Cash Management and Extreme Liquidity Demand of Mutual Funds

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Abstract

We study episodes of extreme liquidity demand at the mutual fund style level and the contribution of individual funds to the aggregate liquidity demand during these episodes. Our measure of liquidity demand incorporates the impacts of both investor redemptions and fund manager cash management decisions. We find that funds entering crisis months with low levels of cash contribute more to the overall liquidity imbalance as they (i) face higher investor redemptions during and after the crisis, and (ii) choose to build up more cash reserves during the crisis. Our results highlight the importance the micro-level mutual fund prudential liquidity management in mitigating the aggregate-level liquidity imbalance.

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1 Introduction

The recent growth in open-ended investment funds has prompted concerns that large-scale fund redemptions could trigger asset sales that significantly depress asset prices. While an individual fund may be too small to be considered systemically relevant, if investors behavior is similar across many funds investing in a particular market, then in aggregate investor redemption and the resulting liquidity demand in that market could exceed the market's absorption capacity, and potentially spill over to other financial markets and the greater economy. Thus funds in aggregate may become a systemic risk concern.[1]

The idea that funds in aggregate, if not individually, could be a concern for systemic risks has drawn attention of domestic and international regulators. In December 2014, the Financial Stability Oversight Council (FSOC) issued a federal register notice seeking public comment to understand whether and how certain asset management activities could pose potential risks to the US financial system. In February 2015, the Financial Stability Board (FSB), in consultation with the International Organization of Securities Commissions (IOSCO), published for public consultation an assessment methodology for identifying Non-Bank Non-Insurer (NBNI) Global Systemically Important Financial Institutions. A year later, FSB put forward proposed policy recommendations to address structural vulnerabilities from Asset Management Activities arising from liquidity mismatch between fund investments and redemption terms, leverage, operational risk, and securities lending activities.

In this paper, we study episodes when the absorption capacity of asset markets in which mutual funds of a particular investment style operate may be strained because of aggregate net fund liquidity demand. For each investment style, we identify the months in which the aggregate

[1]Particularly with less liquid securities, large sales can cause substantial downward price pressure. Coval and Stafford (2007), for example, show that extreme redemptions can have an impact on asset valuation if funds need to sell assets to accommodate such requests. Raddatz and Schmukler (2012) present evidence for a similar conclusion in an international context.

liquidity demand of funds within the style is above the 95th percentile, and refer to them as the stress months or event months. We analyze the contribution of each fund to this imbalance in the framework of Acharya, Pedersen, Philippon, and Richardson (2017). This framework allows an assessment of each fund's contribution to the style's aggregate liquidity demand that is consistent with the aggregate style liquidity shortfall historically observed.

We define the net liquidity demand of a mutual fund as the sum of the net fund outflow and the increase in cash holdings, both expressed as a fraction of the fund's total net assets. Accordingly, the net liquidity supply is defined as the net fund inflows minus the cash increase. Our definition recognizes that a fund's net liquidity demand is driven by both investor behavior and fund manager's cash management. As funds receive redemption requests from investors, they will need to decide how to optimally meet these redemptions. If the redemptions are modest, cash on hand and perhaps credit lines could provide adequate funding. However, large redemptions can be more problematic, particularly if not accurately anticipated.[2] In such circumstances, a fund short of cash or unwilling to use its cash holdings may need to sell substantial amounts of investment assets in a relatively short period of time to meet redemption requests, imposing liquidity pressure on the asset markets.

Using a sample of monthly data for US mutual funds from the CRSP survivor-bias-free database and the Morningstar mutual fund database from 2004 to 2015, we explores a set of research questions that have not been addressed yet in the literature. First, we analyze how much extreme net aggregate mutual funds liquidity demand at the investment style level is accounted by its two components – investors redemptions and funds discretionary liquidity decisions — and whether the contribution of the two components change across investment styles and over time. Second, we analyze under which market conditions severe aggregate liquidity needs at the

[2]Moreover, a fund might intentionally opt for lower cash reserves due to concern about cash drag on performance. That concern could be due to a focus on peer performance evaluation or trying to offset poor past performance. It might simply have insufficient information for an adequate prediction on its liquidity needs. See among others Brown and Starks (1998), Chevalier and Ellison (1997), and Berk and Green (2004).

style level are more likely to emerge. Third, we study the cross-sectional determinants of funds individual liquidity demand and its components that contribute to aggregate liquidity demand.

We find that aggregate liquidity demand displays significant variations across investment styles and time. For example, during the financial crisis Government Bond funds (IG) in aggregate were liquidity suppliers while other funds demanded liquidity. Furthermore, we find that episodes of aggregate large liquidity demand are more likely to occur when the TED spread, term spread, and credit spread are high and when aggregate market liquidity is low. They are also more likely to occur after months of poor performance and outflows at the style level.

More importantly, we find a fund's cash reserves before the stress months have a strong impact on its net liquidity demand during the stress period. First, funds with higher cash ratios prior to the event months experience smaller outflows during the stress months. This suggests that higher levels of pre-crisis cash holdings provide a stabilizing effect during crises, which could help reduce the likelihood of investor runs on the fund. Second, while funds with larger cash reserves use cash to meet redemptions during the event months, funds with a low initial cash ratio tend to increase their cash holdings during the months of aggregate liquidity shortfalls. Therefore, funds with lower cash holdings prior to the stress event contribute more to the extreme style-level liquidity shortfall, through both the investor redemption channel and the fund cash management channel. For Municipal Bond funds, we also find that the cash holdings before the stress events are not only positively related to the overall fund performance of during the stress months, but also positively related to the performance of non-cash components of the fund assets during these months. These results highlight the importance of micro-level prudential liquidity management in mitigating the macro-level liquidity imbalance.

In line with the previous literature on the flow-performance relationship, we also find that past poor and contemporaneous style-adjusted fund performance lead to larger outflows during stress months. Furthermore, we find that fund size and turnover ratio are positively related to funds' decision to build up cash buffer during the event month. The fact that larger funds display a tendency to hoard more cash during crisis-months may reflect concerns on their part that their market activity could move asset prices if they were forced to sell portion of their portfolios. Even though funds liquidity management decisions might reflect individual manager efforts to restore a prudent level of cash holdings in the face of market stress, what is prudent from a micro-prudential point of view may not be optimal from a macro-prudential perspective. This collective action problem associated with coordinated sales and (potential) hoarding of cash may generate procyclical fire-sale externalities.

The academic literature has devoted substantial attention to modeling fund investor behavior as a function of performance.[3] Several papers have found evidence of a non-linear and asymmetric relationship where the top performing funds receive subsequent inflows that increase rapidly with prior performance. In contrast, poor performers experience little outflow, while the medium performers have inflows that increase only modestly with performance. Previous studies examined mutual fund fragility by assessing the sensitivity of funds' outflows to past performance (e.g. Goldstein, Jiang, and Ng (2015) and Chen, Goldstein, and Jiang (2010)). Their findings show that outflows of corporate bond funds and funds with more illiquid assets tend to exhibit stronger sensitivity to poor past performance.

There is an emerging literature that examines the liquidity management decisions by asset managers.[4] These papers find that fund asset allocation and cash holdings are consistent with the view that fund managers trade off between short-term liquidation costs that might jeopardize near-term fund performance and longer-term vulnerabilities arising from illiquid holdings that might threaten future fund viability. For example Jiang, Li, and Wang (2016) show that corporate bond funds, on average, follow an approach selling liquid assets first amid redemptions, but later

[3] See, among others, Ippolito (1992), Chevalier and Ellison (1997), Sirri and Tufano (1998).

[4] See, for example, Hanouna, Novak, Riley, and Stahel (2015), Chernenko and Sunderam (2016), Jiang, Li, and Wang (2016).

engage in trades to restore liquid holdings. Furthermore, they find that when macroeconomic uncertainty rises above its historical median, corporate bond funds are less willing to sell liquid assets first but rather maintain the liquidity profile of their portfolios. The reluctance of corporate bond funds to consume liquid assets to meet investor redemptions during volatile periods points to funds aversion to increased vulnerabilities arising from holding illiquid assets. Similarly, Chernenko and Sunderam (2016) show that cash plays an important role in how mutual funds provide liquidity to their investors. Rather than transacting in equities or bonds, mutual funds use cash to accommodate inflows and outflows. This is particularly true for funds with illiquid assets and at times of low aggregate market liquidity.

One of the few papers that have analyzed the two components of liquidity demand jointly is Shek, Shim, and Shin (2015). Using a sample of 36 emerging market economy (EME) bond funds they investigate to what extent bond sales of EME funds are driven by investor redemptions, whether EME bond funds engage in discretionary bond sales that potentially amplify sales driven by investor, or whether they cushion the investor-driven flows by leaning against the wind to buy beaten-down assets. They find that discretionary bond sales are a significant part of total bond sales by EME funds, and that discretionary sales by fund managers tend to reinforce the sales driven by redemptions by ultimate investors.

Our paper differs from the existing literature along several dimensions. First, we focus on episodes when the aggregate liquidity demand of mutual funds may exceed market absorption capacity and create systemic concerns. Second, we investigate jointly two driving forces of mutual fund net liquidity demand, i.e., investor redemptions and mutual fund liquidity management, and potential interaction between them. Third, we analyze mutual fund liquidity demand in a framework adapted from Acharya, Pedersen, Philippon, and Richardson (2017) that allows a consistent aggregation of individual fund liquidity demands to the net demand at the aggregate level.

The remainder of the paper is structured as follows. In the next section, we provide details on our framework and methodology. Section 3 describes the data and summary statistics. Section 4 investigates the style-level liquidity supply and the determinants of extreme liquidity events. Section 5 analyzes the liquidity supply of individual funds during stress months and the contribution of each fund to the liquidity shortfall at the style level. Section 6 concludes the paper.

2 Methodology

We define fund flow $F_{i,t}$ as the net new money flow into fund i during period t, measured as a percentage of the fund's lagged total net assets, TNA_{t-1}, and use $-F_{i,t}$ to measure the net investor redemption. We further define $C_{i,t-1}$ as fund i's cash balance at the end of period $t-1$ normalized by the fund's lagged total net assets, and $\Delta C_{i,t}$ as the change of the cash balance during period t. Generally, funds are required to meet redemption in cash, and the decision on how much cash to use and how many assets to liquidate is made by fund managers (see, for example, Shek, Shim, and Shin (2015), Chernenko and Sunderam (2016), and Jiang, Li, and Wang (2016)).

We define the net liquidity demand of fund i during time t as the amount of assets the fund i sells during the period, which equals the net investor redemption, $-F_{i,t}$, plus the increase in cash balance, $\Delta C_{i,t}$. For example, if a fund with $\text{TNA}_{t-1} = \$100$ receives a \$10 redemption request and decides to draw down \$4 from its cash balance, the net liquidity demand is then $\$6 = \$10 - \$4$ or 6%. If, instead, a fund increases its cash holdings during the same period by \$3, the fund's net liquidity demand is then $\$13 = \$10 + \$3$ or 13%.

Correspondingly, we refer to $F_{i,t} - \Delta C_{i,t}$ as the net liquidity supply of fund i during period t. Positive values of $F_{i,t} - \Delta C_{i,t}$ indicate that the fund supplies liquidity to the market and negative values indicate a net liquidity demand.

We assign each fund to a style S, which reflects a relatively homogeneous asset class, based on a combination of CRSP's Level 2 classification and Lipper Objective codes. For each style, we calculate the corresponding value-weighted fund flow, cash holdings, and changes in cash balance $F_{S,t}$, $C_{S,t-1}$, and $\Delta C_{S,t}$, respectively. We are interested in events $\mathcal{E}_S$, during which the aggregate net liquidity supply from funds within a style is below a certain threshold. Presumably, those are times when the aggregate selling pressures from mutual funds are most likely to exceed the market absorption capacity, which potentially forces transactions to take place at fire sale prices and raises a systemic risk concern. It important to note that our definition of aggregate net liquidity demand is unaffected by investors reallocating assets from one fund to another within the same style.

Since the net liquidity supply at the style level is a weighted average across firms, the style-level expected liquidity shortfall during a stress event can be written as

$$ES_\alpha = -E\left[F_S - \Delta C_S | \mathcal{E}_S\right] = -\sum_{i \in S} w_i E\left[F_i - \Delta C_i | \mathcal{E}_S\right], \tag{1}$$

where the subscript α indicates the threshold used to define the stress event $\mathcal{E}_S$, and w_i the asset weight of the fund i in style S. Following the definition of Acharya, Pedersen, Philippon, and Richardson (2017), the marginal contribution from fund i to the style's aggregate liquidity shortfall during the stress period is then

$$MES_\alpha^i = \frac{\partial ES_\alpha}{\partial w_i} = -E\left[F_i - \Delta C_i | \mathcal{E}_S\right]. \tag{2}$$

The market absorption capacity at the style level depends on risk taking capacity in the financial sector at large and is likely a function of macro economic and market conditions. Modeling this capacity is outside the scope of this paper. Instead we follow the standard practice in the value-at-risk literature and set the threshold α for the extreme $F_S - \Delta C_S$ at the 5th percentile. That is, we define the stress event as the event when $F_S - \Delta C_S$ falls in the bottom 5% of the sample period.

We are concerned about a fund's contribution to the expected liquidity shortfall at the style level as measured by $-E\left[F_i - \Delta C_i | \mathcal{E}_S\right]$. As discussed, this contribution is a function of both fund investors' redemption decision and the decision of fund managers' cash management decision. The literature has investigated separately these two components during normal times. We extend these two strands of literature by analyzing liquidity shortfall $-E\left[F_i - \Delta C_i | \mathcal{E}_S\right]$ and its components $E\left[F_i | \mathcal{E}_S\right]$ and $E\left[\Delta C_i | \mathcal{E}_S\right]$ during extreme episodes.

3 Data and Summary Statistics

3.1 Sample

We use the CRSP survivor-bias-free database and the Morningstar mutual fund database to construct our sample. We collect data on all fund characteristics except cash holdings from the CRSP from 2004 to 2015, and combine them with monthly cash holdings from the Morningstar.[5] Consistent with Chernenko and Sunderam (2016), our sample starts in the year 2004.

Using the CRSP investment objective code and the Lipper fund classification code, we select from the CRSP database funds in five broad sectors: Domestic Equity, International Equity, Corporate Bond, Municipal Bond, and Mixed Asset. We drop ETFs, ETNs, index funds (identified either by the "index_fund" flag or the word "Index" in the fund name), variable annuity

[5]Starting in 2003, the CRSP database also reports the fraction of fund assets invested in cash and cash equivalents. However, this variable is only available at the quarterly frequency. Furthermore, Chernenko and Sunderam (2016) point out that the CRSP's information appears to be a rather noisy proxy for the cash-to-asset ratio. There is a large discrepancy between the aggregate cash holdings calculated using this variable and the aggregate cash holdings reported by the Investment Company Institute (ICI). Also, in a random sample of 100 funds, they find that the correlation between the CRSP cash ratio and the actual cash ratio disclosed in mutual fund shareholder reports is only 0.40.

funds, sector funds, as well as alternative funds in these sectors. The remaining funds are further classified into eighteen investment styles that represent relatively homogenous asset classes.[6] We require a style to have at least 10 funds in a given month.

Both the CRSP and the Morningstar databases contain data at the share class level. We aggregate all data to the fund level: fund TNA is the sum across the share classes; fund expense ratio and front- and back-end loads are the average across share classes weighted by the current TNA; fund return is the average weighted by the lagged TNA. To eliminate funds that may still be in the incubation stage, we include a fund in our sample only after its TNA has reached $10 million in terms of the year 2009 dollar value.[7] Furthermore, we exclude funds with less than 24 monthly observations.

We merge the share classes in the CRSP and the Morningstar databases using primarily the CUSIP symbol. We check the fund ticker symbols (when available) and fund name of the match share classes to ensure accurate matching. Furthermore, we require a matched fund to have the same set of share classes in both databases, and that the fund-level TNAs are matched closely. Specifically, we divide the CRSP TNA by the average of TNAs from the CRSP and the Morningstar, and require this ratio to be between 0.98 and 1.02 in any given month. Using these criteria, we are able to match 92% of the fund-month observations in our CRSP sample to the Morningstar sample. Our final sample includes 6,369 funds, with a total of 352,503 monthly observations.

[6] The eighteen styles include five domestic equity styles (Large-Cap, Mid-Cap, Small-Cap, Multi-Cap, Equity Income), three international equity styles (International Equity, Global Equity, Emerging Market Equity), three corporate bond styles (Investment Grade, High Yield, and Short- and Intermediate-Term Bond), one municipal bond style, and six mixed-asset styles (Balance, Flexible Portfolio, Mixed-Asset Target Date, Mixed-Asset Target Allocation Conservative, Moderate, and Growth).

[7] To avoid the look-ahead bias, we keep the fund in the sample even if its TNA later drops below $10 million.

3.2 Summary Statistics

We report in Table 1 summary statistics of the main variables and the control variables in our sample at the fund-month level. We present summary statistics for both the full sample (Panel A) and the stressed months (Panel B), in which the style-level liquidity supply is in the bottom 5% over the sample period. Flow(%) is the monthly flow of new money into a fund, which is calculated as the growth rate of the TNA minus the fund return. ΔCash is the increase in the cash-to-asset ratio in a given month.[8]. Liquidity supply is equal to Flow - ΔCash.

The positive value of the reported mean Flow(%) indicates that, on average, there are greater inflows than outflows. However, there is a large positive skewness; and the median fund actually exhibits a small outflow (-0.23%) over the sample period. Furthermore, there is substantial kurtosis leading to a large dispersion across the different quantiles. In other words, monthly percentage flows are relatively modest mostly, but there are fat tails with large percentage inflows and outflows (inflows being greater than outflows). Non tabulated results reveal that, in dollar values, the p5 and p95 flows are relatively modest suggesting the relatively large percentage flows are associated with relatively small funds. Note that the distribution of fund size exhibits considerable positive skewness and the median fund TNA is only $235 million (=exp(5.46)).

Cash(%) has median value equal 2.76% and large positive skewness and kurtosis, indicating that large cash ratios are present in our data set. Both the mean and median of ΔCash are zero. It follows that, on average, liquidity supply, Flow - ΔCash, is driven by fund flows. The standard deviation of ΔCash, however, is non-trivial (2.18%), suggesting that cash policy decisions can play a significant role in the cross-sectional variation of mutual fund liquidity supply and demand. Funds exhibit, on average, a liquidity surplus of 0.32%, though the median fund exhibits a small liquidity demand (-0.17%).

[8]While Flow is available for 99% of the fund-month observations, ΔCash is only available for less than half (42%) of the observations.

Not surprisingly, both the mean and median liquidity supply in Panel B are lower in the stressed months than in the full sample (0.99 vs. 0.32 and -1.10 vs. -0.17, respectively). The negative signs indicate that, during stressed months, funds typically turn into liquidity demanders. The mean and median of fund returns are also lower in the stressed months than in the full sample (-2.61 vs. 0.50 and -1.43 vs. 0.60, respectively). Interestingly, the median of ΔCash continues to be virtually equal zero suggesting that roughly half of funds continue building cash buffer during stress months while the other half dips into its cash reserves.

4 Extreme Liquidity Demand Episodes

4.1 Style-level Liquidity Supply and its Components

We summarize by sector in Table 2 the average style-level liquidity supply, $F_{S,t} - \Delta C_{S,t}$, fund flow, $F_{S,t}$, and cash changes, $\Delta C_{S,t}$, for the full sample and for the stress months. Note that $\mathrm{F_{S,t}}$ and $\Delta \mathrm{C_{S,\,t}}$ are averages across funds weighted by the lagged fund TNA. During the full sample, the average liquidity supply is generally positive and predominantly driven by flows. The changes in cash are generally negative, indicating that funds are using on average cash during the full sample. During the crisis months however, the average liquidity supply is all negative. Moreover, while all flows are negative, funds are generally building cash during these events.

The Corporate Bond fund style shows the largest average liquidity shortfall in stressed months (2.899%), followed by the Municipal Bond fund style (2.209%). For both sectors most of the liquidity demand seems to originate from investors with outflows in stressed months (fund flows being equal to -1.899% and -2.243%, respectively). However, while Municipal Bond liquidity demand is entirely driven by outflows, a considerable part of Corporate Bond's liquidity demand seems to also be generated by funds liquidity management decisions. This is likely due to the illiquidity of Corporate Bond portfolios, which potentially lead funds' managers to build cash buffers in an attempt to limit transaction costs.

Comparing the simple average of fund-level ΔCash in Table 1 (+0.16%) with the style-level $\Delta C_{S,\ t}$ in Table 2 (0.626%), we can infer that larger funds are the ones responsible for building more cash reserves (as a percentage of their TNA) during stress periods. Although larger funds have a tendency to build up larger cash reserves during crisis, this may not necessarily reflect a different strategic behavior on how these funds manage liquidity during crises, but rather simply be the result of differences in investors flows compared to smaller funds. In subsection 5.2, we address this and other questions using a multivariate approach.

4.2 Time Series of Aggregate Liquidity Supply

Figure 1 shows the time series pattern of mutual funds liquidity supply ($F_{S,t}-\Delta C_{S,t}$) for each fund sector (ED, EF, IC, IU, MIX). For comparison, we include in the figure also the Government Bond Fund sector (IG). Within each sector, net liquidity supply is the weighted average across funds with weights proportional to the size of each fund's TNA. During the recent financial crisis, all sectors except Government Bond (IG) became net sellers of securities in their respective markets. Perhaps unsurprisingly, Government Bond funds became, instead, large liquidity suppliers as investors moved away from risk assets and found safety in Treasuries, a phenomenon widely known as flight-to-quality.[9]

In Figure 2 we plot the time series graph for Investment Grade (IG) Corporate Bonds funds (IC) liquidity supply ($F_{S,t}-\Delta C_{S,t}$) and its constituents ($F_{S,t}$ and $\Delta C_{S,t}$). When both components happen to have opposite signs during a given month their effects compounded producing either a larger net liquidity supply or demand. Both liquidity supply and its components display a substantial variation over time, fluctuating at levels below 2% and above -2% for most of the time. The most extreme episode of Investment Grade Bonds liquidity shortfall happened during

[9] Since we are interested in episodes of liquidity shortfall from non-Government Bond asset classes, we drop Government Bond funds from our further analysis.

the recent financial crisis, when the net liquidity supply reached a low of about -4% in November 2008. During that episode, most of the Investment Grade Bonds liquidity demand seemed to have come from investors redeeming rather than fund liquidity management decisions. Spring 2004 and 2013 also witnessed episodes of large Investment Grade Bonds liquidity shortfall, with the latest event being associated with the sharp correction in risk premia that arose in response to a tightening of the Federal Reserve monetary policy (see Michael Feroli and Shin (2014)).

4.3 Determinants of Stress Events

We next explore under what market conditions styles more likely experience an extreme liquidity shortfall. For each style, we define an indicator variable EVENT that is equal to one in a given month if the style's liquidity shortfall that month is below the fifth percentile in the sample ($F_{S,t} - \Delta C_{S,t} \leq 5\%$) and zero otherwise. Table 3 reports the results from Logit models regressing EVENT on macro variables, style flows, flow volatilities, cash holdings, and returns, and style fixed effects. The macro variables are Pastor and Stambaugh's (2003) aggregate market liquidity, the TED spread, Term spread and the Credit spread. The coefficient on market liquidity is negative and highly significant in every model. Similarly, the coefficient on Term spread is positive and significant in each model. These results suggest that poor market liquidity conditions and a steeper slope of the yield curve each seem to motivate investors to move money out of these funds rendering the Non-government Bond styles more likely to experience a stress event. Also, the coefficient on past returns and flows are both negative and significant, indicating that good past performance and large inflows lower the probability of a subsequent stress event. These results suggest that the positive flow-performance relation well-documented at the fund level also holds at the style level.

5 Fund-Level Liquidity Demand during Stress Months

5.1 Marginal Expected Liquidity Shortfall

As discussed above, we identify for each style the stress events, $\mathcal{E}_S$, as the months in which the style's liquidity supply is below the fifth percentile in the sample. To quantify the contribution of each individual fund to the style-level liquidity shortfall in stress months, we calculate for each fund the marginal expected liquidity supply (the negative of marginal expected liquidity shortfall) as the simple average of fund liquidity supply across stress months:

$$E\left[F_{i,t} - \Delta C_{i,t} | \mathcal{E}_S\right] = \frac{1}{N_{\mathcal{E}_S}} \sum_{i \in S} (F_{i,t} - \Delta C_{i,t}). \tag{3}$$

For 3,152 funds with available data, and we report the marginal expected liquidity supply in Panel A of Table 4. For at least half of the funds in each sector, and at least three-quarter of the Municipal Bond funds, the marginal expected liquidity supply is negative. The distribution reflects that even when a style experiences an extreme aggregate liquidly shortfall, not every fund contributes to this shortfall. Some funds are liquidity suppliers. The largest dispersion in the marginal liquidity supply, measured as $p_{95} - p_5$, is observed among Foreign Equity funds, while the smallest dispersion is observed among Municipal Bond funds.

Panel B of Table 4 compares each fund's marginal expected liquidity supply to the fund's average liquidity supply during the full sample. While on average the funds' marginal expected liquidity demands are significantly larger in absolute value than the funds' average liquidity demand, about twenty-five percentage of all funds experience less outflow during the crises months as compared to the full sample.

5.2 Cross-Sectional Analysis

We next analyze the two components of a fund's marginal expected liquidity shortfall, $E\left[F_{i,t}|\mathcal{E}_S\right]$ and $E\left[\Delta C_{i,t}|\mathcal{E}_S\right]$, during extreme events following the fund flow performance literature (*e.g.* Ippolito (1992), Chevalier and Ellison (1997), and Sirri and Tufano (1998), Chen, Goldstein, and Jiang (2010) and Goldstein, Jiang, and Ng (2015)) and the fund cash management literature (*e.g.* Shek, Shim, and Shin (2015), Chernenko and Sunderam (2016), and Jiang, Li, and Wang (2016)).

We first regress $F_{i,t}|\mathcal{E}_S$ on contemporaneous and past performance and cash levels. We control for fund-level characteristics, include month and fund fixed effects and double cluster the errors at the fund and month level. The results are reported in Table 5. Mirroring the results during normal times from the flow performance literature, we find that current flows increase in current and past style-adjusted fund returns even during crisis months. The same holds in the month after the crisis event where investors are reacting to past performance. We also find that fund with a larger cash ratio prior to the stress event experience lower outflows. To the extent that investors understand that a fund has more cash available to meet redemptions during the event month, higher levels of pre-crisis cash holdings provide a stabilizing effect during crises, which could help reduce the likelihood of investor runs on the fund. Besides the impact of cash and performance, we also find that older funds, actively-managed funds that exhibit higher portfolio turnover, and funds with higher expense ratios have larger outflows during the crisis month. Interestingly, fund investor composition proxied by the fraction of institutional investors in a fund does not affect flow during crisis events.

We next analyze how contemporaneous and past flow, performance, and cash levels are related to $\Delta C_{i,t}|\mathcal{E}_S$. We again control for fund-level characteristics, include month and fund fixed effects and double cluster the errors at the fund and month level. The results are reported in Table 6. First, and perhaps not surprisingly, funds on average use cash to meet redemptions during the crisis events. More importantly, however, we find that funds with lower cash balance prior to the stress event increase cash holdings during the crisis month. This suggests that funds with lower cash holdings prior to the crisis are more likely to contribute the style-level liquidity shortfall. We also find that larger funds build up more cash during a stress event maybe because these funds are concerned that a for a given percentage of future liquidity demand the corresponding market transaction in dollar terms is larger than for smaller fund and such transactions could only take place at further depressed prices. However, we do not find any evidence that funds will in anticipation of future outflows, as proxied by Flow_1 or $\text{Flow}_{1\text{-}3}$, build up cash.

Besides the effects of flow, performance, and cash on the cash build-up, we find that funds with lower turnover, lower fund return volatility, and more institutional investors build up less cash during bad times perhaps because they less likely need to transact right after the crisis period or because they expect their flows to be more stable.

Since funds entering into stress months with more cash face less pressure to liquidate assets when liquidity is in high demand, we may expect them to have better performance than peer funds during the stress events. To test this conjecture, we regress the fund's style-adjusted performance during the stress months on the lagged cash balance, and report the results in Table 7. The first two columns show that funds holding more cash prior to the stress events indeed exhibit better peer-adjusted performance during the stress months, with or without controlling for other fund characteristics.

However, this positive relation between cash holdings and fund performance may arise simply because non-cash assets underperform cash during stress months. To account for this effect, we examine the style-adjusted performance of non-cash assets in a fund's portfolio during stress months ($\text{Perf}_{\text{nc},0}$).[10] The last four column of Table 7 show that while $\text{Perf}_{\text{nc},0}$ and the lagged

[10]The return on non-cash assets is calculated as the fund return minus the product of the return on cash and the lagged cash ratio, divided by the weight of non-cash assets in the fund's TNA. The return on cash is proxied by the concurrent value-weighted return of money market funds.

cash balance are unrelated for the full sample, their relation is significantly positive for Municipal Bond funds, whose holdings are generally highly illiquid. In other words, for Municipal Bond funds, cash holdings not only affect the overall fund performance of during the stress months, but also have an impact on the performance of non-cash components of the fund assets during these months. This suggests that during stress months, cash holdings are particularly valuable for funds in the illiquid asset sectors.

6 Conclusion

Open-end mutual funds are subject to substantial fund flow risk because their shares are redeemable on a daily basis. They meet these redemption requests with cash they hold or by selling assets, or by a combination of the two. Therefore, the fund's cash management decision plays an important role in the transmission process from investor redemptions to net liquidity demand in the underlying asset market. Even though funds cash management decisions in the face of market stress might reflect prudent level of cash holdings from a micro-prudential point of view, these decisions from a macro-prudential perspective can be problematic. The collective action problem associated with coordinated sales and (potential) hoarding of cash may generate procyclical fire-sale externalities.

If investors are reallocating their investment from one fund to another fund in the same investment style, the liquidity demand of one fund is largely offset by the liquidity supply of the other. However, if funds in a style in aggregate demand liquidity, other market participants will need to take the other side of these trades. If aggregate net liquidity demand by funds in a given style exceeds the market's absorption capacity, that is, the liquidity supply by other market participants at non-depressed prices, funds in aggregate may become a systemic risk concern.

In this paper we study extreme episodes of mutual funds liquidity demand at the sector level and the contribution of individual funds to the aggregate liquidity demand during these episodes. We identify these episodes as the months during which the aggregated net liquidity demand in a given sector in the top 5% over the sample period. Our measure of mutual fund net liquidity demand summarizes the impact of both investor redemption and fund cash management decisions. We find that stress events are more likely to occur during episodes of poor market liquidity and a steeper slope of the yield curve. At the fund level, we show that funds entering a crisis period with low levels of cash contribute more to the overall liquidity imbalance by receiving higher investor redemptions and choosing to increase cash balance. For Municipal Bond funds, the cash holdings before the stress events are not only positively related to the overall fund performance of during the stress months, but also positively related to the performance of non-cash components of the fund assets during these months. Our results highlight the importance the micro-level mutual fund prudential liquidity management in mitigating the aggregate-level liquidity imbalance.

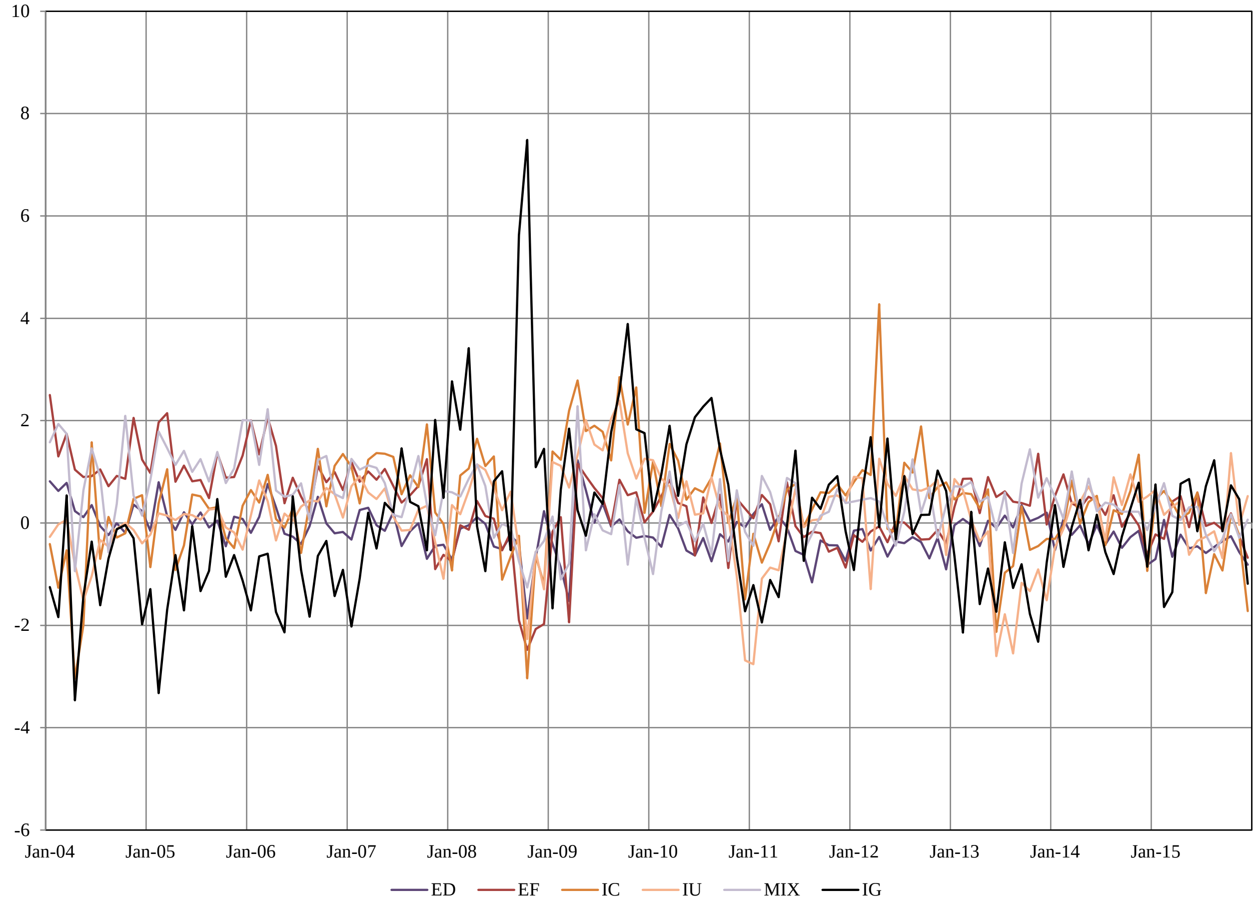

Figure 1: **Sector Liquidity Supply.** This figure shows the time series of monthly net liquidity supply $F_t - \Delta C_t$ for all mutual fund sectors: Domestic Equity (ED), International Equity (EF), Corporate Bond(IC), Municipal Bond(IU), Mixed-Asset (MIX), and Government Bond (IG).

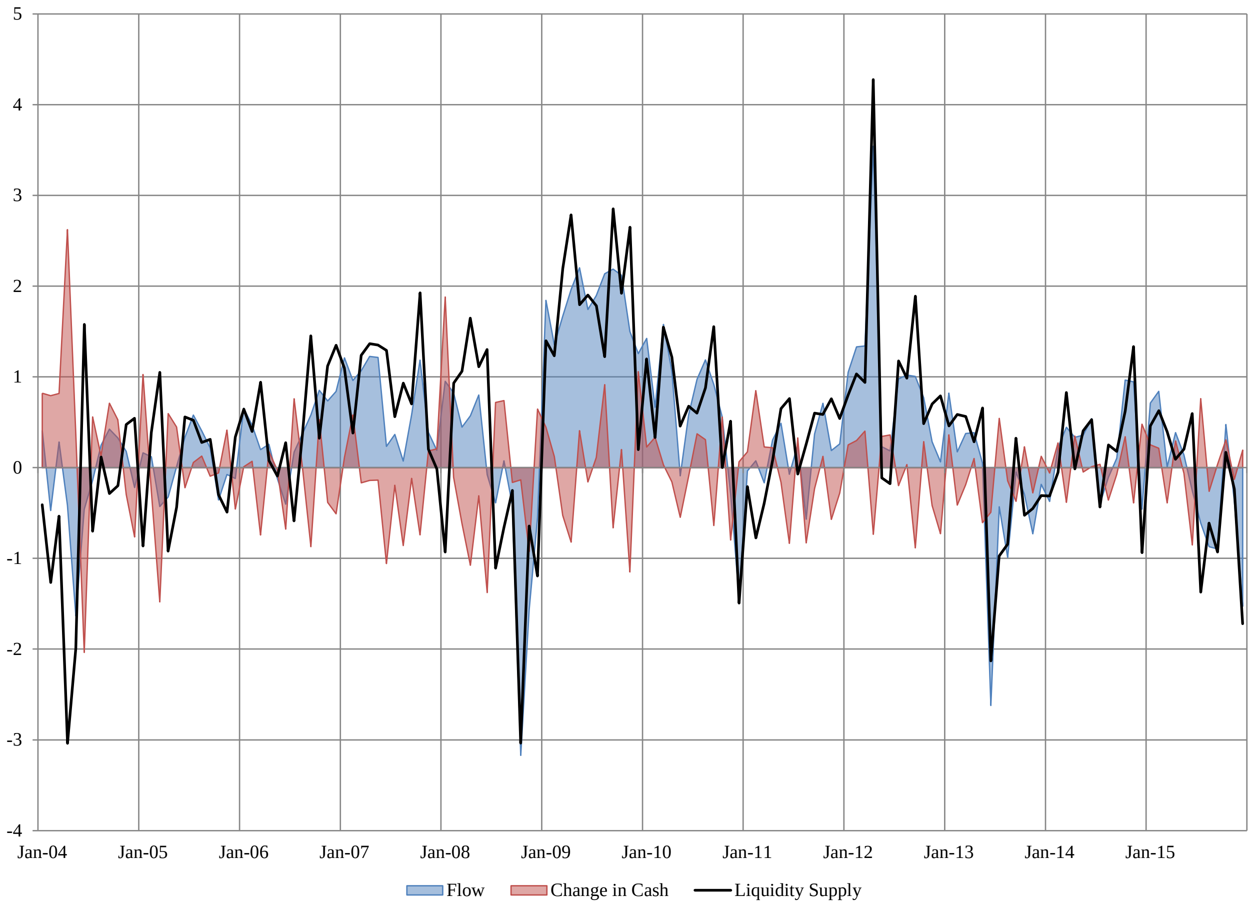

Figure 2: **Liquidity Supply: Investment Grade Bond Funds.** This figure contains the time series of monthly Flows $F_{S,t}$, changes in cash balance $\Delta C_{S,t}$, and net liquidity supply $F_{S,t} - \Delta C_{S,t}$ for the style Investment Grade Bond Funds.

Table 1: **Summary Statistics**

This table shows the summary statistics at the fund-month level for both the full sample (Panel A) and the stressed months (Panel B). We identify stressed months as the months during which the style-level net liquidity supply is in the bottom 5% of the sample period. Our sample includes 6,369 funds, with a total of 352,503 monthly observations over the period 2004 to 2015. Flow is the growth rate of fund TNA minus the realized return. Cash is the ratio of cash and cash equivalent to the fund TNA. ΔCash is the increase in cash ratio. LiqSupply is the net liquidity supply, which equals Flow minus ΔCash. Ret is month fund return. Perf is fund return minus contemporaneous style return. Expense, FrontLoad, and RearLoad are the total expense ratio,front-end and back-end loads, respectively. Turnover is the annual portfolio turnover rate. TNA is the total net asset value (in million dollars). Age is the number of years since fund inception. InstRatio is the ratio of assets of the institutional share class to the TNA. Flow, Cash, ΔCash, and Turnover are winsorized at the 1st and the 99th percentiles.

Panel A. Summary statistics of fund characteristics full sample 2004-2015

	mean	sd	skewness	kurtosis	p5	p50	p95	count
Flow - ΔCash	0.32	5.03	1.72	13.11	-5.85	-0.17	8.05	248,133
Flow (%)	0.35	4.72	2.14	15.28	-4.59	-0.23	7.35	581,656
ΔCash	-0.00	2.18	0.05	8.67	-3.28	0.00	3.27	249,161
Cash (%)	4.93	7.92	5.22	45.06	0.00	2.76	16.98	360,309
Ret	0.50	4.06	-0.77	8.20	-6.60	0.60	6.53	584,872
Perf (%)	-0.03	1.35	-0.49	32.95	-2.02	-0.03	1.96	584,872
Expense (%)	1.06	0.48	1.15	11.87	0.30	1.03	1.86	569,010
FrontLoad (%)	1.28	1.68	1.02	2.74	0.00	0.13	4.59	587,081
RearLoad (%)	0.55	0.82	1.51	4.89	0.00	0.05	2.00	581,760
Turnover	0.74	0.82	2.79	12.72	0.08	0.49	2.28	569,096
Log(TNA)	5.53	1.77	0.23	2.85	2.74	5.46	8.58	585,144
log(Age)	2.28	0.95	-1.02	4.94	0.51	2.46	3.51	587,357
InstRatio	0.34	0.40	0.69	1.76	0.00	0.10	1.00	587,801

Panel B. Summary statistics of fund characteristics during the 5% stress months

	mean	sd	skewness	kurtosis	p5	p50	p95	count
Flow - ΔCash	-0.99	5.27	1.40	12.67	-8.53	-1.10	6.49	13,976
Flow (%)	-0.83	4.81	1.84	14.71	-7.09	-1.03	5.74	31,775
ΔCash	0.16	2.38	0.34	7.61	-3.42	0.01	4.01	14,053
Cash (%)	5.00	8.30	5.40	46.20	0.00	2.78	16.94	20,097
Ret	-2.61	6.51	-0.95	4.56	-16.89	-1.43	7.19	31,938
Perf (%)	-0.00	1.84	0.18	27.87	-2.75	0.00	2.78	31,938
Expense (%)	1.04	0.46	1.01	11.80	0.29	1.02	1.80	31,190
FrontLoad (%)	1.27	1.68	1.05	2.83	0.00	0.13	4.61	32,068
RearLoad (%)	0.52	0.78	1.46	4.35	0.00	0.04	2.00	31,810
Turnover	0.75	0.82	2.79	12.83	0.08	0.51	2.22	31,286
Log(TNA)	5.46	1.78	0.18	2.85	2.65	5.40	8.50	31,946
log(Age)	2.31	0.94	-1.02	5.03	0.61	2.48	3.55	32,067
InstRatio	0.35	0.40	0.66	1.72	0.00	0.12	1.00	32,091

Table 2: **Style-level Liquidity Supply, Flows, and Cash Changes**

This table shows summary statistics of monthly liquidity supply, fund flows ($F_{\mathrm{S,t}}$), and cash change ($\Delta \mathrm{C}_{\mathrm{S,\ t}}$) for the full sample (Panel A) and for the stress months (Panel B). The stress month, $\mathcal{E}_S$, is defined the month during which the style-level liquidity supply is in the bottom 5% of the sample period. $\mathrm{F}_{\mathrm{S,t}}$ and $\Delta \mathrm{C}_{\mathrm{S,\ t}}$ are averages across funds within a style, weighted by the lagged fund TNA, while $\mathrm{C}_{\mathrm{S,\ t}}$ is the average weighted by the current TNA. The five fund sectors are: Domestic Equity (ED), International Equity (EF), Corporate Bond(IC), Municipal Bond(IU), and a Mixed-Asset (MIX). The Domestic Equity sector consists of the five styles: Large-Cap, Small-call, Multi-Cap, and Equity Income. The International Equity sector includes International Equity, Global Equity, and Emerging Market Equity styles. The Corporate Bond sector contains Investment Grade, High Yield, Short and Intermediate-Term Bond styles. And the MIX sector is composed of Balance, Flexible Portfolio, Mixed-Asset Target Date, Mixed-Asset target Allocation Conservative, Moderate and Growth styles. Obs is style-month observations; Mean and Std are the average and standard deviation at the style-month level, respectively.

Panel A. Full sample 2004-2015

		$F_{S,t} - \Delta C_{S,t}$		$F_{S,t}$		$\Delta C_{S,t}$	
	Obs	Mean	Std	Mean	Std	Mean	Std
ED	720	-0.055	0.261	-0.079	0.251	-0.024	0.015
EF	432	0.382	0.255	0.375	0.245	-0.007	0.012
IC	432	0.296	0.227	0.271	0.238	-0.025	0.016
IU	144	0.123	0.000	0.128	0.000	0.005	0.000
MIX	620	0.575	0.521	0.568	0.518	-0.038	0.055
Total	2,348	0.267	0.418	0.253	0.419	-0.023	0.033

Panel B. Stress months

		$F_{S,t} - \Delta C_{S,t} \vert \mathcal{E}$		$F_{S,t} \vert \mathcal{E}$		$\Delta C_{S,t} \vert \mathcal{E}$	
	Obs	Mean	Std	Mean	Std	Mean	Std
ED	40	-1.310	0.195	-0.995	0.305	0.316	0.250
EF	24	-1.974	0.221	-1.321	0.404	0.652	0.445
IC	24	-2.899	0.687	-1.899	0.896	0.999	0.449
IU	8	-2.209	0.000	-2.243	0.000	-0.034	0.000
MIX	32	-1.491	0.693	-0.613	0.640	0.878	0.337
Total	128	-1.834	0.752	-1.208	0.753	0.626	0.469

Table 3: **Determinants of the Probability of Extreme Liquidity Events**

This table shows results from logistic regressions models explaining the probability of extreme liquidity demand at the style level, which is defined as an event during which the style-level net liquidity supply is at the bottom 5% of the sample period. $\text{Flow}_{S,t-1}$, $\text{Cash}_{S,t-1}$, $\text{Return}_{S,t-1}$, $\text{Return}^2_{S,t-1}$, and $\sigma_{\text{Flow},S,t-1}$ are the style's one month lagged aggregate flow, cash balance, return, squared return, and volatile of style flows measured over six months. Market Liquidity, Ted, Term and Credit are the equity market-wide liquidity (Pastor and Stambaugh (2003)), the TED spread, the term spread, and the credit spread, respectively. The models control for style fixed effects. Significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1) EVENT	(2) EVENT	(3) EVENT	(4) EVENT	(5) EVENT
Market Liquidity	-4.927***		-3.888***		-3.060**
TED		0.637***		0.318	0.117
Term		0.324***		0.224*	0.229*
Credit		0.236**		0.177	0.127
$\text{Flow}_{S,t-1}$			-1.030***	-0.945***	-0.979***
$\text{Cash}_{S,t-1}$			-0.060	-0.064	-0.061
$\text{Return}_{S,t-1}$			-0.064**	-0.059**	-0.057**
$\text{Return}^2_{S,t-1}$			0.001	-0.002	-0.001
$\sigma_{\text{Flow},S,t-1}$			-0.262	-0.513	-0.519
Constant	-3.088***	-4.754***	-2.789***	-3.740***	-3.622***
pseudo R-Square	0.017	0.067	0.146	0.147	0.153
Observations	2,348	2,348	2,246	2,246	2,246

* $p < 0.1$, **$p < 0.05$, *** $p < 0.01$

Table 4: **Marginal Expected Liquidity Supply of Individual Funds**

Panel A shows the marginal expected liquidity supply of individual funds, calculated as the simple average of each fund's liquidity supply across the stress months. The stress month is defined as the months in which the style-level net liquidity supply is in the bottom 5% of the sample period. Panel B show the difference between a fund's marginal expected liquidity supply during stress months and its average liquidity supply over the full sample period.

Panel A: $E\left[F_{i,t} - \Delta C_{i,t} | \mathcal{E}_S\right]$

	Obs	Mean	p_5	p_{10}	p_{25}	p_{50}	p_{75}	p_{90}	p_{95}
ED	1,352	-0.856	-6.062	-4.228	-2.335	-0.998	0.390	2.279	4.571
EF	391	-0.568	-7.140	-5.254	-2.699	-0.948	1.034	4.289	8.254
IC	435	-1.592	-7.970	-6.397	-3.801	-1.531	0.374	2.607	4.813
IU	526	-2.013	-5.698	-4.825	-3.287	-2.063	-1.148	0.442	1.521
MIX	448	0.297	-4.919	-3.228	-1.861	-0.328	1.524	3.987	8.934
Total	3,152	-0.951	-6.468	-4.686	-2.697	-1.194	0.399	2.612	5.285

Panel B: $E\left[F_{i,t} - \Delta C_{i,t} | \mathcal{E}_S\right] - E\left[F_{i,t} - \Delta C_{i,t}\right]$

	Obs	Mean	p_5	p_{10}	p_{25}	p_{50}	p_{75}	p_{90}	p_{95}
ED	1,352	-0.884	-5.671	-4.175	-2.198	-0.801	0.333	2.022	3.600
EF	391	-1.177	-8.872	-5.685	-2.891	-1.166	0.463	2.543	5.347
IC	435	-1.878	-8.065	-6.116	-3.676	-1.586	-0.008	1.704	3.885
IU	526	-1.915	-6.386	-4.751	-3.076	-1.764	-0.660	0.605	1.552
MIX	448	-1.006	-6.558	-4.836	-2.553	-1.210	0.037	1.986	5.225
Total	3,152	-1.247	-6.667	-4.901	-2.703	-1.201	0.124	1.759	3.854

Table 5: **Cross-section of Fund Flows during Stress Months**

This table shows the cross-sectional determinants of fund flows during stress months, defined as the months in which the style-level liquidity supply is in the bottom 5% of the sample period. The dependent variable $Flow_0$ is fund flow during the extreme month. $Perf_0$ is the style-adjusted fund return during the stress months, $Perf_{-12,-1}$ is the average style-adjusted fund return over the 12 months prior to the stress month. $Cash_{-1}$ is the cash balance at the end of the month before the stress event. $Perf_0{}^2$ and $Perf_{-12,-1}{}^2$ are the corresponding squared returns. $\sigma_{ret,-1}$ is the standard deviation of fund returns over the 12-month period prior to the stress month. AverageLoad is the average of front-end and back-end loads. The regressions control for both style and month fixed effects, and the t-statistics are based on two-way clustered errors at both the style and the month levels. Significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1) $Flow_0$	(2) $Flow_0$	(3) $Flow_1$	(4) $Flow_1$
$Cash_{-1}$	0.052***	0.030***	0.033***	0.019**
$Perf_0$		0.086*		0.156***
$Perf_0{}^2$		-0.006		0.012***
$Perf_{-12,-1}$		1.749***		1.590***
$Perf_{-12,-1}{}^2$		0.131		0.156***
$\sigma_{ret,-1}$		-0.038		-0.090
$Log(TNA_{-1})$		0.007		0.054
$Log(AGE_{-1})$		-0.736***		-0.684***
$Turnover_{-1}$		-0.170***		-0.096
$Expense_{-1}$		-0.435***		-0.577***
$AverageLoad_{-1}$		-0.007		-0.003
$InstRatio_{-1}$		0.198		-0.034
Constant	3.402***	-0.067	0.091	1.373
Adj. R-Square	0.064	0.110	0.049	0.098
Observations	19,834	17,904	19,216	17,279

* $p < 0.1$, **$p < 0.05$, *** $p < 0.01$

Table 6: **Cross-section of Cash Changes during Stress Months**

This table shows the cross-sectional determinants of changes in cash ratio during stress months, defined as the months in which the style-level liquidity supply is in the bottom 5% of the sample period. The dependent variable ΔCash_0 is the increase in cash ratio during the stress month. Cash_{-1} is the cash balance at the end of the month before the stress event. Flow_0 is the fund flow during the stress month. Flow_1 is the fund flow in the subsequent month. $\text{Flow}_{1,\ 3}$ is the average fund flows during the subsequent three months. Perf_0 is the style-adjusted fund return during the extreme months, $\text{Perf}_{-12,-1}$ is the average style-adjusted fund return over the 12 months prior to the extreme month. $\text{Perf}_0{}^2$ and $\text{Perf}_{-12,-1}{}^2$ are the corresponding squared returns. $\sigma_{\text{ret},-1}$ and $\sigma_{\text{Flow},-1}$ are the standard deviations of fund returns and fund flows, respectively, over the 12-month period prior to the stress month. AverageLoad is the average of front-end and back-end loads. The regressions control for both style and month fixed effects, and the *t*-statistics are based on two-way clustered errors at both the style and the month levels. Significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	(1) ΔCash_0	(2) ΔCash_0	(3) ΔCash_0	(4) ΔCash_0
Flow_0	0.050***	0.054***	0.057***	0.056***
Cash_{-1}		-0.069***	-0.071***	-0.069***
Flow_1			-0.002	
$\text{Flow}_{1\text{-}3}$				-0.002
Perf_0	-0.047*	-0.027	-0.028	-0.028
$\text{Perf}_0{}^2$	0.001	0.003	0.003	0.002
$\text{Perf}_{-12,-1}$	-0.101	-0.119	-0.126*	-0.127*
$\text{Perf}_{-12,-1}{}^2$	0.010	0.084**	0.080**	0.077**
$\sigma_{\text{ret},-1}$	-0.028	-0.155***	-0.152***	-0.146**
$\sigma_{\text{Flow},-1}$	-0.013	-0.002	0.005	0.005
$\text{Log}(\text{TNA}_{-1})$	0.046***	0.045***	0.050***	0.051***
$\text{Log}(\text{AGE}_{-1})$	-0.010	-0.068*	-0.056	-0.055
Turnover_{-1}	0.164**	0.207***	0.211***	0.202***
Expense_{-1}	0.007	0.003	-0.003	0.012
AverageLoad_{-1}	-0.003	-0.039	-0.033	-0.038
InstRatio_{-1}	-0.083	-0.216**	-0.234***	-0.237***
Constant	-0.770**	0.275	1.057*	0.653
Adj. R-Square	0.022	0.057	0.058	0.056
Observations	12,672	12,672	12,098	12,129

* $p < 0.1$, **$p < 0.05$, *** $p < 0.01$

Table 7: **Cross-section of Fund Performance during Stress Months**

This table shows the cross-sectional determinants of fund performance during the stress months, defined as the months in which the style-level liquidity supply is in the bottom 5% of the sample period. The first four column report results for all funds, while the last two columns report results for municipal bond funds. The dependent variable $Perf_0$ is the style-adjusted fund return during the stress months, $Perf_{nc,\,0}$ is the style-adjusted return on non-cash components of fund assets during the stress months. $Cash_{-1}$ is the cash balance at the end of the month before the stress event. $Perf_{-12,-1}$ is the average style-adjusted fund return over the 12 months prior to the stress month. AverageLoad is the average of front-end and back-end loads. The regressions control for both style and month fixed effects, and the *t*-statistics are based on two-way clustered errors at both the style and the month levels. Significance at the 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

	ALL	ALL	ALL	ALL	MUNI	MUNI
	(1)	(2)	(3)	(4)	(5)	(6)
	$Perf_0$	$Perf_0$	$Perf_{nc,0}$	$Perf_{nc,0}$	$Perf_{nc,0}$	$Perf_{nc,0}$
$Cash_{-1}$	0.022**	0.024**	-0.001	0.001	0.059***	0.044***
$Perf_{-12,-1}$		0.435		-0.032		1.083
$Log(TNA_{-1})$		-0.046		-0.016		-0.179**
$Log(AGE_{-1})$		0.081*		0.038		0.387***
$Turnover_{-1}$		-0.042		-0.093**		-0.059
$Expense_{-1}$		-0.281***		-0.211**		-1.181***
AverageLoad		-0.013		-0.021		-0.341***
$InstRatio_{-1}$		0.074*		0.070		0.143*
Constant	1.152	0.773	-1.541	-1.154	0.004	1.192***
Observations	19900	18214	13682	12657	2209	1830
Adjusted R^2	0.031	0.049	0.533	0.542	0.206	0.420

* $p < 0.1$, **$p < 0.05$, *** $p < 0.01$

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