Finance and Economics Discussion Series
Divisions of Research & Statistics and Monetary Affairs
Federal Reserve Board, Washington, D.C.

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2019-055

Please cite this paper as:
Aramonte, Sirio, Chiara Scotti, and Ilknur Zer (2019). "Measuring the Liquidity Profile of Mutual Funds," Finance and Economics Discussion Series 2019-055. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2019.055.

Measuring the Liquidity Profile of Mutual Funds

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July 2019

Abstract

We measure the liquidity profile of open-end mutual funds using the sensitivity of their daily returns to aggregate liquidity. We study how this sensitivity changes around real-activity macroeconomic announcements that reveal large surprises about the state of the economy and after three relevant market events: Bill Gross's departure from PIMCO, Third Avenue Focused Credit Fund's suspension of redemptions, and the effect of Lehman Brothers' collapse on Neuberger Berman. 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 could amplify vulnerabilities in situations of already weak macroeconomic conditions.

Keywords: liquidity transformation, asset management, mutual funds, market liquidity
JEL classification: G11, G20, G23

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[‡]Federal Reserve Board. This paper was previously circulated under the title "The effect of large macro surprises on mutual funds' liquidity profile." We are grateful for useful comments from an anonymous referee and participants of the 2017 RCEA Macro-Money-Finance Workshop, the Georgetown Center for Economic Research 2017 Biennial Conference, the Atiner 2017 Conference, the 2017 Paris Financial Management Conference, the 2018 Meetings of the European Financial Management Association, and the Federal Reserve Board Workshop. We are also grateful to Matthew Carl, Josh Morris-Levenson, and Young-Soo Jang for excellent research assistance. This paper reflects the views of the authors and should not be interpreted as reflecting the views of the Bank for International Settlements, the Board of Governors of the Federal Reserve System, or other members of their staff. Contact: sirio.aramonte@bis.org; chiara.scotti@frb.gov; ilknur.zerboudet@frb.gov.

1 Introduction

We measure the liquidity profile of open-end mutual funds using the sensitivity of their daily portfolio returns to an aggregate liquidity factor, and we offer a methodology to monitor liquidity at a higher frequency than possible with regulatory data. Our way of measuring fund liquidity builds on the asset-pricing literature that studies 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 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. We interpret an increase in the liquidity-factor loading as a deterioration in the fund's liquidity profile, with fund returns becoming more closely related to aggregate liquidity conditions.

As applications of our methodology, we study how the liquidity profile of open-end mutual funds changes around scheduled macroeconomic announcements that reveal unexpected news about the economy. In addition, we study fund liquidity around three significant market events: William H. (Bill) Gross's departure from Pacific Investment Co. (PIMCO); the suspension of redemptions from Third Avenue's Focused Credit Fund; and the effect of Lehman Brothers' collapse on Neuberger Berman, an affiliated asset manager that survived the parent company's bankruptcy.

Our analysis and results are of particular interest to policymakers and academics alike in light of the increased regulatory scrutiny on mutual fund liquidity and potential systemic risks arising from the asset management industry. Liquidity transformation and first-mover advantage have in fact been highlighted as potential vulnerabilities for open-end mutual funds (see Financial Stability Board and International Organization of Securities Commissions, 2015; Chen, Goldstein, and Jiang, 2010).[1] Liquidity transformation refers to the fact that some pooled investment vehicles, while holding

[1] The joint report of the Financial Stability Board and the International Organization of Securities Commissions is available at `http://www.fsb.org/wp-content/uploads/2nd-Con-Doc-on-NBNI-G-SIFI-methodologies.pdf`.

less-liquid assets, allow daily redemptions. A first-mover advantage may arise if the costs of meeting investor redemptions are largely borne by the remaining investors in the fund. During a stress event, these features might raise potential financial stability concerns in that funds might sell liquid assets first, worsening their liquidity profile, further impairing performance, putting downward pressure on prices, and potentially leading to more fund outflows.

In order to monitor the liquidity profile of mutual funds ahead of stress events, the U.S. Securities and Exchange Commission (SEC) proposed in 2016 that mutual funds classify their individual holdings into four liquidity categories, based on the number of days needed to convert each holding into cash without a significant price effect. This liquidity-bucketing provision received substantial comments from the public and the SEC decided to postpone the provision by six months, with the regulations going into effect in the second half of 2019.[2] Importantly, even in the absence of more detailed regulatory disclosures, our methodology can help monitor the liquidity of individual funds at a relatively high frequency. This feature is especially valuable given that stress events—including the three we consider in an application of our methodology—unfold quickly and are difficult to monitor with the low-frequency regulatory disclosures that are currently available.

Different drivers can affect the liquidity profile of a mutual fund over time, as measured by the sensitivity of its daily portfolio returns to an aggregate liquidity factor. Unexpected investor flows can alter the composition of a fund's portfolio—the balance of liquid and illiquid assets held—and hence its liquidity profile. Similarly, such a composition can also be altered by a change in the manager's investment strategy. Finally, a shift in the underlying liquidity of the assets held by the fund could affect its liquidity profile without affecting its portfolio composition. While understanding the source of

[2]For additional details, see `https://www.treasury.gov/press-center/press-releases/Documents/A-Financial-System-That-Creates-Economic-Opportunities-Asset_Management-Insurance.pdf`.

this shift goes beyond the scope of this paper, the literature suggests that the latter channel is the least likely explanation because stock-specific liquidity is driven by slow-moving company characteristics (Frieder and Subrahmanyam, 2005; Grullon, Kanatas, and Weston, 2004). In addition, we distinguish between active and passive funds finding evidence that changes in the liquidity profile of mutual funds are not driven by changes in the liquidity of the underlying assets.[3] In this paper, we therefore interpret our results as changes in the liquidity profile of mutual funds around events that could potentially alter it because of investors' flows or managerial investment decisions.

In a first application of our methodology, we concentrate on significant macro news that could induce portfolio managers to adjust a fund's holdings in light of unexpected news, and could also generate unexpected fund flows driven by investors' decisions to change their exposure to the assets held by the fund. Of note, the literature supports the view that unexpected macro news generates flows into 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 portfolios out of equity funds when they anticipate deteriorating economic conditions, and vice versa.[4] In a second application of our methodology, we monitor the liquidity profile of selected mutual funds around three consequential market events that had the

[3] In an unreported exercise, we explore the different responses of active and passive funds to macroeconomic announcements. We find that index (passive) funds, which are by design constrained to hold their benchmarks, maintain the same exposure to the liquidity factor following unexpected news. In contrast, active funds experience a deterioration in the liquidity profile following negative news. This result corroborates the idea that the liquidity profile of non-index mutual funds more likely changes due to investors' flows or managerial investment decisions, rather than because of changes in the liquidity of the assets in their portfolios.

[4] Using available daily flow data over the 2014–15 period for a subset of funds (equity, high-yield and investment-grade funds), we verify that the average daily outflow in the four weeks following announcements with unexpected negative news equals 0.3 percent of daily AUM, corresponding to an AUM drop of about 6 percent in a four-week window. In the four weeks leading up to the announcements, however, the average flow is not statistically different from zero. Therefore, during these specific days, mutual funds are likely to experience relatively large flows that, by construction, are unexpected to managers.

potential to generate significant investor flows. Importantly, the events we consider, either scheduled announcements with large unexpected news or significant market developments, are unlikely to be endogenous with the changes in liquidity profiles that we observe. Market developments on these days are, by construction, unexpected to managers and investors. In the first exercise, our sample spans the 2004–16 period and 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 four weeks before and the four weeks after the announcements. The set of real-activity macroeconomic announcements we study is selected on the basis of how large their realizations are compared to the corresponding Bloomberg expectations, as measured by 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—in particular, those investing in the stocks of small companies and in high-yield corporate bonds—following the release of unexpected negative macroeconomic news. We interpret this result as a deterioration in the liquidity profile of those funds. The effect is more pronounced during stress periods, suggesting that a deterioration in the funds' liquidity could amplify vulnerabilities in situations of already weak macroeconomic conditions.

In the second application of our methodology, we monitor the liquidity of selected funds around three relevant market events: Bill Gross's departure from PIMCO; the suspension of redemptions from Third Avenue Focused Credit Fund; and the effect of Lehman Brothers' bankruptcy on Neuberger Berman, an asset manager owned by the ailing investment bank. We find that PIMCO fixed-income funds became less liquid after Gross's resignation and that high-yield funds were also less liquid following the suspension of redemptions from Third Avenue's fund. In contrast, Lehman Brothers' default is associated with an improvement in the liquidity profile of Neuberger Berman funds.

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 (2017); Goldstein, Jiang, and Ng (2017); Hanouna, Novak, Riley, and Stahel (2015); and Chernenko and Sunderam (2016). Goldstein, Jiang, and Ng (2017) find that the sensitivity of outflows to bad performance in corporate bond funds is much stronger at 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 (2016) study mutual fund cash holdings and flows using semiannual 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, following unexpected macro news and market events. By construction, such events are unanticipated to managers and investors and hence can help address the endogeneity issue.

Relevant papers in the literature on systematic liquidity-risk pricing are, among others, the seminal work on equities by Pastor and Stambaugh (2003), and the study of bond liquidity by Acharya, Amihud, and Bharath (2013), who find that, in 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 open-end U.S. mutual funds over the period 2004:Q3 to 2016:Q4, excluding money market funds, index funds, exchange-traded funds (ETFs), and sector funds (e.g., healthcare, financials) but including inactive funds to avoid survivorship bias. We obtain fund characteristics, such as age, category, and assets under management (AUM), from Morningstar Direct. On the basis of Morningstar's classification, we consider the following fund categories: large- and medium-cap equity, small-cap equity, government bonds, investment-grade corporate bonds, and high-yield corporate bonds.[5] 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 AUM for each share class (we value-weight ratios like the turnover ratio and sum variables measured in dollars, like AUM). Daily NAV data at the share-

[5]The classification is based on Morningstar Direct's Global Broad Category (GBC), Global Category (GC), Institutional Category (IC), and Category (C) variables. A fund is classified as "Large and Medium Cap Equity" if GC is equal to "US Equity Large Cap." or "US Equity Medium Cap.", 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."

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 afterward. 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 large- and medium-cap equity fund managed $2 billion. Fixed-income funds were smaller than domestic equity funds, with the average size around $1.5 billion at the end of 2016. 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, the average AUM roughly 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 20 years over our sample.

We proxy for aggregate market liquidity with different measures depending on whether we consider equity or fixed-income funds. In the first case, we build a daily measure based on the Pastor and Stambaugh (2003) value-weighted traded factor obtained from the Wharton Research Data Services (WRDS).[6] As is typical in the asset-pricing literature, the replicating portfolio includes common stocks in CRSP that trade on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and NASDAQ. We require that the stocks have at least 60 monthly observations between 1980 and 2016. For each stock, we calculate the liquidity beta with factor regressions of excess returns on the monthly Pastor and Stambaugh (2003) factor in addition to the Fama-French market, small-minus-big (SMB), high-minus-low (HML), and momentum (UMD) factors (from WRDS). Stocks in the top (bottom) 10 percent of the liquidity

[6]The liquidity measure of Pastor and Stambaugh (2003) is based on price reversals conditional on order flow. They use liquidity innovations in a series of asset pricing tests, and also study a factor mimicking portfolio that buys and sells stocks depending on their sensitivity to liquidity innovations. In light of "tantalizing" if not conclusive evidence, Pastor and Stambaugh (2003, pg. 682) conclude that, with a narrow focus on explaining the cross-section of stock returns, the traded factor might be a better proxy for liquidity than innovations to the liquidity measure.

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. This factor-mimicking approach is similar to the one used by Vassalou (2003) to proxy for future gross domestic product (GDP) news. The original Pastor and Stambaugh (2003) factor and the monthly-compounded daily replicating factor have a correlation of 85 percent.

In the case of fixed-income funds, we proxy for aggregate liquidity with the noise measure introduced by Hu, Pan, and Wang (2013). We use the negative of the measure so that higher values imply better liquidity conditions. This variable is based on differences between observed Treasury prices and model prices that use an interpolated Treasury curve. The methodology builds on the intuition that the Treasury yield curve is smooth when financial intermediaries can deploy enough capital to take advantage of arbitrage opportunities and reduce price deviations relative to the benchmark. When financial intermediaries do not have enough capital to engage in arbitrage, and they are most likely unable to provide normal levels of liquidity, the observed Treasury yield curve is more noisy (less smooth). More specifically, Hu, Pan, and Wang (2013) use end-of-day Treasury prices from 1987 through 2011 and back out the zero-coupon yield curve from coupon-bearing Treasury securities. Then the yield curve is used to price all available bonds on a given day. The noise measure is the root mean squared deviation of the model-implied and observed yields (for details, see Hu, Pan, and Wang, 2013). In unreported results, we also repeat 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 includes changes in the level and slope of the term structure, estimated with the Nelson-Siegel model (Nelson and Siegel, 1987) on raw data from the U.S. Treasury's Monthly Statement of Public Debt. We also consider daily spreads for the Markit CDX Investment Grade (CDX_{IG}) and CDX High Yield (CDX_{HY}) credit default swap indexes. These spreads measure the cost of insuring against the default risk of a diversified portfolio of investment-grade and high-yield U.S. companies. Finally, we include various fund-level characteristics: size, measured with assets under management (AUM); age in years (AGE); turnover (TURN); and manager tenure (TEN). Turnover indicates the fraction of fund assets that managers sell in a given year. Tenure is the number of years that a fund is managed by the same portfolio manager.

We present selected summary statistics for the explanatory variables used in our analysis in Table 2. The standard deviation of the asset pricing factors is high, relative to the mean, because the sample includes the 2008 financial crisis. As expected, the CDX_{HY} spread is notably higher than the CDX_{IG} spread. Turnover is dispersed, indicating that a few funds, typically fixed-income funds, trade a large fraction of their assets. On average, the tenure of fund managers (TEN) is about 10 years.

In the first application of our methodology, 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 surprises, measured as actual announcement minus the Bloomberg median expectation for the scheduled announcements of GDP, industrial production, nonfarm payroll, personal income, the Institute for Supply Management (ISM) manufacturing survey, 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 pessimistic (optimistic) about the economy. The Scotti (2016) surprise index is a summary statistic that allows us to look at multiple announcements at the same time.

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 eight 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. As an illustration of our event-study window, Figure 1 shows the announcements that generate the largest positive surprises within each quarter of 2005, together with the corresponding pre-announcement and post-announcement periods. For instance, on January 14, the Scotti (2016) index had the largest increase of the first quarter of 2005 following the scheduled release of industrial production, which read a 0.8 percent increase versus a consensus expectation of 0.4 percent. Similarly, on May 6, July 15, and October 7 of the same year, nonfarm payroll and industrial production caused the largest unexpected positive news, with the data coming in higher than expectations. The non-overlapping periods in which the analysis is conducted are shown by the eight-week interval around the various releases (thick red lines in the figure).

Our final dataset spans from 2004 through the end of 2016 and contains 10,790,971 daily observations across 5,851 unique funds. The data cover 41 (46) days with announcements that yielded the most negative (positive) surprise within each quarter, and the four weeks before and after each announcement day.

In the second application of our methodology, we monitor the liquidity profile of selected mutual funds around three significant market events. First, we consider the sudden resignation of Bill Gross from PIMCO on September 26, 2014, and its effect on PIMCO fixed-income mutual funds (totaling 36 funds). Second, we focus on the liquidity profile of broad-market high-yield bond mutual funds when redemptions from Third Avenue Focused Credit Fund were suspended on December 9, 2015 (226 funds). Finally, we study the funds managed by Neuberger Berman (30 funds), an asset manager affiliated with Lehman Brothers Holdings, around the bankruptcy of the parent company in September 2008.

3 Methodology

We study changes in the sensitivity of mutual funds to aggregate market liquidity, first around scheduled macroeconomic announcements and second around the announcement of significant market events. 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 four weeks long, and the announcement date is included in the second four weeks because the announcements we consider take place during the business day, while the NAV and factors are measured at the end of the day.

We estimate the following fund fixed-effect panel regression, with standard errors double clustered (Cameron, Gelbach, and Miller, 2011) by date and fund:

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

where i indicates the fund; t the day; q the quarter corresponding to day t; RET the daily return on 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 four post-announcement weeks. β is the marginal effect of the liquidity factor in the four weeks before the announcement, and $\beta + \beta_{\Delta}$ is the marginal effect in the four weeks after the announcement ($LIQ_{post,t} = LIQ_t \times D_{post,t}$). Double clustering the standard errors by date and fund means that the t-statistics we report are adjusted for both time series and cross-sectional correlation. As a result, statistical significance is not unduly inflated by the large number of funds we include in our study.

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, as well as the Markit CDX index.[7] 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, respectively.

Funds with a higher β are more sensitive to liquidity risk. The coefficient β_Δ captures changes in liquidity-risk sensitivity—i.e., changes in the liquidity profile—following the announcements. As illustrated in Figure 2, a nonzero β_Δ implies a change in the slope of the relation between fund return and the market liquidity factor. Importantly, the fund-specific slope can change even if aggregate liquidity conditions remain the same (moving from the blue circle to the red triangle). At the same time, changes in aggregate liquidity conditions do not necessarily imply a change in the fund's liquidity profile (remaining on the same line but moving from the solid blue circle to the hollow blue circles). What we capture with β_Δ is a change in the slope, indicating a shift in the sensitivity of fund returns to market liquidity.

3.1 Macro announcements and fund liquidity

In the first application of our methodology, we identify, within each quarter, the announcement with the most positive surprise and the announcement with the most negative surprise. A negative (positive) surprise means that the economy is doing worse (better) than expected by market participants. We run the panel regressions separately on the sets of positive and negative surprises.

We calculate the regression coefficients in (1) for five categories of funds. Funds are classified on the basis of the assets they invest in: large- and mid-cap equity, small-cap equity, government bonds, investment-grade corporate bonds, and high-yield corporate

[7] We also estimate a model where we allow the marginal effect of the variables in Z to change in the post-announcement period. Results reported in Section 4.4 show that our main findings are unaltered.

bonds. Our focus is on changes in the co-movement between 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 announcement. A positive β_Δ points to a deterioration in the fund's liquidity profile, because fund returns co-move more with liquidity conditions. We expect β_Δ to be larger for funds that invest in less-liquid assets, especially following negative releases that indicate worsening economic conditions.

In addition, given the vast theoretical and empirical literature documenting the different reaction of asset prices to macroeconomic surprises during expansion and recession periods, we study how business conditions affect our results. Specifically, we recalculate the coefficients in equation (1) after partitioning the sample based on whether the Aruoba-Diebold-Scotti Business Conditions Index (Aruoba, Diebold, and Scotti, 2009; henceforth, ADS index) is above or below its median value. The index tracks the state of the U.S. economy by combining quarterly, monthly, and weekly real-activity data with a dynamic factor model. A higher value of the index is associated with favorable business conditions.[8] We also consider a sample that only includes the 2008 Global Financial Crisis and its immediate aftermath.

Finally, we investigate whether the impact of these surprises is affected by fund size, initial cash holdings, and the extent to which these funds are held mainly by institutional or retail investors. These characteristics could potentially affect liquidity changes at mutual funds. For example, smaller funds may have different investment styles and less-sophisticated liquidity-management arrangements than larger funds. Similarly, funds with large cash holdings could have more flexible liquidity-management strategies and, for example, might be more inclined to use cash holdings to meet redemptions rather than selling all holdings proportionally. Last but not least, the change in the liquidity profile of mutual funds could reflect differences in the level of investors expertise—that

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

is, whether funds are held mainly by institutional or retail investors may play a role. For instance, flows from institutional investors tend to be more sensitive to fundamental signals like poor risk-adjusted performance, while retail flows tend to be more sensitive to uninformative indicators like past total returns (Evans and Fahlenbrach, 2012).

3.2 Stress events and fund liquidity

In a second application of our methodology, we consider three events that likely had a significant effect on the liquidity profile of selected mutual funds: Bill Gross's departure from PIMCO on September 26, 2014; Third Avenue Focused Credit Fund's suspension of redemptions on December 9, 2015; and the effect of the September 2008 Lehman Brothers collapse on Neuberger Berman. We calculate the coefficients in equation (1) around each of these three market events separately. As before, the dummy variable is equal to zero in the pre-event period and equal to one after the event has taken place. Both the pre- and post-event periods are four weeks long, and the event date is included in the post-event sample.

4 Results

4.1 Macro announcements

For each of the five fund categories, we run regression (1) and present the results for equity funds in Table 3 and for fixed-income funds in Table 4. In each table, we show the coefficients computed on negative- and positive-surprise announcements in the left and right panels, respectively. To ease the interpretation of the estimated coefficients, we standardize the liquidity variables in all specifications.

4.1.1 Equity funds

The results for equity funds are shown in Table 3. The coefficient of interest, β_{Δ}, is positive and statistically significant for small-cap equity funds following negative surprises. The effect is economically significant: a one standard deviation increase in aggregate liquidity implies, after negative news, an increase in the expected return of small-cap funds of about 2 basis points, which is above the 55th percentile of the daily return distribution, corresponding to an annual return of about 5 percent. While 5 percent might not necessarily mean a systemic event, it is an average effect estimated over a long period of time; thus, it does not reflect interactions with other vulnerabilities that are likely to emerge at times of market distress. In addition, the linearity of the model implies that a two or three standard deviation decrease in aggregate liquidity would cause drops in annual returns in the 10 to 15 percent range, which are fairly large. In contrast, the liquidity profile of large- and mid-cap equity funds is not sensitive to negative surprises, likely because the liquidity of large-company stocks is enough to fully accommodate trading from portfolio adjustments.

The findings suggest that the liquidity profiles of small-cap equity funds deteriorate after scheduled macroeconomic announcements that reveal unexpected negative information about the state of the economy. Several factors can drive such changes in the liquidity profile. Managers can alter the composition of their portfolios in response to investor flows (for instance, by meeting redemptions with liquid assets and selling illiquid securities with a delay) or because of their investment strategy (for instance, adjusting their holdings of less-liquid and higher-yielding assets after macroeconomic news). In light of the correlation between fund flows and macroeconomic news highlighted by Jank (2012) and Chalmers, Kaul, and Phillips (2013), a relation between fund liquidity and news-induced flows would be in line with the results in Hanouna, Novak, Riley, and Stahel (2015), who show that outflows reduce the liquidity of equity funds.

In principle, however, the composition of a fund's portfolio could also stay constant but the liquidity of the assets themselves could change. This possibility is unlikely, because stock-specific liquidity is driven by slow-moving company characteristics (Frieder and Subrahmanyam, 2005; Grullon, Kanatas, and Weston, 2004). We corroborate this view in unreported results where we distinguish between active and passive funds, finding that only the liquidity profile of active funds changes after macroeconomic announcements. The holdings of index funds are stable over time because they replicate benchmarks and managers have limited leeway, with the consequence that the liquidity profile would change only to the extent that the liquidity of the assets would change. As a result, we interpret the changes in the liquidity profile of mutual funds, around events that could potentially alter it, as driven by investor flows or investment strategy modifications, rather than by changes in the underlying liquidity of assets.

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 they 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), because they are exposed to broad stock market risk by construction. 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, because SMB expresses the risk profile of small-cap companies by definition. The coefficient on HML is negative for large- and mid-cap funds and positive for small-cap funds. The reason is that HML is long companies with a high book-to-market—that is, companies whose market value is low relative to the replacement cost of assets. These companies are typically small rather than large (see Table 1 in Fama and French, 1993), with the consequence that the returns of large (small) companies are negatively (positively) related to HML. Within each fund category, the loadings on MKT, SMB, and HML are fairly similar across the samples with positive or negative surprises.

4.1.2 Fixed-income funds

The results for fixed-income funds are shown in Table 4. Here, 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 for investment-grade and high-yield funds following negative surprises (left part of the table). A one standard deviation increase in the noise measure raises daily returns by about 4 (9) basis points for investment-grade (high-yield) corporate bond funds, which is around the 55th (65th) percentile of the category-specific distribution of daily fund returns. Similarly to equity funds, the results for fixed-income funds indicate that less-liquid funds become more sensitive to aggregate market liquidity in the aftermath of announcements with large negative surprises. As such, the more-liquid government funds do not exhibit significant changes in sensitivity to underlying market liquidity conditions following negative news about the economy.

The relatively low liquidity of corporate bonds could generate price autocorrelation because prices reflect stale information. Such autocorrelation would dampen the measured sensitivity of asset returns to the liquidity factor (Getmansky, Lo, and Makarov, 2004). In addition, Zhou (2015) shows that sophisticated traders might be correctly forecasting macroeconomic news announcements ahead of the release time, and their views might be impounded into bonds ahead of time. In both cases, the liquidity coefficients we calculate would be biased downward, making our results conservative.

The coefficient on the aggregate liquidity factor (β) is negative and mostly statistically significant for investment-grade and high-yield funds. This result is in sharp contrast with our findings for equity funds, but it is a consequence of outlier observations during the 2008 financial crisis. The result disappears when removing the observations corresponding to the December 2007 to 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. These results reflect the equity-like nature of high-yield bonds.

4.1.3 The role of business conditions

A number of theoretical and empirical studies document 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. Similarly, investors might pull out of their investments more heavily following bad news in a weak macroeconomic environment. 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 4.1.1 and 4.1.2 after partitioning the sample based on whether the ADS index is above (ADS_{high}) or below (ADS_{low}) its median value. 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 5, where the sample used to estimate the coefficients is shown in the column headers. The results reveal larger changes in the liquidity factor loading when business conditions are weak for all but Treasury 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 and larger outflows met by selling more-liquid assets would result in a positive β_Δ. The size of the coefficients is also noticeably higher, especially in the crisis period, than during economic expansions. Finally, in the sample that focuses on positive announcements, only in one case (large- and mid-cap equity in expansions) is the coefficient weakly statistically significant. As in Tables 3 and 4, the coefficients for small-cap equity and high-yield funds are larger than, respectively, large- and mid-cap equities and investment-grade funds.

4.1.4 The role of size, cash holdings, and the investor base

We now turn to how the change in a fund's liquidity profile following macroeconomic surprises is affected by fund size, initial cash holdings, and the ratio of retail versus institutional investors in the fund. Each of these characteristics could potentially affect the results. For example, smaller funds may have different investment styles and less-sophisticated liquidity-management arrangements than larger funds. Similarly, funds with large cash holdings could have more flexible liquidity-management strategies and might be more inclined to use cash holdings to meet redemptions rather than sell all holdings proportionally. Finally, the change in the liquidity profile of mutual funds can vary due to a difference in the investors sophistication level; therefore, the extent to which funds are held mainly by institutional or retail investors may play a role. In particular, fund flows originating from institutional investors react to fundamental signals about the performance of a fund, while those emanating from retail investors respond to less-informative signals, like past returns (Evans and Fahlenbrach, 2012). Fund liquidity is likely managed differently to cope with these more idiosyncratic retail flows.

We first partition our sample into low- and high-AUM funds based on the sample median AUM in the previous year. Second, we split the sample into low- and high-cash buffers based on the average cash holdings relative to AUM in the previous four quarters. Third, we classify funds into institutional and retail based on whether the majority of investors are institutional or retail.[9] We estimate the post-announcement liquidity coefficients in equation (1) separately for funds that belong to each of the following six categories: AUM_{low}, AUM_{high}, CASH_{low}, $\text{CASH}_{\text{high}}$, INST, and RETAIL.

Table 6 shows the results of these three exercises in panels A, B, and C, respectively. While we find that the β_Δ coefficient is still significant for small-cap equity funds, as well as investment-grade and high-yield corporate bond funds, we find that subsampling on the basis of AUM, cash holdings, or institutional base yields statistically weak differences. Overall, however, the deterioration in liquidity appears more pronounced in the aftermath of negative surprises for smaller funds, funds with lower initial cash holdings, and funds held by retail investors.

4.2 Event study around specific stress events

Our methodology can be used to study the change in mutual fund liquidity profiles in response to any event of interest, not just macroeconomic announcements. In a second application, we consider three episodes that had the potential to affect the liquidity profile of selected mutual funds.

First, we focus on the unexpected resignation of Bill Gross from PIMCO on September 26, 2014. He was PIMCO's chief investment officer and the portfolio manager of PIMCO's flagship and largest fixed-income fund, which experienced very large outflows in the aftermath of his resignation, totaling \$51 billion (25 percent of the fund's September-end AUM) through October 2014 (Herbst, Bush, Anderson, and Desai, 2015). Such large outflows might have had a significant effect on the liquidity profile of all fixed-income funds managed by PIMCO, whose investment philosophy was closely tied to the figure of Bill Gross.

[9] We use the Morningstar Direct binary variable "Institutional," which classifies funds as such if any of the following conditions are true: has the word "institutional" in its name; has a minimum initial purchase of \$100,000 or more; states in its prospectus that it is designed for institutional investors or those purchasing on a fiduciary basis.

Second, we study changes in the liquidity profile of high-yield bond mutual funds around the suspension of redemptions from Third Avenue's Focused Credit Fund on December 9, 2015. The fund halted redemptions after being unable to sell its illiquid assets at prices it deemed fair. We consider all high-yield bond funds, rather than just Third Avenue funds, because the troubles at Third Avenue might have been interpreted, by high-yield investors, as symptoms of broader market dysfunction.

Third, we focus on the bankruptcy of Lehman Brothers on September 15, 2008, and we study the funds managed by Neuberger Berman, an asset manager that was part of the Lehman Brothers corporate group and that remained in business after the parent company's bankruptcy. Uncertainty about the fate of Neuberger Berman likely led managers to expect high outflows and to manage their portfolios accordingly.

Table 7 reports the coefficients in equation (1) separately for each event.[10] The main coefficient of interest, β_Δ, is positive and statistically significant in the PIMCO and Third Avenue episodes, and negative for Lehman Brothers' bankruptcy. For Third Avenue, the magnitude of the coefficient is similar to that of macroeconomic announcements on high-yield bond funds, whereas the effect of Gross's resignation is much larger than what we report in Table 4.

The results for Lehman Brothers' default are particularly interesting because the negative and statistically significant coefficient stands in sharp contrast with the largely positive β_Δ we reported in our various specifications so far. The event is also instructive because the portfolio managers were faced with clearly adverse conditions at both the macroeconomic and company-specific level, even though Neuberger Berman was one of Lehman Brothers' viable units (it was spun off and is currently in business). As a result, portfolio managers likely had an incentive to increase the holdings of liquid assets to better meet future redemptions and preserve the company's reputation as a

[10]Not all fund-specific variables are included in the regressions. Certain variables do not vary across months or quarters in the subsamples we study and cannot be included in a fixed-effect regression setting.

viable going concern. An increase in liquid assets would have resulted in an improved liquidity profile and a negative β_{Δ}.

4.3 Monitoring funds' liquidity

We established that liquidity coefficients are useful to track the liquidity of mutual funds at a relatively high frequency around significant events. Our approach can also be used more generally—for instance, to monitor liquidity dynamics on a continuous basis without having to acquire holding-level inputs. These dynamics can be helpful to gauge current market developments. As an example, we find that changes in liquidity betas are correlated with contemporaneous changes in net flows to high-yield corporate bond funds.[11]

We focus on high-yield corporate bond funds because holdings of U.S. corporate bonds by mutual funds increased substantially over the past decade, raising concerns about the mismatch between daily redemptions allowed by these funds and the time required to sell their less liquid assets. While mutual funds were able to meet redemptions during past periods of stress, including the recent period of market turmoil in December 2018, future redemptions amid weaker economic fundamentals could lead to greater stress.

We estimate a fund-specific liquidity coefficient at the quarterly and daily frequencies. That is, for a given quarter q and fund i, we compute $\beta_{i,q}^{fund}$ by regressing daily fund returns on market liquidity and other market and fund controls introduced in Section 3:

$$RET_{i,t} \quad = \quad \alpha + \beta_{i,q}^{fund} LIQ_t + \gamma_Z Z_t + \gamma_X X_{i,q-1} + \varepsilon_t \tag{2}$$

where, $RET_{i,t}$ is the daily return for fund i on day t in quarter q, and LIQ_t is aggregate

[11]Net flows vary around slow-moving trends, in particular increasing after the 2008 financial crisis. As a result, we consider changes in net flows, but changes in betas are also correlated with net flows.

market liquidity on day t in quarter q, proxied by the Hu, Pan, and Wang (2013) noise measure. The coefficient $\beta_{i,q}^{fund}$ from this regression represents the liquidity profile of fund i in quarter q. We also estimate a similar regression using a 60-day rolling window to get daily fund-specific rolling liquidity betas ($\beta_{i,t}^{roll}$).

Figure 3 depicts the time series of changes in the cross-sectional averages of these coefficients, which are easier to visualize than individual liquidity loadings. Panel A shows changes in the average fund-by-fund beta over time at the quarterly frequency; Panel B shows changes in the average rolling beta at the daily frequency. Changes in the average $\beta_{i,q}^{fund}$ and $\beta_{i,q}^{roll}$ are highly correlated (over 90 percent). The rolling liquidity beta, $\beta_{i,t}^{roll}$, has the advantage of being computed in real time and can therefore potentially be used as a monitoring tool to understand whether high-yield funds (or specific funds) are changing their exposure to market liquidity, which implies tilting their portfolios toward more- or less-liquid assets. Panel A in Figure 3 also shows the time-series relationship, at the quarterly frequency, between changes in average liquidity betas ($\beta_{i,q}^{fund}$) and changes in net flows scaled by lagged assets, revealing a high correlation (almost 60 percent) between the two variables. Once more, while fund flows are quarterly and observed with a lag, the daily rolling coefficients $\beta_{i,t}^{roll}$ could offer insights into how flows evolve in real time.

4.4 Robustness

We carry out a variety of robustness tests to gauge the sensitivity of our results to alternative econometric specifications.

In the first robustness exercise, we vary the length of the pre- and post-announcement window. While in the baseline specification we use a four-week window, we replicate the analysis with three- and five- week windows. Table 8 shows that the deterioration in the liquidity profile of mutual funds that we find following negative news for small-cap equity and corporate bond funds is consistent across different windows. Moreover, the effect dies out for small-cap equity funds as the window gets wider, while it increases for investment-grade and high-yield corporate bond funds. This finding highlights the different speeds at which the liquidity profiles of equity and fixed-income funds adjust.

In the second robustness check, we allow the coefficients on factors other than liquidity to change in the post-announcement period. For equity funds, we include $MKT_{post,t}$, $SMB_{post,t}$, $HML_{post,t}$, and $UMD_{post,t}$ in addition to $LIQ_{post,t}$ in equation (1). For fixed-income funds, we add $CDX_{post,t}$, $LEVEL_{post,t}$, and $SLOPE_{post,t}$ besides $LIQ_{post,t}$. As shown in columns IV and VIII of Table 8, the β_{Δ} coefficients are not affected once we allow for such a specification, and they are almost identical to the baseline specification.

Finally, we repeat the event study in Section 4.2 using a differences-in-differences analysis where treated funds are compared to a set of control funds selected according to the specific event considered: Bill Gross's departure from PIMCO, the suspension of redemptions from the Third Avenue Focused Credit Fund, and the effect of Lehman Brothers default on Neuberger Berman. We identify funds that behave similarly to our treated funds using daily return correlations over the full sample up to and including the month preceding the event in question (the control sample is the set of funds with higher correlations with the treated sample). We aggregate the funds in the treated sample by computing the value-weighted (by AUM) return of all funds in the treated sample, and we calculate the correlation of this return with the returns on funds suitable as controls (those in the same category as the treated funds). We value-weight returns on treated funds to make this exercise empirically feasible and to reduce the risk that we select the control sample on the basis of outlier correlations. Unreported results, available upon request from the authors, confirm our key findings and show that the change in liquidity that we report is indeed more pronounced in the treatment sample.

5 Conclusions

We study open-end mutual funds' liquidity profiles, defined as the sensitivity of daily fund returns to aggregate market liquidity. We interpret an increase in sensitivity as a deterioration in the liquidity of the fund. We use our methodology to analyze how fund liquidity changes around two types of events that yield unanticipated information: (i) scheduled macroeconomic announcements that reveal unexpected news about the economy, and (ii) significant but unforeseen market events like Bill Gross's departure from PIMCO, Third Avenue Focused Credit Fund's suspension of redemptions, and the collapse of Lehman Brothers.

Overall, we find that, in the aftermath of announcements that reveal unexpectedly negative information about the state of the economy, small-cap equity funds as well as investment-grade and high-yield corporate bond funds experience a deterioration in their liquidity profiles. We find similar results following adverse market events.

While there might be multiple reasons for this deterioration, we would need to observe managerial actions and portfolio changes at a higher frequency to identify the exact mechanism. The changes we observe could arise because portfolio managers adjust the funds' holdings in light of unexpected news, purchasing higher-yielding illiquid assets after negative news as a wager that macroeconomic conditions will improve. Alternatively, these changes might also be triggered by unexpected outflows after negative surprises, and mutual funds might meet the associated redemptions by selling the most-liquid asset first. However, our analysis suggests that rapid changes in the liquidity characteristics of the assets held by mutual funds are unlikely to explain our results.

Irrespective of the exact drivers, understanding the dynamics of the liquidity profile of mutual funds is important because poorer fund liquidity might amplify certain vulnerabilities, especially at times of market stress. For example, if investors perceive that the liquidity of the fund they are invested in is at risk, they might run on the fund, in a process similar to a bank run. Our approach allows us to study the evolution of mutual fund liquidity at a higher frequency than possible when using regulatory asset-holding disclosures, and a natural application is monitoring fund liquidity around important events that could generate systemic risk.

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Figure 1: An Illustration of Our Event Study

The figure shows the four announcements with large positive surprises that we study in 2005. The vertical lines indicate the dates of the announcements, with the actual announcements and release times shown under the vertical lines. The thick red segments show the eight-week periods surrounding the announcements over which we calculate the factor-model coefficients. Each eight-week period is equally divided into four weeks before the announcement and four weeks after.

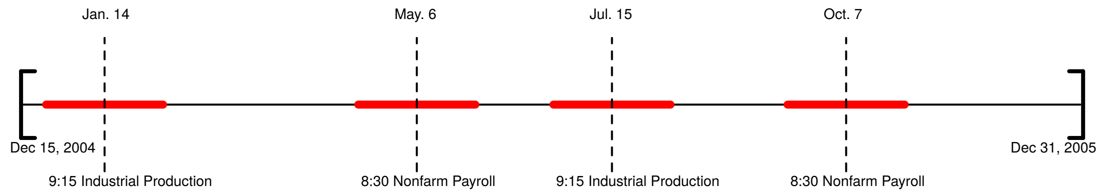


Figure 2: The Relation between Expected Returns and Liquidity

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 market liquidity remains the same after a macroeconomic announcement, changes in aggregate market 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 market liquidity after a shift in the sensitivity to market liquidity occurs. Moving from the blue solid circle to the red hollow triangle represents a change in the liquidity profile with constant underlying market liquidity.

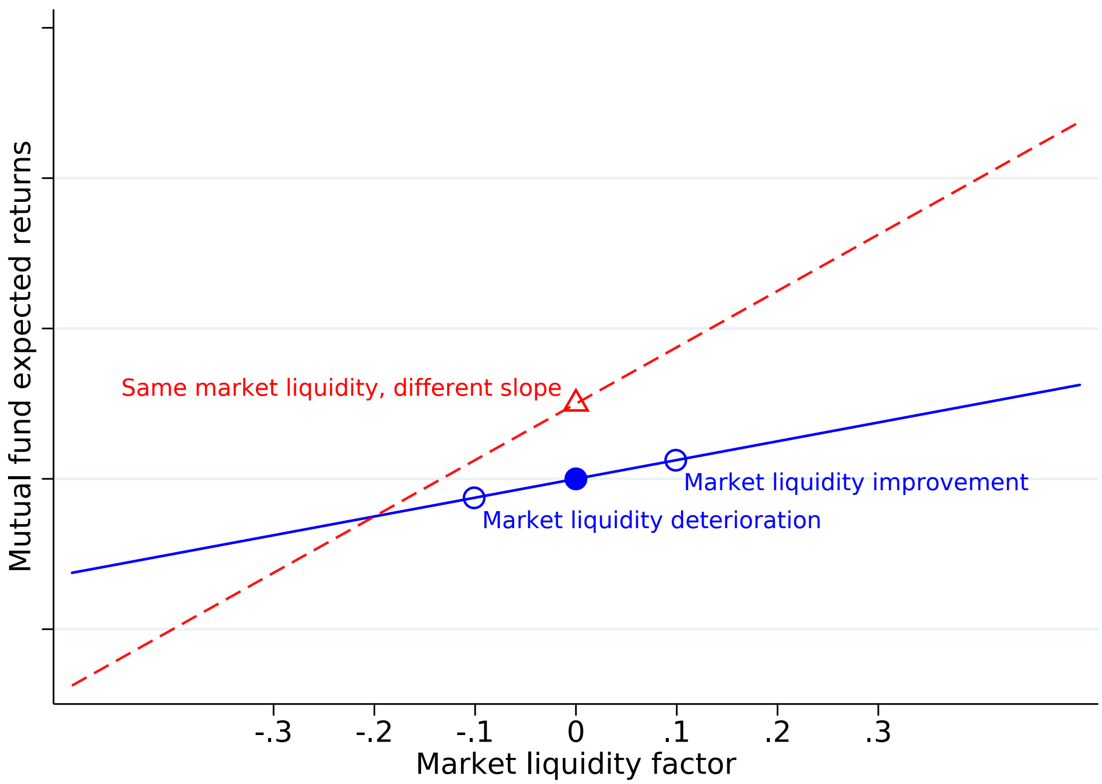
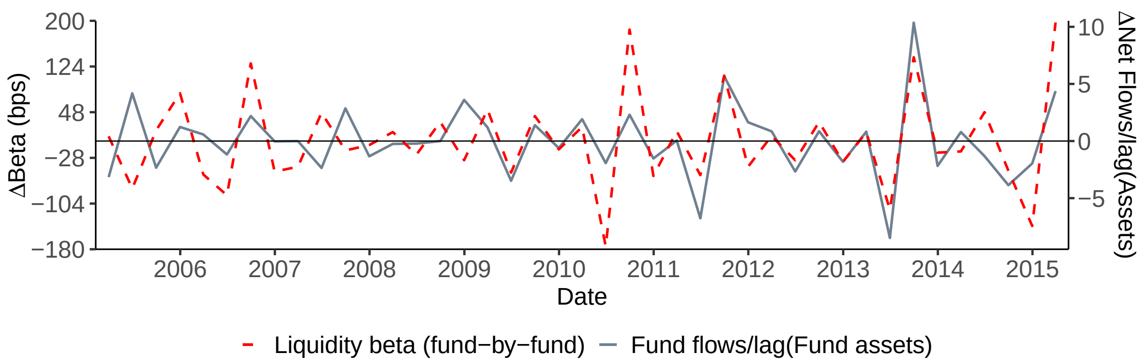
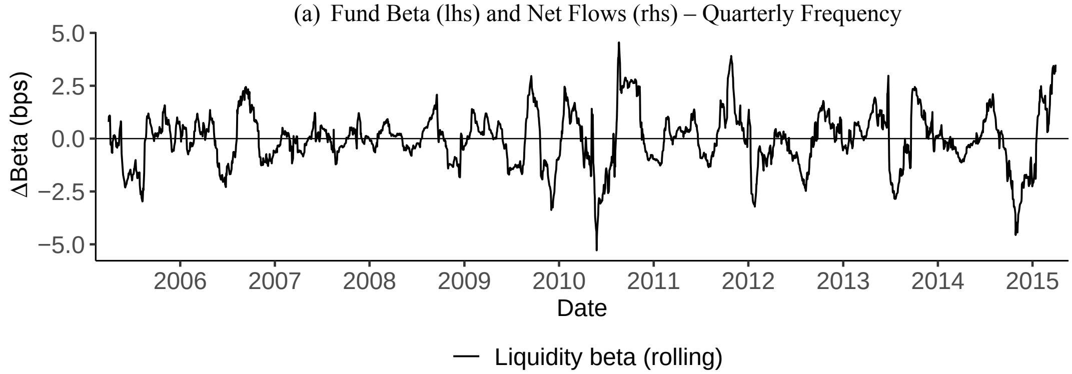


Figure 3: Liquidity Beta and Fund Flows for High-Yield Funds

Panel A shows the change in the cross-sectional average of fund betas ($\beta_{i,q}^{fund}$) estimated via equation (2) and changes in net flows, as a percentage of lagged assets, all at the quarterly frequency. Panel B depicts the 60-day moving average of changes in the cross-sectional average of daily fund-specific rolling liquidity betas ($\beta_{i,t}^{roll}$) throughout the sample period. Both betas are coefficients on the standardized aggregate liquidity factor and are expressed in basis points. Source: Authors' calculations based on Center for Research in Security Prices (CRSP), Wharton Research Data Services (WRDS), and Morningstar Direct.



(a) Fund Beta (lhs) and Net Flows (rhs) – Quarterly Frequency



(b) Rolling Beta – Daily Frequency

Table 1: Fund Summary Statistics

The table shows the number of funds at the beginning, middle, and 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. Source: Authors' calculations based on Morningstar Direct.

		Number of funds	Fund AUM (mm$) Average	Fund AUM (mm$) 25th perc.	Fund AUM (mm$) 75th perc.	Fund age (years) Average	Fund age (years) 25th perc.	Fund age (years) 75th perc.
U.S. large-mid cap	2004	1854	1,224	42	707	12	4	13
	2009	1909	1,128	33	707	13	5	16
	2016	1559	2,072	72	1,517	17	8	22
U.S. small cap	2004	535	449	47	484	8	4	11
	2009	591	429	28	390	11	5	14
	2016	548	693	44	662	14	6	20
Government bonds	2004	179	837	90	621	13	7	19
	2009	194	1,173	107	797	16	9	23
	2016	166	1,289	135	1,036	20	12	29
IG corp. bonds	2004	30	793	73	807	13	3	22
	2009	38	1,164	94	754	15	5	23
	2016	49	1,726	89	1,208	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: Descriptive Statistics

The table shows summary statistics for the main variables used in the regression analysis. PS is the daily portfolio that mimics the Pastor and Stambaugh (2003) traded liquidity factor. NOISE is the negative of the noise measure of Hu, Pan, and Wang (2013). MKT, SMB, HML, and UMD are the coefficients on the Fama-French and momentum factors. LEVEL and SLOPE are the level and slope of the yield curve, respectively. CDX_{IG} and CDX_{HY} are the investment-grade and high-yield CDX spreads, respectively. AUM is fund size, AGE is fund age, TURN is fund turnover, and TEN is fund managers tenure. Units are in percentages unless indicated otherwise. Source: Authors' calculations based on Center for Research in Security Prices (CRSP), Wharton Research Data Services (WRDS), and Morningstar Direct.

	Ave.	St. dev.	10th perc	25th perc	50th perc	75th perc	90th perc
PS	-0.008	0.849	-0.962	-0.449	0.023	0.453	0.919
NOISE	-0.031	0.031	-0.054	-0.031	-0.020	-0.016	-0.014
MKT	0.029	1.229	-1.240	-0.470	0.080	0.580	1.220
SMB	0.001	0.577	-0.680	-0.340	0.010	0.330	0.660
HML	0.002	0.655	-0.580	-0.260	-0.010	0.250	0.580
UMD	0.010	0.992	-0.940	-0.360	0.060	0.440	0.920
LEVEL	3.554	0.575	2.941	3.007	3.450	4.116	4.402
SLOPE	0.847	0.086	0.748	0.764	0.857	0.933	0.954
CDX_{IG}	0.864	0.413	0.415	0.578	0.815	1.028	1.345
CDX_{HY}	5.012	2.484	3.102	3.443	4.256	5.735	7.240
AUM (mm $)	1313	6259	14	53	207	776	2324
AGE (years)	12.5	10.9	2.0	5.0	10.0	17.0	24.0
TURN	96	403	11	23	51	99	184
TEN (years)	10	5	3	6	9	13	17

Table 3: Regression Results–Equity Funds

The table shows the coefficients from regression (1) for large- and medium-cap equity and small-cap equity 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 four weeks before the announcement and the four 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, and 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 the fund manager's tenure, in years plus one. α is the constant and α_Δ is the coefficient on a dummy equal to one in the four weeks after an announcement. We report standardized coefficients for β and β_Δ (in %). Standard errors are double clustered by date and fund, and t-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level (two-sided), respectively. Year and fund fixed effects are included, but the coefficients are not shown. Source: Authors' calculations based on Center for Research in Security Prices (CRSP), Wharton Research Data Services (WRDS), and Morningstar Direct.

	Negative news				Positive news			
	U.S. large-mid cap		U.S. small cap		U.S. large-mid cap		U.S. small cap	
β	2.91***	2.91***	1.92***	1.98***	3.39***	3.40***	3.21***	3.23***
	(8.60)	(8.50)	(3.05)	(3.16)	(8.44)	(8.34)	(4.85)	(4.95)
β_Δ	0.76	0.81	1.85**	1.95**	-0.76	-0.73	0.16	0.42
	(1.57)	(1.63)	(2.13)	(2.26)	(-1.42)	(-1.33)	(0.20)	(0.52)
MKT	97.74***	97.82***	98.77***	98.80***	96.68***	96.74***	97.67***	97.70***
	(210.57)	(208.30)	(141.89)	(139.92)	(179.08)	(173.15)	(118.35)	(114.95)
SMB	5.87***	5.89***	70.67***	70.40***	6.64***	6.70***	72.18***	71.94***
	(8.26)	(8.20)	(68.10)	(67.07)	(6.94)	(6.79)	(58.62)	(57.29)
HML	-2.89***	-2.90***	10.34***	10.14***	-1.39*	-1.24	10.78***	10.87***
	(-4.52)	(-4.47)	(8.55)	(8.36)	(-1.69)	(-1.43)	(9.41)	(9.28)
UMD	0.99**	1.08***	-1.15*	-1.22*	1.31***	1.43***	-0.49	-0.51
	(2.51)	(2.67)	(-1.83)	(-1.94)	(3.06)	(3.18)	(-0.76)	(-0.76)
AUM		-0.37***		-0.43***		-0.15		-0.11
		(-3.17)		(-2.89)		(-1.13)		(-0.63)
AGE		-0.21		-0.11		-0.52		-1.05**
		(-0.64)		(-0.26)		(-1.53)		(-2.33)
TURN		-0.13		-0.07		-0.19**		0.02
		(-1.51)		(-0.52)		(-2.11)		(0.11)
EXPER		-0.29***		-0.23		-0.19*		-0.37**
		(-2.91)		(-1.25)		(-1.88)		(-1.99)
α	-0.01	-0.01	0.00	0.00	0.00	0.00	0.01	0.01
	(-1.47)	(-1.38)	(0.27)	(0.23)	(0.66)	(0.63)	(1.22)	(1.24)
Obs.	2,673,552	2,484,385	841,077	792,365	2,842,710	2,598,905	893,946	828,996
adjR^2	0.898	0.900	0.902	0.904	0.898	0.900	0.903	0.905

Table 4: 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 four weeks before the announcement and the four 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 investment-grade and high-yield CDX spreads. All other variables are introduced in Table 3. For ease of interpretation, we report standardized coefficients for β and β_Δ (in %). Standard errors are double clustered by date and fund, and t-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level (two-sided), respectively. Year and fund fixed effects are included, but the coefficients are not shown. Source: Authors' calculations based on Center for Research in Security Prices (CRSP), Wharton Research Data Services (WRDS), and Morningstar Direct.

	Negative news						Positive news					
	Treasury		IG corp. bond		HY corp. bond		Treasury		IG corp. bond		HY corp. bond	
β	0.59	0.59	-3.61*	-3.56*	-12.81***	-12.96***	-1.07	-1.05	-3.53*	-3.39	-6.70***	-6.50**
	(0.37)	(0.37)	(-1.86)	(-1.83)	(-4.21)	(-4.29)	(-0.59)	(-0.58)	(-1.76)	(-1.68)	(-2.69)	(-2.58)
β_Δ	1.08	1.02	3.70**	3.70**	9.28***	9.45***	-0.57	-0.46	0.41	0.50	2.17	2.32
	(0.87)	(0.82)	(2.39)	(2.37)	(4.00)	(4.05)	(-0.36)	(-0.29)	(0.24)	(0.28)	(0.94)	(0.99)
CDX	0.04	0.04	-0.08	-0.08	-0.05***	-0.05***	-0.02	-0.02	-0.14**	-0.13*	-0.06***	-0.06***
	(0.90)	(0.89)	(-1.31)	(-1.31)	(-5.16)	(-5.17)	(-0.46)	(-0.44)	(-2.12)	(-1.99)	(-4.83)	(-4.67)
ΔLEVEL	5.47***	5.51***	7.45***	7.43***	-0.88	-0.88	5.59***	5.69***	7.51***	7.60***	-1.84***	-1.63***
	(8.16)	(8.11)	(7.84)	(7.77)	(-1.59)	(-1.57)	(8.87)	(8.84)	(8.63)	(8.60)	(-3.35)	(-2.96)
ΔSLOPE	-8.12***	-8.12***	-10.72***	-10.68***	6.21***	6.43***	-7.85***	-7.94***	-10.39***	-10.33***	5.79***	5.67***
	(-4.39)	(-4.36)	(-4.24)	(-4.21)	(3.52)	(3.57)	(-4.42)	(-4.41)	(-4.33)	(-4.27)	(3.25)	(3.12)
AUM		-0.04		-0.03		0.36**		-0.06		-0.05***		0.17
		(-0.64)		(-0.73)		(2.04)		(-0.77)		(-3.87)		(1.00)
AGE		-1.47*		-0.70***		-1.68***		-0.18		-0.56***		-0.77
		(-1.86)		(-4.95)		(-3.21)		(-0.27)		(-3.16)		(-1.64)
TURN		0.02		0.31***		0.33**		0.04		0.22*		0.35***
		(0.44)		(4.40)		(2.52)		(0.97)		(1.89)		(4.17)
EXPER		-0.16**		-0.21***		-0.44***		-0.15***		0.00		-0.42***
		(-2.60)		(-4.65)		(-4.67)		(-2.70)		(0.04)		(-3.25)
α	-0.01	-0.01	-0.01	-0.01	-0.02*	-0.02*	-0.02**	-0.02**	-0.03**	-0.03**	-0.02*	-0.02
	(-1.25)	(-1.30)	(-0.81)	(-0.88)	(-1.76)	(-1.81)	(-2.06)	(-2.02)	(-2.32)	(-2.24)	(-1.68)	(-1.61)
Obs.	284,559	267,957	57,504	55,817	226,628	214,417	303,778	282,849	61,540	58,965	242,146	225,578
adjR^2	0.0542	0.0548	0.0926	0.0922	0.0856	0.0869	0.0582	0.0598	0.0912	0.0935	0.0769	0.0778

Table 5: 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 3 and 4 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. Standard errors are double clustered by date and fund, and t-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level (two-sided), respectively. Year and fund fixed effects are included, but the coefficients are not shown. Source: Authors' calculations based on Center for Research in Security Prices (CRSP), Wharton Research Data Services (WRDS), and Morningstar Direct.

	Negative news				Positive news			
	Full sample	ADS_{low}	ADS_{high}	Crisis period (2008–2010)	Full sample	ADS_{low}	ADS_{high}	Crisis period (2008–2010)
U.S. large-mid cap	0.81	1.16*	0.46	2.33***	-0.73	-0.55	-0.97*	-1.79
	(1.63)	(1.72)	(0.72)	(2.78)	(-1.33)	(-0.71)	(-1.70)	(-1.64)
U.S. small cap	1.95**	2.76**	0.48	3.17*	0.42	0.99	-0.28	0.63
	(2.26)	(2.31)	(0.51)	(1.83)	(0.52)	(0.87)	(-0.34)	(0.39)
Treasury	1.02	1.11	-2.54	0.77	-0.46	-0.40	3.76	-1.59
	(0.82)	(0.84)	(-0.48)	(0.36)	(-0.29)	(-0.23)	(0.62)	(-0.55)
Investment grade corp. bond	3.70**	4.24**	-4.99	6.36**	0.50	0.06	3.25	0.51
	(2.37)	(2.55)	(-0.68)	(2.20)	(0.28)	(0.03)	(0.40)	(0.15)
High-yield corp. bond	9.45***	10.95***	-1.30	17.95***	2.32	0.03	-7.29	6.37
	(4.05)	(4.34)	(-0.17)	(4.07)	(0.99)	(0.01)	(-0.86)	(1.43)

Table 6: The Role of Size, Cash Holdings, and Institutional Base

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 3 and 4 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 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 average cash holdings relative to AUM in the previous four quarters. Finally, in panel C, we partition the sample based on whether the investors are retail or institutional. Standard errors are double clustered by date and fund, and t-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level (two-sided), respectively. Year and fund fixed effects are included, but the coefficients are not reported. Source: Authors' calculations based on Center for Research in Security Prices (CRSP), Wharton Research Data Services (WRDS), and Morningstar Direct.

	Negative news		Positive news	
Panel A	AUM_{low}	AUM_{high}	AUM_{low}	AUM_{high}
U.S. large-mid cap	0.94*	0.83	-0.53	-0.60
	(1.80)	(1.63)	(-0.97)	(-1.07)
U.S. small cap	2.31**	1.81*	1.00	0.16
	(2.53)	(1.96)	(1.23)	(0.19)
Treasury	1.02	0.82	-0.54	-0.42
	(0.81)	(0.66)	(-0.33)	(-0.27)
Investment grade corp. bond	4.22**	3.03**	0.48	0.27
	(2.41)	(2.27)	(0.24)	(0.18)
High-yield corp. bond	9.53***	9.44***	2.34	2.33
	(3.87)	(4.20)	(0.94)	(1.04)
Panel B	CASH_{low}	$\text{CASH}_{\text{high}}$	CASH_{low}	$\text{CASH}_{\text{high}}$
U.S. large-mid cap	0.88*	0.85	-0.49	-0.47
	(1.78)	(1.57)	(-0.91)	(-0.80)
U.S. small cap	1.91**	1.97*	0.79	0.48
	(2.27)	(1.85)	(1.01)	(0.52)
Treasury	0.78	1.02	-0.27	-0.72
	(0.71)	(0.71)	(-0.20)	(-0.39)
Investment grade corp. bond	4.26***	3.25*	0.39	0.63
	(2.74)	(1.94)	(0.23)	(0.33)
High-yield corp. bond	9.60***	9.46***	2.50	2.15
	(4.06)	(3.83)	(1.09)	(0.85)
Panel C	INST	RETAIL	INST	RETAIL
U.S. large-mid cap	0.85*	0.84*	-0.51	-0.79
	(1.65)	(1.71)	(-0.94)	(-1.41)
U.S. small cap	1.95**	2.02**	0.76	0.27
	(2.13)	(2.28)	(0.88)	(0.33)
Treasury	1.14	0.93	-0.30	-0.41
	(0.85)	(0.77)	(-0.18)	(-0.27)
Investment grade corp. bond	3.85**	4.11**	0.60	0.48
	(2.70)	(2.54)	(0.36)	(0.27)
High-yield corp. bond	9.46***	9.72***	2.52	2.42
	(4.03)	(4.10)	(1.06)	(1.02)

Table 7: Case Study Analysis

The table reports the coefficients on asset pricing factors and fund characteristics around three events that are likely to have affected the liquidity profile of certain mutual funds. In the first column, the eight-week period used to estimate the coefficients is centered around September 26, 2014, when William H. Gross left Pacific Investment Management Co. (PIMCO). We study the liquidity profile of PIMCO fixed-income funds. In the second column, the reference date is December 9, 2015, when withdrawals were suspended from the Third Avenue Focused Credit Fund in light of the fund's deteriorating liquidity position. In this case, we study the liquidity profile of broad-market high-yield funds. In the third column, we focus on the bankruptcy of Lehman Brothers on September 15, 2008, and we study the funds managed by Neuberger Berman, an asset manager affiliated with Lehman Brothers that survived the parent company's bankruptcy. Standard errors are double clustered by date and fund, and *t*-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level (two-sided), respectively. Source: Authors' calculations based on Center for Research in Security Prices (CRSP), Wharton Research Data Services (WRDS), and Morningstar Direct.

	PIMCO	Third Avenue	Lehman Brothers
β	-24.43	15.21***	28.05***
	(-1.64)	(4.37)	(4.05)
β_Δ	31.15**	8.61*	-29.75***
	(2.07)	(1.70)	(-3.25)
CDX	-0.30	-1.69***	
	(-0.39)	(-7.08)	
ΔLEVEL	9.85**	11.94**	
	(2.51)	(2.23)	
ΔSLOPE	-23.98	6.77	
	(-1.40)	(1.21)	
MKT			98.53***
			(30.88)
SMB			14.87***
			(3.68)
HML			-7.70
			(-0.77)
UMD			-1.12
			(-0.12)
AUM	-0.22	0.05	1.43**
	(-1.17)	(1.08)	(2.18)
AGE	-0.10		-1.29
	(-0.38)		(-0.66)
TEN	0.00		2.09**
	(0.04)		(2.70)
α	0.02	0.80***	0.02
	(0.16)	(7.52)	(0.24)
α_Δ	2.15	7.24***	-8.29
	(1.06)	(6.62)	(-1.51)
Obs.	1,015	4,918	631
adjR^2	0.105	0.589	0.912

Table 8: Robustness

The table shows the estimated post-announcement change in the liquidity factor loading coefficients, β_Δ, for the indicated U.S. equity and fixed-income fund categories. We include all of the control variables introduced in Tables 3 and 4 but, for sake of brevity, only the standardized β_Δ coefficients (in %) are reported. In columns I and V, we report the baseline specification with a 4-week window pre- and post-announcement (8 weeks in total). We then show results for alternative window sizes: a three-week window in columns II and VI, and a five-week window in columms III and VII. Columns IV and VIII show results for β_Δ from the specification where we allow all factor loadings (such as those on MKT or ΔSLOPE) to change in the post-announcement period. Standard errors are double clustered by date and fund, and *t*-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level (two-sided), respectively. Year and fund fixed effects are included, but the coefficients are not shown. Source: Authors' calculations based on Center for Research in Security Prices (CRSP), Wharton Research Data Services (WRDS), and Morningstar Direct.

	Negative news				Positive news			
	Baseline (4 week)	3-week window	5-week window	All loadings can change	Baseline (4 week)	3-week window	5-week window	All loadings can change
	I	II	III	IV	V	VI	VII	VIII
U.S. large-mid cap	0.81	0.59	0.81	0.90*	-0.73	-1.29**	-0.93	-0.74
	(1.63)	(1.16)	(1.35)	(1.82)	(-1.33)	0.37	(-1.41)	(-1.34)
U.S. small cap	1.95**	2.19**	1.74*	1.94**	0.42	(-2.13)	1.08	0.11
	(2.26)	(2.22)	(1.81)	(2.31)	(0.52)	(0.46)	(1.10)	(0.14)
Treasury	1.02	1.28	2.06	1.04	-0.46	0.38	-1.08	-0.41
	(0.82)	(0.94)	(1.58)	(0.83)	(-0.29)	(0.21)	(-0.65)	(-0.26)
Investment-grade corp. bond	3.70**	3.65**	5.90***	3.74**	0.50	1.94	-1.47	0.55
	(2.37)	(2.13)	(3.60)	(2.39)	(0.28)	(0.96)	(-0.77)	(0.31)
High-yield corp. bond	9.45***	5.91**	11.37***	9.42***	2.32	5.22*	-2.84	2.32
	(4.05)	(2.27)	(4.44)	(4.05)	(0.99)	(1.87)	(-0.99)	(0.99)