Online Appendix to "Runs on Money Market Mutual Funds"

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A. Background Information

This appendix provides a timeline of events of the crisis of September 2008 and describes details of the iMoneynet database.

A.1. Key Money Market Events of September-October 2008

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) "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

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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.

Further, 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. Following these developments, 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.2. 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 estimate that these data cover about 93.5% of prime MMMFs in existence at the end of 2008. We approximate daily fund share class flows as the daily fraction change in share class total net assets.[1] From the perspective of a subscriber to iMoneyNet–mainly those who invest in MMMFs–a day's flow data for a share class are available well before 4 p.m. Eastern Time on the following day. Thus, an institution subscribing to iMoneyNet can easily view outflows from a fund that occurred during the prior day, before making its decision for the current day.

Since the Reserve Primary Fund is widely viewed by market participants as initiating the crisis through its "breaking-the-buck" announcement, we consider flows to this fund as developing exogenous to that of other funds. Other MMMFs within the Reserve complex likely held Lehman and experienced simultaneous outflows, as well. Thus, we exclude observations from all funds within the Reserve complex from our analysis.

One other detail of our data construction is worth noting. Our fund business variable, which is intended to proxy for sponsor reputational concerns emphasized in Kacperczyk and Schnabl (2013), is calculated using a slightly different data set. Kacperczyk and Schnabl calculate total complex mutual fund assets by combining data from a variety of sources, but the primary source is the CRSP mutual fund database. We use a measure of the same quantity which was kindly provided by the Investment Company Institute.

Panel A of Table A1 presents univariate summary statistics for prime institutional share classes as of September 12, 2008. Specifically, we show the mean, standard deviation, and a range of quantiles for the main covariates used in our models for prime institutional

[1]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.

Panel A: Univariate Summary Statistics

				Quantiles			
Variable	N	Mean	Std. Dev.	5%	25%	75%	95%
% Sophisticated (35 bp/yr cutoff)	258	69.6	35.6	0.00	44.0	97.3	100.0
Shareclass total net assets ($ bil)	258	4.82	8.83	0.12	0.46	4.69	24.50
Fund total net assets ($ bil)	258	18.97	23.05	0.54	3.14	26.57	62.26
Shareclass expense ratio (%/yr)	258	0.34	0.20	0.12	0.18	0.45	0.72
Average gross yield (%/yr)	258	2.94	0.15	2.67	2.88	3.04	3.15
Liquid asset share (%)	258	18.57	14.22	2.00	8.00	23.00	49.00
Fund business (%)	258	72.4	18.3	33.1	63.4	84.9	98.9
Std. dev. of daily log flows (%)	258	2.50	1.41	0.55	1.70	2.99	5.23
Cumulative flow 9/15-19 (%)	258	-12.8	23.7	-56.4	-21.5	0.1	8.9

Panel B: Pairwise Correlation Matrix

	% Soph	Log TNA	ER	Yield	Liquid	Fund Bus.	Log SD
Log total fund assets	0.27*						
Shareclass expense ratio (%/yr)	-0.47*	-0.10					
Average gross yield (%/yr)	-0.01	0.25*	0.07				
Liquid asset share (%)	0.05	-0.22*	-0.05	-0.66*			
Fund business (%)	-0.14*	-0.28*	0.03	-0.02	0.09		
Log flow standard deviation	0.36*	-0.09	-0.26*	-0.07	0.11	-0.06	
Cumulative flow 9/15-19 (%)	-0.27*	-0.31*	0.32*	-0.19*	0.20*	0.11	-0.10

TABLE A1—SUMMARY STATISTICS FOR PRIME INSTITUTIONAL FUNDS AS OF 9/15/2008

Note: This table presents summary statistics for the cross section of money market funds in the Prime Institutional category within the iMoneyNet database as of September 12, 2008, the Friday before the failure of Lehman Brothers. Variables are as follows: % Sophisticated, our measure of the % large-scale institutions, defined as the fraction of total fund investment dollars owned by investors of institutional shareclasses with $ER \leq 35$ bp/yr; shareclass and fund total net assets, in billions of dollars; shareclass expense ratio, in percentage points; Average gross yield is the average daily value of the (annualized) 7-day gross yield, in percentage points, from March through August, 2008; liquid asset share, a "real-time" estimate of liquid assets available as a fraction of total net assets, which is calculated by comparing an estimate of maturing assets with net redemptions; fund business, defined as one minus the proportion (by value) of fund complex aggregate mutual fund assets that are represented by prime institutional share classes; the standard deviation of daily changes in log institutional total assets over the period March-August 2008, which is winsorized by 2% in either tail; and Lehman week cumulative flows, defined as the percentage change in share class-level assets under management (i.e., flows as a fraction of lagged assets under management), in percentage points, for each prime institutional money market share class from September 15 through September 19th on expense ratio (ER). Panel A presents distributional statistics, while Panel B presents pairwise correlations between variables from Panel A or their log transformations, where stars indicate significance at the 5% level.

share classes (aggregated to the fund level) during the week of September 15-19, 2008.

Panel B reports cross-sectional correlations between covariates, measured at the share class level, as of that week. Most notable is the strong negative correlation between yield and liquid asset share (-0.66), which reflects that less liquid assets tend to earn higher yields. Also, we find that the fraction of large-scale investors is negatively correlated with shareclass expense ratio. Most of the remaining covariates are only moderately correlated, with all other pairwise correlations being lower than 36% in absolute value. Of particular note is the fact that our measure of the percentage of sophisticated investors has only a -2% correlation with average gross yield and a 5% correlation with liquid asset share, our two controls for portfolio risk, neither of which is statistically significant.

Consistent with other regression results in the paper, the last row of Panel B shows pairwise correlations between cumulative crisis-week flows and each of these characteristics. These correlations, when significant, generally have the signs we would expect: funds with a higher concentration of sophisticated investors, more total assets under management, lower expense ratios, higher yields, lower liquidity, and lower fund business were all associated with significantly higher outflows during the crisis week.[2]

B. Supplementary Analyses

This appendix contains a number of supplementary analyses to complement the main results from the text. Section B.1 presents the proof of Propositon 1. Section B.2 discusses how the key comparative statics from Proposition 1 can emerge in alternative modeling enviornments. Section B.3 presents several regressions of fund-level outflows on a number of fund characteristics, placing an emphasis on the role of average yield, portfolio liquidity, and fund business in predicting investor behavoir. Finally, Sections B.4 and B.5 discuss the robustness of the results from Tables 3 and 6 in the main text to several alternative modeling choices.

B.1. Proof of Proposition 1

The proof of our Proposition 1 is quite similar to Proposition 1 in Angeletos and Werning (2006), itself closely related to Morris and Shin (2001). As such, we emphasize the key aspects of the proof and the minor differences in equlibrium conditions resulting from uninformed agents and refer the reader to these papers for further technical details.

As discussed in the main text, an equilibrium is defined by two objects–a threshold on the fundamental θ^* and a threshold private signal $x^*(z)$ for the marginal agent. Recall that we combined the two optimality conditions into a single fixed point condition (equation 5) in the main text, which depends on θ^* (the corresponding threshold signal $x^*(z)$ is pinned down by equation (3) in the main text):

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

Note that the right hand side of (1) does not depend on θ^*. Since Γ varies from $-\infty$ to ∞, at least one solution will always exist, and the equilibrium will be unique for all public signals z whenever $\Gamma(\theta,\mu)$ is strictly increasing in θ. $\frac{\partial\Gamma}{\partial\theta} = \frac{1}{\mu\phi(\mu^{-1}\theta^*)} - \frac{\alpha_z+\alpha_0}{\sqrt{\alpha_x}}$, which, from the curvature of the normal density, is bounded below by $\frac{\sqrt{2\pi}}{\mu} - \frac{\alpha_z+\alpha_0}{\sqrt{\alpha_x}}$ and thus is strictly positive when $\sqrt{2\pi\alpha_x} > (\alpha_z+\alpha_0)\mu$ (the condition from the proposition).

Next, we derive our key comparative static for the equilibrium objects θ^* and x^*. Since (1) holds with equality, the implicit function theorem implies that the partial derivative

[2] Note, however, the standard errors in Table A1 are not corrected for heteroskedasticity or within-fund covariances.

of a particular element of the equilibrium correspondence with respect to μ is

$$\left.\frac{\partial\theta^*}{\partial\mu}\right|_{\theta^*,\mu} = \frac{\mu^{-2}[\phi(\mu^{-1}\theta^*)]^{-1}}{[\mu\phi(\mu^{-1}\theta^*)]^{-1} - \frac{\alpha_z+\alpha_0}{\sqrt{\alpha_x}}},$$

which is positive whenever the denominator ($\partial\Gamma/\partial\theta$) is positive. As discussed above, $\partial\Gamma/\partial\theta > 0$ when the equilibrium is unique. Also, given that $\lim_{\theta\downarrow-\infty}\Gamma(\theta,\mu) = -\infty$ and $\lim_{\theta\uparrow\infty}\Gamma(\theta,\mu) = \infty$, the denominator will be positive in the neighborhood of the lowest and highest possible equilibrium θ^*, which we will denote by $\underline{\theta}^*(z,\mu)$ and $\overline{\theta}^*(z,\mu)$, respectively, so $\frac{\partial\underline{\theta}^*}{\partial\mu} > 0$ and $\frac{\partial\overline{\theta}^*}{\partial\mu} > 0$. The fact that $\partial\underline{x}^*/\partial\mu > 0$ and $\partial\overline{x}^*/\partial\mu > 0$ follows immediately from applying the implicit function theorem to the indifference condition (4).

Finally, we discuss the optimality of the behavior of uninformed agents. For simplicity, we have simply assumed that these agents choose to play $a_i = 0$. However, it will be optimal for them to do so provided that the prior probability that the regime fails is less than c. This probablilty is well-defined without additional assumptions when the equilibrium is unique; otherwise, we can bound it above by

$$\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\mathbf{1}[\theta \leq \overline{\theta}^*(z,\mu)]\pi(\theta,z)d\theta dz,$$

where $\pi(\theta,z)$ is the prior (bivariate normal) density of the fundamental θ and public signal z. For sufficiently high θ_0, this condition should be satisfied. However, there could exist regions of the parameter space for which their assumed behavior is not consistent with utility maximization. When thinking about our particular context, our assumption that these agents play $a_i = 0$ appears reasonable given that essentially no major MMMF had broken the buck prior to the Lehman episode.

B.2. Robustness of main theoretical predictions to alternative modeling assumptions

We next briefly discuss how similar comparative statics to our Proposition 1 emerge in versions of the bank run games of Goldstein and Pauzner (2005) and He and Manela (forthcoming) when they are augmented with a measure of uninformed agents. Our discussion of these papers is intended only to highlight the basic structure of each model and, in particular, how to derive our key comparative statics. We refer the reader to the papers discussed below for additional details and discussion.

We begin with the Goldstein and Pauzner (2005) model, which adds noisy signals to an environment similar to the Diamond and Dybvig (1988) bank run game, yielding sharp comparative statics. Morris and Shin (2001) present a stylized version of their model which has a very similar structure to ours. Agents must decide whether to withdraw early or maintain their investments based on a noisy signal about the return on a risky asset in a setting with payoff complementarities.[3] The complementarities emerge from

[3]Morris and Shin (2001) do not consider a public signal although their model extends naturally to a case with noisy

the fact that the expected log return on the risky investment is assumed to be a decreasing function of the fraction of agents who withdraw early.

As in our model from Section II, the equilibrium in the bank run game involves a threshold on the private signal received by a marginal agent who is indifferent between attacking and maintaining the status quo. This threshold, which is defined in terms of the posterior mean of an informed agent's beliefs about fundamentals in Morris and Shin's analysis, satisfies a fixed point condition. When private information is sufficiently informative relative to other sources of common (prior/public) information, this threshold is unique. When we extend the model to assume that a fraction of agents receive uninformative signals, it is easy to show that increasing the fraction of uninformed agents moves the threshold upwards, which makes runs less likely to occur. An analogous argument to the one from Section II.B implies that the same three testable predictions derived from the regime change game of Section II also emerge in this context.

More generally, many static global games models of bank runs/regime change involve fixed point equations similar to equation (5) in the main text. As is discussed in Goldstein (2013), these models often partition the support of the fundamental θ into three regions: (i) a region in which the regime fails regardless of any agents' behavior (in our model: $\theta \in (-\infty, 0]$), (ii) a region in which the regime fails but could have survived were agents able to coordinate on the status quo (in our model: $\theta \in (0, \theta^*]$), (iii) a region in which the regime survives (in our model: $\theta \in [\theta^*, \infty)$). By definition, adding a measure of uninformed agents will not affect the boundaries of the first region. However, the basic mechanism of our model is preserved: adding a measure of uninformed agents who play the status quo weakens complementarities, making it easier for agents to coordinate and shifting the boundary (θ^*) separating region (ii) from region (iii) downwards. This is likely to have a similar effect on the fixed point (and, in turn, the optimal strategies of informed agents) in other contexts when analogously extended.

Next, we turn to the dynamic model of He and Manela (forthcoming). He and Manela incorporate uncertainty about the liquidity of a bank's investments and endogenous information acquisition into the asynchronous awareness framework of Abreu and Brunnermeier (2003). At a (stochastic) point in time, a rumor that a bank may be illiquid begins spreading among depositors with a Poisson arrival rate (β, the "rumor-spreading rate"). Agents, upon hearing the rumor, are unable to observe whether or not the bank is truly illiquid nor do they observe the point at which the rumor began to circulate. If the bank is illiquid, it fails if a sufficiently high fraction of investors withdraw their deposits within an exogenously specified period of time (the "awareness window"), generating complementarities. Agents, who choose whether to deposit with a bank at each point in time, additionally have the opportunity to acquire costly private signals about the bank's liquidity after hearing the rumor.

He and Manela's framework includes informed (heard the rumor) and uninformed (did not hear the rumor) agents, and the uninformed agents maintain their existing deposits

public signals. Note, however, that the sufficient condition on the relative signal precision guaranteeing uniqueness will be different.

with the bank.[4] The key parameter of interest is the rumor spreading rate β. As β increases, a higher fraction of agents are aware that the bank may be illiquid at a given point in time, increasing the potential number of agents who may attack the bank. He and Manela show that increases in β decrease the time it takes for an illiquid bank to fail. In particular, informed agents wait less time on average before withdrawing their deposits, implying that expected outflows are higher at each point in time.

The key mechanism which generates our main testable predictions is actually quite similar to this comparative static for β. Informed agents need to forecast the behavior or other agents when deciding how to respond to potentially bad news about liquidity. Complementarities are stronger when more agents also received the bad news, increasing fragility when the bank is illiquid.[5] Therefore, the rumor spreading rate in He and Manela plays a similar role to the fraction of informed agents μ from our static model in Section II. Moreover, a similar argument to that of Section II.B yields the same predictions for cross-sectional flows from funds with multiple shareclasses. These predictions follow if we simply reinterpret β as the average rate at which the rumor spreads across all depositors, then assume that the rumor spreads more quickly among sophisticated relative to unsophisticated investors. The key element of the argument is that, since all agents behave in the same way once they have heard the rumor, an informed agent's optimal strategy only depends on the overall rate at which the rumor spreads in the population.[6]

B.3. Regressions of Fund-level flows on fundamental and investor characteristics

Table B1 regresses cumulative Lehman week flows on the variables featured in the cross-sectional regressions of Table 3. Of particular interest is the explanatory power of "fundamental" measures such as average gross yield, portfolio liquid asset share, and the fund business variable (a proxy for a given MMMF sponsor's reputational considerations, which is likely to indicate a higher willingness to support a troubled fund) in the absence of the other controls. Because all of these variables are constant for all shareclasses within the same fund, we pool all institutional shareclasses to the fund-level before calculating flows.

Panel A presents the estimated coefficients from regressions on various combinations of these three variables. In univariate specifications, each of the variables is significant at either the 5% or 10% level, and the signs are as expected. Higher yield, lower liquidity, and lower sponsor reputational concerns all increase predicted fund-level outflows. In multivariate regressions, the sponsor reputation variable remains significant at the 10%

[4] Analogous to our discussion at the end of our proof of Proposition 1 above, a simple technical condition ensures that it is optimal for agents who do not hear the rumor to behave in this manner. Moreover, among those who have heard the rumor, there is a subset of individuals who receive private signals which perfectly reveal the bank's liquidity state. This additional dimension in which agents are heterogenously informed is of secondary importance for our discussion here.

[5] He and Manela also show that increasing β increases the private incentives for agents to acquire information, a mechanism which further strengthens complementarities.

[6] To apply the comparative statics from He and Manela (forthcoming) in support of our argument, we abstract away from differences in information acquisition costs across different types of investors after they hear the rumor. Allowing these costs to vary across different types of informed agents, while plausible, would complicate the analysis considerably, and we conjecture that it will have little impact on the qualitative predictions emphasized here. We leave the study of such an extension for further research.

Panel A: Specifications without Investor Characteristics

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Average gross yield	-5.04**			-4.97**		-3.08
	(-2.180)			(-2.172)		(-0.875)
Liquid asset share		4.86**			4.83**	2.78
		(2.590)			(2.477)	(0.811)
Fund business			3.63*	3.52*	3.59	3.54
			(1.722)	(1.677)	(1.652)	(1.649)
N	123	123	123	123	123	123
R^2	0.041	0.039	0.022	0.062	0.060	0.069

Panel B: Specifications with Investor Characteristics

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Average gross yield	-3.80*			-3.78*		-2.23
	(-1.855)			(-1.831)		(-0.716)
Liquid asset share		3.80*			3.78*	2.34
		(1.885)			(1.876)	(0.718)
Fund business			-0.66	-0.53	-0.54	-0.51
			(-0.391)	(-0.305)	(-0.303)	(-0.285)
% Soph (35 bp/yr)	-14.26***	-15.45***	-15.56***	-14.53***	-15.72***	-15.06***
	(-2.922)	(-3.208)	(-2.983)	(-2.739)	(-3.003)	(-2.768)
Log total fund assets	-10.53***	-10.57***	-11.61***	-10.68***	-10.72***	-10.51***
	(-5.758)	(-6.270)	(-6.461)	(-5.682)	(-6.296)	(-5.951)
Avg institutional expense ratio	-1.19	-1.83	-2.29	-1.31	-1.95	-1.50
	(-0.623)	(-1.054)	(-1.190)	(-0.643)	(-1.052)	(-0.739)
Log flow standard deviation	-5.11***	-5.24***	-5.01**	-5.17***	-5.31***	-5.29***
	(-2.689)	(-2.839)	(-2.560)	(-2.663)	(-2.800)	(-2.741)
N	123	123	123	123	123	123
R^2	0.366	0.366	0.345	0.366	0.367	0.371

TABLE B1—DETERMINANTS OF FUND-LEVEL INSTITUTIONAL FLOWS DURING LEHMAN WEEK

Note: This table presents estimated coefficients from OLS regressions of the change in the log of fund-level assets under management (i.e., flows as a fraction of lagged assets under management) for prime institutional money market funds ($\times 100$) from September 15 through September 19th on average annualized 7-day SEC gross yield over the six month period prior to the crisis (March-August 2008); liquid asset share, estimated daily by computing dollar proportion Treasury and U.S. agency securities plus repo investments, plus (estimated) maturing securities, minus net redemptions; and fund business, defined as one minus proportion (by value) of fund complex aggregate mutual fund assets that are represented by prime institutional share classes. Panel B adds expense ratio, % large-scale institutions (% Soph; defined as the fraction of total fund investment dollars owned by investors of institutional shareclasses with expense ratios (weakly) below a cutoff–25 bp for the first column.), log of fund size (total assets under management as of September 12, 2008), and the standard deviation of daily log flows, computed from March-August, 2008. All coefficients except for % Soph have been divided by their cross-sectional standard deviations.

level. Yield and liquidity remain highly significant when separately included in a regression along with fund business; however, these two variables are collinear and are both insignificant in the last specification in column 6. It is also worth noting that the explanatory power of these regressions is somewhat low–the maximum R^2 is 6.8% in the cross-section.

Panel B adds four additional variables–average institutional expense ratio, % large scale investors, log fund size, and the log flow standard deviation–to the specifications from Panel A. The latter three of these additional variables are statistically significant, and their associated coefficients are quantitatively large. One can also observe a dramatic increase in R^2 after these variables are included. Yield and liquid asset share remain marginally significant in columns 1-2 and 4-5, but the investor characteristics subsume the explanatory power of the fund business variable.

It is worth noting that these results are not at all incompatible with the basic story emphasized in Kacperczyk and Schnabl (2013). If MMMFs may have been treated almost as perfect substitutes by large-scale institutional investors, small differences in portfolio risk may have been sufficient to generate fairly substantial differences in clientele. Kacperczyk and Schnabl present convincing evidence that fund management companies with substantial reputational concerns took less portfolio risk in the period prior to the Lehman episode, which is also fully consistent with our finding from Table A1 of a significantly negative correlation between our fund business variable and the fraction of large-scale investors. We find that, during the peak of the crisis, these clientele measures appear to possess greater explanatory power than portfolio risk measures, suggesting that cross-sectional heterogeneity in the strength of complementarities across funds may have been somewhat larger than the heterogeneity in portfolio risk across funds.

B.4. Robustness exercises for specifications in Table 3

For the sake of brevity, our regressions in Table 3 only tested prediction 3 of our theoretical model (involving the interaction terms) using a 35 bp/yr cutoff. Table B2 verifies that similar results hold for other choices of the cutoff, both with and without fund fixed-effects.

We have also added other potential control variables such as the standard deviation of daily log fund flows (columns 2 and 7 in Table B3), calculated using data from March-August 2008, and squared versions of the controls and found the results to be robust to these added controls (columns 4 and 8 in Table B3).

Our final covariate is the proportion of total MMMF assets for a complex (e.g., Fidelity), represented by prime institutional share classes (PIPERC, reported in columns 3 and 7 in Table B3) which can be interpreted as a proxy that (negatively) represents the ability of the fund management company to subsidize its funds during the crisis week.[7] PIPERC is not a perfect proxy for implied complex subsidization, as it may also proxy for the percentage of sophisticated investors at the complex level and, thus, for the strength of strategic complementarities. This alternative interpretation might influence our results if sophisticated investors monitor not only their own funds, but also other same-complex MMMFs. Again we find that the results in Table 3 are robust to the inclusion of this control.

In unreported results, we also verify that our results are not sensitive to our choice to calculate logarithmic, rather than arithmetic, cumulative flows. Extremely similar

[7] We also note that PIPERC is (negatively) related to our variable, Fund Business, which is patterned after a similar variable introduced by Kacperczyk and Schnabl (2013). In their paper, funds whose sponsors have a lower level of other mutual fund business take on more risk before the crisis, and, therefore, suffer larger outflows because of this risk-taking. Although our Average Gross Yield variable is designed to proxy for risk-taking, it is entirely possible that it does not do so without measurement error, and, thus, that Fund Business may be capturing some of the effect outlined by Kacperczyk and Schnabl (2013).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
% Soph (25 bp/yr)	-42.3***							
	(-3.18)							
% Soph (25 bp/yr) × ER	13.5***				27.3**			
	(3.18)				(2.54)			
% Soph (30 bp/yr)		-45.2***						
		(-3.45)						
% Soph (30 bp/yr) × ER		14.9***				27.4**		
		(3.49)				(2.49)		
% Soph (50 bp/yr)			-54.9***					
			(-3.95)					
% Soph (50 bp/yr) × ER			18.4***				32.3***	
			(4.21)				(3.16)	
% Soph (150 bp/yr)				-58.4***				
				(-3.67)				
% Soph (150 bp/yr) × ER				17.7***				33.4**
				(3.48)				(2.18)
Shareclass expense ratio	0.3	-0.8	-4.4*	-5.9	-5.8	-6.3	-15.1*	-19.1
	(0.15)	(-0.36)	(-1.73)	(-1.65)	(-0.87)	(-0.89)	(-1.96)	(-1.51)
Log total fund assets	-6.0***	-6.5***	-7.7***	-7.9***				
	(-2.76)	(-3.11)	(-3.56)	(-3.41)				
Average gross yield	-3.2	-3.5	-3.4	-3.9				
	(-0.60)	(-0.66)	(-0.63)	(-0.74)				
Liquid asset share	1.2	0.8	1.0	1.0				
	(0.26)	(0.18)	(0.21)	(0.22)				
Fund business	-1.2	-1.2	-1.8	-1.9				
	(-0.50)	(-0.49)	(-0.68)	(-0.69)				
Sample	All Inst	All Inst	All Inst	All Inst	All Inst	All Inst	All Inst	All Inst
Fixed effects	None	None	None	None	Fund	Fund	Fund	Fund
N	258	258	258	258	258	258	258	258
Degrees of freedom	250	250	250	250	134	134	134	134
R2	0.127	0.128	0.125	0.125	0.579	0.579	0.576	0.570

TABLE B2—CROSS-SECTIONAL REGRESSIONS OF SHARECLASS-LEVEL FLOWS ON FUND- AND INVESTOR CHARACTERISTICS - ROBUSTNESS OF SPECIFICATIONS (7) AND (8) OF TABLE 3 USING DIFFERENT CUTOFFS

Note: This table presents estimated coefficients from OLS regressions of the change in the log of shareclass-level assets under management (i.e., flows as a fraction of lagged assets under management) for prime institutional money market funds ($\times 100$) from September 15th through September 19th on expense ratio, % large-scale institutions (%Soph; defined as the fraction of total fund investment dollars owned by investors of institutional shareclasses with expense ratios (weakly) below a cutoff–25 bp for the first column.), and an interaction term between shareclass expense ratio and $\%Soph$ at the fund-level, as well as the log of fund size (total assets under management as of September 12, 2008) and its average annualized gross yield in the six month period prior to the crisis (March-August 2008), liquid asset share, estimated daily by computing dollar proportion Treasury and U.S. agency securities plus repo investments, plus (estimated) maturing securities, minus net redemptions; and fund business, defined as one minus proportion (by value) of fund complex aggregate mutual fund assets that are represented by prime institutional share classes. All control variables except % Soph are divided by their cross-sectional standard deviations. Different columns use different cutoffs for % Soph. Columns 5-8 include fund fixed effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
% Soph (35 bp/yr)	-33.8***	-29.1***	-26.3**	-30.3**	-50.3***	-51.6***	-41.9***	-45.4***
	(-3.01)	(-2.74)	(-2.50)	(-2.61)	(-3.77)	(-3.80)	(-3.80)	(-3.61)
% Soph (35 bp/yr) $\times$ ER					17.8***	21.6***	15.9***	16.7***
					(3.97)	(3.94)	(3.98)	(3.85)
Shareclass expense ratio	16.0**	15.4**	13.6*	12.3	-2.7	-5.7*	-1.3	-2.1
	(1.99)	(2.04)	(1.80)	(1.62)	(-1.19)	(-1.91)	(-0.59)	(-0.90)
Log total fund assets	-10.3***	-12.0***	-11.3***	-61.4**	-7.5***	-9.1***	-8.3***	-54.4**
	(-3.25)	(-3.68)	(-3.38)	(-2.23)	(-3.48)	(-3.92)	(-3.69)	(-2.39)
Average gross yield	-2.5	-1.4	-2.0	-76.7	-3.4	-2.9	-3.5	-28.2
	(-0.41)	(-0.22)	(-0.32)	(-1.17)	(-0.64)	(-0.55)	(-0.67)	(-0.43)
Liquid asset share	2.8	3.3	2.3	-8.7	1.0	1.6	0.4	-9.9
	(0.52)	(0.61)	(0.47)	(-1.23)	(0.23)	(0.36)	(0.09)	(-1.30)
Fund business	-1.2	-1.9	-3.7	-12.9	-1.3	-1.9	-3.5	-14.1*
	(-0.35)	(-0.56)	(-0.79)	(-1.18)	(-0.53)	(-0.75)	(-1.01)	(-1.68)
Log flow standard deviation		-9.0*				-6.3*		
		(-1.94)				(-1.96)		
Complex % prime institutional			-5.2				-4.6	
			(-1.10)				(-1.28)	
Average gross yield^2				1.9				0.6
				(1.17)				(0.38)
Log total fund assets^2				4.8**				4.3**
				(1.99)				(2.11)
Liquid asset share^2				1.9				2.1
				(1.48)				(1.43)
Fund business^2				1.7				1.9*
				(0.95)				(1.70)
Sample	Sophisticated institutional: ER $\leq$ 35 bp				All institutional shareclasses			
N	161	161	161	161	258	258	258	258
Degrees of freedom	154	153	153	150	250	249	249	246
R^2	0.094	0.118	0.103	0.121	0.128	0.143	0.135	0.151

TABLE B3—CROSS-SECTIONAL REGRESSIONS OF SHARECLASS-LEVEL FLOWS ON FUND- AND INVESTOR CHARACTERISTICS - ROBUSTNESS TO ADDITIONAL CONTROLS

Note: This table presents estimated coefficients from OLS regressions of the change in the log of shareclass-level assets under management (i.e., flows as a fraction of lagged assets under management) for prime institutional money market funds $(\times 100)$ from September 15th through September 19th on expense ratio, % large-scale institutions (%Soph; defined as the fraction of total fund investment dollars owned by investors of institutional shareclasses with expense ratios (weakly) below a cutoff–25 bp for the first column.), and an interaction term between shareclass expense ratio and $\%Soph$ at the fund-level, as well as the log of fund size (total assets under management as of September 12, 2008) and its average annualized gross yield in the six month period prior to the crisis (March-August 2008), liquid asset share, estimated daily by computing dollar proportion Treasury and U.S. agency securities plus repo investments, plus (estimated) maturing securities, minus net redemptions; and fund business, defined as one minus proportion (by value) of fund complex aggregate mutual fund assets that are represented by prime institutional share classes. Specification 2 adds a control for the standard deviation of daily fund-level flows, computed from March-August 2008, while Specification 3 adds a control for the percent of complex total assets under management in prime institutional shareclasses ("PIPERC", measured as of September 12, 2008). All control variables except % Soph are divided by their cross-sectional standard deviations. Specification 4 includes squared values of the original control variables. The right four columns columns add an interaction term between shareclass expense ratio and $\%Soph$ at the fund-level.

Variable	Early Crisis (1)	Peak Crisis (2)	Lehman Week (3)	Early Crisis (4)	Peak Crisis (5)	Lehman Week (6)
$Low_{i,t-1}$	0.20	0.12	0.21*	0.17	0.14	0.24**
	(1.28)	(0.79)	(1.85)	(1.16)	(0.85)	(2.07)
$Low_{i,t-1} \times \%High_{i,t-2}$	-0.22	0.31	0.05	-0.40	0.14	-0.18
	(-0.55)	(0.55)	(0.14)	(-1.18)	(0.26)	(-0.66)
$High_{i,t-1}$	-0.04	-0.31**	-0.17*	-0.04	-0.27*	-0.13
	(-0.39)	(-2.16)	(-1.80)	(-0.36)	(-1.79)	(-1.22)
$High_{i,t-1} \times \%High_{i,t-2}$	0.80**	1.12*	0.91*	0.45	0.98**	0.62
	(2.22)	(1.70)	(1.91)	(1.47)	(2.04)	(1.66)
$High_{i,t}$				-0.23**	-0.08	-0.18
				(-2.44)	(-0.65)	(-1.47)
$High_{i,t} \times \%High_{i,t-1}$				1.57***	1.40**	1.52***
				(4.57)	(2.47)	(3.15)
$\%Low_{i,t-1}$	1.19	-7.86**	-3.31*	0.40	-11.50***	-6.10***
	(0.59)	(-2.36)	(-1.69)	(0.21)	(-3.18)	(-3.61)
Average yield$_{i,t-1}$	0.17	0.25	0.34	-0.06	0.01	0.13
	(0.41)	(0.16)	(0.31)	(-0.17)	(0.00)	(0.15)
Log total fund assets$_{i,t-1}$	-1.11***	-1.86*	-1.87**	-0.97**	-1.42	-1.45**
	(-2.68)	(-1.82)	(-2.56)	(-2.46)	(-1.34)	(-2.35)
Avg institutional expense ratio$_{i,t-1}$	0.63	0.48	1.07	0.54	0.26	1.05
	(0.86)	(0.29)	(0.90)	(0.76)	(0.16)	(1.07)
Liquid asset share$_{i,t-1}$	0.37	2.05*	1.40*	0.42	1.95	1.46**
	(0.82)	(1.71)	(1.90)	(0.95)	(1.58)	(2.11)
Fund business$_{i,t-1}$	-0.46	-1.21	-1.09	-0.35	-0.89	-0.73
	(-1.12)	(-1.00)	(-1.10)	(-1.06)	(-0.81)	(-0.98)
Log flow std. dev.$_{i,t-1}$	-0.31	-2.34**	-1.78*	-0.10	-1.96**	-1.29*
	(-0.73)	(-2.06)	(-1.93)	(-0.24)	(-2.10)	(-2.00)
Complex PIPERC$_{i,t-1}$	-0.50	-2.51	-1.98	-0.24	-1.88	-1.36
	(-0.92)	(-1.67)	(-1.59)	(-0.54)	(-1.61)	(-1.65)
N	320	190	318	320	190	318
R^2	0.169	0.318	0.292	0.234	0.394	0.362

TABLE B4—DETERMINANTS OF DAILY FLOWS FROM SOPHISTICATED (LOW ER) SHARECLASSES - ROBUSTNESS TO ADDITIONAL CONTROLS

Note: For each fund, we separate prime institutional share classes into two categories, based on their expense ratios. The first category, "Low," consists of share classes which have expense ratios that are lower than the median expense ratio (across all institutional share classes within a given fund). All remaining share classes are included in the "High" category, including all retail share classes. The value of shares outstanding is then aggregated across all Low share classes and, separately, across all High share classes within a given fund. (Funds with a single share class are excluded from this analysis.) For each fund and date, we calculate the first difference in the log of aggregate value within each category (i.e., fraction flow), which we denote by $Low_{i,t}$ and $High_{i,t}$. The table presents the coefficients from panel regressions with $Low_{i,t}$ as the dependent variable on $Low_{i,t-1}$ and $High_{i,t-1}$, estimated for three different subperiods in 2008: 9/10-9/16 "Early Crisis", 9/17-9/19 "Peak Crisis", and 9/15-9/19 "Lehman Week", respectively. We multiply $Low_{i,t}$ and $High_{i,t}$ by 100 to express them in log percentage points. We also include interaction variables between, for example, $High_{i,t-1}$ and $\%High_{i,t-2}$, which is defined as two-day lagged fraction of total MMMF value within a MMMF represented by "High" (both institutional and all retail) ER shareclasses. Relative to the baseline specification from Table 6, we add a control for the standard deviation of daily fund-level flows, computed from March-August 2008 and winsorized by 2% in either tail, and a control for the percent of complex total assets under management in prime institutional shareclasses ("PIPERC", measured as of September 12, 2008). Control variables, described in the notes to Table 3, have been divided by their (cross-sectional) standard deviations for ease of interpretation. All specifications also include unreported time dummies. Standard errors are clustered at the fund level. t-statistics are reported in parentheses.

results, which are available upon request, obtain if we instead use arithmetic flows.

B.5. Robustness exercises for specifications in Table 6

Table B4 undertakes a similar set of robustness checks for the time-series VAR specification in Table 6. Specifically, in Table B4 we include log flow standard deviation and complex PIPERC as additional control variables to the model. At 0.80, 1.12, and 0.91 for the early crisis, peak crisis and Lehman week, respectively, the estimated coefficients of the lagged interaction term ($High_{i,t-1} \times \%High_{i,t-2}$, reported in columns 1-3 in Table B4) are only marginally lower than the estimates in Table 6 (0.87, 1.21, and 1.02). Moreover, At 1.57, 1.40 and 1.52, the coefficients on the contemporaneous interaction term ($High_{it} \times \%High_{i,t-1}$, reported in columns 4-6 of Table B4) during the early crisis, peak crisis and Lehman week are very similar to those reported in Table 6 (1.59, 1.53, and 1.64, respectively).

Similarly, the results are robust to not applying a 2% winsorization to the lagged flows. Here, the estimates on the lagged interaction term ($High_{i,t-1} \times \%High_{i,t-2}$) during the three subperiods become (0.74, 1.13, and 0.83) (previously 0.85, 1.22, and 1.02), while the estimated coefficients on the contemporaneous interaction term ($High_{it} \times \%High_{i,t-1}$) change to 1.59, 1.34, and 1.47 (previously 1.59, 1.53, and 1.64) and remain highly statistically significant.

C. Quantile Regression Methodology and Coefficient Estimates

This Appendix introduces the panel quantile regression methodology used in Section VI, explains how we estimate the models, and presents some estimation results and robustness tests.

C.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 variable $Y_{i,t}$:

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

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 β_0, of the flow distribution. We then add (or subtract) spreads, governed by β_1 and β_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. β_0 governs the effect of $X_{i,t}$ on the median level of flows and affects the other conditional quantiles as well. Since β_0 shifts the entire distribution of flows, its interpretation is quite similar to an OLS regression coefficient. We refer to these terms as "median exposures" or "common exposures", though we emphasize that these coefficients affect all quantiles symmetrically. β_1 captures the additional effect of covariates on 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."[8]

Our model for the conditional quantiles has an additional interpretation which is 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 is

$$\begin{aligned}
f_0(X_{i,t},\beta) &= W_{i,t}'\lambda_0 + Z_t'\gamma_0 \equiv W_{i,t}'\lambda_0 + \alpha_{0,t} \\
f_1(X_{i,t},\beta) &= W_{i,t}'\lambda_0 - \exp[W_{i,t}'\lambda_1]\exp[Z_t'\gamma_1] \equiv W_{i,t}'\lambda_0 - \exp[W_{i,t}'\lambda_1]\alpha_{1,t} \\
f_2(X_{i,t},\beta) &= W_{i,t}'\lambda_0 + \exp[W_{i,t}'\lambda_2]\exp[Z_t'\gamma_2] \equiv W_{i,t}'\lambda_0 + \exp[W_{i,t}'\lambda_2]\alpha_{2,t},
\end{aligned} \tag{3}$$

where $\lambda = [\lambda_0', \gamma_0', \lambda_1', \gamma_1', \lambda_2', \gamma_2']'$. 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.[9] 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 coefficients to change over different subperiods.[10]

Before going further, we introduce some terminology to ease the exposition in the discussion that follows. Our specification in (3) 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

[8] If $\beta_1^{(j)}$ and $X_{i,t}^{(j)}$ are the j^{th} elements of β_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. β_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".

[9] This multiplicative structure gives λ_1 and λ_2 useful factor-loading interpretations. If $W_{i,t}'\lambda_1 = 0$, a fund's left tail exposure is equal to the aggregate shock; as $W_{i,t}'\lambda_1$ increases, the sensitivity to the aggregate shock increases.

[10] 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.

are particularly interested in comparing left tail funds with different values of $W_{i,t}$.[11]

RECURSIVE ESTIMATION PROCEDURE

To see how we estimate the parameters of the model in (2), it is helpful to rewrite the data generating process for $Y_{i,t}$ as

$$Y_{i,t} = X'_{i,t}\beta_0 - D_{i,t}\exp[X'_{i,t}\beta_1]\eta_{i,t} + (1 - D_{i,t})\exp[X'_{i,t}\beta_2]\eta_{i,t}, \tag{4}$$

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.[12] 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 β_1 and β_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.

Our analysis uses the method of Schmidt and Zhu (2016) which sequentially estimates the parameters of interest using a series of standard linear quantile regressions. Specifically, we first estimate β_0 using standard linear quantile regression. Next, we estimate β_1 and β_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 β_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, β_0 is replaced 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 β_1.

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. These simulations are used to generate Table 7 in the main text. 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 τ 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 data generating process as described in Equation (4). Given the model parameters, it is straightforward to draw $Y_{i,t}$

[11] 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.

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

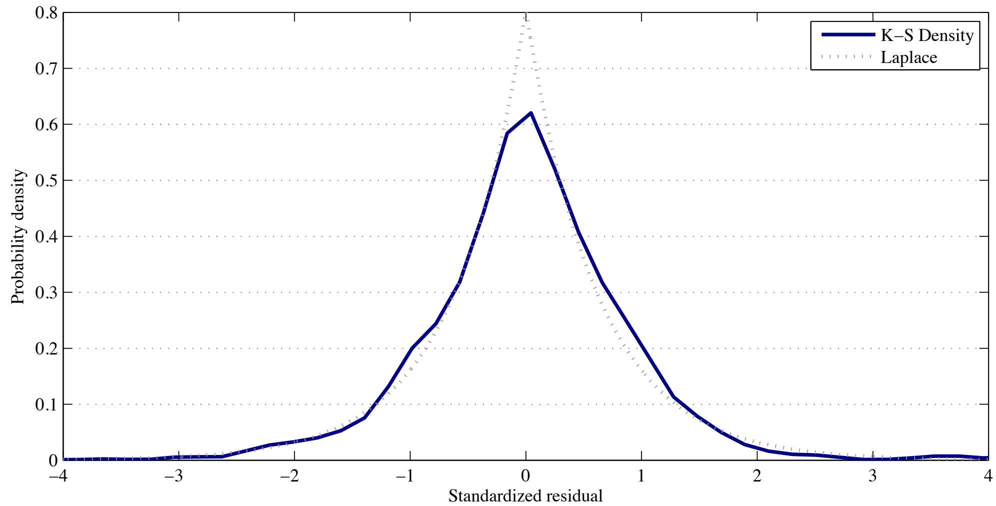

FIGURE C1. STANDARDIZED RESIDUAL DENSITY FROM BASELINE MODEL - INSTITUTIONAL FUNDS

Note: This figure plots the empirical density of the standardized residuals from the estimated model in Table C1, $\hat{\eta}_{i,t}$, which is generated using a kernel smoother. The dashed line plots the density of a Laplace-distributed random variable which has been normalized to satisfy the conditional quantile restriction which is assumed when estimating the model.

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 $P(\eta_{i,t} < 1) = 0.8$. Figure B1 demonstrates that the 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 50,000 total sample paths for cumulative flows. We calculate the 1st, 5th, 10th, 50th, and 90th quantiles of the set of simulated paths, respectively. In addition, using the bootstrapped distribution (10,000 replications) 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 tests whether the difference between the marginal effect at the

	Panel A Common (Median) Exposure		Panel B Left Tail Exposure		Panel C Right Tail Exposure	
Variable	Early Crisis	Peak Crisis	Early Crisis	Peak Crisis	Early Crisis	Peak Crisis
% Sophisticated$_{i,t-1}$	-0.0015 **	-0.0041 **	0.3004 ***	0.3364 **	0.1207	0.0322
	[0.024]	[0.028]	[0.008]	[0.033]	[0.326]	[0.320]
Average gross yield$_{i,t-1}$	-0.0007	-0.0055 ***	0.0820 *	0.0801	0.0144	0.1333
	[0.180]	[0.000]	[0.081]	[0.174]	[0.433]	[0.158]
Log flow std. dev.$_{i,t-1}$	-0.0007	-0.0047 **	0.5830 ***	0.4671 ***	0.4845 ***	0.4789 ***
	[0.199]	[0.030]	[0.000]	[0.004]	[0.000]	[0.002]
Log total fund assets$_{i,t-1}$	-0.0024 ***	-0.0095 ***	0.0180	0.1584	0.0070	0.2488 **
	[0.000]	[0.000]	[0.216]	[0.188]	[0.335]	[0.037]
$y_{i,t-1} - \bar{y}_{t-1} > 0$	0.1109	0.3274 **				
	[0.107]	[0.016]				
$y_{i,t-1} - \bar{y}_{t-1} < 0$	0.2627 ***	0.4527 ***				
	[0.004]	[0.002]				
$\lvert y_{i,t-1} - \bar{y}_{t-1}\rvert$			0.0556 *	-0.0139	0.0949 **	0.0763 *
			[0.089]	[0.493]	[0.043]	[0.063]
N	615	367	615	367	615	367
Pseudo-R^2 (50,10,90)	0.053	0.186	0.284	0.326	0.155	0.052

TABLE C1—FUND-LEVEL PANEL QUANTILE REGRESSION COEFFICIENTS - PRIME INSTITUTIONAL

Note: This table presents the coefficients from estimating equation (2) via quantile regression using the recursive method in Schmidt and Zhu (2016). 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). Panel A, on the left, reports β_0, which controls the conditional median and shifts all quantiles symmetrically. Panel B, in the middle, reports β_1, which governs the width of the left tail (the distance between the median and the 10th percentile). Panel C, on the right, reports β_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 two different periods in 2008: 9/10-9/16 Early Crisis and 9/17-9/19 Peak Crisis, respectively. More detailed variable descriptions may be found in Table A1. In addition to the coefficients in the table, models include time dummies to capture the common shocks, $\alpha_{0,t}$, $\alpha_{1,t}$, and $\alpha_{2,t}$. Numbers in brackets are one-sided bootstrapped p-values clustered at the fund level. With the exception of lagged flows, all variables are divided by their (cross-sectional) standard deviations.

median and a different quantile differs from zero.

C.2. Coefficient estimates

Table C1 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 6, we split the sample into, and allow the model coefficients, β_0, β_1, and β_2 to change, over the early crisis and peak crisis subperiods, and each column of the table presents estimates for a specific subperiod. Panel A presents our estimates of β_0, the coefficients governing the conditional median. Panels B and C present our estimates of β_1 and β_2, the coefficients governing left and right tail exposures, respectively. We express the dependent variable in log percentage points, and divide all characteristics other than lagged flows by their cross-sectional standard deviations.

We briefly summarize the main results from Table C1. At the median, the coefficient on the fraction of sophisticated investors increases in absolute magnitude from -15 bps to -39 bps as we move from the early to the peak crisis. Both coefficients are statistically significant but the associated magnitudes are relatively small. Yields and log flow standard deviations are negatively correlated with median flows during the peak crisis but not in the early crisis, suggesting that riskier portfolios were associated with higher outflows during the peak crisis. Median outflows were also bigger for the largest funds both during the early and late crisis. Finally, median outflows become more strongly serially correlated during the peak crisis compared to the early crisis period and the responsiveness to lagged outflows is somewhat higher (relative to inflows) in both periods.

The estimates for the left tail exposures show that the shift of the flow distribution to the left is accompanied by a widening in the left tail. Specifically, the coefficients on the fraction of sophisticated investors, at 30% and 34% in the early and peak crisis, respectively, are economically large and highly significant in both crisis periods. Thus, a one standard deviation increase in the fraction of sophisticated investors increases the distance between the median and 10th percentile of the flow standard deviation (i.e., increased outflows) by 34% during the peak crisis. Clearly nonlinearities in how flows are related to the fraction of sophisticated investors become very important during the crisis. We observe similarly large effects for the log flow standard deviation during the early and peak crisis periods. In contrast, the yield and fund size variables only have modest effects on the left tail of the flow distribution.

Finally, the estimates for the right tail exposures suggest that funds with higher flow standard deviations also had a greater likelihood of experiencing inflows on a given day during the crisis, suggesting that funds that had more volatile flows prior to the crisis also experienced more volatility (i.e., higher second moments) during the crisis. Also, large funds were particularly likely to experience inflows during the peak crisis.

C.3. Alternative quantile estimation results

The quantile regression results presented in the main text are generated by estimating a daily model for the conditional 10th, 50th, and 90th quantiles of the cross-sectional flow distribution. Given that our choice of the 10th and 90th percentiles for purposes of estimating comparative statics in the left and right tails is somewhat arbitrary, we show that similar results obtain when we instead estimate a model for the conditional 20th and 80th percentiles. These results, which are tabulated in Table C2, are qualitatively and quantitatively similar to those reported in Table 7.

Variable	Value	Cumulative Flow Quantile				
		1%	5%	10%	50%	90%
	$f(\bar{x})$	-50.92	-38.14	-32.42	-14.88	3.20
% Sophisticated	$f(\bar{x}+\sigma_x)$	-62.23	-46.84	-39.96	-18.56	2.38
	$f(\bar{x}-\sigma_x)$	-40.95	-30.62	-25.91	-11.50	4.44
	Difference	-21.27 ***	-16.22 ***	-14.05 ***	-7.07 ***	-2.06
	p-value	[0.002]	[0.001]	[0.001]	[0.001]	[0.431]
	p-value vs. median	[0.007]	[0.006]	[0.005]	-	[0.026]
Average gross yield	$f(\bar{x}+\sigma_x)$	-57.70	-43.62	-37.17	-17.73	1.34
	$f(\bar{x}-\sigma_x)$	-44.61	-33.11	-27.96	-12.08	5.17
	Difference	-13.09 *	-10.51 **	-9.22 **	-5.66 **	-3.83
	p-value	[0.052]	[0.034]	[0.027]	[0.011]	[0.273]
	p-value vs. median	[0.134]	[0.130]	[0.129]	-	[0.193]
Log flow std. dev.	$f(\bar{x}+\sigma_x)$	-62.29	-46.38	-39.24	-16.68	9.57
	$f(\bar{x}-\sigma_x)$	-41.50	-31.23	-26.65	-12.87	0.36
	Difference	-20.79 ***	-15.15 ***	-12.59 ***	-3.81 *	9.21 ***
	p-value	[0.001]	[0.001]	[0.001]	[0.060]	[0.002]
	p-value vs. median	[0.001]	[0.001]	[0.001]	-	[0.000]
Log fund total assets	$f(\bar{x}+\sigma_x)$	-56.59	-42.94	-36.82	-17.63	4.13
	$f(\bar{x}-\sigma_x)$	-45.06	-33.11	-27.85	-11.66	3.80
	Difference	-11.53 **	-9.83 **	-8.97 **	-5.96 ***	0.33
	p-value	[0.042]	[0.029]	[0.021]	[0.007]	[0.421]
	p-value vs. median	[0.109]	[0.102]	[0.096]	-	[0.022]

TABLE C2—MARGINAL EFFECTS OF FUND CHARACTERISTICS ON CUMULATIVE FLOW QUANTILES - COEFFICIENTS ESTIMATED ON 20TH, 50TH, 80TH QUANTILES

Note: This table shows the impact of explanatory variables on cumulative flow distributions (as a percentage of initial assets) for prime institutional share classes (aggregated to the fund level) for the September 15-19 period. These estimates are obtained by simulating from an estimated dynamic quantile panel regression model for daily flows. Whereas the dynamic panel regression model presented in Table 7 is estimated for the 10th, 50th, and 90th quantiles, this table repeats the exercise where the model is instead estimated for the 20th, 50th, and 80th quantiles. Columns report the 1st, 5th, 10th, 50th, and 90th quantiles of the cumulative flow distributions, respectively. We begin by fixing each of the explanatory variables at its average, assuming that the initial value of lagged flows equals the prime institutional category average. Then, we report the impact on the simulated flow distribution of adding and subtracting one standard deviation to each explanatory variable, p-values for a test of whether the difference in the simulated quantiles is statistically significant, obtained by using the bootstrapped distribution of parameter estimates from our model, as well as the p-value of whether the marginal effect is significantly different at a given quantile, relative to the marginal effect at the median (using the bootstrapped distribution).

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