in liquid funds. To further strengthen the support for our story, we now turn to present evidence on this aspect of the model. To assess the effect of outflows on future fund performance, we estimate the following equation, at the fund level:

$$Perf_{i,t} = \beta_0 Outflow_{i,t-1} + \beta_1 Size_{i,t-1} + \beta_2 Expense_{i,t} + \sum_{j=1}^{J=6} \gamma_j PastPerf_{i,t-j} + \varepsilon_{i,t}. \qquad (20)$$

Here, $Perf_{i,t}$ is a fund's current month $Alpha1$ and $Outflow$ is an indicator variable for whether the lagged flow is lower than -5% of total net asset value.[25] Because past returns are included in the regression, a significant coefficient estimate of β_0 would show that large outflows affect a fund's future return beyond what is predicted by past returns.

[Insert Table 7 here]

We estimate (20) separately on liquid funds, illiquid funds (as classified by the $Illiq$ dummy variable), and fund-month observations whose $Amihud$ measure falls below the $25th$ percentile value of the full sample. The results are presented in Columns (1) to (3) of Table 7. Consistent with the prior literature, we find that fund performance (net of fees) is negatively correlated with fees and fund size. Our new finding is that the presence of large outflows in the past month predicts lower returns in the current month in the order of 19 basis points for the 25% least liquid funds (significant at less than the 1% level). The same effect is still significant, but of milder magnitude (13 basis points) for the broader class of illiquid funds. The outflows do not have a detectable effect on returns for liquid funds. The effects are net of the return persistence (since past returns are controlled for), and therefore can be interpreted as the impact of redemptions on fund returns.

In Columns (4) to (6) of Table 7, we use "return gap" for the $Perf$ variable. The return gap is the difference between the fund return and the return of the fund's underlying assets. By construction, this reflects the value-added actions of a fund manager's active management and the trading costs associated with such actions. It is free from the effects of return persistence or reversal of the underlying assets. Since redemptions impose costs on the fund, it should worsen the short-term fund return gap. Following Kacperczyk, Sialm, and Zheng (2006), we calculate the return of a fund's underlying assets as the monthly buy-and-hold return by imputing the value-weighted returns of the most recently disclosed quarterly holdings by the fund. Again, we only include funds with at least 75% of the securities matched to CRSP. We estimate (20) with the return gap as the $Perf$ variable and the results are shown in Columns (4) to (6) of Table 7. We find that for the 25% most illiquid funds, a significant outflow leads to about 21 basis points worsening of fund returns

[25] The results are similar when we use -10% as the cutoff value.

relative to the buy-and-hold returns of the underlying assets. The effect is far from significant for liquid funds.

Overall, the results in Table 7 show that the negative effect of redemptions on future returns in illiquid funds goes above and beyond return persistence of the underlying assets. This supports the basic premise of the model. Untabulated estimation shows that the effect of a large redemption on the return gap of an illiquid fund remains significant for 6 months afterwards, and the accumulated damage on the return gap amounts to about 93 basis points (significant at less than the 1% level). This suggests that if an investor fails to redeem from an illiquid fund that is about to experience a 5% outflow, he would incur a cumulative loss of about 1% return over the next 6 months. This magnitude is comparable to the estimation by Edelen (1999) on the overall cost of outflows for mutual fund performance.

7.3 Fund policies

Mutual funds can take actions to either reduce the incentives of investors to redeem shares or reduce the effect of redemptions on the future return. Given the premise in our paper that redemptions are more damaging for illiquid funds than for liquid funds, one would expect that illiquid funds will be more likely to take such actions. We now investigate the two leading actions mutual funds can take to mitigate the problem: holding cash reserves and setting redemption fees. We analyze how the extent to which these tools are used depends on funds' liquidity.

Cash holdings allow mutual funds to reduce the damage from redemptions by spreading flow-triggered trades over a longer period of time. The cost of holding reserves is that they dilute returns and shift the fund away from its desired trading style. The presence of a trade off implies that illiquid funds should hold more cash reserves than liquid funds. Indeed, a look at the data suggests that the average fund-level cash holdings as a percentage of total net assets is 4.04% for all funds, and 4.96% for illiquid funds. We further examine the determinants of cash holdings in a regression analysis. In addition to fund liquidity (for which we use the *Amihud* measure), we include the following independent variables in the regression: average monthly flows and average monthly $Alpha1$ during the past 6 months, the standard deviation of flows during the past 24 months, fund size, fund age, percentage of institutional shares, and load charges.

[Insert Table 8 here.]

Columns (1) and (4) of Table 8 report the regression results for cash holding for the whole sample and the subsample of illiquid funds, respectively. We find that other things equal, one standard deviation of the *Amihud* measure (which is about 62.11, see Table 1) is associated with 0.41 percentage points ($t = 5.90$) decrease in cash holdings (or about 10% of the full sample average). The coefficient is even stronger among illiquid funds: 0.60 percentage points ($t = 2.57$; about 12% of the illiquid funds' average). Interestingly, we observe a weak positive correlation between current cash holdings and next-period fund net flows (1.3%).[26] This suggests that mutual funds either do not set cash reserves in anticipation of future flows, or do not do a great job in predicting these flows. Thus, it seems that overall cash holdings may help to some extent in reducing damage from outflows in illiquid funds, but they are unlikely to completely eliminate payoff complementarities in redemption decisions.[27]

We conduct similar analysis for redemption fees. In 2005, the SEC formalized rules for funds to impose redemption fees, which are paid by redeeming investors to the fund. We hand-collected information about the redemption fees set by different funds from the Morningstar database. Table 6 contains the results for the predictability of the adoption of redemption fees based on funds' conditions before 2005. In Columns (2) and (5), the dependent variable is a dummy variable equal to one if a fund adopted the redemption fee. The estimation uses the probit method, and the reported coefficients are the marginal probabilities associated with a unit change in the values of regressors from their all-sample mean values. In Columns (3) and (6), the dependent variable is the product of the redemption fee (in percentage points) and the duration for which the redemption fee applies (in number of months). The duration for which the redemption fee applies ranged from one week to 90 months, and the median duration is one month. The multiplicative measure

[26] The correlation remains positive if we control for the serial correlation of fund flows.

[27] Even if some funds are moderately successful in predicting future flows, the planned cash holdings are still exogenous to individual investors. That is, each investor's incentive to redeem is still monotonically increasing in other investors' redemption, given any cash balance level that a fund optimally chooses.

(Redemption Fee * Month) is intended to capture the strength of the restriction on redemption, both in terms of the magnitude of the penalty and of the duration for which the penalty applies. The dependent variable is censored at zero, and the Tobit method is used for estimation. Columns (2) and (3) of Table 8 show that the coefficients for *Amihud* are negative and significant at less than the 1% level, consistent with our prediction that illiquid funds are more likely to impose restrictions on redemptions. This effect is still present even among the subsample of illiquid funds (Columns (5) and (6)), although with lower statistical significance.

8 Conclusion

This paper provides an empirical analysis of the relation between payoff complementarities and financial fragility in the context of mutual fund outflows. We first present a global-game model of strategic complementarities applied to the context of mutual fund flows. The model generates two testable predictions. First, conditional on bad performance, we expect more outflows from illiquid funds than from liquid funds. This is because illiquidity is a source of negative externality imposed by withdrawing investors on remaining investors, and thus funds with illiquid assets are expected to suffer from more outflows that result from the self-fulfilling belief that other investors are going to withdraw. Second, this pattern is expected to be weaker in funds that are held mostly by institutional investors or large investors, since they are expected to internalize the negative externalities. We find strong support for these two predictions in the data. We present evidence to refute alternative explanations for this pattern.

The contribution of our paper is threefold. First, the paper sheds new light on the factors that determine the behavior of mutual-fund investors. It argues that investors' behavior is affected by the expected behavior of fellow investors. This is a destabilizing force that generates outflows based on self-fulfilling beliefs. Second, the paper is the first in the literature to confirm that strategic complementarities generate financial fragility and demonstrate the vulnerability of open-end financial institutions. By offering demandable claims, these institutions become exposed to large withdrawals based on self-fulfilling beliefs. This introduces a role for policy measures designed to mitigate this phenomenon. Such policy measures include redemption fees (which are discussed in our paper), and provision of liquidity by sources external to the fund. Third, the paper shows that global-game tools are very useful in bringing models of strategic complementarities to the data. The prediction coming out of such framework is that the equilibrium outcome monotonically depends on the level of complementarities. It is also affected by whether the players are small or large. Finding proxies in the data for the level of complementarities and for the relative size of the players, one can then identify the causality implied by the predictions of the model. We believe that this identification strategy can help in empirical analysis of other settings with strategic complementarities.

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Table 1: Variable Definitions and Summary Statistics

The sample contains 639,596 fund-share-month observations from 7,777 fund-shares of 3,185 equity funds over 1995-2005. Funds are classified as equity funds when more than 50% of their holdings are in equity investments for all years during 1995-2005. Data items are collected from the CRSP mutual fund database and the Morningstar database.

Panel A: Summary Statistics

	Mean	Std	5%	25%	50%	75%	95%
%Inst	23.85	37.29	0.00	0.00	0.17	37.42	100.00
%Cash	4.49	5.63	0.00	0.90	3.00	6.24	14.9
Age	7.73	8.94	1.75	3.25	5.33	8.50	20.83
Alpha1	-0.05	1.50	-2.49	-0.73	-0.08	0.61	2.54
Alpha4	-0.11	1.41	-2.25	-0.70	-0.15	0.39	2.20
Amihud	92.24	62.11	12.97	37.49	78.70	143.22	203.06
Expense	1.57	0.62	0.66	1.10	1.50	2.00	2.60
Flow	1.37	8.96	-6.19	-1.35	0.12	3.04	19.22
Illiq	0.27	0.45	0.00	0.00	0.00	1.00	1.00
Inst	0.22	0.41	0.00	0.00	0.00	0.00	1.00
Load	2.42	2.45	0.00	0.00	1.00	5.00	6.50
MinPurchase	838	10556	0.00	1.00	1.00	2.50	1000
PIN	16.12	3.47	11.85	13.66	15.27	18.20	22.86
RetExCat	-0.10	0.99	-1.73	-0.53	-0.09	0.33	1.50
RetGap	-0.20	1.33	-2.41	-0.70	-0.16	0.32	1.92
Size	345.23	927.53	0.67	9.49	46.81	210.85	1671.98
Stdflow	6.83	11.8	0.54	1.51	3.09	6.70	25.40
Trade_Vol	170.62	186.16	4.87	26.77	99.91	273.03	518.23

Panel B: Variable Definitions

Variable	Unit	Definition
%Inst	%	Percentage of a fund's assets in institutional shares
%Cash	%	Percentage of fund assets held in cash
Age	Year	Number of years since the fund's inception
Alpha1	%	Average monthly alpha from a one-factor market model during the six month period before the current month
Alpha4	%	Average monthly alpha from a four-factor market model (the Fama-French three factor and the momentum factor) during the six month period before the current month
Amihud	-	The square root version of Amihid (2002) liquidity measure. Calculated for each stock, aggregated at the fund portfolio level using value-weighted average.
Trade_Vol	$million	The average dollar trading volume of stocks, aggregated at the fund portfolio level using value-weighted average.
PIN	%	The probability of informed trading (Easley, et al. (1996)) measure. Calculated for each stock, aggregated at the fund portfolio level using value-weighted average.
Expense	%	Expenses of a fund share as percentage of total assets.
Flow	%	Current month net flow of a fund share as percentage of last month's TNA
Illiq	Dummy	Dummy = 1 if a fund primarily invests in illiquid assets. Funds specializing in small-cap, mid-cap and single country international stocks (except in UK, Canada, and Japan) are classified as illiquid funds.
Inst	Dummy	Dummy = 1 if a fund share is issued to institutions
Load	%	Total load (front plus backend load) charged by a fund shares
MinPurchase	$1,000	Minimum initial purchase required by a fund share
RetExCat	%	Return of a fund in excess of that of the category, averaged over the past six months
RetGap	%	Return of a fund in excess of the return of the holdings measured at the most recent Form 13F filing.
Size	$million	total asset value of a fund share
Stdflow	%	Standard deviation of fund’s monthly flow

Table 2: Effects of Liquidity on Flow-Performance Sensitivities

The dependent variable is the net flow to a fund-share in month *t*. *Perf* is the fund's prior performance, measured with three variables, *Alpha1*, *Alpha4* and *RetExCat*. Table 1 lists the detailed definitions and calculations of all variables in the regression. Columns (1) to (3) use the full sample of fund-share-month observations and columns (4) to (6) use the subsample of observations with negative performance measures. All estimations include year fixed-effects. Standard errors adjust for heteroskedasticity and within-cluster correlation clustered at the fund-level. * and ** indicate statistical significant at less than the 10% and 5% levels, respectively.

	Full Sample						**Subsample of negative performance**					
	(1)		(2)		(3)		(4)		(5)		(6)	
Variable for Perf	Alpha1		Alpha4		RetExCat		Alpha1<0		Alpha4<0		RetExCat<0	
	COEF	T-STAT	COEF	T-STAT	COEF	T-STAT	COEF	T-STAT	COEF	T-STAT	COEF	T-STAT
Perf	**0.70****	22.03	**0.50****	16.35	**0.77****	16.10	**0.27****	4.13	**0.09**	1.32	**0.09**	0.90
*Illiq*Perf*	**0.13****	3.65	**0.13****	3.27	**0.11***	1.94	**0.14****	2.42	**0.15****	2.69	**0.16***	1.88
Control variables:												
Flow(-1)	**0.14****	16.22	**0.15****	16.85	**0.24****	25.71	**0.07****	7.98	**0.10****	10.74	**0.18****	16.86
Size(Ln)	**0.11****	8.70	**0.12****	9.56	**0.13****	9.49	**0.06****	3.29	**0.09****	5.16	**0.08****	4.74
Age(Ln)	**-2.01****	-36.33	**-1.99****	-35.41	**-2.58****	-37.81	**-1.79****	-27.74	**-1.77****	-27.31	**-2.26****	-28.75
Expense	**-0.30****	-6.51	**-0.32****	-6.86	**-0.27****	-5.97	**-0.62****	-9.80	**-0.56****	-8.82	**-0.51****	-8.31
Load	**-0.05****	-4.75	**-0.05****	-4.68	**-0.02****	-2.02	**0.00**	0.06	**0.00**	0.26	**0.02***	1.64
Inst	**-0.74****	-11.19	**-0.74****	-11.26	**-0.84****	-13.02	**-0.50****	-5.32	**-0.53****	-5.90	**-0.64****	-7.13
Illiq	**0.13****	2.26	**0.28****	4.55	**0.25****	4.34	**0.20****	2.26	**0.29****	3.62	**0.19****	2.20
*Size*Perf*	**0.06****	7.37	**0.04****	5.13	**0.09****	8.21	**0.01**	1.11	**0.01**	0.63	**0.01**	0.59
*Age*Perf*	**-0.32****	-12.43	**-0.19****	-7.18	**-0.46****	-11.28	**-0.02**	-0.41	**0.08**	1.51	**0.18****	2.51
*Expense*Perf*	**0.03**	1.05	**0.05**	1.63	**0.08***	1.95	**-0.14****	-3.20	**-0.05**	-1.12	**-0.13****	-2.06
*Load*Perf*	**0.01**	0.86	**0.00**	0.51	**0.02**	1.61	**0.05****	3.52	**0.05****	3.58	**0.06****	3.20
*Inst*Perf*	**-0.16****	-3.79	**-0.10****	-2.40	**-0.16****	-2.57	**0.09**	1.24	**0.12**	1.52	**0.16**	1.49
Year fixed-effects	Yes		Yes		Yes		Yes		Yes		Yes	
#obs & R-sqr	639,596	0.07	639,596	0.06	676,198	0.13	344,127	0.03	374,697	0.03	384,123	0.08

Table 3: Effects of Investor Composition on Flow-Performance Sensitivities

Definitions of all variables are listed in Table 1. The dependent variable is the net flow to a fund-share in month *t*. Included are observations with negative performance measure of *Alpha1*. Analyses from Table 2 are replicated separately on subsamples of all fund-shares in institutional-oriented funds and retail-oriented funds. Institutional-oriented funds are defined as the funds with at least 75% the total assets held by large investors, proxied either by the institutional share class classification (column (1)) or by the minimum initial purchase requirements of at least $250,000 (column (2)). Retail-oriented funds are the funds with no greater than 25% of the fund's total assets held by large investors. Results for these funds are shown in columns (3) and (4). All estimations include year fixed-effects. Standard errors adjust for heteroskedasticity and within-cluster correlation clustered at the fund-level. * and ** indicate statistical significant at less than the 10% and 5% levels, respectively.

	Institutional-Oriented Funds				Retail-Oriented Funds			
	(1)		(2)		(3)		(4)	
Large investor proxies:	*Inst*		*MinPur250k*		*Inst*		*MinPur250k*	
	COEF	T-STAT	COEF	T-STAT	COEF	T-STAT	COEF	T-STAT
Alpha1	**0.27***	1.66	**0.43****	2.26	**0.24****	3.36	**0.25****	3.68
*Illiq*Alpha1*	**0.02**	0.18	**0.06**	0.33	**0.20****	2.91	**0.16****	2.71
Control variables:								
Flow(-1)	**0.07****	4.53	**0.09****	3.56	**0.07****	5.78	**0.07****	6.87
Size(Ln)	**0.13****	3.01	**0.17****	2.49	**0.07****	3.06	**0.05****	2.66
Age(Ln)	**-2.07****	-13.07	**-2.30****	-8.62	**-1.71****	-24.02	**-1.74****	-26.21
Expense	**0.01**	0.06	**-0.06**	-0.19	**-0.61****	-8.42	**-0.64****	-9.73
Load	**0.01**	0.36	**0.09**	1.26	**-0.02**	-1.01	**0.00**	-0.26
Inst	**-0.58****	-2.40	**-0.61***	-1.64	**-0.10**	-0.61	**-0.41****	-3.91
Illiq	**0.06**	0.37	**0.23**	0.81	**0.26****	2.44	**0.22****	2.36
*Size*Alpha1*	**-0.05**	-1.61	**-0.06**	-1.28	**0.02**	1.29	**0.02**	1.15
*Age*Alpha1*	**0.16**	1.51	**0.28**	1.49	**-0.03**	-0.57	**-0.03**	-0.55
*Expense*Alpha1*	**-0.01**	-0.09	**-0.16**	-0.77	**-0.15****	-3.06	**-0.15****	-3.35
*Load*Alpha1*	**-0.02**	-0.60	**-0.04**	-0.69	**0.05****	3.59	**0.05****	3.75
*Inst*Alpha1*	**0.19**	0.98	**0.00**	-0.01	**0.19***	1.75	**0.13**	1.58
Year fixed effects	Yes		Yes		Yes		Yes	
#obs & R-sqr	61194	0.03	22037	0.03	254984	0.03	304845	0.03

Table 4: Predictability of Fund Returns

This table compares the return predictability of funds investing in illiquid and liquid assets. Three benchmark-adjusted return measures, *Alpha1*, *Alpha4*, and *RetExCat* are defined in Table 1. Reported are the equal-weight current-month return performance of a portfolio sorted by the lagged performance (past 6 months) by the same measure, separately for liquid and illiquid funds. The difference between quintiles 5 and 1 is reported for each subsample, so is the difference-of-difference across the two subsamples.

Lag Performance Quintiles	*Alpha1*	*Alpha4*	*RetExCat*
		Liquid Funds	
Q1	-0.007	-0.004	-0.004
Q2	-0.003	-0.002	-0.002
Q3	-0.001	-0.002	-0.001
Q4	0.000	-0.001	-0.001
Q5	0.003	0.001	0.002
Q5-Q1	0.010	0.005	0.005
t-stat	3.96	1.92	3.735
		Illiquid Funds	
Q1	-0.006	-0.003	-0.005
Q2	-0.002	-0.002	-0.002
Q3	0.000	-0.001	-0.001
Q4	0.003	0.001	0.000
Q5	0.006	0.004	0.004
Q5-Q1	0.012	0.006	0.008
t-stat	3.01	1.66	4.306
		Difference	
Liq(Q5-Q1) – Illiq(Q5-Q1)	-0.001	-0.001	-0.003
t-stat	-0.276	-0.287	-1.304

Table 5: Effects of Clientele on Flow-Performance Sensitivities: Large Investors Only

Definitions of all variables are listed in Table 1. The dependent variable is the net flow to a fund-share in month *t*. Included are observations with negative performance measure of *Alpha1*. Analyses from Table 3 are replicated on the subsample of large investor fund-shares only. Columns (1) and (2) report the flow-performance sensitivities of large investors in institutional-oriented funds, while columns (3) and (4) report the sensitivities of large investors in retail-oriented funds. Institutional-and retail-oriented funds are defined in Table 3. All estimations include year fixed-effects. Standard errors adjust for heteroskedasticity and within-cluster correlation clustered at the fund-level. * and ** indicate statistical significant at less than the 10% and 5% levels, respectively.

	Institutional-Oriented Funds				Retail-Oriented Funds			
	(1)		(2)		(3)		(4)	
Large investor proxies:	*Inst*		*MinPur250k*		*Inst*		*MinPur250k*	
	COEF	T-STAT	COEF	T-STAT	COEF	T-STAT	COEF	T-STAT
Alpha1	**0.42****	4.97	**0.52****	3.21	**0.32****	2.79	**0.16**	1.13
*Illiq*Alpha*	**-0.03**	-0.28	**-0.22**	-1.03	**0.34***	1.69	**0.50***	1.94
Control variables:								
Flow(-1)	**0.13****	9.47	**0.15****	8.36	**0.13****	6.32	**0.15****	6.65
Size(Ln)	**0.16****	3.64	**0.26****	3.64	**0.25****	3.88	**0.22****	2.92
Age(Ln)	**-1.76****	-11.35	**-2.10****	-8.18	**-2.05****	-6.28	**-2.67****	-6.68
Expense	**0.56****	2.55	**0.68***	1.82	**-0.30**	-0.98	**0.13**	0.35
Load	**0.01**	0.17	**-0.33**	-1.16	**-0.01**	-0.08	**-0.32**	-1.25
Illiq	**-0.08**	-0.53	**-0.09**	-0.35	**0.95****	2.60	**1.09****	2.35
*Size*Alpha1*	**-0.03**	-0.99	**-0.09***	-1.73	**0.00**	-0.04	**-0.09***	-1.72
*Age*Alpha1*	**0.12**	1.23	**0.31***	1.77	**0.06**	0.25	**-0.06**	-0.22
*Expense*Alpha1*	**-0.09**	-0.62	**-0.26**	-1.05	**-0.26**	-1.57	**-0.40***	-1.91
*Load*Alpha1*	**0.01**	0.28	**0.01**	0.03	**0.05**	0.89	**0.10**	0.59
Year fixed-effects	Yes		Yes		Yes		Yes	
#obs & R-sqr	41105	0.04	14249	0.05	20053	0.03	12607	0.04

Table 6: Alternative measures of assets liquidity based on fund holding

Definitions of all variables are listed in Table 1. The dependent variable is the net flow to a fund-share. Estimation sample includes all observations with *Alpha1<0*. Columns (1) and (2) use the average trading volume (in logarithm) of the underlying holdings as the liquidity measure. Columns (3) and (4) use the Amihud liquidity measure. All estimations include year fixed-effects. Standard errors adjust for heteroskedasticity and within-cluster correlation clustered at the fund-level. * and ** indicate statistical significant at less than the 10% and 5% levels, respectively.

Liq_Holding measure	Ln(trade_vol)				Amihud			
	(1) All observations		(2) %INST>=75%		(3) All observations		(4) %INST>=75%	
	COEF	T-STAT	COEF	T-STAT	COEF	T-STAT	COEF	T-STAT
Alpha	**0.24****	2.61	**0.71****	4.89	**0.32****	3.72	**0.70****	5.02
Liq_Holding Alpha*	**-0.13****	-5.78	**-0.02**	-0.43	**-0.33****	-4.60	**-0.15**	0.05
Flow(-1)	**0.11****	8.30	**0.14****	7.73	**0.11****	8.24	**0.14****	7.73
Size(Ln)	**0.06****	2.87	**0.14****	3.06	**0.04****	2.16	**0.13****	2.83
Age(Ln)	**-1.65****	-23.75	**-2.04****	-11.57	**-1.62****	-23.20	**-2.01****	-11.43
Expense	**-0.74****	-10.03	**-0.08**	-0.46	**-0.75****	-10.19	**-0.10**	-0.58
Load	**0.02**	1.43	**0.01**	0.16	**0.02***	1.65	**0.01**	0.25
Inst	**-0.52****	-5.04	**-0.64****	-2.67	**-0.50****	-4.87	**-0.64****	-2.64
Liq_Holding	**-0.25****	-8.04	**-0.15****	-2.63	**-0.01****	-10.07	**0.00****	-3.37
Size Alpha*	**0.00**	0.08	**0.04**	1.04	**-0.01**	-0.29	**0.03**	0.86
Age Alpha*	**0.06**	0.92	**-0.14**	-1.21	**0.08**	1.16	**-0.11**	-0.90
Expense Alpha*	**-0.24****	-4.07	**0.00**	-0.01	**-0.25****	-4.24	**-0.02**	-0.15
Load Alpha*	**0.07****	3.44	**-0.05***	-1.73	**0.07****	3.50	**-0.05***	-1.68
Inst Alpha*	**0.15**	1.40	**-0.26**	-1.49	**0.16**	1.48	**-0.26**	-1.51
Year fixed-effects	Yes		Yes		Yes		Yes	
#obs & R-sqr	228,899	0.04	40,483	0.05	228,899	0.04	40,483	0.03

Table 7: Effects of Outflows on Fund Returns

The analysis in this table is on fund-month basis. The dependent variable in Columns (1) to (3) is *Alpha1* in month *t* and that in Columns (4) to (6) is the return gap between a fund's actual return and the return of the fund's underlying assets, calculated based on the fund's reported holding of stocks. *Outflow* is a dummy variable equals to 1 if the fund experiences net outflow of at least 5% of its total net asset value in month *t-1,* and 0 otherwise. *Ret(-i)* is the one-factor *Alpha* of the fund during the *i*-th month prior to month *t*. Definitions of other variables are listed in Table 1. * and ** indicate statistical significant at less than the 10% and 5% levels, respectively.

	Dependent variable: *Alpha1*						Dependent variable: *RetGap*					
	(1)		(2)		(3)		(4)		(5)		(6)	
	Liquid funds		Illiquid funds		Funds with the lowest quartile of Amihud measure		Liquid funds		Illiquid funds		Funds with the lowest quartile of Amihud measure	
	COEF	T-STAT	COEF	T-STAT	COEF	T-STAT	COEF	T-STAT	COEF	T-STAT	COEF	T-STAT
Outflow	**-0.014**	-0.97	**-0.126****	-4.24	**-0.189****	-4.58	**-0.016**	-1.24	**-0.115****	-4.16	**-0.210****	-6.17
Ln(TNA)	**-0.013****	-3.74	**-0.036****	-4.34	**-0.033****	-2.45	**0.002**	0.51	**0.026****	2.10	**0.008**	0.45
Expense	**-0.102****	-6.33	**-0.117****	-2.66	**-0.085**	-1.42	**-0.170****	-8.29	**-0.229****	-4.00	**-0.334****	-4.92
Ret(-1)	**0.035****	7.76	**-0.016****	-2.68	**0.001**	0.08	**0.009**	1.27	**0.010**	1.54	**0.003**	0.36
Ret(-2)	**0.067****	17.58	**0.082****	17.61	**0.096****	16.08	**-0.002**	-0.29	**0.017***	1.86	**0.005**	0.46
Ret(-3)	**0.007***	1.85	**0.021****	4.89	**0.029****	5.23	**0.015****	2.47	**0.000**	-0.04	**-0.021****	-2.33
Ret(-4)	**-0.006**	-1.59	**0.003**	0.80	**0.010****	1.96	**-0.002**	-0.33	**-0.005**	-0.60	**0.001**	0.11
Ret(-5)	**0.000**	-0.08	**0.005**	1.23	**0.004**	0.85	**0.004**	0.59	**-0.002**	-0.39	**-0.022****	-3.35
Ret(-6)	**0.077****	17.64	**0.071****	16.66	**0.064****	12.37	**0.027****	2.54	**0.038****	5.72	**0.010**	0.85
CNST	**-0.064****	-6.05	**0.224****	10.10	**0.220****	7.71	**-1.028****	-79.94	**-1.652****	-63.30	**-1.846****	-56.39
# obs and R-sqr	130517	0.01	63467	0.02	37538	0.02	128711	0.00	63063	0.01	37519	0.01

Table 8: Effects of Liquidity on Fund Cash and Redemption Fee Policy

Definitions of all variables are listed in Table 1. Columns (1) to (3) use observations from the whole sample of funds and Columns (4) to (6) use observations from the subsample of illiquid funds. In columns (1) and (4), the dependent variable is the percentage of assets a fund holds in cash and linear regression with year fixed-effects is used in estimation. In columns (2) and (5), the dependent variable is the dummy variable for whether a fund has adopted a redemption fee by 2005 and Probit is used in estimation (reported coefficients are marginal probability changes for one unit change in each regressor, holding other regressors at their sample mean levels). In columns (3) and (6), the dependent variable is the product of the amount of redemption fee (as % of the redeemed amount) and the number of month the redemption fee applies to, and Tobit is used in estimation. * and ** indicate statistical significant at less than the 10% and 5% levels, respectively.

	All Funds						Illiquid Funds					
	(1)		(2)		(3)		(4)		(5)		(6)	
Dependent variable	%Cash		I(Redemption)		Redemption*Month		%Cash		I(Redemption)		Redemption*Month	
Estimation method	Linear regression		Probit		Tobit		Linear regression		Probit		Tobit	
	COEF	T-STAT	Marg. Pr.	T-STAT	COEF	T-STAT	COEF	T-STAT	Marg. Pr.	T-STAT	COEF	T-STAT
Amihud	**-0.654****	-5.90	**-6.9%****	-4.45	**-2.78****	-5.74	**-0.960****	-2.57	**-6.7%**	-1.25	**-3.93***	-1.87
Flow(-1)	**0.076****	5.26	**33.6%**	0.94	**9.17**	0.83	**0.078****	2.99	**-18.6%**	-0.29	**-9.09**	-0.36
TNA	**0.008**	0.66	**36.2%**	1.51	**4.04**	0.53	**0.044**	1.34	**90.8%****	2.03	**20.62**	1.13
AGE	**0.141****	2.86	**7.0%****	4.82	**1.79****	3.93	**0.361****	4.08	**4.6%**	1.57	**2.62****	2.32
%INST	**0.029**	0.51	**1.7%****	2.97	**0.35***	1.90	**-0.004**	-0.04	**3.9%****	3.36	**1.12****	2.40
LOAD	**-0.135**	-0.94	**1.3%**	0.74	**0.09**	0.16	**0.351**	1.26	**-0.6%**	-0.17	**-0.53**	-0.37
ALPHA1	**-1.138****	-5.94	**-3.1%**	-1.25	**-1.32***	-1.68	**-0.993****	-2.77	**-2.1%**	-0.49	**-1.97**	-1.16
STDFLOW	**-0.152****	-2.96	**3.8%****	6.83	**0.90****	5.08	**-0.201****	-2.07	**3.7%****	3.72	**1.11****	2.76
CNST	**4.892****	13.46	--	--	**-9.01****	-5.79	**4.072****	5.13	--	--	**-15.78****	-4.13
# obs & R-sqr	78761	0.031	2575	0.052	2575	0.019	24099	0.042	806	0.04	806	0.014
% Redemption			28.27%						29.90%			

Figure 1: Overview of the effect of liquidity on flow-performance-sensitivities

Plotted is the nonparametric function *f(.)* in the following semiparametric specification:

$$Flow_{i,t} = f(Alpha1_{i,t-1}) + \beta X_{i,t} + \varepsilon,$$

where *i* and *t* are subscripts for fund shares and months. *X* represents a vector of control variables that include: fund size, fund age, expenses, and total sales loads. Estimation follows the Robinson (1988) method.