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Lawrence Schmidt, Allan G Timmermann
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# RUNS ON MONEY MARKET FUNDS

**Lawrence Schmidt, University of California, San Diego**
**Allan G Timmermann, University of California, San Diego, and CEPR**
**Russ Wermers, University of Maryland**

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Centre for Economic Policy Research
77 Bastwick Street, London EC1V 3PZ, UK
Tel: (44 20) 7183 8801, Fax: (44 20) 7183 8820
Email: cepr@cepr.org, Website: www.cepr.org

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# ABSTRACT

## Runs on Money Market Funds*

We study daily money market mutual fund flows at the individual share class level during the crisis of September 2008. The empirical approach that we apply to this fine granularity of data brings new insights into the investor and portfolio holding characteristics that are conducive to run-risk in cash-like asset pools, as well as providing evidence on the time-series dynamics of runs and the equilibria that develop. We find that outflows during the crisis are concentrated among those money funds with higher promised yields, less liquid portfolios, low implicit sponsor backing, and higher prior flow volatility that cater to very large-scale institutional investors. Our data uniquely allows us to study the strategic redemption behavior of investors with differing levels of sophistication by studying flows to different share classes of the same money fund, thus holding constant the quality of the underlying portfolio. Our results are consistent with the most sophisticated (largest scale) institutional investors exhibiting the greatest level of strategic redemptions during the crisis, which created significant negative externalities for more passive institutional investors.

JEL Classification: G01, G21 and G23
Keywords: bank runs, money market mutual funds, quantile regression and strategic complementarities

Lawrence Schmidt
Department of Economics
University of California, San Diego
9500 Gilman Drive
La Jolla CA 92093-0553
USA

Email: lschmidt@ucsd.edu

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Allan G Timmermann
University of California San Diego
Rady School of Management
9500 Gilman Drive
La Jolla CA 92093-0553
USA

Email: atimmerm@ucsd.edu

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Russ Wermers
Smith School of Business
University of Maryland at College Park
College Park,
MD 20742-1815
USA

Email: rwermers@rhsmith.umd.edu

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid=171524

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# 1 Introduction

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 shadow banking system.[1] As a case in point, many types of intermediated asset pools suffered run-like behavior during the recent financial crisis, e.g., exchange-traded funds, asset-backed SIVs, and ultrashort-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 (e.g., mortgage-backed securities, certificates of deposit, or repos). The crisis highlighted that run-like behavior can occur in a far broader set of pooled vehicles than simply bank deposits.

In this paper, we bring unique evidence to the study of run-like behavior in pooled investment vehicles by studying the crisis in money market mutual funds following the bankruptcy of Lehman Brothers on September 15, 2008. On September 16, a single money market mutual fund that held 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. The following day, run-like behavior spread to many other money market mutual funds that cater to institutional investors. Specifically, prime (non-government) money market mutual funds like the Reserve Primary Fund, which invest in commercial paper, repurchase agreements, bank certificates of deposit, and Eurodollar deposits, suffered outflows from institutional investors totaling roughly $300 billion during the week of September 15-19, 2008, even though many of these funds held little or no Lehman debt, and even though no other funds announced to their investors that they broke the buck during that week.

Even a cursory examination of the money market mutual fund crisis strongly suggests that

[1]Allen et al. (2009) point out that "modern runs typically involve the drying up of liquidity in short term capital markets (a wholesale run) instead of, or in addition to, depositor withdrawals from a financial intermediary." Gennaioli et al. (2013) analyze the potential for instability in the shadow banking system due to investors' neglect of tail risks.

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.[2] Indeed, the rules governing money market mutual funds, under Rule 2a-7 of the Investment Company Act of 1940, promote this wide diversification to reduce idiosyncratic exposure, which leads to an increased exposure to extreme aggregate risks, as modeled by Gennaioli, Shleifer, and Vishny (2013).[3] But, the precise mechanism through which this common exposure played out during the crisis week is as yet unknown, and is crucial in preventing another money market mutual fund crisis, or crises in similar intermediated pools having cash-like liabilities paired with assets carrying liquidity risk. For instance, it is crucial to understand whether funds with certain observable portfolio and/or investor characteristics are more susceptible to run-like behavior.

The money market mutual fund (henceforth, MMMF) crisis of September 2008 presents a unique natural experiment that enables a study of the mechanism driving investor runs from a broad segment of similar intermediated portfolios, including whether investors focused their redemptions on funds with lower quality fundamentals in their holdings and on funds with a greater proportion of investors acting strategically. Indeed, few market observers could foresee the sudden collapse of Lehman, and fewer still predicted that the U.S. Treasury would not intervene to save the firm.

Compared with commercial banks, our data on MMMF flows are unique in several dimensions that allow unique insights into the mechanism of runs; our dataset has a high level of granularity in both the cross-sectional and time domains.[4] And, as we will see, during the week of the crisis, runs evolve very quickly. As emphasized by He and Manela (2013), Gu (2011), He and Xiong (2012), and Angeletos, Hellwig, and Pavan (2007), runs are intrinsically dynamic, so it is important to document how they unfold, and how agents learn in "real time." Our daily data on investor flows within each share class allows an analysis of these run dynamics; for instance, we find that less-

[2]An important exception are those money market mutual funds that were overly exposed to asset-backed commercial paper issued by vehicles holding large fractions of subprime real estate loans.

[3]In the model of Gennaioli, et al. (2013), investors' neglect of tail risks can lead to over-exposure to a common risk factor and a sudden dry-up of market liquidity. The failure of Lehman in September 2008 can plausibly be viewed as one such tail risk which unexpectedly made investors realize that they might be exposed to aggregate tail risk in the form of financial institution-related short-term debt obligations.

[4]In 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 vehicles.

informed investors (those with a lower scale of investment) follow more highly informed (large scale) investors, consistent with a prediction of He and Manela (2013).[5] Further, we create a "real-time" *daily* estimate of the level of highly liquid assets in each MMMF by subtracting daily outflows from the level of cash and maturing assets (e.g., commercial paper) remaining at the end of the prior day; with this estimate, we find evidence of "liquidity spirals," a la Brunnermeier and Pedersen (2008), among funds with the fastest deterioration in daily portfolio liquidity during the crisis week.

Another advantage conferred by our data is that MMMF asset holdings and investor types are far more transparent than those available from banks; this increases both the ability of investors to observe daily changes in money fund portfolio and investor makeup, and the ability of the econometrician to measure many different characteristics of money funds on a daily or weekly basis. Specifically, our dataset contains information on the type of investor (institutional or retail, as well as the scale of investment) that resides within a given share class, in addition to weekly summary statistics on the characteristics of the portfolio holdings of each fund (liquidity, yield, and allocations to asset class categories, such as commercial paper or repos) and the characteristics of their management companies ("deep-" vs. "shallow-pockets"). The cross-sectional and time-series granularity of our data allow us to study many "bank-like" vehicles—MMMF share classes—having many different types of investors (very large scale vs. smaller scale) under many different types of institutional arrangements (for instance, implicit insurance—deep management company pockets—vs. partial or no insurance).

We use these features of our data to shed light on recent 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. The precise information structure assumed often plays a critical role in global games models with strategic complementarities. 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

[5]He and Manela (2013) study the interaction between rumors about bank vulnerability (illiquidity) and depositor withdrawals, especially in situations with endogenous (and costly) information acquisition. The possibility that more-informed investors could uncover unfavorable information about a fund's assets may trigger a run among less-informed investors, as they fear being left behind. In a similar vein, Iyer and Puri (2012) study investor redemptions using intraday data for a single Indian bank.

(Goldstein and Pauzner, 2005). Weak fundamentals trigger a run, but the run would not have occurred were it not for agents' self-fulfilling beliefs, which amplify the effect of a bad draw of fundamentals. 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 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.[6]

Such interactions between strategic behavior and fundamentals makes empirical identification of strategic complementarities very difficult (Goldstein, 2013). To meet this challenge, we propose two novel identification strategies, both of which exploit the rich granularity of our MMMF data.

Our first, and simplest, identification strategy is made possible by our daily data on flows to different institutional share classes within the same prime (non-government) MMMF portfolio. With these unique data, we can cleanly identify differences in flows related to clientele characteristics versus differences arising from the characteristics of portfolio holdings or the implicit backstop of the fund sponsor (management company), since different share classes within the same fund differ only in their clientele.[7] Importantly, different share classes typically carry different expense ratios, with the largest scale investors paying lower fees than smaller scale investors. Thus, we study the interaction between redemptions of investors in share classes with lower expense ratios (larger investment minimums) and investors in share classes with higher expense ratios (smaller minimums), both residing within the same fund. 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 potentially

[6]Earlier studies reflect more purely information-based versus panic-based/strategic runs. Information-based theories (Jacklin and Bhattacharya, 1988; Allen and Gale, 1998) explain run dynamics through individual banks' insolvency or "poor fundamentals". Extensions of this mechanism include asymmetric information models (Chari and Jagannathan, 1988, and Chen, 1999), which suggest that withdrawals of money by some (better informed) investors trigger further withdrawals from worse-informed investors, who infer from the early-movers that fundamentals must be poor. A different perspective is offered by the theory of runs that result purely from strategic behavior or from panics (Bryant, 1980, Diamond and Dybvig, 1983, or the sunspot model of Bacchetta, et al. 2012).

[7]That is, investors in each share class of a given money market fund participate, pro-rata, in any portfolio losses, as well as in any sponsor bailouts.

better informed than their smaller counterparts. This share class-level approach offers us a path to identify if flows are due to information cascades (about portfolio fundamentals), or due to strategic complementarity issues (i.e., the fear that other investors' selling activities could impose a negative externality on one's own investment).

Accordingly, we estimate vector autoregressions for a model that explains flows to both low and high expense share classes within the same MMMF portfolio, which includes lags of each as explanatory variables, as well as a term that interacts lagged (fraction) flows from high-expense share classes with the proportion of total fund assets that high-expense share classes represent. We find strong evidence that the most sophisticated (low expense) investors are more likely to be among the first movers, and are more responsive to measures of portfolio quality than less sophisticated investors. We also find evidence that better informed (low expense) investors act strategically in response to actions by their less-informed (high-expense) counterparts within the same MMMF. Specifically, large-scale institutional investors redeem more strongly in response to the redemptions of smaller-scale institutions (in the same fund) when these small investor redemptions represent a large share of fund assets, consistent with large investors reacting to the magnitude of strategic complementarities posed by small investor actions. These results reinforce theories that predict that self-fulfilling runs are more likely to occur when fundamentals weaken beyond a critical value.[8]

Our second identification strategy uses the connection in the theoretical literature between strategic complementarities and multiple equilibria (or fragile, unique equilibria exhibiting strong nonlinearities), which suggests that pooled investment vehicles with very similar characteristics, ex-ante, could experience very different equilibrium outcomes, ex-post. For instance, strategic investors may run on randomly chosen funds, or they may use the strength of fundamentals to coordinate. In the latter case, we should observe substantial heterogeneity in the fund flow distribution and its dependency on investor and fund characteristics. Therefore, we employ a quantile regression approach, since it is able to measure the heterogeneity in outflows at different points in the flow distribution, as well as the heterogeneity in the sensitivity to fund and investor character-

[8]Global games models of bank runs, e.g., Goldstein and Pauzner (2005), typically divide the support of the fundamental into three regions: (1) the fundamental is sufficiently weak that the fund is liquidated regardless of any depositor behavior, (2) the fundamental is sufficiently strong that the fund always survives, and (3) the fund's survival depends on the number of withdrawals. Liquidations, which occur in this third region of the support, result from coordination failures and are often referred to as "panic-based" runs.

istics at different points.[9] As shown by Echenique and Komunjer (2009), when multiple equilibria are present and the dependent and independent variables exhibit complementarity, quantile econometric models are well-suited for identification of otherwise difficult to measure relations between these variables by examining these relations in the tails. For example, in our case, the relation between a lower expense ratio and investor flows during the crisis may change as we examine share classes with differing levels of the dependent variable, investor flows. By focusing on tail regions in the dependent variable–large outflow or large inflow share classes–we can identify the sign and magnitude of the effect of the independent variable–expense ratio–on the dependent variable, thus, identifying the particular equilibria that might be present in these tails.

We find that, ex-post, outflows of MMMFs during the crisis occur in a very heterogeneous way. Although outflows from prime (non-government) MMMFs appear to reflect a general "flight-to-quality" (i.e., to safer cash vehicles), we find that investors in a small minority of funds exhibit the bulk of run-like behavior. Further, we provide evidence about the types of funds that are more likely to exhibit investor runs. First, prime institutional shareclasses exhibit much larger persistence in outflows than retail shareclasses, although retail investors also exhibit some run-like behavior (that lag the outflows of institutions). Next, we find that prime institutional shareclasses that have greater levels of assets, have a lower proportion of highly liquid assets, have a lower expense ratio, are a member of a fund complex with a larger proportion of prime institutional money (as a fraction of total complex money market assets), have higher lagged flow volatility, and/or have higher average yields exhibit greater outflows during the crisis week of September 2008. That is, our estimates suggest that more sophisticated (larger scale and more volatile) institutional "hot money" chase yields and invest in larger, lower-expense funds prior to the crisis; further, this hot money is able to more quickly (relative to other institutions) assess the riskiness of the portfolio and the potential of a complex to "backstop" its institutional funds when deciding on whether to redeem from a MMMF during the crisis.

Although we find that observable fundamentals play a substantial role in explaining outflows,

[9] Angeletos and Pavan (2011) propose a similar identification scheme, arguing that the size of the equilibrium set can be used to identify the mechanism of the model. Our quantile approach allows us a means to measure the fraction of funds in each segment of the flow distribution, as well as the differential impact of investor and fund characteristics in each segment. This allows insights into the type of equilibria that our empirical results support.

a significant residual component remains, suggesting that a purely "fundamentals" based run equilibrium does not adequately describe the crisis. For example, we find a significant probability of a daily outflow as large as 25% of assets, even among funds with comparatively safe fundamentals; thus, strategic externalities are also an important driver of outflows during the crisis. Our above-mentioned findings suggest how these strategic interactions play out between large and small institutional investors.

Our findings contribute to several empirical literatures on financial crises. First, we present new evidence of strategic complementarities, consistent with results in recent work by Chen et al. (2010) and Hertzberg et al. (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 Schmukler (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 et al. (2013), Acharya et al. (2013), and Schroth et al. (2014), who provide evidence of run-like behavior by financial intermediaries in the repo and asset-backed commercial paper markets.[10] Also related are contemporaneous studies on money market events of 2007-2008, e.g., McCabe (2010), Jank and Wedow (2010), Brady et al. (2012), Kacperczyk and Schnabl (2013), Duygan-Bump, et al. (2013), and Strahan and Tanyeri (2014).

Our paper proceeds as follows. Section 2 provides a brief background on money market mutual funds and reviews the events of the crisis. Section 3 discusses our dataset. Section 4 presents evidence of strategic behavior based on the share class data, while sections 5 and 6 analyze how fund- and investor characteristics affected run probabilities and the dynamics of fund flows. We conclude in section 7.

[10] A key source of fragility in these markets, which differs from the money market, is rollover risk; see, e.g., He and Xiong (2012). However, MMMFs are one of the primary sources of demand for these assets. Parlatore (2014) shows how strategic complementarities in MMMF sponsors' support decisions can create incentives for MMMF sponsors to run on the asset (e.g., repo and ABCP) markets.

## 2 The Money Market Mutual Fund Crisis of 2008

Banks and money market mutual funds (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). Thus, MMMFs provide a novel laboratory to study the mechanisms of runs. In addition, MMMF data provide a unique test bed, since we observe daily flows from different investor types in each MMMF (e.g., institutional versus retail share classes, and large-scale vs. smaller-scale institutional share classes). Further, we can observe characteristics of the advisory company overseeing the MMMF, such as the size and scope of their asset management services. Such data are not readily available to researchers for banks and their deposit accounts.

Rule 2a-7 of the Investment Company Act (ICA) of 1940 allows MMMFs to value investor shares at the "amortized cost" or "book value" of assets—an accounting-based rather than a market-based principle. This provision of the ICA allows MMMFs to maintain a constant $1.00 per share net asset value, as long as they follow the portfolio holdings requirements of Rule 2a-7. These requirements include restrictions on the maturity, credit quality, and issuer diversification of portfolio holdings. However, valuing MMMFs at amortized cost creates the potential for a run, because the fund's price per share (which is based on book value) can diverge from the market value of the fund's underlying portfolio securities. In a large sense, investors who redeem at book value represent debtholder-like claims on assets, which can be destabilizing if the per-share market value drops below the book value by a substantial amount. Further details on the MMMF industry are in Appendix A.1.

Prior to September 2008, Rule 2a-7 had worked well to control risks. From the adoption of Rule 2a-7 by the SEC in 1983, until September 2008, a period during which hundreds of banks and thrifts failed, only a single MMMF had "broken the buck" (i.e., failed to return $1.00 per share). Even that event went largely unnoticed, because the fund was small and held by a limited number of institutional investors (primarily banks).[11]

[11] The Community Bankers US Government Fund broke the buck in 1994. It was an institutional fund, and paid investors 96 cents per share.

Numerous traumatic economic events had occurred since August 2007, putting considerable pressure on MMMFs. From August 2007 to August 2008, several unregulated liquidity pools used by institutional investors failed, both in the U.S. and elsewhere. This led to vast inflows to MMMFs, as these institutional investors turned to the tighter regulatory provisions required of MMMFs under Rule 2a-7, and, perhaps, to the implicit backup of sponsors for their MMMFs in a time of peril. It is very likely that this vast inflow of money believed there was little chance that a systematic risk event would significantly impact the mutual fund industry, setting the stage for the widespread impact of a common extreme risk event, as modeled by Gennaioli et al. (2013).

Then, the Federal Government declined to assist a reeling Lehman Brothers, which failed on September 15, 2008. On September 16, 2008, the Reserve Primary Fund (which held about $750 million in commercial paper issued by Lehman Brothers) disclosed that it had broken the buck. Immediately, other prime MMMFs began to see vast outflows totaling over $300 billion within a few days.[12] With credit markets seizing up, prime MMMFs struggled to sell securities to meet these redemptions. On Friday, September 19, 2008, the U.S. Treasury offered a guarantee to MMMFs in exchange for an "insurance premium" payment. Several other U.S. Government guarantee programs were announced on that day and during the ensuing weeks to stabilize MMMFs and short-term fixed-income markets. By the end of October 2008, large-scale redemptions essentially ceased. Further details on key events of September and October 2008 are provided in Appendix A.2.

Figure 1 (top panel) shows daily flows to or from MMMF categories during September and October 2008. Specifically, we report the daily percentage change in aggregate assets under management for prime institutional, prime retail, government institutional, and government retail share classes. Daily outflows from prime institutional share classes amount to more than 10% on September 17, 2008. Movements out of prime retail share classes are far more subdued. In contrast, MMMFs holding U.S. Government-backed securities (mainly Treasuries and agencies) experience strong inflows, as investors seek the liquidity of the U.S. Government market as safety. On a cumulated basis, the bottom panel of Figure 1 shows that the flows out of prime institutional share classes

[12] There is some debate about this figure, as State Street, the custodial agent, apparently froze the assets of the Reserve Primary Fund after the exodus of about $10 billion. The $300 billion figure includes redemptions that were sent, but not honored by shareholders of this fund. See, for example, http://www.sec.gov/spotlight/reserve_primary_fund_investors/gardephe_opinion.pdf. We thank Pete Crane for pointing this out.

amounts to \$400bn during the first two weeks of the crisis. Movements into or out of retail share classes were far smaller, by comparison.

Moreover, these massive category-level outflows were far from equally distributed across funds. To demonstrate this, we calculate the daily percentage change in total assets under management ("flow") for each fund within each category (e.g. prime institutional). For each fund, we compute aggregate daily flows for prime institutional share classes; we separately aggregate for prime retail share classes. For each date in the period of interest, Figure 2 displays the $10^{th}$, $50^{th}$, and $90^{th}$ quantiles of flows for the cross-section of (aggregated) prime institutional and prime retail share classes, respectively.

The top panel of Figure 2 shows that, during the period ending one week prior to the Lehman bankruptcy announcement (Friday, September 5, 2008), the distribution of flows across prime institutional share classes is fairly tight, as indicated by the vertical distance between the $10^{th}$ and $90^{th}$ quantiles. However, the distribution widens during the following week (September 8-12), and further widens on Monday, September 15; this dispersion continues to be abnormally wide during the next several weeks, finally tightening and becoming more stable by the end of October. These observations indicate that, ex post, the massive category-level redemptions are highly concentrated among a small subset of funds. For instance, the $10^{th}$ percentile on September 17 experienced outflows greater than 15% of prior-day total net assets! In contrast, the median fund experienced an outflow of about 2% on the same day.[13]

The lower panel of Figure 2 shows cross-sectional quantiles of flows from prime *retail* share classes. While the pattern of flow quantiles is qualitatively similar to that of prime institutional share classes, the distribution remains much tighter (note that the graph has been magnified, so that the difference between the $10^{th}$ and $90^{th}$ quantiles is, at most, roughly 5% of total net assets on September 18). Thus, retail investors had a more muted response to the crisis. It is also interesting that peak outflows among retail funds occurred on September 18, one day later than peak outflows among institutional funds. Those few retail investors who redeem only do so after information from

[13]It should be noted that a broader run might have occurred, had the crisis played out longer, or if the Federal Reserve Bank and some fund advisors had 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.

the popular media becomes available about the evolving MMMF crisis.

## 3 Data and Initial Results

Our data are purchased from iMoneyNet, a company that collects daily information from over 2,000 U.S. registered money market mutual funds (MMMFs) that invest primarily in U.S. short-term, dollar-denominated debt obligations, and cover the period from February 2008 to June 30, 2009. These MMMFs are offered to retail as well as institutional investors, through different share classes, which are often claims on the same fund security holdings. The iMoneyNet data consists of fund investment objective, fund family/adviser (i.e., "complex"), share class type (i.e., retail vs. institutional), daily total net assets and portfolio average maturity by share class, and weekly sector breakdown of portfolio holdings. Importantly, the data includes 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; expense ratios are inversely related to the required investment minimums for share classes–the lowest expense ratio share classes are accessible only to the largest-scale institutional investors.

We measure several covariates to capture fund and investor characteristics. Fund characteristics are chosen to represent different indicators of the quality of portfolio fundamentals.[14] Investor characteristics are chosen to represent the average quality of investors' private information as well as the tendency to quickly move money. Specifically, we consider

- Average yield, $AVGYIELD$, defined as the average value of the (annualized) 7-day gross yield of fund portfolio holdings from March-August 2008;
- Fund-level expense ratio, $EXPR$, calculated as a TNA-weighted average of share class-level expense ratios;
- Standard deviation of daily log fund flows, $FLOWSTDEV$, calculated using data from March-August 2008;

[14] By "fundamentals," we refer to predetermined characteristics of funds' investments and/or the characteristics of the fund management companies. These variables would affect investors' payoffs regardless of the behavior of other investors (i.e., variables which set the threshold level of redemptions that a fund could sustain without breaking the buck).

- Proportion of total money market mutual fund assets, for a complex (e.g., Fidelity), represented by prime institutional share classes, $PIPERC$;
- Fund size (logged), $LOGTNA$, the sum of total net assets of all share classes (within the category) of a given MMMF; and
- Proportion of fund assets represented by liquid portfolio holdings, $LIQUIDRT$, which is a daily estimate of highly liquid assets available as a fraction of total net assets, calculated by subtracting the difference between daily fund outflows and maturing assets from prior-day liquid assets.[15]

All of the above-mentioned 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.[16] We emphasize that a clean separation of covariates into those that purely represent fundamentals (payoffs) vs. investor characteristics (player types) is not possible. For instance, large-scale, well-informed investors may be attracted to funds with higher yields (weaker fundamentals), as they have the sophistication to enjoy higher yields (higher risk) while being among the first to exit should fundamentals begin to deteriorate in such funds. Or, a fund whose sponsor would face a particularly high reputational cost should one of its funds break the buck may choose to hold a less risky portfolio.[17] However, we identify variables that are more likely to be a good proxy for either fundamentals or investor size and/or sophistication (but not both). Further information on our dataset, including univariate summary statistics and correlations are available in Appendix A.3.

First, for fundamentals, we assume that $AVGYIELD$, $LIQUIDRT$, and $PIPERC$ proxy for, respectively, the overall quality (credit plus liquidity) of portfolio assets in a fund, the liquidity of

[15] Our definition of liquid assets follows Duygan-Bump, et al. (forthcoming) and equals the sum of portfolio weights of repos, Treasury securities, and U.S. agency notes. Asset holding data are available weekly, so we interpolate between weekly values using a method which is similar in spirit to the one in Strahan and Tanyeri (forthcoming). We observe the weighted average maturity of the portfolio on a daily basis, which is used to estimate the fraction of portfolio holdings which mature each day. We then compare this number with that day's 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.

[16] Closing-day TNA data is available by 8 a.m. the following morning, which allows a quick calculation of prior-day flows (thanks to Pete Crane for this information).

[17] Kacperczyk and Schnabl (2013) find evidence to support this conclusion.

these assets, and the insurance behind a fund provided by the implicit backing of a deep-pockets advisor. Second, we use $EXPR$ as a proxy for the level of investor sophistication, since expense ratio tends to be strongly inversely related to the scale of investment, with the lowest expense ratio share classes being the largest-scale, most well-informed, and most sophisticated investors (i.e., those with the most "skin in the game"). $LOGFLOWSTDEV$ represents the presence of "hot money" investors, i.e., the tendency for capital to enter/leave the fund over shorter periods of time, as does $LOGTNA$.[18]

## 4 Evidence of Strategic Behavior from Share Class Data

With heterogeneously informed investors, strategic behavior can unfold in at least two opposing ways in the presence of run externalities. First, He and Manela (2013) show that less-informed agents may optimally wait to observe the actions of early movers (who are, in equilibrium, better-informed) before running from a bank, after learning that the bank's portfolio liquidity may have been impaired by an event. 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). Conversely, in global games models with payoff complementarities, such as Chen et al. (2010), more-informed investors can react to the actions of less-informed investors due to the negative externalities (loss of fund liquidity) associated with the latter's actions.

Better-informed investors may also react to the prior-day redemption behavior of other well-informed investors. In the dynamic model of Angeletos et al. (2007), such investors update beliefs based on a noisy signal about the size of previous attacks and the observation that the regime survived any attacks in previous periods. Large prior attacks, ceteris paribus, reveal negative information about fundamentals, making future attacks more likely.[19] However, an institution's survival from previous attacks can cause investors to revise beliefs upward about the strength of fundamentals. In our setting, informed investors' response to prior-day redemptions of other informed investors reflects the relative importance of these two channels (the existence of large

[18]That is, the largest investors tend to gravitate towards the largest funds, as evidenced by a significant negative correlation between EXPR and LOGTNA.

[19]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.

attacks vs. the survival of funds after large attacks), which may change as the crisis unfolds.

Our MMMF data uniquely allow us to test the predictions of these different theories for the dynamics of runs on bank-like vehicles, since we have information on share class-level expense ratios of a particular MMMF. To explain, it is relatively common for multiple share classes with different levels of expense ratios to coexist in a single MMMF; these share classes always have identical (pro-rata) claims on the fund's assets. Thus, redemptions in one shareclass present strategic externalities for remaining investors in all shareclasses of a given fund equally, pro-rata. 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, while holding all other fund characteristics–notably portfolio quality–constant.

### *4.1 Investor Sophistication and Cumulative Outflows*

Large-scale institutional investors have more "skin in the game," consistent with them being better informed and more closely monitoring shifts in portfolio fundamentals as the crisis evolves (given the fixed costs associated with information acquisition). In Table 1, we cross-sectionally regress share class cumulative investor flow (computed as the first difference in daily log TNA, multiplied by 100, then summed over the five days) during September 15-19 on share class expense ratio (each share class among our prime institutional funds is represented with a single observation in this regression).[20] We find (models 1 to 3) that share class expense ratio is positively and significantly associated with following-day investor flow, regardless of whether fund or complex (e.g., Fidelity) fixed effects are included, meaning that larger-scale institutions redeem much more sharply than higher expense-ratio, smaller-scale institutions.[21]

[20]A fund fixed effect allows us to hold constant the quality of the portfolio as well as the implied insurance; alternatively, the coarser complex fixed effect provides a rougher control for fundamentals and implied insurance, while retaining the effect of differences in clientele across different funds.

[21]Our results are consistent with a prediction, developed and tested by Ziebarth (2013), from a version of the Angeletos and Werning (AW; 2006) model, in which a subset of agents observe a common signal about the behavior of other investors prior to making their decision whether to run. The AW model predicts that, for a sufficiently low level of fundamentals, the probability of a run is increasing in the fraction of well-informed agents.

Moreover, models 4 and 5 show that all of the impact of expense ratio is contained within those share classes having an expense ratio below 25 bps (basis points)/year. Above this breakpoint, there is essentially no effect of scale of investment (expense ratio) on crisis-week flows–indicating a nonlinear effect of scale of investment on tendency to run. We adopt a non-parametric approach in models 6 and 7. Here, we separate prime institutional share classes into finer groups; dummies represent expense ratios lower than 15, 25, and 45 bps per year, respectively.[22] (The base category (model intercept) represents funds with expense ratios above 45 bp; models 6 and 7 include complex and fund fixed effects, respectively.) Note that the lowest expense ratio segment, below 15 bps/year, exhibits a much higher level of outflows than the larger expense ratio breakpoints. Specifically, share classes with an expense ratio below 15 bps experience an additional percentage outflow of 42 log points (35% of AUM). Thus, run-like behavior is heavily focused in share classes with the very largest scale institutional investors. This finding is consistent with the most well-informed investors being the early movers during the crisis week, consistent with the model of He and Manela (2013).

### *4.2 Dynamic Interactions between Investor Types*

Next, to measure flow *dynamics*, we estimate a vector autoregression (VAR) model, where we partition each MMMF's share classes into those with (1) lower- and (2) higher-than-median expense ratios as of September 15, 2008 (columns $Low_{i,t}$ and $High_{i,t}$ in Panel A of Table 2).[23] To focus on dynamics within a given fund between its different scale of institutional investors, we aggregate, at the fund level, all flows across below-median share classes, as well as aggregating flows across all above-median shareclasses. Then, we implement a VAR with two dependent variables, where daily fraction flows to the aggregated fund-level low (or high) share class is regressed on its one-day lagged value, as well as the one-day lagged fraction flow of the high (or low) aggregated fund-level share class of the same fund. In implementing this VAR, (and in the remaining tables of the paper), we separately estimate the model coefficients over four separate sub periods: the "baseline" period (February 1 through September 9, 2008), the "early-crisis" period (Wednesday,

[22] Among funds with available data, the median level of minimum investment is $10 million, $3 million, $1 million, and $25,000 for funds with expense ratios less than 15 bp, between 15 and less than 25 bp, between 25 and less than 45 bp, and greater than 45 bp, respectively. Thus, scale of investment is strongly inversely related to expense ratio.

[23] Only funds with at least one share class above and one share class below the median are included here.

September 10 to Tuesday, September 16, 2008), the "peak crisis" period (Wednesday, September 17 to Friday, September 19), and the "late-crisis" period (September 22-October 17).[24] As control variables, we augment with several lagged fund characteristics described in Section 3.1: $EXPR$, $LOGFLOWSTDEV$, $LIQUIDRT$, and $PIPERC$, each scaled by its respective (cross-sectional) standard deviation, on each day.

Panel A of Table 2 indicates that, during the baseline period, flows are largely segmented, with each segment exhibiting a negative AR(1) coefficient–indicative of investors temporarily parking money in a MMMF between the sale of one asset and the purchase of another.

This picture changes dramatically during the early crisis and peak crisis periods. During the early crisis period, flows in each category become positively cross-correlated with a lag. Sophisticated (low expense ratio) investors react to less-informed (high expense ratio) investors' flow behavior, consistent with a strategic response to the negative externalities emphasized in Chen et al. (2010). As in He and Manela (2013), the cost of waiting can be lower when the average quality of other investors' information is low (e.g., their costs to acquire information are high); therefore, the presence of a large fraction of less-informed investors could give better-informed investors less of an incentive to redeem quickly.[25]

In the next column, we observe that smaller institutions primarily respond to the prior flow behavior of more sophisticated investors. Such a dynamic is consistent with the mechanisms in He and Manela (2013) and Angeletos et al. (2007), where large prior-day redemptions from well-informed investors cause less-informed investors to revise their beliefs downward about fundamentals. So, flow dynamics occur in both directions, with each investor type reinforcing the other's redemptions (or lack thereof); in other words, a feedback mechanism develops between small and large investors during the early days of the crisis.

By the time of the peak crisis period, after the Reserve Primary fund announces that it has "broken the buck," the behavior of smaller institutional investors is essentially unpredictable–

[24] Although Lehman declared bankruptcy on September 15, most market observers (as well as our summary flow statistics) support that the most intense run-like behavior by investors in MMMFs occurred from September 17 until September 19, the date of the first MMMF "breaking the buck" to the date when the Treasury and the Federal Reserve announced programs to support MMMFs and the commercial paper market.

[25] Hellwig and Veldkamp (2009), within a "beauty contest" game with endogenous information acquisition, demonstrate how strategic complementarities in payoffs generate complementarities in information acquisition as well.

consistent with Diamond and Dybvig (1988) panic-type behavior–while strategic redemptions of large investors, $Low_{i,t}$, become very responsive to prior redemptions from other large investors, $Low_{i,t-1}$.[26] During this period, an outflow of 1% by large institutional investors leads to a following-day outflow of 0.29% by other large institutions, suggesting that negative information and/or concerns about liquidation externalities dominate the positive information associated with the fact that no funds (except Reserve Primary) broke the buck at the end of the early crisis period. Thus, the dynamics of flows change from the early period to the peak period, with large investors now focusing on each other's moves. In the late crisis period (after the intervention of the Treasury and Fed), flows are largely unpredictable.

Coefficients on control variables offer further interesting results. During the baseline period, investors' search for higher yields makes them more likely to invest in MMMFs with less liquid portfolios. The sensitivity of flows to a one-standard deviation increase in $LIQUIDRT$ is about -10 bps/day. In addition, funds whose daily flows are more volatile, as indicated by $LOGFLOWSTDEV$, tend to have higher inflows, particularly in low expense ratio share classes.

Consistent with Table 1, the coefficient on $EXPR$ for the $Low_{i,t}$ model during the early crisis period suggests that a one standard deviation decrease is associated with a 57 basis point decrease in the average daily (log) flow to a fund (e.g., an increase in outflow) from large-scale investors.And, a one standard deviation below-average portfolio liquidity predicts outflows of 58 bp per day. Since such information is available from iMoneyNet early the following morning, initial redemptions from sophisticated investors are focused on funds most likely to have been affected by the systematic shock to credit quality/liquidity in the asset market. Further, the relationship between $LOGFLOWSTDEV$ and flows is large and negative, suggesting that early redemptions are much larger in funds with more "hot money."

The role of fund characteristics differs for high expense ratio share classes during the early crisis period. These smaller-scale institutional investors appear only to react to the creditworthiness of the fund management company: a one standard deviation increase in $PIPERC$, the proportion of a complex's money market business that resides in Prime Institutional share classes (the riskiest

[26]The magnitude of the three (fund-aggregated) high expense ratio share classes with the largest outflows are 52%, 45%, and 26% on September 17, 31%, 27%, and 23% on September 18, and 48%, 39%, and 34% on September 19. For the same dates and aggregated shareclass cross-section, the median outflows are only 1%, 2%, and 2%, respectively

category), is associated with an 77 bp per day increase in outflows. Thus, institutional investors with less "skin in the game" appear to be unable to discern whether portfolio fundamentals are deteriorating in their fund during the early days of the crisis, and look only at the stability of the advisor for comfort.

Moving to the peak crisis period, as overall market conditions continue to deteriorate, the response of large-scale investor flows to both portfolio and clientele characteristics significantly amplify. The coefficient on $EXPR$ for model $Low_{i,t}$ roughly doubles, while the coefficients on $LOGFLOWSTDEV$ and $LIQUIDRT$ more than triple.

During the late crisis period, fund characteristics play a relatively minor role, as all coefficients drop substantially in economic magnitude. The two statistically significant coefficients for $Low_{i,t}$ suggest mild evidence that strategic concerns may have motivated some larger investors to redeem even after the Fed's issuance of temporary deposit guarantees.

### *4.3 Additional Evidence of Strategic Behavior by Sophisticated Investors*

If large-scale investors are better-informed about fundamentals than smaller investors, one would expect lagged flows from large-scale investors to be more informative about portfolio quality. As such, any responses of well-informed investors to their more poorly informed counterparts should predominantly reflect strategic concerns. Recall that Panel A indicated that, conditional on $Low_{i,t-1}$ and $PIPERC$, $High_{i,t}$ is essentially unpredictable–particularly after the early crisis period–based on other observables throughout the crisis. Thus, the behavior of less informed investors adds an additional element of randomness which is almost orthogonal to fund characteristics to the potential payoffs of large-scale investors.[27]

To test whether large-scale investors react to outflows from small-scale investors because of strategic externalities, we add a term, in Panel B, that interacts $High_{i,t-1}$, high expense ratio lagged flow (as a fraction of prior day institutional AUM in the High category within a fund), with the lagged percentage of prime institutional assets within a given fund represented by aggregate high

[27]We speculate that such an outcome could happen if, for example, uninformed investors receive no private signals about the fund's portfolio quality and choose whether to redeem based only upon a public signal. Such a model would likely feature multiple equilibria because, for a sufficiently high concentration of uninformed investors, it closely resembles the Diamond-Dybvig (1988) model. In contrast, if there are no uninformed agents, then the model resembles the setup of a global games model–e.g., Goldstein and Pauzner (2005).

expense share classes (denoted by $\%High_{i,t-1}$). These specifications are located in odd columns of Panel B.[28] We would expect the direct coefficient of $Low_{i,t}$ on $High_{i,t-1}$, which represents any information conveyed by $High_{i,t-1}$, to be close to zero, as such investors have relatively little information about portfolio fundamentals (as we showed in Panel A). However, in the presence of strategic externalities posed by less-informed redemptions, we would expect the coefficient on the interaction term, $High_{i,t-1} \times \%High_{i,t-1}$, to be positive during the crisis; that is, when a greater fraction of fund assets are redeemed by small investors (i.e., $\%High_{i,t-1}$ is large, and $High_{i,t-1}$ is large and negative), large investors interpret this as a bigger strategic threat.

We recognize that large-scale investors could also respond to the same-day behavior of small-scale investors.[29] The even columns of Panel B test this second hypothesis by adding *contemporaneous* flows from small-scale investors, $High_{i,t}$, along with an interaction term, $High_{i,t} \times \%High_{i,t-1}$.[30]

Again, the strongest evidence of strategic complementarities occurs during the early crisis period. The specification in the third column indicates an 80 bp outflow from large-scale investors in response to a 1% prior-day outflow from small investors, $High_{i,t-1}$, if almost all of the fund's assets are owned by small-scale investors, and essentially no reaction if the fund is dominated by large investors. In column four, the sensitivity of large-scale investors, $Low_{i,t}$, to same-day flows from small-scale investors, $High_{i,t}$, again strongly depends on the concentration of small investors (see the coefficient on $High_{i,t} \times \%High_{i,t-1}$); fraction outflows from small investors are matched one-for-one from large investors if $\%High_{i,t-1}$ is close to one. This specification also indicates that large investors react much more strongly to concurrent small investor redemptions, rather than lagging by one day.

During the peak crisis period, we find no evidence that large-scale investors respond to lagged flows from small-scale investors, but continue to find evidence that they respond to contemporane-

[28] To clarify, when $\%High_{i,t-1}$ is close to zero (no poorly-informed investors), the response to $High_{i,t-1}$ approximately equals the direct coefficient on $High_{i,t-1}$ (the interaction term plays no role); as $\%High_{i,t-1}$ moves toward one (no well-informed investors), the response to $High_{i,t-1}$ equals the direct term plus the interaction coefficient.

[29] For example, 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 own decisions. Redemption requests at MMMFs are placed throughout the day, but settled at the end of the day. 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.

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

ous flows. In particular, a contemporaneous 1% outflow from small-scale investors is accompanied by a 50 bp outflow from large-scale investors when $\%High_{i,t-1}$ is close to one.

During the late crisis period, the interaction term on lagged flows is large and highly significant. Outflows from large investors move almost one-for-one (in percentage) with lagged flows from small investors, as $\%High_{i,t-1}$ goes to one. In contrast to the earlier periods, there is little evidence of a response to *contemporaneous* flows. Thus, given the availability of deposit guarantees, larger investors appear to have less incentive to monitor the same-day behavior of smaller investors. Overall, the results of this section indicate that large-scale investors react to the actions of small investors only when these actions pose a strategic externality. And, the reaction of large investors is quick (contemporaneous) when it matters most (during the early and peak crisis periods).

## 5 Panel Quantile Regressions

The empirical results presented so far suggest that we should use an estimation methodology that captures time-varying dynamics and heterogeneity in the cross-sectional distribution of fund flows in order to infer the key drivers of run-like behavior in some MMMFs during the crisis. Conventional approaches such as (panel) OLS fail to fully account for these effects, so we adopt an alternative methodology. This section provides panel quantile regression results, focusing on the role of various characteristics in shaping the flow distribution as the crisis unfolds.

To motivate our approach, we refer to Echenique and Komunjer (2009), who consider how to test models with complementarities between the dependent variable (e.g., the outcome of a strategic interaction) and explanatory variables (e.g., characteristics of the players or payoffs), where equilibria may not be unique. They explain that, within this class of models,

> "...despite the possible presence of multiple equilibria, a monotone comparative statics (MCS) prediction holds: there is a smallest and a largest equilibrium, and these change monotonically with explanatory variables... By focusing on the regions in which the monotonicity of equilibria holds, we still obtain that tail (small and large) conditional quantiles of the dependent variable increase in the explanatory variable. Testing for complementarities is thus possible by examining the behavior of the extreme conditional tails of the dependent variable.

Angeletos and Pavan (2012) make a similar argument within the context of testing global games models with endogenous information and multiple equilibria.

Our quantile regression models allow us to identify the fundamental characteristics of a fund that may make it more susceptible to run-like behavior by investors. They also help identify what role the size and/or sophistication level of a fund's investor base may have played in increasing its exposure to run-like risk. The discussion above suggests that, in addition to being empirically relevant, quantile methods may be especially useful for measuring such effects, as they enable us to estimate comparative statics in the tails of the conditional flow distribution, where identification may be more robust to potential fragility or multiplicity of equilibria.

### *5.1 Methodology*

We focus on modeling three quantiles, namely the 10th, 50th (median) and 90th, of the flow distribution, conditional on a vector of observable variables. Three quantiles is the minimum number sufficient to allow for *heterogeneity* and *asymmetry* in the flow distributions. In this way, we can determine whether fund and/or investor characteristics differentially affect funds in different parts (e.g., the center vs. tails) of the conditional cross-sectional distribution.

We adopt the following specification for conditional quantiles of a dependent variable $Y_{i,t}$:

$$\begin{aligned} Y_{i,t} &= f_0(X_{i,t}, \beta) + \epsilon^0_{i,t} = X'_{i,t}\beta_0 + \epsilon^0_{i,t} && P[\epsilon^0_{i,t} < 0|X_{i,t}] = 0.5 \\ Y_{i,t} &= f_1(X_{i,t}, \beta) + \epsilon^1_{i,t} = X'_{i,t}\beta_0 - \exp[X'_{i,t}\beta_1] + \epsilon^1_{i,t} && P[\epsilon^1_{i,t} < 0|X_{i,t}] = 0.1 \\ Y_{i,t} &= f_2(X_{i,t}, \beta) + \epsilon^2_{i,t} = X'_{i,t}\beta_0 + \exp[X'_{i,t}\beta_2] + \epsilon^2_{i,t} && P[\epsilon^2_{i,t} < 0|X_{i,t}] = 0.9. \end{aligned} \tag{1}$$

The functions $f_0(\cdot)$, $f_1(\cdot)$, and $f_2(\cdot)$ represent the median, $10^{th}$, and $90^{th}$ percentiles of the distribution of $Y_{i,t}$ given $X_{i,t}$, respectively.To facilitate interpretation of the results, we anchor the model around the conditional median, governed by $\beta_0$, of the flow distribution. We then add (or subtract) spreads, governed by $\beta_1$ and $\beta_2$, that quantify the difference between the effect of covariates on funds in the left or right tails of the cross-sectional distribution of fund flows. We first look at the effect of covariates on the median, then separately consider any additional effects on these spreads of an exponential affine functional form. This guarantees that the conditional quantiles never cross and yields an internally-consistent dynamic model.

As our specification is relatively new, some discussion of how to interpret parameters is in order. $\beta_0$ governs the effect of $X_{i,t}$ on the median level of flows and affects the other conditional quantiles as well. Since $\beta_0$ shifts the entire distribution of flows, its interpretation is quite similar to an OLS regression coefficient. We refer to these coefficients as "median exposures" or "common exposures", though we emphasize that these coefficients affect all quantiles symmetrically. $\beta_1$ captures the additional effect of covariates on the width of the left tail of the flow distribution–the spread between the median and the $10^{th}$ percentile. For ease of exposition, we refer to this distance as a fund's "left tail exposure." If $\beta_1^{(j)}$ and $X_{i,t}^{(j)}$ are the $j^{th}$ elements of $\beta_1$ and $X_{i,t}$, respectively, then a one unit increase in $X_{i,t}^{(j)}$ generates a $\beta_1^{(j)}$ percent increase in the left tail exposure for a given fund. $\beta_2$ governs a fund's right tail exposure, defined analogously. From a fund's perspective, increases in left tail exposure are "bad" (indicating higher downside risk) while increases in right tail exposure are "good".

Our model for the conditional quantiles has an additional interpretation which is particularly useful in a panel context. Partitioning the vector $X_{i,t} = [W'_{i,t}, Z'_t]'$, where $W_{i,t}$ is a vector of fund-specific characteristics and $Z_t$ is a vector of time-specific factors, our model becomes

$$\begin{aligned}
f_0(X_{i,t},\beta) &= W'_{i,t}\beta_0 + Z'_t\gamma_0 \equiv W'_{i,t}\beta_0 + \alpha_{0,t} \\
f_1(X_{i,t},\beta) &= f_0(X_{i,t},\beta) - \exp[W'_{i,t}\beta_1]\exp[Z'_t\gamma_1] \equiv f_0(X_{i,t},\beta) - \exp[W'_{i,t}\beta_1]\alpha_{1,t} \\
f_2(X_{i,t},\beta) &= f_0(X_{i,t},\beta) + \exp[W'_{i,t}\beta_2]\exp[Z'_t\gamma_2] \equiv f_0(X_{i,t},\beta) + \exp[W'_{i,t}\beta_2]\alpha_{2,t},
\end{aligned} \tag{2}$$

where $\beta = [\beta'_0, \gamma'_0, \beta'_1, \gamma'_1, \beta'_2, \gamma'_2]'$. Here $(\alpha_{0,t}, \alpha_{1,t}, \alpha_{2,t})'$ is a vector of time-specific shocks. $\alpha_{0,t}$ is a shock that shifts the distribution for all funds symmetrically. $\alpha_{1,t}$ and $\alpha_{2,t}$ scale up or down the left and right tail exposures, respectively. This multiplicative structure gives $\beta_1$ and $\beta_2$ useful factor-loading interpretations: If $W'_{i,t}\gamma_1 = 0$, a fund's left tail exposure is equal to the aggregate shock; as $X'_{i,t}\beta_1$ increases, the sensitivity to the aggregate shock increases. This specification makes sense in our application, given the important interactions between market-wide events (e.g., declines in liquidity) and investor behavior. We also allow the relationship between covariates and flows to change over time. For example, perhaps investors put a heavy weight on the riskiness of a fund's holdings during the early stages of a crisis, but place less weight on this during later stages.

Following Koenker and Bassett (1978), a variety of methods have been developed for estimating conditional quantiles. We estimate the relevant parameters using the sequential semi-parametric method in Schmidt (2013) and calculate standard errors using simple bootstrap procedures.[31] Further technical details about estimation are in Appendix section B.

Before going further, we introduce some terminology to ease the exposition in the discussion that follows. Our specification in (2) enables us to compare different quantiles of the conditional flow distribution, holding conditioning variables, $W_{i,t}$, fixed. A "median fund" is not particularly lucky or unlucky when compared with funds with similar observable characteristics, experiencing flows that are relatively close to $f_0(X_{i,t}, \beta)$. In contrast, a "left tail fund" is relatively unlucky, experiencing flows relatively close to $f_1(X_{i,t}, \beta)$, while a "right tail fund" is relatively lucky. Relative to peers with similar observables, left tail funds are most likely to have experienced run-like behavior, so we wish to compare left tail funds with different values of $W_{i,t}$.[32] In a number of cases, a variable has a strong effect on a fund's left tail exposure while having a minor effect on its median and right tail exposures; thus, changes in $W_{i,t}$ have little effect on flows from median or right tail funds, but they make a large difference for left tail funds.

### *5.2 Quantile Regression Results for Prime Institutional Funds*

Table 3 presents our quantile regression estimates for the panel of Prime Institutional share classes. The dependent variable is the daily change in log (fund-level) aggregated share class total net assets. In our discussion to follow, for simplicity, we often refer to the aggregate of prime institutional share classes as a prime institutional "fund," but the reader should be reminded that, strictly speaking, a fund can consist of both prime institutional and prime retail share classes.

As was the case in Table 2, we split the sample into, and allow the model coefficients, $\beta_0$, $\beta_1$, and $\beta_2$ to change, over each of four separate subperiods, and each column of the table presents

[31] Bootstrap procedures, when applicable, are generally thought to be more reliable than asymptotic approximations in quantile regression applications. We use a clustered bootstrap, where we construct our bootstrap data by drawing complete fund time series with replacement, which allows for arbitrary serial correlation in the residuals within funds.

[32] If our estimates of the left and right tail exposures are relatively small, then median, left tail, and right tail funds all experience similar investor behavior. In this case, OLS provides a good summary of the relationship between $Y_{i,t}$ and $W_{i,t}$. The same is true when tail exposures do not change with $W_{i,t}$.

estimates for a specific subperiod. Panel A presents our estimates of $\beta_0$, the coefficients governing the conditional median. Panels B and C present our estimates of $\beta_1$ and $\beta_2$, the coefficients governing left and right tail exposures, respectively. As in Table 2 above, we express the dependent variable in log percentage points, and divide all characteristics other than lagged flows by their cross-sectional standard deviations.

Our specification includes a number of fund-level variables, functions of lagged flows (which are centered relative to an equal-weighted average flow), and an interaction between lagged flows and $LIQUIDRT$, our real-time liquidity measure. We will discuss the coefficients involving lagged flows, which complement the results in Table 2, in section 6 below. In addition to the fund characteristics whose coefficients are given in the table, the model includes three time-specific factors, $\alpha_{0,t}$, $\alpha_{1,t}$, $\alpha_{2,t}$, which we plot in Figure 3. The top panel displays our estimates of $\alpha_{0,t}$, the aggregate shock to the median, and the bottom panel shows the shocks to the tails, $-\alpha_{1,t}$ and $\alpha_{2,t}$. We de-mean the fund characteristics $W_{i,t}$ so that $\alpha_{1,t}$ may be interpreted as the left tail exposure (i.e., the distance between the median and the 10th percentile) for an "average" fund.[33] We parameterize these factors using simple cross-sectional statistics, along with time dummies for the three days in the peak crisis period. Since the associated coefficient estimates add little intuition, we defer any discussion of the parameterization to Appendix section B.2.

#### *5.2.1 Baseline Period*

The column labeled "Baseline period" shows results for a seven-month pre-crisis period from 2/1/2008 through 9/9/2008. Beginning with median coefficients in the top panel, we observe that most covariates insignificantly predict following-day fraction flows and/or have a very small economic magnitude. In addition, the aggregate shocks to the median $\alpha_{0,t}$, plotted in the top panel of Figure 4, are very close to zero. The very low pseudo-$R^2$ of 0.01 indicates that the conditioning variables add little additional explanatory power relative to a model with a constant median.

Next, we turn to the tails. The bottom panel of Figure 3 says that, in the pre-crisis period, the daily flow distribution is fairly symmetric, with funds facing average tail exposures ($\alpha_{1,t}$ and $\alpha_{2,t}$) of about 1.5% per day in both tails. During this period, a left tail fund could expect to lose

[33]Specifically, a fund whose lagged flow and other characteristics both equal the cross-sectional average.

outflows of about 1.5% of AUM per day, with a right tail fund receiving inflows of about the same magnitude. We find stronger evidence of predictability in the tails, though these differences are primarily driven by differences in unconditional volatility across funds. A one standard deviation increase in $LOGFLOWSTDEV$ is associated with a symmetric 56% increase in both the left and right tail exposures (see the coefficients on LOGFLOWSTDEV in the left tail, Panel B, and the right tail, Panel C). This result indicates that some funds have consistently higher levels of investor turnover (i.e., "hot money"), relative to others. We also find that a one standard deviation increase in the expense ratio $EXPR$ is associated with reductions of 5% and 9% in the left and right tail exposures, respectively, suggesting that small-scale investors move money less frequently.[34]

#### *5.2.2 Early-Crisis Period (September 10-16)*

During the early-crisis period, which lasts from Wednesday, September 10th through the following Tuesday, September 16, unusual outflows begin to occur (as shown in Figures 1 and 2), likely due to some investors reacting to news about the growing insolvency of Lehman and its subsequent default. In Figure 3, the early crisis period includes the first two data points in the shaded region (which indicates the Lehman week), as well as the preceding three trading days. During this period $\alpha_{0,t}$ begins to drift into negative territory (where it remains throughout the crisis), and the common left tail exposure $\alpha_{1,t}$ reaches elevated levels, ranging from 2-3%–i.e., the difference between median and left tail funds becomes more pronounced relative to the baseline period–consistent with the increase in cross-sectional heterogeneity in flows in Figure 2.

Of interest is whether, during this period, redemption behavior reflects a general "flight to quality" across all risky assets, or whether investors are more discerning in their withdrawals. Therefore, we first examine the role of fund characteristics, whose coefficients are in the column labeled "Early Crisis" in Table 3, in shaping the conditional distribution of early-crisis outflows. First, we observe that there is little evidence that fundamental and investor characteristics help to predict median flows–the coefficients for the median in Panel A are mostly small and insignificant. An exception is $LOGTNA$, suggesting that a one standard deviation increase in $LOGTNA$ shifts

[34] An alternative explanation is that the size distribution of funds predominantly owned by small-scale investors is more granular, making the aggregate flow (a weighted average of flows from individual accounts) less sensitive to idiosyncratic rebalancing behavior of any single account.

the flow distribution to the left (i.e., towards additional outflows) by 23 bp per day during the pre-crisis period.[35]

In contrast to the median, fundamentals strongly predict increases in early crisis left tail exposures. Specifically, left-tail funds with lower portfolio liquidity (indicated by a lower LIQUIDRT) and higher yield levels (higher AVGYIELD) experience higher outflows, though the latter coefficient is insignificant. Also, left tail exposures are higher in funds that are part of a shallow-pocket complex (indicated by a higher PIPERC, the percentage of complex MMMF assets represented by prime institutional share classes). Thus, these "first-mover investors" implemented a withdrawal of money during the early stages of the crisis from funds with lower liquidity and credit quality, and less of a chance of sponsor subsidization–i.e., funds with poor fundamentals. This finding is consistent with a very focused flight from the poorest quality MMMFs with the highest risk exposures, and not from prime MMMFs in general, consistent with Figure 2.

Next, we look at the role of investor type to address whether investors consider the strategic/informational context when making the decision to redeem. As mentioned in Section 4, a fund's expense ratio covariate (EXPR) captures (inversely) investors' scale, sophistication, attentiveness, and/or access to information. Investors in the lowest expense ratio share classes can be expected to be the most informed about fund quality and flow shocks, as they have the most at-risk. We find weak evidence of a quantitatively small median effect of about 6 bp per day. In contrast, funds with lower expense ratios face significantly larger left tail exposures; a one standard deviation increase in a fund's expense ratio is associated with a 45 (log) percentage point reduction in its left tail exposure. All else constant, left tail funds with more sophisticated investors face a significantly higher exposure to abnormally large outflows relative to left tail funds with smaller, less sophisticated investors.

Recall, from Table 2, that $EXPR$, $LIQUIDRT$, and $PIPERC$ help to predict shareclass-level redemption behavior during the pre-crisis period. Our findings here are fully consistent with Table 2, and they yield further insights about how these average effects are distributed across funds with similar observables. Table 3 indicates that predictability is primarily concentrated among the

[35] We experimented with the inclusion of $LOGTNA$ in the tails but found that it possessed almost no predictive content, so we restrict the tail coefficients to equal zero. However, the median effects, captured by the coefficients in Panel A, also have a symmetric impact in shifting the 10th and 90th percentiles.

hardest-hit (left tail) funds, while having little effect for median or right tail funds. Consistent with He and Manela (2013), a larger fraction of investors might be willing to wait for additional information about the funds when the perceived risks from other investors are lower and/or the fund is more likely to survive additional attacks (safer portfolios or lower costs of sponsor support).

Finally, we observe that the coefficients on $LOGFLOWSTDEV$ are almost unchanged relative to the baseline period. Left tail and right tail exposures, which depend on fund-specific variables, $W_{i,t}$, as well as the common shocks, $\alpha_{1,t}$ and $\alpha_{2,t}$, continue to be higher for funds whose daily flows are more volatile in the baseline period. Since the coefficients are almost identical, the results here would seemingly be at odds with our findings in Table 2, namely that $LOGFLOWSTDEV$ is a negative and significant predicator of flows during the early crisis. However, inspection of Figure 3 reveals that $\alpha_{1,t}$ is larger than $\alpha_{2,t}$ on average, particularly for the last two days of the early crisis period. Therefore, even though $LOGFLOWSTDEV$ has a symmetric effect on the left and right tail "factor loadings", the realizations of the common factors are different, so the effect of the increase in the left tail exposure (which lowers the conditional mean) dominates the increase in the right tail exposure (which increases the conditional mean).

#### *5.2.3 Peak Crisis Period (Wednesday through Friday, September 17-19)*

By the peak time of the crisis, after the Reserve Primary Fund marked its assets below $1 per share (i.e., "broke the buck"), the conditional flow distribution changes dramatically, shifting to the left and becoming highly negatively skewed. The estimated common shocks to the median, $\alpha_{0,t}$, indicate that the conditional median shifts downward by 3%, 4%, and 2% on September 17th, 18th, and 19th, respectively (see Figure 3). At the same time, the common shocks to left tail exposures, $\alpha_{1,t}$, are extremely large, equaling 8, 5, and 4 log percentage points on the three days. In contrast, the common right tail exposures remain around 2% on the 17th and 18th, increasing upwards of 3% on the final day of the period (which coincides with the Fed's announcement of temporary deposit guarantees). Thus, the left tail expands dramatically (indicating higher downside risk) while the response of the right tail (governing large inflows) is less pronounced.

In this period, investors' reactions to fund characteristics begin to shift the entire distribution, as evidenced by the median coefficients in Panel A.[36] Specifically, the coefficients on $AVGYIELD$ and $LIQUIDRT$ significantly affect funds' median exposures.[37] The coefficient in the median on $LOGTNA$ more than quadruples to -1.06, indicating that larger funds continued to be more susceptible to outflows. These coefficients reflect a more broad-based flight to quality by all MMMF investors, when compared with the early crisis period.

Further, while $PIPERC$ is insignificant in the median, it predicts outflows in the left tail. That is, those fund complexes with the greatest proportion of MMMF assets represented by prime institutional funds (thus, those complexes with "shallow pockets") experience exacerbated outflows in the left tail region. Thus, fund investors consider the ability of a management company to rescue a failing fund only when the fund experiences strong outflows for other reasons.[38] Also, while imprecisely estimated, the left tail coefficient on $AVGYIELD$ is quantitatively large, suggesting that a one standard deviation increase in average gross yield is associated with a 30% increase in left tail exposure. The right tail coefficient is quite similar and strongly statistically significant, so the flow distribution is more dispersed overall for high yield funds. Given that $\alpha_{1,t}$ is larger than $\alpha_{2,t}$ throughout this period, the left tail exposures increase in response to $AVGYIELD$ by substantially more than the right tail exposures.

During the peak crisis period we also see some interesting effects on right tail exposures. Specifically, right tail funds with more liquid assets that pay higher yields experience a greater chance of receiving large inflows (or smaller outflows) than the average fund. Such a result is consistent with He and Manela (2013), who, in a model with endogenous information acquisition, show that such dynamics are to be expected for banks with sufficient liquid asset holdings: after sufficiently many investors observe positive signals about the bank's liquidity position, they realize that the bank is not at risk of a run and so begin to re-deposit assets with the bank. Thus, some investors initially redeem from all share classes having higher yields, assuming they are risky, then return to those

[36]Note that predictability, as measured by the pseudo-$R^2$, is at its highest during the peak crisis and, moreover, is higher in the left tail than in other parts of the distribution. This is due, in part, to an increase in the variance of the common shocks to the left tail of the flow distribution ($\alpha_{0,t}$, $\alpha_{1t}$, and $\alpha_{2,t}$).

[37]We discuss the implications of the interaction variable between $LIQUIDRT$ and $(y_{i,t-1} - y_{t-1})$ in Section 6.

[38]Parlatore (2014) develops a model for money market funds that stresses the importance to runs of the sponsor's implicit support to maintain a stable net asset value. She finds that such a support can, in some situations, increase the possibility of a run, due to strategic complementarities in sponsor support decisions and the effect these decisions have on the underlying asset market. If enough sponsors decide not to support their funds, this can lead to a run on the underlying asset market which will suppress asset prices and liquidity in this market.

higher yield funds where they have learned (presumably from the actions of other investors, or from a statement by the fund sponsor) that fundamentals are strong. Figure 3 mirrors this result: some share classes initially experience large withdrawals, only to mean-revert before the Fed's policy announcement on September 19.

Figure 4 presents graphical evidence on the economic magnitude of flows on the peak crisis day, September 17, as well as illustrating the nonlinearity in flows with respect to one covariate: the expense ratio, which is inversely related to minimum investment scale. The figure presents fitted values of log fraction flows, based on perturbing EXPR by one standard deviation for the 10-percentile, median, and 90-percentile outflow funds, and can be viewed as an elasticity of flows with respect to changes in the expense ratio. The cross-sectional mean expense ratio is shown as asterisks, while a one-standard deviation increase is shown with triangles. All other covariates, except for expense ratio, are assumed to be at their cross-sectional means of that day.

We can clearly see that the effect of increasing the expense ratio, from its mean, by one standard deviation is very minor for median or right tail funds. However, EXPR appears to have a substantial effect on the funds' left tail exposures, so the fortunes of left tail funds respond dramatically to changes in EXPR. Thus, our model finds that, all else constant, very large outflows were much more likely to occur in funds with the largest-scale investors (most skin in the game). Again, this is consistent with the predictions discussed in the previous section about the quality of investors' information and the probability and severity of runs.

Finally, $LOGFLOWSTDEV$ continues to be a strong predictor of the shape of the flow distribution, having strong predictive power in both tails. The tail coefficients shrink towards zero, implying that the elasticity of left tail exposures with respect to pre-crisis volatility is lower relative to other periods. However, given the abnormally large values of $\alpha_{1,t}$ and $\alpha_{2,t}$, the marginal effect of $LOGFLOWSTDEV$ on the tail exposures is often larger, particularly for the left tail, relative to other periods. Also, in contrast to other periods, pre-crisis flow volatility is a negative and significant predictor of median outflows. To the extent that higher volatility reflects a higher concentration of "hot money", our estimates suggest that funds with a disproportionate share of "hot money" faced substantially higher exposure to sudden, large outflows.[39]

[39]This result is similar to a finding in Iyer and Puri (2012), namely that the length of time elapsed since an account

#### 5.2.4 *Late-Crisis Period (September 22-October 17)*

Table 3 and Figure 3 show that, after the Federal Reserve and the U.S. Treasury announced backstop programs for MMMFs and for commercial paper, outflows substantially decrease for all funds. The common shocks to the median ($\alpha_{0,t}$) are generally negative but closer to zero, and the common shocks to the tails ($\alpha_{1,t}$ and $\alpha_{2,t}$) remain elevated relative to pre-crisis levels. The median coefficients for this "late crisis" period indicate that money continues to disproportionately flow out from the largest funds with the most sophisticated investors, as well as from funds with above average yields and more volatile flows during the pre-crisis period. Turning to the tails, $LOGFLOWSTDEV$ continues to scale up both tail exposures, roughly symmetrically. The left tail coefficient on $EXPR$ remains significantly negative and is essentially unchanged relative to the peak crisis period.

Given that deposit guarantees are available during this period, it is reasonable to ask why we continue to observe abnormally large outflows well into mid-October 2008. These significant coefficients may capture some "late movers" reacting to the crisis, even though there was less of an incentive to redeem at that point. This was likely mere "window dressing" by some large-scale institutional investors who did not wish to be detected as holding shares in MMMFs, although it may also reflect confusion or uncertainty about the Federal backstop programs during these early weeks. A final explanation comes from He and Manela (2013), who extend their model to allow for multiple banks. They explain that "instead of holding cash, a bank run in this setting involves the transfer of deposited funds from one illiquid bank to another more liquid one. Information is privately more valuable in this setup since the outside option is a nearly identical bank." Thus, even if outflows aren't motivated by fears about funds "breaking the buck", small differences in fund performance (e.g., due to liquidation externalities as emphasized in Chen et al. (2011)) could still give investors an incentive to move money away from hard-hit funds.[40]

opens is a strong predictor of run-like behavior from retail investors in an Indian bank. In particular, more recently acquired customers were less hesitant to withdraw quickly.

[40]Indeed, the dispersion in yields between different MMMFs with prime institutional share classes widened during and after the crisis.

### *5.3 Quantile Regression Results for Prime Retail Funds*

We next implement our baseline quantile panel regressions of Equation (2) across retail funds. Table 4 shows coefficient estimates from this model, applied during each of the four periods studied previously for institutional share classes. Our prior results of Table 3 indicate that institutional investors react to fundamentals during the early crisis period of September 15 and 16. Table 4 shows no such evidence for retail investors. Instead, these investors responded only during the peak and late crisis periods, after the media broadly reported that the crisis was unfolding. Even then, the flows of retail investors are much less sensitive to fundamentals, compared to institutions.

During the peak crisis period, AR(1) coefficients indicate that retail investors finally respond in a significant way to prior-day flows, suggesting that these investors were directed out of certain funds by their financial advisors or brokers, or that they reacted to news reports about certain MMMFs or financial institutions that sponsored MMMFs suspected of having trouble.

## 6 Liquidity Spirals and Flow Dynamics

Our finding in Figure 1 that, in the aggregate, money flowed away from the prime market toward the Treasury market is consistent with liquidity spiral models such as Brunnermeier and Pedersen (2008), and is related to a deterioration in speculators' (market makers') capital, which forced them to switch their liquidity provision towards low-margin, highly liquid Treasury securities, thus creating an increased wedge between the liquidity of the prime and Treasury markets.[41]

Feedback effects may occur in two important ways for MMMFs. First, funds likely first sell their most liquid securities to minimize trading and liquidity costs. If so, then investors may anticipate the reduced liquidity of the fund, and this may trigger further outflows after the initial outflows, as well as a building "price-pressure" in the illiquid assets that may need to be sold.[42] Second, a more severe "liquidity spiral" may occur if funds experience outflows sufficient to force them to

[41]Specifically, money markets saw the equivalent to the margin-liquidity spiral in the form of higher repo haircuts on private ABS and corporate securities relative to U.S. Treasury and Agency notes, as shown empirically by Krishnamurthy, Nagel, and Orlov (2012). Investor redemptions play a similar role for MMMFs as margin calls in Brunnermeier and Pedersen's model, since these funds have a liquidity mismatch which could trigger fire sales.

[42]That is, the depression of illiquid asset prices can occur in the absence of selling–if the probability of future selling increases sufficiently (as perceived by market participants).

sell less liquid assets, which may further depress the price of their remaining assets. The cascading effect of depreciating prices on MMMF holdings may, again, trigger further outflows.

Our daily flow data allow us to study, at a high frequency, how such feedback effects play out in real time during the crisis week. In this section, we begin by discussing the role played by lagged flows in our dynamic quantile regression models and how these feedback effects change as the crisis evolves. Second, since fund characteristics and lagged flows are not independent, and different characteristics affect flows in different ways throughout the crisis, we next use our estimated dynamic model to simulate the cumulative effects of fund characteristics on flows. These multi-period flow simulations shed additional light on the economic magnitudes implied by the high-frequency estimates.

### *6.1 Changes in Flow Persistence*

Our panel quantile model in Table 3 presents AR(1) coefficients of fraction flows (measured relative to value-weighted-average fund flows), $y_{it-1} - \bar{y}_{t-1}$, divided into above-average lagged flows, $y_{it-1} - \bar{y}_{t-1} > 0$, and below-average lagged flows, $y_{it-1} - \bar{y}_{t-1} < 0$. By separately considering the effect of flows above and below the same-day cross-sectional average, we determine if persistence in fund flows differs among funds with the largest (relative) inflows vs. those with the largest outflows.[43] We also include a term which interacts $LIQUIDRT$ with $y_{it-1} - \bar{y}_{t-1}$.

During the baseline period, there is mild evidence of negative persistence in flows, as one may expect if funds temporarily park money in a fund between the sale of one asset and the purchase of another (which is normal in MMMFs). This effect switches sign during the early-crisis period, when some investors persistently withdraw money from selected funds, as indicated by the significantly positive AR(1) coefficient on the dummy slope representing lagged outflows that are below the cross-sectional mean ($y_{it-1} - \bar{y}_{t-1} < 0$). Specifically, the "early-crisis" column of Table 3 shows that a 1% outflow during one day resulted in an (expected) outflow of 0.26% during the following day, across all funds (the median effect). These persistent outflows to the median share class (i.e., to the entire distribution) appear to reflect a general flight to quality, as some investors likely react to the Lehman default by withdrawing money out of any risky funds, including those holding

[43] Similar results obtain if we center relative to zero instead of the category average.

commercial paper of any kind (i.e., away from prime MMMFs). It is likely that such a flight to quality developed over several days, which is reflected in the AR(1) coefficient–certain clientele were more likely to exit risky assets than others. Indeed, there were also large inflows to institutional government share classes developing during this period; they would get larger in the days to come.

During the peak crisis period, this AR(1) coefficient for the median fund roughly doubles, for funds with negative relative lagged flows ($y_{it-1} - \bar{y}_{t-1} < 0$), and becomes very significant for funds with positive relative lagged flows ($y_{it-1} - \bar{y}_{t-1} > 0$). Clearly, funds with early extreme flows continue to exhibit same-direction extreme flows; thus, run-like behavior is concentrated in certain funds that had already experienced outflows in prior days. Further, the negative coefficient on the interaction variable, $LIQUIDRT \times (y_{it-1} - \bar{y}_{t-1})$, indicates that investors were less likely to run from funds with greater portfolio liquidity, controlling for prior-day outflows. This finding is consistent with liquidity spirals developing among share classes experiencing early outflows and having less liquidity in their portfolios.[44]

During the late-crisis period, persistence was substantially weakened. However, a significant (but smaller) positive AR(1) coefficient on outflows from the median fund remains, indicating that investors continued to respond to the prior-day redemption behavior of other investors.[45]

### *6.2 Effects of Covariates on Cumulative Flows*

Next, we illustrate how the dynamics of fund flows evolved, day-by-day, during the crisis. To this end, we use our model to simulate the impact of perturbations in the value of exogenous variables on multi-period flow distributions. We fix initial values for the fund characteristics, yielding initial conditional quantile forecasts. Next, we interpolate between quantiles and simulate the current

[44] We note that it is also possible that persistence in outflows among low-liquidity funds occurred partly due to information cascades. Less-informed investors may infer from their more sophisticated first-mover competitors (who redeem shares early) that the fundamentals of a fund are worse than expected. For instance, it is likely that only more sophisticated investors had access to information on portfolio liquidity, through iMoneynet or Crane. If so, we will observe persistence in outflows among less-informed investors, which further depress the prices of common asset holdings of the funds.

[45] We also find some evidence of conditional heteroskedasticity in daily flows. Our specification for the tails includes $|y_{i,t-1} - \bar{y}_{t-1}|$, the absolute value of mean-adjusted prior-day fraction flows, which allows for volatility clustering (ARCH-type effects) in the tails. This finding indicates that days with large investor flows (positive or negative, relative to the mean fund) tend to cluster together in time.

day's flow from a parametric distribution.[46] Plugging 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 distribution of cumulative flows over the course of the crisis. Further details about these simulations are in Appendix section B.3.

In Table 5, we present this analysis for all covariates, where flows are now cumulated over the entire crisis week, September 15-19, 2008. We show the magnitude of the expected impact of a one standard deviation increase vs. decrease of a particular covariate at various quantile points in the flow distribution (left four columns) as well as the difference in their expected impacts (see "Difference"). The right four columns show the probability of outflows exceeding various breakpoints ranging from 5% to 40%.

Focusing on the difference as a measure of the impact of covariates, we can see that non-linear effects exist in AVGYIELD, EXPR, PIPERC, and LOGFLOWSTDEV. Specifically, the differential (expected) economic impact of a one-standard deviation shift upward vs. downward, in these covariates, is much larger in the left tail than for the median fund. For instance, the difference in the effect on outflows of increasing vs. decreasing AVGYIELD by one standard deviation amounts to 16.2% for the 1-percentile fund, compared to 5.0% for the median fund. Clearly, the magnitude of the impact of fund- as well as clientele characteristics on outflows is greatly magnified in the left tail, although there are also effects on the median.

The right four columns provide an alternative measure of the economic effect of the covariates on weekly flows during the crisis. For example, a fund with AVGYIELD one standard deviation above the average has a 7.8% chance of experiencing weekly outflows exceeding 40%, while a fund with AVGYIELD one standard deviation below the average only has a 1.1% chance of this occurring.

Results from the dynamic simulation exercise are illustrated in Figure 5. At the beginning of each window (September 10), we fix each of the explanatory variables at its average plus or minus one standard deviation. The results show that there are long-lasting effects of changes to many covariates, approaching 30-40% by September 26, 2008, especially for funds with the greatest left

[46]Given the non-crossing property of our conditional quantile estimates, we can generate internally consistent density/distribution estimates by interpolating between quantiles. This interpolation adds little information if we want to look at flow distributions over a single day, but it can be useful for looking at multi-period cumulative flow distributions. This turns out to be important, since covariates and lagged flows are not independent from one another.

tail exposure. Importantly, note the asymmetry in the impact of the covariates on flow distributions.

Figure 6 provides comparative statics for the cumulative outflows during the week following the failure of Lehman Brothers. We change the explanatory variables one at a time, while holding the other variables fixed at their sample means. For each of the explanatory variables, the left panel shows the 10%, 50%, and 90% quantiles of the cumulative flow distributions, while the right panel shows the probability that the cumulative outflows exceed 10%, 25%, or 40%. The plots show that the left tail of the cumulative outflows is strongly associated with a high average yield, a low liquid asset share, a low expense ratio, and a high standard deviation of log flows. Variables such as the average yield, the liquid asset share, and the standard deviation of log flows also affect the right tail very strongly.

# 7 Conclusion

This paper studies money market mutual fund (MMMF) runs during the crisis period of September and October of 2008. We find that run-like behavior was especially pronounced among MMMFs that catered predominantly to institutional investors, although we also find weak evidence of correlated withdrawals among retail MMMFs during the crisis. This finding indicates that "sophisticated" investors mainly present a "bank-run" risk (a negative externality) to each other, and present a weaker risk to "passive" (retail) investors in same-complex MMMFs.

Second, we find that runs were more pronounced among funds that had less liquid portfolios. We also find that MMMF runs were more likely when the fund didn't have "deep pocket backing," indicating that investors infer that funds are guaranteed by their management company. Moreover, we find that funds with higher prior flow volatility and large-scale investors were more likely to experience runs. Finally, we use data on different share classes within the same fund to explore differences in the flow behavior of sophisticated (low expense ratio) and less sophisticated (high expense ratio) investors, keeping portfolio holdings (and thus risk characteristics) constant. We find evidence of both strategic redemption behavior by the better informed investors and of information cascading from the better-informed to the less-informed investors during the crisis.

Our paper provides a set of new empirical findings which can be set against theoretical models of runs. First, we show that runs can evolve in a matter of days and that they involve important feedback effects from past (out-) flows on future flows. Second, we show that it is difficult to identify ex-ante which funds are subject to runs ex-post, although there is also clear evidence that large scale investors were keenly aware of fund fundamentals as measured by the quality of the fund holdings and the characteristics of investors in the same funds.

Our empirical findings, coupled with the large scale of investment in such funds, 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.[47] 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, suggesting the presence of a potentially important interaction between aggregate and idiosyncratic risk. We believe that 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.

[47]Money market mutual funds held assets of roughly $2.7 trillion, as of September 2013.

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# Appendix

## A Background Information

This appendix provides more background on some institutional details of money market mutual funds and a timeline of events of the crisis of September 2008.

### *A.1 Institutional Background on MMMFs*

In principle, MMMFs are much like other mutual funds. Like other mutual funds, they 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 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. It allows retail investors to use their MMMFs for transactions purposes, such as paying bills and settling securities trades, without worrying about daily fluctuation in MMMF balances. They are also able to tie their MMMFs to bank products, such as checking accounts, ATMs, and credit cards. 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 they are generally restricted from investing 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 long-term mutual fund.

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, unable to meet redemption requests, despite holding highly liquid assets.[48] These risks have been controlled differently in banks and MMMFs.

[48]This issue can also arise with long-term mutual funds. Mutual funds are required by law to offer investors the

Banks are required to maintain capital, and depositors are insured, 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 may employ leverage. MMMFs, in contrast, under Rule 2a-7, must hold only highly liquid, high quality assets, and generally may not use leverage.[49] The Securities and Exchange Commission (SEC) and others have long recognized the potential exposure of MMMFs to investor runs; the SEC has recently tightened the provisions under which MMMFs operate, and are currently considering further regulations to control this potential exposure.[50]

Total net assets (TNA) in MMMFs increased vastly in the period leading up to 2008. Specifically, the total assets held in MMMFs increased from almost \$500 billion at the end of 1990 to more than \$3.8 trillion at the end of 2008, reflecting the huge increase in popularity of these funds among individuals and institutions. As of December 2008, the total M2 money supply in the United States was \$8.3 trillion, of which \$1.3 trillion was invested in retail share classes of money market mutual funds.[51] Therefore, MMMFs are a substantial share of liquid assets for individuals in the U.S. (the so-called "cash economy"). Until the crisis of 2008, MMMFs holding predominantly non-government securities dominated the asset value of the sample (during 2008, assets held in government MMMFs nearly doubled, to \$1.45 trillion). As of December 2008, there were 38 million shareholder accounts, most of which were retail accounts. Therefore, a large cross-section of individuals in the U.S. hold assets in MMMFs, indicating that any perceived instability of MMMFs could impact a large proportion of U.S. households. Institutions own about two-thirds of the TNA of MMMF in a much smaller number of accounts. Therefore, even outflows from a relatively small

ability to redeem their shares on a daily basis at the fund's net asset value per share. 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., high yield bonds).

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

[50] Specifically, amendments to Rule 2a-7, effective on May 5, 2010, have imposed several new requirements on money market mutual funds. These include, among other things: (1) requiring that a fund hold 10% of its portfolio value in securities that may be easily liquidated within one day, and 30% that may be easily liquidated within one week; (2) reduce the maximum weighted average maturity from 90 to 60 days, and (3) require fund management to "know your clients" to judge flow volatility, and to increase asset liquidity, if necessary. Among other things, the SEC is considering further requiring funds to convert to a floating NAV or to impose redemption fees when they face a significant risk of an asset value depreciation.

[51] M2 consists of currency, travelers' checks, demand deposits, other checkable deposits, retail money market mutual funds, savings, and small time deposits. See www.federalreserve.gov/releases/h6/hist/h6hist1.txt for yearly values of M2 and www.ici.org for yearly retail money fund assets.

number of institutional accounts can impact the stability of MMMFs.

### *A.2 Key Money Market Events of September-October 2008*

On September 16, 2008, the Reserve Primary Fund (which held about $750 million in commercial paper issued by Lehman Brothers) "broke the buck." Immediately, prime MMMFs began to see vast outflows, and they struggled to sell securities to meet these redemptions. On Friday, September 19, 2008, the U.S. Treasury offered a guarantee to MMMFs in exchange for an "insurance premium" payment. On that same day, the Federal Reserve announced The Asset-Backed Commercial Paper Money Market Mutual Fund Liquidity Facility to provide funding to U.S. depository institutions and bank holding companies to finance purchases of high-quality asset-backed commercial paper (ABCP) from money market mutual funds under certain conditions. This program was set up to assist MMMFs holding such paper to meet redemption demands and to promote liquidity in the ABCP market and money markets, more generally. This program began operations on September 22, 2008, and was closed on February 1, 2010.

In addition, in response to the growing difficulty of corporations in rolling over their short-term commercial paper, the Fed announced The Commercial Paper Funding Facility on October 7, 2008, followed by additional details on October 14, 2008. This program took effect on October 27, 2008, and was designed to provide credit to a special purpose vehicle that would purchase three-month commercial paper from U.S. issuers.

On October 21, 2008, the Federal Reserve announced yet another program, The Money Market Investor Funding Facility (MMIFF). The MMIFF was a credit facility provided by the Federal Reserve to a series of special purpose vehicles established by the private sector. Each SPV was able to purchase eligible money market instruments from eligible investors using financing from the MMIFF and from the issuance of ABCP. Eligible Assets included certificates of deposit, bank notes and commercial paper with a remaining maturity of at least seven days and no more than 90 days.

In addition, the SEC took a number of actions, perhaps the most important being to allow MMMFs to price their underlying securities at amortized cost at a point during the crisis when quotes on commercial paper were generally regarded as unreliable.[52] Following these developments,

[52]This was an interesting development, especially since the SEC later proposed a floating NAV as a potential

investors continued to redeem shares from prime MMMFs, but at a diminishing rate. By the end of October 2008, the MMMF crisis was essentially over.

### *A.3 Further Details on iMoneynet Database*

Our daily MMMF data from iMoneyNet cover the period February 2008 to June 30, 2009, and include data on funds that no longer exist. We approximate daily fund share class flows as the daily fraction change in share class total net assets.[53] We also exclude observations from the Reserve complex from our analysis.

Panel A of Table A1 presents univariate summary statistics for prime institutional share classes as of September 15, 2008. Specifically, we show the mean, standard deviation, and a range of quantiles for all covariates listed above, in addition to the TNA and cumulative fraction flows for the prime institutional share classes (aggregated to the fund level) during the week of September 15-19, 2008.

Panel B reports cross-sectional correlations between share class characteristics. Most notable is the strong negative correlation between AVGYIELD and LIQUIDRT (-0.67), which reflects that less liquid assets tend to earn higher yields. Most of the remaining covariates are only weakly correlated, which is reassuring given our discussion above about the difficulty of cleanly separating variables into fundamentals vs. investor characteristics. An exception is the expense ratio, which is significantly negatively correlated with LOGFLOWSTDEV and LOGTNA: larger scale investors tend to move their money more frequently, and invest in larger funds–undoubtedly to minimize any impact on the fund (and themselves) when they move the money.

Consistent with our more formal model results, the last row of Panel B shows the correlations between cumulative crisis-week flows (CUMFLOWS) and each of these characteristics. We find that LIQUIDRT and EXPR are positively correlated with crisis-week flows (less liquid share classes with larger scale investors are more likely to see outflows during the crisis), while the remaining characteristics, AVGYIELD, LOGFLOWSTDEV, PIPERC, and TNA, are negatively correlated (higher risk and larger share classes that have hot money clientele and that are a larger portion of

solution to runs on money market funds.

[53]Almost all money fund dividends are reinvested in the same money fund share class, so distributions (and their passive reinvestments) have a negligible effect on our estimates of flows.

MMMF assets at the fund family level are more likely to see outflows during the crisis).

# B Quantile Regression Methodological Details

This appendix gives further detail about our panel quantile regression methodology: the recursive estimation method, our parameterization of time-specific shocks, and multi-period flow simulations.

### *B.1 Recursive estimation procedure*

This section provides a brief overview of recursive method in Schmidt (2013), which we use to recursively estimate the parameters of (1). To see how the estimation method works, it is helpful to rewrite the data generating process for $Y_{i,t}$ as

$$Y_{i,t} = X_{i,t}'\beta_0 - D_{i,t}\exp[X_{i,t}'\beta_1]\eta_{i,t} + (1 - D_{i,t})\exp[X_{i,t}'\beta_2]\eta_{i,t}, \tag{3}$$

where $\eta_{i,t}$ is a nonnegative random variable with $P[\eta_{i,t} < 1|X_{i,t}] = 0.8$ and $D_{i,t}$ is a Bernoulli random variable which equals 1 with probability 0.5.[54] The left tail and right tail exposures, $\exp(X_{i,t}'\beta_1)$ and $\exp(X_{i,t}'\beta_2)$, are analogous to "semi-variances", where $\beta_1$ and $\beta_2$ separately govern the variance of bad and good shocks, respectively. If $\beta_1 = \beta_2$, this is consistent with a simple mean-variance model where the variance is a loglinear function of $X_{i,t}$. This alternative way of writing the DGP also mirrors the manner in which we estimate the relevant parameters.

Schmidt's (2013) method sequentially estimates the parameters of interest using a series of standard linear quantile regressions. Specifically, we first estimate $\beta_0$ using standard linear quantile regression. Next, we estimate $\beta_1$ and $\beta_2$ by splitting the sample into two halves based on the signs of the residuals and performing an additional linear quantile regression on the log of these residuals. Using the positive residuals, we can estimate $\beta_2$. To see why this works, note that if $Y_{i,t} - X_{i,t}'\beta_0 > 0$, $Y_{i,t} - X_{i,t}\beta_0 = \exp[X_{i,t}'\beta_2]\eta_{i,t}$. Taking logs, we get that $\log[Y_{i,t} - X_{i,t}'\beta_0] = X_{i,t}'\beta_2 + \log\eta_{i,t}$. Given our assumption that $P[\eta_{i,t} < 1|X_{i,t}] = P[\log\eta_{i,t} < 0|X_{i,t}] = 0.8$, the transformed model satisfies the standard assumptions for linear quantile regression. To get feasible estimators, $\beta_0$ is replaced

[54] The conditional quantile restrictions hold since if $P(\eta_{i,t} < 1|X_{i,t}) = 0.8$, $P(Y_{i,t} < X_{i,t}'\beta_0 - \exp[X_{i,t}'\beta_1]|X_{i,t}) = P(D_{i,t} = 1|X_{i,t}) \times P(\eta_{i,t} > 1|X_{i,t}) = 0.5 \times (1 - 0.8) = 0.1$.

with $\hat{\beta}_0$, the initial estimate from the quantile regression for the median. An analogous procedure works for the absolute value of the negative residuals, enabling us to estimate $\beta_1$.

### *B.2 Time-specific regressors*

Our panel specification in (2) includes a vector $Z_t$ of time-specific regressors, with associated parameters $\gamma_0$, $\gamma_1$, and $\gamma_2$. Using these variables, we define the "aggregate shocks" $\alpha_{0,t} = Z_t'\gamma_0$, $\alpha_{1,t} = \exp[Z_t'\gamma_1]$, and $\alpha_{2,t} = \exp[Z_t'\gamma_2]$. We next describe the choices of $Z_t$ which yield the estimated shocks depicted graphically in Figure 3.

The most flexible specification for $\alpha_{0,t}$, $\alpha_{1,t}$, $\alpha_{2,t}$ is to include a dummy variable for each date in the sample in $Z_t$. However, a simpler specification reduces bias and improves the efficiency of the other coefficient estimates, which is desirable given our sample sizes. Potential bias is introduced in second stage estimation of $\beta_1$ and $\beta_2$, which can become more pronounced as the dimension of the parameter vector increases.[55]

We began by estimating a version of the model with time dummies and found that, for all periods other than September 17-19, the estimated coefficients could be almost perfectly predicted by simple cross-sectional statistics. Our initial estimates of the aggregate shocks to the median, $\alpha_{0,t}$, closely tracked the median of the cross-sectional distribution of log flows, denoted by $Q50_t$. As such, we assumed that $\alpha_{0,t} = \gamma_{0,0}+\gamma_{0,1}Q50_t$. For the tails, we found that $\log \alpha_{1,t} = \gamma_{1,0}+\gamma_{1,1}\log(Q50_t-Q10_t)$ and $\log \alpha_{2,t} = \gamma_{2,0} + \gamma_{2,1}\log(Q90_t - Q50_t)$ were sufficient to capture common variation in the left and right tails, respectively. Thus, $Z_t = [1, Q50_t, \log(Q50_t - Q10_t), \log(Q90_t - Q50_t)]'$, and we enforce zero restrictions on coefficients as necessary. We do, however, allow the coefficients $\gamma_0$, $\gamma_1$, and $\gamma_2$ on these cross-sectional statistics to differ in the baseline period, relative to the crisis period.

For the peak crisis period, these relationships break down to some extent, so we augment $Z_t$ with time dummies in both the median and the tails for each of the three dates. Results with time dummies for all dates in the sample are similar and available upon request.

[55] This bias results from a well-known property of linear quantile regression, namely that it will set exactly $K$ fitted residuals to zero, where $K$ is the dimension of $X_{i,t}$. Since we require the log of the absolute value of the fitted residuals to estimate the tail parameters, we must exclude observations with fitted residuals exactly equal to zero from the second stage estimation, generating the bias. The efficiency argument is standard; parameter estimation error shrinks with the complexity of the model.

### *B.3 Multi-period flow simulations*

We next explain how we simulate from the dynamic model to study the relationship between explanatory variables and cumulative flows during the crisis period. We begin by fixing each of the explanatory variables at its average, while the initial value of lagged flows is assumed to be equal to the category average, i.e., $Y_{i,\tau-1} = \bar{Y}_{\tau-1}$, where $\tau$ is the first date in the simulation. Next, we take one of the elements of $X_{i,\tau}$ and add or subtract one standard deviation.

Our method for simulating a single daily flow mirrors the DGP as described in Equation (3). Given the model parameters, it is straightforward to draw $Y_{i,t}$ given $X_{i,t}$ by drawing a Bernoulli random variable, $D_{i,t}$, along with $\eta_{i,t}$, whose distribution remains to be specified. We assume that $\eta_{i,t}$ is distributed as an exponential random variable with rate parameter $-\log 0.2$, which ensures that $P(\eta_{i,t} < 1) = 0.8$. This distribution fits the data quite well; kernel density estimates of the fitted residuals, $\hat{\eta}_{i,t}$, are essentially indistinguishable from the parametric density, for both positive and negative residuals. We calculate cumulative flows by summing up the simulated $\{Y_{i,t}\}_{t=\tau}^{\tau+h}$.

We update several elements of $X_{i,t}$, given a simulated value of $Y_{i,t-1}$. The first is $Y_{i,t-1} - \bar{Y}_{t-1}$, which we calculate by subtracting off the actual cross-sectional mean from the data. Second, we update $LOGTNA$ by adding $Y_{i,t-1}$. Third, we update $LIQUIDRT$ by assuming that any redemptions in excess of maturing assets (estimated using the average cross-sectional weighted average maturity) are met by selling liquid assets. Then, given $X_{i,t}$, we simulate $Y_{i,t}$. Iterating back and forth, we trace out the path of cumulative flows.

For each set of initial $X_{i,\tau}$, we simulate 10,000 total sample paths for cumulative flows. We calculate the 1st, 10th, 50th, and 90th quantiles of the set of simulated paths as well as the probability of experiencing cumulative outflows in excess of 40%, 25%, 10%, and 5%, respectively. In addition, using the bootstrapped distribution of parameter estimates, we compute two statistical tests. The first tests whether the marginal effect of the variable of interest on cumulative flows is significantly different from zero. The second, which is only applicable for quantiles, tests whether the difference between the marginal effect at the median and a different quantile differs from zero.

| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| $EXPR$ (bp) | 0.67*** | 0.67*** | 0.77*** | 3.57*** | 5.57*** | | |
| | (4.786) | (4.244) | (2.942) | (3.156) | (3.246) | | |
| $\max(EXPR - 25, 0)$ | | | | -3.37*** | -5.59*** | | |
| | | | | (-2.793) | (-3.034) | | |
| Indicators: | | | | | | | |
| $EXPR < 15$ | | | | | | -42.80** | -64.97** |
| | | | | | | (-2.636) | (-2.110) |
| $EXPR < 25$ | | | | | | -21.47** | -22.65** |
| | | | | | | (-2.649) | (-2.373) |
| $EXPR < 45$ | | | | | | -1.70 | -1.17 |
| | | | | | | (-0.216) | (-0.116) |
| Dummies | None | Complex | Fund | Complex | Fund | Complex | Fund |
| Clustering | Fund | Complex | Fund | Complex | Fund | Complex | Fund |
| N | 245 | 245 | 245 | 245 | 245 | 245 | 245 |
| $R^2$ | 0.102 | 0.349 | 0.519 | 0.404 | 0.610 | 0.423 | 0.624 |

**Table 1:** Share Class-level Regression for Cumulative Flows following the Failure of Lehman Brothers

This table presents the coefficients from OLS regressions of the change in the log of share class-level assets under management for share classes of prime institutional money market funds ($\times 100$) during the week of September 15-19, 2008 on expense ratios. Depending on the specification, we include no fixed effects, complex fixed effects, or fund fixed effects. The final two columns replace the continuous variable $EXPR$ with a series of dummy variables which are successively turned on as the expense ratio declines. The sum of the three dummy variables in columns 5 and 6 is -65.97 and -88.79 log points, respectively.

Panel A: VAR with Controls

| Variable | Baseline $Low_{i,t}$ | Baseline $High_{i,t}$ | Early Crisis $Low_{i,t}$ | Early Crisis $High_{i,t}$ | Peak Crisis $Low_{i,t}$ | Peak Crisis $High_{i,t}$ | Late Crisis $Low_{i,t}$ | Late Crisis $High_{i,t}$ |
|---|---|---|---|---|---|---|---|---|
| $Low_{i,t-1}$ | -0.098*** | 0.018 | 0.136 | 0.230** | 0.291** | 0.081 | 0.044 | 0.042 |
| | (-3.655) | (1.194) | (0.916) | (2.358) | (2.604) | (0.432) | (0.451) | (1.110) |
| $High_{i,t-1}$ | 0.014 | -0.178* | 0.207** | 0.043 | -0.057 | 0.176 | 0.049 | -0.049 |
| | (1.302) | (-1.998) | (2.287) | (0.445) | (-1.026) | (0.963) | (0.878) | (-0.611) |
| $EXPR$ | 0.017 | -0.056 | 0.568*** | 0.147 | 1.072* | 0.328 | 0.151 | -0.068 |
| | (0.660) | (-1.616) | (2.884) | (0.975) | (1.871) | (0.392) | (1.237) | (-0.404) |
| $LOGFLOWSTDEV$ | 0.077*** | 0.061 | -0.467** | -0.169 | -1.471** | 0.515 | -0.272** | -0.260 |
| | (2.704) | (1.191) | (-2.217) | (-0.655) | (-2.206) | (0.353) | (-2.235) | (-1.313) |
| $LIQUIDRT$ | -0.118*** | -0.084** | 0.582*** | -0.148 | 1.904*** | 2.923 | 0.175* | -0.249 |
| | (-3.092) | (-2.608) | (2.750) | (-0.565) | (2.822) | (1.402) | (1.730) | (-0.992) |
| $PIPERC$ | -0.024 | 0.009 | 0.064 | -0.769** | -1.157 | 0.210 | -0.226* | 0.100 |
| | (-0.787) | (0.327) | (0.237) | (-2.644) | (-1.636) | (0.288) | (-1.910) | (0.937) |
| N | 9,050 | 9,050 | 301 | 301 | 180 | 180 | 1,067 | 1,067 |
| $R^2$ | 0.071 | 0.056 | 0.173 | 0.141 | 0.263 | 0.075 | 0.055 | 0.017 |

Panel B: Additional Specifications for Low Expense Ratio Share Classes

| Variable | Baseline $Low_{i,t}$ | Baseline $Low_{i,t}$ | Early Crisis $Low_{i,t}$ | Early Crisis $Low_{i,t}$ | Peak Crisis $Low_{i,t}$ | Peak Crisis $Low_{i,t}$ | Late Crisis $Low_{i,t}$ | Late Crisis $Low_{i,t}$ |
|---|---|---|---|---|---|---|---|---|
| $Low_{i,t-1}$ | -0.098*** | -0.098*** | 0.078 | -0.007 | 0.290** | 0.268*** | 0.003 | 0.005 |
| | (-3.642) | (-3.667) | (0.587) | (-0.053) | (2.624) | (3.598) | (0.053) | (0.091) |
| $High_{i,t-1}$ | 0.022 | 0.025 | 0.009 | 0.032 | -0.072 | -0.043 | -0.122* | -0.122** |
| | (1.319) | (1.378) | (0.128) | (0.647) | (-0.827) | (-0.535) | (-1.997) | (-2.008) |
| $High_{i,t-1} \times \%High_{i,t-1}$ | -0.052 | -0.059 | 0.805** | 0.436 | 0.059 | -0.075 | 1.047** | 1.050** |
| | (-0.693) | (-0.773) | (2.203) | (1.608) | (0.193) | (-0.247) | (2.654) | (2.637) |
| $High_{i,t}$ | | 0.012 | | -0.162* | | -0.037 | | 0.028 |
| | | (1.164) | | (-1.868) | | (-0.626) | | (0.956) |
| $High_{i,t} \times \%High_{i,t-1}$ | | -0.017 | | 1.179*** | | 0.495 | | -0.111 |
| | | (-0.298) | | (3.230) | | (1.638) | | (-0.635) |
| $EXPR$ | 0.017 | 0.017 | 0.543*** | 0.500*** | 1.080* | 1.196** | 0.160 | 0.158 |
| | (0.664) | (0.682) | (2.863) | (2.735) | (1.864) | (2.085) | (1.280) | (1.273) |
| $LOGFLOWSTDEV$ | 0.078*** | 0.077*** | -0.488** | -0.474** | -1.479** | -1.550** | -0.368*** | -0.366*** |
| | (2.719) | (2.706) | (-2.381) | (-2.158) | (-2.210) | (-2.167) | (-2.786) | (-2.787) |
| $LIQUIDRT$ | -0.117*** | -0.116*** | 0.625*** | 0.710*** | 1.906*** | 1.849*** | 0.146 | 0.149 |
| | (-3.040) | (-3.020) | (3.087) | (3.537) | (2.806) | (2.665) | (1.280) | (1.297) |
| $PIPERC$ | -0.025 | -0.025 | 0.159 | 0.282 | -1.166 | -1.240* | -0.214** | -0.213** |
| | (-0.805) | (-0.814) | (0.623) | (1.113) | (-1.633) | (-1.792) | (-2.161) | (-2.158) |
| N | 9,050 | 9050 | 301 | 301 | 180 | 180 | 1,067 | 1,067 |
| $R^2$ | 0.072 | 0.072 | 0.192 | 0.243 | 0.263 | 0.303 | 0.139 | 0.140 |

**Table 2:** Fund-level Vector Autoregressions - Prime Institutional

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 which are strictly less than the median expense ratio. All remaining share classes are included in the "High" category. Funds with a single share class are excluded from the analysis. For each date in the sample, we calculate the first difference in the log of total assets under management within each category, which we denote by $Low_{i,t}$ and $High_{i,t}$. Panel A presents the coefficients from panel vector autoregressions for $Low_{i,t}$ and $High_{i,t}$ estimated for four different subperiods in 2008: 2/1-9/9 Baseline, 9/10-9/16 Early Crisis, 9/17-9/19 Peak Crisis, and 9/22-10/17 Late Crisis, respectively. We multiply $Low_{i,t}$ and $High_{i,t}$ by 100 to express them in log percentage points. We also include additional fund characteristics: $EXPR$, $LOGFLOWSTDEV$, $LIQUIDRT$, and $PIPERC$, which are described in greater detail in Table A.1 and have been divided by their (cross-sectional) standard deviations for ease of interpretation. Panel B focuses on low expense ratio share classes and adds interactions between flows and $\%High_{i,t-1}$, which is the fraction of lagged total fund assets in institutional share classes in the "High" category as of date $t-1$. All specifications also include time dummies, which are omitted for brevity. Standard errors are clustered at the fund level.

| Variable | Panel A: Common (Median) Exposure | | | |
|---|---|---|---|---|
| | Baseline | Early Crisis | Peak Crisis | Late Crisis |
| $AVGYIELD$ | -0.0021 | -0.0095 | -0.5619 ** | -0.1075 *** |
| | [0.493] | [0.285] | [0.019] | [0.001] |
| $EXPR$ | -0.0021 | 0.0630 * | 0.2150 | 0.0672 ** |
| | [0.448] | [0.080] | [0.189] | [0.011] |
| $LOGFLOWSTDEV$ | 0.0164 * | -0.0198 | -0.4407 ** | -0.1559 *** |
| | [0.087] | [0.355] | [0.039] | [0.002] |
| $PIPERC$ | -0.0234 ** | -0.0452 | 0.0031 | -0.0116 |
| | [0.039] | [0.302] | [0.595] | [0.450] |
| $LOGTNA$ | 0.0228 *** | -0.2312 *** | -1.0642 *** | -0.1379 *** |
| | [0.009] | [0.000] | [0.000] | [0.004] |
| $LIQUIDRT$ | -0.0300 ** | 0.0425 | 0.5581 * | -0.0489 |
| | [0.034] | [0.396] | [0.087] | [0.103] |
| $y_{i,t-1} - \bar{y}_{t-1} > 0$ | -0.0378 *** | 0.0649 | 0.4136 *** | 0.0072 |
| | [0.000] | [0.240] | [0.009] | [0.318] |
| $y_{i,t-1} - \bar{y}_{t-1} < 0$ | 0.0005 | 0.2589 *** | 0.4746 *** | 0.1027 ** |
| | [0.481] | [0.007] | [0.002] | [0.013] |
| $LIQUIDRT \times (y_{i,t-1} - \bar{y}_{t-1})$ | -0.0030 | 0.0179 | -0.1218 ** | -0.0150 |
| | [0.318] | [0.155] | [0.019] | [0.171] |

| Variable | Panel B: Left Tail Exposure | | | |
|---|---|---|---|---|
| | Baseline | Early Crisis | Peak Crisis | Late Crisis |
| $AVGYIELD$ | -0.0049 | 0.1266 | 0.2976 | 0.0999 |
| | [0.485] | [0.159] | [0.154] | [0.158] |
| $EXPR$ | -0.0503 ** | -0.4528 *** | -0.1908 * | -0.1977 *** |
| | [0.034] | [0.003] | [0.077] | [0.003] |
| $LOGFLOWSTDEV$ | 0.5576 *** | 0.5735 *** | 0.3114 ** | 0.4546 *** |
| | [0.000] | [0.000] | [0.015] | [0.000] |
| $PIPERC$ | 0.0333 | 0.0807 * | 0.2181 * | 0.0019 |
| | [0.134] | [0.081] | [0.065] | [0.385] |
| $LIQUIDRT$ | -0.0123 | -0.1339 * | 0.0439 | 0.0002 |
| | [0.327] | [0.051] | [0.499] | [0.482] |
| $\lvert y_{i,t-1} - \bar{y}_{t-1} \rvert$ | 0.0651 *** | 0.0206 | 0.0028 | 0.0460 *** |
| | [0.000] | [0.111] | [0.550] | [0.000] |

| Variable | Panel C: Right Tail Exposure | | | |
|---|---|---|---|---|
| | Baseline | Early Crisis | Peak Crisis | Late Crisis |
| $AVGYIELD$ | 0.0140 | -0.0829 | 0.3284 ** | 0.0123 |
| | [0.272] | [0.167] | [0.024] | [0.374] |
| $EXPR$ | -0.0899 *** | 0.1198 | -0.1292 | -0.0204 |
| | [0.000] | [0.216] | [0.190] | [0.457] |
| $LOGFLOWSTDEV$ | 0.5575 *** | 0.5642 *** | 0.2653 ** | 0.4700 *** |
| | [0.000] | [0.000] | [0.012] | [0.000] |
| $PIPERC$ | 0.0453 ** | 0.0134 | 0.0272 | -0.0486 |
| | [0.044] | [0.244] | [0.382] | [0.216] |
| $LIQUIDRT$ | 0.0110 | -0.0894 | 0.4194 ** | 0.0257 |
| | [0.415] | [0.154] | [0.039] | [0.300] |
| $\lvert y_{i,t-1} - \bar{y}_{t-1} \rvert$ | 0.0344 *** | 0.0855 ** | 0.0599 *** | 0.0488 *** |
| | [0.000] | [0.016] | [0.008] | [0.004] |
| N | 19,332 | 615 | 367 | 2,299 |
| Q10 Pseudo-$R^2$ | 0.138 | 0.288 | 0.348 | 0.108 |
| Q50 Pseudo-$R^2$ | 0.010 | 0.054 | 0.188 | 0.028 |
| Q90 Pseudo-$R^2$ | 0.114 | 0.146 | 0.155 | 0.064 |

**Table 3:** Fund-Level Panel Quantile Regressions - Prime Institutional

This table presents the coefficients from estimating equation (2) via quantile regression using the recursive method in Schmidt (2013). The dependent variable ($y_{i,t}$) is the daily log difference in fund-level assets under management for prime institutional funds, in percentage points (i.e. $\times$ 100). The top panel reports $\beta_0$, which controls the conditional median and shifts all quantiles symmetrically. The middle panel reports $\beta_1$, which governs the width of the left tail (the distance between the median and the 10th percentile). The bottom panel reports $\beta_2$, which controls the width of the right tail (the distance between the 90th percentile and the median). All three sets of coefficients are allowed to vary over four different periods in 2008: 2/1-9/9 Baseline, 9/10-9/16 Early Crisis, 9/17-9/19 Peak Crisis, and 9/22-10/17 Late Crisis, respectively. More detailed variable descriptions may be found in Table A.1. In addition to the coefficients in the table, we include time-specific regressors to capture the common shocks, $\alpha_{0,t}$, $\alpha_{1,t}$, and $\alpha_{2,t}$, which are depicted graphically in Figure 3 and described in further detail in Appendix B.2. Numbers in brackets are one-sided bootstrapped p-values clustered at the fund level. With the exception of lagged flows, all other variables have been divided by their (cross-sectional) standard deviations for ease of interpretation.

| | Panel A: Common (Median) Exposure | | | |
|---|---|---|---|---|
| Variable | Baseline | Early Crisis | Peak Crisis | Late Crisis |
| $AVGYIELD$ | 0.0048 | -0.0155 | -0.2036 ** | -0.0613 ** |
| | [0.201] | [0.289] | [0.022] | [0.036] |
| $EXPR$ | -0.0035 | 0.0496 *** | -0.0101 | 0.0584 ** |
| | [0.230] | [0.009] | [0.328] | [0.036] |
| $LOGFLOWSTDEV$ | -0.0018 | 0.0246 | -0.1788 ** | -0.0296 |
| | [0.432] | [0.210] | [0.014] | [0.129] |
| $PIPERC$ | -0.0021 | -0.0096 | -0.0371 | -0.0131 |
| | [0.290] | [0.266] | [0.464] | [0.337] |
| $LOGTNA$ | -0.0030 | 0.0133 | -0.2079 *** | -0.1321 *** |
| | [0.270] | [0.295] | [0.001] | [0.001] |
| $LIQUIDRT$ | 0.0025 | -0.0118 | -0.0750 | -0.0467 * |
| | [0.380] | [0.415] | [0.186] | [0.066] |
| $y_{i,t-1} - \bar{y}_{t-1} > 0$ | -0.0454 *** | 0.0691 | 0.2841 *** | 0.0874 * |
| | [0.000] | [0.325] | [0.002] | [0.070] |
| $y_{i,t-1} - \bar{y}_{t-1} < 0$ | 0.0183 | 0.0466 * | 0.4274 ** | 0.0806 * |
| | [0.214] | [0.098] | [0.023] | [0.082] |
| $LIQUIDRT \times (y_{i,t-1} - \bar{y}_{t-1})$ | -0.0125 | -0.0856 ** | -0.0280 | -0.0265 |
| | [0.272] | [0.042] | [0.319] | [0.104] |
| | Panel B: Left Tail Exposure | | | |
| Variable | Baseline | Early Crisis | Peak Crisis | Late Crisis |
| $AVGYIELD$ | 0.0356 | 0.0428 | 0.1559 | 0.0743 |
| | [0.168] | [0.288] | [0.325] | [0.173] |
| $EXPR$ | 0.0298 | -0.0691 | -0.1289 | 0.0131 |
| | [0.208] | [0.263] | [0.398] | [0.405] |
| $LOGFLOWSTDEV$ | 0.7277 *** | 0.8970 *** | 0.4328 ** | 0.5842 *** |
| | [0.000] | [0.000] | [0.017] | [0.000] |
| $PIPERC$ | 0.0330 | -0.0113 | -0.2236 | 0.0637 |
| | [0.193] | [0.425] | [0.426] | [0.229] |
| $LIQUIDRT$ | 0.0852 *** | 0.0036 | 0.1411 | 0.0831 ** |
| | [0.003] | [0.521] | [0.263] | [0.043] |
| $\lvert y_{i,t-1} - \bar{y}_{t-1} \rvert$ | 0.1849 *** | 0.1209 *** | 0.1987 * | 0.1628 *** |
| | [0.000] | [0.001] | [0.086] | [0.000] |
| | Panel C: Right Tail Exposure | | | |
| Variable | Baseline | Early Crisis | Peak Crisis | Late Crisis |
| $AVGYIELD$ | -0.0345 | 0.1129 | 0.0630 | -0.0154 |
| | [0.146] | [0.257] | [0.319] | [0.322] |
| $EXPR$ | 0.0486 * | 0.0644 | 0.0802 | 0.0757 * |
| | [0.099] | [0.312] | [0.172] | [0.097] |
| $LOGFLOWSTDEV$ | 0.8639 *** | 1.0489 *** | 0.6715 *** | 0.4176 *** |
| | [0.000] | [0.000] | [0.001] | [0.000] |
| $PIPERC$ | 0.0279 | 0.0677 | 0.0078 | 0.1183 * |
| | [0.160] | [0.230] | [0.315] | [0.060] |
| $LIQUIDRT$ | 0.0312 | 0.0862 | 0.0838 | 0.2096 *** |
| | [0.166] | [0.112] | [0.321] | [0.004] |
| $\lvert y_{i,t-1} - \bar{y}_{t-1} \rvert$ | 0.1199 *** | 0.1049 * | 0.1508 ** | 0.1583 *** |
| | [0.000] | [0.058] | [0.016] | [0.000] |
| N | 20,634 | 669 | 400 | 2,506 |
| Q10 Pseudo-$R^2$ | 0.203 | 0.320 | 0.295 | 0.180 |
| Q50 Pseudo-$R^2$ | 0.012 | 0.012 | 0.068 | 0.041 |
| Q90 Pseudo-$R^2$ | 0.186 | 0.323 | 0.188 | 0.172 |

**Table 4:** Fund-Level Panel Quantile Regressions - Prime Retail

This table presents the coefficients from estimating equation (2) via quantile regression using the recursive method in Schmidt (2013). The dependent variable ($y_{i,t}$) is the daily log difference in fund-level assets under management for prime retail funds, in percentage points (i.e. $\times$ 100). The top panel reports $\beta_0$, which controls the conditional median and shifts all quantiles symmetrically. The middle panel reports $\beta_1$, which governs the width of the left tail (the distance between the median and the 10th percentile). The bottom panel reports $\beta_2$, which controls the width of the right tail (the distance between the 90th percentile and the median). All three sets of coefficients are allowed to vary over four different periods in 2008: 2/1-9/9 Baseline, 9/10-9/16 Early Crisis, 9/17-9/19 Peak Crisis, and 9/22-10/17 Late Crisis, respectively. More detailed variable descriptions may be found in Table A.1. In addition to the coefficients in the table, we include time-specific regressors to capture the common shocks, $\alpha_{0,t}$, $\alpha_{1,t}$, and $\alpha_{2,t}$, which are depicted graphically in Figure 3 and described in further detail in Appendix B.2. Numbers in brackets are one-sided bootstrapped p-values clustered at the fund level. With the exception of lagged flows, all other variables have been divided by their (cross-sectional) standard deviations for ease of interpretation.

| | | Cumulative Flow Quantile | | | | Probability that Cumulative Outflows Exceed | | | |
|---|---|---|---|---|---|---|---|---|---|
| Variable | Value | 1% | 10% | 50% | 90% | 40% | 25% | 10% | 5% |
| AVGYIELD | $f(\bar{x}+\sigma_x)$ | -56.65 | -37.55 | -16.52 | 3.42 | 7.80 | 28.72 | 67.55 | 78.56 |
| | $f(\bar{x}-\sigma_x)$ | -40.42 | -26.18 | -11.50 | 1.59 | 1.08 | 11.56 | 56.02 | 74.55 |
| | Difference | -16.23 * | -11.37 ** | -5.01 ** | 1.83 | 6.72 * | 17.16 ** | 11.53 * | 4.01 |
| | p-value | [0.078] | [0.050] | [0.047] | [0.456] | [0.069] | [0.044] | [0.072] | [0.192] |
| | p-value vs. median | [0.119] | [0.092] | - | [0.031] | | | | |
| LIQUIDRT | $f(\bar{x}+\sigma_x)$ | -45.01 | -28.64 | -11.03 | 8.86 | 2.13 | 15.01 | 53.15 | 67.96 |
| | $f(\bar{x}-\sigma_x)$ | -52.02 | -34.79 | -17.26 | -2.38 | 5.33 | 27.59 | 73.13 | 85.30 |
| | Difference | 7.01 | 6.15 | 6.23 ** | 11.24 ** | -3.20 | -12.58 * | -19.98 ** | -17.34 ** |
| | p-value | [0.161] | [0.119] | [0.041] | [0.049] | [0.133] | [0.093] | [0.033] | [0.041] |
| | p-value vs. median | [0.338] | [0.631] | - | [0.248] | | | | |
| EXPR | $f(\bar{x}+\sigma_x)$ | -43.40 | -27.17 | -11.95 | 2.46 | 1.66 | 13.33 | 57.01 | 74.31 |
| | $f(\bar{x}-\sigma_x)$ | -54.44 | -36.14 | -16.76 | 1.31 | 6.52 | 28.30 | 68.75 | 80.34 |
| | Difference | 11.03 *** | 8.97 *** | 4.81 ** | 1.15 | -4.86 *** | -14.97 *** | -11.74 ** | -6.03 |
| | p-value | [0.004] | [0.000] | [0.013] | [0.379] | [0.003] | [0.000] | [0.050] | [0.165] |
| | p-value vs. median | [0.033] | [0.014] | - | [0.029] | | | | |
| LOGFLOWSTDEV | $f(\bar{x}+\sigma_x)$ | -57.81 | -38.01 | -16.86 | 5.47 | 8.28 | 30.23 | 66.62 | 77.14 |
| | $f(\bar{x}-\sigma_x)$ | -40.71 | -26.50 | -12.08 | 0.56 | 1.16 | 12.30 | 58.05 | 76.42 |
| | Difference | -17.10 *** | -11.50 *** | -4.77 *** | 4.91 ** | 7.12 *** | 17.93 *** | 8.57 ** | 0.72 |
| | p-value | [0.000] | [0.000] | [0.005] | [0.043] | [0.000] | [0.000] | [0.038] | [0.444] |
| | p-value vs. median | [0.001] | [0.001] | - | [0.000] | | | | |
| PIPERC | $f(\bar{x}+\sigma_x)$ | -53.46 | -35.40 | -15.73 | 1.64 | 5.90 | 26.15 | 66.33 | 78.76 |
| | $f(\bar{x}-\sigma_x)$ | -41.92 | -27.65 | -12.75 | 1.89 | 1.44 | 14.47 | 60.12 | 76.38 |
| | Difference | -11.55 ** | -7.74 ** | -2.98 ** | -0.24 | 4.46 ** | 11.68 ** | 6.21 * | 2.38 |
| | p-value | [0.025] | [0.022] | [0.049] | [0.455] | [0.024] | [0.027] | [0.096] | [0.275] |
| | p-value vs. median | [0.026] | [0.018] | - | [0.087] | | | | |
| LOGTNA | $f(\bar{x}+\sigma_x)$ | -50.58 | -34.55 | -18.13 | -3.17 | 4.87 | 29.00 | 76.50 | 87.54 |
| | $f(\bar{x}-\sigma_x)$ | -45.73 | -28.37 | -9.88 | 7.19 | 2.37 | 14.58 | 49.62 | 65.35 |
| | Difference | -4.85 *** | -6.18 *** | -8.25 *** | -10.36 *** | 2.50 *** | 14.42 *** | 26.88 *** | 22.19 *** |
| | p-value | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] | [0.000] |
| | p-value vs. median | [0.000] | [0.000] | - | [0.000] | | | | |

**Table 5:** Comparative Statics for Cumulative Flow Quantiles during Lehman Week - Prime Institutional

This table shows the impact of explanatory variables on cumulative flow distributions (as a percentage of initial assets) for prime institutional funds for the September 15-19 period. These estimates are obtained by simulating from the estimated model for daily flows presented in Table 3. Detailed variable descriptions may be found in the notes to Table A.1. The left columns report the 1st, 10th, 50th, and 90th quantiles of the cumulative flow distributions, respectively. The right columns report the probability of experiencing cumulative outflows in excess of 40%, 25%, 10%, and 5%, respectively. We begin by fixing each of the explanatory variables at its average, while the initial value of lagged flows is assumed to be equal to the category average. Then, one variable at a time, we report the impact of adding and subtracting one standard deviation on the simulated outflow distribution. See Appendix B.4 for more details. We also report p-values for a test of whether the difference is statistically significant, obtained by using the bootstrapped distribution of parameter estimates from our model. In addition, for the left panel, we report the p-value of a test for whether the marginal effect is significantly different at a given quantile relative to the marginal effect at the median (also obtained using the bootstrapped distribution).

**(a)** Univariate Summary Statistics

| Variable | Mean | StdDev | Quantiles 5% | 10% | 25% | 50% | 75% | 90% | 95% |
|---|---|---|---|---|---|---|---|---|---|
| AVGYIELD | 2.933 | 0.176 | 2.590 | 2.715 | 2.832 | 2.945 | 3.040 | 3.123 | 3.159 |
| LIQUIDRT | 0.197 | 0.165 | 0.000 | 0.030 | 0.080 | 0.170 | 0.247 | 0.410 | 0.538 |
| EXPR | 0.294 | 0.181 | 0.087 | 0.130 | 0.176 | 0.242 | 0.360 | 0.534 | 0.720 |
| LOGFLOWSTDEV | -3.870 | 0.744 | -5.383 | -5.062 | -4.161 | -3.803 | -3.429 | -2.995 | -2.839 |
| PIPERC | 0.445 | 0.230 | 0.115 | 0.165 | 0.286 | 0.416 | 0.612 | 0.783 | 0.918 |
| LOGTNA | 8.104 | 1.705 | 5.184 | 5.522 | 6.801 | 8.153 | 9.587 | 10.264 | 10.526 |
| TNA ($ Bil) | 10.209 | 15.865 | 0.178 | 0.251 | 0.898 | 3.474 | 14.578 | 28.695 | 37.285 |
| CUMFLOWS | -10.189 | 18.215 | -40.380 | -36.584 | -19.792 | -6.171 | 0.658 | 4.632 | 17.603 |

**(b)** Pairwise Correlation Matrix

| Variable | AVGYIELD | LIQUIDRT | EXPR | LOGFLOWSD | PIPERC | LOGTNA | TNA | Cum Flows |
|---|---|---|---|---|---|---|---|---|
| AVGYIELD | 1.000 | | | | | | | |
| LIQUIDRT | -0.667 | 1.000 | | | | | | |
| EXPR | 0.112 | -0.063 | 1.000 | | | | | |
| LOGFLOWSD | -0.114 | 0.148 | -0.395 | 1.000 | | | | |
| PIPERC | 0.080 | -0.059 | -0.173 | 0.196 | 1.000 | | | |
| LOGTNA | 0.116 | -0.141 | -0.342 | 0.009 | 0.196 | 1.000 | | |
| TNA ($ Bil) | 0.141 | -0.078 | -0.202 | -0.020 | 0.083 | 0.733 | 1.000 | |
| CUMFLOWS | -0.247 | 0.250 | 0.317 | -0.169 | -0.265 | -0.572 | -0.388 | 1.000 |

**Table A.1:** Summary Statistics for Prime Institutional Funds as of 9/15/2008

This table presents several summary statistics for the cross section of money market funds in the Prime Institutional category within the iMoneyNet database as of September 15, 2008, the Monday following the failure of Lehman Brothers. $AVGYIELD$ is the average of the (annualized) 7-day gross yield from March through August, 2008. $LIQUIDRT$ is a "real-time" estimate of liquid assets available as a fraction of total net assets, and is calculated by comparing an estimate of maturing assets with net redemptions. $EXPR$ is asset-weighted average of the expense ratios (in percentage points) of the shareclasses of each fund. $LOGFLOWSTDEV$ is the natural logarithm of the standard deviation of daily percentage changes in fund assets over the period March-August 2008. $PIPERC$ is the ratio of complex-level assets under management in prime institutional funds to total money market fund assets under management. $LOGTNA$ is the natural logarithm of total assets under management (in billions), and CUMFLOWS provides the total change in fund-level assets under management from September 15-19, in percentage points.

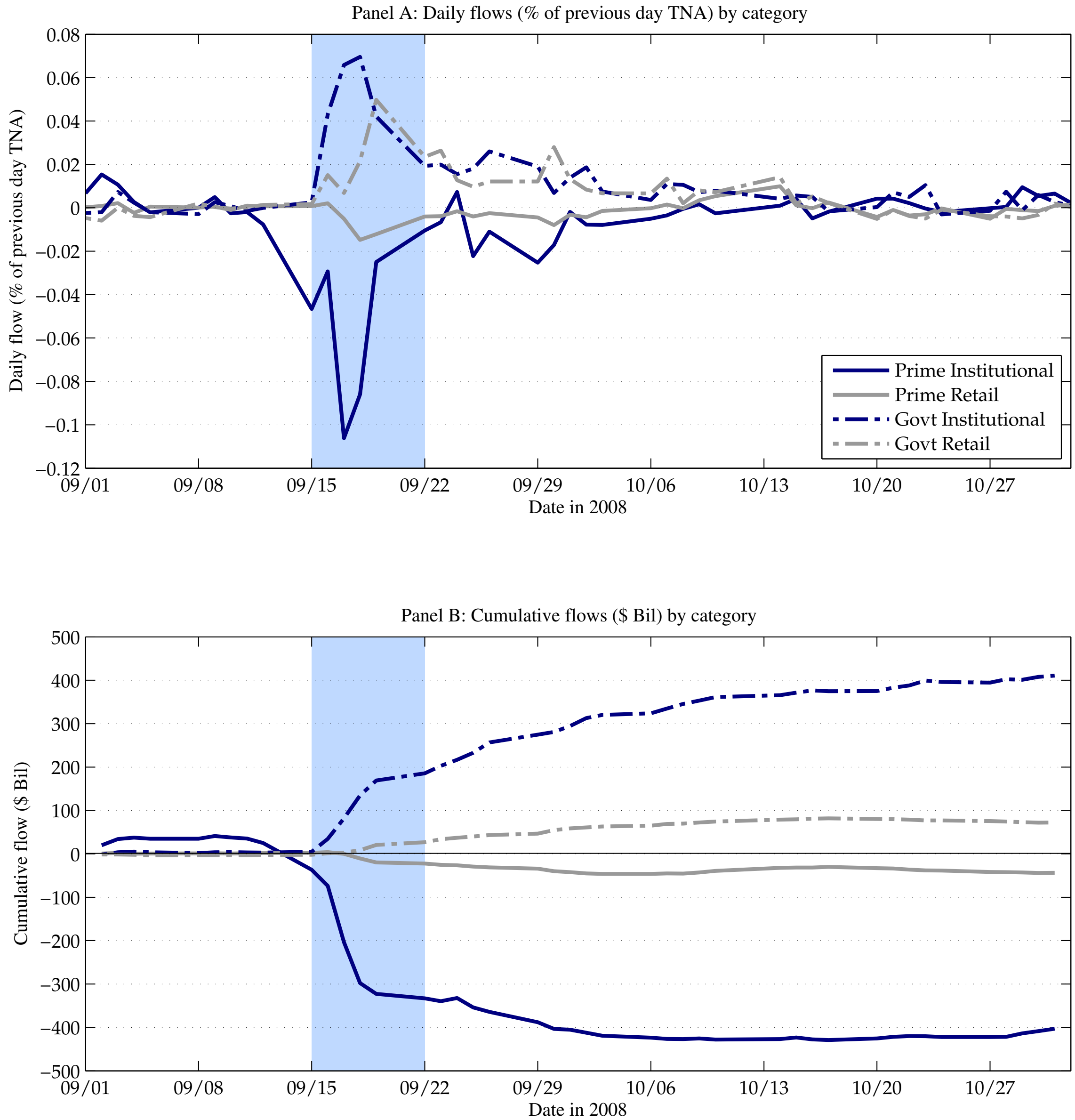
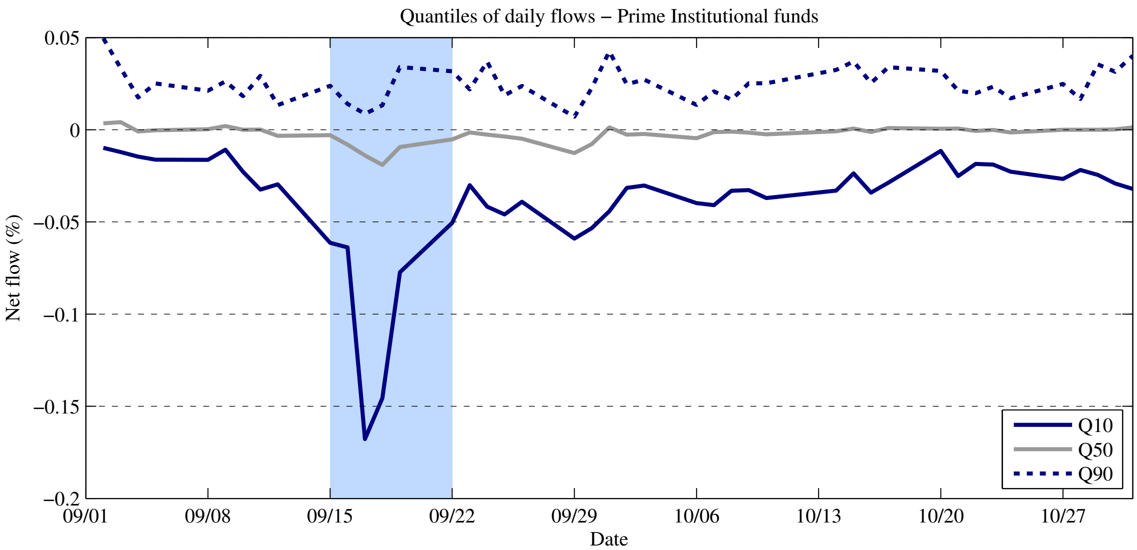



**Figure 1:** Daily Flows to/from money fund categories in September-October 2008

This figure plots summary statistics for flows to/from money market mutual fund share classes in different categories during September and October 2008. The top panel displays the daily percentage change in total assets under management for each category, while the bottom panel plots the cumulative change in assets under management for each category, in billions of dollars, over the two-month period. September 15-22, 2008, the week following the failure of Lehman Brothers is indicated by blue shading.



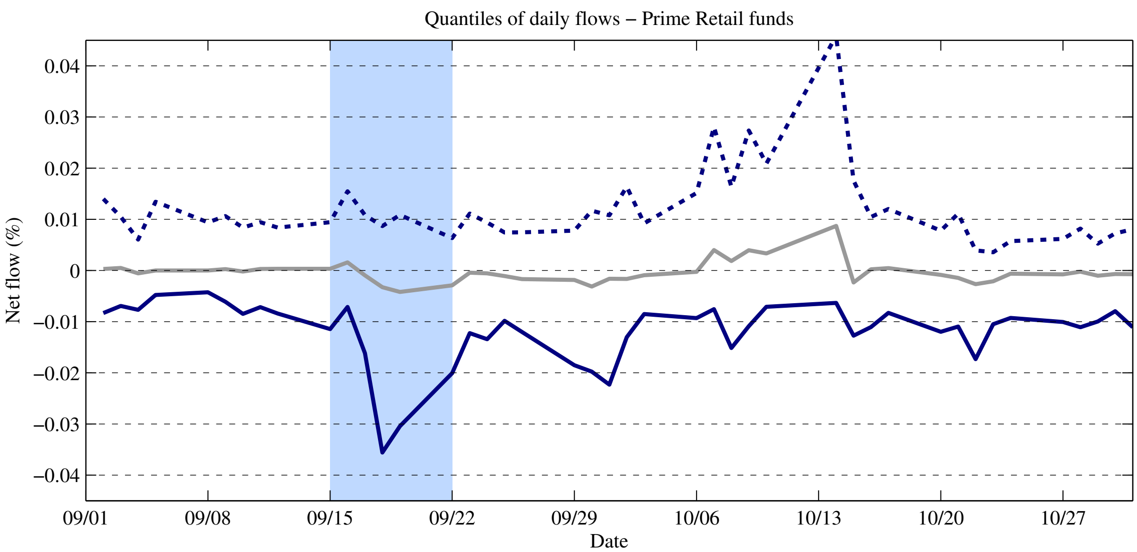




**Figure 2:** Quantiles of Daily Flow Distributions by Category in September-October 2008 (in %)

This figure plots the 10th, 50th, and 90th quantiles of fund-level flows in each category (as a fraction of fund assets) for September-October 2008. The top panel corresponds with Prime Institutional funds, and the bottom panel corresponds with Prime Retail funds. September 15-22, 2008, the week following the failure of Lehman Brothers is indicated by blue shading.

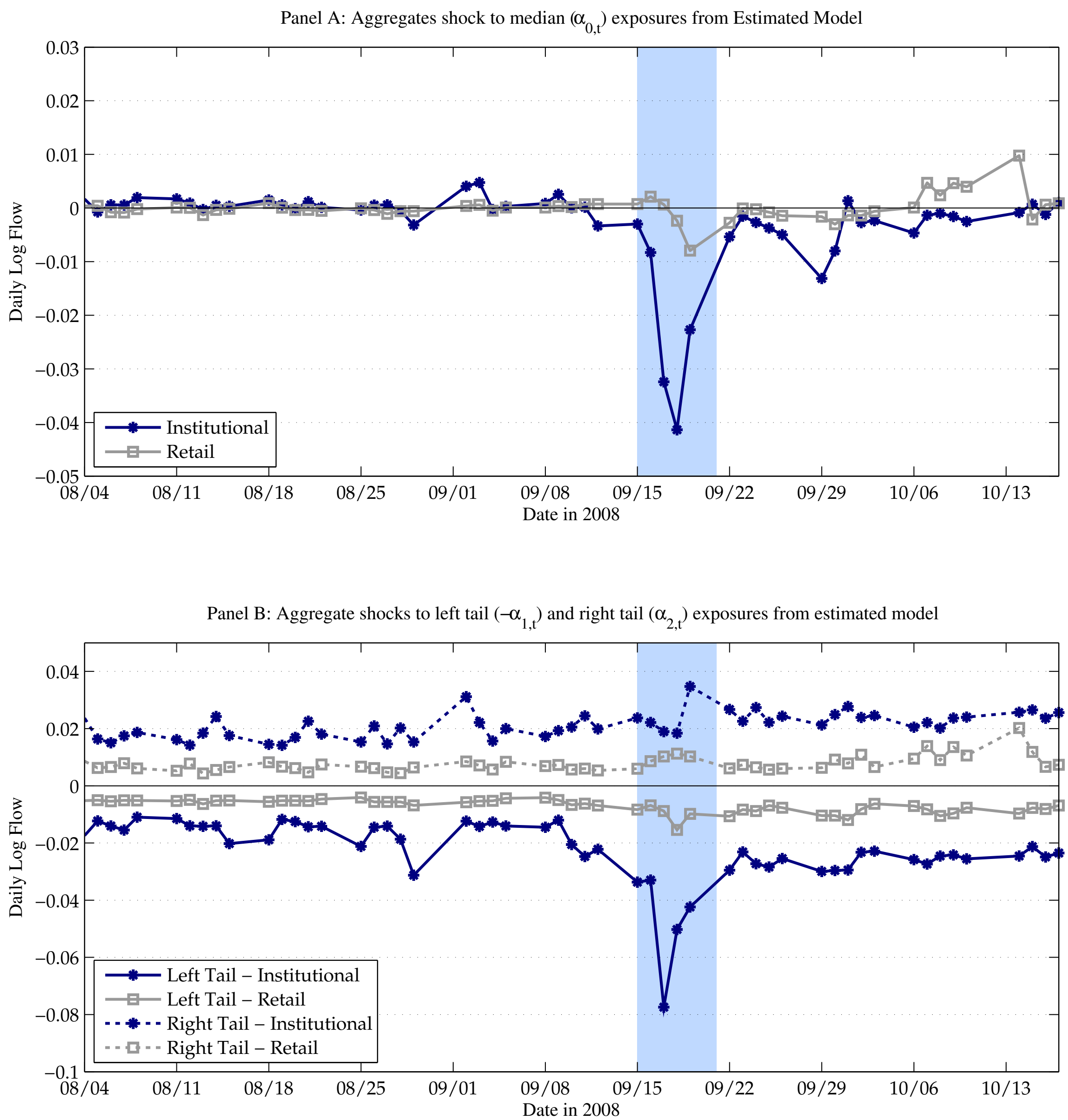



**Figure 3:** Common Median and Tail Exposures from Estimated Models

This figure plots our estimates of the common median ($\alpha_{0,t}$), left tail ($\alpha_{1,t}$), and right tail ($\alpha_{2,t}$) exposures from our panel quantile regressions for Prime Institutional and Prime Retail funds. Left tail exposures have been multiplied by negative 1 for ease of interpretation. The other estimated coefficients from Equation (2) may be found in Tables 3-4. September 15-22, 2008, the week following the failure of Lehman Brothers is indicated by blue shading.

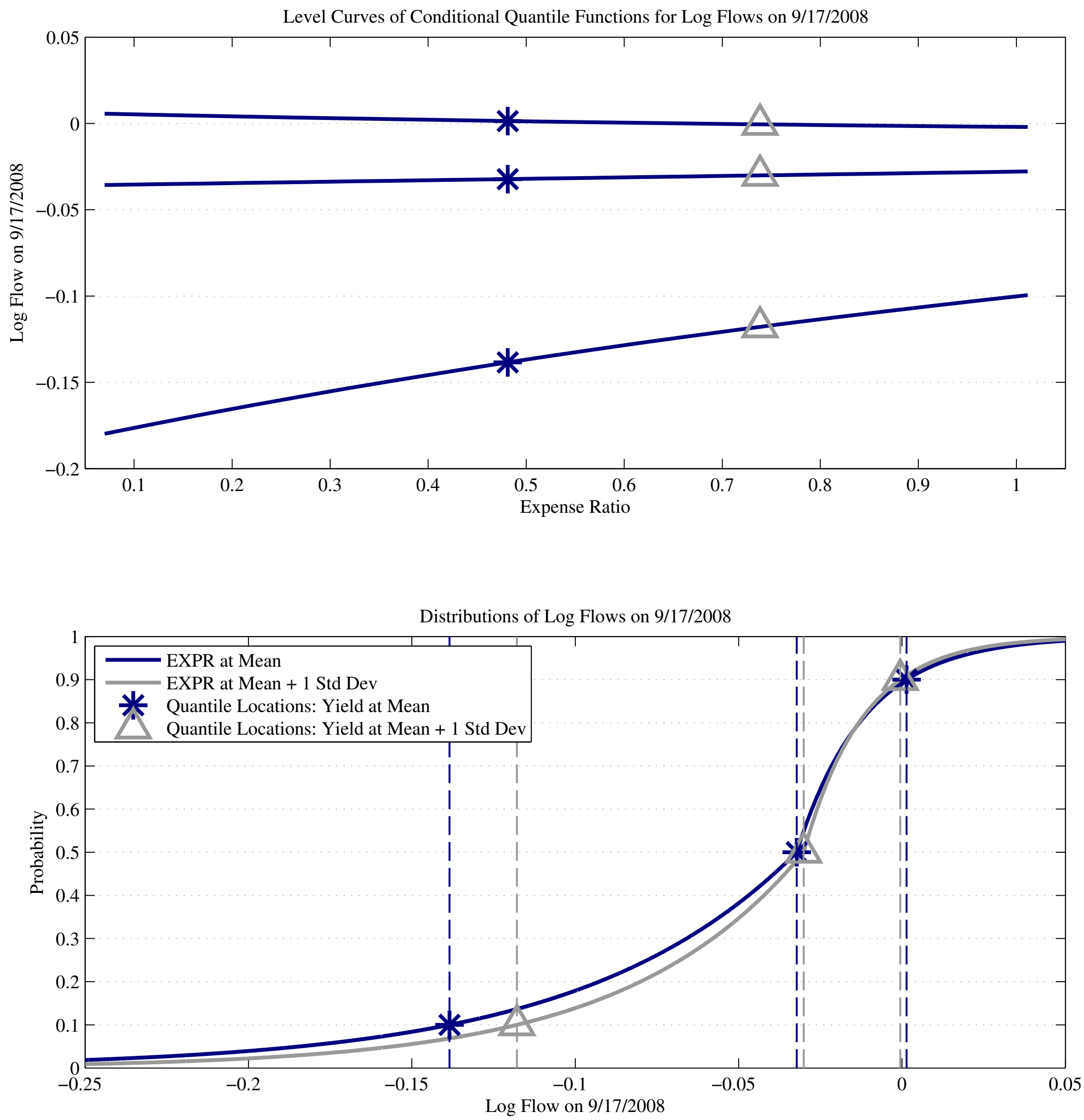



**Figure 4:** Marginal Effects of Expense Ratio on Log Flow Distribution for 9/17/2008 - Prime Institutional Funds

The top panel plots the effect of changing the variable $EXPR$ on the 10th, 50th, and 90th conditional quantiles of the flow distribution for prime institutional funds on 9/17/2008. Lagged flows are held constant at the category-level flow and all other variables are held constant at their cross-sectional averages. Stars mark the location of the cross-sectional average value of $EXPR$, and triangles add 1 standard deviation to this value. The bottom panel plots the conditional distribution functions of flows at these two points, where we interpolate between quantiles by assuming that $\eta_{i,t}$, as defined in the equation (3) in Appendix B.1, is drawn from an exponential distribution. This distributional assumption is not imposed in the estimation procedure. As above, stars and triangles (along with dashed lines) mark the locations of the conditional quantiles for each value of $EXPR$.

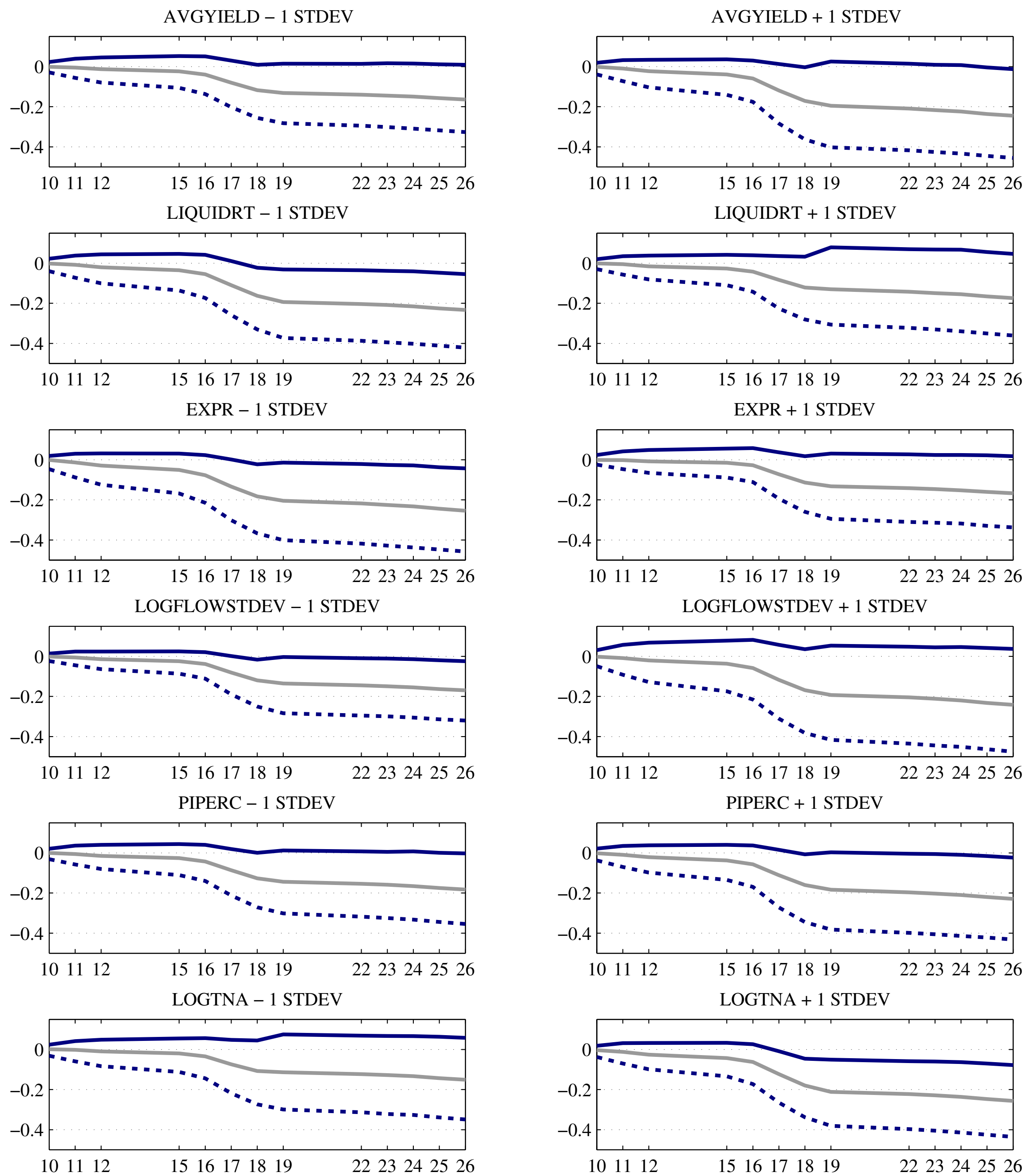
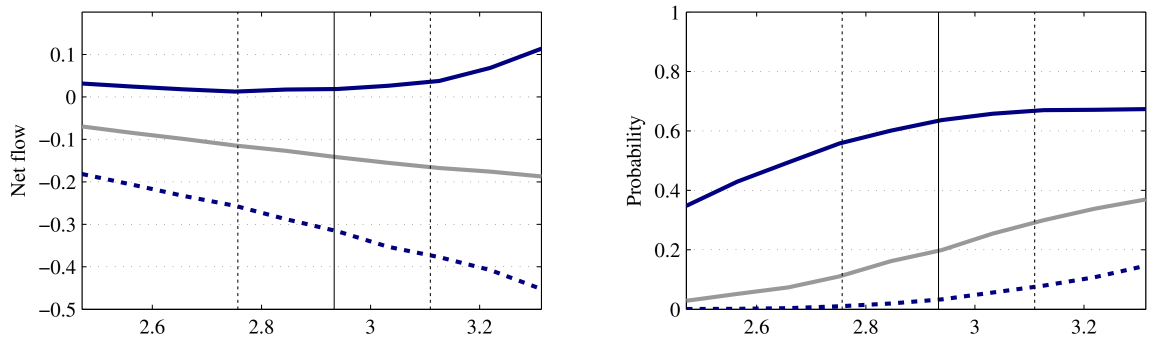


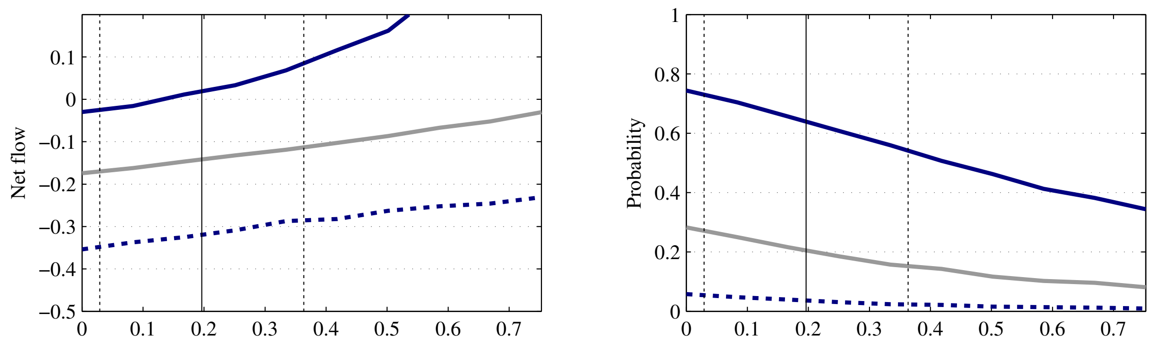

**Figure 5:** Impact of Explanatory Variables on Multi-Period Flow Distributions - Institutional Funds

This figure shows the impact of explanatory variables on quantiles of multi-period cumulative flow distributions (as a percent of initial assets). The lines plot the 10th, 50th, and 90th quantiles of the cumulative flow distributions, respectively. We fix each of the explanatory variables at its average plus or minus one standard deviation. The initial value of lagged flows is assumed to be equal to the category average, and all other variables are fixed at their averages. We estimate the quantiles by drawing shocks from the Laplace distribution and using the recursive definition of the dependent variable to simulate 10,000 sample paths for each set of conditioning variables. See Appendix B.4 for further details.

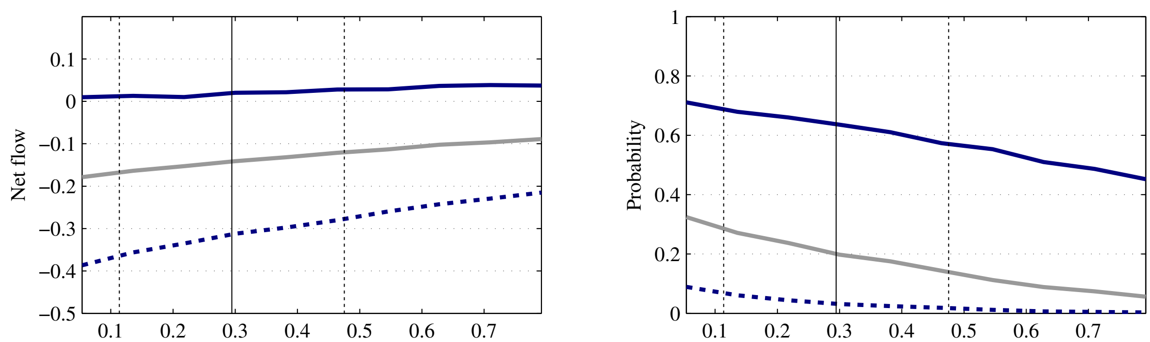
**(a)** Average Yield




**(b)** Liquid Asset Share




**(c)** Expense Ratio




**(d)** Standard Deviation of Log Flows

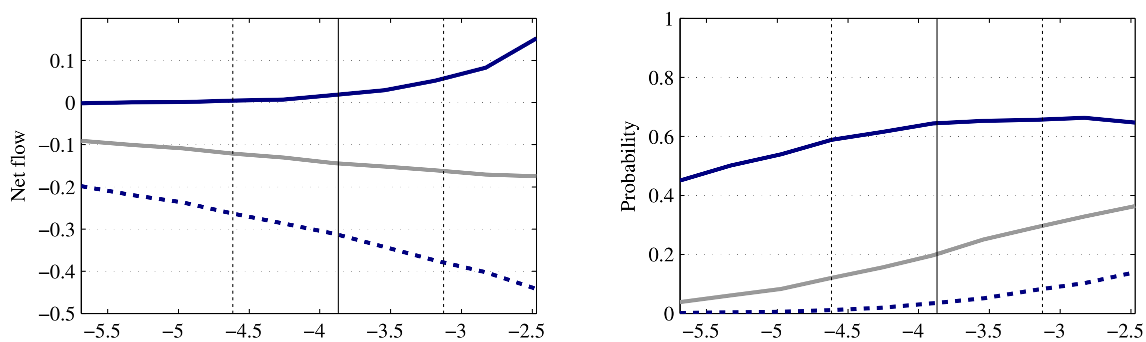
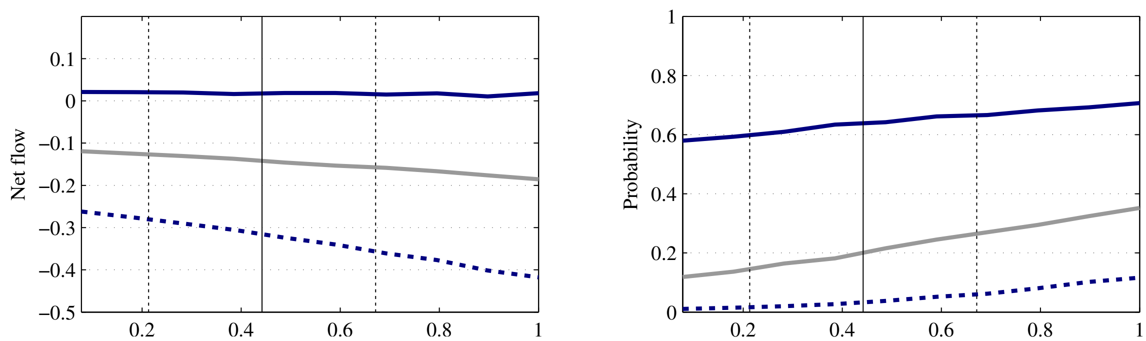



**Figure 6:** Comparative Statics for Cumulative Outflows During the Week after the Failure of Lehman Brothers - Institutional Funds

Note: This is a multi-page figure. See detailed caption below.

**(e)** Fraction of Complex Assets in Prime Institutional Funds




**(f)** Log Total Net Assets

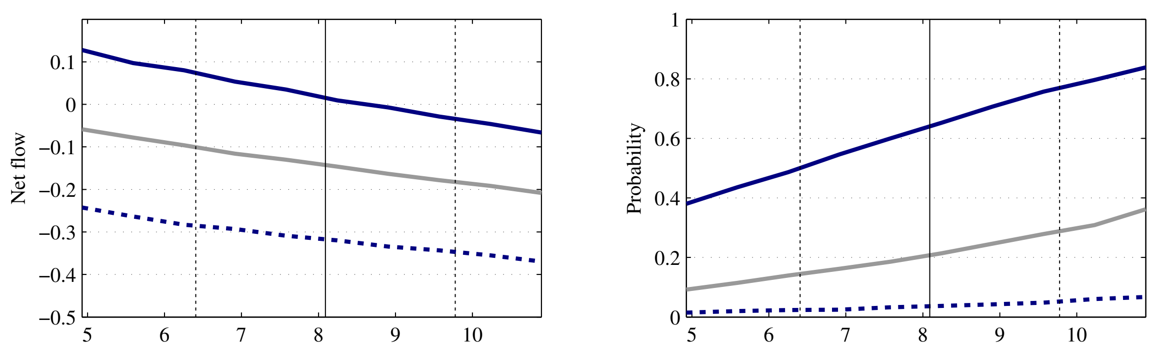



**Figure 6:** Comparative Statics for Cumulative Outflows During the Week after the Failure of Lehman Brothers - Institutional Funds

This figure shows the impact of explanatory variables on the distribution of cumulative flow distributions (as a % of initial assets) from September 15-19, 2008. The lines in the left panel plot the 10th, 50th, and 90th quantiles of the cumulative flow distributions, respectively. The right panel shows the probability of having cumulative outflows exceeding 10%, 25%, and 40%, respectively. We plot the marginal effect of changing each of the explanatory variables on these statistics, holding all other variables equal to their sample means. Each subpanel corresponds with a different fund-specific explanatory variable.

We estimate these quantiles by drawing shocks from the Laplace distribution and using the recursive definition of the dependent variable to simulate 10,000 sample paths, beginning at the start of the pre-crisis period (9/10/2008) for each set of conditioning variables. The value of lagged flows on 9/10/2008 for each simulation is assumed to be equal to the category average, while all other variables are held fixed at their averages. See Appendix B.4 for further details.