The effect of large macro surprises on mutual funds' liquidity profile

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Abstract

We measure the liquidity profile of open-end mutual funds with the sensitivity of their daily returns to aggregate liquidity, and we study how this sensitivity changes around real-activity macro announcements that reveal large surprises about the state of the economy. The results show that, following negative news, the sensitivity to aggregate liquidity increases for less liquid mutual funds, like those that invest in the stocks of small companies and in high-yield corporate bonds. The effect is more pronounced during stress periods, suggesting that a deterioration in the funds' liquidity profiles might potentially amplify vulnerabilities in situations of already weak macroeconomic conditions.

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1 Introduction

We study how the liquidity profile of open-end mutual funds changes around scheduled macroeconomic announcements that reveal unexpected news about the economy. We define a fund's liquidity profile as the sensitivity of its daily portfolio returns to an aggregate liquidity factor, and we interpret an increase in the liquidity-factor loading as a deterioration in the fund's liquidity profile.

Our way of measuring a fund's liquidity profile builds on the asset-pricing literature studying asset returns in terms of systematic-risk factors (as in, for instance, Fama and French, 1993). Instead of characterizing a mutual fund portfolio using the set of assets it holds, we rely on a set of factor sensitivities that capture the non-diversifiable risk to which the assets in the portfolio are exposed.

There are two advantages of our approach. First, we are able to study certain aspects of a mutual fund's portfolio liquidity at higher frequency than possible when using regulatory disclosures of asset holdings, that are typically available at a monthly or quarterly frequency. Second, studying a fund's liquidity profile around scheduled macroeconomic announcements helps us address the endogeneity between a fund's liquidity profile and the flows generated by unexpected news. This framework makes our statements causal in nature under the assumption that fund managers' expectations are in line with median expectations about the scheduled announcements.[1]

While changes in the sensitivity to aggregate liquidity might simply reflect shifts in the asset composition due to managerial choice, rather than the flows, the literature

[1] One example of how endogeneity can arise is the fact that managers who expect large out flows in quarter $t+1$ may start increasing liquidity buffers in quarter t, and a negative relation between out flows and changes in liquidity buffers would simply reflect flow expectations rather than the effect of realized flows on liquidity buffers.

supports the view that unexpected macro news generate flows in and out of mutual funds. For example, Jank (2012) provides evidence that the correlation between stock returns and inflows into equity funds is due to a reaction to macroeconomic news. Similarly, Chalmers, Kaul, and Phillips (2013) find that mutual fund investors rebalance their portfolio out of equity funds when they anticipate deteriorating economic conditions, and viceversa. For a subset of risky funds with available daily flow data, we verify that the average outflow in the three weeks following announcements with unexpected negative news equals 0.3% of AUM. In the three weeks leading to the announcements, on the other hand, the average flow is not statistically different from zero.[2] Therefore, during these specific days, mutual funds are likely to experience relatively high flows that, by construction, are unexpected to managers.

Irrespective of the reason why liquidity is changing (due to investment strategy or flows), it is important to track fund liquidity in high frequency. Hence, our analysis is especially useful to understand how fund liquidity evolves at times of market stress. Avoiding a significant deterioration in the liquidity of a fund's assets is particularly important because episodes of market stress are typically associated with large out flows from funds that invest in risky assets, and the liquidity of a fund's assets plays a key role in the orderly functioning of the fund redemption process. In case of unusually large out flows at times of market stress, mutual fund mangers might be forced to sell assets in a market with reduced liquidity. Investors could have an incentive to redeem their mutual fund shares before funds start selling assets at a significant discount, further exacerbating out flows in a process that shares similarities with a bank run (See FSB and IOSCO, 2015; Chen et al., 2010).

[2]This sample includes equity, high-yield and investment-grade funds in 2014 and 2015.

Our sample spans the period 2004-2016 and it includes U.S. equity, government, high-yield and investment-grade corporate bond funds. Liquidity loadings are estimated in a panel setting, where we regress daily changes in funds' net asset values (NAV) on market liquidity, while controlling for other relevant market factors and fund-specific characteristics. We compare changes in the liquidity-factor loadings between the three weeks before and the three weeks after the announcements. The set of real-activity macroeconomic announcements we study is selected on the basis of how large their realization is compared to the corresponding Bloomberg expectations, which we evaluate with the Scotti (2016) surprise index. We restrict our attention to events with the largest positive or negative surprise within a given quarter.

We find an increase in the sensitivity of less liquid mutual funds, like those investing in the stocks of small companies and in high-yield corporate bonds, following the release of scheduled macro news that reveal unexpected negative information about the economy. We interpret this result as a deterioration in the liquidity profile of those funds. The effect is more pronounced during recessions, for smaller funds, and for funds with lower initial cash holdings.

Our paper is related to two main branches of the literature: one on mutual-fund flows and their interaction with portfolio liquidity, and one on the pricing of systematic liquidity risk. Papers belonging to the first group include, among others, Chen, Goldstein, and Jiang (2010), Feroli, Kashyap, Schoenholtz, and Shin (2014), Zeng (2015), Goldstein, Jiang, and Ng (2016), Hanouna, Novak, Riley, and Stahel (2015), and Chernenko and Sunderam (2015). Goldstein, Jiang, and Ng (2016) find that the sensitivity of outflows to bad performance in corporate bond funds is much stronger in times of aggregate illiquidity and among funds that hold more illiquid assets; Hanouna, Novak, Riley, and Stahel (2015) find that U.S. equity funds with lower portfolio liquidity experience a greater decrease in liquidity due to large redemptions. Chernenko and Sunderam (2015) study mutual fund cash holdings and flows using semi-annual holdings obtained from regulatory filings. They find that mutual funds manage a significant share of flows by changing their cash holdings rather than by buying and selling the underlying assets, especially in the case of funds that invest in illiquid assets and during periods of poor market liquidity. As the authors note, however, their results largely reflect endogenous relations, because the variables they analyze are jointly determined.

We contribute to this literature by studying the liquidity profile of mutual funds in a daily setting. To the extend that the changes in liquidity we observe are associated with fund flows, we adress the endogeneity issue.

Relevant papers in the literature about systemic liquidity risk pricing are, among others, the seminal work of Pastor and Stambaugh (2003) for equities, and the study of bond liquidity by Acharya, Amihud, and Bharath (2013), who find that, at times of weak macro conditions, the prices of investment-grade bonds rise and the prices of junk bonds fall following a deterioration in overall liquidity.

The question we are interested in is related to but different from the liquidity-based market timing studied by Cao, Simin, and Wang (2013). They investigate changes in the exposure to the market factor, rather than the liquidity factor, conditional on monthly deviations of market liquidity from its 60-month moving average. Their results are also not driven by liquidity risk, which is the focus of our analysis.

The remainder of the paper is organized as follows. Section 2 presents the data used in the analysis, Section 3 describes the panel regression framework, Section 4 discusses the results, and Section 5 concludes.

2 Data

We study active and inactive open-end U.S. mutual funds, excluding money-market funds, over the period 2004Q3–2016Q4. We obtain fund characteristics, such as age, category, and assets under management, from Morningstar Direct. On the basis of Morningstar's classification, we consider the following fund categories: equity, small cap, government bonds, investment-grade corporate bonds, and high-yield corporate bonds.[3] The data are at the share-class level, but our focus is on fund-level variables. When aggregating share-level data, we sum or value-weight the variables as appropriate, with weights based on the assets under management (AUM) for each share class (we value-weight ratios like the turnover ratio and sum variables measured in dollars, like AUM). Daily net asset value (NAV) data at the share-class level are from the Center for Research in Security Prices (CRSP) and are matched to the Morningstar Direct data with CUSIP numbers.

Table 1 reports selected summary statistics for the sample we study. The number of funds generally increased between 2004 and 2009 and declined afterwards. Exceptions are the high-yield and investment-grade corporate bond funds, which increased through 2016, although they started from a lower number in 2004. As of December 2016, the average domestic equity fund managed $2 billion. Fixed-income funds were smaller than domestic equity funds, with the average size between roughly $0.8 billion and $1.7

[3]The classification is based on Morningstar's Global Broad Category (GBC), Global Category (GC), Institutional Category (IC) and Category (C) variables. A fund is classified as "Domestic Equity" if GBC is equal to "Equity", and as "U.S. Small Cap" if GC is "US Equity Small Cap." It is classified as "Government Bond" if (1) C contains "Gov" or "Inflation-Protected" and GBC is equal to "Fixed Income" or (2) C is equal to "Fixed Income" and the fund's name contains "Gov" or "Treas" or IC contains "Gov" or "Treas." A fund is classified as "High-Yield Corporate Bond" if IC is equal to "High Yield Bond" and C to "Corporate Bond." A fund is classified as "Investment Grade Corporate Bond" if C is "Corporate Bond" and IC contains "Grade" or "A-Rated" or "BBB-Rated."

billion. The average AUM is typically larger than the 75th percentile, indicating the presence of a small number of very large funds in each category. Between 2004 and 2016, average AUM doubled for almost all funds' categories. Average fund age increased over time, highlighting the presence of well-established funds, and it was between 8 and 19 years over our sample.

We proxy for aggregate market liquidity with a variety of measures. For the equity market, we build a daily measure based on the Pastor and Stambaugh (2003) value-weighted traded factor obtained from the Wharton Research Data Services (WRDS). We consider common stocks in CRSP that trade on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the National Association of Securities Dealers (NASDAQ) with at least 60 monthly observations between 1980 and 2016. We calculate the liquidity beta in factor regressions of each stock's excess returns on the Fama-French market, small-minus-big (SMB), high-minus-low (HML), and momentum (UMD) factors (from WRDS), in addition to the Pastor and Stambaugh (2003) replicating factor. Stocks in the top (bottom) 10 percent of the liquidity beta distribution are included in the long (short) leg of a replicating portfolio that we use to measure daily liquidity conditions in the equity market.

In the case of fixed income funds, we proxy for aggregate liquidity with the noise measure introduced by Hu, Pan, and Wang (2013).[4] This variable builds on the intuition that the Treasury yield curve is smooth when financial intermediaries can deploy enough capital to take advantage of arbitrage opportunities that arise from price discrepancies between Treasury bonds with different maturities. When financial intermediaries are unlikely to have enough capital to engage in arbitrage, and most likely they are unable to

[4]We use the negative of the measure so that higher values imply better liquidity conditions.

provide normal levels of liquidity, the Treasury yield curve is more noisy (less smooth). In unreported results, we also replicate the analysis with high-yield, investment-grade, and 10-year treasury bid-ask spreads obtained from the Federal Reserve Bank of New York.

Our set of explanatory variables also includes the change in the level and slope of the term structure, estimated via Nelson-Siegel model (Nelson and Siegel, 1987). The raw data are from the U.S. Treasury's Monthly Statement of Public Debt. Finally, we obtain daily spreads for the credit default swap indexes CDX Investment Grade and CDX High Yield from Markit to control for economy-wide default risk.

We identify scheduled macroeconomic announcements that yield positive or negative surprises with changes in the Scotti (2016) index of real-activity macroeconomic surprises for the United States. The index summarizes standardized surprises, measured as actual announcement minus median Bloomberg expectation for the scheduled announcements of Gross Domestic Product, Industrial Production, Nonfarm Payroll, Personal Income, ISM and Retail Sales. The data are standardized for comparability: a positive (negative) reading of the surprise index suggests that economic releases have on balance been higher (lower) than consensus, meaning that investors were more pessimistic (optimistic) about the economy.

Within each quarter, we consider the macroeconomic announcement for which the release deviates the most from expectations, and we require that a release is at least six weeks later than the previous quarter's highest-deviation release, to ensure that there is no overlap between the pre- and post-announcement windows of two consecutive releases. We consider releases with positive and negative surprises separately.

Merged with the announcement days, our final dataset spans 2004 though the end of 2016 and contains 10,790,971 daily observations across 5,851 unique funds.

3 Macro announcements and fund liquidity

We study changes in the sensitivity of mutual funds to aggregate market liquidity around scheduled macroeconomic announcements for which the data releases deviate the most from consensus expectations. Following a higher/lower-than-expected real-activity data release, we study whether there is a change in the coefficient that measures the sensitivity of a fund's daily return to the liquidity factor. We use the change in the estimated sensitivity to the liquidity factor as proxy for the change in the liquidity profile of the fund.

Using fixed-effects panel regressions, we estimate changes in the liquidity factor loadings by interacting the liquidity factor with a dummy variable. The dummy variable is equal to zero in the pre-announcement period and equal to one after the announcement. Both the pre- and post-announcement periods are three-week long, and the announcement date is included in the second three weeks because macroeconomic data are released in the morning, while the NAV and factors are measured at the end of the day. Within each quarter, we identify the announcement with the the most positive surprise and the announcement with the most negative surprise. We consider the sets of positive and negative announcements separately when estimating the coefficients. In particular, negative (positive) surprises are defined as those when the realization is below (above) expectation, meaning that the economy is doing worse (better) than expected by market participants.

We estimate the following fund fixed-effect panel regression, with standard errors clustered by date:

$$
\begin{aligned}
RET_{i,t} &= \alpha + \alpha_{\Delta} D_{post,t} + \beta LIQ_t + \beta_{\Delta} LIQ_{post,t} + \gamma_Z Z_t \\
&+ \gamma_X X_{i,q-1} + \nu_y + \eta_i + \varepsilon_{i,q}
\end{aligned} \qquad (1)
$$

where i indicates the fund, t the date, RET are the daily returns of a given fund, calculated as daily NAV log-changes, in excess of the risk-free rate, and LIQ is the aggregate market liquidity measure, proxied by the Pastor and Stambaugh (2003) liquidity measure for equity and the Hu, Pan, and Wang (2013) noise measure for fixed income funds. $D_{post,t}$ is a dummy equal to 1 in the post-announcement three weeks. β is the marginal effect of the liquidity factor over the pre-announcement three weeks, and $\beta + \beta_{\Delta}$ is the marginal effect over the post-announcement three weeks ($LIQ_{post,t} = LIQ_t \times D_{post,t}$).

For equity funds, the matrix Z of control variables includes the Fama-French (MKT, SMB, and HML) and momentum factors. For fixed-income funds, Z includes changes in the level and slope of the yield curve, and the Markit CDX index.[5] Fund level controls (X) include AUM, fund age, turnover ratio, and average tenure of the fund managers in years, all measured as of the end of the previous quarter. ν_y and η_i are the year and fund-level fixed effects.

Funds with a higher β are more sensitive to liquidity risk. The coefficient β_{Δ} captures changes in the liquidity-risk sensitivity – i.e., changes in the liquidity profile – following the macroeconomic announcements. Figure 1 illustrates that a non-zero β_{Δ} (positive, in the example) implies a change in the slope of the relation between a fund's expected

[5]We also estimate a model where we allow the marginal effect of the variables in Z to change in the post announcement period. For instance, the model for equity funds includes $MKT_{post,t}$, $SMB_{post,t}$, and $HML_{post,t}$ as well as $LIQ_{post,t}$. We find that our findings are unaltered.

return and the market liquidity factor. The slope can change even if liquidity conditions remain the same (moving from the blue circle to the red triangle), and changes in liquidity conditions do not necessarily imply a change in the slope (moving from the solid blue circle to the hollow blue circles).

Our focus is on changes in the comovement between expected fund returns and the liquidity factor. As a result, our coefficient of interest is β_Δ: a positive (negative) and statistically significant β_Δ indicates that funds are more (less) exposed to market liquidity in the weeks following the macroeconomic surprises. A positive β_Δ points to a deterioration in the fund's liquidity profile, because a fund's returns comove more with liquidity conditions.

4 Results

We run regression (1) separately for five categories of funds, depending on the type of assets they invest in: equity, small cap, government bonds, investment-grade corporate bonds, and high-yield corporate bonds. Results are presented in Table 2 for equity funds and in Table 3 for fixed-income bond funds. For every fund type, we consider announcements that result in the largest negative surprise in each quarter (left part of the tables), as well as those that result in the largest positive surprise (right part of the tables). To ease the interpretation of the estimated coefficients, we standardize the liquidity variables used in all the specifications.

4.1 Equity funds

The results for equity funds are shown in Table 2. The coefficient of interest, β_Δ, is positive and statistically significant only for small-cap funds following negative surprises. The impact is economically significant: following a negative surprise, a one standard deviation change in the underlying aggregate liquidity increases the daily expected return of small-cap funds by about 2 basis points, corresponding to an annual return of about 5 percent. The results suggest that liquidity profiles of small-cap funds deteriorate after scheduled macroeconomic announcements that reveal unexpected negative information about the state of the economy. This finding, together with the correlation between fund flows and macroeconomic news highlighted by Jank (2012) and Chalmers, Kaul, and Phillips (2013), is in line with Hanouna, Novak, Riley, and Stahel (2015). They use quarterly regressions of portfolio liquidity on realized flows to show that outflows reduce the liquidity of equity funds.

Domestic equity funds are generally not sensitive to such information, possibly due to the fact that aggregate liquidity is ample in domestic equity markets and the liquidity profiles of these funds tend not to be affected by large changes in their portfolios. That is, because those assets can easily be liquidated, funds can sell any part of their portfolio with no significant change in their sensitivity to aggregate liquidity, even following unexpected macro news that can potentially trigger large redemptions or other portfolio changes. The results are similar whether we include or exclude funds characteristics like AUM, fund age, turnover and manager tenure.

Turning to the other coefficients in regression (1), the loadings on the standardized liquidity factor (LIQ) are, as expected, positive and statistically significant for all domestic equity funds, but are lower for small-cap funds. The positive sign implies that funds' returns increase with market liquidity. Equity funds load heavily on the market factor (MKT). As expected, the coefficient on the Fama-French factor that is long small companies and short large companies (SMB) is largest for small-cap equity funds. The loadings on MKT, SMB and HML are fairly similar, within each fund category, when they are estimated using the samples with positive or negative surprises.

4.2 Fixed-income funds

The results for fixed-income funds are shown in Table 3. In the panel regression for fixed-income funds we proxy for liquidity with the negative of the Hu, Pan, and Wang (2013) noise measure. The coefficient of interest, β_Δ, is positive and statistically significant at a 5% level for investment-grade and high-yield funds following negative surprises (left part of the table). The magnitude of the coefficient implies that, following a negative surprise, a one standard deviation change in the aggregate liquidity increases the daily expected return of small-cap funds by about 4 basis points (corresponding to an annual return of about 10 percent). Similar to equity funds, the results for fixed-income funds are in line with less-liquid funds becoming more sensitive to aggregate market liquidity in the aftermath of announcements with large negative surprises. Consistent with this view, the more liquid government funds do not exhibit significant changes in the sensitivity to underlying market liquidity conditions following negative news about the economy.

The relatively low liquidity of corporate bonds could generate price autocorrelation because the information reflected in prices is stale. Such autocorrelation would dampen the measured sensitivity of asset returns to the liquidity factor (Getmansky, Lo, and Makarov, 2004). As a result, the liquidity coefficients we calculate are likely to be biased downward, thus making our results conservative.

Interestingly, the liquidity profiles of high-yield funds are sensitive to positive surprises as well, with a noticeably weaker statistical significance. It is possible that high-yield fund managers, moved by precautionary motives, alter the liquidity profile of their funds by accumulating precautionary liquidity holdings ahead of macro announcement, irrespective of the expected outcome. See, for instance, Bansal and Yaron (2004) and Savor and Wilson (2013) who argue that higher risk on macroeconomic announcement days increases demand for precautionary holdings. Following a macroeconomic announcement, fund liquidity declines a little for positive surprises, too, because the precautionary liquidity holdings are no longer necessary.

The coefficient on the aggregate liquidity factor (β) is negative and mostly statistically significant for investment-grade and high-yield funds, a result largely driven by the December 2007-June 2009 recession. Changes in the yield curve level are generally statistically significant across fixed-income fund types. These coefficients are positive for government and investment-grade corporate bond funds, while they are negative for high-yield corporate bond funds. Changes in the slope are also statistically significant for the different types of funds: they are negative for government and investment-grade funds, and positive for high yield funds.

4.3 The role of business conditions

A number of theoretical and empirical studies documented that the reaction of asset prices to macroeconomic news depends on whether the economy is experiencing a recession or a period of robust growth (see Andersen, Bollerslev, Diebold, and Vega, 2007, Boyd, Hu, and Jagannathan, 2005 and Veronesi, 2015, among others). Similarly, the effect of macroeconomic surprises on fund liquidity could depend on the state of the economy. For instance, managers may be more worried about future outflows after negative surprises in an already weak economy. As a result, they may make more noticeable adjustments to fund liquidity during a recession. Hence, we investigate whether post-announcement changes in liquidity coefficients (β_Δ) depend on the broader economic backdrop.

To this end, we first repeat the analysis discussed in Sections 4.1 and 4.2 after partitioning the sample based on whether the Aruoba-Diebold-Scotti Business Conditions (ADS) index (Aruoba, Diebold, and Scotti, 2009) is above (ADS_{high}) or below (ADS_{low}) its median value (a higher value of the index is associated with favorable business conditions). The index tracks the state of the U.S. economy using a dynamic factor model based on a mix of quarterly, monthly, and weekly real activity data.[6] Second, we consider a sample that only includes the 2008 global financial crisis and its immediate aftermath.

The post-announcement liquidity coefficients, β_Δ, are reported in Table 4, where the sample used to estimate the coefficients is shown in the column headers. The results reveal higher changes to the liquidity factor loading when business conditions are weak

[6]The variables included in this index correspond to those used in the Scotti (2016) surprise index.

for small-cap, investment grade, and high-yield corporate bond funds, following bad news. Higher sensitivity is intuitive given that portfolio reallocation and outflows are more likely when the economy is performing poorly. Both reallocation to less liquid assets (which are higher-yielding in expectation) and larger outflows that are met by selling more liquid assets would result in a positive β_{Δ}. The size of the coefficients is also noticeably higher than during economic expansions. Finally, in the sample that focuses on positive announcements, all coefficients are statistically insignificant in each of the subsamples.

4.4 The role of size and initial cash holdings

The change in a fund's liquidity profile following macroeconomic surprises might be affected by two additional variables: the fund size and its initial cash holdings. Smaller funds, for instance, may have less sophisticated liquidity management arrangements that might force them to sell liquid assets more aggressively than larger funds. Typically, smaller funds have limited access to inter-fund loans or to bank credit lines. In order to investigate the first hypothesis, we partition the sample based fund AUM at the end of the previous year.

Similarly, we evaluate the second hypothesis by partitioning the funds based on their initial holdings of cash-like securities in the previous quarter. Funds with lower cash holdings may be forced to sell their most liquid assets to meet redemptions quickly. Alternatively, they may also have a more aggressive investment style and engage in market timing with the purchase of less liquid securities after negative macroeconomic news.

In Table 5, we estimate the post-announcement liquidity coefficients separately for funds that, within each category, have AUM and cash-to-AUM ratios below and above the median. AUM_{low} and CASH_{low} indicate funds with values of AUM and cash-to-AUM below the median, and AUM_{high} and $\text{CASH}_{\text{high}}$ indicate funds with values of AUM and cash-to-AUM above the median.

We find that subsampling on the basis of AUM does not make a large difference in terms of the β_{Δ} coefficient, with the exception of investment-grade bond funds. In this case, the deterioration in liquidity is more pronounced in the aftermath of negative surprises for low-AUM funds. With regards to initial cash holdings, there is a clear difference only for domestic equity funds, for which the coefficient β_{Δ} is higher when the funds have low initial cash.

5 Conclusions

We investigate how the liquidity profile of mutual funds is affected by macroeconomic surprises revealed by scheduled announcements. We define a mutual fund's liquidity profile as the sensitivity of its daily returns to aggregate market liquidity. We interpret an increase in the liquidity-factor sensitivity as a deterioration in the liquidity profile of the fund. Our approach allows us to study the evolution of mutual fund liquidity at higher frequency than possible when using regulatory asset-holding disclosures.

The reasons behind changes in liquidity profile could be different. For instance, portfolio managers might adjust a fund's holdings in light of the unexpected news, or mutual funds might face outflows driven by investor redemptions. Irrespective of the reason why the liquidity profile of mutual fund changes after macroeconomic announcements, understanding its dynamics is important because poorer fund liquidity might amplify certain vulnerabilities, especially at times of market stress. In particular, investors might run on the fund, in a process similar to a bank run, if they are concerned that waiting to redeem their shares means that they could incur a liquidity discount after early redemptions are met by selling the most liquid fund assets.

Overall, our results highlight that, in the aftermath of announcements that reveal unexpectedly negative information about the state of the economy, small-cap equity funds and investment-grade and high-yield corporate bond funds experience a deterioration in their liquidity profile.

These results offer an insight into how funds might react to negative unexpected news. In doing so, our work can help to identify those funds that could amplify vulnerabilities and contribute to systemic risk.

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Figure 1: **The Relation between Expected Returns and Liquidity**

The figure illustrates the relation between fund expected returns (Y-axis) and changes in the liquidity factor (X-axis). If the sensitivity of the fund to aggregate liquidity does not change after a macroeconomic announcement, changes in the underlying aggregate liquidity only imply movements along the blue solid line, from the solid marker to the hollow ones. The red dashed line is an example of the relation between fund expected returns and liquidity-factor changes after a shift in the sensitivity to market liquidity occurs. Moving from the blue solid circle to the red solid triangle represents a change in the liquidity profile with constant underlying market liquidity.

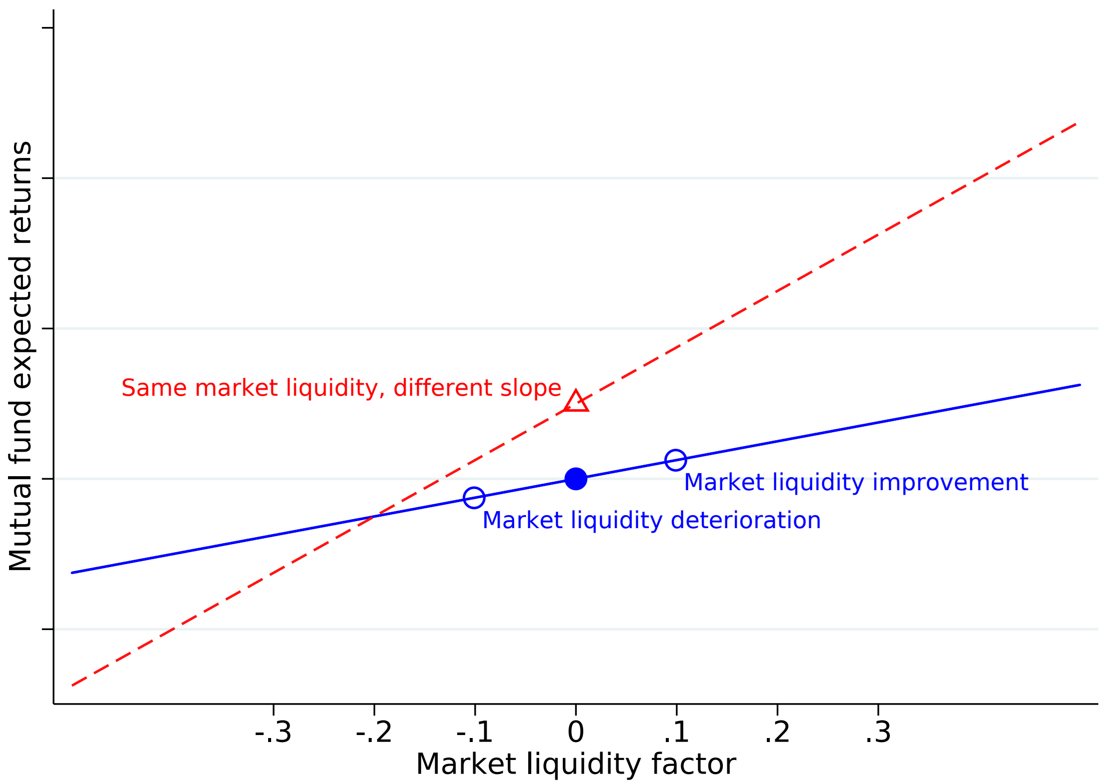

Table 1: Fund Summary Statistics
The table shows the number of funds at the beginning of the sample, in the middle of the sample, and at the end of the sample. For the same years, the table also shows the average and selected percentiles of assets under management (AUM, in $ million) and fund age in years.

		Number	Fund AUM (mn$)			Fund Age (years)		
		of funds	Average	25th perc.	75th perc.	Average	25th perc.	75th perc.
Domestic Equity	2004	2986	1,036	44	598	10	4	12
	2009	3110	1,020	35	628	12	5	16
	2016	2717	2,048	64	1,274	16	7	21
U.S. Small cap	2004	571	463	48	484	8	4	11
	2009	629	460	29	402	11	5	14
	2016	589	814	43	692	14	6	20
Government Bonds	2004	182	829	88	661	13	7	19
	2009	205	1,143	109	808	16	8	23
	2016	183	1,355	140	1,113	19	11	29
IG Corp. Bonds	2004	30	793	73	807	13	3	22
	2009	40	1,106	83	750	14	5	21
	2016	51	1,688	89	1,202	17	7	24
HY Corp. Bonds	2004	124	944	88	1,043	12	5	18
	2009	153	1,010	104	827	14	5	17
	2016	183	1,383	77	1,123	15	5	19

Table 2: Regression Results–Equity Funds

The table shows the coefficients from regression (1) for equity and small-cap funds. For each quarter between 2004 and 2016, we identify the macro announcement that reveals the most unexpected information by using the Scotti (2016) index. We consider the three weeks before the announcement and the three weeks following (and including) the announcement. β is the coefficient on the daily return of a long/short portfolio that replicates the Pastor and Stambaugh (2003) traded liquidity factor. β_Δ is the change in β over the post-announcement period. MKT, SMB, HML, UMD are the coefficients on the Fama-French and momentum factors. AUM is the logarithm of fund size. Age is the logarithm of fund age plus one, TURN is fund turnover, and TEN is the logarithm of fund managers tenure, in years plus one. α is the constant and α_Δ is the coefficient on a dummy equal to one in the three weeks after an announcement. We report standardized coefficients for β and β_Δ (in %). Standard errors are clustered by date, and t-statistics are in parentheses. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level (two-sided), respectively. Year and fund fixed effects are included, but the coefficients are not shown.

	Negative surprises				Positive surprises			
	Equity		U.S. Small cap		Equity		U.S. Small cap	
β	3.02***	3.04***	1.54**	1.65**	3.58***	3.59***	2.59***	2.62***
	(6.39)	(6.47)	(2.32)	(2.51)	(7.18)	(7.08)	(4.64)	(4.65)
β_Δ	1.02	1.02	2.04**	2.08**	-0.57	-0.66	0.30	0.48
	(1.51)	(1.51)	(2.06)	(2.12)	(-0.86)	(-0.97)	(0.39)	(0.62)
MKT	97.60***	97.67***	99.70***	99.73***	96.17***	96.28***	97.74***	97.80***
	(240.55)	(241.45)	(209.25)	(209.44)	(124.77)	(121.52)	(129.94)	(126.21)
SMB	20.54***	20.60***	70.75***	70.48***	21.19***	21.32***	73.27***	73.04***
	(25.31)	(25.32)	(70.16)	(69.49)	(16.00)	(15.70)	(58.90)	(57.00)
HML	1.82**	1.80**	10.90***	10.66***	2.24**	2.29**	10.88***	10.82***
	(2.25)	(2.19)	(8.69)	(8.51)	(2.28)	(2.26)	(10.52)	(10.08)
UMD	-0.32	-0.26	-1.35**	-1.40**	0.02	0.14	-0.51	-0.60
	(-0.75)	(-0.59)	(-2.34)	(-2.44)	(0.03)	(0.29)	(-0.81)	(-0.91)
AUM		-0.04		-0.32**		0.28		0.17
		(-0.23)		(-2.01)		(1.26)		(0.80)
AGE		-0.79		0.01		-1.02**		-1.45***
		(-1.64)		(0.02)		(-2.03)		(-2.83)
TURN		-0.20		-0.17		-0.29**		0.06
		(-1.64)		(-0.96)		(-2.29)		(0.36)
TEN		-0.16		-0.06		-0.22*		-0.48**
		(-1.19)		(-0.29)		(-1.82)		(-2.05)
α	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.01	0.01
	(-0.77)	(-0.66)	(-0.13)	(-0.13)	(-0.36)	(-0.33)	(0.91)	(0.98)
α_Δ	0.01	0.03*	-0.00	0.02	0.03***	0.05***	0.03**	0.04***
	(0.51)	(1.83)	(-0.32)	(1.15)	(3.77)	(3.78)	(2.53)	(2.76)
Obs.	3,408,008	3,190,688	691,814	653,774	3,711,007	3,418,031	753,286	700,548
adjR^2	0.832	0.834	0.904	0.907	0.835	0.837	0.903	0.905

Table 3: Regression Results–Fixed Income Funds

The table reports the estimated coefficients of regression (1) for U.S. fixed-income funds. For each quarter between 2004 and 2016, we identify the macro announcement that reveals the most unexpected information by using the Scotti (2016) index. We consider the three weeks before the announcement and the three weeks following (and including) the announcement. β is the coefficient on market liquidity proxied by the negative of the noise measure of Hu, Pan, and Wang (2013). β_Δ is the change in β over the post-announcement period. ΔLEVEL and ΔSLOPE are the changes in the level and slope of the yield curve, respectively. We control for the investment grade and high yield CDX spreads. All other variables are introduced in Table 2. For ease of interpretation, we report standardized coefficients for β and β_Δ (in %). Standard errors are clustered by date, and t-statistics are in parentheses. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent level (two-sided), respectively. Year and fund fixed effects are included, but the coefficients are not shown.

	Negative surprises						**Positive surprises**					
	Treasury		IG corp. bond		HY corp. bond		Treasury		IG corp. bond		HY corp. bond	
β	-0.44	-0.43	-4.59**	-4.59**	-9.77***	-9.96***	-0.53	-0.54	-2.80	-2.63	-8.97***	-8.76***
	(-0.24)	(-0.23)	(-2.08)	(-2.07)	(-2.75)	(-2.80)	(-0.26)	(-0.26)	(-1.30)	(-1.21)	(-3.39)	(-3.27)
β_Δ	1.35	1.30	3.60**	3.59**	5.76**	5.91**	0.28	0.36	1.92	2.00	5.10*	5.22*
	(0.95)	(0.91)	(2.12)	(2.10)	(2.21)	(2.27)	(0.15)	(0.19)	(0.97)	(1.00)	(1.85)	(1.87)
CDX	0.04	0.04	-0.09	-0.09	-0.04***	-0.04***	0.01	0.01	-0.09	-0.08	-0.06***	-0.06***
	(0.70)	(0.70)	(-1.31)	(-1.32)	(-3.51)	(-3.52)	(0.25)	(0.24)	(-1.22)	(-1.10)	(-4.95)	(-4.78)
ΔLEVEL	5.23***	5.26***	6.87***	6.85***	-0.73	-0.72	5.47***	5.57***	7.02***	7.11***	-1.82***	-1.61***
	(8.23)	(8.18)	(7.99)	(7.92)	(-1.23)	(-1.20)	(9.00)	(8.99)	(8.84)	(8.79)	(-3.17)	(-2.81)
ΔSLOPE	-7.47***	-7.37***	-9.47***	-9.32***	5.42***	5.53***	-6.32***	-6.46***	-8.03***	-8.04***	4.98***	4.86**
	(-3.99)	(-3.93)	(-3.90)	(-3.83)	(3.03)	(3.05)	(-3.37)	(-3.37)	(-3.25)	(-3.21)	(2.69)	(2.57)
AUM		-0.03		0.01		0.38**		-0.08		-0.13		0.07
		(-0.23)		(0.05)		(2.52)		(-0.55)		(-0.74)		(0.45)
AGE		-1.16		-0.90		-0.91*		-0.20		-0.60		-0.79
		(-1.25)		(-1.31)		(-1.67)		(-0.23)		(-0.93)		(-1.62)
TURN		-0.01		0.26*		0.35***		0.05		0.21		0.31**
		(-0.08)		(1.66)		(2.70)		(0.53)		(1.36)		(2.35)
EXPER		-0.20		-0.23		-0.40***		-0.17		0.29		-0.53***
		(-1.29)		(-0.98)		(-2.63)		(-1.21)		(1.31)		(-3.57)
α	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02*	-0.03**	-0.03**	-0.04**	-0.04**	-0.04***	-0.04***
	(-1.62)	(-1.64)	(-1.29)	(-1.34)	(-1.60)	(-1.66)	(-2.29)	(-2.27)	(-2.55)	(-2.49)	(-3.09)	(-3.01)
α_Δ	0.00	0.03	0.09	0.10*	0.21***	0.21***	0.02	0.03	0.11**	0.10*	0.36***	0.36***
	(0.01)	(0.62)	(1.60)	(1.80)	(4.34)	(4.00)	(0.46)	(0.61)	(2.00)	(1.87)	(6.43)	(5.87)
Obs.	230,919	218,464	45,849	44,719	174,984	166,242	253,146	236,695	50,642	48,697	192,657	180,248
adjR^2	0.0500	0.0503	0.0833	0.0829	0.0609	0.0632	0.0602	0.0614	0.0918	0.0933	0.101	0.0991

Table 4: The Role of Business Conditions

The table shows estimated coefficients from regression (1) for the indicated U.S. equity and fixed income fund categories. We include all of the control variables introduced in Tables 2 and 3, but for the sake of brevity, only the standardized coefficients (in %) measuring the post-announcement change in the liquidity factor loadings β_Δ are reported. We partition the sample based on the median Auroba-Diebold-Scotti Business Conditions (ADS) index (Aruoba et al., 2009). ADS_{low} and ADS_{high} refer to the samples where the ADS index is below and above the median value, respectively.

	Negative news				Positive news			
	Full sample	ADS_{low}	ADS_{high}	Crisis period (2008–2010)	Full sample	ADS_{low}	ADS_{high}	Crisis period (2008–2010)
Equity	1.02	1.20	0.88	2.80**	-0.66	-0.57	-0.85	-1.46
	(1.51)	(1.30)	(1.17)	(2.03)	(-0.97)	(-0.60)	(-1.10)	(-1.08)
Small cap	2.08**	2.85**	0.61	4.16**	0.48	1.11	-0.52	0.78
	(2.12)	(2.11)	(0.61)	(2.02)	(0.62)	(1.00)	(-0.55)	(0.50)
Treasury	1.30	1.23	-0.51	0.56	0.36	0.41	10.60	-0.26
	(0.91)	(0.82)	(-0.09)	(0.23)	(0.19)	(0.20)	(1.46)	(-0.07)
Investment grade corp. bond	3.59**	3.79**	2.46	4.58	2.00	1.42	13.65	2.81
	(2.10)	(2.10)	(0.31)	(1.47)	(1.00)	(0.64)	(1.46)	(0.67)
High-yield corp. bond	5.91**	7.04**	4.84	10.92**	5.22*	2.26	-1.98	10.59*
	(2.27)	(2.50)	(0.62)	(2.20)	(1.87)	(0.77)	(-0.19)	(1.92)

Table 5: The Role of Fund Size and Initial Cash Holdings

The table shows the estimated coefficients from regression (1) for the indicated U.S. equity and fixed-income fund categories. We include all of the control variables introduced in Tables 2 and 3, but for the sake of brevity, only the standardized coefficients (in %) measuring the post-announcement change in the liquidity factor loadings β_Δ are reported. In Panel A, we partition the sample based on the fund AUM in the previous year. AUM_{low} and AUM_{high} refer to the samples where fund size is below and above the median value, respectively. In Panel B, we similarly partition the sample based on the average cash holdings relative to AUM in the previous four quarters.

	Negative news		Positive news	
	AUM_{low}	AUM_{high}	AUM_{low}	AUM_{high}
Equity	1.14	0.94	-0.30	-0.46
	(1.57)	(1.34)	(-0.45)	(-0.66)
Small cap	2.20**	2.05**	1.03	0.40
	(2.10)	(1.97)	(1.32)	(0.47)
Treasury	1.18	1.24	0.40	0.18
	(0.82)	(0.84)	(0.21)	(0.10)
Investment grade corp. bond	4.08**	2.87*	2.34	1.18
	(2.10)	(1.93)	(1.02)	(0.68)
High-yield corp. bond	5.83**	6.08**	5.21*	5.17*
	(2.09)	(2.47)	(1.76)	(1.93)
Panel B	CASH_{low}	$\text{CASH}_{\text{high}}$	CASH_{low}	$\text{CASH}_{\text{high}}$
Equity	1.13*	0.72	-0.45	-0.10
	(1.71)	(0.90)	(-0.71)	(-0.14)
Small cap	1.91**	2.08*	0.79	0.68
	(2.00)	(1.75)	(1.02)	(0.81)
Treasury	0.96	1.43	0.35	0.10
	(0.77)	(0.84)	(0.22)	(0.04)
Investment grade corp. bond	3.80**	3.41*	1.61	2.63
	(2.30)	(1.75)	(0.83)	(1.18)
High-yield corp. bond	6.05**	5.75**	5.39*	5.29*
	(2.31)	(2.12)	(1.95)	(1.78)