

Runs on Money Market Mutual Funds[†]

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We study daily money market mutual fund flows at the individual share class level during September 2008. This fine granularity of data allows new insights into investor and portfolio holding characteristics conducive to run risk in cash-like asset pools. We find that cross-sectional flow data observed during the week of the Lehman failure are consistent with key implications of a simple model of coordination with incomplete information and strategic complementarities. Similar conclusions follow from daily models fitted to capture dynamic interactions between investors with differing levels of sophistication within the same money fund, holding constant the underlying portfolio. (JEL D14, G11, G23)

Runs on financial institutions have long been a subject of academic and regulatory interest, and are widely thought to have important welfare consequences. Although a large part of the theoretical literature on runs has focused on commercial banks, recent studies such as Allen, Babus, and Carletti (2009) and Gennaioli, Shleifer, and Vishny (2013) consider the broader issue of instability in the so-called shadow banking system. During the recent financial crisis, many types of intermediated asset pools suffered run-like behavior, e.g., ETFs, asset-backed SIVs, and ultra-short duration bond funds. Especially vulnerable were vehicles with cash-like liabilities, for which the liquidity mismatch became magnified during the crisis: creditors demanded unusually high-frequency access to their cash, while the liquidity of assets plunged. The crisis highlighted that run-like behavior can occur in a far broader set of pooled vehicles than bank deposits.

This paper brings unique evidence to the study of run-like behavior in pooled investment vehicles by studying the crisis in money market mutual funds (MMMFs) following the bankruptcy of Lehman Brothers on September 15, 2008. During the

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year prior to September 2008, Kacperczyk and Schnabl (2013) find that the riskiness of asset holdings of MMMFs increased dramatically, and that the dispersion in yields across MMMFs increased from less than 30 to more than 150 bps/year. To be sure, these fundamental shifts increased the cross-sectional heterogeneity in MMMF riskiness, making the crisis that unfolded in September 2008 a unique testbed within which to study runs in pooled investments that are similar in structure, but have very different risks and yields, as well as having different investor clienteles.

On September 16, a single money market mutual fund that held just over 1 percent of its portfolio in Lehman commercial paper, the Reserve Primary Fund, “broke the buck,” that is, marked the net asset value of the fund below the \$1 book value per share that investors normally expect as their redemption value; billions of dollars in investor redemptions occurred almost immediately.¹ The following day, run-like behavior spread to many other MMMFs that cater to institutional investors.

Panel A of Figure 1 shows daily percentage flows to (from) MMMF categories during September and October 2008. Outflows from prime institutional share classes amount to more than 10 percent of assets on a single fateful day, September 17, 2008 (prime money funds hold corporate debt in addition to government debt). Movements out of prime retail share classes were far more subdued. In contrast, MMMFs holding US government-backed securities (mainly Treasuries and agencies) experienced strong inflows, as investors sought the liquidity of the US government market as part of a flight-to-safety. On a cumulated basis, as shown in panel B, the flows out of prime institutional share classes amounted to \$400 billion during the first two weeks of the crisis. Moreover, these massive category-level outflows were far from equally distributed across funds. To demonstrate this, we calculate the Lehman week percentage change in total assets under management (flow) for each fund separately within the prime institutional and prime retail categories. Panel C of Figure 1 shows evidence of extremely high dispersion in flows among prime institutional funds over the crisis week, with some funds experiencing a withdrawal greater than 50 percent of assets during the week, and others experiencing either modest withdrawals or even large inflows. In contrast, the vast majority of prime retail funds experienced only minor withdrawals or deposits.²

Even a cursory examination of the MMMF crisis strongly suggests that investors feared that fund managers were exposed to a common risk—a sudden and sharp reduction in the liquidity of commercial paper backed by financial institutions—even though they had largely diversified away most issuer-specific and sector-specific idiosyncratic risks. We view the MMMF crisis of September 2008 as a unique natural experiment—after a major, unexpected shock—that enables a study of the mechanism driving investor runs from a broad segment of similar intermediated portfolios.

Our daily data on flows to different institutional share classes within the same prime MMMF portfolio allow us to study the interaction between redemptions of

¹This fund held, as of August 31, 2008, \$64.5 billion in total net assets, of which 0.82 percent was invested in Lehman commercial paper (all due during October 2008) and 0.39 percent in Lehman medium-term notes (due March 20, 2009). A press release from the Reserve states that the Primary Fund honored redemptions prior to 3 PM eastern standard time on September 16 at \$1 per share, but closed the day at \$0.97 per share.

²We note that a broader run might have occurred, had the crisis played out longer, or if the Treasury, the Federal Reserve, and some fund advisors not stepped in with implicit or explicit assurances of backup support. For instance, Wachovia announced, on September 17, that it would support three of its money funds that were vulnerable to excessive outflows.

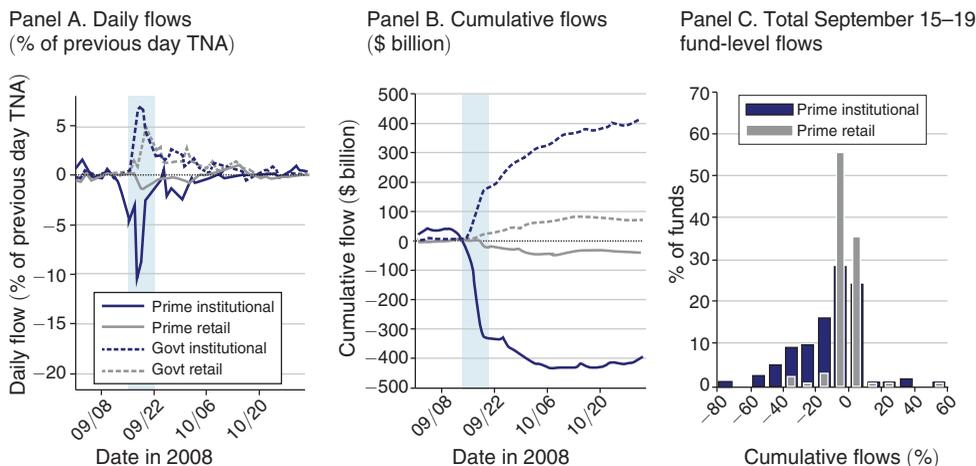


FIGURE 1. MONEY MARKET MUTUAL FUND FLOWS IN SEPTEMBER–OCTOBER 2008

Notes: This figure plots summary statistics for fraction flows (one-day difference in log assets) to/from money market mutual fund share classes in different aggregate categories during September and October 2008. For each category, panel A displays the daily percentage flow, while panel B plots the cumulative flow (in billions of dollars) over this period. Panel C presents a histogram of the cross-sectional distribution of fund-level percentage change in total assets under management for share classes within each category during September 15–19 (i.e., flows during the MMMF crisis week following the failure of Lehman Brothers, which is indicated by shading).

institutional investors in share classes with lower expense ratios (larger investment minimums) and institutional investors in share classes with higher expense ratios (smaller minimums), both residing within the same fund and holding pro rata shares in the same portfolio of securities (thus, keeping constant the fundamental quality of these holdings as well as any subsidization, explicit or implicit, by the fund advisor). Since the largest institutional investors have more “skin in the game” and, presumably, have access to more resources (analysts and data) than smaller institutional investors, we would expect them to be both more attentive and better informed than their smaller counterparts about the quality of the portfolio that they hold together.

We use these features of our data to shed light on theoretical models of financial intermediation, a key feature of which is the interaction between fundamentals and investors’ strategic behavior, and how this interaction depends on investor information. In Morris and Shin’s (1998) benchmark model of regime change, agents exogenously receive private and public signals about the strength of fundamentals. The common public signal acts as an additional coordination device for agents’ actions, affecting the probability of regime changes (Goldstein and Pauzner 2005). Weak fundamentals trigger a run, but the run would not have occurred were it not for agents’ self-fulfilling beliefs (Diamond and Dybvig 1983) about the actions of other agents, which amplify the effect of a bad draw of fundamentals.³ Such interactions

³ Angeletos and Werning (2006) allow the public signal to be generated endogenously as an equilibrium outcome from a financial market. When public signals are endogenous, there can be regions with multiple equilibria. Angeletos, Hellwig, and Pavan (2007) present an extension of their baseline model, where agents receive noisy signals about the size of attacks during the previous period. This can generate snowballing effects similar to those

between strategic behavior and fundamentals makes empirical identification of strategic complementarities very difficult (Goldstein 2013).

Our paper develops a simple, static coordination game with strategic complementarities and information asymmetries to derive a set of predictions on the relationship between investor sophistication and fund flows. These predictions are that, first, within a particular MMMF, sophisticated investor outflows in reaction to a negative shock to portfolio fundamentals are greater than unsophisticated investor outflows. Second, holding constant the level of sophistication of each of a fund's investor types, outflows following such a shock are weakly increasing in the fraction of more sophisticated investors (within the same fund). Third, after such a shock, the *difference* between the outflows of sophisticated and unsophisticated investor types should be enhanced, the larger the fraction of sophisticated investors (and, thus, the stronger the strategic complementarities).

Using expense ratios at the share class level as a proxy for investor sophistication, since expense ratios are strongly (and negatively) correlated with the required minimum dollar investment level in MMMFs, we empirically test these theoretical predictions with a set of cross-sectional regressions. We find evidence to support all three predictions, consistent with strategic externalities playing an important role in the September 2008 run episode. Moreover, we find that (better-informed) sophisticated investors respond to the actions of their (less-informed) unsophisticated counterparts within the same MMMF. Large-scale institutional investors redeem more strongly in response to the redemptions of smaller-scale institutions (in the same MMMF) when these small investor redemptions represent a larger share of fund assets, consistent with large investors reacting to the magnitude of strategic complementarities posed by small investor actions.

Several key themes differentiate our analysis from that of prior studies. First, while previous studies document that institutional and retail investors behaved differently during the financial crisis, we exploit investor heterogeneity to identify that strategic complementarities within and between these investor types were in play, using theoretically motivated tests. We find that the context of the mixture of institutional and retail investors, as well as the quality of portfolio fundamentals, drove a large dispersion in the way that institutional investors reacted. In some cases, their reaction was quite muted; in other cases, their reaction posed an existential threat to the MMMF from which they redeemed. We find that a higher concentration of less sophisticated investors—which includes both small-scale institutions and retail investors—within a fund weakens complementarities, and mitigates the strategic incentives of the most sophisticated investors to run.

Second, we study the dynamics of fund flows at the daily interval, and use the multiple share class structure of the MMMF data to study the daily interaction between institutional investors of different levels of sophistication.⁴ Third, we use a difference in differences approach that compares flows in ultra-short bond funds with those in MMMFs during the week following the Lehman default. In these

in the herding literature (e.g., Chari and Kehoe 2003; Gu 2011), where large attacks can be immediately followed by additional attacks, as investors update their beliefs based upon the actions of other investors.

⁴Previous studies such as McCabe (2010) and Kacperczyk and Schnabl (2013) do not exploit the multiple share class structure of MMMFs, nor propose formal tests for strategic complementarities.

empirical tests, we find evidence that flows out of same-complex prime MMMFs are larger than flows out of ultra-short funds that invest in comparable securities, consistent with strategic complementarities being stronger for fixed net asset value (NAV) (share price) MMMFs than for comparable floating NAV ultra-short funds. Fourth, while prior studies estimate average effects, we use quantile panel regressions to study the distribution of flows conditional on observables, allowing us to quantify the degree of heterogeneity in investor outflows for funds with similar asset holdings and investor characteristics.

More broadly, our analysis contributes to several empirical literatures on financial crises. First, we present new evidence of strategic complementarities, consistent with results in recent work by Chen, Goldstein, and Jiang (2010), Qian and Tanyeri (2013), and Hertzberg, Liberti, and Paravisini (2011), albeit in a different institutional setting and identified via different methods. Second, we provide evidence on the link between risk-taking and run-like behavior, supporting work on banking panics by Gorton (1988), Schumacher (2000), Martinez-Peria and Schumkler (2001), and Calomiris and Mason (2003). Third, similar to Kelly and Ó Gráda (2000), Ó Gráda and White (2003), and Iyer and Puri (2012), we identify investor characteristics which are linked to runs, and consider dynamic interactions between different types of investors in a strategic setting. Finally, we contribute to the literature on the recent financial crisis, particularly Gorton and Metrick (2012), Covitz, Liang, and Suarez (2013), Acharya, Schnabl, and Suarez (2013), and Schroth, Suarez, and Taylor (2014), who provide evidence of run-like behavior by financial intermediaries in the repo and asset-backed commercial paper markets.⁵

Our analysis proceeds as follows. Section I provides details of the institutional background to our analysis. Section II presents our simple theoretical model, while Section III introduces our data and tests the predictions from the theoretical model. Section IV compares the run on MMMFs to that experienced by ultra-short bond funds during the financial crisis. Section V analyzes the dynamic interactions between investor types through vector autoregressions fitted to daily flows, Section VI quantifies the effect of different factors on the cross-sectional distribution of flows, while Section VII concludes.

I. Institutional Background

Traditional commercial bank deposit accounts and MMMFs are similar in some respects (e.g., the presumption of dollar-in-dollar-out), but quite different in others (e.g., no explicit deposit guarantees and vastly different regulatory structures, including disclosure requirements). Like other mutual funds, MMMFs are regulated under the Investment Company Act of 1940 and its various amendments (henceforth, ICA). However, they operate under a special provision of the ICA, Rule 2a-7, which allows them to value investor shares at the amortized cost or book value of assets—an accounting-based rather than a market-based principle—that is, shares

⁵A key source of fragility in these markets, which differs from the money market, is rollover risk; see, e.g., He and Xiong (2012a, b). However, MMMFs are one of the primary sources of demand for these assets, and, thus, inherit rollover risk on the asset side of their balance sheets; a corporation unable to roll its paper will default on its maturing paper. Parlatore (forthcoming) shows how strategic complementarities in MMMF sponsors' support decisions can create incentives for MMMFs within a sponsor's umbrella to run on the asset (e.g., repo and ABCP) markets.

are valued at the purchase price of securities minus computed premium or discount, amortized over the securities' remaining life. This provision of the ICA allows MMMFs to maintain a constant \$1.00 per share net asset value. For investors, this fixed-value has many advantages.⁶

Like banks, MMMFs seek to offer highly liquid liabilities, while holding less liquid assets. To be sure, this liquidity mismatch is much less extreme for MMMFs, but still raises the possibility that a MMMF might become liquidity-constrained and unable to meet redemption requests.⁷ These risks have been controlled differently in banks and MMMFs. Banks are required to maintain capital, and depositors are insured up to a certain level, but banks may generally hold highly illiquid assets (e.g., 30-year mortgages), hold assets that may be lower-rated or difficult to rate or price, and employ leverage. MMMFs, in contrast, under Rule 2a-7, must hold only assets that are (normally) highly liquid with high credit quality, and generally may not use leverage.⁸

Due to the presence of significant fixed costs of operating, it is common for multiple share classes with different levels of expense ratios to coexist in a single MMMF: a feature which we exploit heavily in our empirical tests to follow. Apart from potentially different expense ratios, these share classes always enjoy identical (pro rata) claims on the fund's assets. Thus, redemptions in one share class—should they result in a reduction in portfolio liquidity for a fund—negatively impact remaining investors in all share classes of that fund equally. Those share classes with low expense ratios require high investment minimums, which allow only large-scale (and, presumably, more sophisticated and attentive) investors to buy them; those with high expense ratios are populated with smaller-scale investors. Thus, funds with multiple share classes enable us to compare the behavior of players who differ in the precision of their information about fundamentals and/or the behavior of other investors, holding constant all fund characteristics: notably portfolio quality and fund management company characteristics (e.g., the ability to subsidize fund losses to prevent a run).

II. A Simple Theoretical Model

Next, we develop a set of robust predictions using a theoretical setting which captures several of the features of the MMMF market described above. We do so in

⁶This provision allows retail investors to use their MMMFs for transactions purposes, such as paying bills and settling securities trades, without worrying about daily fluctuations in MMMF balances. A constant \$1.00 NAV also allows many kinds of institutions (e.g., state and local governments) to hold their liquid balances in MMMFs, since their charters or corporate by-laws generally disallow liquidity fund investments in variable NAV products; many industrial corporations have similar restrictions on investments of their excess cash balances. And, for both retail and institutional investors, a constant \$1.00 NAV vastly simplifies tax accounting by eliminating the need to track the capital gains and losses that arise with a variable-NAV mutual fund.

⁷This issue can also arise with long-term mutual funds. Mutual funds are required to offer investors the ability to redeem their shares on a daily basis at the fund's end-of-day NAV. It is at least theoretically possible that requests for redemptions could outstrip a fund's ability to liquidate its underlying portfolio in order to satisfy those redemptions. This possibility is more meaningful for bond mutual funds, such as during a financial crisis if liquidity were to dry up in certain fixed income instruments (e.g., emerging market bonds). See Chen, Goldstein, and Jiang (2010) for empirical evidence of strategic behavior by investors in long-term mutual funds consistent with investors perceiving this liquidity risk and, more recently, Goldstein, Jiang, and Ng (2015) for evidence of liquidation externalities generated by strategic complementarities among corporate bond funds.

⁸Over the years prior to 2008, the provisions of Rule 2a-7 have been tightened to further reduce systemic risks (see Collins and Mack 1994).

the context of a simple coordination game with regime change, then discuss several testable implications for investor redemption behavior in funds with multiple share classes. Our model introduces a simple form of heterogeneity—uninformed versus informed investors—into a representative example from the class of global games models which have been used to study run-like behavior.

A. Basic Structure

Our setup and exposition follows studies such as Morris and Shin (2001) and Angeletos and Werning (2006), except that we will allow for a fraction of uninformed agents that monitor the market less closely, and, as such, are unaware of a potential run as it is developing.⁹ The model's status quo—maintaining a NAV of \$1 per share—will be abandoned if a sufficiently large fraction of agents withdraw from the fund.

As is standard in the global games literature, we assume that there is an exogenous fundamental θ , which nature draws from a prior distribution $\theta \sim N(\theta_0, \sigma_0)$. A continuum of ex ante identical agents (indexed by i) decide whether to run on the fund based on noisy signals about θ . As is standard, we normalize the sign of θ so that higher values indicate stronger fundamentals; as θ increases, the fund becomes less vulnerable to runs.

After observing noisy signals about θ , each agent i chooses between two possible actions, a_i : withdraw from the fund ($a_i = 1$) or maintain the existing investment ($a_i = 0$). We normalize the payoff from not attacking to 0, and assume that the payoff from attacking is $1 - c$ if the status quo is abandoned and $-c$ otherwise. Defining the aggregate action $A = \int_0^1 a_i di$, the status quo is abandoned when $A > \theta$. The payoff of agent i is

$$(1) \quad U(a_i, A, \theta) = a_i(1\{A > \theta\} - c),$$

where 1 is an indicator which equals 1 when the status quo is abandoned. The interesting feature of the game is the presence of a coordination motive. Each agent's expected payoff from playing $a_i = 1$ increases as the mass of other attacking agents, A , increases.

In contrast to Angeletos and Werning (2006), we assume that agents do not always monitor conditions in money markets. For simplicity, we assume that measure $\mu > 0$ of the agents (informed agents) update their beliefs about market conditions. These agents receive informative signals about the fundamental, θ , and choose actions to best respond to beliefs about the behavior of other informed agents. Each informed agent receives two signals: a private signal, $x_i = \theta + \sigma_x \xi_i$, where $\xi_i \sim N(0, 1)$ and i.i.d. across agents, and an exogenous public signal, $z = \theta + \sigma_z \varepsilon$, where $\varepsilon \sim N(0, 1)$ captures common noise. The remaining measure $1 - \mu$ of agents

⁹Morris and Shin (2001) develop a version of the Goldstein and Pauzner (2005) model that follows a very similar structure as the model developed here. An analogous extension to the one here yields the same cross-sectional predictions.

receive a completely uninformative signal about fundamentals and play the strategy $a_i = 0$.¹⁰

We focus on monotone equilibria, defined as perfect Bayesian equilibria in which each informed agent attacks if and only if her private signal is below a threshold $x^*(z)$, which may depend on the public signal, z . Given the assumed behavior of uninformed agents, the aggregate attack size is

$$(2) A(\theta, z) = P[\text{agent } i \text{ is informed}] \cdot P[x < x^*(z) | \theta] = \mu \cdot \Phi[\sqrt{\alpha_x}(x^*(z) - \theta)],$$

where $\Phi(\cdot)$ is the standard normal cdf, and $\alpha_x \equiv 1/\sigma_x^2$ is the precision of the private signal. Define the precisions $\alpha_0 \equiv 1/\sigma_0^2$ and $\alpha_z \equiv 1/\sigma_z^2$ analogously. The equilibrium is defined by two objects. The first, $\theta^*(z)$, implicitly defined by $A(\theta, z) = \theta$, satisfies

$$(3) \quad x^*(z) = \theta^*(z) + \frac{1}{\sqrt{\alpha_x}} \Phi^{-1}\left[\frac{1}{\mu} \theta^*(z)\right].$$

$\theta^*(z)$ is the maximum value of the fundamental such that the status quo is abandoned when the realization of the public signal is z . The second object is an indifference condition. The marginal agent, who receives a signal $x^*(z)$, should be indifferent between withdrawing and remaining invested in the fund. Hence, $x^*(z)$ solves $P[\theta \leq \theta^*(z) | x, z] = c$. An informed agent’s posterior belief about $\theta \sim N\left(\frac{1}{\alpha^*}(\alpha_x \cdot x + \alpha_z \cdot z + \alpha_0 \cdot \theta_0), \alpha^*\right)$, where $\alpha^* \equiv \alpha_x + \alpha_z + \alpha_0$, so the indifference condition is

$$(4) \quad \Phi\left[\sqrt{\alpha^*}\left(\theta^*(z) - \frac{\alpha_x}{\alpha^*}x^*(z) - \frac{\alpha_z}{\alpha^*}z - \frac{\alpha_0}{\alpha^*}\theta_0\right)\right] = c.$$

Combining (3) and (4) yields a fixed point condition in θ^* defining the threshold $\theta^*(z)$,

$$(5) \quad \Phi^{-1}\left[\frac{1}{\mu} \theta^*\right] - \frac{\alpha_z + \alpha_0}{\sqrt{\alpha_x}} \theta^* = \sqrt{1 + \frac{\alpha_z}{\alpha_x} + \frac{\alpha_0}{\alpha_x}} \cdot \Phi^{-1}[1 - c] - \frac{\alpha_z}{\sqrt{\alpha_x}} z - \frac{\alpha_0}{\sqrt{\alpha_x}} \theta_0.$$

The key to our identification argument is that, all else constant, increases in μ make the left-hand side of (5) strictly smaller, while the expression on the right-hand side stays the same. Proposition 1, which characterizes the effect of μ on $x^*(z)$, follows from (5).

PROPOSITION 1: *For all θ and z , $x^*(z)$ is bounded below and above by functions $\underline{x}^*(z, \mu)$ and $\bar{x}^*(z, \mu)$, respectively, both of which are increasing in μ . The*

¹⁰Implicitly, this amounts to an assumption that, in equilibrium, the prior distribution of θ —the unconditional distribution of fundamentals—assigns sufficiently high probability that the fund will not break the buck such that an agent’s expected utility is positive when she receives an uninformative signal. We provide a sufficient condition for this behavior to be optimal in our proof of Proposition 1 in the online Appendix.

equilibrium is unique for all z and $\underline{x}^*(z, \mu) = \bar{x}^*(z, \mu)$ iff $\sqrt{2\pi\alpha_x} > (\alpha_z + \alpha_0)\mu$. In the unique case, the probability that an informed agent attacks is weakly increasing in μ .

Proposition 1, proved in the online Appendix, states that, all else constant, increases in the measure of informed agents μ raise the probability that an informed agent attacks whenever the equilibrium is unique. To see this, note that when the expression on the left-hand side of (5) is increasing near a fixed point $\theta^*(z)$, increases in μ will increase the threshold $\theta^*(z)$ which triggers a run. From (3), an increase in $\theta^*(z)$ increases the threshold for the private signal of the marginal agent, $x^*(z)$. Therefore, coordination on the status quo becomes more difficult to sustain, and more agents will choose to run as μ increases. When $\sqrt{2\pi\alpha_x} > (\alpha_z + \alpha_0)\mu$, the left-hand side of (5) is globally increasing, the equilibrium is always unique, and our comparative static is sharp.

When $\sqrt{2\pi\alpha_x} < (\alpha_z + \alpha_0)\mu$, there exist values of z such that multiple x^* and θ^* solve (3–5). For these signal realizations, there are three possible equilibria, and the model can only place upper and lower bounds on the fraction of agents who choose to attack. Our proposition states that both of these bounds shift upward in response to increases in μ . In this limited sense, our comparative static is robust to potential multiplicity of equilibria.

Our setup is intentionally kept simple. In the online Appendix we discuss how similar comparative statics emerge in versions of the bank run games of Goldstein and Pauzner (2005) and He and Manela (2016) when they are augmented with a measure of uninformed agents. Alternative models such as Hellwig and Veldkamp (2009) endogenize the acquisition of information but involve similar trade-offs and will imply similar comparative statics results, i.e., adding a fraction of investors who maintain the status quo weakens the complementarities and thus makes it easier for the strategic investors to coordinate on the status quo.

B. Testable Predictions

For purposes of solving the model, it is sufficient to know the fraction of investors who receive informative signals each period. Accordingly, we introduce a simple way of interpreting the flows from funds with multiple share classes, which generates several testable predictions. As a simple illustration, assume there are two types of investors, and each fund has two share classes. Large, sophisticated investors invest in share class S, and smaller, unsophisticated investors invest in share class U. If monitoring money market conditions largely involves fixed costs, then type S investors will face lower monitoring costs per dollar invested. As such, we would expect them to monitor conditions more frequently. Accordingly, we will assume that type S and U investors receive informative signals with probabilities p and q , respectively, where $0 \leq q < p \leq 1$.

Now, imagine that we observe data from a cross section of funds, which are indexed by j . These funds receive i.i.d. draws of the fundamental, θ_j , and are ex ante heterogeneous in the fraction of assets under management, ω_j , owned by share class S. Then, after the failure of Lehman, measure $\omega_j p + (1 - \omega_j)q$ receive informative signals and make strategic choices. Therefore, ω_j is proportional to the

(asset-weighted) average level of investor sophistication for a given fund. Our tests only require that we observe cumulative actions of investors in each share class, as well as empirical proxies for ω_j .

Our model makes three key predictions which are testable at the share class level. Suppose that the conditions are satisfied such that a unique equilibrium exists. Then, we can uniquely define $A^*(\theta, z, \omega)$ as the expected action of an agent who has received an informative signal in a fund with fundamental θ , public signal z , and fraction ω of investors in share class S. Conditional on θ and z , the following comparative statics hold (note that outflow, as used below, is defined as the net of investor dollar sales minus purchases, all divided by lagged total net assets of a share class):

- (i) Within funds, outflows from share class S, $p \cdot A^*(\theta, z, \omega)$, are larger than outflows from share class U, $q \cdot A^*(\theta, z, \omega)$.
- (ii) Since $A^*(\theta, z, \omega_2) - A^*(\theta, z, \omega_1) \geq 0$ for any $\omega_2 \geq \omega_1$, expected outflows for each type of share class are weakly increasing in the fraction of sophisticated investors, ω . Moreover, the marginal effect of changing ω on expected outflows is higher for type S than for type U investors.
- (iii) Within funds, the difference in outflows between share class S and share class U, $(p - q) \cdot A^*(\theta, z, \omega)$, is increasing in ω .

Since these comparative statics hold conditional on θ and z , they also hold unconditionally. Note that predictions (i) and (iii) hold *within* funds and are, therefore, identifiable in regressions with fund fixed effects.

III. Testing the Theory: Evidence of Strategic Behavior from Investor Share Class Flows

Compared with commercial banks, our data on money market mutual funds (MMMFs) are unique in several dimensions that allow unprecedented insights into the mechanism of runs through a high level of granularity in both the cross-sectional and time domains.¹¹ This section first introduces our data, before proceeding with a set of cross-sectional empirical tests of the predictions from the simple model of Section II.

A. Data

Our data are purchased from iMoneyNet, a company that collects daily information from over 2,000 US registered MMMFs that invest primarily in US short-term, dollar-denominated debt obligations, and cover the period from February to December 2008. A comparison with statistics from the Investment Company

¹¹In addition, during the week of the crisis, MMMFs carried no explicit insurance, further making them a unique subject for the study of run-like behavior in cash-like pooled vehicles where investors derive liquidity insurance from each other.

Institute indicates that iMoneyNet covers about 93.5 percent of the dollar value of the entire US prime MMMF universe—funds that can invest in assets such as repurchase agreements and commercial paper—as of the end of 2008, which is the main focus of this study. These MMMFs are offered to retail as well as institutional investors, through different share classes, which are pro rata claims on cash flows from the fund portfolio's security holdings. The iMoneyNet data consist of fund investment objective, fund family/adviser (i.e., complex) identity, share class type (i.e., retail versus institutional), daily total net assets by share class, portfolio average maturity of (fixed-income) holdings, and weekly sector breakdown (e.g., commercial paper versus repurchase agreement) of portfolio holdings. Importantly, the data include share class-level expense ratios. These data are especially crucial for our study, as they allow us to identify investor skin in the game, which is likely to be highly related to investor sophistication and attentiveness.

Further, note that an institution subscribing to iMoneyNet can easily determine outflows from a share class that occurred during the prior day, before that institution makes its investment decision for the current day. Therefore, each institution can condition its decision to invest/disinvest on information about the actions of all other institutions (and retail investors) during any prior days.¹²

Also, since the Reserve Primary Fund is widely viewed by market participants as initiating the crisis through its breaking-the-buck announcement, we consider flows to this fund as occurring exogenous to those of other funds. Two other small MMMFs within the Reserve complex, Liquid Performance and Primary II, did not hold Lehman debt (at least as of August 31, 2008), but did experience some outflows, as well, that may have been tied to a negative investor perception about the Reserve brand.¹³ In order to exclude any potential brand effect, we exclude observations from all funds within the Reserve complex from our analysis.

Further information on our dataset, including univariate summary statistics, are available in the online Appendix.

B. Expense Ratios and Account Sizes

Our empirical analysis uses the expense ratio charged to a given share class as a proxy for the level of sophistication of investors in that share class. Table 1 empirically documents that lower expense ratio share classes are generally only available to investors with larger amounts of money to invest. Specifically, for each institutional share class, i , for which data on the minimum required investment amount is available as of September 12, 2008 (the Friday prior to the Lehman default), we regress the log of minimum dollar investment on expense ratio (ER). These coefficients are reported in panel A of Table 1. The specifications in panel B replace the continuous measure ER with a dummy variable which equals 1 when the expense ratio is less than 35 basis points, and 0, otherwise. We report results separately for prime share

¹²Fund total net assets (TNA) and other variables are available to subscribers of iMoneyNet, and we expect that larger scale (skin in the game) investors subscribe to the database and actively analyze it. Closing-day TNA data is available by 8 AM the following morning, which allows a quick calculation of prior-day flows (thanks to Pete Crane, publisher of Money Fund Intelligence, for this information).

¹³It is important to note, however, that some uncertainty surrounded the holdings of all three Reserve funds, as their August 31, 2008 portfolio holdings were not made public until October 29, 2008.

TABLE 1—REGRESSIONS OF MINIMUM INVESTMENT LEVELS ON SHARE CLASS EXPENSE RATIOS

	Prime only		Government only		Prime and government	
<i>Panel A. Continuous expense ratio measure</i>						
Share class expense ratio (pp/yr)	-6.05 (-2.668)	-5.23 (-3.052)	-7.64 (-4.683)	-4.91 (-3.934)	-6.80 (-4.975)	-5.04 (-4.977)
R^2	0.055	0.907	0.102	0.876	0.075	0.892
Fund dummies	No	Yes	No	Yes	No	Yes
Observations	226	226	265	265	491	491
Degrees of freedom	224	132	263	175	489	308
<i>Panel B. Discrete expense ratio measure</i>						
Dummy: Expense ratio < 35 bp/yr	2.68 (3.290)	2.06 (3.293)	3.01 (5.736)	1.64 (3.955)	2.83 (6.071)	1.81 (5.142)
R^2	0.055	0.905	0.086	0.868	0.069	0.887
Fund dummies	No	Yes	No	Yes	No	Yes
Observations	226	226	265	265	491	491
Degrees of freedom	224	132	263	175	489	308

Notes: This table presents evidence that lower expense ratios are associated with higher investment minimums in the cross section of institutional share classes of MMMFs with available data on minimums, measured as of September 12, 2008. In panel A, each cell in the table provides the coefficient and *t*-statistic from a univariate regression of the log of the minimum dollar investment level of a given share class on its expense ratio, measured in pp/yr. Each pair of columns corresponds to different subsets of the institutional share class population: prime institutional share classes, government institutional share classes, and both populations pooled, with and without fund fixed effects, respectively. In panel B, we replace the continuous expense ratio with a dummy variable which equals one when the expense ratio is less than 35 bp/yr, and zero, otherwise.

classes, government share classes, and both prime and government share classes pooled in the same regression.¹⁴

Table 1 shows that there is a strongly negative and highly significant relation between minimum investment and expense ratio across share classes, and that this finding is robust to whether or not a fund fixed effect is included. Moreover, this finding holds separately for prime funds and for government funds, as well as when we pool both types. Using the continuous *ER* measure (panel A), a one bp/year increase in the *ER* is associated with a 5 to 6 percent decrease in the minimum investment for prime share classes. Panel B indicates that prime institutional share classes with an *ER* less than 35 bp have dollar investment minimums which are, on average, almost 7 times ($\exp(2.06) - 1 \approx 6.8$) larger than other share classes, suggesting, again, that the lowest *ER*s are found in share classes requiring the largest (by far) minimum investment. This evidence is consistent with more sophisticated investors residing in low *ER* institutional share classes, in the sense that they hold larger accounts, have more skin in the game, and, thus, greater incentives to continuously monitor the fundamentals of the MMMFs in which they invest.

¹⁴ It is important to note that so-called institutional share classes are sometimes offered to retirement plans (e.g., 401(k) plans), which are ultimately controlled by individual investors. Based on industry sources, we estimate that less than 1 percent (by value) of prime institutional share classes charging no more than 35 bps/yr in expense ratio consist of a majority of retirement accounts, while such accounts account for almost 10 percent of institutional share classes with an expense ratio greater than 35 bps/yr. Thus, almost all retirement accounts are included in our definition (using 35 bps/yr) of less sophisticated institutions throughout this paper, and they are a minority even in that category.

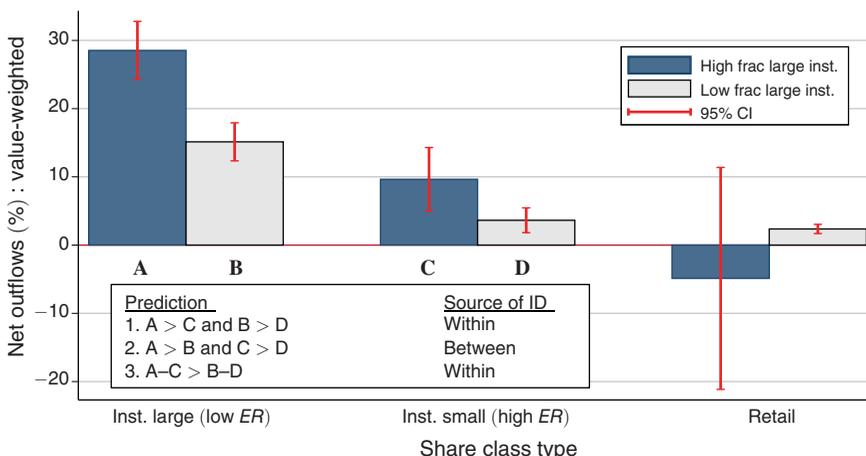


FIGURE 2. SUMMARY OF TESTS OF THEORETICAL PREDICTIONS

Notes: This graph shows net outflows (the percentage change in total fund assets under management multiplied by -1) by share class type, across all prime MMMFs from September 15 to September 19. First, each share class within each prime fund is placed in one of three bins: (i) retail share classes, and institutional share classes having an expense ratio (ii) above or (iii) no more than 35 bps/yr. Next, each of these three bins is subdivided, according to whether or not the share class is a claim on a prime fund with a high fraction—at least 75 percent—of its investment dollars (across all share classes, retail and institutional) represented by institutional share classes with an expense ratio no more than 35 bps/yr. Value-weighted average net outflows with 95 percent confidence intervals (CI), are shown for each of the six bins.

C. Cross-Sectional Tests

Expanding our analysis to use the share class expense ratio (ER)—which, unlike investment minimums, is available for all share classes in iMoneyNet—as a (negatively signed) proxy for investor sophistication, we next conduct a set of simple tests of the theoretical predictions of our model. To this end, we compute value-weighted percentage outflows (investor redemptions minus purchases divided by total net assets) of all share classes within one of three bins (retail share classes, and institutional share classes with an ER above or less than or equal to 35 bps/year) in individual prime funds during September 15–19, 2008. Then, Figure 2 plots the average of these bin values across all prime funds, separately for funds having a high versus low fraction of large institutional share classes relative to total prime fund assets (with the threshold at 75 percent, by value, of large institutional share classes), ω .¹⁵ For purposes of generating the figure, we classify all institutional share classes with expense ratios less than or equal to 35 bps/year (essentially the cross-sectional mean of 34 bps/year) as sophisticated, while the remaining are classified as unsophisticated.¹⁶

The first prediction from our model of Section II is that, within funds, outflows from sophisticated investors (S) should exceed outflows from unsophisticated investors (U). This implies that outflows from low ER share class investors should exceed

¹⁵The 75 percent figure is chosen so as to try to balance the number of funds represented in columns A–D, but the results are very robust to using different thresholds.

¹⁶The findings are robust to using other values, such as 25 or 45 bp/yr.

those from high *ER* share class investors, both among funds dominated by large institutional investors ($A > C$ in Figure 2) and within funds dominated by small institutional investors ($B > D$). This prediction is strongly supported by the data.

The second prediction is that, among share classes with similar levels of investor sophistication, outflows following a negative shock to fundamentals should be larger when the share class is a claim on a fund with a higher fraction of sophisticated investors (ω). Our empirical test for low *ER* share classes ($A > B$) and for high *ER* share classes ($C > D$) also strongly supports this prediction.

The third prediction is that the difference in outflows between within-fund high and low sophistication investors (low *ER* and high *ER* share classes, respectively) is increasing in the fraction of sophisticated investors, ω , that reside within the fund. In our graph, this amounts to $A - C > B - D$. Again this prediction is supported by the data.

Tables 2 and 3 provide more formal tests of these predictions. In Table 2, we consider prediction (i) by regressing share class-level percentage flows (here, an outflow is negatively signed) over September 15–19 on share class expense ratio.¹⁷ We employ, in the various specifications, either no fixed effect, a fund fixed effect, or a fund complex fixed effect.¹⁸ We find (models 1 to 3) that the share class expense ratio is positively and significantly associated with one-week investor flow, regardless of whether fund or complex fixed effects are included. To illustrate, using model 3, a prime institutional share class with an *ER* that is one standard deviation (20 bps/year) above that of another share class (in the same fund) carrying an average level (34 bps/year) of *ER* is predicted to experience an outflow during the crisis week that is 13.2 percent of assets lower.

This finding is further confirmed in models 4 to 6, where we adopt a nonparametric approach. Here, we separate prime institutional share classes into three bins based on their *ER*. The base category (model intercept) represents funds with an *ER* above 35 bps/year. These specifications show that the lowest *ER* segment (charging no more than 15 bps/year) exhibits a much higher level of outflows than the next segment (between 15 and 35 bps/year). Specifically, model 4 indicates that share classes having an *ER* between 15 and 35 bps/year experience an outflow of 14 percent of assets, while those with an *ER* below 15 bps/year experience an outflow of 29.5 percent of assets, both relative to share classes with an *ER* above 35 bps/year (which experience an outflow of 8 percent during that week). Relative outflows when $ER < 15$ bps/year only mildly increase to 30 percent and 32 percent of assets when complex and fund fixed-effects are included, respectively (models 5 and 6). These findings, again, confirm prediction (i) from Section II: the most sophisticated investors redeem much more strongly during the crisis week.

Table 3 presents cross-sectional regressions of the cumulative “Lehman-week” change in logged assets (i.e., fraction flows, multiplied by 100), at the individual

¹⁷ Throughout the paper, with the exception of Table 1, share class-level and fund-level regressions only include observations with at least \$100 million in assets, respectively. This approach generally excludes small-scale funds that have a limited number of investors. Results are unchanged, albeit a bit noisier, if we lower this threshold to \$10 million.

¹⁸ A fund fixed effect allows us to hold constant the quality of the portfolio, as well as the implied insurance provided by any potential subsidization by the management company as we examine the reaction of different share classes; alternatively, the coarser complex fixed effect provides a (less precise) control for fundamentals and implied insurance, while retaining the effect of differences in clientele across different funds (which increases the statistical power to detect the effect of clientele differences on flows).

TABLE 2—REGRESSIONS OF PRIME INSTITUTIONAL SHARE CLASS-LEVEL FLOWS ON EXPENSE RATIO

	(1)	(2)	(3)	(4)	(5)	(6)
Share class expense ratio	10.89 (5.181)	11.14 (4.153)	12.42 (3.153)			
Indicators:						
15 < ER ≤ 35				-15.59 (-4.865)	-21.29 (-5.122)	-20.85 (-2.682)
ER ≤ 15				-34.88 (-3.913)	-36.09 (-2.894)	-38.97 (-2.395)
Dummies	None	Complex	Fund	None	Complex	Fund
Clustering	Fund	Complex	Fund	Fund	Complex	Fund
Observations	258	258	258	258	258	258
Degrees of freedom	256	191	135	255	190	134
R ²	0.057	0.369	0.565	0.065	0.381	0.575

Notes: To test model prediction (i), this table presents estimated coefficients from OLS regressions of the change in logged prime institutional share class assets under management (i.e., flows as a fraction of lagged assets under management, $\times 100$) from September 15 to September 19 on that share class's expense ratio (*ER*), which has been normalized by its cross-sectional standard deviation. Depending on the specification, we include no fixed effects, complex fixed effects, or fund fixed effects. The final three columns replace the continuous share class *ER* with two dummy variables for different ranges of *ER*; the omitted category includes all prime institutional share classes with an *ER* > 35 bp/yr (*t*-statistics in parentheses).

share class level (for sophisticated share classes only), on the dollar percentage of sophisticated investors (ω) at the fund level and five control variables: share class expense ratio; fund size (log assets); fund risk, proxied by gross 7-day SEC yield; fund liquid asset share;¹⁹ and proportion (by assets) of the complex's mutual fund business other than its prime institutional money funds. This last variable is also used by Kacperczyk and Schnabl (2013), as a proxy for the tendency of a sponsor to avoid taking risk in its prime MMMFs, in order to protect its remaining fund business.²⁰

To measure the sensitivity of our classification scheme to the threshold used to separate sophisticated from unsophisticated institutional investors, columns 1–5 consider a range of expense ratio cutoff values (25, 30, 35, 50, and 150 bps/year) in deciding which share classes to consider sophisticated, and, thus, to include in the regression. We point out that all institutional share classes have an expense ratio below 150 bps/year, so regression 5 identifies all institutional share classes as sophisticated.

¹⁹Our definition of liquid assets starts with that of Duygan-Bump et al. (2013), which equals the sum of the portfolio weights of investments in repo, Treasury, and US agency securities. Asset holding data is available weekly from iMoneyNet, so we interpolate between weekly values using a method which is similar to the one in Strahan and Tanyeri (2015). We estimate the fraction of portfolio holdings that mature each day by dividing the percentage of the portfolio that matures within the next week by five, the number of trading days in a week. We then compare the cumulative change in assets under management since the value was last updated with that day's investor flow (change in TNA). If the share of maturing assets exceeds net redemptions, we assume that the liquid asset share remains unchanged. If redemptions exceed maturing assets—which is extremely rare prior to the start of the crisis period—we assume that the difference between redemptions and maturing assets is met by selling liquid securities. Results are similar if we use the weekly liquid asset share from iMoneyNet in place of our daily real-time variable.

²⁰Specifically, Kacperczyk and Schnabl (2013) find a (negative) relation between this variable and the willingness of the management company to take higher risks in their prime money funds. While Average Gross Yield should pick up risk-taking, it might do so with measurement error since it is measured over a several-month lagged period; thus, Fund Business might partially be capturing this unmeasured risk.

TABLE 3—REGRESSIONS OF PRIME INSTITUTIONAL SHARE CLASS-LEVEL FLOWS ON FUND AND INVESTOR CHARACTERISTICS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
%Soph (25 bp/yr)	-42.2 (-2.47)							
%Soph (30 bp/yr)		-36.4 (-2.80)						
%Soph (35 bp/yr)			-33.8 (-3.01)			-12.6 (-1.04)	-50.3 (-3.77)	
%Soph (50 bp/yr)				-31.2 (-3.12)				
%Soph (150 bp/yr)					-28.6 (-2.92)			
%Soph (35 bp/yr) × ER							17.8 (3.97)	31.5 (3.34)
Share class expense ratio	8.4 (0.54)	16.8 (1.56)	16.0 (1.99)	15.0 (4.02)	10.4 (4.93)	5.7 (1.28)	-2.7 (-1.19)	-10.0 (-1.84)
log total fund assets	-12.7 (-2.93)	-10.8 (-2.80)	-10.3 (-3.25)	-8.2 (-3.22)	-7.5 (-3.36)	-1.6 (-0.67)	-7.5 (-3.48)	
Average gross yield	-1.1 (-0.15)	-2.1 (-0.33)	-2.5 (-0.41)	-5.0 (-0.78)	-3.7 (-0.71)	-6.9 (-1.26)	-3.4 (-0.64)	
Liquid asset share	4.9 (0.73)	2.8 (0.48)	2.8 (0.52)	0.1 (0.01)	1.4 (0.30)	-0.9 (-0.18)	1.0 (0.23)	
Fund business	-0.5 (-0.11)	-1.0 (-0.25)	-1.2 (-0.35)	-1.6 (-0.56)	-1.7 (-0.64)	-2.0 (-0.90)	-1.3 (-0.53)	
Sample selection	Sophisticated institutional: ER ≤ cutoff					ER > 35 bp/yr	All	All
Fixed effects	None	None	None	None	None	None	None	Fund
Observations	118	138	161	215	258	97	258	258
Degrees of freedom	111	131	154	208	251	90	250	134
R ²	0.080	0.089	0.094	0.111	0.118	0.076	0.128	0.582

Notes: To test model prediction (ii), this table presents estimated coefficients from OLS regressions of the change in logged share class-level assets under management (i.e., flows as a fraction of lagged assets under management ($\times 100$)) for each prime institutional money market share class from September 15 through September 19 on expense ratio (ER); percent large-scale institutions ($\%Soph$; defined as the fraction of total fund investment dollars owned by investors of institutional share classes with $ER \leq$ a particular cutoff: 25 bp for the first column); logged fund-level size; average annualized 7-day SEC gross yield over the six month period prior to the crisis (March–August 2008); liquid asset share, estimated daily by computing dollar proportion Treasury and US agency securities plus repo investments, plus (estimated) maturing securities, minus net redemptions; and fund business, defined as one minus proportion (by value) of fund complex aggregate mutual fund assets that are represented by prime institutional share classes. The bottom five variables in the table have each been divided by their most recently available cross-sectional standard deviations to normalize. Different columns correspond with different cutoffs and different sample selection criteria. To test prediction (iii) of our theoretical model, the final two columns add an interaction term between share class expense ratio and $\%Soph$ at the fund level. Note that the specification in the last column includes fund fixed effects. t -statistics are indicated in parentheses.

Recall that prediction (i) of our model is that outflows during the crisis week, all else equal, are expected to be largest in share classes with the lowest expense ratios. This is supported by the positive coefficients on share class expense ratio in columns 1–5; these coefficients are statistically significant in those specifications that do not truncate share class observations (i.e., retain a larger sample size) when the ER variable exceeds low thresholds (columns 3–5).²¹ The negative coefficient on (logged) fund size shows that, for large funds, the same outflow in percentage

²¹To verify this, we estimated a version of specification 3 in Table 3 that includes all share classes, and found that the coefficient on the share class expense ratio is positive and highly statistically significant.

terms is associated with a larger liquidation, in dollar terms, with the potential for a larger (negative) price impact on securities sold. The coefficient on the yield variable is negative, as we would expect—funds holding riskier assets experience larger redemptions—but is imprecisely estimated. Finally, coefficients on liquidity and fund business are insignificant, indicating that, relative to substantial differences in clientele, these considerations are of secondary importance to investors, perhaps because they are viewed as being inadequate to stem a run should a large fraction of sophisticated investors decide to redeem.²² Interestingly, in univariate regressions of fund-level flows on yield, liquidity, or fund business, each of these variables is significant at either the 5 percent or 10 percent level, and the signs are as expected. However, the explanatory power of these variables in multivariate regressions is quite low, indicating that cross-sectional heterogeneity in the strength of complementarities in funding liquidity across funds may have been somewhat larger than the heterogeneity in portfolio risk (market liquidity) across funds.

Columns 1–5 test the second prediction from our model, namely that outflows increase in the fraction of sophisticated investors that reside in a particular money fund. For example, the first model measures the dollar percentage of the prime fund that is financed by institutional share classes carrying an *ER*, at most, of 25 bps/year. Across these models, consistent with theory we find (independent of the cutoff used to classify sophisticated institutional share classes) a strongly negative and highly significant relation between fund flows and the fraction of sophisticated investors residing in a fund. For example, model 1 predicts that a fund having 40 percent sophisticated investors (defined as $ER \leq 25$ bps/year) will have outflows from those sophisticated investors that are 8.1 percent of assets greater (all else equal) than a fund having 20 percent sophisticated investors. Moreover, the magnitude of this coefficient increases monotonically (in absolute value) as the threshold decreases, across models, from 150 bps/year to 25 bps/year, indicating that our proxy (*ER*) captures increasingly sophisticated investors as it decreases.

Our model implies that the relation between flows from less sophisticated investors and the fraction of sophisticated investors should be weaker than the relation for flows from more sophisticated investors. To test this feature, column 6 estimates the same specification for institutional share classes with $ER \geq 35$ bps. Indeed, the magnitude of the coefficient on the fraction of sophisticated investors is smaller (and no longer statistically significant) than in columns 1–5, although its sign remains negative.

The third prediction of our model is that the difference in outflows between within-fund high and low sophistication investors is increasing in the fraction of sophisticated investors that reside within the fund. Columns 7–8 of Table 3 test this prediction by including an interaction term between the total fraction of a money fund's assets held by sophisticated investors and the sophistication of a given share class of that fund, proxied (negatively) by the expense ratio. The positive and highly significant coefficient on this interaction term strongly indicates that higher levels of sophisticated (i.e., low expense ratio) investors in a given money fund lead to

²²For instance, the median prime fund, on September 12, 2008, holds only 17 percent highly liquid assets.

larger differences between the predicted behavior of sophisticated and unsophisticated investors.²³

We note, here, that the liquidity mismatch of a MMMF's balance sheet is captured by the variable *%Soph*, on the liability side, and by liquid asset share, on the asset side. The regression results in Table 3 indicate that funding (liability side) liquidity is a much more significant driver of investor redemption behavior than market (asset side) liquidity. However, this is very likely due to the implications of funding liquidity for asset liquidity; changes in funding liquidity (i.e., increases in *%Soph*) must be met with changes in asset liquidity (i.e., increases in liquid asset share). In the sense that abrupt changes in funding liquidity lead to changes in asset liquidity, we should expect the former to be a more significant predictor of investor behavior, and it is.

Our tests in Tables 2–3 examined the determinants of share class-level flows cumulated over the entire week following Lehman's failure. Table 4 provides additional insights about dynamics by demonstrating how these cross-sectional differences evolved over the course of the week. Each panel of the table has four columns. Column 1 reports coefficients for a regression whose dependent variable is the share class-level flow for Monday, September 15; the dependent variable from column 2 includes flows from September 15 and 16, and so forth. Different panels correspond to different specifications from Tables 2 and 3: panel A corresponds to specification 3 of Table 2, while panels B–D correspond to specifications 3, 8, and 7 of Table 3, respectively.

The results are qualitatively similar across all three panels: The cross-sectional differences emphasized in Tables 2 and 3, which are consistent with all three predictions of the model, are already present on September 15, and these differences become more pronounced as the week progresses. This pattern is consistent with the most sophisticated investors being among the early movers, particularly when complementarities at the fund level are strong.²⁴

Our finding that large investors are more prone to run contrasts with the evidence in Chen, Goldstein, and Jiang (2010) who, for a sample of equity mutual funds, find that large investors are less likely to run. In our setting, institutional investors are assumed to be atomistic but better-informed about fundamentals, making them more likely to run. In contrast, Chen, Goldstein, and Jiang (2010) model a large investor that internalizes the negative effects of its future actions—weakening complementarities—when the primary source of complementarities is the price impact of future redemptions. While these findings contrast, note that the two studies' settings are markedly different. First, MMMFs' fixed NAV structure and potential sponsor support create additional first-mover advantages which are not present for equity

²³We perform a number of additional exercises in order to verify the robustness of the results of Table 3. In particular, we show that our results are not particularly sensitive to the inclusion of additional control variables, as well as nonlinear transformations of the existing control variables. We also verify that our findings with the interaction terms (specifications 7–8 in Table 3) hold for other choices of the cutoff separating sophisticated from unsophisticated types. Given space considerations, these results are reported in the online Appendix.

²⁴These findings are consistent with He and Manela's (2016) dynamic model, in which investors, upon hearing a rumor that a bank may become illiquid, optimally wait for a time before running on the bank. Crucially, the equilibrium waiting time decreases when other agents are more likely to be informed, implying that the cross-sectional differences in run-like behavior should grow (as we see in the data) during the course of the crisis. As we discuss in the online Appendix, a version of their model also implies similar comparative statics to those from our static model.

TABLE 4—REGRESSIONS OF SHARE CLASS-LEVEL FLOWS ON FUND AND INVESTOR CHARACTERISTICS: CUMULATIVE FLOWS OVER THE COURSE OF LEHMAN WEEK

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	<i>Panel A. Prediction (i)</i>				<i>Panel C. Predictions (i)–(iii)</i>			
	9/15	9/15–16	9/15–17	9/15–18	9/15	9/15–16	9/15–17	9/15–18
Share class expense ratio	1.6 (2.35)	3.0 (2.26)	7.8 (3.01)	10.1 (3.26)	–1.2 (–1.12)	–2.7 (–1.40)	–6.1 (–1.69)	–8.4 (–1.97)
%Soph (35 bp/yr) × ER					4.1 (2.21)	8.0 (2.48)	19.5 (3.48)	26.1 (3.94)
Specification	All institutional, fund F.E. (N = 258)				All institutional, fund F.E. (N = 258)			
R ²	0.542	0.538	0.436	0.521	0.552	0.555	0.461	0.546
	<i>Panel B. Predictions (i)–(ii)</i>				<i>Panel D. Predictions (i)–(iii)</i>			
	9/15	9/15–16	9/15–17	9/15–18	9/15	9/15–16	9/15–17	9/15–18
%Soph (35 bp/yr)	–6.4 (–2.63)	–9.9 (–3.07)	–19.1 (–3.92)	–27.7 (–4.41)	–8.8 (–2.93)	–13.8 (–3.44)	–29.5 (–4.77)	–44.2 (–5.34)
%Soph (35 bp/yr) × ER					3.3 (2.92)	4.9 (3.22)	11.0 (4.71)	15.5 (4.88)
Share class expense ratio	2.4 (1.17)	3.4 (1.03)	13.1 (2.52)	15.7 (2.40)	–0.9 (–1.59)	–1.1 (–1.48)	–2.2 (–1.84)	–3.1 (–1.89)
log total fund assets	–1.5 (–2.77)	–2.6 (–2.69)	–5.7 (–3.47)	–8.3 (–4.05)	–1.0 (–2.75)	–1.9 (–2.75)	–4.0 (–3.51)	–5.9 (–4.05)
Specification	ER ≤ 35 bp/yr, controls, no F.E. (N = 161)				All institutional, controls, no F.E. (N = 258)			
R ²	0.062	0.072	0.107	0.151	0.088	0.115	0.129	0.166

Notes: This table presents estimated coefficients (*t*-statistics) from OLS regressions of the change in the log of share class-level assets under management (i.e., flows as a fraction of lagged assets under management) for prime institutional money market funds ($\times 100$), cumulated over parts of the period from September 15–18, 2008, on expense ratio, percent large-scale institutions (%Soph; calculated with 35 bp/yr cutoff), as well as the log of fund size. Regressions in panels B and D also control for average annualized gross yield, liquid asset share, and fund business; these (insignificant) coefficients are suppressed. See notes to Table 3 for more detailed variable descriptions. Expense ratio (*ER*) and size are divided by their cross-sectional standard deviations. Different columns denote different sample periods. Panels C and D add an interaction term between share class expense ratio and %Soph at the fund level.

mutual funds. MMMF payoffs are specifically designed so as to be informationally insensitive, making price discovery difficult, whereas equity prices are readily available. Prior to the Lehman episode, larger MMMF investors had a much stronger incentive to invest in information acquisition technologies, and, as such, were much more likely to be aware of the potential gap between book and market values relative to smaller investors, strengthening complementarities. Second, even though institutional investors' money market accounts could be very large, typically no single institutional investor dominates a single large MMMF. The differences in model assumptions and empirical results highlight the importance of the market setting for investor incentives and suggests that there is room for further empirical and theoretical work on the subject.

A caveat is in order before proceeding. Our analysis uses investor clientele for identification of strategic complementarities. Other (omitted) variables could be correlated with variation in clientele across funds, and so, ultimately, we cannot rule out alternative explanations of our findings related to the influence of unobserved asset quality (beyond the proxies for asset quality that we already include, such as

yield and liquidity) or unobserved investor characteristics (beyond our proxy of expense ratio). For instance, it is plausible that investors are more likely to receive a bad signal about the quality of asset holdings in funds with high fractions of sophisticated investors, and, so, redeem more aggressively from such funds—versus our hypothesis that sophisticated investors are reacting strategically to each other. We note, however, that such increased information, under this mechanism, would have to be available to sophisticated investors, and not to the unsophisticated—otherwise, our within-fund tests would still control for the information environment. Moreover, this alternative mechanism does not explain why (as we will show shortly) sophisticated investor flows should depend on unsophisticated investor actions. Thus, we believe that our hypotheses regarding strategic complementarities are more reasonable, given our empirical results, than this alternative hypothesis.

IV. The Role of Fixed NAV: Comparison with Ultra-Short (Variable NAV) Bond Funds

The cross-sectional tests of Table 3 explore strategic complementarities by changing the type of investor (large-scale sophisticated versus smaller-scale unsophisticated institutional investors), while controlling for portfolio fundamentals (quality of assets), as proxied by the lagged 7-day portfolio gross yield. A current issue of contention among academics, regulators, and the investment management industry is whether the fixed share price of MMMFs is a significant contributor to the potential for investor runs.²⁵ Indeed, the latest round of SEC regulatory changes, effective October 2016, requires all prime institutional share classes to be offered for purchase and sale (by the management company) at a floating NAV, defined as a per-share price that reflects an assessment by the management company of the daily market valuation of portfolio assets.²⁶

The regulatory point of view is that a fixed \$1 per share creates an enhanced first-mover advantage in response to an adverse shock to credit quality. In this setting, the ideal test for the effect of the fixed NAV structure on investors' redemption behavior would be to compare the actions of similar investors which hold mutual funds with similar credit exposures, where one group of investors has a floating NAV while the other has a fixed NAV. Since no MMMFs carried a variable share price in 2008, we examine the sector of mutual funds with holdings closest to prime MMMFs, and carrying a variable price: ultra-short bond funds. We analyze those ultra-short funds closest to prime MMMFs: ultra-short funds that hold both government and non-government debt (i.e., we exclude ultra-short government-only funds). Ultra-short funds do not fix their share price so, according to this point of view, we would expect complementarities between investors to be more keen in MMMFs than in ultra-short bond funds during the September 2008 market run since a floating (market) share price is designed to internalize a greater portion of the (negative) externalities of running from a fund as its fundamentals deteriorate.

²⁵ See, for example, Gordon and Gandia (2014), SEC (2014), and Fidelity Management and Research (2013).

²⁶ See SEC (2014). As another acknowledgment of the enhanced first-mover advantage among institutions, prime institutional share classes will no longer be allowed to co-exist as claims on a fund (a portfolio) with retail share classes.

We propose a simple test which provides suggestive evidence for the effect of the fixed NAV on investor redemption behavior. Our key identifying assumption is that the change in credit quality of the ultra-short portfolios was weakly larger relative to the change experienced by MMMFs operated by the same fund management company. Then, under the hypothesis that the fixed NAV structure has no effect on investors' incentives to redeem quickly, we would expect redemptions in ultra-short funds to be weakly larger than redemptions from comparable MMMF investors.

Ultra-short bond funds serve a clientele consisting almost exclusively of retail investors.²⁷ Thus, a perfect comparison to our prime institutional MMMF share classes, which consist of much larger proportions of truly non-retail investors, is not possible. However, we compare flows during and after the crisis week of 2008 between ultra-short funds and both retail and institutional prime MMMFs to gain insights about the role of a floating share price in generating fragility. Here, we conduct such an analysis using monthly flow data and other fund characteristics from the Center for Research in Security Prices (CRSP) for both ultra-short funds and prime MMMFs.²⁸

Table 5 reports the results from regressing crisis-month share class level flows to ultra-short mixed (non-government) bond funds on same-complex flows to prime MMMF retail share classes (models 1 and 3) or to same-complex prime retail plus prime institutional share class MMMF flows (models 2 and 4).²⁹ The regressions include a dummy equaling one for institutional (versus retail) ultra-short share classes, as well as (normalized) controls for the expense ratio, yield, and ultra-short fund size (aggregated across all share classes). The rightmost two columns exclude very small ultra-short bond fund share classes (< \$10 million in assets) from the analysis as a robustness test. In the regressions of ultra-short flows on retail MMMF flows (1 and 3), the estimated slope coefficient is 0.51 to 0.58, and is (statistically) significantly different from both zero and one; this reflects that flows to or from ultra-short share classes have the same direction (generally outflows), but roughly half the amplitude of same-complex prime retail MMMF share classes during the crisis week. Models 2 and 4 show that the amplitude of ultra-short share class flows is even more muted, compared to all prime MMMF share classes within the same complex. (As expected, the institutional ultra-short dummy has little relevance, since most investors in this class are, in reality, retail investors).

To give a broader sense of the fundamental shock and the resulting price pressure on the shares of ultra-short funds, panel A of Figure 3 shows the average cumulative

²⁷ Closer inspection of the ultra-short funds data suggests that approximately 85 percent of assets under management in institutional share classes are held either directly or indirectly by retail investors. Retail investors are able to purchase lower-cost institutional share classes in ultra-short funds through, for example, their 401(k) plans. We thank the Investment Company Institute for this information.

²⁸ We use CRSP MMMF data, instead of iMoneyNet data because CRSP provides a unique identifier which allows us to link MMMFs with ultra-short funds managed within the same fund complex. Since ultra-short funds that hold only government securities are not separately identified by the Lipper classification in CRSP, we manually identify those funds that also invest in nongovernment securities in order to provide a better comparator group to prime MMMFs, which also invest outside government securities. CRSP asset data are only available on a monthly basis; accordingly, we focus on explaining investor flows over the entire month of September 2008. Monthly flows (as a fraction of beginning-of-month assets) for a given share class during September are estimated as $flow_{Sep} = \ln(tna_{Sep}) - \ln(tna_{Aug}) - r_{Sep}$, where tna_{Sep} and r_{Sep} denote total net assets under management at the end of September 2008 and (continuously compounded) return during that month for a given share class.

²⁹ We compare flows within the same complex as a rough control for the implicit potential subsidization by the complex during a crisis and for the quality of portfolio holdings.

TABLE 5—REGRESSIONS OF SHARE CLASS-LEVEL FLOWS FOR SAME-COMPLEX ULTRA-SHORT BOND FUNDS ON FLOWS FOR PRIME MMMFS

	(1)	(2)	(3)	(4)
Complex prime retail MMF flow	0.51 (3.929)		0.58 (3.352)	
Complex prime MMF flow		0.33 (2.112)		0.18 (1.795)
Institutional share class dummy	0.51 (0.139)	-1.06 (-0.245)	0.74 (0.144)	0.46 (0.088)
Expense ratio	1.73 (1.156)	2.68 (1.628)	2.45 (0.940)	2.18 (0.749)
Annualized yield	0.68 (0.491)	1.23 (0.894)	0.39 (0.245)	1.12 (0.697)
log total fund assets	-5.99 (-3.387)	-5.55 (-2.846)	-7.08 (-2.660)	-4.66 (-1.859)
Sample selection	All ultra-short funds		Ultra-short funds > \$10 MM	
Observations	45	50	36	39
R ²	0.285	0.226	0.264	0.129

Notes: This table presents estimated coefficients from OLS regressions of share class-level flows as a fraction of lagged assets under management (i.e., the change in log assets under management, adjusted for changes in market value × 100) for mixed (non-government) ultra-short bond fund institutional share classes during the month of September 2008 on flows over the same period from same-complex prime retail MMMF (models 1 and 3) or same-complex prime retail plus prime institutional MMMF share classes (models 2 and 4); in each case, these same-complex MMMF flows are aggregated to the complex level. In addition, each regression includes a dummy variable which equals one for an institutional share class, the share class expense ratio, the log of fund size (total net assets under management as of August 31, 2008) and its annualized gross yield (fund interest distributions over the previous 12 months, divided by current share price); the latter three variables have been divided by their cross-sectional standard deviations. All variables (including money market flows) are constructed using the CRSP mutual fund database.

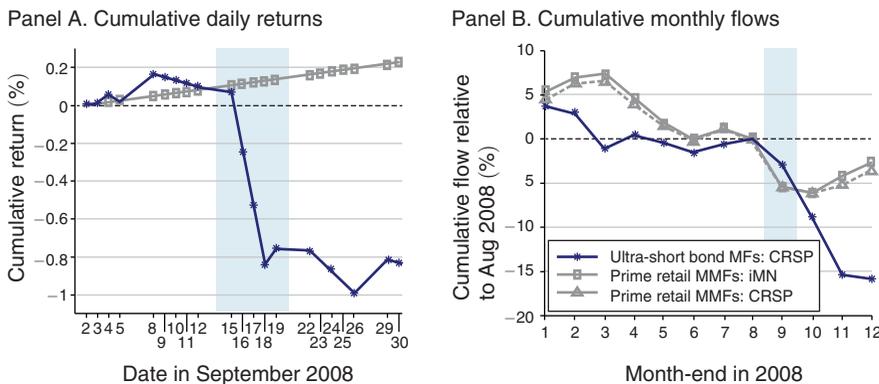


FIGURE 3. CUMULATIVE RETURNS AND FLOWS FOR MMMF AND ULTRA-SHORT BOND FUNDS

Notes: Panel A shows the daily return of prime MMMFs and ultra-short bond funds, averaged (value-weighted) across all funds each day, then cumulated from the beginning of the month to each day during September 2008. Panel B shows the monthly flow (i.e., the change in log of assets under management, adjusted for investment returns) each month during 2008, averaged (value-weighted) across all prime MMMF retail share classes (using both the iMoneyNet dataset and the CRSP dataset, which match closely) and all ultra-short bond funds, then cumulated over consecutive months in 2008. We normalize the cumulative flow to zero as of the end of August 2008.

holding period return for ultra-short funds during each day of September 2008. Ultra-short funds experienced three consecutive daily returns more than three standard deviations below zero, with cumulative losses of -75 bps during the Lehman week. In contrast, MMMFs (excluding funds managed by the Reserve complex) experienced modest gains from earned interest. Note, from panel B, that the floating value of ultra-short funds reduced outflows from these funds during the month of September.

By October 2008, MMMF shares were backstopped through several programs initiated by the Federal Reserve and the US Treasury, which significantly reduced the scope for complementarities.³⁰ In contrast, no backup programs were implemented explicitly for ultra-short bond funds (although they may have indirectly benefited from the commercial paper backup programs). This is consistent with the longer-term cumulative flow patterns observed in panel B, which show that ultra-short bond funds experienced less-severe outflows during September 2008, but continued to experience moderate outflows (and losses) during October and November. By contrast, outflows from prime MMMFs largely ended by early October.

Differences between MMMFs and ultra-short bond funds prevent us from drawing too strong conclusions from these results about the role of a variable share price in reducing the importance of payoff complementarities. While ultra-short funds normally hold riskier assets than MMMFs (thus, the variable share price), they might not have participated as heavily in the degradation of asset quality in the financial commercial paper market during September 2008. With this caveat, our results point to fixed share prices as likely amplifying the run on prime MMMFs triggered by the deterioration in the fundamentals during the Lehman week. Further, as is studied in greater detail for corporate bond funds by Goldstein, Jiang, and Ng (2015), there is still scope for complementarities even with a floating NAV. Investors still have an incentive to redeem early given the low degree of secondary market liquidity and the potential lack of reliable market prices for use in NAV calculations. Moreover, the new regulations will effectively segment the MMMF market between institutional and retail investors, which, according to our model above, will potentially strengthen complementarities among institutional investors.

V. Dynamic Interactions between Investor Types

As noted earlier, a unique feature of our data is that we observe the daily flows of share classes associated with investor types of different levels of sophistication. In this section, we use our data to study whether the actions of unsophisticated investors affect the actions of sophisticated investors in a dynamic setting.

To measure flow dynamics, we estimate a model that captures daily interactions between sophisticated and unsophisticated investors within the same MMMF. As above, we partition institutional share classes as sophisticated or unsophisticated based on the level of their expense ratios, while retail share classes are always

³⁰Specifically, programs were announced on September 19 (Treasury) and October 7 and 21 (Federal Reserve). Further, the SEC allowed MMMFs to price their portfolio holdings at amortized cost for a period (when quotes on commercial paper were generally regarded as unreliable), which potentially helped to forestall more MMMFs from breaking the buck.

classified as unsophisticated.³¹ To maximize the number of paired observations in our sample while retaining consistency across funds, institutional share classes are classified as sophisticated if their expense ratio (i) falls below the median expense ratio within the institutional share classes of that fund; and (ii) is no greater than 35 bps/year.³²

Table 6 reports results from regressions that use daily (fraction) flow from low expense ratio (sophisticated institutional) share classes, Low_{it} , aggregated within a given MMMF, as the dependent variable. We regress this variable on its own one-day lag, Low_{it-1} , as well as one-day lagged flow from aggregated (within a given MMMF) high expense ratio (unsophisticated institutional and all retail) share classes, $High_{it-1}$, and interactions of these variables with $\%High_{it-1}$ and $\%High_{it-2}$, the one- and two-day lagged investment value of unsophisticated investors (institutional plus all retail) in a given prime MMMF as a fraction of fund TNA.³³ These interaction terms are key to our analysis: they test whether sophisticated investors react differently to the behavior of unsophisticated investors when the latter comprise a high fraction of the fund's assets.

Finally, we include five control variables (yield, log fund size, and average institutional expense ratio within a given MMMF, liquid asset share, and fund business, defined as described previously for Table 3) in our regression. Average institutional expense ratio is used to control for differences in clientele across different MMMFs.

To explore differences in the dynamics of flows over potentially very different market regimes, we estimate the model over two separate subperiods, namely, the early-crisis period (Wednesday, September 10 to Tuesday, September 16, 2008) and the peak crisis period (Wednesday, September 17 to Friday, September 19).³⁴ We also provide estimates over the full Lehman week (September 15 to September 19).

First, consider the coefficient on the interaction term $High_{it-1} \times \%High_{it-2}$, which captures the concentration of unsophisticated investors ($\%High_{it-2}$) in amplifying the reaction of sophisticated investors to the outflows of the unsophisticated, $High_{it-1}$ (prediction (ii) from our model of Section II). In both subsamples, and in the entire Lehman week, this coefficient is positive, close to one, and highly significant. These estimates show very different responses of sophisticated investors to prior-day flows of unsophisticated investors across funds with different concentrations of unsophisticated investors. To illustrate, during the Lehman week as a whole, in response to a 5 percent outflow by unsophisticated investors, a prime MMMF that consists of a 50 percent concentration of unsophisticated money experiences a one-day (expected) outflow that is 2 percent of assets greater, among sophisticated investors, relative to a prime MMMF with a 10 percent concentration ($\exp(1.02 \times -0.05 \times 0.4) - 1$).

³¹Funds with a single share class are excluded from the analysis, which leads to a reduction in the sample size from 123 to 64 funds. The excluded share classes have similar yield, liquidity and flow standard deviations but tend to be smaller with a lower concentration of sophisticated investors (higher *ERs*) than funds with multiple share classes. We also require share classes to have a minimum of \$100 million in assets throughout the estimation sample period.

³²In a few cases, two share classes within the same fund have the same expense ratio. Prior to generating the ordering, we pool the assets under management for such share classes. In cases with an odd number of institutional share classes, we code the median share class as sophisticated only if its expense ratio is no greater than 35 bps.

³³ $High_{it-1} \times \%High_{it-2}$ is the contribution to total lagged fund flows coming from unsophisticated investors.

³⁴We partition in this manner because the news that the Reserve Primary Fund broke the buck due to its Lehman holdings first became known by the public late in the day on September 16. By the following morning, the media had widely circulated this information.

TABLE 6—DETERMINANTS OF DAILY FLOWS FROM SOPHISTICATED (LOW *ER*) SHARE CLASSES

Variable	Early crisis (1)	Peak crisis (2)	Lehman week (3)	Early crisis (4)	Peak crisis (5)	Lehman week (6)
$Low_{i,t-1}$	0.20 (1.29)	0.18 (1.15)	0.25 (2.31)	0.16 (1.15)	0.19 (1.14)	0.27 (2.37)
$Low_{i,t-1} \times \%High_{i,t-2}$	-0.24 (-0.60)	0.34 (0.52)	0.03 (0.07)	-0.41 (-1.23)	0.14 (0.24)	-0.21 (-0.74)
$High_{i,t-1}$	-0.04 (-0.39)	-0.32 (-2.24)	-0.16 (-1.76)	-0.03 (-0.35)	-0.27 (-1.82)	-0.12 (-1.16)
$High_{i,t-1} \times \%High_{i,t-2}$	0.87 (2.23)	1.21 (2.23)	1.02 (2.42)	0.47 (1.51)	1.05 (2.55)	0.67 (1.99)
$High_{i,t}$				-0.23 (-2.43)	-0.10 (-0.77)	-0.19 (-1.56)
$High_{i,t} \times \%High_{i,t-1}$				1.59 (4.76)	1.53 (2.45)	1.64 (3.11)
$\%Low_{i,t-1}$	0.78 (0.42)	-9.15 (-2.93)	-4.58 (-2.96)	0.19 (0.11)	-12.76 (-3.55)	-7.14 (-4.55)
Average yield $_{i,t-1}$	-0.01 (-0.03)	-0.71 (-0.53)	-0.45 (-0.51)	-0.14 (-0.39)	-0.73 (-0.58)	-0.43 (-0.59)
log total fund assets $_{i,t-1}$	-0.81 (-2.18)	-0.15 (-0.17)	-0.56 (-0.95)	-0.83 (-2.15)	-0.11 (-0.12)	-0.55 (-0.98)
Avg institutional expense ratio $_{i,t-1}$	1.05 (1.69)	2.67 (1.60)	2.80 (2.45)	0.71 (1.13)	1.92 (1.26)	2.21 (2.42)
Liquid asset share $_{i,t-1}$	0.40 (0.90)	1.90 (1.55)	1.29 (1.70)	0.45 (1.04)	1.82 (1.49)	1.38 (2.05)
Fund business $_{i,t-1}$	-0.21 (-0.71)	0.02 (0.02)	-0.10 (-0.17)	-0.23 (-0.82)	0.04 (0.05)	-0.05 (-0.09)
Observations	320	190	318	320	190	318
R^2	0.165	0.279	0.263	0.233	0.370	0.348

Notes: For each fund, we separate prime institutional share classes into two categories, based on their expense ratios. The first category, Low, consists of share classes which have expense ratios that are lower than the median expense ratio (across all institutional share classes within a given fund). All remaining share classes are included in the High category, including all retail share classes. The value of shares outstanding is then aggregated across all Low share classes and, separately, across all High share classes within a given fund. (Funds with a single share class are excluded from this analysis.) For each fund and date, we calculate the first difference in the log of aggregate value within each category (i.e., fraction flow), which we denote by $Low_{i,t}$ and $High_{i,t}$. The table presents the coefficients from panel regressions with $Low_{i,t}$ as the dependent variable on $Low_{i,t-1}$ and $High_{i,t-1}$, estimated for three different subperiods in 2008: 9/10–9/16 early crisis, 9/17–9/19 peak crisis, and 9/15–9/19 Lehman week, respectively. We multiply $Low_{i,t}$ and $High_{i,t}$ by 100 to express them in log percentage points. We also include interaction variables between, for example, $High_{i,t-1}$ and $\%High_{i,t-2}$, which is defined as two-day lagged fraction of total MMMF value within a MMMF represented by High (both institutional and all retail) *ER* share classes. Control variables, described in the notes to Table 3, have been divided by their (cross-sectional) standard deviations for ease of interpretation. All specifications also include unreported time dummies. Standard errors are clustered at the fund level. R^2 reports the overall R^2 . *t*-statistics are reported in parentheses.

These results suggest that the actions of sophisticated and unsophisticated investors become more coordinated in funds where the latter group plays a greater role. To our knowledge, these dynamic interactions between heterogeneously-informed investors have not been modeled formally in the literature. However, we find results which are intuitively consistent with complementarities. When agents' payoffs depend on the actions of others and there are complementarities, agents want their actions to be positively correlated with the aggregate action, so that they run when other investors run. This implies that, in funds dominated by unsophisticated

investors, sophisticated investors optimally wish to observe the actions of unsophisticated investors before timing their withdrawals, which is what we find.

We note here that one might interpret the positive coefficient on the interaction term in an alternative way that has little to do with strategic complementarities. That is, if funds sell their highest quality assets first to meet redemptions of any kind, lagged outflows from low and high expense ratio share classes should have the same effect on Low_{it} —the idea being that sophisticated investors are merely reacting to worsening fundamentals, which might be inferred from observing one-day lagged outflows. We provide some evidence counter to this alternative mechanism: in Table 6, the coefficients on $Low_{it-1} \times \%High_{it-2}$ and $High_{it-1} \times \%High_{it-2}$ having the same magnitude, but opposite signs. Thus, it appears that outflows are viewed, by sophisticated investors, not in isolation, but in the context of the concentration of unsophisticated investors in the MMMF.³⁵

We further note that, consistent with prediction (ii) of our model, the coefficient on $\%Low_{it-1}$ is statistically significant and economically large during the peak crisis and Lehman week. During the peak crisis, the coefficient on this variable suggests cumulative three-day redemptions about 25 percent higher for funds consisting purely of sophisticated investors, compared with funds consisting almost entirely of unsophisticated investors.

To put this into perspective, in the dynamic model of Angeletos, Hellwig, and Pavan (2007), informed investors update their beliefs based on a noisy signal about the size of previous attacks, and the observation of whether the regime (in our case, the probability of maintaining the \$1 NAV) survived the previous-period attack. Large prior attacks, *ceteris paribus*, reveal negative information about fundamentals, making future attacks more likely.³⁶ However, an institution's survival from previous attacks may also result in upwardly revised beliefs among investors about the strength of fundamentals. Our empirical results on informed investors' response to prior-day redemptions of other informed investors reflects the relative importance of these two channels (the existence of large attacks versus the survival of funds after large attacks). Overall, our evidence suggests that attacks by sophisticated investors were viewed negatively during the crisis week, and did not result in upwardly revised beliefs about fundamentals (even though no other funds, besides the Reserve Primary Fund, officially broke the buck).³⁷

Turning to the control variables, liquid asset share has a statistically significant effect on flows during the peak crisis period, and during the entire Lehman week, but not during the early crisis, suggesting that concerns about asset liquidity became much more keen as the crisis unfolded. As in prior tables of this paper, we also find

³⁵ Another interesting dynamic is modeled by He and Manela (2016), who show that less-informed agents may optimally wait and withdraw after early movers (who are, in equilibrium, better informed) after learning that the bank's portfolio liquidity may have been impaired. That is, less-informed investors wait until the marginal cost of waiting (imposed by the risk of additional better-informed investors running) equals the marginal benefit of waiting (through earning interest). In unreported tests, we find some evidence of unsophisticated investors reacting to the lagged outflows of sophisticated investors, however, this effect is weaker than the reaction of sophisticated shown in Table 6.

³⁶ If prior attacks also serve to weaken fundamentals (e.g., by forcing funds to sell their most liquid asset holdings), future attacks become even more likely in the presence of large prior attacks.

³⁷ We note here, however, that several funds ventured close to breaking the buck, and may have avoided doing so only because their fund boards were reluctant to make this move even though fundamentals indicated that the buck had already, in reality, been broken. Others avoided breaking the buck through subsidizations by their advisors.

some evidence that sophisticated investors are more likely to run in larger funds, although this evidence is strong only during the early crisis period. Funds with larger average institutional expense ratios, and therefore less sophisticated investors (relative to other funds), on average experienced weaker redemptions. This finding reinforces that the level of sophistication of an investor plays a key role in the tendency to redeem during the crisis.

Finally, we recognize that low *ER* investors could also respond to the same-day behavior of high *ER* investors.³⁸ Redemption requests at MMMFs are placed throughout the day. While most funds redeem all shares at the end of the day, some institutional share classes allow redemptions at various points during the day. Regardless, investors submit redemption requests throughout the day, even if their redemptions are not honored until 4 PM eastern standard time. Thus, it is plausible that large investors could be tipped off about the behavior of small investors in plenty of time to redeem their own shares on the same day.³⁹ Columns 4–6 in Table 6 account for this effect by adding *contemporaneous* flows from small-scale investors, $High_{i,t}$, along with an interaction term, $High_{i,t} \times \%High_{i,t-1}$. We find only a modest effect of the contemporaneous value of $High_{it}$ on Low_{it} .⁴⁰ In contrast, the contemporaneous interaction term $High_{i,t} \times \%High_{i,t-1}$ is significant and economically large. Sophisticated and unsophisticated investor actions are apparently more likely to be coordinated precisely when our model predicts that they have the strongest incentives to coordinate.

VI. Nonlinearities and Magnitudes: Evidence from Dynamic Quantile Regressions

We next adopt a panel quantile regression approach that further allows us to identify the fundamental characteristics of a fund that may make it more susceptible to run-like behavior by investors and helps identify what role the size and/or sophistication level of a fund's investor base play in increasing its exposure to run-like risk. Our quantile approach may also be more robust to potential multiplicity of equilibria.⁴¹ We see the primary purpose of this analysis as helping to uncover the magnitude of cross-sectional heterogeneity, both before and after controlling for observable characteristics. Second, in the absence of a liquid secondary market, optimal policy and welfare calculations are likely to be sensitive to the ex post distribution of outflows across funds.⁴²

³⁸ Angeletos and Werning (2006) present a model in which a subset of (better informed) investors receive a noisy signal about redemptions of other (less informed) investors. They consider this public signal in conjunction with their own private signals prior to making their decisions.

³⁹ On September 19, 2008, Ameriprise sued the Reserve Management Company, alleging that larger institutions were tipped off about the Primary Fund's holdings of Lehman on Monday, September 15, but not smaller investors. Note that the information from the August 31, 2008 portfolio report was not filed with the SEC until October 29, 2008.

⁴⁰ Admittedly, the simultaneity of $Low_{i,t}$ and $High_{i,t}$ makes this test somewhat more crude, particularly with respect to interpreting the coefficient on $High_{i,t}$. However, the main coefficient of interest is the interaction term.

⁴¹ Global games models with sufficiently precise private information result in a unique equilibrium and so allow for clear predictions and comparative statics results; our Proposition 1 is an example of this. However, these conditions may not hold, leaving a role for multiplicity and for nonfundamental sources of volatility to affect outcomes. See Echenique and Komunjer (2009) and Angeletos and Pavan (2013) for further details about this robustness property.

⁴² This is true even if all funds face the same ex ante run risk, particularly if there is nontrivial heterogeneity in portfolio holdings. This would be the case if, for example, fund-level redemption costs are a convex function of outflows. If runs are concentrated at a small number of funds, those assets that are overweighted by these funds are

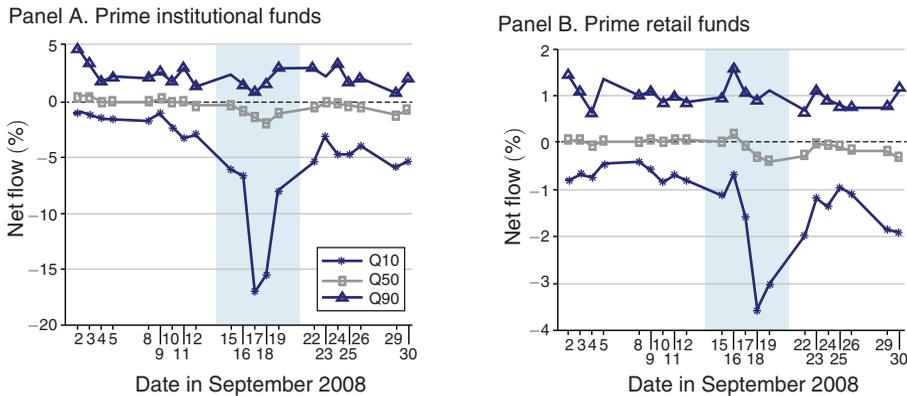


FIGURE 4. QUANTILES OF DAILY FLOW DISTRIBUTIONS BY CATEGORY DURING SEPTEMBER 2008

Notes: This figure plots the 10th, 50th, and 90th daily quantiles of $\log(\text{fund level})$ aggregated prime institutional share class total net assets (i.e., daily fraction flows) in panel A, and prime retail in panel B, during September 2008. The week following the failure of Lehman Brothers, September 15–19, is shaded.

Figure 4 plots the 10th, 50th, and 90th quantiles of the daily percentage change in total assets under management (flow) for each fund within prime institutional and prime retail share classes (each dollar-aggregated within the fund). During the period ending on Friday, September 5, 2008, one week prior to the Lehman bankruptcy, the distribution of flows across prime institutional share classes (panel A) is fairly tight. However, the distribution widens during the following two weeks; massive redemptions are highly concentrated among a small subset of funds. For instance, the tenth percentile, on September 17, experiences outflows greater than 15 percent of prior-day total net assets. In contrast, the median fund experiences an outflow of about 2 percent on the same day.

While the pattern of flow quantiles for prime retail share classes (panel B) is qualitatively similar to that of prime institutional share classes, retail investors exhibited a much more muted response to the crisis. Furthermore, peak outflows among retail funds occurred on September 18, a day later than peak outflows among institutional funds. Those few retail investors who redeem only do so after information from the popular media becomes widely available (on September 17–18) about the evolving crisis.⁴³

Next, we estimate a dynamic model for the distribution of flows, as summarized by these tenth, fiftieth, and ninetieth percentiles of daily changes in fraction flows, given observable characteristics, using dynamic panel quantile regressions.⁴⁴ In this

likely to face substantial selling pressure, potentially leading to fire sales, followed by further outflows. These fire sales could also create lucrative opportunities for funds which do not experience excessive outflows, since yields on the distressed assets would rise due to these frictions, creating an additional incentive for investors to move their money in the same direction as other investors. Not only might redemptions be absorbed more easily in the former, relative to the latter case, but there is also less likelihood of amplification through future withdrawals.

⁴³ See, for example, Tara Siegel Bernard, "Money Market Funds Enter a World of Risk," *New York Times*, September 17, 2008, http://www.nytimes.com/2008/09/18/business/yourmoney/18money.html?_r=0.

⁴⁴ For simplicity, we now refer to the aggregate of prime institutional share classes as a prime institutional fund, but the readers should be reminded that a fund can consist of both prime institutional and prime retail share classes.

way, we can determine whether fund and/or investor characteristics differentially influence flows in different parts (e.g., the center versus tails) of the conditional cross-sectional distribution. Other than lagged fund flows, our model includes the following covariates: %*Soph* investors (prime institutional share classes with $ER \leq 35$ bps/year), logged flow standard deviation, average yield, and logged fund total assets.⁴⁵ We estimate the relevant parameters using the sequential semi-parametric method of Schmidt and Zhu (2016), and calculate standard errors using simple bootstrap procedures.⁴⁶ As in Table 6, we allow the coefficients of the dynamic model to change between early and peak crisis periods. Further details and estimates for the model are provided in the online Appendix.

We use our fitted model to simulate the impact of perturbations in initial observable characteristics on one-week (cumulative) flow distributions.⁴⁷ Table 7 presents a summary of this simulation, which provides two primary insights. First, as shown in the first row of Table 7, regardless of fund characteristics, there is substantial heterogeneity in fund flows even for funds with similar observable characteristics. Second, we find much stronger evidence (statistically and economically) of a nonlinear dependency of flows on investor characteristics in left-tail quantiles (1 percent and 5 percent), relative to the median or right tail quantiles (50 percent and 90 percent). For example, at the one percentile of flows (the largest outflows), a one standard deviation perturbation upward in the percentage of a prime institutional fund owned by sophisticated investors is expected to produce an outflow that is 20 percent of assets greater than that of a one standard deviation perturbation downward; at the median, this sensitivity is a much lower 9 percent of assets; a statistical test that the difference between the impact of %*Soph* between these two quantiles is zero exhibits a p -value of 2 percent. Compared to these effects, the nonlinear impact of the yield and fund total asset variables are somewhat muted. Given the backward-looking nature of the reported yield, it is likely that such information quickly became stale during the fast-moving Lehman week. Finally, the (lagged) flow standard deviation has a modest effect on the median (-5 percent), but increases the spread of the distribution.

VII. Conclusion

This paper studies prime MMMF run-like behavior during the crisis period following the Lehman default of September 2008. We find that run behavior was especially pronounced among prime MMMF share classes that cater predominantly to very large-scale institutional investors. We use data on different share classes within

⁴⁵To account for asymmetries in fund flows, our model allows lagged fund flows above the cross-sectional median flows to have a differential effect, relative to lagged fund flows below the median. Moreover, to keep the specification simple (as quantile regressions already use a large number of degrees-of-freedom), we employ only four covariates, but our results are robust to including other covariates in the model. Furthermore, for robustness, our results winsorize the lagged flow variables and the flow standard deviation at their 2 percent values within each tail.

⁴⁶We use a clustered bootstrap, where we construct our bootstrap-sampled data by drawing a complete fund time series with replacement, which allows for arbitrary serial correlation in the residuals within funds.

⁴⁷We fix initial values for the fund characteristics, yielding initial conditional quantile forecasts, and simulate from a parametric distribution which satisfies the conditional quantile restrictions. Substituting this simulated draw into the law of motion from the estimated model generates conditional quantile estimates for the next day. Iterating forward, we are able to trace out the (simulated) distribution of cumulative flows over the course of the crisis. Further details, along with some additional graphical results, are in the online Appendix.

TABLE 7—MARGINAL EFFECTS OF FUND CHARACTERISTICS ON CUMULATIVE FLOW QUANTILES

Variable	Value	Cumulative flow quantile				
		1%	5%	10%	50%	90%
	$f(\bar{x})$	-52.02	-41.30	-35.81	-17.24	0.62
%Soph	$f(\bar{x} + \sigma_x)$	-62.30	-50.29	-44.18	-21.96	-0.47
	$f(\bar{x} - \sigma_x)$	-42.22	-32.87	-28.19	-12.93	2.59
	Difference	-20.08	-17.42	-15.99	-9.03	-3.06
	<i>p</i> -value	[0.003]	[0.002]	[0.001]	[0.001]	[0.170]
	<i>p</i> -value versus median	[0.020]	[0.019]	[0.018]	-	[0.046]
Average gross yield	$f(\bar{x} + \sigma_x)$	-55.04	-44.07	-38.51	-19.18	0.03
	$f(\bar{x} - \sigma_x)$	-48.92	-38.42	-33.04	-15.17	1.54
	Difference	-6.12	-5.65	-5.47	-4.02	-1.50
	<i>p</i> -value	[0.052]	[0.038]	[0.030]	[0.012]	[0.221]
	<i>p</i> -value versus median	[0.181]	[0.173]	[0.167]	-	[0.144]
log flow standard deviation	$f(\bar{x} + \sigma_x)$	-63.18	-50.45	-43.72	-19.36	10.86
	$f(\bar{x} - \sigma_x)$	-42.28	-33.14	-28.64	-14.42	-2.18
	Difference	-20.90	-17.31	-15.08	-4.94	13.04
	<i>p</i> -value	[0.000]	[0.000]	[0.000]	[0.013]	[0.014]
	<i>p</i> -value versus median	[0.000]	[0.000]	[0.000]	-	[0.000]
log fund total assets	$f(\bar{x} + \sigma_x)$	-56.93	-45.97	-40.31	-20.57	-0.32
	$f(\bar{x} - \sigma_x)$	-46.90	-36.32	-31.08	-13.49	2.74
	Difference	-10.02	-9.64	-9.23	-7.08	-3.06
	<i>p</i> -value	[0.042]	[0.019]	[0.011]	[0.001]	[0.163]
	<i>p</i> -value versus median	[0.257]	[0.235]	[0.221]	-	[0.090]

Notes: This table shows the impact of explanatory variables on cumulative flow distributions (as a percentage of initial assets) for prime institutional share classes (aggregated to the fund level) for the September 15–19 period. These estimates are obtained by simulating from an estimated dynamic quantile panel regression model for daily flows that is further described in the online Appendix. Columns report the 1st, 5th, 10th, 50th, and 90th quantiles of the cumulative flow distributions, respectively. We begin by fixing each of the explanatory variables at its average, assuming that the initial value of lagged flows equals the prime institutional category average. Then, we report the impact on the simulated flow distribution of adding and subtracting one standard deviation to each explanatory variable, as well as *p*-values for a test of whether the difference in the simulated quantiles is statistically significant, obtained by using the bootstrapped distribution of parameter estimates from our model, as well as the *p*-value of whether the marginal effect is significantly different at a given quantile, relative to the marginal effect at the median (using the bootstrapped distribution).

the same fund to identify differences in the flow behavior of sophisticated (low expense ratio) versus less sophisticated (high expense ratio) investors, keeping portfolio holdings and other fund characteristics, such as implied sponsor subsidization, constant. Our empirical tests show strong evidence consistent with strategic complementarities playing an important role in investor actions during the crisis.

In addition to these tests, our paper provides a set of new empirical findings which shed light on theoretical models of runs on financial intermediaries. First, we show that runs can develop and evolve in a matter of days, and that they involve important feedback effects from past flows on following-day flows. Second, we show that it is difficult to identify, *ex ante*, which funds are subject to runs, although there is clear evidence that large scale investors are keenly aware of the quality of the fund holdings, the financial strength of the fund advisor, and the characteristics of other investors in the same funds.

We draw several policy conclusions from our findings. First, the presence of retail share classes and small-scale share classes weaken the strategic incentives for large-scale institutional investors to redeem their shares. This may have implications for the latest round of regulatory reforms, which require both a floating share price (NAV) and no commingling of portfolio assets between an institutional and a retail share class. Our results suggest that, even if floating net asset values weaken complementarities, the segregation of institutional money might strengthen the strategic complementarities among institutional investors; the size of this effect will depend on the mix of sophisticated versus unsophisticated institutions within a given fund that results after the segregation is implemented. Indeed, our empirical results on ultra-short bond funds, which already carry floating share prices, indicate that such complementarities may persist in prime institutional MMMFs after October 2016.

Finally, our paper brings some suggestions for future research, some of which may carry implications for commercial banks. That is, our findings suggest that further theoretical work is needed on the stability of pooled funds with a large and time-varying maturity and/or liquidity mismatch between assets and liabilities. Most theoretical models tend to consider a static environment, where a single financial institution interacts with investors in isolation, whereas the run-like episodes of the recent financial crisis simultaneously affected multiple financial institutions. Our results shed additional light on the role of market-wide conditions in affecting run-like behavior at individual institutions, which may inform future theoretical work that more fully models the feedback between markets and pooled vehicles that are both under stress.

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