Liquidity Transformation in Asset Management: Evidence from the Cash Holdings of Mutual Funds*

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Abstract

Using a novel data set on the cash holdings of mutual funds, we show that cash plays a key role in how mutual funds provide liquidity to their investors. Consistent with the idea that they perform a significant amount of liquidity transformation, mutual funds use cash to accommodate inflows and outflows rather than transacting in equities or bonds, even at long horizons. This is particularly true for funds with illiquid assets and at times of low market liquidity. We provide evidence suggesting that, despite their size, the cash holdings of mutual funds are not sufficiently large to fully mitigate price impact externalities created by the liquidity transformation they engage in.

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I. Introduction

Liquidity transformation – the creation of liquid claims that are backed by illiquid assets – is a key function of many financial intermediaries. Banks, for instance, hold illiquid loans but supply investors with highly liquid deposits. Many asset managers provide similar liquidity services through open-ending. Although they may invest in relatively illiquid assets such as corporate bonds, bank loans, and emerging market stocks, open-end mutual funds have liquid liabilities. Specifically, mutual funds allow investors to redeem any number of shares at the fund's end-of-day net asset value (NAV), effectively pooling liquidation costs across investors. In contrast, investors who directly hold the underlying investments directly bear their own liquidation costs when they sell those assets.

Since the financial crisis, there has been vigorous debate among academics, policymakers, and asset managers about whether liquidity transformation by asset managers can cause financial stability problems the same way that liquidity transformation by banks can (e.g., Goldstein et al, 2015; International Monetary Fund, 2015; Financial Stability Oversight Council, 2014; Feroli et al, 2014; Chen, Goldstein, and Jiang, 2010). A key concern on one side of the debate is that liquidity transformation increases the scope for fire sales to amplify fundamental shocks. Redemptions from an open-ended fund can force sales of illiquid assets, depressing asset prices and thereby stimulating more redemptions. Motivated by such concerns, in September 2015, the SEC proposed new rules designed to promote more effective liquidity risk management by mutual funds.[1]

On the opposite side of the debate are two main arguments. First, many contend that asset managers are essentially a veil, simply transacting in the underlying equities and bonds on behalf of investors without performing much liquidity transformation (Investment Company Institute 2015). Second, others argue that asset managers are well aware of the risks of fire sales and take steps to manage their liquidity needs (Independent Directors Council 2016, Investment Company Institute 2016).

In this paper, we use the cash holdings of mutual funds that invest in equities and long-term corporate bonds as a window into the liquidity transformation activities of asset managers.

[1] http://www.sec.gov/rules/proposed/2015/33-9922.pdf

Our key insight is that the way mutual funds manage their own liquidity to provide the benefits of open-ending to investors sheds light on how much liquidity transformation funds are performing. In particular, a fund acting as a pass-through, simply buying and selling the underlying assets on behalf of its investors, has little need for cash holdings to manage its liquidity. In contrast, a fund performing substantial liquidity transformation will seek to use cash holdings to mitigate the costs associated with providing investors with claims that are more liquid than the underlying assets.

Two features of the mutual fund industry make it a good laboratory for studying liquidity transformation by asset managers. First, mutual funds account for a large fraction of the overall asset management industry. As of 2015Q1, mutual funds had aggregate assets of $12.9 trillion and held 20.5% of corporate equities and 20.6% of corporate and foreign bonds.[2] Second, while other asset managers have some ability to manage investor redemptions, most mutual funds are completely open-ended, so there is significant scope for liquidity transformation.

We study mutual fund liquidity management using a novel data set on the cash holdings of equity and long-term corporate bond funds.[3] Importantly, our data set covers holdings of both cash and cash substitutes such as money market mutual fund shares. Cash substitutes have become an increasingly important source of liquidity for asset managers in recent years. The IMF estimates that asset managers as a whole held about $2 trillion of cash and cash substitutes in 2013 (Pozsar, 2013). This is approximately the same amount as US corporations, which have received significant scrutiny from both academics and the press (e.g., Bates et al., 2009). Approximately 37% of asset manager holdings is in the form of cash substitutes. Figure 1 shows that a similar pattern holds for the equity and long-term bond mutual funds in our data set. By 2014, they held $600 billion of cash and cash substitutes, with nearly 50% taking the form of cash substitutes.

We present four main results on mutual fund liquidity management, all showing that mutual funds do not simply act as pass-throughs. Instead, consistent with the idea that mutual funds perform a significant amount of liquidity transformation, funds use holdings of cash to

[2] Tables L.211 and L.212 of the Flow of Funds Financial Accounts of the United States (Federal Reserve data release Z.1). These numbers do not include the assets of money market mutual funds.

[3] Because we focus on the mismatch in liquidity between fund assets and liabilities, our sample excludes money market mutual funds, closed end funds, ETFs, and short-term bond mutual funds.

actively manage their liquidity provision and to reduce their impact on the prices of the underlying assets. Our first main result is that, rather than transacting in equities and bonds, mutual funds use cash to accommodate inflows and outflows. Funds build up cash positions when they receive inflows and draw down cash when they suffer outflows. The magnitudes are economically significant. For each dollar of inflows or outflows in a given month, 23 to 32 cents of that flow is accommodated through changes in cash rather than through trading in the fund's portfolio securities. This impact of flows on cash balances lasts for multiple months.

Second, asset liquidity affects the propensity of funds to use cash holdings to manage fund flows. In the cross section, funds with illiquid assets are more aggressive in using cash to meet inflows and outflows. At the quarterly horizon, a one-standard deviation increase in asset illiquidity is associated with about 20% increase in the fraction of fund flows accommodated through changes in cash. We find similar evidence in the time series: during periods of low aggregate market liquidity, funds accommodate a larger fraction of fund flows with cash. These results would not obtain if funds were simply a veil, trading on behalf of their investors. Instead, our results are consistent with the idea that mutual funds perform a significant amount of liquidity transformation, with their cash holdings playing a critical role.

Third, we show that funds that perform more liquidity transformation hold significantly more cash. We develop a simple model of optimal cash holdings that pinpoints asset illiquidity, the volatility of fund flows, and their interaction as the key determinants of how much liquidity transformation a given fund engages in. Consistent with the model, we find that all three variables are strongly related to cash holdings. For equity funds, for example, a one-standard deviation increase in asset illiquidity (flow volatility) is associated with a 0.9 (0.4) percentage points higher cash-to-assets ratio. Furthermore, the interaction of asset illiquidity and flow volatility is positive and statistically significant, indicating that funds that invest in illiquid assets and provide investors with ample liquidity have particularly high cash-to-assets ratios.

We find no evidence in our data of economies of scale in liquidity management at the fund level. In the cross-section of funds, there is little correlation between cash-to-assets ratios and fund size. In contrast, cash-to-assets ratios of banks and other financial intermediaries engaged in liquidity transformation tend to fall with size. A key reason for this difference between mutual funds and other intermediaries is that redemptions are much more correlated across investors for mutual funds. For most financial intermediaries, individual investor redemptions are relatively uncorrelated, so aggregate redemptions are quite predictable because of the law of large numbers. In contrast, for mutual funds and other asset managers, performance-flow relationships mean that investor redemptions are coordinated by returns. Thus, investor behavior limits economies of scale in liquidity provision by mutual funds, which must keep more cash on hand in order to provide the same liquidity services as other intermediaries. Overall however, because they use cash for liquidity management purposes, mutual funds hold large aggregate amounts of cash. According to the Investment Company Institute, as of 2014, long-term mutual funds held $726 billion, or 5.5% of total assets, in cash and other liquid assets.

Finally, we ask whether mutual funds hold enough cash to fully mitigate any price impact externalities that they may exert on other market participants. We provide two pieces of suggestive evidence that they do not. The first piece of evidence arises from the intuition that a monopolist internalizes its price impact. We show that funds that hold a larger fraction of the outstanding amount of the assets they invest in tend to hold more cash. This finding is consistent with such funds more fully internalizing the price impact of their trading in the securities they hold. Our second piece of evidence is at the fund family level. We show that funds that have significant holdings overlap with other funds in the same family hold more cash. This finding is consistent with the idea that these funds are more cautious about exerting price impact when it may adversely affect other funds in the family.

We also explore the extent to which funds use alternative liquidity management tools, including redemption restrictions, credit lines, and interfund lending programs in lieu of cash. Our evidence indicates that these alternative tools are imperfect substitutes for cash and that cash is the key tool funds use for liquidity management. These results validate our insight that cash holdings are a good measure of a fund's liquidity transformation activities.

In summary, our analysis highlights three key properties of liquidity transformation in asset management. First, it is economically significant. Mutual funds are not a veil, simply transacting in bonds and equities on behalf of their investors. Instead, funds have substantial cash holdings and use them to accommodate inflows and outflows, even at horizons of a few months.

Second, liquidity transformation in asset management is highly dependent on liquidity provision by the traditional and shadow banking sectors. In order to provide liquidity to their investors, mutual funds must hold substantial amounts of cash, bank deposits, and money market mutual fund shares. These holdings do not decrease much with fund size, suggesting that economies of scale in liquidity provision are weak.

Third, despite their size, the cash holdings of mutual funds are not sufficiently large to completely mitigate the price impact externalities created by funds' liquidity transformation activities. Our evidence suggests that, consistent with theory, funds do not fully internalize the effect that providing investors with daily liquidity has on the prices of the underlying securities.

Our paper is related to several strands of the literature. First, there is a small but growing literature studying the potential for liquidity transformation among mutual funds to generate run-like dynamics, including Chen, Goldstein, and Jiang (2010), Feroli et al (2014), Goldstein, Jiang, and Ng (2015), Wang (2015), and Zeng (2015). Second, there is a large theoretical and empirical literature studying fire sales in debt and equity markets, including Shleifer and Vishny (1992), Shleifer and Vishny (1997), Coval and Stafford (2007), Ellul, Jotikasthira and Lundblad (2011), Greenwood and Thesmar (2011), and Merrill et al (2012).[4] Our results show how mutual funds use cash holdings to manage the risk of fire sales created by their liquidity transformation activities and suggest that they may not hold enough cash to fully mitigate fire sale externalities.

Our paper is also related to the large literature on liquidity transformation in banks, starting with Diamond and Dybvig (1983) and Gorton and Pennacchi (1990) and progressing to recent empirical work including Berger and Bouwman (2009) and Cornett et al (2011). This literature has grown rapidly of late, fueled by the observation that liquidity transformation may also play an important role in explaining the growth of the shadow banking system and the subsequent financial crisis, as suggested by Gorton and Metrick (2010), Kacperczyk and Schnabl (2013), Krishnamurthy and Vissing-Jorgenson (2015), Moreira and Savov (2016), Nagel (2015), and Sunderam (2015).

[4] In addition, there is a broader literature on debt and equity market liquidity, including Roll (1984), Amihud and Mendelsohn (1986), Chordia, Roll, and Subrahmanyam (2001), Amihud (2002), Longstaff (2004), Acharya and Pedersen (2005), Bao, Pan, and Wang (2011), Dick-Nielsen, Feldhütter, and Lando (2012), Feldhütter (2012), and many others. Our results demonstrate that asset managers perform liquidity transformation in a manner similar to banks, providing investors with liquid claims while holding less liquid securities, which they must ultimately trade in the debt and equity markets.

Finally, we contribute to a small but growing literature on the determinants and effects of mutual fund cash holdings, including Yan (2006), Simutin (2014), Fulkerson and Riley (2015), and Hanouna, Novak, Riley, and Stahel (2015). We make three main contributions to this literature. First, we demonstrate that mutual funds' cash holdings are a proxy for the amount of liquidity transformation that funds engage in. Second, we study liquidity transformation of both equity and corporate bond funds. And third, we look at the extent to which funds internalize the price impact they exert on security prices.

The remainder of the paper is organized as follows. Section II presents a simple model that demonstrates the link between liquidity transformation and optimal cash holdings. Section III describes the data. Section IV presents our main results on cash management by mutual funds. Section V provides evidence on how much of their price impact individual mutual funds internalize. Section VI discusses alternative liquidity management tools and argues that they play a secondary role relative to cash holdings, and Section VII concludes.

II. Model

A. Setup

Throughout the paper, we use liquidity transformation to mean that the price-quantity schedule faced by a fund investor in buying or selling fund shares is different than it would be if the investor directly traded in the underlying assets. To help fix ideas, we begin by presenting a simple static model linking liquidity transformation to cash holdings.[5] Consider a single mutual fund that has M investors, each of whom has invested a dollar. Each investor is associated with outflows x_m next period. For simplicity, we assume that these outflows are normally distributed, with mean zero and variance σ^2. Further, assume that the correlation of outflows across investors is ρ. This correlation captures, in reduced form, both that liquidity shocks may be correlated across investors and that flows may be correlated because they respond to past performance (i.e., there is a performance-flow relationship).

The fund may accommodate redemptions in two ways. First, it may choose to hold cash reserves R. These reserves are liquid claims that can be sold costlessly to meet outflows. In

[5] To get similar intuitions in a dynamic model, one needs to assume either convex costs of liquidating the illiquid asset or time varying liquidation costs. Zeng (2015) shows that these intuitions remain in a full-fledged dynamic model using the latter approach.

practice, these claims are supplied by the traditional banking system or shadow banking system, but, for simplicity, we model them here as existing in elastic supply. Each dollar of cash reserves is associated with carrying cost i. One may think of i as the cost of tracking error for the fund. If it does not have sufficient cash reserves, the fund meets outflows by liquidating some of its illiquid security holdings. When it does so, the fund incurs average cost c per dollar of sales.

Given these assumptions, the total outflows suffered by the fund are

$$x = \sum_m x_m \sim N\left(0, \sigma^2 M\left(1 + \left(M-1\right)\rho\right)\right).$$

The fund chooses its cash reserves R to minimize the sum of carry costs and expected liquidation costs:

$$iR + \int_R^\infty c\left(x - R\right) dF\left(x\right), \tag{1}$$

where F is the cumulative distribution function of x.

B. Discussion of setup

This setup, though stylized, captures key features of how mutual funds perform liquidity transformation. The model is akin to the problem a fund faces at the end of a trading day. At the end of a trading day, the fund's NAV is set, so the fundamental value of the illiquid securities is fixed. We are normalizing the NAV so that the value of each investor's shares is \$1 and then allowing them to redeem some fraction of those shares. The fund then meets those fixed value redemptions in the optimal manner.

The fund in the model is performing liquidity transformation in two ways. First, it allows the investors to sell an unlimited fraction of their shares at a \$1 NAV despite the fact that the fund itself faces costs if it sells the illiquid asset. Second, the fund aggregates buying and selling across investors, costlessly netting trades between them and only selling the illiquid asset if it faces large net outflows. Individual investors trading for themselves in a market would only achieve this if they traded simultaneously. Outside of the model, the presence of a cash buffer allows funds to perform this kind of netting across longer periods of time.

The model could be generalized in two ways. First, we could more carefully model net inflows. As structured, the model is set up to consider how the fund manages outflows, but the fund faces a similar problem when it has inflows. On one hand, the fund increases its tracking error if it holds the inflows as cash. But on the other hand, holding cash reduces the price impact the fund generates in buying the illiquid asset. Thus, the logic of the model suggests that cash is useful for managing both inflows and outflows.

A second generalization would be to endogenize the volatility of investor flows. Presumably the fact that investors do not directly face the costs of liquidation that they generate for the fund means that they are more willing to trade fund shares than they would be if they bore their own liquidation costs. This means that gross flows in the model are higher than gross trade would be in a setting where investors traded the illiquid asset themselves.

C. Optimal cash reserves for a single fund

We now solve for the fund's optimal holdings of cash reserves *R*. Proposition 1 characterizes the optimal reserve holdings R^*.

Proposition 1. Assuming $i \leq \frac{c}{2}$ ***, optimal cash holdings*** R^* ***satisfy the first order condition*** $F\left(R^*\right) = 1 - i/c$. ***Because x is normally distributed, we have*** $R^* = k\sqrt{\sigma^2 M\left(1 + \left(M-1\right)\rho\right)}$, ***where*** $k = \Phi^{-1}\left(1 - i/c\right)$ ***and*** Φ ***is the standard normal cumulative distribution function***.

Proof: All proofs are given in the Appendix.

Intuitively, the fund trades off the carrying costs of cash reserves against the expected liquidation costs. The fund always pays the carrying cost *i*, while if it carries zero cash, it pays liquidation costs only half of the time – when it has outflows. Thus, we need $i \leq \frac{c}{2}$ for the fund to hold any cash.

The fund engages in liquidity transformation in two ways. First, it diversifies across investor liquidity shocks: inflows from one investor can be used to meet outflows from another without incurring any liquidation costs. This is analogous to the way diversification across depositors allows banks to hold illiquid assets, as in Diamond and Dybvig (1983). Second, when $i < \frac{c}{2}$, the fund uses cash holdings to further reduce its expected liquidation costs. These costs depend on total outflows, which are determined by the number of investors, the volatility of their individual outflows, and the correlation between the individual outflows.

It follows from the fund's trade off that optimal cash reserves are increasing in the fund's expected liquidation costs. Intuitively, if the fund chooses to hold more cash, it is choosing to pay higher carrying costs. This is optimal only if the fund faces higher expected liquidation costs. Thus, if we take expected liquidation costs as a measure of the amount of liquidity transformation the fund is performing on behalf of its investors, the fund's optimal cash holdings are a measure of the amount of liquidity transformation it performs.

Proposition 2: Let $L^* = \int_{R^*}^{\infty} c\left(x - R^*\right) dF\left(x\right)$ ***be the fund's expected liquidation costs when it holds the optimal amount of cash reserves. When*** $\boldsymbol{i \leq \frac{c}{2}}$***, optimal cash holdings are proportional to the expected liquidation costs:*** $L^* = R^*\left(c\phi\left(k\right)/k - i\right)$ **.**

Let $r^* = R^* / M$ be the fund's optimal cash-to-assets ratio. Proposition 3 derives some simple comparative statics.

Proposition 3. Assuming $\boldsymbol{i \leq \frac{c}{2}}$***, optimal cash holdings*** R^* ***and optimal cash-to-assets ratio*** r^* ***satisfy the following comparative statics:***

$\partial r^* / \partial c > 0$: The optimal cash-to-assets ratio increases with asset illiquidity.

$\partial r^* / \partial \sigma > 0$: The optimal cash-to-assets ratio increases with the volatility of fund flows.

$\partial^2 r^* / \partial \sigma \partial c > 0$: The relationship between cash-to-assets ratios and fund flow volatility is stronger for funds with more illiquid assets.

$\partial R^* / \partial M > 0$ and $\partial r^* / \partial M < 0$: Optimal cash holdings rise with fund size. As long as $\rho < 1$, optimal cash-to-assets ratio falls with fund size.

$\partial^2 r^* / \partial M \partial \rho > 0$: The optimal cash-to-assets ratio falls more slowly with fund size when investor flows are more correlated.

The first three comparative statics relate cash holdings to liquidity transformation. Liquidity transformation is driven by the intersection of investor behavior and asset illiquidity. If the fund faces more volatile flows, it is providing greater liquidity services to its investors. Similarly, if the fund's assets are more illiquid, it is providing greater liquidity services to its investors. Consistent with our insight that cash holdings are a measure of liquidity transformation, the fund optimally chooses a higher cash-to-assets ratio when it faces more volatile flows and holds more illiquid assets. These two effects interact: the more illiquid the assets, the stronger the relationship between cash-to-assets ratios and flow volatility.

The fourth and fifth comparative statics involve economies of scale in liquidity management. As the size of the fund rises, the volatility of dollar outflows rises. Thus, the fund must hold more cash reserves. However, because there is diversification across investors, the cash-to-assets ratio falls with fund size: the amount of additional cash reserves the fund holds for each incremental dollar of assets falls as fund size increases. The comparative statics also show that this diversification benefit dissipates as the correlation between individual investor flows rises. As flows become more correlated, economies of scale in liquidity management diminish.

D. Internalizing price impact

We next consider the problem of many funds and ask whether, in the aggregate, they hold enough cash to avoid exerting price impact externalities on one another. Suppose there are G funds, each of size M. For simplicity, assume that flows to all funds are perfectly correlated. This simplifies the algebra but does not change the intuition. Further, suppose that the per-dollar of sales liquidation cost c faced by an individual fund is a function of the total asset sales by all funds: $c = c\left(\sum_j x_j - R_j\right)$.

Fund j now seeks to minimize costs

$$iR + \int_R^\infty c\left(x - R + \sum_{k \neq j}\left(x_k - R_k\right)\right)\left(x - R\right) dF\left(x\right). \tag{2}$$

Eq. (2) is the same as Eq. (1), except now we have the costs of liquidation c depending on the reserve choices and flows faced by all G funds. Differentiating with respect to R and imposing a symmetric equilibrium ($R_k = R_j$), we have:

$$i - \int_{R^*}^\infty \left[c\left(G\left(x - R^*\right)\right) + \left(x - R^*\right)c'\left(G\left(x - R^*\right)\right)\right] dF(x) = 0. \tag{3}$$

Next, consider the problem of a social planner seeking to minimize costs across all mutual funds.[6] The planner seeks to minimize

$$G\left[iR + \int_{R}^{\infty} c\left(G\left(x-R\right)\right)\left(x-R\right)dF\left(x\right)\right]. \tag{4}$$

Crucially, from the planner's perspective, it moves all funds' cash reserves at the same time. In contrast, in the private market equilibrium, each individual fund treats other funds' reserve policies as fixed when choosing its own reserves. Essentially, in the private market equilibrium, an individual fund does not internalize the positive effect its cash holdings have on the liquidation costs faced by other funds. This can be seen in the planner's first order condition:

$$i - \int_{R^{**}}^{\infty}\left[c\left(G\left(x-R^{**}\right)\right) + G\left(x-R^{**}\right)c'\left(G\left(x-R^{**}\right)\right)dF(x)\right] = 0. \tag{5}$$

Eq. (5) is the same as the private market first order condition in Eq. (3), with one exception. In the last term, the effect of the choice of reserves on marginal costs of liquidation is multiplied by *G*. Essentially, the planner internalizes the fact that high reserves benefit all funds through lower liquidation costs. Proposition 4 says that this leads the social planner to a higher level of reserves than the private market outcome.

Proposition 4: A planner coordinating among funds would choose a level of cash holdings R^{**} higher than the level of cash holdings chosen in the private market equilibrium R^{*}.

A corollary that follows from this logic is that a monopolist in a particular security internalizes its price impact, particularly if that security is illiquid. The externality that makes private market cash holdings R^{*} lower than the socially optimal level of cash holdings R^{**} arises because funds take into account how cash holdings mitigate their own price impact but not how that price impact affects other funds. Of course, if one fund owns the whole market, there is no externality. Generalizing this intuition, the higher is the fraction of the underlying assets owned by a given fund, the more will the fund internalize its price impact.

Corollary: Funds that own a larger fraction of their portfolio assets more fully internalize their price impact and therefore hold more cash reserves.

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[6] Note that for there to be a social loss in general equilibrium, the liquidation costs to the funds must not simply be a transfer to an outside liquidity provider. This would be the case if, as in Stein (2012), those outside liquidity providers had to forgo other positive-NPV projects in order to buy the assets being sold by mutual funds.

III. Data

A. Cash holdings

We combine novel data on the cash holdings of mutual funds with several other data sets. Our primary data comes from the SEC form N-SAR. These forms are filed semi-annually by all mutual funds and provide data on asset composition, including holdings of cash and cash substitutes. Specifically, we measure holdings of cash and cash substitutes as the sum of cash (item 74A), repurchase agreements (74B), short-term debt securities other than repurchase agreements (74C), and other investments (74I). Short-term debt securities have remaining maturities of less than a year and consist mostly of US Treasury Bills and commercial paper.

The other investments category (74I) consists mostly of investments in money market mutual funds (MMMFs), other mutual funds, loan participations, and physical commodities. Using hand-collected data, we have examined the composition of the other investments category for a random sample of 320 funds for which other investments accounted for at least 10% of total net assets. The mean and median fractions of MMMFs in other investments were 75% and 100%. Holdings of other mutual funds accounted for most of the remaining value of other investments. We use our security-level holdings data, described below, to subtract holdings of long-term mutual funds from other investments. Otherwise, we treat the other investments category as consisting entirely of MMMFs. This should only introduce measurement error into our dependent variable and potentially inflate our standard errors.[7]

Our dependent variable is thus the sum of cash and cash equivalents scaled by TNA (item 74T). We winsorize this cash ratio at the 1st and 99th percentiles.

In addition to data on asset composition, form N-SAR contains data on fund flows and investment practices. Gross and net fund flows for each month since the last semi-annual filing

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[7] CRSP Mutual Fund Database includes a variable called per_cash that is supposed to report the fraction of the fund's portfolio invested in cash and equivalents. This variable appears to be a rather noisy proxy for the cash-to-assets ratio. First, we compared aggregate cash holdings of all long-term mutual funds in CRSP with the aggregate holdings of liquid assets of long-term mutual funds as reported by the Investment Company Institute (ICI). The two series track each other closely until 2007, but the relationship breaks down after that. Aggregate cash holdings decline according to CRSP but continue to increase according to ICI. By 2014, there is a gap of more than $400 billion, or more than 50% of the aggregate cash holdings reported by ICI. Second, for a random sample of 100 funds, we calculated cash holdings form the bottom up using security-level data from the SEC form N-CSR. The correlation between the true value of cash-to-assets ratio computed using N-CSR data and our N-SAR based proxy is 0.75. The correlation between the true value and CRSP is only 0.40.

are reported in item 28. Item 70 reports indicators for whether the fund uses various types of derivatives, borrows, lends out it securities, or engages in short sales.[8]

B. Link to CRSP mutual fund database

For additional fund characteristics such as investment objective, fraction of institutional share classes, and holdings liquidity, we link our N-SAR data to the CRSP Mutual Fund Database. Using a name-matching algorithm, we can match the majority of funds in N-SAR to CRSP.[9] We match more than 70% of all fund-year observations in N-SAR to CRSP. In dollar terms, we match more than 80% of all assets.

After linking our data to CRSP, we apply the following screens to our sample of funds. We focus on open-end funds and exclude small business investment companies (SBIC), unit investment trusts (UIT), exchange-traded funds (ETFs),[10] variable annuities,[11,12] funds of funds,[13] and money market mutual funds. In addition, we exclude observations with zero assets according to N-SAR and those for which the financial statements do not cover a regular 6- or 12-month reporting period. As we discuss below, we are able to measure asset liquidity for domestic equity funds, identified using CRSP objective codes starting with ED, and for long-term corporate bond funds.[14] To further make sure that we can accurately measure fund flow volatility and asset liquidity, we focus on funds with at least $100 million in assets. Finally, we exclude index funds

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[8] Almazan et al (2004) also use form N-SAR's investment practices data.

[9] Our procedure takes advantage of the structure of fund names in CRSP. The full fund name in CRSP is generally of the form "trust name: fund name; share class." For example, "Vanguard Index Funds: Vanguard 500 Index Fund; Admiral Shares". The first piece, "Vanguard Index Funds", is the name of the legal trust that offers Vanguard 500 Index Fund as well as a number of other funds. Vanguard Index Funds is the legal entity that files on behalf of Vanguard 500 Index Fund with the SEC. The second piece, "Vanguard 500 Index Fund," is the name of the fund itself. The final piece, "Admiral Shares" indicates different share classes that are claims on the same portfolio but that offer different bundles of fees, minimum investment requirements, sales loads, and other restrictions.

[10] ETFs operate under a very different model of liquidity transformation. They rely on investors to provide liquidity in the secondary market for the fund's share and on authorized participants (APs) to maintain parity between the market price of the fund's shares and their NAV. In untabulated results, we find that ETFs hold significantly less cash and that to the extent that they do hold more than a token amount of cash, it is almost entirely due to securities lending and derivatives trading.

[11] SBICs, UITs, and open-end funds are identified based on N-SAR items 5, 6, and 27. ETFs are identified based on the ETF dummy in CRSP or fund name including the words ETF, exchange-traded, iShares, or PowerShares.

[12] Variable annuities are identified based on N-SAR item 58.

[13] We obtain lists of active funds of funds from Morningstar and Bloomberg. We also use the security-level data from CRSP and Morningstar to calculate the share of the portfolio invested in other mutual funds. Funds that, on average, invest more than 80% of their portfolio in other funds are considered to be funds of funds.

[14] Corporate bond funds are defined as funds that have Lipper objective codes A, BBB, HY, IID, MSI, and MSI and that invest more than 50% of their portfolio in intermediate and long-term corporate bonds (NSAR item 62P).

for two reasons. First, index funds are likely to have higher carrying costs (i.e., costs of tracking error) than other funds. Thus, for index funds, cash holdings are likely to be lower and less sensitive to asset liquidity and fund flow volatility, and therefore a noisier measure of liquidity transformation. Second, index funds largely track the most liquid securities, so there is little variation in asset liquidity for us to analyze among them.

C. Asset liquidity

We use holdings data from the CRSP Mutual Fund Database to measure the liquidity of equity mutual fund holdings.[15] These data start in 2003. Following Chen, Goldstein, and Jiang (2010), we construct the square root version of the Amihud (2002) liquidity measure for each stock. We then aggregate up to the fund-quarter level, taking the value-weighted average of individual stock liquidity.

For bond funds, we use monthly holdings data from Morningstar, which covers the 2002Q2-2012Q2 period.[16] Following Dick-Nielsen, Feldhütter, and Lando (2012) we measure liquidity of individual bonds as λ, the equal-weighted average of four other liquidity measures: Amihud, Imputed Roundtrip Cost (IRC) of Feldhutter (2012), Amihud risk, and IRC risk.[17] The latter two are the standard deviations of the daily values of Amihud and IRC within a given quarter. Once we have the λ measure for each bond, we aggregate up to the fund level, taking the value-weighted average of individual bond liquidity.

D. Summary statistics

Our final data set is a semi-annual fund-level panel that combines the N-SAR data with additional fund information from CRSP and data on asset liquidity from CRSP and Morningstar. Throughout the paper, we conduct our analysis at the fund-half year level.

The sample periods are determined by the availability of holdings data in CRSP and Morningstar and of bond transaction data in TRACE. For equity funds, the sample period is January 2003 – December 2014. For bond funds, it is September 2002 – June 2012.

[15] In unreported analyses, we obtain very similar results when we use Thomson Reuters Mutual Funds Holdings data.
[16] Although CRSP has holdings data for some bond funds going back to 2004Q2, coverage is poor until 2010Q4.
[17] We are grateful to Peter Feldhütter for sharing his code with us.

Table 1 reports basic summary statistics for funds in our data, splitting them into equity versus bond funds. Our sample of equity funds consists of about 22,000 observations. Our sample of bond funds is much smaller, only about one ninth the size of the equity fund sample.[18] Equity and bond funds are broadly comparable in size with median and mean TNA of about \$500 million and \$1.5 – 2.1 billion.

Bond funds tend to hold more cash. The median bond fund has a cash-to-assets ratio of 5.3%, while the median equity fund has a cash-to-assets ratio of 4.3%. Bond funds have significantly higher turnover.[19] The volatility of fund flows is comparable for bond and equity funds, averaging approximately 9-10% per year. Institutional ownership is also similar. Except for securities lending, bond funds are somewhat more likely than equity funds to engage in various sophisticated investment practices such as trading options and futures and shorting.

Appendix Table A1 gives formal definitions for the construction of all variables used in the analysis.

IV. Results

We now present our main results. We start by showing that cash holdings play an economically significant role in how mutual funds manage their liquidity to meet inflows and outflows, as we assumed in the model in Section II. We then study the determinants of cash holdings, showing that, consistent with the model, cash holdings are strongly related to asset liquidity and volatility of fund flows. It is worth noting that throughout the analysis, we are documenting endogenous relationships. Fund characteristics, investor behavior, and cash holdings are all jointly determined, and our results trace out the endogenous relationships between them.[20]

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[18] The number of bond funds in our sample is significantly smaller than the number of equity funds because we focus on bond funds that invest at least 50% of their portfolio in corporate bonds.

[19] Higher turnover of bond funds is in part due to a) bond maturities being treated as sales and b) trading in the to-be-announced market for agency MBS.

[20] In most cases, endogeneity should lead to coefficients that are smaller in magnitude. For instance, Chen, Goldstein, and Jiang (2010) argue that higher cash holdings should endogenously lower the volatility of fund flows because investors are less worried about fire sales. This should weaken the relationship between cash and fund flow volatility relative to the case where fund flow volatility is exogenous.

A. Liquidity management through cash holdings

We begin by showing that cash holdings play an important role in the way mutual funds manage inflows and outflows. In Table 2, we estimate regressions of the change in a fund's cash holdings over the last six months on the net flows it received during each of those six months:

$$\Delta Cash_{i,t-6\to t} = \alpha + \beta_0 Flows_{i,t} + ... + \beta_5 Flows_{i,t-5} + \varepsilon_{i,t}. \tag{6}$$

Fund flows are winsorized at the 5th and 95th percentiles. In Appendix Table A2, we show that we obtain similar results winsorizing at the 1st and 99th percentiles.

Panel A reports the results for equity funds. In the first three columns, the dependent variable is the change in cash holdings over the last six months as a fraction of net assets six months ago: $\Delta Cash_{i,t-6\to t} / Assets_{i,t-6}$. In the first column, the coefficient β_0 = 0.23 is large and highly statistically significant. Since flows are scaled by the same denominator – assets six months ago – as the dependent variable, the coefficients can be interpreted as dollars. Thus, β_0 = 0.23 indicates that a dollar of outflows during month *t* decreases cash holdings by 23 cents. Similarly, a dollar of inflows increases cash holdings by 23 cents. The other 77 cents are met by transacting in the fund's holdings of equities.[21] In untabulated results, when we run regressions separating inflows and outflows, we find that funds respond relatively symmetrically to them. This is consistent with the idea that funds care about the price pressure they exert on the underlying assets when both buying and selling.

The coefficient β_0 shows that an economically significant portion of flows is accommodated through cash holdings. Even though equities are quite liquid, and a month is a relatively long period, 23% of flows at a monthly horizon are accommodated through changes in cash holdings. Presumably, at higher frequencies (e.g., daily or weekly), cash plays an even more important role. The remaining coefficients show that the effect of fund flows on cash holdings declines over time. However, even fund flows in month *t*-4 still have a detectable effect on cash holdings at time *t*.

The second column of Table 2 adds time (half-year) fixed effects. The results are unaffected, so we are not just picking up a correlation between aggregate flows and aggregate

[21] These results are broadly consistent with Edelen (1999), who finds that a dollar of fund flows is associated with about 70 cents in trading activity.

cash holdings. In the cross section, funds that have inflows build up their cash positions by more than funds that have outflows. The third column adds Lipper objective code cross time fixed effects. The results are again unaffected, indicating that the results are not driven by relationships between flows and cash holdings in particular fund objectives.

In the last three columns of Table 2, the dependent variable is the change in the fund's cash-to-assets ratio:

$$\Delta\left(\frac{Cash}{Assets}\right)_{i,t} = \left(\frac{Cash}{Assets}\right)_{i,t} - \left(\frac{Cash}{Assets}\right)_{i,t-6}.$$

These regressions show that funds are not simply responding to flows by scaling their portfolios up and down. The overall composition of the portfolio is changing, becoming more cash-heavy when the fund receives inflows and less cash-heavy when the fund suffers outflows.

In the fourth column, the coefficient β_0 = 0.08 is statistically and economically significant. Flows equal to 100% of assets increase the fund's cash-to-assets ratio by 8% (percentage points). For reference, the standard deviation of fund flows is 9%. The fifth and sixth columns show that these results are robust to including time and objective-time fixed effects.

Panel B of Table 2 reports analogous results for bond funds. The coefficients are again large and statistically significant, and the economic magnitudes are larger. Specifically, in the first column, the coefficient β_0 = 0.36 indicates that one dollar of outflows in month t decreases cash holdings by 36 cents. Similarly, in the fourth column, the coefficient β_0 = 0.15 indicates that flows equal to 100% of assets increase the fund's cash-to-assets ratio by 15% (percentage points). The larger magnitudes we find for bond funds are consistent with bonds being less liquid than equities. Because funds face a larger price impact trading in bonds, they accommodate a larger share of fund flows through changes in cash.

B. Effect of asset liquidity

To further flesh out the idea that asset illiquidity affects funds' propensity to use cash to manage inflows and outflows, Table 3 estimates specifications of the form

$$\begin{aligned}\Delta Cash_{i,t-6\to t} &= \alpha + \beta_1 Flows_{i,t-2\to t} \times Illiq_{i,t-6} + \beta_2 Flows_{i,t-5\to t-3} \times Illiq_{i,t-6} \\ &+ \beta_3 Flows_{i,t-2\to t} + \beta_4 Flows_{i,t-5\to t-3} + \beta_5 Illiq_{i,t-6} + \varepsilon_{i,t}.\end{aligned} \quad (7)$$

For compactness, we aggregate flows into quarters, i.e., those from month *t*-5 to *t*-3 and month *t*-2 to *t*.[22] We interact each of these quarterly flows with lagged values of holdings illiquidity. This specification effectively asks: given the illiquidity of the holdings that a fund started out with two quarters ago, how did it respond to fund flows during the last two quarters?

For the equity funds studied in Panel A, illiquidity is measured as the square root version of the Amihud (2002) measure. In the first three columns, the dependent variable is the change in cash holdings over the last six months as a fraction of assets six months ago: $\Delta Cash_{i,t-6\rightarrow t} / Assets_{i,t-6}$. We standardize the illiquidity variables so that their coefficients can be interpreted as the effect of a one-standard deviation change in asset illiquidity. Thus, the first column of Table 3 Panel A shows that for the average equity fund, one dollar of flows over months *t*-2 to *t* changes cash holdings by β_3 = 18 cents. For a fund with assets one standard deviation more illiquid than the average fund, the same dollar of flows changes cash holdings by $\beta_1 + \beta_3$ = 22 cents, a 24% larger effect.

The second and third columns of Table 3 Panel A show that these results are robust to controlling for time and objective-time fixed effects. In the last three columns of Table 3 Panel A, the dependent variable is the change in the fund's cash-to-assets ratio. Once again, fund flows over the last three months have a larger effect on funds with more illiquid assets.

Panel B of Table 3 reports analogous analyses for bond funds. The magnitudes are similar. The first column of Table 3 Panel P shows that for the average bond fund, one dollar of flows over months *t*-2 to *t* changes cash holdings by β_3 = 17 cents. For a fund with assets one standard deviation more illiquid than the average fund, the same dollar of flows changes cash holdings by $\beta_1 + \beta_3$ = 20 cents, a 20% larger effect. The effect is robust to the inclusion of time and objective-time fixed effects.

C. *Effect of aggregate market liquidity*

We next turn to time variation in how funds manage their liquidity. When markets for the underlying securities are less liquid, funds should have a higher propensity to accommodate flows through changes in cash. Table 4 estimates specifications of the form:

[22] Interacting monthly flows with asset illiquidity generates somewhat stronger results for more recent fund flows.

$$\Delta Cash_{i,t-6\to t} = \alpha + \beta_1 Flows_{i,t-2\to t} \times LowAggLiq_{i,t-2\to t} + \beta_2 Flows_{i,t-5\to t-3} \times LowAggLiq_{i,t-5\to t-3} + \beta_3 Flows_{i,t-2\to t} + \beta_4 Flows_{i,t-5\to t-3} + \beta_5 LowAggLiq_{i,t-2\to t} + \beta_6 LowAggLiq_{i,t-5\to t-3} + \varepsilon_{i,t}. \quad (8)$$

We measure aggregate market liquidity during separate quarters and then define the bottom tercile as periods of low aggregate market liquidity. For the equity funds studied in Panel A, our measure of aggregate market liquidity is the Pastor and Stambaugh (2003) measure.[23] In the first three columns, the dependent variable is the change in cash holdings over the last six months as a fraction of assets six months ago: $\Delta Cash_{i,t-6\to t} / Assets_{i,t-6}$.

The first column of Table 4 Panel A shows that for the average half-year, one dollar of fund flows during months t-2 to t changes cash balances by β_3 = 17 cents. When aggregate market liquidity is low, the same dollar of flows changes cash balances by $\beta_1 + \beta_3$ = 23 cents, or nearly 40% more. The second and third columns of Table 4 Panel A show broadly similar results when time and objective-time fixed effects are included. In the last three columns of Table 4 Panel A, the dependent variable is the change in the fund's cash-to-assets ratio. Here again, we see evidence that cash-to-assets ratios are more sensitive to fund flows when aggregate market liquidity is low.

In Panel B, we turn to bond funds. There is less agreement in the literature over the appropriate way to measure the liquidity of the aggregate bond market. We use the lambda measure proposed by Dick-Nielsen, Feldhütter, and Lando (2012). Lambda is the first principal component of four separate liquidity measures: Amihud (2002), Feldhütter (2012)'s Imputed Roundtrip Cost (IRC), as well as their volatilities.

The first column of Panel B shows point estimates with magnitudes similar to what we find for equity funds. One dollar of fund flows during months t-2 to t changes cash balances by β_3 = 16 cents. When aggregate market liquidity is low, the same dollar of flows changes cash balances by $\beta_1 + \beta_3$ = 22 cents, or nearly 40% more. However, for bond funds, the interaction between market liquidity and flows is not statistically significant. We have much less power to detect the effect of aggregate market liquidity in our bond sample because our sample size is

[23] We use the Pastor-Stambaugh measure rather than averaging the Amihud measure across stocks because changes in market capitalization mechanically induce changes in the Amihud measure. This means that time variation in the average Amihud measure does not necessarily reflect time variation in aggregate stock market liquidity.

significantly smaller and, crucially for the tests in Table 4, the time series dimension is shorter at eleven and a half years.

D. Determinants of cash holdings

Having shown that cash holdings play an important role in how mutual funds manage inflows and outflows, we next turn to the stock of cash holdings. We estimate regressions motivated by the model in Section II, which seek to link fund cash holdings to liquidity transformation. Specifically, Table 5 reports the results of regressions of the form:

$$\frac{Cash_{i,t}}{Assets_{i,t}} = \alpha + \boldsymbol{\beta}_1' \mathbf{LiquidityTransformation_{i,t}} + \boldsymbol{\beta}_2' \mathbf{Scale_{i,t}} + \boldsymbol{\beta}_3' \mathbf{InvestorBehavior_{i,t}} + \boldsymbol{\beta}_4' \mathbf{TradingPractices_{i,t}} + \varepsilon_{i,t}. \quad (9)$$

We group the regressors into four categories. The first category consists of regressors related to liquidity transformation. As suggested by the model, we include in this category the illiquidity of fund assets, the volatility of fund flows, and their interaction. The second category consists of regressors that capture economies of scale: the (log) size of the fund and the (log) size of the fund family. Our proxy for investor behavior is the fraction of the fund's assets that are in institutional share classes. Measures of trading practices include the fund's asset turnover and indicators for whether the fund uses various derivatives, borrows, lends out its securities, or engages in short sales.

The first two columns of Table 5 report the results for equity funds. All specifications include objective-time fixed effects with standard errors clustered at the fund family level. All continuous variables are standardized so that the coefficients can be interpreted as the effect of a one-standard deviation change in the independent variable.

The results indicate that funds that engage in more liquidity transformation hold more cash. Focusing on the second column, where we control for all explanatory variables simultaneously, a one-standard deviation increase in asset illiquidity increases the cash-to-assets ratio by 0.9 percentage points. Similarly, the volatility of fund flows comes in positive and significant. A one-standard deviation increase in flow volatility is associated with a 0.4 percentage points higher cash-to-assets ratio. Finally, the interaction between asset illiquidity and flow volatility is also positive and significant.

Another way to see the importance of liquidity transformation in determining fund's cash holdings is to compare the predicted cash-to-assets ratio of two otherwise identical funds that have liquidity transformation measures one standard deviation below the mean and one standard deviation above the mean respectively. Based on the estimates in column 2, that difference is 2.9 percentage points. This is about two-thirds of the median and almost 40% of the mean value of the cash-to-assets ratio, consistent with the idea that cash holdings play an important role in liquidity transformation.

Trading practices are also a significant determinant of cash holdings. Funds that engage in securities lending hold much more cash (6.6 percentage points) because they receive cash collateral when lending out securities. Similarly, funds that trade options and futures and that are engaged in short sales tend to hold more cash because they may need to pledge collateral.

Finally, our results provide mixed evidence of economies of scale in liquidity management. There is no evidence of economies of scale at the individual fund level. Why might this be the case? As suggested by the model, one reason is that highly correlated investor flows diminish the scope for scale economies. In particular, effective liquidity provision by mutual funds depends in part on gross inflows and outflows from different investors netting out. This is analogous to banks, where withdrawals from some depositors are met in part using incoming deposits from other depositors. This diversification across liquidity shocks to depositors allows banks to hold illiquid assets while providing depositors with demandable claims (Diamond and Dybvig, 1983). As shown in Section II, this diversification benefit increases with the number of investors in the fund, but increases more slowly when investor flows are more correlated.

In the context of mutual funds, past returns are a natural public signal that results in correlated flows and thus diminished economies of scale. It is well known that net investor flows respond to past returns (e.g., Chevalier and Ellison, 1997; Sirri and Tufano, 1998). In particular, following poor fund returns, each individual investor is more likely to redeem shares from the fund. This reduces the fund's ability to diversify across investor flows and means that the fund is more likely to suffer net outflows. In untabulated results, we find strong evidence of this mechanism at work. The ratio of net flows faced to gross flows faced by a fund is strongly correlated with past returns.

We do find evidence of economies of scale at the fund family level rather than the fund level. A one-standard deviation increase in fund family total assets decreases the cash-to-assets ratio by 1.3 percentage points. As we discuss further below, these economies of scale do not appear to be driven by the fact that larger families tend to have alterative liquidity management tools like lines of credit, interfund lending programs (Agarwal and Zhao, 2015), or funds of funds (Bhattacharya, Lee, and Pool, 2013). Instead it appears that larger fund families have better back office infrastructure that allow them to economize on cash holdings, or that they have more scope to net offsetting trades across individual funds (Goncalves-Pinto and Schmidt, 2013).

In the last two columns of Table 5, we find broadly similar effects for bond mutual funds. Once again, the amount of liquidity transformation the fund engages in plays a key role. The coefficients on the volatility of fund flows and flow volatility interacted with asset illiquidity are both positive and significant. The magnitudes on these coefficients are larger than for equity funds. However, for bond funds, the coefficient on asset illiquidity does not come in significant. Because there is less agreement in the literature about the appropriate way to measure bond liquidity, Appendix Table A3 shows that we obtain similar results with other measures, including the Roll (1984) measure, the Amihud (2002) measure, and the imputed roundtrip cost.

The cash holdings we study in Table 5 are large in the aggregate and have grown rapidly over recent years. Figure 1 shows the time series of holdings of both cash and cash substitutes. Holdings of cash and cash substitutes rise from $100 billion in 1996 to $600 billion in 2014. This is large as a fraction of total asset manager cash holdings, estimated by Pozsar (2013) to be approximately $2 trillion. It is also large in comparison to corporate cash holdings, which also stand at approximately $2 trillion.

The large cash holdings of mutual funds make clear that in the aggregate, liquidity transformation by asset managers relies heavily on liquidity provision by the banking and shadow banking systems. In order to provide their investors with liquid claims, asset managers must themselves hold large quantities of cash and cash substitutes. Moreover, these cash holdings come largely from the financial sector, not the government. In our data, over 80% of cash holdings are bank deposits and money market mutual fund shares, not Treasury securities. This presumably reflects an unwillingness of fund managers to pay the high liquidity premia associated with Treasuries when the banking and shadow banking systems can provide cheaper cash substitutes (e.g., Greenwood, Hanson, and Stein, 2015; Nagel, 2015; Sunderam, 2015).

E. Robustness

Table 6 reports a variety of robustness tests for our results on the determinants of cash holdings. We split our sample in several ways, showing that liquidity transformation is an important driver of cash holdings in all subsamples. Panel A shows the results for equity funds. The first two columns split funds by size and show that the results are not driven by a large number of small funds that account for a small fraction of aggregate mutual fund assets. The second pair of columns presents the results before and after the financial crisis, and the last two columns show the results excluding and including money market mutual funds from our definition of cash. Asset illiquidity always comes in positive and significant, flow volatility is positive and significant in all but one specification, and their interaction is positive and significant in three out of the six columns.

Panel B shows the results for bond funds. The results are less consistent here, which is not surprising given the small size of the sample. Nonetheless, the volatility of fund flows is positive and significant in all but one specification, and the interaction of flow volatility and asset illiquidity is positive and significant in three out of the six columns.

F. Alternative interpretations

We next consider three alternative interpretations for the results in Tables 5 and 6. The first alternative is that, rather than measuring liquidity transformation, cash holdings reflect managers' expectations of risk and return. Specifically, fund managers may choose to hold more cash whenever they expect future returns to be low or risk to be high.[24] If these expectations correlate with our measures of liquidity transformation, they could explain the results in Tables 5 and 6. This alternative is most likely to operate at the asset class or investment strategy level. For example, when managers of small-cap growth funds expect their stocks to underperform, they might tilt their portfolios towards cash. Our inclusion of fund objective cross time fixed effects in Tables 5 and 6 should absorb most such time variation in risk and expected returns. Since all our identification is coming within a given fund objective at a given point in time, it is unlikely that

[24] Huang (2013) provides evidence consistent with this story.

our results are driven by simple considerations of risk and return. In Table 7, we study this alternative more formally by adding future fund returns as controls in Eq. (9). Specifically, we analyze fund *i*'s cash holdings at time *t*, controlling for returns between *t* and *t+k*. The table shows that for equity funds, there is some evidence of market timing. Funds hold more cash when future returns are going to be low. However, the coefficients on our liquidity transformation variables, flow volatility, asset illiquidity, and their interaction, are not impacted suggesting that they are not being driven by market timing considerations.

Another alternative interpretation of the results in Tables 5 and 6 is that cash holdings are driven by the fund investment strategies, not by their liquidity transformation. Specifically, it could be the case that funds hold cash as dry powder to allow them to quickly take advantage of investment opportunities when they arise (Simutin 2014). If the propensity to hold dry powder is related to the illiquidity of the assets the fund invests in, then the coefficient on asset illiquidity could be capturing the effects of dry powder as opposed to liquidity transformation.

We examine this alternative in Table 8. We augment our regression specification in Eq. (9) with proxies for funds that are more likely to want to hold dry powder to quickly place bets on attractive investment opportunities. Our proxies for dry powder are driven by the idea that funds following such strategies are likely to make relatively large bets. Thus, we use the Herfindahl index of the fund's holdings and the portfolio share of the largest position. The coefficients on these variables are positive and statistically significant. A one standard deviation increase in holdings HHI is associated with 0.97% higher cash-to-assets ratio for equity funds and 1.44% higher cash-to-assets ratio for bond funds. The share of the largest position has a similar effect. Thus, funds that have concentrated positions and might want to quickly take large positions in the future, hold more cash as dry powder.

Crucially, controlling for dry powder has almost no effect on the estimated coefficients on the liquidity transformation variables: flow volatility, asset illiquidity, and their interaction. This suggests that our results are in fact capturing the association between cash holdings and liquidity transformation.

The third alternative explanation is that cash holdings are driven by managerial characteristics like risk aversion or skill. If some fund managers are more risk averse than others, and these managers tend to hold more illiquid assets, this could explain the results in Tables 5 and 6. Similarly, more skilled managers may choose to hold more cash in order to quickly take advantage of new investment opportunities when they arise. In Table 9, we examine this hypothesis by controlling for a variety of manager characteristics that have been used in the literature as proxies for ability or risk aversion. These characteristics include total industry experience, tenure with the current fund, possession of a certified financial analyst (CFA) credential, and ACT score.[25] We report the results for the sample of observations for which we have all explanatory variables. The sample size is reduced by about a third for equity funds and a quarter for bond funds. For both equity funds and bond funds, controlling for these managerial characteristics has virtually not impact on the liquidity transformation variables.

In Appendix Table A4, we take another approach to addressing alternative explanations, instrumenting for asset liquidity and flow volatility with the fund's Lipper objective code and its age respectively. The idea is that funds' asset holdings are constrained by their objective: high-yield funds must hold high-yield bonds. Thus, variation in liquidity driven by objective is not an endogenous choice. Similarly, it is well known that the volatility of fund flows declines with age, because investors have less to learn about a fund with a long history. Objective code is a somewhat limited instrument because it is time invariant, but it helps rule out alternative explanations based on market timing and managerial risk aversion. Because it could still be the case that certain objectives are more amenable to dry powder strategies, we make sure to directly control for dry powder considerations using holdings HHI. This makes it more likely that the exclusion restriction – fund's objective affects cash holdings only through the illiquidity of the fund's assets - is satisfied. The appendix table shows that our main results go through using this IV strategy.

V. Internalizing Price Impact

A. Fund-level results

We next ask whether mutual fund cash holdings are large enough to fully mitigate the price impact externalities created by the liquidity transformation that funds engage in. In this

[25] Chevalier and Ellison (1999) and Greenwood and Nagel (2009), among others, use SAT scores as a proxy for ability. We use the average ACT rather than SAT score of students admitted to manager's undergraduate institution because in our data the ACT score is available for a larger number of institutions. Using SAT scores generates similar results.

section, we provide suggestive fund-level evidence that they are not. The logic of the model suggests that funds that own a larger fraction of the securities they invest in should internalize more of their price impact and as a result should have higher cash-to-assets ratios.

Table 10 examines this prediction. We estimate regressions similar to those in Eq. (9) but augment them with measures of the fund's share of the securities it owns. Specifically, for each security that the fund holds, we first calculate the fund's share of either aggregate mutual fund holdings of that security or of the security's outstanding amount. We then calculate the value-weighted average across all securities in the fund's portfolio. Finally we standardize the resulting variables so that their coefficients represent the effect of a one-standard deviation change.

Columns 1 and 2 report the results for equity funds. In column 1, the coefficient on the fund's share of the securities it owns as a fraction of aggregate mutual fund holdings is positive and statistically significant. It is also economically meaningful – a one standard deviation higher share of aggregate holdings increases the cash-to-assets ratio by 0.8 percentage points. In column 2, we look at the fund's share of the securities it owns as a fraction of the securities' outstanding amounts. We obtain similar results, though the economic magnitude is smaller.

Columns 3 and 4 report the results of analogous regressions for bond funds. Here we do not find any statistically significant results. One empirical challenge with bond funds is understanding the set of securities for which trading creates price impact. For equities, most price impact from trading is likely to occur in the firm's single class of common stock. However, most firms issue multiple bonds that are imperfect substitutes. Thus, trading in one bond can create price impact in the firm's other bonds. This uncertainty about the scope for price impact makes it difficult to measuring the likelihood that a bond fund will internalize its price impact. For instance, a fund may own a large fraction of a single bond, leading our measurement to suggest that the fund should internalize much of its price impact. However, if this bond is one of many issued by the same firm, the fund may actually be internalizing only a small fraction of its total impact across these substitute bonds.[26]

Overall, the results for equity funds are consistent with the predictions of the model. They suggest that in a counterfactual world in which a single fund owned hundred percent of the

[26] Following this logic, one can think about measuring each fund's share of all bonds issued by a given firm. A priori, however, it is not obvious which bonds are more versus less substitutable.

securities it invested in, cash holdings would be substantially higher in order to mitigate price impact associated with liquidity transformation.

B. Family-level results

We can also look at the fund family level for evidence that cash holdings are not sufficiently large to fully mitigate price impact externalities. Specifically, fund families may at least partially internalize price impact across different funds in the family. Thus, if a fund holds assets that are also held by other funds in the same family, then the fund may be more likely to internalize the price impact of its trading on those funds than on funds outside the fund family. This suggests that funds should hold more cash when there is greater overlap in their holdings with other funds within the fund family. Furthermore, we might expect this effect to be stronger for larger funds. By their sheer size, larger funds might have to dump more assets on the market, resulting in larger price impact than smaller funds (for the same percentage of asset fund flows and asset sales).

We examine these predictions in Table 11. We run panel regressions similar to those in Eq. (9) but augment with them a measure of holdings overlap. For each security that the fund holds, we calculate the share of this security in the aggregate holdings of all other funds within the family. We then calculate the value-weighted average of this measure across all securities in the fund's portfolio. If none of the fund's securities are held by other funds in the same family, the holdings overlap measure will be zero. The more of the fund's securities are held by other funds in the same family, the greater will be the holdings overlap measure.[27]

Columns 1 and 2 report the results for equity funds. The coefficient on overlap itself is positive but not statistically significant. In column 2, the coefficient on the interaction of overlap and fund size is positive and statistically significant. This indicates that large funds that have significant overlap in holdings with other funds in the same family hold more cash. This is consistent with the idea that such funds try to mitigate the price impact externalities they would otherwise impose on other funds in the family.

[27] In untabulated regressions, we find that holdings overlap is driven by manager overlap. If two funds in the same family share a manager, they are more likely to have similar holdings.

Columns 3 and 4 report the results for bond funds. The coefficient on overlap is large, positive, and statistically significant. For bond funds, a one standard deviation increase in holdings overlap with other family funds is associated with a 0.9 percentage points higher cash-to-assets ratio. In column 4, the coefficient on the interaction of holdings overlap and fund size is not statistically significant, however.

Overall, the evidence in this section is consistent with theory, which suggests that funds do not fully internalize the price impact of their trading on one another.

VI. Alternative Liquidity Management Tools

In our analysis throughout the paper, we have assumed that cash is the only tool funds have for liquidity management. In this section, we discuss four alternative liquidity management tools that funds have at their disposal. Two of these alternative tools, lines of credit and in-kind redemption options, may be useful for liquidity management in times of stress. The other two, within-family lending programs and redemption fees, may be useful in normal times as well as times of stress. The key takeaway of our analysis is that although funds do have access to alternative liquidity management tools, they appear to use them very little in practice. In equilibrium, cash is still strongly related with liquidity transformation despite the existence of alternative liquidity management tools.

A. Lines of credit and in-kind redemption options

We start by analyzing the two liquidity management tools that may be useful in times of stress: lines of credit and in-kind redemption options. Lines of credit can be used to meet redemption requests without having to sell illiquid assets. They are generally arranged at the fund family level and made available to all funds within the family. Individual funds pay their pro-rata share of any commitment fees and pay interest based on the fund’s actual borrowings.

We first examine whether fund families typically have credit lines at all. We read annual reports on form N-CSR and prospectuses on form 485BPOS to collect information on credit lines for the top 150 mutual fund families as of the end of 2014. These fund families account for more than 97% of aggregate mutual fund assets in the CRSP Mutual Fund Database. About 60% of families in the sample report having a line of credit. Because larger families are more likely to have a line of credit, at least 80% of total mutual fund assets is held by families with lines of credit. Lines of credit are generally small relative to the assets of the fund family. The median credit facility is less than 0.44% of the fund family assets.

Our primary data source, SEC form N-SAR, also gives us a window into drawdowns on lines of credit. Funds report whether at any point during the six-month reporting period they had bank loans exceeding 1% of TNA. Figure 2 reports the fraction of funds that had bank loans exceeding 1% of TNA as a function of fund flows. The figure shows that usage is generally quite low. About 5% (7%) of equity (bond) funds have bank loans exceed 1% of TNA during a typical reporting period. Large outflows are associated with a higher probability of drawing on a line of credit. But even funds experiencing very large outflows are unlikely to draw down their line of credit. The five percent of observations with the largest outflows suffer average outflows of more than 20% of assets. Yet, even for these funds, the probability of having bank loans exceed 1% of TNA is only 15%.

Thus, although most funds do have access to a line of credit, utilization rates are low. This suggests that funds view lines of credit as an imperfect substitute for cash holdings. This is consistent with Acharya, Almeida, and Campello (2012), who argue that nonfinancial firms with greater aggregate liquidity risk should use cash rather than lines of credit. The idea is that because banks pool risks across nonfinancial firms, credit lines are less likely to be a reliable source of liquidity if there is an aggregate liquidity shock, when many firms are likely to draw their lines simultaneously. Thus, for firms more exposed to aggregate liquidity shocks, cash is a safer option. In our case, mutual funds are quite exposed to aggregate liquidity shocks because fund flows are strongly correlated with aggregate market returns. This implies that mutual funds should prefer cash to credit lines as a source of liquidity.

Redeeming in kind – giving investors a pro-rata share of the fund's portfolio instead of cash – is another way for mutual funds to offer less liquidity to investors in times of stress. In normal times, in-kind redemptions are typically both legally and mechanically challenging for mutual funds.[28] However, in times of stress, funds may utilize the option.

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[28] Most funds irrevocably commit themselves under Rule 18f-1 to redeem all retail investors in cash. Funds can still redeem in-kind requests from institutional investors, but even the latter might find it costly, if not impossible, to hold certain types of assets. Repurchase agreements and Eurodollar deposits, for example, are over-the-counter contracts that cannot be transferred to multiple investors. There can be restrictions on the funds' ability to transfer syndicated loan participations, as these can require approval from the borrower.

We collect data from SEC filings to get a rough estimate of the quantitative importance of in-kind redemptions. Since retail funds are extremely unlikely to redeem in-kind, we focus on institutional funds with at least $1 billion in assets. For each fund, we choose the quarter the fund experienced its largest dollar outflow and discard the other quarters. We then examine the 50 fund-quarter observations with the largest outflows. Out of these 50 observations, only 3 had in-kind redemptions. In value terms, our observations suffered combined net outflows of $123.3 billion. Out of this, $7.7 billion, or about 6%, was redeemed in-kind. These results confirm that in-kind redemptions are rare and play a limited role as an alternative liquidity management tool.

B. Interfund lending programs and redemption fees

We next analyze the two liquidity management tools that may be useful in both normal times and times of stress: interfund lending programs, in which funds borrow from other funds in the same family, and redemption fees. Interfund lending is typically forbidden.[29] However, fund families can ask the SEC for exemptive relief if such borrowing is "appropriate in the public interest and consistent with the protection of investors." Agarwal and Zhao (2015) provide more background on interfund lending programs and study the determinants and consequences of such programs. In particular, they find that as of 2013, only thirty fund families had set up interfund lending programs.

In Table 12, we ask whether having an interfund lending program weakens the relationship between cash holdings and liquidity transformation. We run regressions like Eq. (9), splitting the sample into funds with interfund lending programs and funds without them. Columns 1 and 2 report the results for equity funds. The results are broadly similar across the sample split. Although the coefficient on flow volatility for funds with interfund lending programs is not statistically significant, the coefficients on asset illiquidity and its interaction with flow volatility are. Moreover, their magnitudes are actually larger than for funds without an interfund lending program. Columns 5 and 6 report the results of an analogous sample split for bond funds. The sample of bond funds that have an interfund lending program is very small. As a result, none of the liquidity transformation coefficients are statistically significant. Their magnitudes, however, are comparable to the sample of funds without access to an interfund

[29] Section 17(a) of the Investment Company Act of 1940 prohibits transactions between affiliates, while section 21(b) prohibits funds from lending to any entity under common control.

lending program. Overall, the results are consistent with the idea that liquidity transformation plays an equally important role in determining cash holdings whether a fund has an interfund lending program or not. This suggests that interfund lending programs do not strongly substitute for cash holdings as liquidity management tools.

Finally, we examine redemption fees. Funds that impose redemption fees and deferred sales load charges effectively offer less liquidity to their investors. Only 26% of our equity fund observations and 30% of our bond fund observations have such fees. Are they an effective substitute for liquidity management through cash holdings? In Table 12, we also report the results of estimating Eq. (9) when we split the sample into funds with redemption fees versus funds without such fees. We once again get broadly similar results for both groups of funds, suggesting that even funds that impose redemption fees must rely on cash holdings as their primary liquidity management tool.

Overall, the analysis in this section suggests that funds appear to use their alternative liquidity management tools very little in practice. Cash is the main tool mutual funds use to manage their liquidity. These results validate our insight that cash holdings are a good measure of a fund's liquidity transformation activities.

VII. Conclusion

We study the cash management strategies of equity and bond mutual funds to shed light on liquidity transformation by asset managers. Our analysis highlights three key features of this liquidity transformation. First, cash management practices suggest it is significant. Mutual funds accommodate a substantial fraction of fund flows through changes in cash holdings as opposed to trading in portfolio securities. For equity funds, a $1 of fund outflows in month t decreases cash holdings by 23 cents. For bond funds, the same $1 of outflows decreases cash holdings by 32 cents.

Second, the fact that mutual funds accommodate fund flows through changes in cash holdings indicates that liquidity transformation in asset management is highly dependent on liquidity provision by the traditional banking and shadow banking sectors. In order to provide liquidity to end investors, mutual funds must hold substantial amounts of cash, bank deposits, and money market mutual fund shares.

Third, despite their size, cash holdings of mutual funds are not large enough to completely mitigate price impact externalities created by the liquidity transformation that mutual funds engage in. Our evidence shows that, consistent with theory, funds do not fully internalize the effects that providing investors with daily liquidity have on the prices of the underlying securities.

Appendix

Proof of Proposition 1

Differentiating the fund's objective function with respect to R yields the first-order condition

$$-i + c\int_{R}^{\infty} dF(x) = -i + c\left(1 - F(R)\right) = 0.$$

Rearranging yields $F\left(R^{*}\right) = 1 - i / c.$ Because x is normally distributed with standard deviation $\sqrt{\sigma^{2} M\left(1+(M-1)\rho\right)}$, we have

$$\frac{x}{\sqrt{\sigma^{2} M\left(1+(M-1)\rho\right)}} \sim N(0,1),$$

which is standard normal.

Proof of Proposition 2

Expected liquidation costs are given by

$$\begin{aligned} L^{*} &= \int_{R^{*}}^{\infty} c\left(x - R^{*}\right) dF(x) \\ &= c\int_{R^{*}}^{\infty} x dF(x) - R^{*}\left(1 - F\left(R^{*}\right)\right) \\ &= c\left(\phi(k)\right)\sigma\sqrt{M\left(1+(M-1)\rho\right)} - R^{*} i \\ &= R^{*}\left(c\phi(k)/k - i\right). \end{aligned}$$

Proof of Proposition 3

We have

$$r^{*} = k\sqrt{\sigma^{2}\left(1+(M-1)\rho\right)/M} \quad ,$$

where $k = \Phi^{-1}\left(1 - i / c\right)$. Differentiation yields

$$\frac{\partial r^*}{\partial c} = \frac{\partial k}{\partial c}\sqrt{\sigma^2\left(1+\left(M-1\right)\rho\right)/M} > 0$$
$$\frac{\partial r^*}{\partial \sigma} = k\sqrt{\left(1+\left(M-1\right)\rho\right)/M} > 0$$
$$\frac{\partial^2 r^*}{\partial \sigma \partial c} = \frac{\partial k}{\partial c}\sqrt{\left(1+\left(M-1\right)\rho\right)/M} > 0$$
$$\frac{\partial r^*}{\partial M} = \frac{k}{2M}\left(M\sigma^2 + M\left(M-1\right)\sigma^2\rho\right)^{-1/2}\sigma^2\left(\rho-1\right) < 0$$
$$\frac{\partial^2 r^*}{\partial M^2} = \frac{k}{2M}\left(M\sigma^2 + M\left(M-1\right)\sigma^2\rho\right)^{-1/2}\sigma^2 > 0.$$

<u>Proof of Proposition 4</u>

The private market equilibrium is characterized by the first-order condition

$$i - \int_{R^*}^{\infty}\left[c\left(G\left(x-R^*\right)\right) + \left(x-R^*\right)c'\left(G\left(x-R^*\right)\right)\right] = 0.$$

The social planner's solution is characterized by the first-order condition

$$i - \int_{R^{**}}^{\infty}\left[c\left(G\left(x-R^{**}\right)\right) + G\left(x-R^{**}\right)c'\left(G\left(x-R^{**}\right)\right)\right] = 0.$$

Evaluating the social planner's first-order condition at the private market equilibrium R^* and substituting in the private market first-order condition, we have

$$\begin{aligned} & i - \int_{R^*}^{\infty}\left[c\left(G\left(x-R^*\right)\right) + G\left(x-R^*\right)c'\left(G\left(x-R^*\right)\right)\right]dF\left(x\right) \\ & = -\int_{R^*}^{\infty}\left[\left(G-1\right)\left(x-R^*\right)c'\left(G\left(x-R^*\right)\right)\right]dF\left(x\right) < 0. \end{aligned}$$

Thus, the planner's first-order condition does not hold at the private market equilibrium R^*. Note that the planner's first-order condition is increasing in R, so we must have $R^{**} > R^*$.

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Figure 1
Aggregate cash holdings of equity and bond mutual funds

Mutual funds reporting on semiannual form N-SAR are matched to the CRSP Mutual Fund Database. The sample excludes variable annuities, ETFs, fund-of-funds, and levered index funds. Cash is cash, repurchase agreements, and short-term debt securities. Cash and substitutes is the sum of cash, repurchase agreements, short-term debt securities, and money market fund shares. See Appendix Table A1 for more details on measurement of cash substitutes.

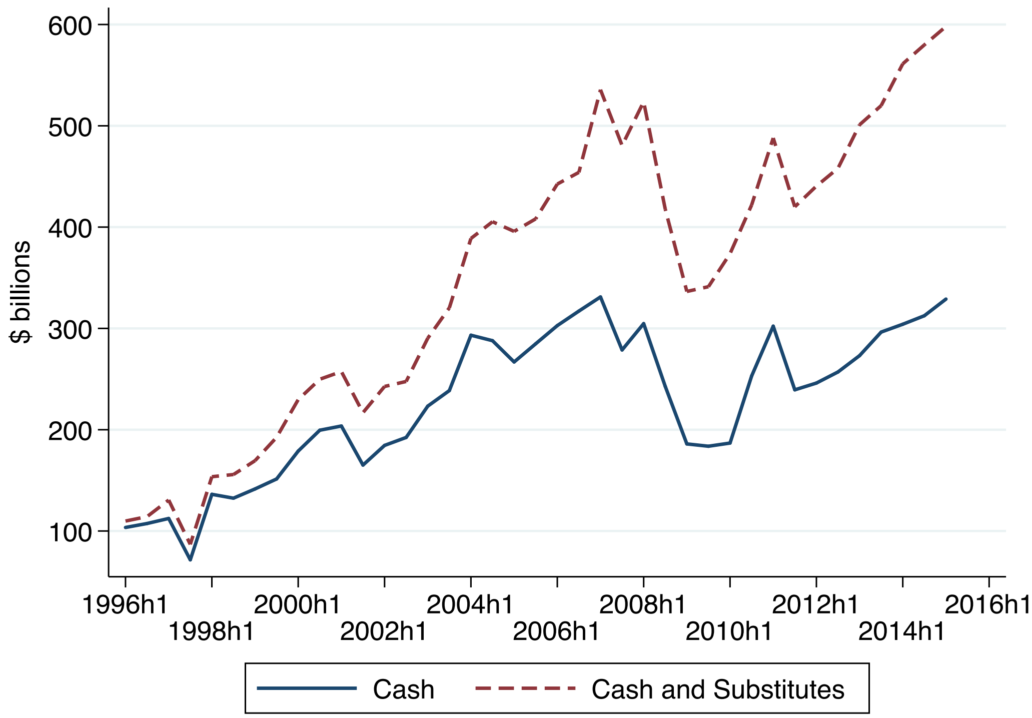
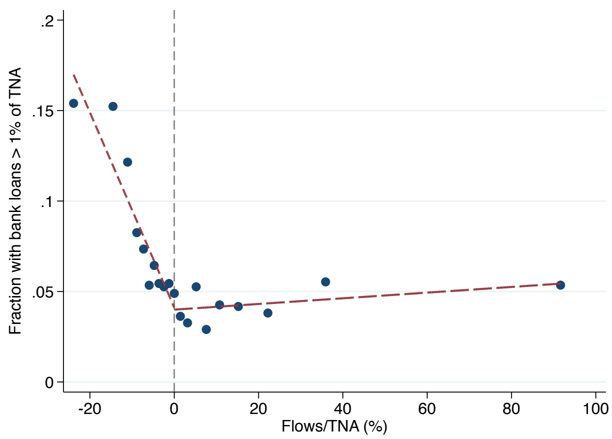


Figure 2
Utilization of lines of credit

This figure shows the relationship between fund flows and utilization of lines of credit. Each funds reports whether at any point during the semi-annual reporting period it had bank loans exceeding 1% of TNA. We sort observations into twenty bins based on their cumulative semi-annual fund flows scaled by lagged assets. For each bin we then calculate the average value of fund flows as well as the fraction of observations with bank loans exceeding 1% of TNA. Each dot represents a single bin that accounts for five percent of the sample.

(a) Equity funds



(b) Bond funds

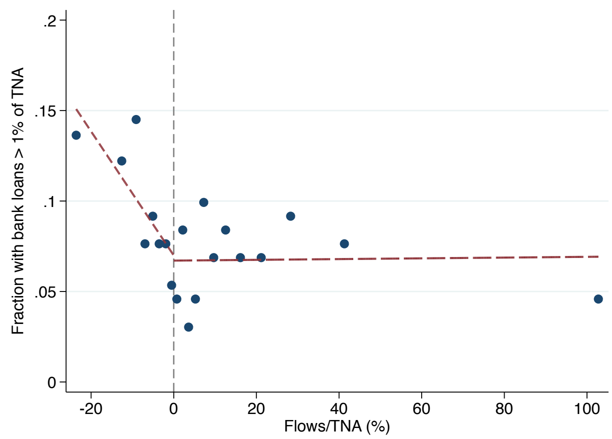


Table 1
Summary Statistics

This table reports summary statistics for the sample of mutual funds studied in the paper. Equity and bond open-end funds reporting on semi-annual form N-SAR are matched to the CRSP Mutual Fund Database. Money market funds, ETFs, and variable annuity are excluded. Funds with less than \$100 million in TNA (measured in 2012 dollars) are also excluded. The sample of equity funds is limited to domestic equity funds. The sample of bond funds is limited to funds with Lipper objectives A, BBB, HY, IID, MSI, SII that invest at least 50% of their portfolio in corporate bonds. The sample period for equity funds is 2003–2014. The sample period for bond funds is January 2004–June 2012. *Illiq* is Amihud (2002) for equity funds and Dick-Nielsen, Feldhütter, and Lando (2012) for bond funds. *Share of Agg Holdings* is the weighted-average of the fund's holdings of each portfolio security relative to aggregate holdings by all mutual funds in CRSP. *Share of Outstanding* is the weighted-average of the fund's holdings of each portfolio security relative to the security's outstanding amount. *Holdings Overlap* measures overlap in holdings with other funds within the same family. *Size* is $ln(TNA)$. *Family size* is $ln(familyTNA)$. $Flows_{j\to k}$ is net flows from month j to k, scaled by net assets six months ago. Fund flows are winsorized at the 5th and 95th percentiles. $Turnover$ is the minimum of purchases and sales divided by the monthly average size of the portfolio. $\sigma(Flows)$ is the standard deviation of monthly net flows during the semi-annual reporting period. Sec lending/Shorting/Options/Other are indicators for funds that engage in securities lending/shorting/trading of options and other derivatives/and other investment practices specified in question 70 of form N-SAR.

	Equity funds						Bond funds					
				Percentile						Percentile		
	N	Mean	SD	25	50	75	N	Mean	SD	25	50	75
TNA	22214	2072.37	5810.67	228.59	578.16	1551.61	2640	1484.69	2588.38	235.41	530.67	1402.09
Size	22214	6.52	1.33	5.43	6.36	7.35	2640	6.44	1.25	5.46	6.27	7.25
Family size	22214	10.56	2.14	9.11	10.73	12.00	2640	10.57	1.71	9.55	10.77	11.57
$Cash/Assets$	22214	7.43	8.45	1.92	4.31	9.43	2640	7.88	7.49	2.56	5.31	10.70
$\Delta Cash/Assets$	22214	0.66	6.56	−1.65	0.13	2.29	2572	0.75	7.64	−2.52	0.12	2.91
$\Delta(Cash/Assets)$	22214	−0.13	5.17	−1.86	−0.04	1.63	2572	−0.19	6.07	−2.66	−0.11	2.24
$Flows_{t-5\to t-3}$	22214	2.75	13.89	−3.55	−0.65	4.55	2640	4.63	14.63	−2.37	1.36	7.21
$Flows_{t-2\to t}$	22214	2.35	12.11	−3.47	−0.44	4.77	2640	4.57	14.42	−2.19	1.44	7.06
Illiq	22214	0.02	0.02	0.01	0.01	0.03	2640	−0.21	0.18	−0.34	−0.25	−0.12
Institutional share	22214	29.06	37.07	0.00	7.40	56.44	2640	31.44	37.67	0.00	10.41	61.02
$Turnover$	22214	56.17	50.01	22.00	41.00	74.00	2640	73.26	78.85	27.00	47.50	85.00
$\sigma(Flows)$	22214	8.92	11.47	2.27	4.93	10.74	2640	10.12	11.64	3.06	6.08	12.42
Sec lending	22214	0.49	0.50	0.00	0.00	1.00	2640	0.41	0.49	0.00	0.00	1.00
Shorting	22214	0.02	0.16	0.00	0.00	0.00	2640	0.04	0.20	0.00	0.00	0.00
Options	22214	0.03	0.06	0.00	0.00	0.00	2640	0.05	0.10	0.00	0.00	0.12
Other practices	22214	0.36	0.18	0.25	0.38	0.50	2640	0.44	0.15	0.38	0.50	0.50
Holdings HHI	22214	0.02	0.01	0.01	0.02	0.03	2640	0.01	0.01	0.01	0.01	0.01
Top share	22214	5.01	4.75	2.86	4.17	5.84	2640	3.54	3.23	1.62	2.33	4.11
Share of Agg Holdings	22214	2.37	3.84	0.25	0.81	2.69	2640	11.45	10.93	3.89	7.60	14.93
Share of Outstanding	22214	0.45	0.72	0.05	0.16	0.50	2640	1.48	1.94	0.35	0.73	1.61
Holdings Overlap	22214	0.38	0.48	0.07	0.25	0.48	2640	0.15	0.32	0.01	0.05	0.15

Table 2
Flow management through cash holdings

This table reports the results of regressions of changes in cash holdings on fund flows. In columns 1–3, the dependent variable is the change in cash over a six-month period, scaled by assets six months ago. In columns 4–6, the dependent variable is the change in the cash-to-assets ratio over a six-month period. The independent variables are monthly net fund flows, scaled by net assets six months ago. Time (half-year) fixed effects are included in columns 2 and 5. Objective-time fixed effects are included in columns 3 and 6. Panel A reports the results for equity funds 2003–2014. Panel B reports the results for bond funds January 2004–June 2012. Standard errors are adjusted for clustering by time.

Panel A: Equity funds

	$\frac{\Delta Cash_{i,t-6\to t}}{Assets_{i,t-6}}$			$\Delta\left(\frac{Cash}{Assets}\right)_{i,t-6\to t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$Flows_{i,t}$	0.228***	0.230***	0.234***	0.084***	0.084***	0.088***
	(0.030)	(0.030)	(0.030)	(0.020)	(0.020)	(0.019)
$Flows_{i,t-1}$	0.222***	0.216***	0.208***	0.051*	0.054*	0.049
	(0.036)	(0.035)	(0.035)	(0.028)	(0.028)	(0.029)
$Flows_{i,t-2}$	0.196***	0.185***	0.174***	0.046	0.048	0.039
	(0.038)	(0.037)	(0.036)	(0.029)	(0.029)	(0.028)
$Flows_{i,t-3}$	0.140***	0.133***	0.132***	0.000	−0.006	−0.003
	(0.026)	(0.025)	(0.026)	(0.021)	(0.019)	(0.019)
$Flows_{i,t-4}$	0.076**	0.071***	0.073***	−0.017	−0.025*	−0.024
	(0.027)	(0.025)	(0.025)	(0.017)	(0.014)	(0.015)
$Flows_{i,t-5}$	−0.027	−0.046	−0.041	−0.118***	−0.125***	−0.120***
	(0.028)	(0.030)	(0.031)	(0.020)	(0.021)	(0.023)
N	19,037	19,037	19,037	19,037	19,037	19,037
Adjusted R^2	0.102	0.126	0.137	0.006	0.015	0.025
FE		YH	YH × Obj		YH	YH × Obj

Panel B: Bond funds

	$\frac{\Delta Cash_{i,t-6\to t}}{Assets_{i,t-6}}$			$\Delta\left(\frac{Cash}{Assets}\right)_{i,t-6\to t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$Flows_{i,t}$	0.358***	0.326***	0.324***	0.152***	0.132**	0.121**
	(0.061)	(0.070)	(0.077)	(0.042)	(0.047)	(0.052)
$Flows_{i,t-1}$	0.100*	0.096*	0.107*	−0.019	−0.014	−0.004
	(0.051)	(0.053)	(0.053)	(0.041)	(0.041)	(0.042)
$Flows_{i,t-2}$	0.231**	0.215**	0.215**	0.089	0.075	0.069
	(0.081)	(0.081)	(0.084)	(0.057)	(0.057)	(0.060)
$Flows_{i,t-3}$	0.033	0.037	0.051	−0.090	−0.085	−0.074
	(0.070)	(0.067)	(0.075)	(0.067)	(0.067)	(0.075)
$Flows_{i,t-4}$	0.018	0.026	0.018	−0.085	−0.078	−0.081
	(0.066)	(0.066)	(0.067)	(0.073)	(0.074)	(0.076)
$Flows_{i,t-5}$	0.132*	0.157**	0.150**	−0.043	−0.024	−0.019
	(0.066)	(0.066)	(0.071)	(0.051)	(0.047)	(0.050)
N	2,494	2,494	2,494	2,494	2,494	2,494
Adjusted R^2	0.101	0.110	0.104	0.007	0.021	0.014
FE		YH	YH × Obj		YH	YH × Obj

Table 3
Interactions with asset illiquidity

This table reports the result of regressions of changes in cash holdings on fund flows interacted with the fund's asset illiquidity. In columns 1–3, the dependent variable is the change in cash over a six-month period, scaled by assets six months ago. In columns 4–6, the dependent variable is the change in the cash-to-assets ratio over a six-month period. Asset illiquidity is measured as of the beginning of the six-month period and is standardized so that the coefficients on illiquidity and its interactions represent the effect of a one-standard deviation change in illiquidity. Time (half-year) fixed effects are included in columns 2 and 5. Objective-time fixed effects are included in columns 3 and 6. Panel A reports the results for equity funds 2003–2014. For equity funds, *Illiq* is the square-root version of Amihud (2002). Panel B reports the results for bond funds January 2004–June 2012. For bond funds, *Illiq* is the Dick-Nielsen, Feldhütter, and Lando (2012) measure. Standard errors are adjusted for clustering by time.

Panel A: Equity funds

	$\frac{\Delta Cash_{i,t-6\to t}}{Assets_{i,t-6}}$			$\Delta\left(\frac{Cash}{Assets}\right)_{i,t-6\to t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$Flows_{i,t-2\to t}$	0.180***	0.176***	0.173***	0.046***	0.046***	0.044***
	(0.011)	(0.011)	(0.010)	(0.006)	(0.006)	(0.006)
$Flows_{i,t-2\to t} \times Illiq_{i,t-6}$	0.042***	0.041***	0.037***	0.018*	0.017*	0.018**
	(0.011)	(0.011)	(0.011)	(0.009)	(0.009)	(0.008)
$Flows_{i,t-5\to t-3}$	0.085***	0.078***	0.079***	−0.024***	−0.029***	−0.027***
	(0.012)	(0.012)	(0.012)	(0.007)	(0.006)	(0.007)
$Flows_{i,t-5\to t-3} \times Illiq_{i,t-6}$	0.020**	0.017*	0.016	−0.003	−0.003	−0.005
	(0.008)	(0.009)	(0.010)	(0.008)	(0.008)	(0.008)
$Illiq_{i,t-6}$	0.125	0.028	0.091	−0.055	−0.047	−0.066
	(0.088)	(0.092)	(0.131)	(0.065)	(0.071)	(0.084)
N	19,037	19,037	19,037	19,037	19,037	19,037
Adjusted R^2	0.113	0.135	0.145	0.005	0.014	0.023
FE		YH	YH × Obj		YH	YH × Obj

Panel B: Bond funds

	$\frac{\Delta Cash_{i,t-6\to t}}{Assets_{i,t-6}}$			$\Delta\left(\frac{Cash}{Assets}\right)_{i,t-6\to t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$Flows_{i,t-2\to t}$	0.167***	0.153***	0.152***	0.044**	0.036*	0.032
	(0.027)	(0.031)	(0.032)	(0.017)	(0.019)	(0.020)
$Flows_{i,t-2\to t} \times Illiq_{i,t-6}$	0.034**	0.032*	0.037*	0.008	0.009	0.011
	(0.016)	(0.018)	(0.020)	(0.013)	(0.015)	(0.016)
$Flows_{i,t-5\to t-3}$	0.128***	0.140***	0.144***	−0.028	−0.019	−0.013
	(0.031)	(0.033)	(0.036)	(0.032)	(0.035)	(0.039)
$Flows_{i,t-5\to t-3} \times Illiq_{i,t-6}$	−0.023	−0.023	−0.032	−0.011	−0.011	−0.015
	(0.036)	(0.035)	(0.038)	(0.024)	(0.023)	(0.025)
$Illiq_{i,t-6}$	0.078	0.390	0.399	−0.011	0.225	0.159
	(0.173)	(0.264)	(0.362)	(0.161)	(0.219)	(0.312)
N	2,494	2,494	2,494	2,494	2,494	2,494
Adjusted R^2	0.107	0.118	0.112	0.001	0.018	0.011
FE		YH	YH × Obj		YH	YH × Obj

Table 4
Interactions with market illiquidity

This table reports the results of regressions of changes in cash holdings on fund flows interacted with the aggregate market illiquidity. In columns 1–3, the dependent variable is the change in cash over a six-month period, scaled by assets six months ago. In columns 4–6, the dependent variable is the change in the cash-to-assets ratio over a six-month period. The independent variables are net fund flows, scaled by assets six months ago, an indicator for low aggregate market liquidity, and their interaction. *Low Agg Liq* is a dummy variable equal to one for observations in the bottom tercile of aggregate market liquidity. Time (half-year) fixed effects are included in columns 2 and 5. Objective-time fixed effects are included in columns 3 and 6. Panel A reports the results for equity funds 2003–2014. For equity funds, aggregate market liquidity is measured following Pastor and Stambaugh (2006). Panel B reports the results for bond funds January 2004–June 2012. For bond funds, aggregate market liquidity is measured following Dick-Nielsen, Feldhütter, and Lando (2012). Standard errors are adjusted for clustering by time.

Panel A: Equity funds

	$\frac{\Delta Cash_{i,t-6\to t}}{Assets_{i,t-6}}$			$\Delta\left(\frac{Cash}{Assets}\right)_{i,t-6\to t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$Flows_{i,t-2\to t}$	0.166***	0.162***	0.166***	0.037***	0.037***	0.039***
	(0.012)	(0.012)	(0.012)	(0.007)	(0.007)	(0.007)
$Flows_{i,t-2\to t} \times Low\ Agg\ Liq_{t-2\to t}$	0.067***	0.052**	0.052**	0.034***	0.027**	0.030**
	(0.022)	(0.022)	(0.023)	(0.012)	(0.013)	(0.013)
$Flows_{i,t-5\to t-3}$	0.080***	0.079***	0.078***	−0.029***	−0.029***	−0.031***
	(0.016)	(0.015)	(0.014)	(0.006)	(0.006)	(0.006)
$Flows_{i,t-5\to t-3} \times Low\ Agg\ Liq_{t-5\to t-3}$	0.022	0.006	0.005	0.011	0.004	0.002
	(0.028)	(0.027)	(0.027)	(0.018)	(0.016)	(0.015)
$Low\ Agg\ Liq_{t-2\to t}$	−0.543			0.010		
	(0.410)			(0.243)		
$Low\ Agg\ Liq_{t-5\to t-3}$	−0.452			−0.102		
	(0.366)			(0.240)		
N	19,037	19,037	19,037	19,037	19,037	19,037
Adjusted R^2	0.110	0.141	0.130	0.005	0.023	0.013
FE		YH	YH × Obj		YH	YH × Obj

Panel B: Bond funds

	$\frac{\Delta Cash_{i,t-6\to t}}{Assets_{i,t-6}}$			$\Delta\left(\frac{Cash}{Assets}\right)_{i,t-6\to t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$Flows_{i,t-2\to t}$	0.155***	0.142***	0.141***	0.053**	0.039	0.035
	(0.040)	(0.043)	(0.044)	(0.024)	(0.024)	(0.025)
$Flows_{i,t-2\to t} \times Low\ Agg\ Liq_{t-2\to t}$	0.060	0.044	0.046	−0.002	0.001	0.003
	(0.063)	(0.064)	(0.068)	(0.038)	(0.038)	(0.039)
$Flows_{i,t-5\to t-3}$	0.158***	0.170***	0.182***	0.025	0.036*	0.048**
	(0.036)	(0.038)	(0.040)	(0.020)	(0.021)	(0.023)
$Flows_{i,t-5\to t-3} \times Low\ Agg\ Liq_{t-5\to t-3}$	−0.071	−0.076	−0.095	−0.126**	−0.136**	−0.150**
	(0.062)	(0.061)	(0.067)	(0.052)	(0.052)	(0.057)
$Low\ Agg\ Liq_{t-2\to t}$	−0.618			−0.167		
	(0.650)			(0.706)		
$Low\ Agg\ Liq_{t-5\to t-3}$	−0.090			−0.141		
	(0.689)			(0.724)		
N	2,494	2,494	2,494	2,494	2,494	2,494
Adjusted R^2	0.108	0.117	0.112	0.012	0.027	0.022
FE		YH	YH × Obj		YH	YH × Obj

Table 5
Level of cash holdings

This table reports the results of regressions of the cash-to-assets ratio on fund characteristics. All specifications include objective-time fixed effects. Panel A reports the results for equity funds 2003–2014. For equity funds, *Illiq* is the square-root version of Amihud (2002). Panel B reports the results for bond funds January 2004–June 2012. For bond funds, *Illiq* is the Dick-Nielsen, Feldhütter, and Lando (2012) measure. All continuous variables are standardized so that their coefficients represent the effect of a one-standard deviation change in each variable. Standard errors are adjusted for clustering by fund family.

	Equity funds		Bond funds	
	(1)	(2)	(3)	(4)
$\sigma(Flows)_{i,t}$	0.365***	0.363***	0.632***	0.594***
	(0.090)	(0.089)	(0.216)	(0.211)
$Illiq_{i,t}$	0.946***	0.922***	−0.438	−0.445
	(0.260)	(0.261)	(0.318)	(0.315)
$Illiq \times \sigma(Flows)_{i,t}$		0.174**		0.324**
		(0.085)		(0.150)
$Size_{i,t}$	0.073	0.068	0.183	0.183
	(0.195)	(0.193)	(0.347)	(0.348)
$Family\ size_{i,t}$	−1.322***	−1.319***	−0.815**	−0.811**
	(0.312)	(0.313)	(0.352)	(0.351)
$Institutional\ share_{i,t}$	0.380	0.386	0.998***	1.011***
	(0.249)	(0.249)	(0.288)	(0.287)
$Turnover_{i,t}$	−0.008	−0.009	0.324	0.326
	(0.147)	(0.147)	(0.431)	(0.430)
$Sec\ lending_{i,t}$	6.603***	6.603***	5.232***	5.234***
	(0.622)	(0.622)	(0.756)	(0.756)
$Short\ selling_{i,t}$	3.222***	3.207***	−1.272	−1.317
	(1.146)	(1.148)	(1.017)	(1.022)
$Options_{i,t}$	5.131*	5.121*	7.463**	7.458**
	(2.784)	(2.788)	(3.121)	(3.129)
$Other\ practices_{i,t}$	−3.213**	−3.196**	2.189	2.167
	(1.495)	(1.496)	(1.662)	(1.659)
N	22,214	22,214	2,640	2,640
Adjusted R^2	0.226	0.227	0.195	0.196

Table 6
Robustness

This table shows the robustness of main results to alternative sample splits and measures of cash. All specifications include objective-time fixed effects. For equity funds, *Illiq* is the square-root version of Amihud (2002). For bond funds, *Illiq* is the Dick-Nielsen, Feldhütter, and Lando (2012) measure. All continuous variables are standardized so that their coefficients represent the effect of a one-standard deviation change in each variable. Standard errors are adjusted for clustering by fund family.

Panel A: Equity funds						
	by Size		by Time		Cash includes MMMFs	
	Small	Large	< 2008H1	> 2009H1	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)
$\sigma(Flows)_{i,t}$	0.487***	0.208*	0.381**	0.264**	0.126	0.363***
	(0.112)	(0.112)	(0.166)	(0.112)	(0.087)	(0.089)
$Illiq_{i,t}$	0.618**	1.742***	1.243***	0.966***	0.503***	0.922***
	(0.241)	(0.558)	(0.390)	(0.330)	(0.185)	(0.261)
$Illiq \times \sigma(Flows)_{i,t}$	0.128	0.480**	0.002	0.096	0.129**	0.174**
	(0.099)	(0.188)	(0.119)	(0.116)	(0.064)	(0.085)
$Size_{i,t}$	−0.209	0.110	0.173	0.021	0.492***	0.068
	(0.327)	(0.403)	(0.297)	(0.189)	(0.172)	(0.193)
$Family\ size_{i,t}$	−1.010***	−1.817***	−1.844***	−1.033***	−1.279***	−1.319***
	(0.284)	(0.436)	(0.475)	(0.281)	(0.260)	(0.313)
$Institutional\ share_{i,t}$	0.138	0.634*	1.130**	−0.072	0.033	0.386
	(0.217)	(0.350)	(0.461)	(0.222)	(0.199)	(0.249)
$Turnover_{i,t}$	−0.026	−0.028	−0.012	−0.009	−0.201*	−0.009
	(0.149)	(0.211)	(0.209)	(0.148)	(0.109)	(0.147)
$Sec\ lending_{i,t}$	7.884***	5.318***	7.903***	5.255***	1.637***	6.603***
	(0.640)	(0.753)	(0.862)	(0.686)	(0.476)	(0.622)
$Short\ selling_{i,t}$	3.756**	2.666**	2.670*	4.164**	2.235**	3.207***
	(1.454)	(1.280)	(1.428)	(1.733)	(0.956)	(1.148)
$Options_{i,t}$	4.445	4.914*	1.289	7.766**	6.556***	5.121*
	(3.376)	(2.842)	(3.566)	(3.141)	(2.056)	(2.788)
$Other\ practices_{i,t}$	−2.910**	−2.156	−1.752	−3.576**	−0.843	−3.196**
	(1.433)	(1.602)	(2.078)	(1.559)	(1.420)	(1.496)
N	11,100	11,114	7,989	11,248	22,214	22,214
Adjusted R^2	0.257	0.210	0.249	0.166	0.128	0.227

(continued)

Table 6
Robustness (continued)

Panel B: Bond funds						
	by Size		by Time		Cash includes MMMFs	
	Small	Large	$<$ 2008H1	$>$ 2009H1	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)
$\sigma(Flows)_{i,t}$	0.980***	0.041	0.552*	1.013***	0.308*	0.594***
	(0.239)	(0.377)	(0.300)	(0.315)	(0.184)	(0.211)
$Illiq_{i,t}$	0.081	−0.749	−0.786	−0.501	−0.530*	−0.445
	(0.377)	(0.484)	(0.617)	(0.500)	(0.275)	(0.315)
$Illiq \times \sigma(Flows)_{i,t}$	0.085	0.722**	0.552***	0.411	0.149	0.324**
	(0.181)	(0.362)	(0.196)	(0.533)	(0.142)	(0.150)
$Size_{i,t}$	−0.821	0.311	0.065	0.499	0.236	0.183
	(0.826)	(0.484)	(0.504)	(0.450)	(0.262)	(0.348)
$Family\ size_{i,t}$	−0.525	−1.276**	−0.668	−1.342***	−1.180***	−0.811**
	(0.346)	(0.604)	(0.556)	(0.458)	(0.319)	(0.351)
$Institutional\ share_{i,t}$	0.737**	1.473***	1.148***	0.756**	0.414*	1.011***
	(0.291)	(0.427)	(0.436)	(0.340)	(0.219)	(0.287)
$Turnover_{i,t}$	−0.319	0.582	0.434	0.540	0.344	0.326
	(0.438)	(0.449)	(0.485)	(0.433)	(0.291)	(0.430)
$Sec\ lending_{i,t}$	6.032***	4.420***	7.018***	4.241***	1.701***	5.234***
	(0.892)	(1.025)	(0.942)	(1.002)	(0.578)	(0.756)
$Short\ selling_{i,t}$	−1.205	−1.913	−1.903	−0.443	−0.494	−1.317
	(1.145)	(1.619)	(1.426)	(1.420)	(0.846)	(1.022)
$Options_{i,t}$	15.113***	1.107	7.195	5.161	9.888***	7.458**
	(3.620)	(4.099)	(5.214)	(3.394)	(2.489)	(3.129)
$Other\ practices_{i,t}$	1.274	3.492	1.483	4.561**	−0.261	2.167
	(1.854)	(2.338)	(2.733)	(2.209)	(1.632)	(1.659)
N	1,314	1,326	1,258	960	2,640	2,640
Adjusted R^2	0.244	0.206	0.230	0.193	0.111	0.196

Table 7
Risk and return

This table shows that the correlation between cash-to-assets ratio and liquidity transformation proxies is not driven by fund manager's expectations of future returns. The table estimate regressions of the cash-to-assets ratio on fund characteristics, including average monthly returns over the following one, three, six, and twelve months. All specifications include objective-time fixed effects. For equity funds, *Illiq* is the square-root version of Amihud (2002). For bond funds, *Illiq* is the Dick-Nielsen, Feldhütter, and Lando (2012) measure. All continuous variables are standardized so that their coefficients represent the effect of a one-standard deviation change in each variable. Standard errors are adjusted for clustering by fund family.

	Equity funds				Bond funds			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Illiq_{i,t}$	0.918***	0.923***	0.942***	0.945***	−0.441	−0.450	−0.458	−0.414
	(0.262)	(0.262)	(0.264)	(0.266)	(0.316)	(0.320)	(0.325)	(0.350)
$\sigma(Flows)_{i,t}$	0.348***	0.356***	0.356***	0.350***	0.599***	0.594***	0.604***	0.532**
	(0.090)	(0.091)	(0.091)	(0.092)	(0.214)	(0.215)	(0.218)	(0.211)
$Illiq \times \sigma(Flows)_{i,t}$	0.174**	0.176**	0.176**	0.180**	0.322**	0.311**	0.323**	0.364**
	(0.085)	(0.085)	(0.085)	(0.086)	(0.150)	(0.151)	(0.153)	(0.151)
$Size_{i,t}$	0.067	0.063	0.065	0.061	0.186	0.188	0.181	0.173
	(0.194)	(0.195)	(0.197)	(0.199)	(0.350)	(0.350)	(0.353)	(0.353)
$Family\ size_{i,t}$	−1.321***	−1.305***	−1.302***	−1.300***	−0.809**	−0.841**	−0.854**	−0.871**
	(0.313)	(0.315)	(0.316)	(0.320)	(0.353)	(0.356)	(0.358)	(0.364)
$Institutional\ share_{i,t}$	0.383	0.387	0.384	0.393	1.015***	1.014***	1.001***	1.012***
	(0.249)	(0.250)	(0.253)	(0.257)	(0.288)	(0.288)	(0.290)	(0.297)
$Turnover_{i,t}$	−0.011	−0.014	−0.008	−0.013	0.329	0.310	0.301	0.300
	(0.148)	(0.148)	(0.150)	(0.151)	(0.429)	(0.428)	(0.428)	(0.424)
$Sec\ lending_{i,t}$	6.608***	6.613***	6.613***	6.616***	5.221***	5.238***	5.245***	5.175***
	(0.621)	(0.625)	(0.629)	(0.637)	(0.759)	(0.756)	(0.762)	(0.770)
$Short\ selling_{i,t}$	3.186***	3.198***	3.198***	3.183***	−1.334	−1.289	−1.316	−1.328
	(1.146)	(1.147)	(1.153)	(1.162)	(1.020)	(1.031)	(1.036)	(1.037)
$Options_{i,t}$	5.240*	5.146*	5.193*	5.018*	7.466**	7.397**	7.366**	7.519**
	(2.778)	(2.773)	(2.772)	(2.789)	(3.134)	(3.121)	(3.126)	(3.211)
$Other\ practices_{i,t}$	−3.217**	−3.223**	−3.202**	−3.238**	2.176	2.388	2.458	2.723
	(1.491)	(1.501)	(1.506)	(1.517)	(1.664)	(1.656)	(1.671)	(1.685)
$Ret_{i,t+1}$	0.004				−0.008			
	(0.017)				(0.052)			
$Ret_{i,t+1\rightarrow t+3}$		−0.060*				0.024		
		(0.036)				(0.121)		
$Ret_{i,t+1\rightarrow t+6}$			−0.116***				0.093	
			(0.044)				(0.151)	
$Ret_{i,t+1\rightarrow t+12}$				−0.252**				−0.045
				(0.123)				(0.445)
Constant	5.076***	5.121***	5.158***	5.293***	4.432***	4.319***	4.256***	4.234***
	(0.562)	(0.567)	(0.567)	(0.582)	(0.691)	(0.683)	(0.687)	(0.712)
N	22,181	22,062	21,848	21,457	2,634	2,617	2,594	2,545
Adjusted R^2	0.227	0.227	0.227	0.227	0.195	0.196	0.196	0.192

Table 8
Dry powder

This table shows the robustness of the main results to controlling for dry powder. All specifications include objective-time fixed effects. *Holdings HHI* is the Herfindahl index of the fund's holdings. For equity funds, *Illiq* is the square-root version of Amihud (2002). For bond funds, *Illiq* is the Dick-Nielsen, Feldhütter, and Lando (2012) measure. All continuous variables are standardized so that their coefficients represent the effect of a one-standard deviation change in each variable. Standard errors are adjusted for clustering by fund family.

	Equity funds		Bond funds	
	(1)	(2)	(3)	(4)
$Holdings\ HHI_{i,t}$	0.970***		1.444***	
	(0.259)		(0.360)	
$Top\ share_{i,t}$		0.437**		1.370***
		(0.197)		(0.385)
$\sigma(Flows)_{i,t}$	0.300***	0.339***	0.577***	0.562***
	(0.088)	(0.087)	(0.206)	(0.209)
$Illiq_{i,t}$	0.970***	0.928***	−0.377	−0.421
	(0.254)	(0.259)	(0.322)	(0.316)
$Illiq \times \sigma(Flows)_{i,t}$	0.170**	0.171**	0.317**	0.329**
	(0.083)	(0.084)	(0.151)	(0.151)
$Size_{i,t}$	0.053	0.054	0.372	0.305
	(0.195)	(0.192)	(0.352)	(0.339)
$Family\ size_{i,t}$	−1.190***	−1.301***	−0.556*	−0.721**
	(0.332)	(0.317)	(0.318)	(0.326)
$Institutional\ share_{i,t}$	0.477*	0.402	0.949***	0.978***
	(0.250)	(0.249)	(0.283)	(0.281)
$Turnover_{i,t}$	0.062	0.009	0.154	0.119
	(0.153)	(0.148)	(0.413)	(0.418)
$Sec\ lending_{i,t}$	6.732***	6.618***	5.332***	5.295***
	(0.633)	(0.624)	(0.744)	(0.745)
$Short\ selling_{i,t}$	2.749**	2.992***	−1.341	−1.374
	(1.107)	(1.131)	(1.050)	(1.071)
$Options_{i,t}$	5.988**	5.059*	5.343*	4.402
	(2.715)	(2.771)	(3.035)	(3.172)
$Other\ practices_{i,t}$	−3.181**	−3.293**	2.447	1.967
	(1.503)	(1.500)	(1.593)	(1.563)
N	22,214	22,214	2,640	2,640
Adjusted R^2	0.235	0.229	0.222	0.219

Table 9
Controlling for manager characteristics

This table shows the robustness of the main results to controlling for manager characteristics. All specifications include objective-time fixed effects. *Tenure* is the number of years managing the fund. *Experience* is the number of years managing any mutual fund. *ACT* is the average ACT score of students admitted to the university from which the manager received his or her undergraduate degree. ACT is measured as of 2001–2002. For team managed funds, we use the average of individual manager characteristics. For equity funds, *Illiq* is the square-root version of Amihud (2002). For bond funds, *Illiq* is the Dick-Nielsen, Feldhütter, and Lando (2012) measure. All continuous variables are standardized so that their coefficients represent the effect of a one-standard deviation change in each variable. Standard errors are adjusted for clustering by fund family.

Panel A: Equity funds							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\sigma(Flows)_{i,t}$	0.370***	0.372***	0.370***	0.376***	0.371***	0.370***	0.381***
	(0.112)	(0.112)	(0.112)	(0.111)	(0.112)	(0.112)	(0.111)
$Illiq_{i,t}$	0.907***	0.900***	0.907***	0.922***	0.916***	0.907***	0.923***
	(0.291)	(0.288)	(0.289)	(0.293)	(0.290)	(0.291)	(0.289)
$Illiq \times \sigma(Flows)_{i,t}$	0.212**	0.214**	0.212**	0.209**	0.212**	0.212**	0.211**
	(0.093)	(0.093)	(0.092)	(0.093)	(0.093)	(0.093)	(0.094)
$Size_{i,t}$	0.038	0.019	0.038	0.040	0.043	0.039	0.025
	(0.196)	(0.202)	(0.206)	(0.193)	(0.196)	(0.194)	(0.201)
$Family\ size_{i,t}$	−1.515***	−1.506***	−1.515***	−1.486***	−1.513***	−1.515***	−1.473***
	(0.345)	(0.345)	(0.351)	(0.338)	(0.344)	(0.345)	(0.338)
$Institutional\ share_{i,t}$	0.502*	0.506*	0.502*	0.479*	0.498*	0.501*	0.476*
	(0.270)	(0.268)	(0.270)	(0.268)	(0.268)	(0.270)	(0.268)
$Turnover_{i,t}$	−0.042	−0.036	−0.042	−0.042	−0.046	−0.042	−0.036
	(0.177)	(0.174)	(0.175)	(0.173)	(0.177)	(0.177)	(0.169)
$Sec\ lending_{i,t}$	7.190***	7.190***	7.190***	7.180***	7.198***	7.191***	7.180***
	(0.702)	(0.702)	(0.697)	(0.699)	(0.704)	(0.708)	(0.706)
$Short\ selling_{i,t}$	3.078**	3.081**	3.078**	3.041**	3.048**	3.078**	3.005**
	(1.322)	(1.314)	(1.322)	(1.318)	(1.319)	(1.322)	(1.301)
$Options_{i,t}$	5.226*	5.388*	5.226	5.098	5.171*	5.220*	5.302
	(3.103)	(3.196)	(3.189)	(3.147)	(3.103)	(3.108)	(3.234)
$Other\ practices_{i,t}$	−2.470*	−2.506*	−2.470*	−2.188	−2.440*	−2.467*	−2.196
	(1.455)	(1.450)	(1.455)	(1.400)	(1.448)	(1.436)	(1.370)
$Experience_{i,t}$		0.093					0.227
		(0.202)					(0.240)
$Tenure_{i,t}$			0.000				−0.068
			(0.166)				(0.186)
$Team\ managed_{i,t}$				0.799**			0.898**
				(0.401)			(0.410)
$CFA_{i,t}$					0.107		0.131
					(0.179)		(0.181)
$ACT_{i,t}$						−0.006	−0.010
						(0.186)	(0.183)
N	14,506	14,506	14,506	14,506	14,506	14,506	14,506
Adjusted R^2	0.241	0.241	0.241	0.242	0.241	0.241	0.242

(continued)

Table 9
Controlling for manager characteristics (continued)

Panel B: Bond funds							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\sigma(Flows)_{i,t}$	0.489**	0.473**	0.474**	0.492**	0.489**	0.500**	0.485**
	(0.228)	(0.229)	(0.228)	(0.230)	(0.228)	(0.228)	(0.227)
$Illiq_{i,t}$	−0.415	−0.404	−0.413	−0.406	−0.423	−0.452	−0.455
	(0.350)	(0.345)	(0.351)	(0.355)	(0.343)	(0.350)	(0.344)
$Illiq \times \sigma(Flows)_{i,t}$	0.370**	0.381**	0.378**	0.360**	0.371**	0.372**	0.378**
	(0.163)	(0.165)	(0.163)	(0.163)	(0.163)	(0.161)	(0.162)
$Size_{i,t}$	0.234	0.252	0.267	0.239	0.224	0.297	0.291
	(0.382)	(0.376)	(0.377)	(0.385)	(0.378)	(0.364)	(0.368)
$Family\ size_{i,t}$	−0.896**	−0.859**	−0.883**	−0.944**	−0.886**	−0.881**	−0.852**
	(0.355)	(0.363)	(0.358)	(0.366)	(0.353)	(0.344)	(0.355)
$Institutional\ share_{i,t}$	0.942***	0.947***	0.928***	0.956***	0.939***	0.895***	0.910***
	(0.313)	(0.308)	(0.316)	(0.322)	(0.313)	(0.300)	(0.293)
$Turnover_{i,t}$	0.298	0.256	0.281	0.296	0.297	0.393	0.339
	(0.431)	(0.432)	(0.431)	(0.427)	(0.430)	(0.429)	(0.420)
$Sec\ lending_{i,t}$	5.165***	5.163***	5.156***	5.203***	5.149***	5.152***	5.141***
	(0.848)	(0.846)	(0.844)	(0.829)	(0.862)	(0.840)	(0.833)
$Short\ selling_{i,t}$	−1.412	−1.433	−1.382	−1.521	−1.428	−1.248	−1.431
	(1.127)	(1.115)	(1.130)	(1.192)	(1.144)	(1.121)	(1.158)
$Options_{i,t}$	6.036**	6.134**	5.903*	6.270**	5.960*	6.441**	6.643**
	(3.049)	(3.024)	(3.021)	(3.123)	(3.038)	(2.980)	(2.829)
$Other\ practices_{i,t}$	1.261	1.084	1.136	1.256	1.289	1.411	1.289
	(1.983)	(1.949)	(1.970)	(1.985)	(2.006)	(2.002)	(2.025)
$Experience_{i,t}$		−0.286					−0.392
		(0.335)					(0.456)
$Tenure_{i,t}$			−0.166				0.058
			(0.241)				(0.390)
$Team\ managed_{i,t}$				−0.537			−0.501
				(0.772)			(0.726)
$CFA_{i,t}$					−0.078		−0.214
					(0.337)		(0.322)
$ACT_{i,t}$						−0.648**	−0.667**
						(0.272)	(0.285)
N	1,975	1,975	1,975	1,975	1,975	1,975	1,975
Adjusted R^2	0.185	0.186	0.185	0.185	0.184	0.192	0.193

Table 10
Internalizing price impact at the fund level

This table reports the results of regressions of the cash-to-assets ratio on fund characteristics. All specifications include objective-time fixed effects. Panel A reports the results for equity funds 2003–2014. For equity funds, *Illiq* is the square-root version of Amihud (2002). Panel B reports the results for bond funds January 2004–June 2012. For bond funds, *Illiq* is the Dick-Nielsen, Feldhütter, and Lando (2012) measure. All continuous variables are standardized so that their coefficients represent the effect of a one-standard deviation change in each variable. Standard errors are adjusted for clustering by fund family.

	Equity funds		Bond funds	
	(1)	(2)	(3)	(4)
$Share\ of\ agg\ holdings_{i,t}$	0.822***		0.099	
	(0.229)		(0.482)	
$Share\ of\ outstanding_{i,t}$		0.493**		0.230
		(0.218)		(0.443)
$\sigma(Flows)_{i,t}$	0.343***	0.354***	0.595***	0.597***
	(0.089)	(0.089)	(0.211)	(0.210)
$Illiq_{i,t}$	0.459*	0.712***	−0.461	−0.475
	(0.246)	(0.251)	(0.324)	(0.318)
$Illiq \times \sigma(Flows)_{i,t}$	0.186**	0.197**	0.325**	0.328**
	(0.083)	(0.083)	(0.150)	(0.150)
$Size_{i,t}$	−0.368*	−0.248	0.116	−0.009
	(0.201)	(0.224)	(0.458)	(0.521)
$Family\ size_{i,t}$	−1.229***	−1.273***	−0.791**	−0.781**
	(0.315)	(0.315)	(0.365)	(0.365)
$Institutional\ share_{i,t}$	0.445*	0.428*	1.023***	1.027***
	(0.249)	(0.249)	(0.300)	(0.291)
$Turnover_{i,t}$	0.028	0.019	0.329	0.314
	(0.147)	(0.148)	(0.426)	(0.427)
$Sec\ lending_{i,t}$	6.678***	6.651***	5.233***	5.227***
	(0.620)	(0.622)	(0.758)	(0.762)
$Short\ selling_{i,t}$	2.913***	3.101***	−1.346	−1.384
	(1.115)	(1.138)	(1.042)	(1.027)
$Options_{i,t}$	5.305*	5.481*	7.533**	7.703**
	(2.778)	(2.799)	(3.203)	(3.165)
$Other\ practices_{i,t}$	−3.387**	−3.249**	2.233	2.312
	(1.515)	(1.503)	(1.691)	(1.662)
N	22,214	22,214	2,640	2,640
Adjusted R^2	0.231	0.228	0.196	0.196

Table 11
Internalizing price impact at the family level

This table reports the results of regressions of the cash-to-assets ratio on fund characteristics. *Holdings Overlap* measures holdings overlap with other funds in the same family. For equity funds, *Illiq* is the square-root version of Amihud (2002). For bond funds, *Illiq* is the Dick-Nielsen, Feldhütter, and Lando (2012) measure. All continuous variables are standardized so that their coefficients represent the effect of a one-standard deviation change in each variable. All specifications include objective-time fixed effects. Standard errors are adjusted for clustering by fund family.

	Equity funds		Bond funds	
	(1)	(2)	(3)	(4)
$Overlap_{i,t}$	0.149	0.114	0.874***	0.901***
	(0.291)	(0.294)	(0.267)	(0.327)
$Overlap \times Size_{i,t}$		0.312**		−0.036
		(0.153)		(0.149)
$\sigma(Flows)_{i,t}$	0.361***	0.359***	0.542**	0.540**
	(0.089)	(0.089)	(0.210)	(0.209)
$Illiq_{i,t}$	0.935***	0.944***	−0.552	−0.554
	(0.262)	(0.262)	(0.334)	(0.335)
$Illiq \times \sigma(Flows)_{i,t}$	0.175**	0.163*	0.312**	0.312**
	(0.085)	(0.085)	(0.144)	(0.145)
$Size_{i,t}$	0.042	0.001	0.042	0.049
	(0.193)	(0.181)	(0.350)	(0.357)
$Family\ size_{i,t}$	−1.281***	−1.284***	−0.795**	−0.801**
	(0.317)	(0.315)	(0.369)	(0.373)
$Institutional\ share_{i,t}$	0.396	0.392	0.901***	0.902***
	(0.248)	(0.248)	(0.292)	(0.292)
$Turnover_{i,t}$	−0.003	−0.015	0.309	0.308
	(0.147)	(0.146)	(0.412)	(0.412)
$Sec\ lending_{i,t}$	6.625***	6.637***	5.240***	5.236***
	(0.625)	(0.622)	(0.746)	(0.746)
$Short\ selling_{i,t}$	3.164***	3.153***	−1.529	−1.521
	(1.152)	(1.142)	(1.044)	(1.046)
$Options_{i,t}$	5.079*	5.252*	7.447**	7.417**
	(2.767)	(2.737)	(3.068)	(3.092)
$Other\ practices_{i,t}$	−3.236**	−3.177**	1.720	1.721
	(1.495)	(1.484)	(1.685)	(1.686)
N	22,214	22,214	2,640	2,640
Adjusted R^2	0.227	0.228	0.208	0.208

Table 12
Alternative liquidity management tools

This table reports the results of regressions of the cash-to-assets ratio on fund characteristics. In columns 1–2 and 5–6 we split funds into the ones with interfund lending programs versus the ones without such programs. In columns 3–4 and 7–8 we split funds into the ones with redemption fees or deferred sales loads versus the ones without such fees. For equity funds, *Illiq* is the square-root version of Amihud (2002). For bond funds, *Illiq* is the Dick-Nielsen, Feldhütter, and Lando (2012) measure. All continuous variables are standardized so that their coefficients represent the effect of a one-standard deviation change in each variable. Standard errors are adjusted for clustering by fund family.

	Equity funds				Bond funds			
	Interfund lending		Redemption fees		Interfund lending		Redemption fees	
	No	Yes	No	Yes	No	Yes	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\sigma(Flows)_{i,t}$	0.455***	0.207	0.285***	0.583***	0.639***	0.358	0.624***	0.490
	(0.106)	(0.246)	(0.098)	(0.164)	(0.224)	(0.642)	(0.235)	(0.387)
$Illiq_{i,t}$	0.987***	1.506**	0.975***	0.771**	−0.547	−0.714	−0.907**	0.794*
	(0.262)	(0.733)	(0.331)	(0.375)	(0.337)	(1.405)	(0.398)	(0.463)
$Illiq \times \sigma(Flows)_{i,t}$	0.176*	0.339**	0.036	0.465**	0.173	0.361	0.322*	0.508**
	(0.098)	(0.165)	(0.070)	(0.190)	(0.160)	(0.558)	(0.179)	(0.251)
$Size_{i,t}$	0.079	0.155	0.043	0.214	0.284	0.104	0.374	−0.083
	(0.216)	(0.259)	(0.234)	(0.299)	(0.377)	(1.001)	(0.364)	(0.633)
$Family\ size_{i,t}$	−1.060***	−3.099***	−1.139***	−1.734***	−1.042***	−0.347	−0.504	−0.929
	(0.306)	(0.951)	(0.333)	(0.527)	(0.366)	(0.917)	(0.373)	(0.722)
$Institutional\ share_{i,t}$	0.119	1.546*	0.487*	0.266	0.762***	1.304	1.273***	0.790**
	(0.201)	(0.902)	(0.290)	(0.241)	(0.274)	(0.915)	(0.351)	(0.381)
$Turnover_{i,t}$	−0.088	0.450	0.121	−0.378	0.269	0.903*	0.021	0.966**
	(0.142)	(0.432)	(0.154)	(0.245)	(0.469)	(0.515)	(0.479)	(0.438)
$Sec\ lending_{i,t}$	6.715***	7.097***	6.383***	7.512***	5.162***	5.092**	5.524***	4.454***
	(0.657)	(1.605)	(0.657)	(1.105)	(0.797)	(1.839)	(0.802)	(1.240)
$Short\ selling_{i,t}$	3.427***	0.315	4.387***	1.360	−1.291	−3.429	−0.374	−2.452
	(1.151)	(2.751)	(1.503)	(1.248)	(1.233)	(2.034)	(1.190)	(1.738)
$Options_{i,t}$	3.359	3.916	5.227	4.523	4.369	24.880***	8.004**	5.531
	(2.945)	(7.143)	(3.403)	(4.125)	(2.987)	(8.633)	(3.249)	(7.250)
$Other\ practices_{i,t}$	−2.290*	−1.333	−2.536	−4.739*	2.392	2.604	3.300	−0.314
	(1.285)	(2.501)	(1.600)	(2.847)	(1.627)	(5.493)	(2.065)	(2.475)
N	17,446	4,073	16,238	5,711	2,206	306	1,840	779
Adjusted R^2	0.230	0.345	0.258	0.185	0.194	0.343	0.211	0.262

Appendix

Table A1
Variable definitions

$Cash/Assets$	Cash is cash (74A) + repurchase agreements (74B) + short-term debt securities other than repurchase agreements (74C) + other investments (74I). Other investments consist mostly of money market mutual funds but sometimes include holdings of long-term mutual funds. We subtract the latter based on security-level holdings data from CRSP Mutual Fund Database (for equity funds) and Morningstar (for bond funds). Cash is scaled by total net assets (74T). Winsorized at the 1st and 99th percentiles.
$\Delta Cash_{i,t-6\to t}/Assets_{i,t-6}$	Change in cash between two semi-annual reporting periods divided by TNA as of the previous semi-annual reporting period. Winsorized at the 1st and 99th percentiles.
$\Delta(Cash/Assets)_{i,t-6\to t}$	Change in the cash-to-assets ratio between two semi-annual reporting periods. Winsorized at the 1st and 99th percentiles.
$Flows$	Net fund flows during each of the preceding six months (28) are scaled by TNA at the end of the previous semi-annual reporting period. Winsorized at the 5th and 95th percentiles. Appendix Table A2 reports the results of robustness checks using fund flows winsorized at the 1st and 99th percentiles.
$Illiq$	**Equity funds:** We first calculate the square-root version of Amihud (2002) liquidity measure for each stock in a funds portfolio. We use daily data for the preceding six months. We then calculate the value-weighted average across all stocks held by a given mutual fund. Equity fund portfolio holdings are from the CRSP Mutual Fund Database. Winsorized at the 1st and 99th percentiles. **Bond funds:** We first calculate Dick-Nielsen, Feldhütter, and Lando (2012) λ measure for each bond in a fund's portfolio. We then calculate the value-weighted average across all corporate bonds held by a given mutual fund. Portfolio holdings are from Morningstar. Bond transaction data are from Enhanced TRACE.

Table A1—*Continued*

Low Agg Liq	For equity funds, we use the Pastor and Stambaugh (2003) measure of market liquidity. For bond funds, we use the aggregate version of Dick-Nielsen, Feldhütter, and Lando (2012). Periods of low aggregate liquidity are defined as those in the bottom tercile of the distribution of aggregate market liquidity within our sample.
Family size	Log of aggregate TNA across all CRSP mutual funds within the same family.
$\sigma(Flows)$	Standard deviation of monthly fund flows (28) over the preceeding six months. Fund flows are scaled by TNA as of the beginning of the semi-annual reporting period.
Institutional share	Fraction of institutional share classes, identified following Chen, Goldstein, and Jiang (2010). A share class is considered to be institutional if a) CRSPs institutional dummy is equal to Y and retail dummy is equal to N, or b) fund name includes the word institutional or its abbreviation, or c) class name includes one of the following suffixes: I, X, Y, or Z. Share classes with the word retirement in their name or suffixes J, K, and R are considered to be retail.
$Turnover$	Portfolio turnover for the current semi-annual reporting period (71D). Portfolio turnover is the minimum of purchases and sales (including all maturities), divided by the monthly average value of the portfolio. Portfolio turnover is winsorized at the 1st and 99th percentiles.
Sec lending	Binary variable equal to one for funds that engage in loaning portfolio securities (70N).
Short selling	Binary variable equal to one for funds that engage in short selling (70R).
Options	Average of 8 binary variables, each equal to one if a fund engages in writing or investing in 1) options on equities (70B), 2) options on debt securities (70C), 3) options on stock indices (70D), 4) interest rate futures (70E), 5) stock index futures (70F), 6) options on futures (70G), 7) options on stock index futures (70H), and 8) other commodity futures (70I).

Table A1—*Continued*

Other practices	Average of 7 binary variables for engaging in the following investment practices: 1) investment in restricted securities (70J), 2) investment in shares of other investment companies (70K), 3) investments in securities of foreign issuers (70L), 4) currency exchange transactions (70M), 5) borrowing of money (70O), 6) purchases/sales by certain exempted affiliated persons (70P), 7) margin purchases (70Q).
Redemption fees	Binary variable equal to one for funds that impose a deferred or contingent deferred sales load (34) or a redemption fee other than a deferred or contingent sales load (37).
Share of agg holdings	Weighted-average of the funds holdings of each security relative to aggregate holdings by all mutual funds: $\sum_s \frac{V_{f,s}}{\sum_s V_{f,s}} \frac{V_{f,s}}{\sum_f V_{f,s}}$ where f indexes funds and s indexes securities. For equities (bonds), aggregate fund holdings are calculated using CSRP (Morningstar).
Share of outstanding	Weighted-average of the funds holdings of each portfolio security relative to the security's outstanding amount: $\sum_s \frac{V_{f,s}}{\sum_s V_{f,s}} \times \frac{V_{f,s}}{Outstanding_s}$, where f indexes funds and s indexes securities. For stocks, the outstanding is the market capitalization, calculated using the price and number of shares reported in CRSP. For bonds, outstanding is the face value at issuance.
Overlap	For each security s held by fund f, we calculate aggregate holdings of security s by all other funds that belong to the same family and divide this by the aggregate TNA of family funds, excluding fund f. We then take the value-weighted average across all securities held by fund f. Specifically $Overlap_f = \sum_s \frac{V_{f,s}}{\sum_s V_{f,s}} \times \frac{\sum_{j \in family(f), j \neq f} V_{f,s}}{\sum_{j \in family(f), j \neq f} TNA_j}$, where f and j index funds and s indexes securities.
Tenure	Number of years managing the fund. For team managed funds, *Tenure* is the average across individual managers. Manager identities and characteristics are from Morningstar and cover the period through September 2013.
Experience	Number of years managing any mutual funds.
ACT	Average ACT score of the students admitted to the university from which the fund manager received his or her undergraduate degree. ACT scores are for the 2001–2002 incoming class. Source: National Center for Education Statistics, IPEDS Data Center.

Table A2
Flow management through cash holdings: Alternative winsorization

This table shows the robustness of the flow management results to winsorizing fund flows at the 1st and 99th percentiles. In columns 1–3, the dependent variable is the change in cash over a six-month period, scaled by assets six months ago. In columns 4–6, the dependent variable is the change in the cash-to-assets ratio over a six-month period. The independent variables are monthly net fund flows, scaled by net assets six months ago. Time (half-year) fixed effects are included in columns 2 and 5. Objective-time fixed effects are included in columns 3 and 6. Panel A reports the results for equity funds 2003–2014. Panel B reports the results for bond funds January 2004–June 2012. Standard errors are adjusted for clustering by time.

Panel A: Equity funds

	$\frac{\Delta Cash_{i,t-6\to t}}{Assets_{i,t-6}}$			$\Delta\left(\frac{Cash}{Assets}\right)_{i,t-6\to t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$Flows_{i,t}$	0.178***	0.176***	0.179***	0.058***	0.058***	0.060***
	(0.017)	(0.016)	(0.016)	(0.012)	(0.011)	(0.011)
$Flows_{i,t-1}$	0.139***	0.137***	0.131***	0.020	0.021	0.016
	(0.023)	(0.023)	(0.023)	(0.014)	(0.014)	(0.014)
$Flows_{i,t-2}$	0.125***	0.120***	0.114***	0.023	0.024	0.017
	(0.024)	(0.024)	(0.023)	(0.016)	(0.016)	(0.015)
$Flows_{i,t-3}$	0.093***	0.089***	0.090***	−0.012	−0.014	−0.011
	(0.018)	(0.018)	(0.019)	(0.011)	(0.010)	(0.010)
$Flows_{i,t-4}$	0.066***	0.062***	0.064***	−0.005	−0.010	−0.009
	(0.021)	(0.021)	(0.021)	(0.011)	(0.010)	(0.010)
$Flows_{i,t-5}$	0.014	0.001	0.002	−0.061***	−0.066***	−0.064***
	(0.022)	(0.024)	(0.024)	(0.015)	(0.015)	(0.016)
N	19,037	19,037	19,037	19,037	19,037	19,037
Adjusted R^2	0.128	0.151	0.161	0.005	0.014	0.024
FE		YH	YH × Obj		YH	YH × Obj

Panel B: Bond funds

	$\frac{\Delta Cash_{i,t-6\to t}}{Assets_{i,t-6}}$			$\Delta\left(\frac{Cash}{Assets}\right)_{i,t-6\to t}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$Flows_{i,t}$	0.262***	0.245***	0.242***	0.109***	0.095***	0.088***
	(0.036)	(0.044)	(0.046)	(0.021)	(0.026)	(0.027)
$Flows_{i,t-1}$	0.017	0.015	0.026	−0.048	−0.047	−0.043
	(0.044)	(0.044)	(0.045)	(0.031)	(0.030)	(0.031)
$Flows_{i,t-2}$	0.207***	0.199***	0.195**	0.093*	0.085	0.079
	(0.068)	(0.070)	(0.070)	(0.050)	(0.051)	(0.052)
$Flows_{i,t-3}$	0.022	0.030	0.042	−0.086	−0.078	−0.068
	(0.060)	(0.060)	(0.068)	(0.052)	(0.053)	(0.060)
$Flows_{i,t-4}$	0.029	0.039	0.035	−0.048	−0.040	−0.040
	(0.051)	(0.050)	(0.051)	(0.053)	(0.052)	(0.053)
$Flows_{i,t-5}$	0.149**	0.157**	0.151**	−0.008	0.002	0.002
	(0.057)	(0.061)	(0.064)	(0.032)	(0.031)	(0.032)
N	2,494	2,494	2,494	2,494	2,494	2,494
Adjusted R^2	0.138	0.148	0.141	0.010	0.024	0.017
FE		YH	YH × Obj		YH	YH × Obj

Table A3
Cash-to-assets ratio and alternative measures of bond illiquidity

This table reports the results of the regressions of the cash-to-assets ratio on alternative measures of bond illiquidity. λ is the Dick-Nielsen, Feldhütter, and Lando (2012) measure of bond illiquidity. *Amihud (2002)* is calculated following Dick-Nielsen, Feldhütter, and Lando (2012). *IRC* is the Imputed Roundtrip Cost (Feldhütter 2012). γ is the Roll (1984) measure of illiquidity, calculated following Bao, Pan, and Wang (2011). All specifications include objective-time fixed effects. The sample period is January 2004–June 2012. All continuous variables are standardized so that their coefficients represent the effect of a one-standard deviation change in each variable. Standard errors are adjusted for clustering by fund family.

	λ	γ	$\sqrt{Amihud}$	IRC
	(1)	(2)	(3)	(4)
$\sigma(Flows)_{i,t}$	0.594***	0.776***	0.604***	0.573***
	(0.211)	(0.236)	(0.213)	(0.209)
$Illiq_{i,t}$	−0.445	0.758**	−0.530	−0.338
	(0.315)	(0.330)	(0.369)	(0.360)
$Illiq \times \sigma(Flows)_{i,t}$	0.324**	0.174	0.238*	0.367**
	(0.150)	(0.297)	(0.140)	(0.152)
$Size_{i,t}$	0.183	0.473	0.163	0.182
	(0.348)	(0.333)	(0.345)	(0.347)
$Family\ size_{i,t}$	−0.811**	−0.834**	−0.824**	−0.808**
	(0.351)	(0.386)	(0.349)	(0.352)
$Institutional\ share_{i,t}$	1.011***	0.847**	1.010***	1.003***
	(0.287)	(0.329)	(0.287)	(0.289)
$Turnover_{i,t}$	0.326	0.566	0.280	0.339
	(0.430)	(0.361)	(0.426)	(0.430)
$Sec\ lending_{i,t}$	5.234***	5.079***	5.221***	5.218***
	(0.756)	(0.880)	(0.761)	(0.762)
$Short\ selling_{i,t}$	−1.317	−2.261*	−1.339	−1.319
	(1.022)	(1.180)	(1.023)	(1.025)
$Options_{i,t}$	7.458**	6.288	7.427**	7.514**
	(3.129)	(3.863)	(3.100)	(3.105)
$Other\ practices_{i,t}$	2.167	2.397	2.093	2.131
	(1.659)	(1.767)	(1.650)	(1.660)
N	2,640	1,714	2,640	2,640
Adjusted R^2	0.196	0.223	0.196	0.196

Table A4
Instrumenting for asset illiquidity and flow volatility

This table reports the results of 2SLS regressions of the cash-to-assets ratio on asset illiquidity and flow volatility, instrumented with Lipper objective dummies interacted with fund age. OLS specifications include objective cross date fixed effects. 2SLS specifications include date fixed effects. All continuous variables are standardized so that their coefficients represent the effect of a one-standard deviation change in each variable. Standard errors are adjusted for clustering by Lipper objective.

	Equity funds		Bond funds	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
$Illiq_{i,t}$	0.981**	1.889***	−0.375	−1.379
	(0.464)	(0.416)	(0.411)	(2.436)
$\sigma(Flows)_{i,t}$	0.301***	0.867	0.569***	3.128***
	(0.083)	(0.712)	(0.139)	(0.619)
$Illiq \times \sigma(Flows)_{i,t}$	0.167*	1.275**	0.257	3.177
	(0.080)	(0.510)	(0.247)	(4.927)
$Holdings\ HHI_{i,t}$	0.965***	0.668**	1.455***	1.268***
	(0.256)	(0.262)	(0.094)	(0.097)
$Size_{i,t}$	0.044	0.265	0.354	0.819***
	(0.186)	(0.164)	(0.255)	(0.171)
$Family\ size_{i,t}$	−1.192***	−1.117***	−0.545**	−0.449
	(0.123)	(0.128)	(0.158)	(0.285)
$Institutional\ share_{i,t}$	0.471	0.558*	0.944***	0.507**
	(0.301)	(0.329)	(0.161)	(0.226)
$Turnover_{i,t}$	0.053	0.092	0.166	−0.200
	(0.116)	(0.126)	(0.299)	(0.276)
$Sec\ lending_{i,t}$	6.739***	6.769***	5.342***	5.518***
	(1.021)	(0.957)	(0.119)	(0.134)
$Short\ selling_{i,t}$	2.692**	1.995**	−1.289	−1.663
	(1.107)	(0.974)	(0.968)	(1.185)
$Options_{i,t}$	5.956***	5.070***	4.849*	4.106**
	(1.378)	(1.158)	(2.176)	(1.766)
$Other\ practices_{i,t}$	−3.170***	−3.752***	2.652*	3.652***
	(0.643)	(0.853)	(1.097)	(1.164)
N	22,201	22,201	2,643	2,643
Adjusted R^2	0.235	0.192	0.222	.