Journal of Financial Economics 97 (2010) 239–262

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

Payoff complementarities and financial fragility: Evidence from mutual fund outflows ☆

Qi Chen [a], Itay Goldstein [b,*], Wei Jiang [c]

[a] The Fuqua School of Business, Duke University, USA
[b] The Wharton School, University of Pennsylvania, USA
[c] The Graduate School of Business, Columbia University, USA

ARTICLE INFO

Article history:
Received 12 February 2009
Received in revised form
10 August 2009
Accepted 8 September 2009
Available online 2 April 2010

JEL classification:
G01
G23

Keywords:
Payoff complementarities
Financial fragility
Mutual fund redemptions

ABSTRACT

The paper provides empirical evidence that strategic complementarities among investors generate fragility in financial markets. Analyzing mutual fund data, we find that, consistent with a theoretical model, funds with illiquid assets (where complementarities are stronger) exhibit stronger sensitivity of outflows to bad past performance than funds with liquid assets. We also find that this pattern disappears in funds where the shareholder base is composed mostly of large investors. We present further evidence that these results are not attributable to alternative explanations based on the informativeness of past performance or on clientele effects. We analyze the implications for funds' performance and policies.

1. Introduction

Financial fragility is often attributed to the presence of strategic complementarities among investors.[1] When investors' incentive to take a certain action increases in the expectation that other investors will take the same action, a multiplier effect is expected to emerge, amplifying the effect of fundamentals on investors' behavior. Despite a large theoretical literature, virtually no empirical study identifies this relation in data. This paper aims to provide such empirical evidence.

☆ We thank Franklin Allen, Philip Bond, Markus Brunnermeier, Miguel Cantillo, Amil Dasgupta, Richard Evans, Mark Flannery, Simon Gervais, Gary Gorton, Christopher James, Debbie Lucas, David Musto, Bryan Routledge, Jacob Sagi, Jose Scheinkman, Hyun Song Shin, Chester Spatt, Robert Stambaugh, Ted Temzelides, Xavier Vives, and an anonymous referee for useful discussions and comments. We also thank seminar participants at Boston College, Columbia University, Duke University, ECB, Goethe University (Frankfurt), Hong Kong University of Science and Technology, Northwestern University, University of Notre Dame, Peking University, Pennsylvania State University, the Federal Reserve Bank of Philadelphia, Princeton University, Stockholm School of Economics, Tsinghua University, Dartmouth University, University of British Columbia, University of Massachusetts, University of Minnesota, University of North Carolina-Chapel Hill, University of Southern California, Vanderbilt University, and University of Pennsylvania, and participants at the following conferences: Corporate Governance Incubator (China), IESE Conference on Information and Complementarities (Barcelona), WFA annual meeting, NBER Capital Markets and the Economy Workshop, Global Games Workshop at SUNY Stony Brook, FDIC Annual Bank Research Conference, Unicredit Conference on Banking and Finance (Naples), Utah Winter Finance Conference, and Cleveland Fed Conference on Financial Crises. Finally, we thank Suan Foo at Morgan Stanley for sharing his knowledge on the key aspects of flow management in the mutual fund industry. Itay Goldstein gratefully acknowledges financial support from the Rodney White Center at the Wharton School of the University of Pennsylvania.

* Corresponding author.
E-mail addresses: qc2@duke.edu (Q. Chen), itayg@wharton.upenn.edu (I. Goldstein), wj2006@columbia.edu (W. Jiang).

[1] This idea is at the core of various theories on bank runs (e.g. Diamond and Dybvig, 1983), currency attacks (e.g. Morris and Shin, 1998), bubbles and crashes in financial markets (e.g. Abreu and Brunnermeier, 2003), and others.

0304-405X/$ - see front matter
doi:10.1016/j.jfineco.2010.03.016

We conduct our study using (open-end) mutual fund data. In mutual funds, investors have the right to redeem their shares at the fund's daily-close net asset value (NAV) on any given day. As shown in previous studies (e.g., Edelen, 1999; Coval and Stafford, 2006), following substantial outflows, funds need to adjust their portfolios and conduct costly and unprofitable trades, which damage the future returns. Because mutual funds conduct most of the resulting trades after the day of redemption, most of the costs are not reflected in the NAV paid out to redeeming investors, but rather are borne by the remaining investors. This leads to strategic complementarities—the expectation that other investors will withdraw their money reduces the expected return from staying in the fund and increases the incentive for each individual investor to withdraw as well—and amplifies the damage to the fund.

Detecting this mechanism in the data is a difficult task. Testing directly whether agents choose the same action as others cannot credibly identify the effects of strategic complementarities because this approach is prone to a missing variable problem, that is, agents could act alike because they are subject to some common shocks or react to information about fundamentals unobserved by the econometrician. This so-called reflection problem posed a challenge for empiricists trying to detect peer effects for a long time (see discussion by Manski, 1993; Glaeser, Sacerdote, and Scheinkman, 2003). Recently, Hertzberg, Liberti, and Paravisini (2009) resort to a special setting that generates discontinuity in the information variable for identification. Instead, our empirical approach relies on the differences across mutual funds in the level of strategic complementarities faced by their investors. Investors in funds that hold illiquid assets (hereafter, illiquid funds) face a higher degree of strategic complementarities than investors in funds that hold liquid assets (hereafter, liquid funds). This is because redemptions impose higher costs on the illiquid funds than the liquid funds. Our empirical analysis tests for differences in redemption patterns across these types of funds.

We start by developing a stylized model of mutual fund redemptions that delivers our basic hypotheses. Given that the basic premise of the model is the presence of strategic complementarities in mutual fund redemptions, getting empirical predictions is non-trivial. This is because models with strategic complementarities typically have multiple equilibria and thus cannot be easily taken to the data.[2] Our theoretical model (detailed in the Appendix) uses the global-game framework (assuming that agents do not have common knowledge about some fundamental variable that affects the returns of the fund) to overcome the problem of multiple equilibria and generate clear-cut empirical predictions.[3]

Our main hypothesis is that the sensitivity of outflows to bad past performance is stronger in illiquid funds than in liquid funds. Intuitively, consider investors holding shares in an emerging market fund versus investors holding shares in a fund that invests in large-cap US stocks. Faced with bad performance, the former have a stronger tendency to redeem their shares because they know that redemptions by others impose non-negligible costs on the fund, which hurts 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. Knowing that they control large shares of the fund assets, large investors are less concerned about the behavior of others. Hence, the prediction is that the effect of the illiquidity of fund assets on investors' redemptions is smaller in funds held primarily by large investors.[4] Using data on the net outflows from US equity mutual funds from 1995 to 2005 and various measures of illiquidity (captured either by the stated investment style or the trading liquidity of the underlying assets), we find strong support for our two hypotheses.

We consider two alternative explanations for our findings. The first one is reminiscent of the empirical literature that attributes banking failures to bad fundamentals (e.g., Gorton, 1988; Calomiris and Mason, 1997, 2003; Schumacher, 2000; Martinez-Peria and Schmukler, 2001). In our context, illiquid funds could 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 entertain this explanation by examining in data whether, absent large outflows, performance in illiquid funds is more persistent than in liquid funds. We find no such evidence, both for open-end funds (after excluding observations with extremely large outflows) and for closed-end funds (where, by definition, outflows 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, institutional investors. We show that in the subsample of retail-oriented funds where strategic complementarities are expected to have an effect, large 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

[2] 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).

[3] The theoretical 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 (*footnote continued*) stock-market liquidity (Morris and Shin, 2004; Plantin, 2009). It is also related to the model of Abreu and Brunnermeier (2003) on financial market bubbles and crashes. 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).

[4] Large investors could 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.

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. These differences provide a key piece of evidence to identify the role of strategic interaction 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 trading or minimize their impact on fund performance. Such measures include restrictions on redemptions after a 2005 Securities and Exchange Commission (SEC) rule and holding more cash reserves. We find that illiquid funds are more likely to take each one of the two measures. Hence, the effects we detect in equilibrium are observed after the mitigating effect of these measures.

The institutional features of mutual funds that motivate our study possibly facilitate occasional extreme turbulences, such as the run on the money market funds in the US during the midst of the subprime crisis in September 2008.[5] To benefit from the richness and diversity of the mutual fund data, we deliberately use a large sample instead of confining ourselves to short periods and selected funds in which extreme turbulences occurred. In particular, our ability to distinguish between funds with different degrees of strategic complementarities and with different types of investors is crucial for testing our hypotheses and for ruling out the alternative explanations. While looking at a large sample that consists mostly of calm periods reduces the magnitude of the mechanism we are interested in, we are still able to find evidence to support our hypotheses.[6]

Our findings manifest 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. This opens questions on optimal fund policies and regulation. For example, our results suggest that this fragility is tightly linked to the level of liquidity of the fund's underlying assets and that funds investing in highly illiquid assets may be better off operating in a closed-end form. This idea underlies the model of Cherkes, Sagi, and Stanton (2006). Yet, as pointed out by Stein (2005), in equilibrium, due to signaling considerations, an inefficiently high proportion of open-end funds exists. Our study suggests that this is particularly damaging for funds that hold illiquid assets. Beyond the funds and their investors, this fragility 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 paper also contributes to the mutual fund literature. Many papers study mutual fund flows. A partial list includes Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997), Sirri and Tufano (1998), and Zheng (1999). Our results 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 has not considered the interaction among fund investors.

The remainder of the paper is organized as follows. In Section 2, we describe the institutional details that support the design of our study and present the main hypotheses (the model on which the hypotheses are based is provided in Appendix). In Section 3, we describe the data used for our empirical study. In Section 4, we test our hypotheses regarding the effect of funds' liquidity and investor base on outflows. Section 5 considers the potential alternative explanations and provides evidence to rule them out. In Section 6, we provide robustness checks and further evidence. Section 7 concludes.

2. Institutional background and hypotheses

2.1. Institutional background

Two important ingredients give rise to payoff complementarities in redemptions from illiquid mutual funds. The first one is that redemptions are costly to the funds. The costs stem mostly from the trades that funds make in response to outflows, including both direct costs such as commissions, bid–ask spreads, price impact and indirect costs that result when redemptions force fund managers to deviate from their optimal portfolios.

These costs, as shown and analyzed in a large body of literature (for example, Chordia, 1996; Edelen, 1999; Wermers, 2000; Greene and Hodges, 2002; Johnson, 2004; Coval and Stafford, 2006; Alexander, Cici, and Gibson, 2007; Christoffersen, Keim, and Musto, 2007), are quite substantial. For example, Edelen (1999) estimates that for every dollar of outflow, approximately \$0.76 goes to a marginal increase in the fund's trading volume. He estimates that the average transaction cost on these tradings is 2.2% per unit of trading and these costs contribute to a significant negative abnormal fund return of up to -1.4% annually. 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) find that stocks sold by mutual funds for liquidity reasons (because of outflows) outperform those sold at discretion by 1.55% annually. All these costs are larger in illiquid funds due to the higher

[5] Other examples of runs on mutual funds include the runs on real estate funds in Germany in 2006 (see Bannier, Fecht, and Tyrell, 2006) and in the UK in 2007.

[6] For the same reason, we did not choose hedge-fund or bank data, in which the magnitude of the effect could be stronger but the quality of the available data is low.

trading costs on their illiquid assets (see Coval and Stafford, 2006). This is the basis for our identification strategy.

The second ingredient for payoff complementarities in redemptions from illiquid funds is that the costs imposed by redemptions are generally not reflected in the price (NAV) investors get when they redeem their shares. Instead, 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 their shares in the funds is calculated using the same-day market close prices of the underlying securities. It is determined at 4:00 pm and reported to the National Association of Securities Dealers (NASD) by 6:00 pm. 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 4:00 pm 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 could still prefer to conduct the resulting trades at later dates. The timing of the trades depends on the funds' assessment of optimal trading strategies in light of investment opportunities and trading costs.

On the quantitative side, a simple calculation, based on the estimates from the literature, suggests that investors' redemptions can cause substantial costs to induce other investors to redeem their own shares. According to data from Christoffersen, Evans, and Musto (2007), the 95th and 99th percentile values of monthly redemption at US mutual funds from 1996 to 2003 are 20% and 37% of the total assets, respectively.[7] Combining these numbers with the estimated parameters from Edelen (1999)—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 basis points, respectively.[8] These are still conservative estimates. For illiquid assets, forced trading causes 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 basis points or more of their entire investment in a month, just due to the redemptions of others. This should be sufficient to induce 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]

Certain measures taken by mutual funds in an attempt to mitigate the damage from redemptions speak to this important aspect of the institutional background. Section 6.3 provides empirical analysis on some of these measures. One prominent measure used by almost all funds is to carry a small proportion (usually 1–5%) of the assets in cash, which could 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 they are not able to absorb large flows. Also, after the fund uses cash to meet redemptions, it still needs 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, an increasing number of funds started imposing restrictions on trading frequency. This was encouraged to a large extent by the Securities and Exchange Commission's 2005 rule 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, but, in reality, the rule is far from perfect.[10] First, usually redemption fees are only assessed when the holding period falls short of some threshold length. Second, so far many funds choose not to implement the rule, either because of the competition (to offer ordinary investors the liquidity service) or because of insufficient information regarding individual redemptions from the omnibus accounts.[11] Our main analysis uses data from 1995 to 2005 when redemption restrictions were very uncommon.

Overall, the fact that funds take various mitigating measures proves that they are concerned about costs

---

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

[8] Thirty seven (or 76) bps = 20% (or 37%)∗ 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.

[9] An important question is, what causes investors to expect a certain amount of outflows. In our empirical analysis, past performance plays the key role. Despite the fact that it is the most powerful and highly significant predictor of future flows, it captures only 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] 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.

[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.

imposed by redemptions. However, none of these measures is capable of perfectly solving the problem. Most important, all the cost estimates provided in the existing literature 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. Thus, our findings provide a conservative estimate on the impact of strategic complementarities on investors redemption behavior.

Finally, other mechanisms could also lead to strategic complementarities in mutual fund redemptions. A leading mechanism is based on capital gain taxes. When a mutual fund sells assets due to net redemptions, it might trigger an early realization of capital gain tax for those investors who remain in the fund. Then, expecting redemptions by others, an investor who joined the fund at a high price basis could have an incentive to redeem early to avoid bearing a share of the capital gains that were earned before he joined the fund. Tax externalities of this sort are discussed by Dickson, Shoven, and Sialm (2000) and Barclay, Pearson, and Weisbach (1998). Illiquid funds may have more unrealized capital gains because they trade less often. Then, the capital-gains mechanism strengthens the strategic complementarities in these funds, making our comparison between liquid and illiquid funds even more appropriate for testing the effect of strategic complementarities on mutual fund redemptions.[12]

2.2. Hypotheses

In Appendix, we develop a simple model of complementarities in mutual fund redemptions, which is based on the premises discussed above. Using the global-game methodology, we solve the model and derive the following two hypotheses.

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

Intuitively, in funds that hold illiquid assets, investors who withdraw their money impose a negative externality on those who stay in the fund. This is because they generate a cost to the fund, and the cost is borne mostly by the investors who keep their money in. As a result, the expectation that some investors will withdraw increases the incentive of other investors to do the same thing. This generates self-fulfilling redemptions (i.e., redemptions that are based on the expectation that others will redeem), which increase the overall amount of redemptions. The same force does not work when past performance is relatively high. In this case, 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.

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.

For simplicity, this hypothesis is developed by introducing a single large investor to the shareholder base and analyzing the effect on redemptions. The intuition is that a large investor holds a large proportion of the fund's shares and is thus less affected by the actions of other investors. The large investor 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 in illiquid funds is weaker for a large investor, and therefore he is less likely to withdraw. Moreover, knowing that the fund is held by a large investor, other investors also are less likely to withdraw. This is because the large investor injects strategic stability and thus reduces the inclination of all shareholders to withdraw.

While the hypothesis is developed for only one large investor (utilizing the theoretical tools in Corsetti, Dasgupta, Morris, and Shin, 2004), we conjecture that the same effect is in place in a richer framework that allows for multiple large investors.[13] Hence, going into the empirical analysis we are 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.

3. Data

Our empirical analysis focuses on 4,393 equity funds from the Center for Research in Securities Prices (CRSP) Mutual Fund database in the years 1995–2005.[14] 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

[12] We conduct additional analysis, in which we exclude fund-month observations that are likely to have significant accumulated capital gains (we exclude funds that made large returns in the past two or three years). We found that our results on the differences between illiquid and liquid funds did not change. This indicates that the main driver behind our results on the effect of strategic complementarities is the difference in liquidity of the fund assets and not the difference in the accumulated capital gains. Details are available upon request.

[13] The result described here goes through easily if the large investors play a cooperative equilibrium. This is 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 stays intact, although other forces could arise.

[14] Although the intuition and prediction of our theoretical model apply also to bond funds, we did not include bond funds in our sample. This is mostly because bond trading data are limited and bond funds holdings data are not available, and so we are not able to measure asset liquidity of bond funds. The literature on mutual fund flow-to-performance has thus far been almost exclusively on equity funds. Hence, concentrating on equity, we can make our results comparable to related papers. Clearly, more research on bond funds is warranted when more data become available.

defined-contribution plans, such as 401(k) and 403(b) plans, because they limit the flexibility for investors.[15]

A mutual fund often issues several share classes. The fund pools purchases and redemptions in different share classes to the same portfolio. Different share classes carry different combinations of fees and loads and minimum investment requirements to cater to investors with different wealth levels and investment horizons. Given that these differences affect the incentives of investors to liquidate their positions, our main analysis of fund flows is conducted at the fund-share level.[16] Our final sample contains 639,596 fund share–month observations with 10,404 unique fund shares in 4,393 unique funds. Throughout the paper all regressions incorporate year fixed effects, and all standard errors adjust for heteroskedasticity and within-cluster correlations at the fund level. Therefore the effective number of observations in regressions is in the order of the number of clusters or funds (i.e., 4,393 for the full sample and smaller numbers for subsample analysis).

Our main interest is in the illiquidity of a fund's underlying assets. We use CRSP Standard & Poor's style code and area code to identify the types of assets each fund invests in and create a dummy variable *Illiq* based on these codes. *Illiq* equals one if these codes indicate that the fund invests primarily in one of the following categories: small-cap equities (domestic or international), mid-cap equities (domestic or international), or single-country assets excluding US, UK, Japan, and Canada. We cross-check these classifications for consistency with the CRSP Mutual Funds asset class code and category code. Because 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 6.1).

Out of the 4,393 unique funds in our sample, 1,227 are classified as illiquid funds. Illiquid funds are overall smaller in terms of assets under management than liquid funds ($533 million versus $872 million for average, and $140 million versus $145 million for median), are slightly younger in age (9.2 versus 11.5 years for average, and 6.5 versus 7.2 years for median), and have somewhat higher institutional ownership (28.0% versus 22.8%). Finally, illiquid funds outperform liquid funds by 23 basis points monthly measured by one-factor *Alpha* (significant at the 5% level). Once we control for the usual factors (size, book-to-market, momentum), the outperformance of illiquid funds disappears as the difference drops to 4 basis points monthly and is not statistically significant.

Our ability to obtain evidence consistent with Hypothesis 1 relies on the presence of large differences in liquidity across different funds in our sample. We resort to Hasbrouck (2006) for trading costs estimates at the fund level for domestic equity funds. A typical large-cap fund invests almost exclusively in top-quartile market-cap stocks, which, according to Hasbrouck (2006), would incur an average trading cost of 30–50 basis points during our sample period. If a small-cap fund's portfolio is equally spread among stocks from the bottom market-cap quartile, then the average trading cost would be about 150–200 basis points in 1995 (the beginning of our sample) and about 100 basis points in 2005 (the last year of our sample). This represents a sizable difference in liquidity. Measuring liquidity using the trading volume (in dollars) of funds' holdings, we can directly see the large variation in liquidity across domestic mutual funds in our sample. For example, a fund at the 1st percentile of our sample holds securities with average daily volume of $1.33 million, while a fund at the 99th percentile holds securities with average daily volume of $825.15 million. These volume numbers correspond to the 7th percentile and 80th percentile, respectively, in the universe of domestic stocks. Hence, our sample of open-end mutual funds captures most of the variation in liquidity that exists among stocks.[17]

For our tests, we are also 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.[18] We then determine the *Inst* dummy to the earlier period by matching the fund share's unique identification in CRSP (the Investment Company Data Institute, or ICDI code). The remaining sample is then manually classified according to the Morningstar rule in which a fund share is considered an institutional one if its name carries one of the following suffixes: *I* (including various abbreviations of "institutional" such as "Inst", "Instl", etc.), *X*, *Y*, and *Z*. A fund share is considered retail if it carries one of the following suffixes: *A*, *B*, *C*, *D*, *S*, and *T*. Fund shares with the word "Retirement" (or its various abbreviations such as

[15] 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).

[16] Sensitivity analysis repeated at the fund level (where we aggregate fund-share data that belong to the same fund) generates similar results to our main analysis.

[17] Moreover, considering international equity funds adds more diversity in liquidity to our sample. Most of the international funds that are defined as illiquid in our analysis invest in emerging markets. Bekaert, Harvey, and Lundblad (2007) measure illiquidity with the percentage of stock-level zero-return days. The average percentage of zero-return days across stocks in their sample of emerging markets is 30.8%, while for the US this number is only 10.7%.

[18] 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.

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 Center for Research in Security Prices (CRSP) mutual fund database and the Morningstar database.

Panel A : Summary statistics

Variable	Mean	Standard deviation	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
*Alpha*1	−0.05	1.50	−2.49	−0.73	−0.08	0.61	2.54
*Alpha*4	−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
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
TradeVol	170.62	186.16	4.87	26.77	99.91	273.03	518.23

Panel B : Variable definitions

Variable	Unit	Definition
%Inst	Percent	Percentage of a fund's assets in institutional shares
%Cash	Percent	Percentage of fund assets held in cash
Age	Year	Number of years since the fund's inception
*Alpha*1	Percent	Average monthly alpha from a one-factor market model during the six month period before the current month
*Alpha*4	Percent	Average monthly alpha from a four-factor market model (the Fama and 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	Average dollar trading volume of stocks, aggregated at the fund portfolio level using value-weighted average
Expense	Percent	Expenses of a fund share as percentage of total assets
Flow	Percent	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) classified as illiquid funds
Inst	Dummy	Dummy = 1 if a fund share is issued to institutions
Load	Percent	Total load (front- plus back-end load) charged by a fund shares
MinPurchase	$1,000	Minimum initial purchase required by a fund share
RetExCat	Percent	Return of a fund in excess of that of the category, averaged over the past six months
RetGap	Percent	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	Percent	Standard deviation of fund's monthly flow

"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 $\geq$ $50,000 (a standard practice adopted by the mutual fund literature).[19]

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), non-profit 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.

The definitions and summary statistics of the main variables are reported in Table 1.

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

4. Empirical evidence

4.1. Hypothesis 1: the effect of liquidity

4.1.1. Overview

Our first hypothesis is that, conditional on poor performance, funds that invest primarily in illiquid assets (i.e., illiquid funds) experience more outflows because investors take into account the negative externalities 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, implying a higher flow-to-poor performance sensitivity. Essentially, the complementarities that come with redemptions in response to poor performance have a multiplier effect that amplifies outflows in illiquid funds.

In this section, we show evidence that outflows are more sensitive to bad performance in illiquid funds than in liquid funds. We start with a semiparametric approach, in which the relation between flow and performance is not restricted to be linear, to 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 nonlinear relation between flow and performance (see Chevalier and Ellison, 1997). The drawback of the semiparametric approach is the low significance levels due to the flexible functional specification. Hence, we then move to a regression analysis that allows us to conduct proper tests of statistical significance.

Fig. 1 shows the results of the semiparametric analysis. In the figure, the vertical axis is the percentage net flow into the fund share in month t ($Flow_{i,t}$) 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 $t-6$ to $t-1$ ($Alpha_{i,t-1}$).[20] The net flow (*Flow*) is measured following the standard practice in the literature:

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

where *TNA* is the total net assets managed by the fund share, and *Ret* is the raw return.

Fig. 1 plots, separately for the sample of liquid funds and the sample of illiquid funds, the relation between flow and performance as estimated by the nonparametric functions $f(\cdot)$ in the following semiparametric specification:

$$Flow_{i,t} = f(Alpha_{i,t-1}) + \beta X_{i,t} + \varepsilon_{i,t}, \tag{2}$$

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 fund flows. The estimation of Eq. (2) applies the method introduced by Robinson (1988) and used by Chevalier and Ellison (1997) in studying the sensitivity of flow-to-performance sensitivity in mutual funds. While the focus in their study is on the convexity of the flow-to-performance graph, our focus is on the difference in flow behavior between liquid and illiquid funds for the range of negative performance.

The thick solid (dotted) line in Fig. 1 represents the plot of $f(\cdot)$ for the liquid (illiquid) funds, and the corresponding thin lines represent the 90% confidence intervals. Fig. 1 reveals two features that are consistent with investors' behavior under complementarities in redemption decisions. First, while liquid and illiquid funds have similar flow-to-performance sensitivities in the positive *Alpha* region, illiquid funds experience noticeably more sensitive flows when performance is negative, 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).[21] 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%.

Other alternative explanations exist to the result of higher flow-to-performance sensitivity in illiquid funds. After all, illiquid funds invest in different assets and hence bad performance in them could be more indicative of future bad performance, justifying high sensitivity of outflow to bad performance even without appealing to strategic complementarities. The two types of funds also could have different clienteles, and investors in illiquid funds could simply be more tuned to bad news than investors in liquid funds. In Section 5, we entertain these alternative explanations and present evidence that is inconsistent with them.

4.1.2. Regression analysis

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

$$Flow_{i,t} = \beta_0 Perf_{i,t-1} + \beta_1 Illiq_i \cdot Perf_{i,t-1} + \beta_2 Illiq_i + \beta_3 Control_{i,t} + \beta_4 Control_{i,t} \cdot Perf_{i,t-1} + \varepsilon_{i,t}. \tag{3}$$

[20] We calculate *Alpha* using the return of the month under consideration, and *Beta* is estimated using monthly return data of the previous 36 months (or as many as the data allow). The value is set to be missing if there are <12 observations in the estimation. When describing the regression analysis below, we provide fuller discussion on the choice and construction of performance measures.

[21] The non-parametric method allows flexible specification in the shape of the function, at the expense of much wider confidence intervals.

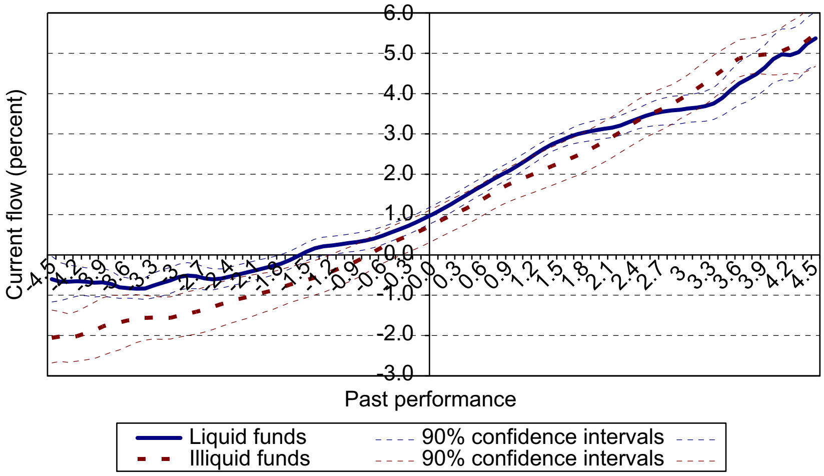

Fig. 1. Overview of the effect of liquidity on flow-performance-sensitivities. Plotted is the nonparametric function $f(.)$ in the following semiparametric specification:

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

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 method developed by Robinson (1988) and applied in Chevalier and Ellison (1997).

In Eq. (3), $Perf_{i,t-1}$ is a lagged performance measure. In Table 2, Columns 1–3, we use three common performance measures: *Alpha* from a one-factor market model (*Alpha*1), *Alpha* from a four-factor (the Fama and 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.[22] 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 1–3 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 4–6 we focus on the subsample in which funds underperform the benchmark returns. Consistent with prior literature, we see that investors are more responsive to good performance than to bad performance: The coefficients on *Perf* in Columns 4–6 of Table 2 are significantly lower than their counterparts in the full sample. Interestingly, the responsiveness to poor performance differs significantly across the three performance measures. When using *Alpha*1, one percentage point of sub-benchmark performance leads to 0.27% of reduced flows for liquid funds (significant at less than the 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 expected behavior of other investors, and therefore the appropriate performance measure for our analysis is the one that investors are overall more responsive to after poor performance. Consistent with the prior literature on mutual fund flows, we find that investors respond more strongly to simple market-benchmark adjusted returns (such as *Alpha*1) than to refined multifactor-adjusted excess returns (such as *Alpha*4). Hence, based on the results in Columns 4–6 of Table 2, we mostly focus on *Alpha*1 for the rest of the paper.

The focus of our analysis is the coefficient for $Illiq \cdot Perf$. Table 2 shows that all coefficient estimates for $Illiq \cdot Perf$ are positive, and all except for one 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)–(6). Specifically, the estimated coefficient for $Illiq \cdot Alpha1$ is 0.14 for the negative *Alpha*1 subsample. Thus, when *Alpha*1 is negative, the flow-performance sensitivity in illiquid funds is 52% higher than that in liquid funds (0.41% versus 0.27%). For the full sample, the sensitivity is 19% higher for the illiquid funds (0.83% versus 0.70%). This result provides support for

[22] We calculate performance based on the period of the past six months following the results of a diagnostic analysis we perform. Specifically, we regress flows on lagged individual monthly returns up to a year and find that the effects of the recent six months' returns on current flows are substantially higher than the effects of performance in the period of 7–12 months before the current month (there is a discrete and statistically significant jump down between $t-6$ and $t-7$). Further, in robustness analysis, we add the performance of month $t-12$ to $t-7$ as another control variable in our main regressions. This did not have a qualitative effect on our results.

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, *Alpha* 1, *Alpha* 4, and *RetExCat*. Table 1 lists the detailed definitions and calculations of all variables in the regression. Observations are at the fund share-month level. Columns 1 to 3 use the full sample, and Columns 4 to 6 use the subsample of observations with negative performance measures. All estimations include year fixed effects. Standard errors adjust for heteroskedasticity and within-cluster correlation clustered at the fund level, and therefore 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% level, respectively.

Variable for Perf	Full sample						Subsample of negative performance					
	Alpha 1		*Alpha* 4		*RetExCat*		*Alpha*1 < 0		*Alpha*4 < 0		*RetExCat* < 0	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
	(1)		(2)		(3)		(4)		(5)		(6)	
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 variable:												
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
Number of unique funds and 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*. Observations are at the fund share-month level. Included are observations with negative performance measure of *Alpha* 1. 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 $>25\%$ of the fund's total assets held by large investors. Results for these funds are shown in Columns 3 and 4. All estimations include year fixed effects. Standard errors adjust for heteroskedasticity and within-cluster correlation clustered at the fund level, and therefore 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% level, respectively.

	Institutional-oriented funds				Retail-oriented funds			
Large investor proxy:	*Inst*		*MinPur250k*		*Inst*		*MinPur250k*	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
	(1)		(2)		(3)		(4)	
Alpha 1	**0.27** *	1.66	**0.43** **	2.26	**0.24** **	3.36	**0.25** **	3.68
*Illiq*Alpha* 1	**0.02**	0.18	**0.06**	0.33	**0.20** **	2.91	**0.16** **	2.71
Control variable:								
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*Alpha* 1	**−0.05**	−1.61	**−0.06**	−1.28	**0.02**	1.29	**0.02**	1.15
*Age*Alpha* 1	**0.16**	1.51	**0.28**	1.49	**−0.03**	−0.57	**−0.03**	−0.55
*Expense*Alpha* 1	**−0.01**	−0.09	**−0.16**	−0.77	**−0.15** **	−3.06	**−0.15** **	−3.35
*Load*Alpha* 1	**−0.02**	−0.60	**−0.04**	−0.69	**0.05** **	3.59	**0.05** **	3.75
*Inst*Alpha* 1	**0.19**	0.98	**0.00**	−0.01	**0.19** *	1.75	**0.13**	1.58
Number of unique funds and 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

our first hypothesis that outflows are more sensitive to bad performance in illiquid funds than in liquid funds.

An immediate robustness question is about the effect of size. The summary statistics in Section 3 indicate that very large funds tend to invest in liquid asset: Though the median assets of liquid and illiquid funds are very similar ($145 million versus $140 million), the mean values are substantially different ($872 million versus $533 million). To make sure that the incremental flow sensitivity among illiquid funds is not due to inadequate size control (*Size* enters the regression as a control variable both on its own and in interaction with *Perf*), we repeat the exercise by excluding observations when *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).

4.2. 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 with 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 (*MinPur*250*K*). The second measure sorts fund shares based on the minimum 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 $>75\%$ of the fund assets are issued to institutional share, 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 $<25\%$ 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.

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 observations are at the fund-month level. The sample of closed-end funds contains all 142 equity closed-end funds that are tracked by the Center for Research in Security Prices (CRSP) during 1988 to 2004. Three benchmark-adjusted return measures, *Alpha* 1, *Alpha* 4, and *RetExCat* are defined in Table 1. We report the equal-weight current-month return performance of a portfolio sorted by the lagged performance (past six 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 quintile	*Alpha* 1	*Alpha*4	*RetExCat*	*Alpha*1	*Alpha*4	*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-statistic	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-statistic	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-statistic	−0.28	−0.29	−1.30	1.21	1.63	2.84

Table 3 shows that the effect of asset liquidity on the flow-to-poor-performance sensitivity is present only 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 subsample of institutional oriented funds could be due to the small sample size, the lower point estimate in this subsample 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 a lack of large-investor mass in the shareholder base. Similar results prevail when we use the minimum initial purchase requirement as the proxy for large investors. These results are consistent with the second hypothesis of the model.

5. Alternative explanations

5.1. Information

The result that investors are more sensitive to bad performance in illiquid funds than in liquid funds could arise if bad past 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 that argues that withdrawals from banks are largely driven by bad fundamentals (Gorton, 1988; Calomiris and Mason, 1997; Schumacher, 2000; Martinez-Peria and Schmukler, 2001; Calomiris and Mason, 2003). This alternative explanation 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. In this section, we directly examine the empirical validity of the assumption that past performance in illiquid funds is more informative about future returns than that in liquid funds.

If the assumption holds, one should expect to see more persistence in the performance in illiquid funds. This is what we look for in the data to see if this alternative explanation finds support. There are a couple of problems, however. First, the story developed in our paper also generates some return persistence in illiquid, but not in liquid, funds, due to the damages from redemptions. Hence, even if the former show more persistence, it can still support the complementarities story. In the comparison we conduct, we try to isolate the effect of information about fundamentals from that of the damage caused by self-fulfilling redemptions. We thus compare the persistence in performance in illiquid versus liquid funds after excluding all observations with more than 5% net outflows during the past month (about 6.3% of the sample). The results are provided in the first three columns of Table 4.

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*. Observations are at the fund share-month level. Included are observations with negative performance measure of *Alpha* 1. Analyses from Table 3 are replicated on the subsample of large investor fund-shares only. Columns 1 and 2 report the flow-performance sensitivities of large investors in institutional-oriented funds, while Columns 3 and 4 report the sensitivities of large investors in retail-oriented funds. Institutional- and retail-oriented funds are defined in Table 3. All estimations include year fixed effects. Standard errors adjust for heteroskedasticity and within-cluster correlation clustered at the fund level, and therefore 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% level, respectively.

	Institutional-oriented funds				Retail-oriented funds			
Large investor proxy:	*Inst*		*MinPur250k*		*Inst*		*MinPur250k*	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
	(1)		(2)		(3)		(4)	
*Alpha*1	**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*Alpha*1	**−0.03**	−0.99	**−0.09** *	−1.73	**0.00**	−0.04	**−0.09** *	−1.72
*Age*Alpha*1	**0.12**	1.23	**0.31** *	1.77	**0.06**	0.25	**−0.06**	−0.22
*Expense*Alpha*1	**−0.09**	−0.62	**−0.26**	−1.05	**−0.26**	−1.57	**−0.40** *	−1.91
*Load*Alpha*1	**0.01**	0.28	**0.01**	0.03	**0.05**	0.89	**0.10**	0.59
Number of unique funds and 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

Second, according to Berk and Green (2004), the lack of persistence in the returns of open-end funds might not be indicative of the lack of persistence in the quality of the managers because the response of flow to performance affects future performance when there are decreasing returns to scale in asset management. To address this problem, 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, the return persistence patterns of closed-end funds offer a unique opportunity to identify the persistence of managerial skills or asset quality, without being contaminated by the effect of the fund flows. Also, looking at closed-end funds has another advantage. By excluding observations with extreme past outflows in the sample of open-end funds, 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. This problem does not arise in the closed-end fund data. We analyze the sample of closed-end funds used by Bradley, Brav, Goldstein, and Jiang (2009). This sample 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 report the results on persistence in the NAV returns of closed-end funds in the last three columns of Table 4.[23]

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 three performance measures (*Alpha*1, *Alpha*4, and *RETEXCAT*, all defined in Table 1) during the past six months. Then, we report the average performance in each quintile in the current month. In interpreting the results, we focus on *Alpha*1, which is the performance measure we focus on thus far in the paper. We first describe the tests in the first three columns of Table 4. Two main observations come out of the analysis. 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. As shown in the table, while this measure ($Q5-Q1$) 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

[23] 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.

only the funds with the worst performance, as they experience most of the outflows and thus are the subject of our investigation. 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 slightly higher (but the difference is also not statistically significant). Hence, there seems to be no evidence that illiquid funds in general, or illiquid funds with worst past performance in particular, show more return persistence than their liquid counterparts.

The results become even stronger when considering the sample of closed-end funds in the last three columns of Table 4. This is because the NAV returns of closed-end funds investing in liquid assets 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 evidence in the asset pricing literature on illiquid stocks. For example, 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.

5.2. *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. This mechanism is unlikely to be driving our results given that the dummy variable for institutional shares enters our main regression Eq. (3) both on its own and interactive with performance.

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, measured as either the proportion of fund assets held in institutional share classes or held in share classes with a minimum initial purchase of at least \$250,000. We report the results in Table 5.

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, large investors are more sensitive to bad performance in illiquid funds than in liquid funds.[24] 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 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 large investors are surrounded by retail investors or by fellow large 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 driven neither by the possibility that small and large investors have different preferences for asset liquidity nor by the possible heterogeneity among investors that hold liquid and illiquid funds.

6. Robustness tests and additional evidence

6.1. *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 because 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 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*). 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 when $<75\%$ of the underlying securities are matched to the CRSP database.[25]

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

[24] 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.

[25] 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.

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. Observations are at the fund share-month level. Estimation sample includes all observations with *Alpha*1 < 0. Column 1 uses the portfolio average trading volume (in logarithm) of the underlying holdings as the liquidity measure. Column 2 uses 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, and therefore 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% level, 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%	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
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
Number of unique funds and fund share-months	3,127	262,313	740	44,965	3,127	262,313	740	44,965	3,077	246,374	732	44,468
R-squared		0.04		0.05		0.04		0.05		0.04		0.05

(which is our basis for constructing the *Illiq* measure). For example, within the category of small-cap funds, considerable variation could still exist in the liquidity of the underlying assets. However, one needs to assume some level of investor sophistication to expect different flow-to-performance responses 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 a stock can absorb for one unit of price change). For each stock, it is calculated as the annual average of $0.001\sqrt{\$Trading\ Volume}/|Return|$ (using daily data). We download this measure for all CRSP stocks from Joel Hasbrouck's website.[26] 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. The results are also economically significant. Take Column 1, for example. Unconditionally, if a fund's past performance worsens by one percentage point, it loses 0.24% of its assets as net outflows. An inter-quartile increase in trading volume reduces the sensitivity of flow to performance by 0.30% $(0.30=-0.13*[\ln(273.03)-\ln(26.77)])$. Hence, the effect of an inter-quartile change in liquidity is associated with a change in flow-to-performance sensitivity that amounts to 125% of the unconditional sensitivity. Finally, consistent with Hypothesis 2, 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.

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 could 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 conduct 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 a coarser proxy of funds' liquidity compared with holding data–based measures (and therefore loses its significance in the presence of a finer measure of liquidity). We also reestimate the regression in Table 6 for the subsample of illiquid funds and 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.

6.2. Outflows, liquidity, and fund performance

An important aspect of our thesis is that large outflows should damage future fund performance in illiquid funds more than in liquid funds. We now turn to present evidence on this implication. To assess the effect of outflows on future fund performance, we estimate the following equation, at the fund level:

$$Perf_{i,t} = \beta_0 Outflow_{i,t-1} + \beta_1 Size_{i,t-1} + \beta_2 Expense_{i,t} + \sum_{j=1}^{J=6} \gamma_j PastPerf_{i,t-j} + \varepsilon_{i,t}. \quad (4)$$

Here, $Perf_{i,t}$ is a fund's current month *Alpha*1 and *Outflow* is an indicator variable for whether the lagged net flow is lower than -5% of total net asset value.[27] 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.

We estimate Eq. (4) 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 1–3 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

[26] We are grateful to Joel Hasbrouck for providing the Amihud measure data for individual stocks on his website at http://pages.stern.nyu.edu/~jhasbrou/. The measure we adopt is named "L2" by Hasbrouck.

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

Table 7
Effects of outflows on fund returns

The dependent variable in Columns 1 to 3 is *Alpha* 1 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. Observations are at the fund-month level. *Outflow* is a dummy variable equals to one if the fund experiences net outflow of at least 5% of its total net asset value in month $t-1$, and zero 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, and therefore 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% level, respectively.

	Dependent variable: *Alpha*1						Dependent variable: *RetGap*					
	Liquid funds		Illiquid funds		Funds with the lowest quartile of Amihud measure		Liquid funds		Illiquid funds		Funds with the lowest quartile of Amihud measure	
	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic
	(1)		(2)		(3)		(4)		(5)		(6)	
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
Number of unique funds and fund share-months	1,940	130,517	969	63,467	915	37,538	1,949	128,711	975	63063	934	37519
R-squared		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, observations are at the fund-year level. 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, observations are at the fund level for one cross section. 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 percent of the redeemed amount) and the number of month the redemption fee applies to, and tobit is used in estimation. Standard errors adjust for heteroskedasticity for all regressions and also adjust for within-cluster correlation clustered at the fund level for the panel data used in Columns 1 and 2. * and ** indicate statistical significant at less than the 10% and 5% level, respectively.

	All funds						Illiquid funds					
Dependent variable	*%Cash*		*I(Redemption)*		*Redemption*Month*		*%Cash*		*I(Redemption)*		*Redemption*Month*	
Estimation method	linear regression		probit		tobit		linear regression		probit		tobit	
	Coefficient	*t*-statistic	Marginal probability	*t*-statistic	Coefficient	*t*-statistic	Coefficient	*t*-statistic	Marginal probability	*t*-statistic	Coefficient	*t*-statistic
	(1)		(2)		(3)		(4)		(5)		(6)	
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
*Alpha*1	**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
Number of observations and 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%			

detectable effect on returns for liquid funds. This is consistent with our theory.

In Columns 4–6 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 by the actions of a fund manager's active management net of the trading costs associated with such actions. This measure is free from the effects of return persistence or reversal of the underlying assets. Because redemptions impose costs on the fund, they should worsen the short-term fund return gap. Following Kacperczyk, Sialm, and Zheng (2007), 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 include only funds with at least 75% of the securities matched to CRSP. We estimate Eq. (4) with the return gap as the *Perf* variable and the results are shown in Columns 4–6 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. This is again consistent with our theory.

Finally, in untabulated analysis we estimate the accumulated damage on the return gap resulting from significant outflows. We show that, in illiquid funds, this 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 above and beyond the change in the value of the underlying assets.

6.3. *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 are 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 restrictions. 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. The sample 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 less than the 1% level). Table 8 examines the determinants of cash holdings at the annual frequency (when 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 as control variables the average monthly flows, the standard deviation of flows, the average monthly *Alpha*1 during the year, fund size, fund age, percentage of institutional shares, and load charges, measured at the end of the year.

Columns 1 and 4 of Table 8 report the regression results for the whole sample and the subsample of illiquid funds, respectively, at the fund-year level. 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 of 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.[28] 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 could help reduce damage from outflows in illiquid funds, but they are unlikely to completely eliminate payoff complementarities in redemption decisions.[29] 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 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 instead of 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-collect 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, at the fund level. 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

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

[29] 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.

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 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 also impose stricter restriction (significant at less than the 1% level in the full sample as well as the subsample of illiquid funds).

7. Conclusion

This paper provides an empirical analysis of the relation between payoff complementarities and financial fragility in the context of mutual fund outflows. Based on a global-game model of mutual fund redemptions, we test two hypotheses. First, in illiquid funds, payoff complementarities are stronger, we expect that outflows are 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, because they are expected to internalize the negative externalities. We find strong support for these two predictions in the data. We present evidence that is inconsistent with the alternative explanations based on the informativeness of past performance and on different clienteles.

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. 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 provide evidence 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. Our paper uses mutual fund data to demonstrate this relation. These data offer 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 demonstrates the usefulness of the global-game framework in bringing models of strategic complementarities to the data. This framework predicts that the equilibrium outcome monotonically depends on the level of complementarities, as well as the size of the player. 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.

Appendix A. Theoretical model

A.1. The basic setup: liquidity and outflows

There are two dates 1 and 2. Prior to $t=1$, each investor from a continuum [0,1] holds one share in a mutual fund; the total amount of investment is normalized to one. 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. This assumption helps to simplify the model by ruling out the possibility that the fund goes bankrupt.[30] 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 one 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, 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, 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[31]:

$$\frac{1-(1+\lambda)N}{1-N} R_1 R_2(\theta). \tag{5}$$

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 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 or to the strength of the investment strategy that the fund has picked, or both. For simplicity, we assume that θ is drawn from the uniform

[30] The possibility of bankruptcy complicates the global-games analysis significantly (see: Goldstein and Pauzner, 2005). Moreover, the assumption is consistent with empirical evidence that many investors do not actively review their portfolios (see Johnson, 2006; Agnew, Pierluigi, and Sunden, 2003).

[31] 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 Section 2.

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 $\overline{N} < 1/1+\lambda$.

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 until t=2 decreases, because the outflows cause damage to the value of the remaining portfolio. In the mutual fund context, however, an additional force 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 needs to sell only $(1+\lambda)\max\{0,(N-I(R_1))\}$ 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 until t=2 receive[32]:

$$\frac{1-(1+\lambda)\max\{0,(N-I(R_1))\}}{1-\max\{0,(N-I(R_1))\}}R_1R_2(\theta). \tag{6}$$

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 (6). 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 depends 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,

$$R_2(\underline{\theta})=1. \tag{7}$$

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

$$R_2(\overline{\theta})=\frac{1-\max\{0,(\overline{N}-I(R_1))\}}{1-(1+\lambda)\max\{0,(\overline{N}-I(R_1))\}}, \tag{8}$$

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

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

$$\overline{\theta}(R_1)>\underline{\theta} \quad \text{if } R_1<\overline{R_1},$$

and

$$\overline{\theta}(R_1)=\underline{\theta} \quad \text{if } R_1\geq\overline{R_1}. \tag{9}$$

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 until t=2 when $\theta>\overline{\theta}(R_1)$. When θ is between $\underline{\theta}$ and $\overline{\theta}(R_1)$ (which is possible when $R_1<\overline{R_1}$), there are two equilibria: In one equilibrium, all investors withdraw at t=1; in the other equilibrium, they all wait until t=2.

To overcome the problem of multiplicity, we apply the techniques developed in the literature on global games. 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. See the review article by Morris and Shin (2003) and the many papers cited therein. We turn to characterize the threshold θ^*, which captures the propensity of outflows in equilibrium and forms the basis for our empirical predictions.

In equilibrium, investors who observe a signal above (below) θ^* choose to wait until t=2 (withdraw in t=1). Then, by continuity, an investor who observes θ^* is indifferent between withdrawing and remaining in the fund. This implies that,

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

Here, conditional on the signal θ^*, the posterior density over θ is $1/\sigma g(\theta^*-\theta/\sigma)$. Then, given the state θ, the proportion of investors (out of $\overline{N}$) who receive a signal below θ^* is $G(\theta^*-\theta/\sigma)$. Thus, the amount of withdrawals $N(\theta,\theta^*)$ is equal to $G(\theta^*-\theta/\sigma)\overline{N}$. Denoting $G(\theta^*-\theta/\sigma)=\alpha$

[32] Here, we assume that when the mutual fund receives positive net inflows, no externalities are 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).

and changing the variable of integration, we get the following equation that implicitly characterizes θ^*:

$$\int_0^1 \frac{1-(1+\lambda)\max\{0,(\alpha\overline{N}-I(R_1))\}}{1-\max\{0,(\alpha\overline{N}-I(R_1))\}} R_2(\theta^*-G^{-1}(\alpha)\sigma)\,d\alpha = 1. \tag{11}$$

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. Threshold θ^* is then implicitly given by

$$R_2(\theta^*) = \frac{1}{\int_0^1 \frac{1-(1+\lambda)\max\{0,(\alpha\overline{N}-I(R_1))\}}{1-\max\{0,(\alpha\overline{N}-I(R_1))\}}\,d\alpha}. \tag{12}$$

Inspection of Eq. (12) leads directly to Hypothesis 1 in the paper. When the performance is high, i.e., $R_1 \geq \overline{R_1}$, the threshold signal θ^* is constant in λ. When the performance is low, i.e., $R_1 < \overline{R_1}$, the threshold signal θ^* is increasing in λ (and decreasing in R_1).

Before turning to our second hypothesis, we wish to discuss the role of two assumptions made above for expositional simplicity. The first one is 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, because they have been following the fund more closely in the past (see Plantin, 2009 for a similar assumption). In such a model, for every R_1, insiders' decision on whether to redeem or not is still characterized by a threshold signal θ^*, below which they redeem, and above which they do not. As before, this threshold is increasing in λ. It also is decreasing in R_1, which does not change our prediction. Interestingly, the decision of outsiders on whether to invest new money in the fund depends on R_1, so that the increasing function $I(R_1)$ is endogenous. This is because a high R_1 indicates a higher likelihood of a high R_2, and this attracts more inflows. The only important difference in the extended model is that the inflow decision also depends on the liquidity of the fund's assets. For every R_1, outside investors are less inclined to invest new money in illiquid funds because they know that these funds are more likely to be subject to large outflows. This, however, only strengthens our result by increasing the payoff complementarity among inside investors in illiquid funds and thus increasing the amount of outflows in these funds.

A.2. Extension: the role of large investors

So far, we analyze a situation in which 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 gets a noisy signal on the fundamental θ. Conditional on θ, the signal of the institutional investor is independent of the signals of the retail investors. For simplicity, the amount of noise σ is the same for all investors. As before, investors need to decide at t=1 whether to redeem their shares or not. The large investor either redeems proportion β or does not redeem at all. This is because it is never optimal for him to redeem only part of his position, as he can always increase the return on the part he keeps in the fund by keeping more.

The results in Corsetti, Dasgupta, Morris, and Shin (2004) establish that there is again a unique equilibrium in the game. This equilibrium is characterized by two thresholds: retail investors redeem if, and only if, their signals fall below θ^R, and the institutional investor redeems if, and only if, his signal is below θ^I.

Let us characterize the threshold signals θ^R and θ^I. As before, a retail investor that observed θ^R is indifferent between redeeming and not redeeming:

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

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

$$\int_{-\infty}^{\infty}\left[\frac{1-(1+\lambda)\max\left\{0,\left(G\left(\frac{\theta^R-\theta}{\sigma}\right)(1-\beta)\overline{N}-I(R_1)\right)\right\}}{1-\max\left\{0,\left(G\left(\frac{\theta^R-\theta}{\sigma}\right)(1-\beta)\overline{N}-I(R_1)\right)\right\}}\right]\times R_2(\theta)\frac{1}{\sigma}g\left(\frac{\theta^I-\theta}{\sigma}\right)d\theta=1. \quad (14)$$

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

After changing variables of integration, we obtain the following two equations:

$$\int_{-\infty}^{\infty}\left[G\left(\frac{\theta^I-\theta^R+G^{-1}(\alpha)\sigma}{\sigma}\right)\frac{1-(1+\lambda)\max\{0,((\alpha(1-\beta)+\beta)\overline{N}-I(R_1))\}}{1-\max\{0,((\alpha(1-\beta)+\beta)\overline{N}-I(R_1))\}}+\left(1-G\left(\frac{\theta^I-\theta^R+G^{-1}(\alpha)\sigma}{\sigma}\right)\right)\frac{1-(1+\lambda)\max\{0,(\alpha(1-\beta)\overline{N}-I(R_1))\}}{1-\max\{0,(\alpha(1-\beta)\overline{N}-I(R_1))\}}\right]R_2(\theta^R-G^{-1}(\alpha)\sigma)\,d\alpha=1 \quad (15)$$

and

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

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 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 $(\theta^R-\theta^I)/\sigma$, which from now on we denote as x.[33] Then, the solution to the model boils down to solving the following two equations for θ^{**} and x (here, the first equation is for the retail investors and the second one is for the institutional investor):

$$R_2(\theta^{**})=\frac{1}{\int_0^1\left[\begin{array}{l}G(G^{-1}(\alpha)-x)\frac{1-(1+\lambda)\max\{0,((\alpha(1-\beta)+\beta)\overline{N}-I(R_1))\}}{1-\max\{0,((\alpha(1-\beta)+\beta)\overline{N}-I(R_1))\}}\\+(1-G(G^{-1}(\alpha)-x))\frac{1-(1+\lambda)\max\{0,((\alpha(1-\beta)+\beta)\overline{N}-I(R_1))\}}{1-\max\{0,((\alpha(1-\beta)+\beta)\overline{N}-I(R_1))\}}\end{array}\right]d\alpha} \quad (17)$$

and

$$R_2(\theta^{**})=\frac{1}{\int_0^1\left[\frac{1-(1+\lambda)\max\{0,(G(G^{-1}(\alpha)+x)(1-\beta)\overline{N}-I(R_1))\}}{1-\max\{0,(G(G^{-1}(\alpha)+x)(1-\beta)\overline{N}-I(R_1))\}}\right]d\alpha}. \quad (18)$$

Using Eq. (18), we can derive an upper bound on θ^{**} by setting $G(G^{-1}(\alpha)+x)=1$. This upper bound, θ^{UB}, is given as

$$R_2(\theta^{**})<\frac{1}{\int_0^1\left[\frac{1-(1+\lambda)\max\{0,((1-\beta)\overline{N}-I(R_1))\}}{1-\max\{0,((1-\beta)\overline{N}-I(R_1))\}}\right]d\alpha}\equiv R_2(\theta^{UB}). \quad (19)$$

Analyzing Eq. (19), 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 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) is weaker. This is the basis for Hypothesis 2 of the paper.

[33] From the argument above, both the numerator and the denominator approach zero, and the fraction is well defined.

References

Abreu, D., Brunnermeier, M., 2003. Bubbles and crashes. Econometrica 71, 173–204.

Agnew, J., Pierluigi, B., Sunden, A., 2003. Portfolio choice and trading in a large 401(k) plan. American Economics Review 93, 193–215.

Alexander, G., Cici, G., Gibson, S., 2007. Does motivation matter when assessing trade performance? An analysis of mutual funds. Review of Financial Studies 20, 125–150.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets 5, 31–56.

Avramov, D., Chordia, T., Goyal, A., 2006. Liquidity and autocorrelations in individual stock returns. Journal of Finance 61, 2365–2394.

Bannier, C.E., Fecht, F., Tyrell, M., 2006. Open-end real estate funds in germany: genesis and crisis. Working Paper, Goethe University, Frankfurt.

Barclay, M., Pearson, N., Weisbach, M., 1998. Open-end mutual funds and capital-gains taxes. Journal of Financial Economics 49, 3–43.

Bekaert, G., Harvey, C., Lundblad, C., 2007. Liquidity and expected returns: lessons from emerging markets. Review of Financial Studies 20, 1783–1831.

Berk, J., Green, R., 2004. Mutual fund flows and performance in rational markets. Journal of Political Economy 112, 1169–1295.

Bradley, M., Brav, A., Goldstein, I., Jiang, W., 2010. Activist arbitrage: a study of open-ending attempts of closed-end funds. Journal of Financial Economics 95, 1–19.

Brown, K., Harlow, V., Starks, L., 1996. Of tournaments and temptations: an analysis of managerial incentives in the mutual fund industry. Journal of Finance 51, 85–110.

Calomiris, C., Mason, J.R, 1997. Contagion and bank failures during the great depression: the June 1932 Chicago banking panic. American Economic Review 87, 863–883.

Calomiris, C., Mason, J.R., 2003. Fundamentals, panics, and bank distress during the depression. American Economic Review 93, 1615–1647.

Carlsson, H., Van Damme, E., 1993. Global games and equilibrium selection. Econometrica 61, 981–1018.

Cherkes, M., Sagi, J., Stanton, R., 2009. A liquidity-based theory of closed-end funds. Review of Financial Studies 22, 257–297.

Chevalier, J., Ellison, G., 1997. Risk taking by mutual funds as a response to incentives. Journal of Political Economy 105, 1167–1200.

Chordia, T., 1996. The structure of mutual fund charges. Journal of Financial Economics 41, 3–39.

Christoffersen, S., Evans, R., Musto, D., 2007. The economics of mutual fund brokerage: evidence from the cross-section of investment channels. Working Paper, McGill University, University of Virginia, University of Pennsylvania.

Christoffersen, S., Keim, D., Musto, D., 2007. Valuable information and costly liquidity: evidence from individual mutual fund trades. Working Paper, McGill University, University of Pennsylvania.

Corsetti, G., Dasgupta, A., Morris, S., Shin, H.S., 2004. Does one Soros make a difference? A theory of currency crises with large and small traders. Review of Economic Studies 71, 87–114.

Coval, J., Stafford, E., 2006. Asset fire sales (and purchases) in equity markets. Journal of Financial Economics 86, 479–512.

Dasgupta, A., 2004. Financial contagion through capital connections: a model of the origin and spread of bank panics. Journal of the European Economic Association 2, 1049–1084.

Diamond, D.W., Dybvig, P.H., 1983. Bank runs, deposit insurance, and liquidity. Journal of Political Economy 91, 401–419.

Dickson, J.M., Shoven, J.B., Sialm, C., 2000. Tax externalities of equity mutual funds. National Tax Journal 53, 607–628.

Edelen, R.M., 1999. Investor flows and the assessed performance of open-end mutual funds. Journal of Financial Economics 53, 439–466.

Glaeser, E., Sacerdote, B., Scheinkman, J., 2003. The social multiplier. Journal of the European Economic Association 1, 345–353.

Goldstein, I., Pauzner, A., 2004. Contagion of self-fulfilling financial crises due to diversification of investment portfolios. Journal of Economic Theory 119, 151–183.

Goldstein, I., Pauzner, A., 2005. Demand deposit contracts and the probability of bank runs. Journal of Finance 60, 1293–1328.

Gorton, G., 1988. Banking panics and business cycles. Oxford Economic Papers 40, 751–781.

Greene, J.T., Hodges, C.W., 2002. The dilution impact of daily fund flows on open-end mutual funds. Journal of Financial Economics 65, 131–159.

Hasbrouck, J., 2006. Trading costs and returns for us equities: estimating effective costs from daily data. Working Paper, New York University.

Heinemann, F., Nagel, R., Ockenfels, P., 2004. The theory of global games on test: experimental analysis of coordination games with public and private information. Econometrica 72, 1583–1599.

Hertzberg, A., Liberti, J.M., Paravisini, D., 2009. Public information and coordination: evidence from a credit registry expansion. Working Paper, Columbia Business School.

James, C., Karceski, J., 2006. Investor monitoring and differences in mutual fund performance. Journal of Banking and Finance 30, 2787–2808.

Johnson, W.T., 2004. Predictable investment horizons and wealth transfers among mutual fund shareholders. Journal of Finance 59, 1979–2011.

Johnson, W.T., 2006. Who monitors the mutual fund manager, new or old shareholders? aFA 2006 Boston Meetings Paper available at SSRN: ⟨http://ssrn.com/abstract=687547⟩.

Kacperczyk, M., Sialm, C., Zheng, L., 2007. Unobserved actions of mutual funds. Review of Financial Studies 21, 2379–2416.

Koo, G., 2006. Anticipated versus unanticipated flows: do mutual funds hedge liquidity risk? Doctoral Dissertation, Northwestern University.

Manski, C., 1993. Identification of endogenous social effects: the reflection problem. Review of Economic Studies 60, 531–542.

Martinez-Peria, M.S., Schmukler, S.L., 2001. Do depositors punish banks for bad behavior? Market discipline, deposit insurance, and banking crises. Journal of Finance 56, 1029–1051.

Morris, S., Shin, H.S., 1998. Unique equilibrium in a model of self-fulfilling currency attacks. American Economic Review 88, 587–597.

Morris, S., Shin, H.S., 2003. Global games: theory and applications. In: M. Dewatripont, L.P. Hansen, S.T. (Eds.), Advances in Economics and Econometrics. Cambridge University Press, Cambridge.

Morris, S., Shin, H.S., 2004. Liquidity black holes. Review of Finance 8, 1–18.

Plantin, G., 2009. Learning by holding and liquidity. Review of Economic Studies 76, 395–412.

Robinson, P.T., 1988. Root-n-consistent semiparametric regression. Econometrica 56, 931–954.

Rochet, J.-C., Vives, X., 2004. Coordination failures and the lender of last resort: was Bagehot right after all? Journal of the European Economic Association 2, 1116–1147.

Schumacher, L., 2000. Bank runs and currency run in a system without a safety net: Argentina and the 'tequila' shock. Journal of Monetary Economics 46, 257–277.

Sirri, E., Tufano, P., 1998. Costly search and mutual fund flows. Journal of Finance 53, 1589–1622.

Stein, J., 2005. Why are most funds open-end? Competition and the limits of arbitrage. Quarterly Journal of Economics 120, 247–272.

Wermers, R., 2000. Mutual fund performance: an empirical decomposition into stock-picking talent, style, transactions costs, and expenses. Journal of Finance 50, 1655–1695.

Zheng, L., 1999. Is money smart? a study of mutual fund investors' fund selection ability. Journal of Finance 54, 901–933.