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

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ABSTRACT

The paper provides empirical evidence on the effect of strategic complementarities on investors' behavior in financial markets. 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 in funds with illiquid assets (where complementarities are stronger), outflows are more sensitive to bad past performance than in funds with liquid assets; we also find that investors' behavior depends on the composition of the shareholder base. We present further evidence that these results are not attributable to alternative explanations that are based on information conveyed by past performance or on clientele effects. Overall, our empirical findings suggest that strategic complementarities amplify the response of investors to fundamentals and generate financial fragility.

1 Introduction

Strategic interaction is a key determinant of investors' behavior in financial markets and institutions. When choosing their investment strategy, investors have to consider, not only the expected fundamentals of the investment, but also the expected behavior of other investors, which could have a first-order effect on investment returns. Particularly interesting are situations with *payoff complementarities*, where investors' incentives to take a certain action increase if they expect that more investors will take such an action. Payoff complementarities are expected to generate a multiplier effect, by which they amplify the impact that shocks to fundamentals have on investors' behavior. Such amplification is often referred to as *financial fragility.* An extreme example where such mechanism is at work is a bank run (see Diamond and Dybvig (1983)), where all depositors rush to withdraw their money because they expect others will do so.[1] It is commonly believed that payoff complementarities bring fragility in many other, less extreme, situations.

[1] Also related is the currency-attack literature (see Morris and Shin (1998)).

Despite the wide interest and large volume of theoretical work, there has been virtually no attempt in the literature to provide empirical evidence for the effect of strategic complementarities on financial fragility. In this paper, we attempt to provide such evidence. We start by presenting a stylized model of strategic complementarities in investors' decisions in an open-end financial institution. Using the global-game paradigm, we derive empirical predictions from such a model. Then, we test these predictions in the context of mutual fund outflows.

Let us clarify the role of the two key ingredients of the paper. First, what is the role of global games? A theoretical challenge in taking models of strategic complementarities to the data is that they usually have multiple equilibria, and thus do not generate clear empirical predictions. In fact, a common view on such models has been that they impose no restrictions on the data, and thus cannot be tested (see Gorton (1988)). The global-game framework enables us to overcome this obstacle. 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 investment returns. Introducing this assumption in a model of strategic complementarities generates a unique equilibrium, and this enables us to derive empirical predictions that can be taken to the data. The global-game literature was pioneered by Carlsson and Van Damme (1993). The methodology has been used in recent years to study various finance-related phenomena, 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)). It is also related to the model of Abreu and Brunnermeier (2003) on financial-market bubbles and crashes.

Second, why do we use mutual-fund data? Section 2 describes the institutional set-up that gives rise to payoff complementarities in mutual-fund outflows. 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) on any given day. Following substantial outflows, funds will need to adjust their portfolios and conduct costly and unprofitable trades, which damage the future returns. Since mutual funds conduct most of the resulting trades after the day of redemption, the costs are not reflected in the NAV obtained by redeeming investors, but rather are borne mostly by the remaining investors (the detailed institutional background is described in Section 2). The result is that the expectation that other investors will withdraw their money increases the incentive for each individual investor to do the same thing. As we argue in Section 2, the magnitude of the damage due to expected investors' withdrawals is significant enough to alter the behavior of a sizable group of investors and cause them to redeem early.

It should be noted that there are settings where strategic complementarities are probably stronger and lead to bigger consequences than in mutual funds. Institutions like banks (if they are uninsured) or hedge funds tend to hold more illiquid assets, which lead remaining investors to face bigger damage following redemptions. Indeed, full-fledged runs almost never occur in mutual funds[2], and the effect of strategic complementarities may only be reflected in the amplification of investors' redemptions. We choose the mutual-fund setting as a laboratory to detect the underlying mechanism despite the lower magnitude. This is because this setting offers high-quality data and rich diversity in both assets classes and investor clientele, which enable us to provide sharp tests for our hypotheses and for potential alternative explanations. In contrast, hedge fund data are not only limited in scope, but also suffer from various issues related to self-reporting. Furthermore, unlike mutual funds which maintain the largely exogenous open-ended structure with light restrictions on in- and out-flows (especially before 2005), hedge funds tend to impose strict restrictions such as lock-up periods, restrictions on redemption frequency, and requirement for advance purchase/redemption notices to manage liquidity. These preemptive measures dampen the effect of complementarities.

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. As a result, our main prediction is that the sensitivity of outflows to bad past performance will be stronger in funds that hold illiquid assets (hereafter, "illiquid funds") than in funds that hold liquid assets (hereafter, "liquid funds"). Intuitively, consider investors holding shares in an emerging-market fund vs. investors that hold

[2]Exceptions include runs on real-estate funds in Germany in 2006 (see Bannier, Fecht, and Tyrell (2006)) and in the U.K. in 2007 (see "Real-Estate Finance: U.K. Property Funds Prove Difficult for Investors to Exit," Wall Street Journal, December 17, 2007).

shares in a fund that invests in large-cap U.S. stocks. Faced with bad performance, the former will have a stronger tendency to redeem their shares because they know that the redemptions by others will impose non-negligible costs on the fund, which will hurt them if they choose to stay in the fund. Our second prediction is based on the idea that large investors are more likely to internalize the externalities in redemptions (in the spirit of Corsetti, Dasgupta, Morris, and Shin (2004)). Knowing that they control large shares of the fund assets, they are less concerned about the behavior of others. Hence, the prediction is that the effect of the illiquidity of fund assets on investors' redemptions will be smaller in funds that are held primarily by large investors.[3]

Using data on net outflows from U.S. equity mutual funds from 1995 to 2005, we find strong support for our two predictions: First, outflows from the illiquid funds are more sensitive to bad performance than outflows from the liquid funds. This result is 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). Second, 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, absent large outflows, performance in illiquid funds is no more persistent than in liquid funds. We show this both for open-end

[3] Note that large investors may still redeem more for informational reasons. The feature that we emphasize is that they respond less to the complementarities, which are proxied by the level of illiquidity.

funds – after excluding observations with particularly large outflows – and for closed-end funds – where, by definition, outflows (and inflows) do not exist.

The second alternative explanation is based on a clientele effect. Suppose that investors in illiquid funds are more tuned to the market than investors in liquid funds, and thus they redeem more promptly after bad performance. We address this point by analyzing the behavior of one sophisticated clientele – that of institutional investors. We show that in the subsample of retail-oriented funds – where strategic complementarities are expected to have an effect – institutional investors' redemptions are more sensitive to bad performance in illiquid funds than in liquid funds. Moreover, this result does not hold in the subsample of institutional-oriented funds. These results suggest that the clientele effect is not driving our results. An interesting aspect of the result is that institutional investors behave differently, depending on whether they are surrounded by other institutional investors or by retail investors. This suggests very clearly that strategic interaction plays a role in mutual-fund redemptions.

Finally, we provide two additional pieces of evidence that support the mechanism of 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. Second, given that outflows are much costlier for illiquid funds, one would expect illiquid funds to be more inclined to taking measures to either reduce the frequency of outflows or minimize their impact on fund performance. Such measures include restrictions on redemptions and holding more cash reserves. Indeed, we find that illiquid funds are more likely to take each one of these measures. Hence, the effects we detect in equilibrium are observed after the mitigating effect of these measures.

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. 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. 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 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 or react to information about fundamentals 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

[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)).

to be very useful for empirical analysis. Generally speaking, the predictions from a global-game framework are that the equilibrium outcome monotonically depends on the level of complementarities and is 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, and distinguish the complementarity-driven behavior from the fundamental-driven behavior. We believe that this identification strategy can help in empirical analysis of other settings with strategic complementarities.[5]

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. Redemptions impose costs on mutual funds, and in particular on illiquid mutual funds. An important feature is that a significant portion of the costs is borne by the remaining, rather than the redeeming, shareholders. The nature and consequences of these institutional features in mutual funds have been analyzed in several papers (for example, Chordia (1996), Edelen (1999), Greene and Hodges (2002), Johnson (2004), Coval and Stafford (2006), and Christoffersen, Keim, and Musto (2007)). They are the source of the strategic complementarities that form the basic premise of our study. We now discuss the institutional details behind these premises more thoroughly.

The first important ingredient for the emergence of payoff complementarities in redemptions is

[5] Strictly speaking, what we test in the paper is the joint hypothesis about the effect of strategic complementarities and the validity of the global-game structure. Previous attempts to test predictions from a global-game setting were based on laboratory experiments (see: Heinemann, Nagel, and Ockenfels (2004)).

that redemptions are costly to mutual funds. Overall, there are two types of costs that redemptions impose. First, there are the direct transaction costs resulting from the trades that funds make in response to outflows. They include commissions, bid-ask spreads and price impact. Second, fund flows may generate indirect costs by forcing fund managers to deviate from their optimal portfolios. Obviously, both types of costs are bigger for illiquid funds than for liquid funds, and this will be the basis for our empirical predictions.

The other important ingredient for our analysis is that the costs imposed by redemptions are not generally reflected in the price (NAV) investors get when they redeem their shares. Rather, they are mostly imposed on investors who keep their money in the fund. The reason is that the NAV at which investors can buy and sell is calculated using the same-day market close prices of the underlying securities. It is determined at 4:00pm and reported to the NASD by 6:00pm. In many cases, however, the trades made by mutual funds in response to redemptions happen only after the day of the redemptions and thus their costs are not reflected in the NAV of that day. This happens for two reasons. First, in most funds during our sample period, 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. Second, even if mutual funds know the size of flows in some cases, they may still prefer to conduct the resulting trades at later dates. The timing of the trades depends on their assessment of optimal trading strategies in light of investment opportunities and trading costs.[6]

How big are the costs imposed by investors' redemptions? The literature has thus far offered firm evidence that redemptions are very costly for mutual funds' performance. For example, Edelen

[6] It should be noted that mutual fund investors can impose externalities on their fellow shareholders through channels that are distinct from the one analyzed in our paper. First, the redemptions by some investors may cause funds to distribute capital gains to the remaining investors (such tax externalities were discussed and analized by Dickson, Shoven, and Sialm (2000) and Barclay, Pearson, and Weisbach (1998)). Second, certain management fees, negotiated in fixed amount ex ante, would be amortized on a smaller asset base if the fund experiences substantial outflows ex post. The strength of these effects is unrelated to the illiquidity of the fund's underlying assets, and so they are distinct from our empirical tests.

(1999) estimates that for every dollar of outflow, approximately \$0.76 goes to a marginal increase in the fund's trading volume. The average transaction cost on these tradings is estimated by him to be 2.2% per unit of trading. Overall, Edelen (1999) estimates that these costs contribute to a significant negative abnormal fund return of up to -1.4% annually. In fact, 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. Relatedly, Alexander, Cici, and Gibson (2007) found that stocks sold by mutual funds for liquidity reasons (because of outflows) outperform those sold at discretion by 1.55% annually. Even more important for our hypotheses, Coval and Stafford (2006) show that the costs of forced selling are much higher when the fund holds illiquid assets.

Still, a remaining question is whether the costs of some investors' redemptions are big enough to induce other investors to redeem their own shares. A back-of-the-envelope calculation based on estimates from the literature suggests that they should be. According to data from Christoffersen, Evans, and Musto (2007), the $95th$ and $99th$ percentile values of monthly redemption at U.S. mutual funds from 1996 to 2003, as percentage of assets, are 20% and 37%, respectively.[7] Combining these numbers with the estimated parameters from Edelen (1999) mentioned above (that on average 76% of gross outflows lead to forced sales and that forced trading is on average associated with 2.2% lowered return), the total damage from investors' redemptions in a month with heavy outflows amounts to 37 and 76 bps, respectively.[8] Obviously, for illiquid assets, forced trading is likely to cause more damage to returns than estimated by Edelen (1999). Moreover, for unusually large redemptions, the proportion of redemptions that leads to forced trading is also likely to be larger than his estimation. Hence, when investors in illiquid funds expect the possibility of large redemptions by other investors, they could reasonably fear losing 100 bps or more of their entire investment in a month, *just due to the redemptions of others*. This should be sufficient to induce

[7] We thank Susan Christofferson for providing us the summary data.

[8] 37 bps $= 20\% * 76\% * 2.2\%/(1 - 20\%/2)$. We assume here that the outflows occur evenly during the month and therefore the average assets under management are (1-20%/2) of the beginning-of-the-month level. The number 76 bps is obtained analogously

a sizable group of investors (who are sensitive to performance and enjoy relatively low switching cost) to redeem and potentially lead to self-fulfilling redemptions.[9]

Given the damaging effect of investors' redemptions, it is not surprising that mutual funds adopt various mitigating measures. Section 7.3 analyzes some of these measures. One prominent measure used by almost all funds is to carry a small proportion (usually 1% to 5%) of the assets in cash. This could serve to absorb flows without triggering instant trading. The ability of funds to reduce the damage from redemptions by using cash is, however, limited. Cash holdings are costly because they compromise performance relative to investment objectives and styles, and are not able to absorb large flows. Also, after the fund uses cash to meet redemptions, it will still need to sell assets to rebuild its cash positions in case there are no immediate inflows. Another measure used by funds is to attempt to predict future flows. In practice, however, this proves to be difficult. As emergency measures, some funds state in their prospectus that they reserve the right to suspend redemption or to deliver redemption in kind (i.e., with a basket of underlying securities). But, these measures have almost never been applied for retail investors.

Recently, more and more funds started imposing restrictions on trading frequency. This was encouraged to a large extent by the Securities and Exchange Commission's 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,[10] but 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

[9] Of course, a key question is what causes investors to expect a certain amount of outflows. In our empirical analysis, past performance plays the key role. Yet, despite the fact that it is the most powerful and highly significant predictor of future flows, it only captures a relatively small portion of the variations in fund flows. We believe it is very likely that investors use other signals (in addition to past performance) in predicting other investors' propensity to redeem. As econometricians, however, we do not have access to these signals and are confined to using the observed past performance as the proxy for the information that investors have.

[10] 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.

service), or because of insufficient information regarding individual redemptions from the omnibus accounts.[11] Our main analysis uses data from 1995-2005 when redemption restrictions were very uncommon. We further use the 2005 policy change as additional evidence in support of our theory (see discussion in Section 7.3).

Overall, the fact that funds take various mitigating measures proves that they are concerned about the issues raised in our paper. As discussed above, however, none of these measures is capable of perfectly solving the problem. Most importantly, all the cost estimates provided in the existing literature (discussed above) represent the cost of redemption in equilibrium, that is, after incorporating the measures taken by mutual funds to mitigate such effects. Hence, the presence of these mitigating measures works against our ability to find evidence for the effect of strategic complementarities. The fact that we still find such evidence in the presence of various mitigating measures is thus an even stronger proof of the importance of the underlying forces.

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 dates 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

[11] 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.

(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.[12] 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 between $t = 1$ and $t = 2$. 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 at $t = 1$. 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:[13]

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

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

[12] The possibility of bankruptcy complicates the global-games analysis significantly (see: Goldstein and Pauzner (2005)).

[13] 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.

till $t = 2$ decreases, since the outflows cause damage to the value of the remaining portfolio. 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 $I(.)$ is an increasing function. 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:[14]

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

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

[14] 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 (see: Christoffersen, Keim, and Musto (2007)).

stay in the fund till $t = 2$, no matter what they believe other investors are going to do. Thus,

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

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

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

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

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 $\theta > \overline{\theta}\left(R_1\right)$. When θ is between $\underline{\theta}$ and $\overline{\theta}\left(R_1\right)$ (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^*. In the appendix, we derive the characterization of θ^*. At the limit, as information converges to common knowledge, i.e., as σ approaches 0, θ^* is implicitly given by the following equation:[15]

$$R_2(\theta^*) = \frac{1}{\int_0^1 \frac{1-(1+\lambda)\max\left\{0,\left(\alpha\overline{N}-I(R_1)\right)\right\}}{1-\max\left\{0,\left(\alpha\overline{N}-I(R_1)\right)\right\}}d\alpha}. \tag{6}$$

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. 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

[15] Taking the limit is not important for our empirical implications. It just helps getting a more intuitive expression.

discussion leads to our first and main hypothesis.[16]

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

[16] The parameterization of the degree of strategic complementarities as λ is in spirit of the model of Rochet and Vives (2004).

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

So far, we analyzed a situation where there are many small investors. This corresponds to a fund that is held by retail investors. The nature of the coordination game described above changes substantially when institutional investors with large positions are involved.

To illustrate the effect of large investors, we conduct an exercise similar to that in Corsetti, Dasgupta, Morris, and Shin (2004) and 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. We characterize these thresholds in the Appendix. We also show in the appendix that when $\sigma \to 0$, θ^I and θ^R converge to the same value, which we denote as θ^{**}. Finally, to compare between θ^{**} and θ^* (characterized by (6)), the appendix also derives an upper bound on θ^{**} (denoted as θ^{UB}). It is given as follows:

$$R_2\left(\theta^{**}\right) < \frac{1}{\int_0^1 \left[\frac{1-(1+\lambda)\max\left\{0,\left((1-\beta)\overline{N}-I(R_1)\right)\right\}}{1-\max\left\{0,\left((1-\beta)\overline{N}-I(R_1)\right)\right\}}\right] d\alpha} \equiv R_2\left(\theta^{UB}\right). \tag{7}$$

Analyzing (7), 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. The intuition goes as follows: Because the large investor holds a large proportion of the fund's shares, he is less affected by the actions of other investors. He at least knows that by not withdrawing he guarantees that his 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 the large investor, and therefore he is less likely to withdraw. Moreover, knowing that the fund is held by a large investor, other investors will also be less likely to withdraw. This is because the large investor injects strategic stability and thus reduces the inclination of all shareholders to withdraw. In essence, 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.

Importantly, to keep things simple in this paper, whose focus is on the empirical analysis, our theoretical illustration followed directly the one in Corsetti, Dasgupta, Morris, and Shin (2004) and looked at the effect of introducing one large investor. But, the basic force affecting the behavior of large investors, as described above, should be the same in a more empirically relevant framework where there are several large investors.[17] Hence, going into the empirical analysis we will be interested in the difference in redemption patterns between funds that are held mostly by large/institutional investors and funds that are held mostly by small/retail investors. In particular,

[17] The formal analysis gets more complicated when multiple large shareholders are introduced. The result described here will go through easily if the large investors play a cooperative equilibrium. This is quite realistic given that large shareholders often coordinate their actions with each other. If the large investors do not cooperate, the basic force behind the result here will stay intact, although other forces may arise.

we will assess whether the following hypothesis holds in the data.

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

Finally, there could be other mechanisms that lead investors in funds that are held mostly by large investors to respond less to strategic complementarities. In particular, mutual funds have certain arrangements with their institutional investors that force these investors to internalize the cost of their redemption. An example of such an arrangement is redemption in kind, i.e., a delivery of the basket of underlying securities rather than cash. Under such arrangement, the redeeming shareholder bears the cost of liquidation, which, as a by-product, reduces the strategic complementarity among investors. This leads to weaker concerns among all investors about what other investors are going to do. Hence, the idea that large investors internalize the externalities and inject stability by making other investors respond less to strategic complementarities is quite general and can go beyond the particular mechanism described above. Our second hypothesis utilizes this idea to predict that differences in outflow-to-performance sensitivities between illiquid and liquid funds will be smaller in institutional-oriented funds than in retail-oriented funds.

4 Data

Our empirical analysis focuses on 4,393 equity funds from the CRSP Mutual Fund database in the years 1995-2005.[18] A fund is defined as an equity fund if at least 50% of its portfolio is in equity throughout the sample period. 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 also exclude retirement shares that are usually issued for defined-contribution plans, such as 401(k) and 403(b) plans, because they limit the flexibility for investors.[19]

We use CRSP S&P style code and area code to identify the types of assets each fund invests

[18] 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 assets in bond funds.

[19] Although defined-contribution plans usually grant participants the right to reallocate their balances up to the frequency allowed by the funds, the reallocation is confined within the set of investment choices offered by the plans (usually a group of funds within the same fund family).

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 and funds rarely switch categories, for data before 2002, we determine 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).

A mutual fund often issues several share classes out of the same portfolio. These share classes carry different combinations of fees/loads and minimum investment requirements to cater to investors with different wealth levels and investment horizons. The purchases and redemptions of different class shares belonging to the same fund are pooled. For our tests, we are interested in whether a share is issued to institutions or to retail investors. 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.[20] We then determine 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

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

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).[21]

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. Prior literature has established that institutional investors in mutual funds behave differently from retail investors (James and Karceski (2006)). 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. Our final sample includes 639,596 fund share-month observations with 10,404 unique fund shares in 4,393 unique funds, among which 1,227 are classified as illiquid funds. Illiquid funds are overall smaller in terms of assets under management than liquid funds ($533 vs. $872 million for average, and $140 vs. $145 million for median), are slightly younger in age (9.2 vs. 11.5 years for average, and 6.5 vs. 7.2 years for median), and have somewhat higher institutional ownership (28.0% vs. 22.8%). Finally, illiquid funds outperform liquid funds by 23 (4) basis points monthly measured by one-factor (four-factor) *Alpha*, consistent with the return premium for illiquid assets. Throughout the paper all regressions allow year fixed effects and all standard errors adjust for clustering at the fund level. Therefore the effective number of observations in regressions is in

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

the order of the number of funds (i.e., 4,393 for the full sample, and smaller numbers for subsample analysis).

[Insert Table 1 here]

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. Essentially, the complementarities that come with redemptions in response to poor performance have a feedback effect that amplifies outflows in illiquid funds.

Most of our analysis will be on explaining the sensitivity of flows to performance in linear regressions. However, 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 of this type of analysis is, of course, that significance levels are much lower due to the flexible functional specification. 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 $t-1$.[22] The net flow (*Flow*) is measured following the standard practice in the literature:

$$Flow_t = \frac{TNA_t - TNA_{t-1}\left(1 + Ret_t\right)}{TNA_{t-1}}, \tag{8}$$

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:

$$Flow_{i,t} = f\left(Alpha_{i,t-1}\right) + \beta X_{i,t} + \varepsilon_{i,t}, \tag{9}$$

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 (9) applies the method introduced by Robinson (1988).[23] 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[24]:

$$Flow_{i,t} - \widehat{\beta} X_{i,t} = f\left(Alpha_{i,t-1}\right) + \varepsilon'_{i,t}. \tag{10}$$

[22] 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.

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

[24] 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).

The intercept in (10) 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 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).[25] 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).

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

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:

$$Flow_{i,t} = \beta_0 Perf_{i,t-1} + \beta_1 Illiq_i \cdot Perf_{i,t-1} + \beta_2 Illiq_i + \beta_3 Control_{i,t} + \beta_4 Control_{i,t} \cdot Perf_{i,t-1} + \varepsilon_{i,t}. \tag{11}$$

[Insert Table 2 here]

In (11), $Perf_{i,t-1}$ 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 four-factor (the Fama-French three factors plus the momentum factor) model (*Alpha*4), 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.[26] 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 *Alpha*1 leads to an increased net inflow in the magnitude of 0.70% of the fund's total net assets. The flow responses to *Alpha*4 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

[26] 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. Our results remain qualitatively similar if we use shorter lags to measure past performance

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).

For our analysis, the choice of performance metric is guided by different considerations than those for standard performance attribution. We are interested in how investors behave as a function of the behavior of other investors, and therefore the appropriate performance measure for our analysis is the one that investors use and are overall more responsive to, particularly after poor performance. Consistent with the prior literature on mutual fund flows, we find that investors respond more strongly to simple market-benchmarked returns (such as $Alpha1$) than to refined multifactor-adjusted excess returns (such as $Alpha4$). Hence, based on the results in columns (4) to (6) of Table 2, 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 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.

An immediate robustness question is about the effect of size. The summary statistics in Section 4 indicate that very large funds tend to invest in liquid assets: Though the median assets of liquid and illiquid funds are very similar ($145 vs. $140 million), the mean values are substantially different ($872 vs. $533 million). To make sure that the incremental flow sensitivity among illiquid funds is not due to inadequate size control ($Size$ indeed enters the regression as a control variable both on its own and in interaction with $Perf$), we repeat the exercise by excluding observations where $Size$ falls into the top quartile value of the full sample. With this filtering, the sizes of liquid and illiquid funds are comparably distributed. The resulting coefficient on $Illiq \cdot Perf$ obtained in this alternative analysis is very similar: 0.16 (t-statistic = 2.25).

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 and larger shareholders (such as institutional investors). The idea is that fewer and larger shareholders are more likely to internalize the payoff externalities and their presence reduces 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 ($MinPur250K$). The second measure sorts fund shares based on the amount of investment by investors, which could be institutional or retail. 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 held primarily by large investors. While the reduced significance in the sub-sample of institutional oriented funds may be due to the small sample size, the lower point estimate in this sub-sample is definitely informative about the different behavior in institutional oriented funds. Hence, the results indicate that flows are more sensitive to poor performance in illiquid funds only when there is 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.

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 for our results, and present evidence that refutes 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 (liquid and illiquid).

6.1 Information

The result that investors are more sensitive to bad performance in illiquid funds than in liquid funds may be due to the fact that bad performance in illiquid funds is more informative about the quality of the fund's assets or managers. 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 largely driven by bad fundamentals. We first note that this alternative explanation is unlikely to be driving our results because it does not explain the findings of Table 3, according to which the stronger response of investors to bad performance in illiquid funds is not observed among institutional-oriented funds. Still, in the rest of this subsection, we describe further tests that try to refute this alternative explanation more directly.

If bad performance in illiquid funds is indeed more indicative of future bad performance, for reasons other than the resulting withdrawals by fund investors, then one should expect that funds investing in illiquid assets will display more return persistence, especially when the past performance is poor. The first three columns of Table 4 look directly at this aspect of the data and present a formal comparison between the liquid and illiquid funds in our sample. One difficulty arises, however, because the story developed in our paper also generates some return persistence in illiquid, but not in liquid, funds, due to the damaging redemptions in illiquid funds. Hence, in the comparison we conduct, we try to isolate the effect of information about fundamentals from that of the damage caused by other redemptions by excluding all observations that experience more than 5% outflows during the past month (about 6.3% of the sample).

[Insert Table 4 here]

We use the standard portfolio-sorting approach in the asset pricing literature to examine performance persistence. 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. In interpreting the results, we focus on $Alpha1$, which is the performance measure we focused on thus far in the paper. Two main observations come out of the data. 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). Hence, there seem to be no evidence that illiquid funds show more return persistence than liquid funds, and thus the information conveyed by past performance about future performance is unlikely to explain the results in our paper.

The comparison between the return persistence of liquid vs. illiquid *open-end* funds admittedly suffers from a couple of problems. First, by excluding observations with extreme past outflows, we are not able to refute the possibility that the past performance of these extreme observations (and not others) is exceptionally informative about future performance, and that this is known to the investors, who react accordingly. Second, having in mind the model of Berk and Green (2004), it is possible that persistence in returns of open-end funds is not indicative of persistence in the quality of managers because the response of flow to performance will affect future performance when there are decreasing returns to scale in asset management.

To address these two problems, we conduct an out-of-sample test on equity *closed-end* funds. These closed-end funds manage similar assets as the open-end funds in our sample, but with one crucial difference: investors cannot take money out of (or put money in) closed-end funds. Hence, looking at the return persistence patterns of closed-end funds offers a unique opportunity for identification: the persistence of managerial skills or asset quality in closed-end funds should be the same as in open-end funds, yet in closed-end funds there are no flows that exert an additional effect on persistence.

Our sample of closed-end funds is obtained from and described in Bradley, Brav, Goldstein, and Jiang (2007). It contains all CRSP-covered closed-end funds that invest primarily in equity (domestic and international). There are 142 such funds and the sample spans from 1988 to 2004. We repeat the return persistence test using the NAV returns of closed-end funds, and report the results in the last three columns of Table 4.[27] Interestingly, the NAV returns of closed-end funds investing in liquid assets actually show more persistence than those of closed-end funds investing in illiquid assets. This lack of return persistence in illiquid closed-end funds is consistent with

[27]It is worth noting that in open-end funds, NAV returns coincide with fund returns because fund shares values are equated to their NAVs by construction. In contrast, the two notions of returns could diverge for closed-end funds because of the stochastic evolution of discounts (approximately, closed-end fund returns are the summation of NAV returns and discount change). We focus on the NAV returns because we are testing the return persistence of the underlying portfolios.

evidence in the asset pricing literature on illiquid stocks. For example, a recent paper by Avramov, Chordia, and Goyal (2006) show that illiquid stocks display stronger return reversal at the monthly frequency. Overall, this set of results provides even stronger indication that the information in past performance about future performance cannot provide a convincing explanation for the results in our paper.

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 different types of 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 is not likely to be generating our results. According to our data, liquid funds are more likely than illiquid funds to be held by institutions (See Section 4). 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.

[Insert Table 5 here]

The results in Table 5 – obtained for the subsample of large/institutional shares – are very similar to those in Table 3 – obtained for the whole sample. This suggests that our previous results are not driven by the clientele effect. In detail, the table shows that among retail-oriented funds –

where we expect strategic complementarities to affect outflows[28] – 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. As in Table 3, this result is not obtained when we look among institutional-oriented funds.

Overall, this set of results provides additional indication that coordination motives play a role in the behavior of mutual-fund investors. Essentially, we find that the behavior of one particular clientele (large/institutional investors) in the same type of funds (illiquid funds), is different depending on whether they are surrounded by retail investors or by fellow large/institutional investors. When surrounded by retail investors, institutional investors are still affected by strategic complementarities and thus respond more to bad performance in illiquid than in liquid funds. When surrounded by other institutional investors, they do not exhibit such behavior. This differential behavior indicates that our results are not driven by the possibility that small and large investors have different preferences for asset liquidity, nor are they driven by the possible heterogeneity among large investors that hold liquid and illiquid funds.

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). The advantage of this measure is that it captures a fund feature that is transparent to even the most unsophisticated investors. Moreover, it is exogenous to fund flows since the stated objectives of the fund are formed at the inception of the fund. One potential concern with using this dummy variable is that differences in flow-to-poor performance sensitivities might be caused by unobservable fund characteristics that are unrelated to the liquidity of the underlying assets. To confirm that our earlier findings are related to the liquidity of the fund assets, we retrieve from the Thompson

[28] Recall that purchases and redemptions in all share classes belonging to the same fund are pooled. Therefore, outflows in retail share classes impose costs on the institutional share classes within the same fund.

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) ($Amihud$).[29] 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.[30]

The liquidity measures based on holdings offer two additional advantages. First, they track variation both across and within funds, and therefore enable more powerful identification. Second, they allow funds to have different degrees of adherence to their stated objective (on the basis of which the $Illiq$ measure is constructed). For example, within the category of small-cap funds, there could still be considerable variation in the liquidity of the underlying assets. On the other hand, as discussed above, one needs to assume some level of investor sophistication to model the differential flow-to-performance response based on these refined liquidity measures. Further, the construction of the measures necessarily narrows down our sample to domestic equity funds only. Overall, we view the holding-based liquidity measure as complementary to our main measure $Illiq$.

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

[29] See discussions in a recent paper by Spiegel and Wang (2006) on the performance of the two measures in capturing return premium due to illiquidity.

[30] 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.

stocks from Joel Hasbrouck's web site.[31] The correlation coefficient between the trading volume 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. In the full sample, 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, the effect is reduced to near zero in magnitude and becomes insignificant for both measures.

[Insert Table 6 here]

As a sensitivity check, we replace the *Amihud* variable for the whole fund holding with a similarly-constructed variable for the most liquid securities that account for one-quarter (in value) of a mutual fund's holdings. The results are reported in the last column of Table 6. The motivation is that a mutual fund may sell the most liquid portion of its portfolio first when facing outflows (Koo (2006)), and hence the marginal liquidity of the portfolio could be as important as the average liquidity. The median value of this new measure is comparable to the 75th percentile of all-sample portfolio average *Amihud*, and the correlation between the two is 0.89. The results show that the coefficient on $Liq\_Holding * Alpha$ remains statistically significant (at the 1% level) for the full sample, and is not significant for the subsample of institutional-oriented funds. Similar results prevail if we use the average liquidity measures for the most liquid 10% or 50% of the individual portfolios.

Finally, we conducted two additional robustness checks (untabulated). First, 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 one, we re-estimate the regression in Table

[31] 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.

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:

$$Perf_{i,t} = \beta_0 Outflow_{i,t-1} + \beta_1 Size_{i,t-1} + \beta_2 Expense_{i,t} + \sum_{j=1}^{J=6} \gamma_j PastPerf_{i,t-j} + \varepsilon_{i,t}. \tag{12}$$

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.[32] 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 (12) 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

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

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 (12) 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 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. The monthly-frequency estimates may not represent the full impact of significant outflows because of within-month trading. Further, untabulated estimation shows that the accumulated damage on the return gap amounts to about 93 basis points (significant at less than the 1% level) in the six-month period after the month with significant outflow. This suggests that if an investor fails to redeem from an illiquid fund that experiences a 5% outflow, he would incur a cumulative loss of about 1% in return over the next six months.

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 aggressive in taking 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 (the difference is statistically significant at the 1% level). Table 8 examines the determinants of cash holdings at the annual frequency (where cash is measured at the year end as the percentage of total assets. In addition to fund liquidity (for which we use the *Amihud* measure), we include the following independent variables in the regression: the average monthly flows, the standard deviation of flows, the average monthly $Alpha1$ during the year, fund size, fund age, percentage of institutional shares, and load charges, measured at the end of the year.

[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 0.87 percentage points ($t = 15.62$) decrease in cash holdings (or about 20% of the full sample average). The coefficient is very similar among the subsample illiquid funds. Cash holding is highly sensitive to past flows, indicating its role in absorbing flows to mitigate the urgency of trading. Preemptive cash policy requires that cash holdings be higher in anticipation of negative future flows. However, we observe (not tabulated) an insignificant but slightly positive correlation between current cash holdings and next-period fund net flows.[33] 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. The two pieces of evidence combined show that overall cash holdings may help reducing damage from

[33] The positive correlation is weakened but does not turn negative if we control for the serial correlation of fund flows.

outflows in illiquid funds, but they are unlikely to completely eliminate payoff complementarities in redemption decisions.[34] In addition, high institutional ownership is associated with less cash holding, consistent with our previous analysis on how the presence of large investors weakens the effect of payoff complementarities. Surprisingly, high volatility in monthly flows ($STDFLOW$), which calls for more liquidity buffer, is actually associated with lower cash holdings. This could be attributed to the asymmetric effects of inflows and outflows. It turns out that the empirical cash-to-flow sensitivity is four times as large for outflows than for inflows. Again, this relation shows that cash holdings largely accommodate past flows rather than anticipate future ones.

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 8 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, and the independent variables are measured either at the end of 2004 (TNA and AGE) or averaged during the two-year period of 2003-2004 (other variables). 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 (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

[34] 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' redemptions, given any cash balance level that a fund optimally chooses.

restrictions on redemptions. This effect is present among the subsample of illiquid funds (Columns (5) and (6)), with similar magnitude, although at lower statistical significance. Funds with more volatile flows in the past impose stricter restriction (significant at less than the 1% level in the full sample as well as the subsample of liquid funds).

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 mutual funds. The model generates two testable predictions. First, in illiquid funds – where payoff complementarities are stronger – we expect that outflows will be more sensitive to bad performance than in liquid funds. This is because investors' tendency to withdraw increases when they fear the damaging effect of other investors' redemptions. 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. Obviously, this is a result of the existing mutual-fund contracts. It would be interesting to analyze optimal contracts and policy implications for mutual funds in this light. 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. The current paper uses mutual-fund data to demonstrate this relation. This data offers several advantages that are discussed in the paper. It would be interesting, if data allow, to use our approach to shed light on settings that are even more prone to fragility, such as hedge funds. 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.

9 Appendix

Characterization of θ^* (derivation of equation (6)):

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,

$$\int_{-\infty}^{\infty} \frac{1 - (1+\lambda) \max\left\{0, \left(G\left(\frac{\theta^*-\theta}{\sigma}\right)\overline{N} - I\left(R_1\right)\right)\right\}}{1 - \max\left\{0, \left(G\left(\frac{\theta^*-\theta}{\sigma}\right)\overline{N} - I\left(R_1\right)\right)\right\}} R_2\left(\theta\right) \frac{1}{\sigma} g\left(\frac{\theta^*-\theta}{\sigma}\right) d\theta = 1. \tag{13}$$

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 $N\left(\theta, \theta^*\right)$ 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^*:

$$\int_{0}^{1} \frac{1 - (1+\lambda) \max\left\{0, \left(\alpha\overline{N} - I\left(R_1\right)\right)\right\}}{1 - \max\left\{0, \left(\alpha\overline{N} - I\left(R_1\right)\right)\right\}} \cdot R_2\left(\theta^* - G^{-1}\left(\alpha\right)\sigma\right) d\alpha = 1. \tag{14}$$

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. This yields equation (6).

Characterization of θ^{**} (the analysis of the model with a large investor):

We characterize the threshold signals θ^R and θ^I. As before, a retail investor that observed θ^R

is indifferent between redeeming and not redeeming:

$$\int_{-\infty}^{\infty}\left[\begin{array}{c} G\left(\frac{\theta^I-\theta}{\sigma}\right)\cdot\frac{1-(1+\lambda)\max\left\{0,\left(\left(G\left(\frac{\theta^R-\theta}{\sigma}\right)(1-\beta)+\beta\right)\overline{N}-I(R_1)\right)\right\}}{1-\max\left\{0,\left(\left(G\left(\frac{\theta^R-\theta}{\sigma}\right)(1-\beta)+\beta\right)\overline{N}-I(R_1)\right)\right\}} \\ +\left(1-G\left(\frac{\theta^I-\theta}{\sigma}\right)\right)\cdot\frac{1-(1+\lambda)\max\left\{0,\left(G\left(\frac{\theta^R-\theta}{\sigma}\right)(1-\beta)\overline{N}-I(R_1)\right)\right\}}{1-\max\left\{0,\left(G\left(\frac{\theta^R-\theta}{\sigma}\right)(1-\beta)\overline{N}-I(R_1)\right)\right\}}\end{array}\right]\cdot R_2(\theta)\frac{1}{\sigma}g\left(\frac{\theta^R-\theta}{\sigma}\right)d\theta=1. \tag{15}$$

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:

$$\int_{-\infty}^{\infty}\left[\frac{1-(1+\lambda)\max\left\{0,\left(G\left(\frac{\theta^R-\theta}{\sigma}\right)(1-\beta)\overline{N}-I(R_1)\right)\right\}}{1-\max\left\{0,\left(G\left(\frac{\theta^R-\theta}{\sigma}\right)(1-\beta)\overline{N}-I(R_1)\right)\right\}}\right]\cdot R_2(\theta)\frac{1}{\sigma}g\left(\frac{\theta^I-\theta}{\sigma}\right)d\theta=1. \tag{16}$$

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:

$$\int_{-\infty}^{\infty}\left[\begin{array}{c} G\left(\frac{\theta^I-\theta^R+G^{-1}(\alpha)\sigma}{\sigma}\right)\cdot\frac{1-(1+\lambda)\max\left\{0,\left((\alpha(1-\beta)+\beta)\overline{N}-I(R_1)\right)\right\}}{1-\max\left\{0,\left((\alpha(1-\beta)+\beta)\overline{N}-I(R_1)\right)\right\}} \\ +\left(1-G\left(\frac{\theta^I-\theta^R+G^{-1}(\alpha)\sigma}{\sigma}\right)\right)\cdot\frac{1-(1+\lambda)\max\left\{0,\left(\alpha(1-\beta)\overline{N}-I(R_1)\right)\right\}}{1-\max\left\{0,\left(\alpha(1-\beta)\overline{N}-I(R_1)\right)\right\}}\end{array}\right]\cdot R_2\left(\theta^R-G^{-1}(\alpha)\sigma\right)d\alpha=1. \tag{17}$$

$$\int_{-\infty}^{\infty}\left[\frac{1-(1+\lambda)\max\left\{0,\left(G\left(\frac{\theta^R-\theta^I+G^{-1}(\alpha)\sigma}{\sigma}\right)(1-\beta)\overline{N}-I(R_1)\right)\right\}}{1-\max\left\{0,\left(G\left(\frac{\theta^R-\theta^I+G^{-1}(\alpha)\sigma}{\sigma}\right)(1-\beta)\overline{N}-I(R_1)\right)\right\}}\right]\cdot R_2\left(\theta^I-G^{-1}(\alpha)\sigma\right)d\alpha=1. \tag{18}$$

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 $\frac{\theta^R-\theta^I}{\sigma}$,[35] 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):

$$R_2\left(\theta^{**}\right) = \frac{1}{\int_0^1 \left[\begin{array}{c} G\left(G^{-1}\left(\alpha\right)-x\right)\cdot\frac{1-(1+\lambda)\max\left\{0,\left((\alpha(1-\beta)+\beta)\overline{N}-I(R_1)\right)\right\}}{1-\max\left\{0,\left((\alpha(1-\beta)+\beta)\overline{N}-I(R_1)\right)\right\}} \\ +\left(1-G\left(G^{-1}\left(\alpha\right)-x\right)\right)\cdot\frac{1-(1+\lambda)\max\left\{0,\left((\alpha(1-\beta)+\beta)\overline{N}-I(R_1)\right)\right\}}{1-\max\left\{0,\left((\alpha(1-\beta)+\beta)\overline{N}-I(R_1)\right)\right\}}\end{array}\right]d\alpha}. \tag{19}$$

$$R_2\left(\theta^{**}\right) = \frac{1}{\int_0^1 \left[\frac{1-(1+\lambda)\max\left\{0,\left(G(G^{-1}(\alpha)+x)(1-\beta)\overline{N}-I(R_1)\right)\right\}}{1-\max\left\{0,\left(G(G^{-1}(\alpha)+x)(1-\beta)\overline{N}-I(R_1)\right)\right\}}\right]d\alpha}. \tag{20}$$

Using (20), we can derive an upper bound on θ^{**} by setting $G\left(G^{-1}\left(\alpha\right)+x\right) = 1$. This upper bound is given in (7).

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

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Table 1: Variable Definitions and Summary Statistics

The sample contains 639,596 fund-share-month observations from 10,404 fund-shares of 4,393 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. The effective number of observations is on the order of number of unique funds. * 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
#unique funds & fund-share-months	4,393	639,596	4,393	639,596	4,407	676,198	4,320	344,127	4,320	374,697	4,367	384,123
R-squared	0.07		0.06		0.13		0.03		0.03		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. The effective number of observations is on the order of number of unique funds. * 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
#unique funds & fund-share-months	1,082	61,194	520	22.037	3,495	282,933	4,071	322,090
R-squared		0.03		0.03		0.03		0.03

Table 4: Predictability of Fund Returns

This table compares the return predictability of funds investing in illiquid and liquid assets for both (open-end) mutual funds and closed-end funds. The sample of close-end funds contain all 142 equity closed-end funds that are tracked by CRSP during 1988 to 2004. 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.

	Open-end Mutual Funds			Closed-end Funds		
Lag Performance Quintiles	*Alpha1*	*Alpha4*	*RetExCat*	*Alpha1*	*Alpha4*	*RetExCat*
			Liquid Funds			
Q1	-0.007	-0.004	-0.004	-0.005	-0.004	-0.005
Q2	-0.003	-0.002	-0.002	0.000	0.001	0.001
Q3	-0.001	-0.002	-0.001	0.002	0.000	0.000
Q4	0.000	-0.001	-0.001	-0.001	0.001	-0.001
Q5	0.003	0.001	0.002	0.003	0.001	0.004
Q5-Q1	0.010	0.005	0.005	0.008	0.005	0.009
t-stat	3.96	1.92	3.73	2.48	2.07	3.20
			Illiquid Funds			
Q1	-0.006	-0.003	-0.005	-0.007	-0.005	0.001
Q2	-0.002	-0.002	-0.002	-0.005	-0.007	0.001
Q3	0.000	-0.001	-0.001	-0.005	-0.008	0.001
Q4	0.003	0.001	0.000	-0.007	-0.008	0.001
Q5	0.006	0.004	0.004	-0.007	-0.009	-0.002
Q5-Q1	0.012	0.006	0.008	0.001	-0.004	-0.003
t-stat	3.01	1.66	4.30	0.10	-0.76	-0.99
			Difference			
Liq(Q5-Q1) – Illiq(Q5-Q1)	-0.001	-0.001	-0.003	0.007	0.009	0.012
t-stat	-0.28	-0.29	-1.30	1.21	1.63	2.84

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. The effective number of observations is on the order of number of unique funds. * 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
#unique funds & fund-share-months	1,074	41,105	510	14,249	980	28,289	699	17,677
R-squared		0.04		0.05		0.03		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*. Column (1) uses the portfolio average trading volume (in logarithm) of the underlying holdings as the liquidity measure. Column (2) the portfolio average Amihud liquidity measure (in logarithm). Column (3) uses the average Amihud liquidity measure of the most liquid quartile of a portfolio. Each specification is conducted on the full sample and the subsample of institutional-oriented funds. All regressions include year fixed-effects. Standard errors adjust for heteroskedasticity and within-cluster correlation clustered at the fund-level. The effective number of observations is on the order of number of unique funds. * and ** indicate statistical significant at less than the 10% and 5% levels, respectively.

Liq_Holding measure	(1) Ln(trade_vol)				(2) Amihud				(3) Amihud (most liquid quartile)			
	All observations		%INST>=75%		All observations		%INST>=75%		All observations		%INST>=75%	
	COEF	T-STAT	COEF	T-STAT	COEF	T-STAT	COEF	T-STAT	COEF	T-STAT	COEF	T-STAT
Alpha	**0.24****	2.61	**0.71****	4.89	**0.20****	2.11	**0.68****	4.63	**0.26****	2.56	**0.68****	4.35
Liq_Holding Alpha*	**-0.13****	-5.78	**-0.02**	-0.43	**-0.18****	-4.01	**0.03**	0.36	**-0.09****	-2.69	**0.03**	0.48
Flow(-1)	**0.11****	8.30	**0.14****	7.73	**0.11****	8.16	**0.13****	7.59	**0.11****	8.69	**0.14****	7.75
Size(Ln)	**0.06****	2.87	**0.14****	3.06	**0.04****	2.00	**0.15****	3.04	**0.04****	2.01	**0.15****	3.11
Age(Ln)	**-1.65****	-23.75	**-2.04****	-11.57	**-1.59****	-22.81	**-2.02****	-11.36	**-1.57****	-21.96	**-2.03****	-11.15
Expense	**-0.74****	-10.03	**-0.08**	-0.46	**-0.64****	-8.65	**0.03**	0.18	**-0.61****	-8.04	**0.08**	0.44
Load	**0.02**	1.43	**0.01**	0.16	**0.03***	1.72	**0.02**	0.43	**0.03**	1.62	**0.03**	0.77
Inst	**-0.52****	-5.04	**-0.64****	-2.67	**-0.42****	-4.06	**-0.58****	-2.40	**-0.42****	-3.98	**-0.51****	-2.18
Liq_Holding	**-0.25****	-8.04	**-0.15****	-2.63	**-0.24****	-3.93	**-0.15**	-1.36	**-0.15****	-2.64	**-0.05**	-0.56
Size Alpha*	**0.00**	0.08	**0.04**	1.04	**0.00**	0.15	**0.05**	1.16	**-0.01**	-0.33	**0.04**	0.98
Age Alpha*	**0.06**	0.92	**-0.14**	-1.21	**0.07**	1.07	**-0.13**	-1.12	**0.10**	1.39	**-0.08**	-0.66
Expense Alpha*	**-0.24****	-4.07	**0.00**	-0.01	**-0.20****	-3.45	**0.08**	0.55	**-0.15****	-2.44	**0.09**	0.58
Load Alpha*	**0.07****	3.44	**-0.05***	-1.73	**0.07****	3.51	**-0.05**	-1.60	**0.07****	2.87	**-0.05**	-1.62
Inst Alpha*	**0.15**	1.40	**-0.26**	-1.49	**0.17**	1.60	**-0.22**	-1.26	**0.15**	1.29	**-0.24**	-1.32
#unique funds & fund-share-months	3,127	262,313	740	44,965	3,127	262,313	740	44,965	3,077	246,374	732	44,468
#obs & R-sqr		0.04		0.05		0.04		0.05		0.04		0.05

Table 7: Effects of Outflows on Fund Returns

The analysis in this table is on fund-month (rather than fund-share-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 most recent 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* or return gap of the fund during the *i*-th month prior to month *t*. Definitions of other variables are listed in Table 1. Standard errors adjust for heteroskedasticity and within-cluster correlation clustered at the fund-level. The effective number of observations is on the order of number of unique funds. * 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
#unique funds & fund-months	1,940	130,517	969	63,467	915	37,538	1,949	128,711	975	63063	934	37519
R-squred		0.01		0.02		0.02		0.00		0.01		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), all variables are measured at the annual frequency. The dependent variable is the percentage of assets a fund holds in cash at year end 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	**-0.014****	-15.62	**-6.9%****	-4.45	**-2.78****	-5.74	**-0.014****	-3.79	**-6.7%**	-1.25	**-3.93***	-1.87
Flow(-1)	**0.121****	7.64	**33.6%**	0.94	**9.17**	0.83	**0.118****	4.40	**-18.6%**	-0.29	**-9.09**	-0.36
TNA	**-0.059**	-1.35	**36.2%**	1.51	**4.04**	0.53	**0.031**	0.35	**90.8%****	2.03	**20.62**	1.13
Age	**0.289****	2.56	**7.0%****	4.82	**1.79****	3.93	**0.254**	1.08	**4.6%**	1.57	**2.62****	2.32
%Inst	**-0.695****	-4.51	**1.7%****	2.97	**0.35***	1.90	**-0.489***	-1.74	**3.9%****	3.36	**1.12****	2.40
Load	**-0.016**	-0.48	**1.3%**	0.74	**0.09**	0.16	**-0.083**	-1.28	**-0.6%**	-0.17	**-0.53**	-0.37
Alpha1	**0.067****	2.27	**-3.1%**	-1.25	**-1.32***	-1.68	**0.131****	2.65	**-2.1%**	-0.49	**-1.97**	-1.16
StdFlow	**-0.106****	-3.78	**3.8%****	6.83	**0.90****	5.08	**-0.068**	-1.15	**3.7%****	3.72	**1.11****	2.76
Cnst	**5.585****	22.38	**--**	**--**	**-9.01****	-5.79	**5.077****	9.96	**--**	**--**	**-15.78****	-4.13
#obs & R-squared	23,025	0.032	2,575	0.052	2,575	0.019	7,219	0.015	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.