Do Fire Sales Create Externalities?*

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Abstract

We develop three novel measures of how much of the price impact of their trading different mutual funds internalize. We show that mutual funds that internalize more of their price impact hold larger cash buffers and use these buffers more aggressively to accommodate inflows and outflows. As a result, stocks held by these funds have lower volatility, and flows out of these funds have smaller spillover effects on other funds holding the same securities. Our results suggest that there are meaningful fire sale externalities in the mutual fund industry, and that a planner coordinating among funds would choose different liquidity management policies.

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Fire sales are at the center of our understanding of financial stability problems in securities markets. The mechanism generating financial stability problems is that forced sales by one market participant tighten constraints on others and thereby lead to further forced sales (e.g., Geanakoplos, 2009; Stein, 2012). For instance, redemptions from an open-end mutual fund can force sales of the fund's portfolio securities. These sales depress security prices, hurting the performance of other funds holding the same securities and thus stimulating redemptions at these funds through the performance-flow relationship. These redemptions lead to further sales, thus amplifying the initial shock. The key conceptual feature of such amplification cycles is that they generate externalities: a planner coordinating among funds would choose different actions, dampening the feedback effects across funds that arise from their forced trading.

A large empirical literature documents the existence of some of the main ingredients of the fire sales mechanism. Forced sales do result in depressed security prices (e.g., Coval and Stafford, 2007; Ellul, Jotikasthira and Lundblad, 2011; Greenwood and Thesmar, 2011; and Merrill et. al., 2012). Furthermore, these depressed prices do appear to affect other funds holding the same securities (Lou, 2012; Falato et. al., 2016). However, the empirical literature has not yet directly addressed the main conceptual question about fire sales: are there significant externalities so that a planner coordinating among funds would chose different actions? Although this question has important implications for both our conceptual understanding of fire sales and for the regulatory debate about the systemic risks posed by asset managers, it cannot be answered from the existing literature. Though there is evidence that forced sales exist, they may not be frequent enough that a planner would not choose a different outcome from the private market equilibrium. Similarly, it could well be the case that the costs of spillovers across funds are low enough that a planner would choose the same policies as private market participants.

In this paper, we take on this empirical challenge and provide strong evidence that a planner coordinating among funds would indeed choose different policies. We construct three novel, theoretically motivated measures of how much of the price impact of their trading different mutual funds are likely to internalize. We then relate these measures to the liquidity management policies of funds, the volatility of the securities they hold, and the spillover effects funds impose on each other. We find that funds that internalize more of the price impact of their trading[1] do behave

[1] For brevity, we refer to such funds as "high internalization funds."

substantially differently from those that do not, suggesting that there are indeed meaningful fire sale externalities in the mutual fund industry.

Our analysis uses a novel data set on the cash holdings of equity mutual funds collected from the SEC form N-SAR filings. Importantly, our data set covers holdings of both cash and cash substitutes such as money market mutual fund shares. In recent years, cash substitutes have become an increasingly important source of liquidity for asset managers, but are not always accurately tracked by some of the existing data sets. For instance, in 2014, mutual funds held $600 billion of cash and cash substitutes, with nearly 50% taking the form of cash substitutes.

We begin by proposing three new empirical measures of internalization for mutual funds. The first one is based upon the intuition that a monopolist fully internalizes its price impact. Indeed, in most theories of fire sales, the planner's problem is essentially the problem a monopolist would face. This suggests that funds that are more like monopolists in the securities they hold should internalize more of their price impact. Our second measure leverages the fact that many portfolio managers manage multiple funds and presumably care about exerting adverse price pressure across these funds. Our third measure exploits the idea that a fund may be cautious about exerting price impact when it would adversely affect other funds in the same fund family, even if those funds are not managed by the same portfolio manager.

We analyze actively managed open-end domestic equity funds over the 2003 – 2016 period and find four main results. Throughout our analysis, we use all three of our internalization measures. Even though these measures are only weakly correlated with each other, all three deliver similar results. Our first result concerns how funds' management of the inflows and outflows they receive varies with our internalization measures. We find that high internalization funds use their cash buffers more aggressively to accommodate flows. The economic magnitudes are significant. A fund that is one standard deviation higher on our internalization measures is 21 – 56% more aggressive in using cash to accommodate fund flows than the average fund. The magnitude of this effect is similar to the effect of investing in securities that are one standard deviation less liquid. Our evidence suggests that there is a price impact externality: a planner that fully internalizes price impact across funds would have funds follow a different strategy for accommodating inflows and outflows, just as the funds that are higher on our internalization measures do.

These results are robust to a variety of controls for alternative explanations. Specifically, we provide evidence that our results cannot be explained by asset liquidity, market timing on the part of individual funds, fund strategy, variation in investor clienteles across funds, or manager characteristics. In addition, we get similar results when we split the sample into small and large funds or split the sample before and after the financial crisis.

Our second main result is at the stock level. We show that when a stock is held by high internalization funds, its realized volatility is lower over the following quarter. Magnitudes here are modest in absolute terms, but significant relative to excess volatility that is induced by trading in response to fund flows (Greenwood and Thesmar, 2011). The variation in volatility induced by our internalization measures is similar in magnitude to the variation induced by fund flows overall. This suggests that the price impact externality that funds impose on one another has meaningful consequences for the behavior of asset prices.

Our third main result concerns the degree to which flows into one fund impact the performance of other funds holding the same securities (Lou, 2012). We show that flows into high internalization funds exert a smaller spillover effect on the returns of other funds than flows into low internalization funds. Specifically, we show that when a given fund's securities are held by other funds that internalize more of their price impact, the relationship between flows into these other funds and returns of the first fund is diminished. The economic magnitudes are again meaningful: a one-standard deviation increase in our internalization measures is associated with an 8-11% reduction in the strength of the relation between returns and flows into other funds with overlapping holdings.

Finally, we examine the relation between our internalization measures and the fund's cash-to-assets ratio. We find that high internalization funds hold larger cash buffers. The magnitudes are economically significant, again comparable to the variation in cash-to-assets ratios induced by variation in asset liquidity. While our first three main results are about funds' ex post behavior, i.e., how funds respond to realized inflow and outflows, the cash holdings result is fundamentally ex ante: it shows that high internalization funds behave differently essentially before fund flows are realized. This is a close empirical analog to the problem a planner would solve in a theoretical model.[2]

[2] Appendix A2 contains a simple model along these lines.

Overall, our results provide strong evidence that fire sale externalities operate across equity mutual funds. A planner coordinating among funds would have them act very differently from how they act in the private market equilibrium. It is important to note that our results do not imply a welfare statement. For there to be a social loss from the behavior of low internalization funds in general equilibrium, the liquidation costs borne by mutual funds when they sell must not simply be a transfer to an outside liquidity provider.[3]

Our paper is related to several strands of the literature. First, 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.

In addition, we contribute to a small but growing literature on the determinants and effects of mutual fund cash holdings, including Yan (2006), Simutin (2014), and Hanouna, et al (2015). While this literature focuses primarily on funds' market timing ability and the impact cash holdings have on returns, we use cash holdings along with our internalization measures to empirically measure the extent to which funds internalize the price impact they exert on security prices.

The remainder of the paper is organized as follows. Section I outlines our empirical tests. Section II describes the data. Section III presents our main results, and Section IV concludes.

[3] For example, fire sales that result in banks suffering losses may impair the functioning of the bank lending channel (see, for example, Bernanke and Blinder, 1988; Kashyap and Stein, 2000; Stein, 2012). Similarly, losses and redemptions by high yield mutual funds can negatively affect the investment of speculative-grade firms (Chernenko and Sunderam, 2012). Even highly rated firms that borrow in money markets may find it difficult to immediately substitute to other sources of financing when money market mutual funds experience large redemptions (Chernenko and Sunderam, 2014).

[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.

I. Framework

This section outlines the economic logic behind our internalization measures and empirical tests.

A. Measures of Internalization

Throughout the paper, we use three different measures of internalization. We describe the construction of these variables in more detail in Section II below; our focus here is on the economic motivation for examining each variable. Our first internalization measure is *Share outstanding*—the weighted average of a fund's holdings of each portfolio security relative to the security's outstanding amount. The idea here is that fire sale externalities stem from the fact that multiple funds hold the same security. When any individual fund sells the security, the fund does not internalize the effect of forced sales on the other funds that hold the same security. This logic implies that a monopolist in a particular security fully internalizes its own price impact. When a monopolist creates price impact through trading, it is the only fund that suffers because it is the only fund that holds the security. Our *Share outstanding* variable generalizes this intuition: the higher it is, the closer to a monopolist the fund is in the securities it holds.

Our second measure of internalization leverages the fact that many mutual fund managers manage multiple funds. Our *Manager overlap* variable measures the overlap in portfolio holdings across multiple funds managed by a given portfolio manager. The idea here is that fund managers care about the joint performance of all the funds they manage. Thus, managers will be reluctant to trade if the price impact generated by the trading of one of their funds adversely affects the performance of their other funds. The scope for such adverse impact is greater when portfolio holdings overlap a lot across the funds the manager manages.

Our third measure of internalization is based on the idea that fund families may at least partially internalize price impact across different funds in the family. This kind of internalization is sometimes incentivized by the compensation contracts of fund managers.[5] For instance, according to the prospectus of Metropolitan West Funds, "Many portfolio managers participate in equity incentives based on overall firm performance of the TCW Group and its affiliates, through ownership or participation in restricted unit plans that vest over time or unit appreciation plans of

[5] Ibert et. al. (2017) show the importance of firm-level revenues and profit for the compensation of mutual fund managers in Sweden.

the Adviser's parent company." [6] Similarly, the prospectus of Oppenheimer Rising Dividends Fund states, "the long-term award component consists of grants in the form of appreciation rights in regard to the common stock of the Sub-Advisers holding company parent, restricted shares of such common stock, as well as deferred cash investments in the fund(s) managed by a portfolio manager." [7] 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. Our *Family overlap* measure captures the overlap in portfolio holdings across multiple funds in the same fund family.

B. Empirical Predictions

We next outline the main empirical predictions we test in the body of the paper. Appendix A2 contains a simple model that formalizes some of the key predictions. The first prediction concerns how mutual funds respond to inflows and outflows from their investors.

Prediction 1. Funds that internalize more of their price impact will use their cash holdings more aggressively to accommodate inflows and outflows.

The idea here is that funds that internalize more of their price impact will be more reluctant to immediately trade in their portfolio securities because doing so would exert significant price pressure. Instead, high internalization funds will use cash buffers to temporarily accommodate inflows and outflows, trading more slowly in their portfolio securities to minimize price impact over time.

Our next two predictions explore the implications of these differences in flow management practices across funds. The second prediction concerns the effect of flow management behavior on security prices.

Prediction 2. Securities held by funds that internalize more of their price impact will experience lower realized volatility.

Mutual fund trading of portfolio securities in response to fund flows introduces excess volatility in the returns of those securities (Greenwood and Thesmar, 2011). However, if high internalization

[6] https://www.sec.gov/Archives/edgar/data/1028621/000119312516656538/d204146d485bpos.htm
[7] https://www.sec.gov/Archives/edgar/data/312555/000072888916004375/risingdividends485bpos.htm

funds are successful at using their cash buffers to accommodate inflows and outflows, then securities held by high internalization funds will experience lower flow-induced volatility than securities held by low internalization funds that are subject to the same fund flow volatility.

The third prediction concerns the effect of flow management on other funds holding the same securities.

Prediction 3. The relationship between a fund's returns and the flows of other funds holding the same securities will be weaker when the other funds internalize more of their price impact.

Lou (2012) shows that because they may result in flow-induced trading, flows into other funds holding the same securities as a given fund have a temporary effect on the fund's returns that reverses over time as price pressure dissipates and prices return to fundamental values. The idea behind Prediction 3 is that if the other funds holding the same securities as fund *f* internalize more of their price impact, then these funds will be more cautious when it comes to trading portfolio securities in response to fund flows. As a result, the relation between their flows and fund *f*'s returns will be weaker.

Our final prediction is that in order to accommodate a larger fraction of fund flows through changes in cash, high internalization funds will hold larger cash buffers.

Prediction 4. Funds that internalize more of their price impact will hold larger cash buffers.

While our first three main results are about funds' ex post behavior, i.e., how funds respond to realized inflow and outflows, the cash holdings result is fundamentally ex ante: it shows that high internalization funds behave differently prior to the realization of fund flows.

II. Data

A. Cash holdings

We combine novel data on the cash holdings of open-end mutual funds with several other data sets. Our primary data comes from the SEC form N-SAR filings.[8] These forms are filed semi-annually by all mutual funds and, among other things, provide data on asset composition, including

[8] We discuss parsing of N-SAR filings in the appendix.

holdings of cash and cash substitutes. Specifically, we measure holdings of cash and cash substitutes as

> *cash* (item 74A) + *repurchase agreements* (74B) + *short-term debt securities other than repurchase agreements* (74C) + *other investments* (74I) – *securities-lending collateral.*

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)[9], other mutual funds, loan participations, and physical commodities. The last three apply mostly to funds of funds, loan funds, and commodity funds that are excluded from our sample of actively managed domestic equity funds. 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 main dependent variable, and thus should only inflate our standard errors, biasing us against finding significant results.[10]

Cash holdings reported on a fund's balance include cash collateral received when lending out portfolio securities. This cash collateral is usually legally segregated and therefore not available to meet redemption requests. We use a Python script to extract the amount of securities

[9] Holdings of MMMFs are reported either under short-term debt securities other than repurchase agreements (74C), based on the underlying assets of these funds being short-term debt securities, or alternatively under other investments (74I), since MMMFs do not naturally fit in the other categories.

[10] The 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. Aggregate cash holdings of all long-term mutual funds in CRSP track aggregate holdings of liquid assets of long-term mutual funds as reported by the Investment Company Institute (ICI) until 2007, but the relationship breaks down after that. By 2014, there is a gap of more than $400 billion, or more than 50% of the aggregate cash holdings reported by ICI. At a more granular level, we calculated cash holdings from the bottom up using security-level data from the SEC form N-CSR for a random sample of 200 funds. The correlation between the true value of the cash-to-assets ratio computed using N-CSR data and our N-SAR based proxy is 0.93. The correlation between the true value and CRSP is 0.57.

lending collateral from N-CSR filings, and subtract securities lending collateral from the gross value of cash holdings reported in N-SAR filings.

Our dependent variable is thus the sum of cash and cash equivalents, net of securities lending collateral, scaled by TNA (item 74T). We winsorize this cash-to-assets 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 are reported in item 28. Item 70 reports indicators for whether the fund uses various types of derivatives, borrows, lends out its securities, or engages in short sales.

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. Our matching algorithm, described in greater detail in the appendix, consists of two main steps. In the first step, we attempt to link funds based on their ticker, which is available for most funds in N-SAR data starting in 2006. If a fund has multiple share classes, we require all class tickers to agree on the CRSP_CL_GRP fund identifier that a given fund in N-SAR links to. In the second step, we link unmatched funds—those without tickers and those not matched in the first step—based on their name.[11] Finally, we check that the ratio of TNA in N-SAR relative to CRSP lies in the [0.5, 1.5] interval and discard any observations outside this interval. We match more than 70% of all fund-time observations in N-SAR to CRSP. In dollar terms, we match more than 80% of all assets.

After linking N-SAR data to CRSP, we limit the sample to open-end actively managed domestic equity funds that are open to investors. We limit the sample to actively managed, open-end funds because these are the funds that are free to accommodate fund flows using either changes in cash or trading in the underlying portfolio securities. In contrast, open-end index funds hold little cash and mostly scale their portfolios up and down with fund flows, while ETFs rely on

[11] The name-based merge 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. 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.

investors to provide liquidity in the secondary market and limit share creation and redemption to authorized participants (APs) who maintain parity between the market price of the fund's shares and their NAV.[12]

We restrict the sample to domestic equity funds because these are the funds for which we can relatively accurately measure asset liquidity and internalization.[13] Many corporate bonds trade too infrequently to measure their liquidity. Furthermore, since most firms issue multiple bonds that are imperfect substitutes for each other, it is unclear how to measure the scope for spillover effects and thus for internalization in the context of corporate bonds. Finally, to further ensure that we can accurately measure fund flow volatility and asset liquidity, we focus on funds with TNA of at least $100 million in 2012 dollars.

C. Asset liquidity

We use holdings data from the CRSP Mutual Fund Database to measure the liquidity of equity mutual fund holdings.[14] 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 level, taking the value-weighted average of individual stock liquidity.

D. Internalization

Using CRSP Mutual Fund holdings data, we construct three measures of internalization. The first one is *Share outstanding* - the weighted average of a fund's holdings of each portfolio security relative to the security's outstanding amount:

$$Share\ outstanding_f = \sum_s \frac{V_{f,s}}{\sum_s\ V_{f,s}} \times \frac{V_{f,s}}{Outstanding_s},$$

where f indexes funds, s indexes securities, $V_{f,s}$ is the value of fund f's holdings of security s, and $Outstanding_s$ is the total amount of security s outstanding. Because data on the amount outstanding comes from CRSP, calculation of *Share outstanding* is limited to portfolio securities with valid

[12] Internet appendix tables IA1 and IA2 confirm that cash holdings of index funds are less responsive to fund flows than cash holdings of actively managed funds and that the cash-to-assets ratio of index funds does not depend much on the illiquidity of their assets or the extent to which they may internalize price impact.
[13] Domestic equity funds are identified based on CRSP objective codes that begin with ED.
[14] In unreported analyses, we obtain similar results when we use Thomson Reuters Mutual Funds Holdings data.

PERMNOs and ignores holdings of non-equity or private securities.[15] Because our sample consists of domestic equity funds, omission of securities not in CRSP constitutes a small fraction of fund holdings.

Our second measure of internalization is *Manager overlap,* which measures the overlap in portfolio holdings across multiple funds managed by a given portfolio manager. For each security *s* held by fund *f*, we calculate aggregate holdings of the security by all other funds managed by the same portfolio manager and divide this by the aggregate portfolio value of all funds managed by the portfolio manager. We then calculate the value-weighted average across all securities held by fund *f*. Specifically, we define

$$Manager\ overlap_f = \sum_s \frac{V_{f,s}}{\sum_s V_{f,s}} \times \frac{\sum_{j,mgr(j)=mgr(f),j\neq f} V_{f,s}}{\sum_{j,mgr(j)=mgr(f)} \sum_s V_{j,s}},$$

where *mgr(f)* is the manager of fund *f*. We obtain portfolio manager identities from Morningstar. For funds managed by multiple portfolio managers, we split total holdings of each security equally among the fund's managers.

Our third measure of internalization, *Family overlap,* is meant to capture the overlap in portfolio holdings across multiple funds in the same fund family. Even if such funds are not managed by the same individual portfolio managers, the fund family may provide incentives for portfolio managers to at least partially internalize the impact of their trading decisions on the performance of other funds within the family. For each security *s* held by fund *f*, we calculate aggregate holdings of the security by all other funds in the same family and divide this by the aggregate portfolio value of all funds in the family. We then calculate the value-weighted average across all securities held by fund *f*. Formally, we define

$$Family\ overlap_f = \sum_s \frac{V_{f,s}}{\sum_s V_{f,s}} \times \frac{\sum_{j,family(j)=family(f),j\neq f} V_{f,s}}{\sum_{j,family(j)=family(f)} \sum_s V_{j,s}},$$

where *family(f)* is the family of fund *f*. Note that since *Manager overlap* and *Family overlap* do not use data on securities' total amounts outstanding, we can construct these measures using all portfolio securities (with valid CUSIPs) and not restrict the calculation to stocks in CRSP. Our

[15] Chernenko et. al. (2017) show, for example, that some US equity mutual funds have been increasing their investment in unicorns: private firms with valuations of at least $1 billion. For the average fund, however, holdings of unicorns still account for only two basis points of TNA.

family overlap measure is similar to the measure used by Elton, Gruber, and Green (2007), who find that fund returns are more correlated within fund families than across fund families. They compute pairwise overlap between two funds in a family, while our measure generalizes the idea and compares a given fund to all other funds in the same fund family.

Where does variation in our measures comes from? Our measures all rely on the size of the positions individual funds hold in particular stocks. As such, the primary determinant of our measures is likely to be the distribution across fund managers of perceptions of risk and expected returns for each stock. If a particular manager has strong, positive expectations for a stock relative to other managers, they are likely to hold a large position in that stock, which would drive up their *Share outstanding*. Similarly, if the manager managed two funds and had strong, positive expectations for a stock, they would likely hold the stock in both funds, driving up their *Manager overlap*. In addition, for the *Manager overlap* and *Family overlap* measures, the distribution of fund objectives is likely to play an important role. If a manager manages two large-cap value funds, overlap is likely to be higher than if they manage a large-cap value and a small-cap value fund. Overall, we think the distribution of perceived expected returns and the distribution of fund objectives are unlikely to be correlated with other explanations for our results. Below we perform a detailed examination of alternative explanations that supports this conclusion.

E. 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 holdings liquidity and internalization from CRSP and Morningstar. We conduct most of our analyses at the fund-half year level. The sample period, determined by the availability of holdings data in CRSP, is January 2003 – December 2016.

Table 1 reports basic summary statistics for funds in our data. Our sample of actively managed domestic equity funds consists of about 23,500 observations. The median fund has TNA of about $600 million, of which about 2.6% is held in cash and equivalents. There is significant variation across funds in the cash-to-assets ratio: the interquartile range is 1.1%-5.0%. Consistent with an aggregate shift towards index funds, the median fund in our data experiences quarterly fund flows of -0.6%.

Turning to the internalization measures, the typical fund owns 0.15% of the total outstanding amount of the securities it owns. The typical fund also has *Manager overlap* and *Family overlap* of 0.20% and 0.20% with significant cross-sectional variation across funds.

Table 2 reports correlations of key variables in our data. *Share outstanding* is essentially uncorrelated with our two other internalization measures, while *Manager overlap* and *Family overlap* have a correlation of 0.45. These results suggest that our measures are not redundant and instead capture different aspects of the propensity to internalize price impact. Table 2 also reports correlations between our internalization measures and a host of fund characteristics. In general, our measures are quite weakly correlated with fund characteristics. There are 39 correlations between our three internalization measures and the 13 fund characteristics reported in Table 2, and only two are above 0.2 in absolute magnitude.

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

III. Results

We now present tests of the empirical predictions outlined above. For much of 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. As noted above, however, Table 2 shows that our internalization measures have relatively low correlations with other fund characteristics, and we consider and rule out a variety of alternative explanations for our results below.

A. Liquidity management through cash holdings

To ensure our later tests have power, we begin by analyzing the baseline flow management behavior of mutual funds. We show that cash holdings play an important role in the way mutual funds manage inflows and outflows, which means that studying the behavior of cash holdings is a powerful way to detect differences in flow management across funds. We observe fund flows every month, but only observe funds' cash holdings every six months. Therefore, in Table 3, we estimate regressions of the change in a fund's cash-to-assets ratio over the last six months on the net flows received during each of those six months:

$$\Delta Cash_{f,m-6:m} = \alpha_{obj(f),m} + \beta_0 Flows_{f,m} + \ldots + \beta_5 Flows_{f,m-5} + \varepsilon_{f,m}. \tag{1}$$

Fund flows are winsorized at the 5th and 95th percentiles; results are similar when winsorizing at the 1st and 99th percentiles. The dependent variable is the change in the fund's cash-to-assets ratio:

$$\Delta Cash_{f,m-6:m} = \left(\frac{Cash}{TNA}\right)_{f,m} - \left(\frac{Cash}{TNA}\right)_{f,t-6}.$$

The coefficient $\beta_0 = 0.10$ is statistically and economically significant. Flows equal to 100% of assets increase the fund's cash-to-assets ratio by 10% (percentage points). For reference, the standard deviation of monthly fund flows is 9%. The specification includes Lipper objective code by time (half-year) fixed effects, indicating that the results are not driven by relationships between flows and cash holdings in particular fund objectives.

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, funds do not simply scale their portfolios up and down in response to fund flows. Instead, the overall composition of their portfolio is changing, becoming more cash-heavy when a fund receives inflows and less cash-heavy when it suffers outflows. 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. By month *m-3*, the coefficient is 0.043. The coefficients then turn negative, indicating that over the full six-month period, the total effect of flows on cash holdings is essentially zero.

The second column of Table 3 shows that the results are similar if we include fund fixed effects, showing that the results are not driven by a correlation between the average change in cash and the average flows an individual fund faces over the sample period. Finally, the third column shows that the results remain essentially unchanged if we include both fund fixed effects and Lipper objective code cross time fixed effects.[16]

Appendix Table A2 estimates Eq. (1), splitting fund flows into subscriptions versus redemptions. We find that funds respond relatively symmetrically to inflows and outflows. This is consistent with the idea that funds care about the price pressure they exert on the underlying assets when both buying and selling.

B. Internalization and flow management

We next examine how the propensity to accommodate fund flows using cash holdings varies with our internalization measures. Table 4 estimates specifications that allow flow

[16] We lose 161 observations when both fund and Lipper objective by time fixed effects are included.

management practices to differ across the cross section of funds based on our internalization measures:

$$\begin{aligned}\Delta Cash_{f,t-2:t} = \alpha_{obj(f),t} &+ \beta_1 Flows_{f,t} + \beta_2 Flows_{f,t} \times FundInternalize_{f,t-2} + \beta_3 Flows_{f,t} \times Illiq_{f,t-2} \\ &+ \beta_4 Flows_{f,t-1} + \beta_5 Flows_{f,t-1} \times FundInternalize_{f,t-2} + \beta_6 Flows_{f,t-1} \times Illiq_{f,t-2} \\ &+ \beta_7 FundInternalize_{f,t-2} + \beta_8 Illiq_{f,t-2} + \varepsilon_{f,t}.\end{aligned} \tag{2}$$

For compactness, we aggregate flows into quarters and refer to time in quarters. We interact quarterly flows with the lagged values of our internalization measures. Thus, the specification asks: does the way a fund responds to flows depend on how much we expect the fund to internalize its price impact?

Eq. (2) controls for quarterly flows interacted with the illiquidity of the fund's holdings, as measured by the value-weighted average of the square root version of the Amihud (2002) measure for each of fund's holdings (Chen et. al., 2010). This helps us separate liquidity from internalization. Liquidity is essentially independent of who holds the security: any fund holding a given illiquid security will be expected to use cash more aggressively to accommodate fund flows because the fund itself incurs large transaction costs when it trades that security. Internalization is a holdings-level concept: it is determined by which funds hold the security and how much they care about exerting price impact on one another. Two funds holding the same security would incur the same transaction costs but may internalize more or less of the price impact they impose on other funds.

The dependent variable in Eq. (2) is once again the change in the fund's cash-to-assets ratio. We standardize the internalization and illiquidity variables so that their coefficients can be interpreted as the effect of a one-standard deviation change in each variable. Again, all specifications include Lipper objective cross time fixed effects.

The first column of Table 4 shows that for the average equity fund, flows equal to 100% of assets over the most recent quarter t change the cash-to-assets ratio by $\beta_1 = 5.3$ percentage points. For a fund that internalizes its price impact one standard deviation more than the average fund, as measured by *Share outstanding*, the same flows change the cash-to-assets ratio by $\beta_1 + \beta_2 = 6.4$ percentage points, a 21% larger effect. For a fund with assets one standard deviation less liquid than the average fund, the effect of flows on cash holdings is of a similar magnitude. Thus, the impact of our internalization measures is economically sizeable. The reduction in trading we would observe if funds internalized more of their price impact from trading is similar to the reduction we would observe if their assets were substantially less liquid.

Since *Share outstanding* is correlated with fund size (0.46), it may be that the interaction of fund flows with *Share outstanding* captures differences in flow management across funds of different size rather than differences in internalization. To address this concern, column 2 of Table 4 controls for the interaction of fund size with fund flows. Essentially, this specification compares two funds of the same size, one of which should internalize more of its price impact than the other. In this specification, the interactions of size and fund flows are not statistically significant, but their inclusion increases the standard error of the interaction of *Share outstanding* with fund flows so that its coefficient is now significant at 7%.

Columns 3—6 of Table 4 show that similar results obtain using our other measures of internalization: *Manager overlap* and *Family overlap.* When using *Manager overlap* in column 4, we control for the interaction of fund flows with the number of other funds managed by the fund's portfolio managers. This specification therefore compares managers who manage the same number of funds but where some managers have greater overlap in holdings across their funds. When using *Family overlap* in column 6, we control for the interaction of fund flows with family size. This specification effectively compares funds that belong to families of similar size but where some funds have greater overlap in holdings with other funds in the same family.

The economic magnitude of the effects of *Manager overlap* and *Family overlap* on a fund's propensity to use cash to manage flow is quite sizable. A fund that internalizes its price impact one standard deviation more than the average fund, as measured by *Manager overlap* (*Family overlap*), is 37% (56%) more aggressive in using cash to manage flows than the average fund. Our *Family overlap* results are interesting in light of Goncalves-Pinto and Schmidt (2013), who find that when funds suffering outflows are forced to sell some of their securities, other funds within the same family increase their positions in the fire sold securities. This kind of cross trading across funds is positively correlated with our measures of internalization, and thus biases us against finding our results: if funds can cross-trade, they do not need to hold as much cash. Nonetheless, funds with high *Family overlap* do manage fund flows more aggressively using cash.

Overall, despite the fact that our measures are not highly correlated with each other, we obtain similar results with all of them. Funds that internalize more of their price impact are more aggressive in using cash to manage inflows and outflows. These results are consistent with Cella, Ellul, and Giannetti (2013), who show that during episodes of market turmoil, institutional investors with short trading horizons sell their stock holdings to a larger extent than institutional investors with longer trading horizons. Since funds that do not internalize the costs of their trading are likely to trade more, low internalization funds are endogenously likely to have shorter trading horizons. Thus, they will be more likely to sell their stocks, rather than draw down their cash buffers in times of market turmoil.

C. *Robustness of Flows Results*

The results in Table 4 show that our measures of internalization strongly affect funds' flow management strategies. Funds that score highly on our internalization measures use cash more aggressively to meet inflows and outflows. This is consistent with the idea that they care more about minimizing the price impact of their trades. However, given that our internalization measures are proxies, there could be other explanations for these results.

Table 5 reports a battery of robustness tests that examine these alternative explanations. In particular, we examine the possibility that our results are driven by market timing on the part of individual funds, asset liquidity, fund strategy, variation in investor clienteles across funds, and manager characteristics. Each row of the table shows the results of a different robustness test. All specifications include Lipper objective by time fixed effects. Row (1) replicates our baseline results from columns (1), (3), and (5) of Table 4. For compactness, we only report the coefficient on our variable of interest, the interaction of fund flows during the most recent quarter with our internalization measures. It is worth noting that some of the alternative explanations we examine do affect how funds manage their flows. That is, the controls we add to the regression do themselves enter significantly. However, controlling for these alternative explanations does not affect our key result that internalization is associated with greater propensity to accommodate fund flows through cash holdings.

In Row (2) of Table 5, we control for the fund's monthly returns during the semi-annual reporting period. Because of the performance-flow relationship, funds with positive flows are likely to have generated high returns. These high returns mechanically depress a fund's cash-to-assets ratio, and thereby bias down the coefficient on fund flows. If there are differences in the strength of the performance-flow relationship between high- and low-internalization funds,[17] the degree of this bias will vary across funds and could explain our finding of a positive interaction between fund flows and internalization. Row (2) of Table 5 shows that controlling for past returns has no impact on our results.

Whether funds accommodate fund flows through changes in cash or trading in the underlying securities could depend on fund managers' expectations of future returns. If our measures of internalization, *Share outstanding* and *Manager overlap* in particular, proxy for the strength of a fund manager's conviction about portfolio securities' expected returns, then the manager may want to satisfy redemption requests using the fund's cash buffer rather than selling portfolio securities. This could help explain the stronger sensitivity of cash to fund flows for high internalization funds.[18] Row (3) of Table 5 uses future returns realized over the following one, three, six, and 12 months as proxies for expected returns. Controlling for these proxies does not affect the coefficient of interest.

We next consider the possibility that our internalization measures are just additional proxies for the illiquidity of fund holdings. Though Table 4 controls for the interaction of flows and illiquidity, our measure of illiquidity is potentially noisy, and its effect on cash holdings may be non-linear. Rows (4), (5), and (6) of Table 5 explore this alternative. Row (4) shows that controlling for five powers of illiquidity and their interactions with flows has no effect on our results. Row (5) shows that the same conclusion holds when we control for deciles of illiquidity and their interactions with flows.[19]

In row (6), we examine the possibility that the weighted average liquidity of a portfolio may not fully capture the effect of holdings illiquidity on flow management. Consider two funds, A and B, whose holdings have the same average liquidity. Suppose all securities held by fund A have the same level of liquidity, while half of securities held by fund B are very liquid and the other half are very illiquid. Even though the two funds have the same average liquidity, fund B may trade its liquid securities and may avoid adjusting its cash holdings in response to fund flows. A negative correlation between our internalization measures and dispersion in liquidity across

[17] For instance, more experienced managers generally face weaker performance-flow. They may also manage more funds and have greater overlap in holdings, leading them to have higher internalization measures.
[18] At the same time, the manager may want to use any inflows to increases her positions, resulting in a weaker sensitivity of cash to fund flows.
[19] Deciles of illiquidity are defined relative to the full sample of fund-half year observations.

securities held by a given fund could then explain the positive coefficient on the interaction of fund flows and internalization. To rule out this possibility, row (6) of Table 5 separately controls for the liquidity of each 10% slice of fund's portfolio from most to least liquid (and the interaction of each of these with fund flows). Overall, rows (4), (5), and (6) of Table 5 are strong evidence that our internalization measures are not simply proxies for the illiquidity of fund holdings. In Internet Appendix Tables IA3 and IA4, we also show our results are robust to including security-time fixed effects when using position-level (i.e., security-fund-time) data, which ensures that our results are not driven by any time-varying security characteristics.[20]

We next consider the idea that our internalization measures could be correlated with fund strategies. For instance, having a high value of *Share outstanding* could indicate that the fund manager tends to make big bets. We explore this alternative in rows (7), (8), and (9) of Table 5. In row (7), we control for the concentration of the fund's holdings, as measured by the Herfindahl-Hirschmann Index (HHI) of portfolio weights, and its interaction with fund flows. This does not affect our results. The same is true in row (8), where we control for the share of the single largest position in the fund's portfolio and its interaction with flows. In row (9), we control for the fund's active share as defined by Cremers and Petajisto (2009) and its interaction with flows. The point estimates on the interaction between our internalization measures and flows here are bigger than in the baseline sample. Overall, rows (7), (8), and (9) of Table 5 provide strong evidence that our results are not driven by differences in strategies across funds.

In row (10), we consider the possibility that our internalization measures are correlated with the investor clienteles that different funds serve. The main concern here is the following. In a dynamic model, Zeng (2016) shows that aggressive use of cash to manage fund flows may create an incentive for fund shareholders to run on the fund. Chen, Goldstein, and Jiang (2010) and Goldstein, Jiang, and Ng (2016) argue that retail investors are subject to stronger strategic complementarities, while institutional investors are more likely to internalize the effect of their

[20] Specifically, we form a security-fund-time panel and run regressions analogous to those in Table 4. The dependent variable for security s held by fund f at time t is the cash-to-assets ratio of fund f at time t. The independent variable of interest is an internalization measure for fund f at time t. Thus, we are effectively running fund-time level regressions within our security-fund-time level dataset. The key difference between Tables 4 and IA3 is that we can include security fixed effects in Table IA3. Thus, the results in Table IA3 look at variation within security, absorbing variation across securities in the average characteristics of the funds holding that security. Put differently, the results compare two funds that hold the same security, one of which internalizes more of its price impact than the other. The results in Table IA 3 are very similar to results in Table 4.

redemptions on a fund's performance. Funds catering to retail investors may therefore want to be less aggressive in using cash to manage fund flows, since doing otherwise risks incentivizing shareholder runs (Zeng, 2016). At the same time, concerned about the fickle nature of retail investors, funds with high retail share may avoid taking large concentrated positions that would result in high *Share outstanding*. Correlation between our internalization measures and fund clienteles could therefore help explain differences in flow management. To address this concern, row (10) controls for institutional share as well as the number of share classes, the concentration of fund assets across share classes, and whether the fund charges a front load, and the interaction of these clientele proxies with flows. These controls have no effect on our results.

In row (11), we consider the possibility that our internalization measures reflect differences in fund manager characteristics. For example, more experienced portfolio managers tend to manage more funds, which may have greater overlap in their holdings.[21] It could be that instead of capturing the effect of internalization, our results are capturing differences in the behavior of more- versus less-experienced managers. To rule out this possibility, we control for whether the fund is team managed, the number of managers, the years of experience of the manager, whether the manager has a CFA, and the interactions of these variables with fund flows. Again, this has no effect on our main results.

Finally, in rows (12)-(15), we examine two sample splits. First, rows (12) and (13) show that we get similar results for small (below median TNA) and large (above median) funds. In rows (14) and (15), we examine the impact of our internalization measures during the first and second half of our sample period. Given the smaller sample size, the standard errors here are larger, and statistical significance is weaker. Overall, however, we find broadly similar results during the two subperiods.

Overall, Table 5 provides strong evidence that we are picking up the impact of internalization on flow management. Our examination of a wide variety of plausible alternative explanations for our results does not seem consistent with those explanations driving our results.

[21] An inexperienced manager who manages a single fund will by construction have zero *Manager overlap.*

D. Internalization and Fragility

What are the implications of differences in flow management practices across funds for the price behavior of the assets that different funds hold? Greenwood and Thesmar (2011) show that stocks held by funds with volatile or highly correlated fund flows experience higher volatility. As these funds trade the same stocks at the same time in response to inflows and outflows, their trading activity introduces excess volatility in the returns of the underlying stocks. In this section, we ask whether stocks held by high internalization funds experience lower realized volatility. One might expect this to be the case because high internalization funds are less likely to trade in their holdings right away in response to flows. To test this prediction, we estimate the regression

$$Vol_{s,t+1} = \alpha_s + \alpha_{t+1} + \beta \cdot StockInternalize_{s,t} + \gamma' X_{s,t} + \varepsilon_{s,t+1},$$

where $Vol_{s,t+1}$ is the realized volatility of stock s in quarter t+1 and $StockInternalize_{s,t}$ is the average of one of our internalization measures across all holders of stock s at the end of quarter t, weighted by the size of their holdings.[22] The regression includes stock and time fixed effects. In addition, we include in the set of controls $X_{s,t}$ the size (log market capitalization) of the stock, the fraction of the total market capitalization held by mutual funds, and the fragility measure of Greenwood and Thesmar (2011). For each stock, the fragility measure combines mutual fund holdings data on the stock with the variance-covariance matrix of flows faced by each mutual fund to compute the volatility of flows netted across all funds holding the stock.[23] Thus, our specification asks whether controlling for the volatility of flows into funds holding different stocks, the ones held by high internalization funds experience lower volatility.

Table 6 reports the results, with the dependent variable expressed in percentage form. In the first column, we use *Share outstanding* as our internalization measure. A one-standard deviation increase in the average level of internalization across holders of a given stock is

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[22] To account for the fact that a given fund may trade in different portfolio securities in response to fund flows, we use the fund's propensity to internalize price pressure in stock s rather than the portfolio average measures used in our flow management regressions.

[23] Specifically, let $W_{f,s}$ be the matrix describing holders of stock s by fund f at time t and let Ω_t be the variance covariance matrix of flows across funds. The fragility measure is given by $W'\Omega W$. Given the computational difficulties of estimating cross-fund correlations in fund flows, we use the "diagonal" version of the Greenwood and Thesmar (2011) fragility measure that ignores the correlation in fund flows across funds. Column (4) of Table 3 in Greenwood and Thesmar (2011) shows that the diagonal version of fragility generates similar results to the full version that accounts for cross-correlation.

associated with a 0.38-percentage point reduction in the stock's volatility. Given that mean volatility for the stocks in our sample is 38.7%, this is not a large effect in absolute terms. However, the relevant benchmark here is not overall volatility but excess volatility induced by mutual fund trading. Internalization cannot affect the part of a stock's volatility that is generated by news about fundamentals; it can only affect the volatility induced by trading. Thus, it is more natural to compare the effect of internalization to the effect of the Greenwood and Thesmar (2011) fragility measure. As the first column of Table 6 shows, a one-standard deviation increase in fragility is associated with a 0.18-percentage point increase in volatility, similar to what Greenwood and Thesmar (2011) find. Compared to this benchmark, the effect of internalization is significant.

In the second and third columns of Table 6, we split stocks into liquid (below median illiquidity) and illiquid (above median). As expected, the effects of internalization (and of fragility) are stronger for less liquid stocks. In these stocks, the reluctance of funds that internalize their price impact to trade has a larger impact on volatility.

The remaining columns of Table 6 show that we get similar results for our other internalization measures. A one-standard deviation increase in *Manager overlap* is associated with a 0.23-percentage point decrease in volatility, while a one-standard deviation increase in *Family overlap* is associated with a 0.18-percentage point decrease. These magnitudes are again similar to the impact of flow-induced mutual fund trading overall, as measured by fragility. And again, the effects are significantly stronger for illiquid stocks.

In summary, Table 6 shows strong evidence that when high internalization funds hold the same stock, that stock's volatility is lower.

E. Internalization and Spillovers on Fund Performance

In most theoretical models of fire sales, forced sales by some mutual funds exert negative price pressure, thereby driving down the returns of other mutual funds, which because of the performance-flow relation are in turn forced to liquidate some of their holdings. In this section, we assess how our internalization measures affect the relation between fund returns and flows into other funds with overlapping holdings.

Consider a particular fund *f*. When other funds that hold the same stocks as *f* suffer outflows, their trading in the overlapping stocks may drive down prices and thus fund *f*'s returns (Lou, 2012). However, to the extent that those other funds internalize more of the price pressure from their trading, the effect on *f*'s returns will be smaller. To examine this prediction, we estimate the regression

$$R_{f,m} = \alpha_m + \beta_1 \cdot Pressure_{f,m} + \beta_2 \cdot Pressure_{f,m} \times CoHolderInternalize_{f,m-1}$$
$$+\beta_3 \cdot CoHolderInternalize_{f,m-1} + \beta_4 \cdot Flows_{f,m} + \varepsilon_{f,m},$$

where $R_{f,m}$ is the return of fund *f* during month *m*. $Pressure_{f,m}$ is the average over the securities that fund *f* holds of flows into other funds that hold the same security, weighted by share of each security in *f*'s portfolio and the share of each other fund in total holdings of the security. $CoHolderInternalize_{f,m}$ is the average over securities that fund *f* holds of our internalization measure for other funds that hold the same security.[24] In addition, we control directly for the flows into fund *f* and include time fixed effects in all specifications.

Table 7 shows the results. In the first column, we measure internalization using *Share outstanding*. The coefficient β_1 on *Pressure* is positive: when funds that have holdings overlapping with *f* have outflows, fund *f* has lower returns.[25] Since *Pressure* is expressed as flows relative to fund TNA, the β_1 coefficient of 1.11 in column (1) indicates that when the other funds holding the same stocks as fund *f* experience outflows equal to 1% of their TNA, fund *f* experiences about 1% lower returns. However, the coefficient β_2 on the interaction $Pressure \times CoHolderInternalize$ is negative. The effect is muted when those funds with overlapping holdings internalize more of their price pressure. A one-standard deviation increase in internalization decreases the effect of *Pressure* by 14%. The second column of Table 7 shows that the results are similar when we include fund and time fixed effects, rather than objective cross time fixed effects. In this specification, a one-standard deviation increase in internalization decreases the effect of *Pressure* by 11%.

Columns (3)-(4) of Table 7, show that similar results obtain when we measure internalization using *Manager overlap*. The economic magnitudes are also similar: a one-standard

[24] Because index funds have little scope to accommodate fund flows through changes in cash holdings, we set their value of internalization to zero.

[25] Our results here are qualitatively and quantitatively similar to Lou (2012). The main difference is that while he is interested in predicting mutual fund returns based on expected flows into other funds holding the same securities as a given fund, our focus here is on the ex post behavior: how does internalization moderate the effect of flow-induced trading on other funds?

deviation increase in internalization decreases the effect of *Pressure* by 8-18%. Similarly, in columns (5)-(6) of Table 7, we measure internalization using *Family overlap*. Here, a one-standard deviation increase in internalization decreases the effect of *Pressure* by 10-24%.

F. Internalization and Cash Holdings

Our results so far are about ex post behavior: they show how funds manage fund flows once they receive them and how flow management depends on a fund's propensity to internalize the price impact of its trading. We now turn to the ex ante choice of cash buffers and show that funds that internalize more of their price impact choose to hold higher cash buffers. In some sense, this is the closest empirical analog to the problem a planner would solve in a theoretical model.

Table 8 estimates regressions of the cash-to-assets ratio on our internalization measures:

$$\frac{Cash_{f,t}}{TNA_{f,t}} = \alpha + \beta \cdot FundInternalize_{f,t} + \gamma' X_{f,t} + \varepsilon_{f,t}.$$

Controls $X_{f,t}$ include four sets of variables. The first set is variables that capture the mismatch between liquidity of a fund's assets and liquidity demanded by its investors: the liquidity of the assets, the volatility of fund flows, and the interaction of the two. 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. In the third category is the fraction of the fund's assets that are in institutional share classes, a proxy for investor behavior and the investor clienteles the fund serves. Finally, we control for a number of measures of trading practices, including the fund's asset turnover and indicators for whether the fund uses various derivatives, borrows, or engages in short sales.

The first column of Table 8 shows that our internalization measures have a substantial impact on cash holdings. A fund that internalizes its price impact one standard deviation more than the average fund, as measured by *Share outstanding*, has a 0.69 percentage point higher cash-to-assets ratio. In comparison, a one-standard deviation increase in the illiquidity of the fund's assets is associated with a 0.22 percentage point higher cash-to-assets ratio. Thus, as in our flow management regressions, internalization has an economically significant effect. A fund internalizing more of its price impact has as much cash as a fund with significantly less liquid assets.

The second column of Table 8 adds objective cross time fixed effects to the regression. The results are unchanged, indicating that they are not driven by common time variation in internalization and cash holdings within fund objectives.

The remaining columns of Table 8 show that results are similar for our other internalization measures. A fund that internalizes its price impact one standard deviation more than the average fund, as measured by *Manager overlap* (*Family overlap*), has a cash-to-assets ratio that is 0.53 (0.87) percentage points higher than the average fund.

G. Robustness of Cash Holdings Results

In Table 9, we examine the robustness of our cash holdings results. We use the same battery of tests as we did in Table 5. The table shows that our results are robust to controls for market timing (i.e., fund returns), asset liquidity, fund strategy, investor clienteles, and manager characteristics. In addition, we get similar results when we split the sample into small and large funds or split the sample period in two.[26]

Overall, Table 9 provides strong evidence that we are picking up the impact of internalization on ex ante cash holdings. Our examination of alternative explanations for our results does not seem consistent with those explanations driving our results.

IV. Conclusion

Theoretical models of fire sales suggest that investors do not fully internalize the cost of fire sales they create. They may therefore set their leverage too high or hold too little liquidity to meet redemption requests. The existing empirical literature documents that forced sales do result in depressed security prices and that these depressed prices do appear to have adverse effects on other investors. However, there is no direct empirical evidence that the costs of spillovers effects are significant enough that a planner coordinating among funds would choose a different outcome from the private market equilibrium.

We construct three novel, theoretically-motivated measures of how much of the price impact of their trading different mutual funds are likely to internalize. While they are not strongly

[26] In Internet Appendix Table IA4, we show these results are robust to using position-level (security-fund-time) data and including security-time fixed effects, which shows that the results are not driven by time-varying security characteristics.

correlated, all three measures deliver the same message—high internalization funds behave differently from other funds. In particular, high internalization funds use cash more aggressively to accommodate fund flows. As a result, stocks held by these funds experience less excess volatility, and flows into these funds have smaller spillover effects on other funds with overlapping holdings. High internalization funds also choose to hold larger cash buffers ex ante. Overall, these results suggest that there are indeed meaningful price impact externalities in the mutual fund industry and that, like high internalization funds, a planner coordinating among funds would choose different liquidity management policies.

Our results speak to the policy debate among academics, practitioners, and regulators about whether liquidity transformation in asset management can cause financial stability problems (e.g., Goldstein et al, 2016; International Monetary Fund, 2015; Financial Stability Oversight Council, 2014; Feroli et al, 2014; Chen, Goldstein, and Jiang, 2010). Indeed, concerned in part by the potential for fire sales, the Securities and Exchange Commission (SEC) has recently proposed new rules to promote more effective liquidity risk management by mutual funds (SEC, 2015). Our results suggest that because individual mutual funds do not fully internalize the price impact of their trading, they are likely to hold less cash and to meet redemption requests by trading more aggressively in the underlying securities than would a planner coordinating among funds.

Finally, the results in this paper contribute to our understanding of the role of large institutional investors in securities markets (Ben-David et al., 2016). While larger investors have the potential to generate greater price impact, they may also more fully internalize the price impact of their trading. In our data, mutual funds that have greater overlap in holdings with other funds in the same fund family hold larger cash buffers and use these buffers more aggressively to accommodate fund flows. As a result, stocks held by such funds experience lower volatility, while other funds holding such stocks are more insulated from their fund flows.

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Table 1
Summary Statistics

This table reports summary statistics for the sample of actively managed domestic equity open-end mutual funds studied in the paper. The sample excludes variable annuities, funds closed to investors, and funds with less than $100 million in TNA (measured in 2012 dollars). The sample period is January 2003 to December 2016. *Illiq* is the weighted average across portfolio securities of the square-root version of Amihud (2002) for each stock. *Share outstanding* is the value-weighted average of holdings of each portfolio security relative to the security's market cap. *Manager overlap* is the value-weighted average of the ratio of aggregate holdings of each security s in fund f's portfolio by all other funds managed by the same portfolio manager to the aggregate portfolio value of all funds managed by fund f's portfolio manager. *Family overlap* is the value-weighted average of the ratio of aggregate holdings of each security s in fund f's portfolio by all other funds that belong to the same fund family to the aggregate portfolio value of all funds in the family. $Flows$ is net flows during quarter t scaled by TNA at the beginning of the six-month reporting period. 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. 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.

				Percentile		
	N	Mean	SD	25	50	75
TNA	23635	2068.84	5857.82	236.93	603.48	1612.45
$Size$	23635	6.54	1.32	5.47	6.40	7.39
Family size	23635	10.56	2.23	9.15	10.79	12.10
$Cash/TNA$ (%)	23635	3.96	4.64	1.09	2.62	4.98
$\Delta(Cash/TNA)$ (%)	23635	−0.17	5.45	−1.26	−0.02	1.13
$Flows_t$ (%)	23635	1.63	8.37	−3.49	−0.63	4.45
$Flows_{t-1}$ (%)	23635	1.67	8.00	−3.35	−0.30	4.94
Illiq ($\times 10^4$)	23635	0.21	0.29	0.07	0.12	0.25
$\sigma(Flows)$ (%)	23635	9.02	10.30	2.42	5.40	11.48
Institutional share (%)	23635	0.33	0.38	0.00	0.13	0.67
$Turnover$ (%)	23635	53.20	48.09	20.00	39.00	70.00
$Shorting$	23635	0.02	0.15	0.00	0.00	0.00
$Options$	23635	0.03	0.07	0.00	0.00	0.00
Other practices	23635	0.35	0.18	0.25	0.38	0.50
Share outstanding (%)	23635	0.40	0.71	0.05	0.15	0.43
Manager overlap (%)	23635	0.46	0.68	0.01	0.20	0.60
Family overlap (%)	23635	0.29	0.37	0.06	0.20	0.41
Holdings HHI	23635	0.03	0.05	0.01	0.02	0.03

Table 2
Correlations

This table reports the correlations between key variables in our data.

	Share out	Mgr overlap	Fam overlap	Fund size	Fam size	$\frac{Cash}{TNA}$	$\Delta\frac{Cash}{TNA}$	Flows	Illiq	$\sigma(Flows)$	Inst share	Turn	Short	Options	Other	Hldgs HHI
Share outstanding	1.00															
Manager overlap	−0.12	1.00														
Family overlap	−0.02	0.45	1.00													
Fund size	0.46	−0.06	0.13	1.00												
Family size	0.07	0.10	0.04	0.44	1.00											
$\frac{Cash}{TNA}$	0.17	−0.01	0.05	−0.03	−0.17	1.00										
$\Delta\frac{Cash}{TNA}$	0.00	0.00	0.01	−0.00	−0.00	0.33	1.00									
Flows	−0.02	−0.01	−0.01	−0.06	−0.06	0.17	0.03	1.00								
Illiq	0.34	−0.15	−0.18	−0.15	−0.14	0.16	0.00	0.03	1.00							
$\sigma(Flows)$	−0.07	0.03	−0.03	−0.19	−0.06	0.09	0.00	0.45	0.05	1.00						
Share institutional	−0.15	0.05	−0.09	−0.06	−0.05	−0.08	−0.02	0.06	−0.04	0.10	1.00					
Turnover	−0.13	−0.03	−0.04	−0.17	0.05	−0.04	0.00	−0.01	−0.01	0.11	−0.04	1.00				
Shorting	0.08	0.00	0.07	0.03	−0.05	0.14	−0.01	0.01	0.10	0.01	−0.06	0.08	1.00			
Options	−0.00	−0.02	0.06	0.07	0.09	0.08	0.00	−0.01	0.02	−0.00	0.03	0.11	0.24	1.00		
Other practices	0.18	0.08	0.09	0.33	0.45	−0.03	0.01	−0.06	−0.00	−0.07	−0.20	0.06	0.08	0.12	1.00	
Holdings HHI	0.07	0.12	0.14	−0.01	−0.05	0.07	0.01	0.02	−0.01	0.04	−0.04	−0.02	0.05	−0.01	0.00	1.00

Table 3
Flow Management

This table reports results of regressions of changes in the cash-to-assets ratio on monthly fund flows:

$$\Delta\left(\frac{Cash}{TNA}\right)_{f,m-6:m} = \alpha + \sum_{s=0}^{5}\beta_s \cdot Flows_{f,m-s} + \varepsilon_{f,m},$$

where f indexes funds and m indexes months. Independent variables are monthly net fund flows, scaled by TNA six months ago. Fund flows are winsorized at the 5th and 95th percentiles. The sample period is January 2003 to December 2016. Objective-time fixed effects are based on Lipper objective codes and semi-annual reporting periods. Standard errors are adjusted for clustering by fund. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)	(3)
$Flows_{f,m}$	0.102***	0.110***	0.118***
	(0.010)	(0.012)	(0.012)
$Flows_{f,m-1}$	0.054***	0.042***	0.048***
	(0.013)	(0.015)	(0.014)
$Flows_{f,m-2}$	0.043***	0.051***	0.057***
	(0.012)	(0.014)	(0.014)
$Flows_{f,m-3}$	−0.041***	−0.048***	−0.049***
	(0.011)	(0.013)	(0.012)
$Flows_{f,m-4}$	−0.027**	−0.026**	−0.028**
	(0.011)	(0.013)	(0.012)
$Flows_{f,m-5}$	−0.117***	−0.133***	−0.127***
	(0.013)	(0.015)	(0.015)
N	23,635	23,635	23,474
R^2	0.043	0.067	0.085
Objective-time FEs	✓		✓
Fund FEs		✓	✓

Table 4
Flow Management and Propensity to Internalize Price Impact

This table reports results of regressions of changes in the cash-to-assets ratio on fund flows interacted with internalization proxies:

$$\Delta\left(\frac{Cash}{TNA}\right)_{f,t} = \alpha_{obj(f),t} + \beta_1 \cdot Flows_{f,t} + \beta_2 \cdot Flows_{f,t} \times FundInternalize_{f,t-2} + \beta_3 \cdot Flows_{f,t} \times Illiq_{f,t-2}$$
$$+ \beta_4 \cdot Flows_{f,t-1} + \beta_5 \cdot Flows_{f,t-1} \times FundInternalize_{f,t-2} + \beta_6 \cdot Flows_{f,t-1} \times Illiq_{f,t-2}$$
$$+ \beta_7 \cdot FundInternalize_{f,t-2} + \beta_8 \cdot Illiq_{f,t-2} + \varepsilon_{f,t},$$

where f indexes funds and t indexes quarters. All specifications include objective-time fixed effects. 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. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Share outstanding		Manager overlap		Family overlap	
	(1)	(2)	(3)	(4)	(5)	(6)
$Flows_{f,t}$	0.054***	0.053***	0.052***	0.051***	0.053***	0.053***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$Flows_{f,t} \times FundInternalize_{f,t-2}$	0.011**	0.012*	0.018**	0.020**	0.029***	0.029***
	(0.005)	(0.007)	(0.009)	(0.009)	(0.009)	(0.009)
$Flows_{f,t} \times Illiq_{f,t-2}$	0.012**	0.011*	0.016***	0.016***	0.017***	0.017***
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
$Flows_{f,t-1}$	−0.042***	−0.041***	−0.042***	−0.042***	−0.043***	−0.043***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
$Flows_{f,t-1} \times FundInternalize_{f,t-2}$	0.008	0.006	−0.009	−0.011	−0.015	−0.015
	(0.006)	(0.006)	(0.009)	(0.009)	(0.009)	(0.009)
$Flows_{f,t-1} \times Illiq_{f,t-2}$	−0.006	−0.005	−0.005	−0.005	−0.006	−0.005
	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
$Illiq_{f,t-2}$	0.009	−0.003	0.006	0.005	0.009	0.008
	(0.034)	(0.036)	(0.036)	(0.036)	(0.035)	(0.035)
$FundInternalize_{f,t-2}$	0.021	0.038	−0.057	−0.048	0.041	0.041
	(0.023)	(0.032)	(0.037)	(0.039)	(0.040)	(0.041)
$Flows_{f,t} \times Fund\ size_{f,t-2}$		−0.003				
		(0.006)				
$Flows_{f,t-1} \times Fund\ size_{f,t-2}$		0.004				
		(0.006)				
$Fund\ size_{f,t-2}$		−0.029				
		(0.024)				
$Flows_{f,t} \times Ln(1 + Other\ funds)_{f,t-2}$				−0.005		
				(0.005)		
$Flows_{f,t-1} \times Ln(1 + Other\ funds)_{f,t-2}$				0.004		
				(0.004)		
$Ln(1 + Other\ funds)_{f,t-2}$				−0.013		
				(0.017)		
$Flows_{f,t} \times Family\ size_{f,t-2}$						−0.002
						(0.004)
$Flows_{f,t-1} \times Family\ size_{f,t-2}$						0.003
						(0.004)
$Family\ size_{f,t-2}$						−0.002
						(0.016)
N	21,315	21,315	21,315	21,315	21,315	21,315
R^2	0.045	0.045	0.045	0.045	0.045	0.045

Table 5
Flow Management: Alternative Explanations

This table shows the robustness of the results in Table 4 to alternative explanations for the relation between internalization proxies and a fund's propensity to accommodate fund flows through changes in cash. For each regression we report the β_2 coefficient on the interaction of fund flows during quarter t with the beginning of the semi-annual period value of the internalization proxy indicated by the column heading. All additional controls, except for returns, are interacted with quarterly fund flows. All specifications include objective-time fixed effects. Standard errors are adjusted for clustering by fund. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

		Share outstanding		Manager overlap		Family overlap	
	N	β	R^2	β	R^2	β	R^2
(1) Baseline	21,315	0.011^{**}	0.045	0.018^{**}	0.045	0.029^{***}	0.045
		(0.005)		(0.009)		(0.009)	
Additional controls:							
(2) Past returns	21,210	0.009	0.046	0.019^{**}	0.045	0.029^{***}	0.046
		(0.005)		(0.008)		(0.009)	
(3) Future returns	19,324	0.009^{*}	0.047	0.020^{**}	0.046	0.026^{***}	0.047
		(0.005)		(0.009)		(0.009)	
(4) Powers of illiquidity	21,315	0.011^{**}	0.046	0.017^{**}	0.046	0.028^{***}	0.046
		(0.005)		(0.009)		(0.009)	
(5) Deciles of illiquidity	21,315	0.013^{**}	0.046	0.017^{*}	0.046	0.028^{***}	0.046
		(0.005)		(0.009)		(0.009)	
(6) Layers of liquidity	21,315	0.010^{**}	0.052	0.015^{*}	0.051	0.023^{***}	0.052
		(0.005)		(0.009)		(0.009)	
(7) Holdings HHI	21,315	0.011^{*}	0.046	0.018^{**}	0.045	0.029^{***}	0.045
		(0.006)		(0.009)		(0.009)	
(8) Top share	21,315	0.011^{*}	0.045	0.019^{**}	0.045	0.030^{***}	0.045
		(0.006)		(0.009)		(0.009)	
(9) Active share	8,245	0.025	0.070	0.035^{**}	0.070	0.070^{***}	0.073
		(0.015)		(0.016)		(0.018)	
(10) Clientele	21,315	0.012^{**}	0.046	0.017^{**}	0.045	0.029^{***}	0.046
		(0.005)		(0.008)		(0.009)	
(11) Fund managers	20,441	0.009	0.047	0.017^{**}	0.047	0.028^{***}	0.047
		(0.006)		(0.009)		(0.009)	
Sample splits:							
(12) Small funds	10,649	0.012	0.068	0.023^{*}	0.069	0.030^{**}	0.069
		(0.025)		(0.012)		(0.012)	
(13) Large funds	10,666	0.012^{*}	0.064	0.013	0.063	0.030^{**}	0.065
		(0.007)		(0.011)		(0.013)	
(14) 2003–2009	7,570	0.006	0.054	0.029^{*}	0.053	0.012	0.054
		(0.011)		(0.016)		(0.013)	
(15) 2010–2016	13,745	0.013^{**}	0.035	0.014	0.035	0.040^{***}	0.036
		(0.006)		(0.011)		(0.014)	

Table 6
Internalization and Fragility

This table reports results of regressions of stock volatility during quarter $t+1$ on internalization proxies:

$$Vol_{s,t+1} = \alpha_s + \alpha_{t+1} + \beta \cdot StockInternalize_{s,t} + \gamma' \mathbf{X}_{s,t} + \varepsilon_{s,t+1},$$

where s indexes stocks and t indexes quarter dates. Stock and date fixed effects are included in all specifications. *Mutual funds share* is the fraction of outstanding owned by all mutual funds. *Fragility* is the diagonal version of Greenwood and Thesmar (2011) stock fragility measure. 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 stock. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Share outstanding			Manager overlap			Family overlap		
		Liquid	Illiquid		Liquid	Illiquid		Liquid	Illiquid
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$Internalize_{s,t}$	-0.383^{***}	-0.334^{*}	-0.473^{***}	-0.231^{***}	-0.079	-0.351^{**}	-0.181^{*}	-0.001	-0.620^{***}
	(0.099)	(0.173)	(0.119)	(0.086)	(0.099)	(0.159)	(0.105)	(0.115)	(0.204)
$Fragility_{s,t}$	0.182^{***}	0.093^{*}	0.346^{***}	0.181^{***}	0.094^{*}	0.344^{***}	0.184^{***}	0.094^{*}	0.343^{***}
	(0.047)	(0.052)	(0.096)	(0.047)	(0.052)	(0.096)	(0.047)	(0.052)	(0.096)
$Size_{s,t}$	-5.484^{***}	-5.778^{***}	-5.850^{***}	-5.223^{***}	-5.612^{***}	-5.548^{***}	-5.253^{***}	-5.652^{***}	-5.553^{***}
	(0.211)	(0.297)	(0.316)	(0.209)	(0.300)	(0.310)	(0.208)	(0.298)	(0.310)
Mutual funds share$_{s,t}$	0.484^{***}	0.220	0.637^{***}	0.267^{*}	0.055	0.271	0.249^{*}	0.037	0.258
	(0.159)	(0.210)	(0.243)	(0.147)	(0.189)	(0.223)	(0.147)	(0.193)	(0.222)
N	133,087	66,545	66,177	133,087	66,545	66,177	133,087	66,545	66,177
R^2	0.665	0.692	0.642	0.665	0.691	0.642	0.665	0.691	0.642

Table 7
Fund Returns, Flow Pressure, and Internalization

This table reports results of regressions of monthly fund returns on the flow pressure experienced by other funds holding the same securities as fund f:

$$R_{f,m} = \alpha + \beta_0 \cdot Press_{f,m} + \beta_1 \cdot Press \times CoHolderInternalize_{f,m} + \beta_2 \cdot CoHolderInternalize_{f,m-1} + \varepsilon_{f,m},$$

where f indexes funds and m indexes months. $Pressure_{f,m}$ is weighted-average fund flows experienced during month m by other funds holding the same securities as fund f. First, for each security s held by fund f at the end of the previous quarter, we calculate weighted-average fund flows into all other funds holding security s. The weights are each fund's holding of security s relative to aggregate holdings of security s by all funds except for fund f. Second, we calculate the weighted average across all securities held by fund f, with the weights being portfolio shares. $Pressure \times CoHolderInternalize_{f,m}$ is constructed similarly to $Pressure_{f,m}$ except that each fund's flow is multiplied by the fund's propensity to internalize price impact in a given security. $CoHolderInternalize_{f,m}$ is the propensity of other funds holding the same securities as fund f to internalize price impact in the securities held by fund f. Internalization measures are standardized in the holdings data. The sample consists of all domestic equity funds in CRSP Mutual Fund Database with at least $10 million in TNA and for which the ratio of the value of securities with pressure data to fund TNA is in the $[0.75, 1.25]$ interval. Standard errors are adjusted for clustering by Lipper objective-date. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Share outstanding		Manager overlap		Family overlap	
	(1)	(2)	(3)	(4)	(5)	(6)
$Pressure_{f,m}$	1.111***	1.592***	0.586***	1.024***	1.020***	1.356***
	(0.145)	(0.223)	(0.086)	(0.126)	(0.105)	(0.148)
$Pressure \times Internalize_{f,m}$	−0.156***	−0.169***	−0.104**	−0.086	−0.244***	−0.141***
	(0.037)	(0.065)	(0.042)	(0.064)	(0.038)	(0.055)
$Internalize_{f,m}$	0.001**	0.005***	−0.000	0.004	−0.001	−0.002*
	(0.000)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
$Flows_{f,m}$	0.014***	0.022***	0.012***	0.018***	0.014***	0.022***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
N	178,300	178,280	178,172	178,152	178,307	178,287
R^2	0.906	0.832	0.905	0.827	0.906	0.831
Objective × Month date FEs	✓		✓		✓	
Fund FEs		✓		✓		✓
Month date FEs		✓		✓		✓

Table 8
Cash Holdings

This table reports results of regressions of the cash-to-assets ratio on internalization proxies and fund characteristics:

$$\left(\frac{Cash}{TNA}\right)_{f,t} = \alpha + \beta \cdot FundInternalize_{f,t} + \gamma'\mathbf{X}_{f,t} + \varepsilon_{f,t},$$

where f indexes funds and t indexes time. All specifications include objective-time fixed effects. *Share outstanding* is the value-weighted average of holdings of each portfolio security relative to the security's market cap. *Manager overlap* is the value-weighted average of the ratio of aggregate holdings of each security s in fund f's portfolio by all other funds managed by the same portfolio manager to the aggregate portfolio value of all funds managed by fund f's portfolio manager. *Family overlap* is the value-weighted average of the ratio of aggregate holdings of each security s in fund f's portfolio by all other funds that belong to the same fund family to the aggregate portfolio value of all funds in the family. *Illiq* is the weighted average across portfolio securities of the square-root version of Amihud (2002) for each stock. 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. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)	(3)	(4)	(5)	(6)
$Share\ of\ outstanding_{f,t}$	0.691^{***}	0.710^{***}				
	(0.098)	(0.099)				
$Manager\ overlap_{f,t}$			0.389^{*}	0.532^{**}		
			(0.211)	(0.212)		
$Family\ overlap_{f,t}$					0.646^{*}	0.867^{**}
					(0.358)	(0.374)
$Illiq_{f,t}$	0.219^{*}	0.132	0.542^{***}	0.404^{***}	0.567^{***}	0.416^{***}
	(0.113)	(0.124)	(0.121)	(0.142)	(0.126)	(0.143)
$\sigma(Flows)_{f,t}$	0.448^{***}	0.445^{***}	0.468^{***}	0.456^{***}	0.467^{***}	0.455^{***}
	(0.050)	(0.049)	(0.051)	(0.049)	(0.050)	(0.049)
$Illiq \times \sigma(Flows)_{f,t}$	0.188^{***}	0.216^{***}	0.132^{***}	0.171^{***}	0.127^{***}	0.169^{***}
	(0.046)	(0.044)	(0.048)	(0.045)	(0.048)	(0.045)
$Size_{f,t}$	-0.114	-0.155	0.314^{***}	0.313^{***}	0.264^{***}	0.246^{***}
	(0.098)	(0.101)	(0.096)	(0.097)	(0.091)	(0.092)
$Family\ size_{f,t}$	-0.683^{***}	-0.657^{***}	-0.787^{***}	-0.791^{***}	-0.761^{***}	-0.750^{***}
	(0.094)	(0.095)	(0.101)	(0.101)	(0.097)	(0.096)
$Institutional\ share_{f,t}$	-0.307^{***}	-0.311^{***}	-0.383^{***}	-0.400^{***}	-0.352^{***}	-0.364^{***}
	(0.064)	(0.066)	(0.066)	(0.068)	(0.064)	(0.066)
$Turnover_{f,t}$	-0.226^{***}	-0.240^{***}	-0.239^{***}	-0.263^{***}	-0.239^{***}	-0.268^{***}
	(0.065)	(0.062)	(0.066)	(0.063)	(0.065)	(0.062)
$Short\ selling_{f,t}$	2.808^{***}	2.792^{***}	2.869^{***}	2.900^{***}	2.804^{***}	2.828^{***}
	(0.743)	(0.714)	(0.753)	(0.725)	(0.752)	(0.722)
$Options_{f,t}$	5.187^{***}	5.279^{***}	4.736^{***}	5.011^{***}	4.502^{***}	4.751^{***}
	(1.151)	(1.157)	(1.149)	(1.162)	(1.122)	(1.131)
$Other\ practices_{f,t}$	0.077	0.068	0.162	0.117	0.149	0.100
	(0.355)	(0.371)	(0.373)	(0.385)	(0.371)	(0.382)
Constant	3.659^{***}	3.659^{***}	3.671^{***}	3.678^{***}	3.687^{***}	3.697^{***}
	(0.149)	(0.151)	(0.155)	(0.157)	(0.156)	(0.158)
N	23,635	23,635	23,635	23,635	23,635	23,635
R^2	0.113	0.126	0.100	0.114	0.102	0.117
Time FEs	✓		✓		✓	
Objective-time FEs		✓		✓		✓

Table 9
Cash Holdings: Alternative Explanations

This table shows robustness of the results in Table 8 to alternative explanations for the relation between cash holdings and internalization proxies. Baseline specifications are from the even-numbered columns in Table 8, i.e., models that control for objective-date fixed effects. Only the coefficient on internalization proxies is reported, other coefficients are omitted for brevity. Standard errors are adjusted for clustering by fund. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

		Share outstanding		Manager overlap		Family overlap	
	N	β	R^2	β	R^2	β	R^2
(1) Baseline	23,635	0.710^{***}	0.126	0.532^{**}	0.114	0.867^{**}	0.117
		(0.099)		(0.212)		(0.374)	
Additional controls:							
(2) Future returns	21,438	0.774^{***}	0.134	0.525^{**}	0.121	0.819^{**}	0.124
		(0.121)		(0.227)		(0.366)	
(3) Past returns	23,462	0.709^{***}	0.126	0.538^{**}	0.114	0.887^{**}	0.117
		(0.099)		(0.213)		(0.376)	
(4) Powers of illiquidity	23,635	0.633^{***}	0.131	0.629^{***}	0.124	0.960^{***}	0.127
		(0.102)		(0.205)		(0.362)	
(5) Deciles of illiquidity	23,635	0.582^{***}	0.135	0.678^{***}	0.129	1.005^{***}	0.132
		(0.104)		(0.203)		(0.355)	
(6) Layers of liquidity	23,635	0.717^{***}	0.130	0.510^{**}	0.118	0.866^{**}	0.121
		(0.112)		(0.214)		(0.378)	
(7) Holdings HHI	23,635	0.683^{***}	0.128	0.458^{**}	0.117	0.783^{**}	0.119
		(0.097)		(0.210)		(0.379)	
(8) Top share	23,635	0.668^{***}	0.128	0.416^{**}	0.118	0.740^{*}	0.120
		(0.096)		(0.209)		(0.381)	
(9) Active share	8,657	0.438^{***}	0.164	0.363	0.160	1.561^{***}	0.174
		(0.144)		(0.323)		(0.547)	
(10) Clientele	23,635	0.706^{***}	0.126	0.527^{**}	0.114	0.866^{**}	0.117
		(0.100)		(0.211)		(0.372)	
(11) Fund managers	22,571	0.734^{***}	0.134	0.478^{**}	0.121	0.873^{**}	0.125
		(0.100)		(0.211)		(0.379)	
Sample splits:							
(12) Small funds	11,811	1.382^{***}	0.132	0.459^{**}	0.126	0.672^{*}	0.127
		(0.371)		(0.211)		(0.393)	
(13) Large funds	11,824	0.643^{***}	0.162	0.725^{**}	0.148	1.101^{*}	0.153
		(0.116)		(0.349)		(0.573)	
(14) 2003–2009	9,300	0.799^{***}	0.131	0.670^{***}	0.119	0.694^{*}	0.119
		(0.138)		(0.254)		(0.389)	
(15) 2010–2016	14,335	0.628^{***}	0.109	0.449^{**}	0.098	1.028^{**}	0.104
		(0.115)		(0.229)		(0.450)	

Figure 1
Distribution of the Cash-to-Assets Ratio

This figure shows the distribution of the cash-to-assets ratio.

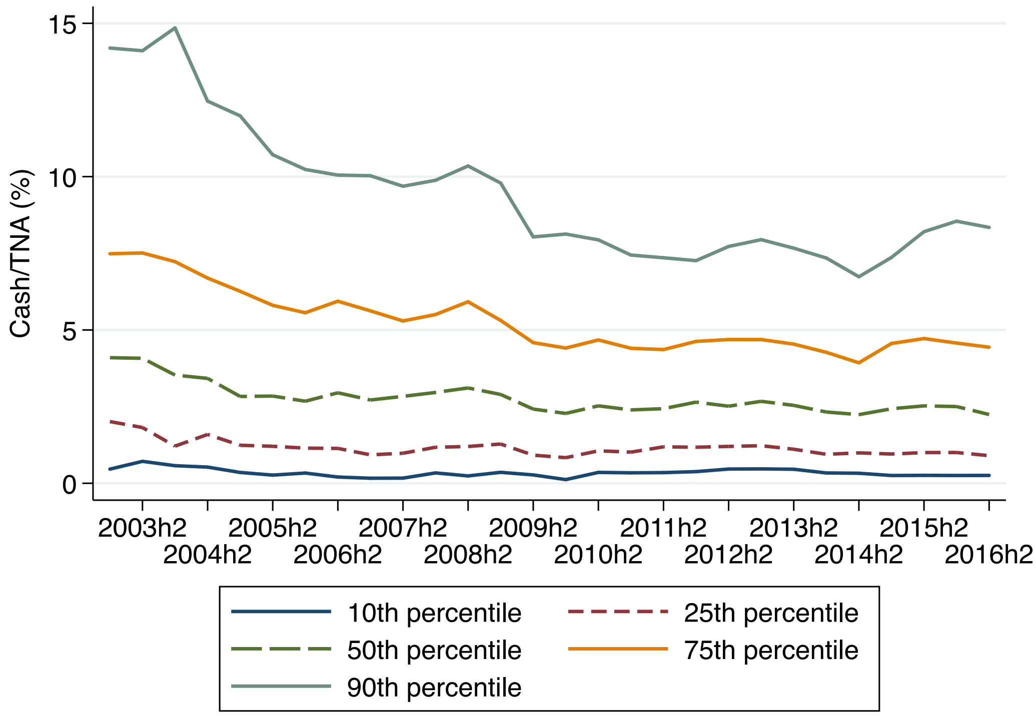
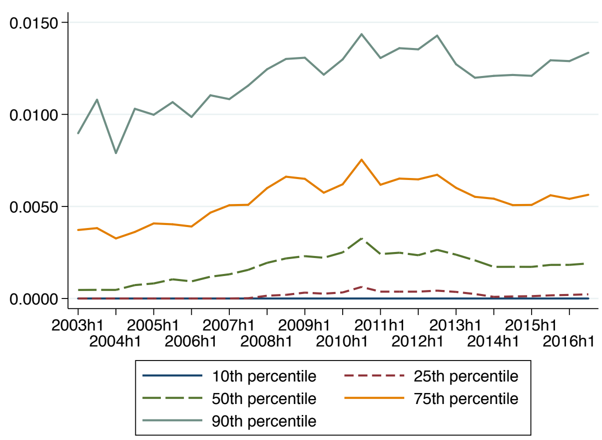


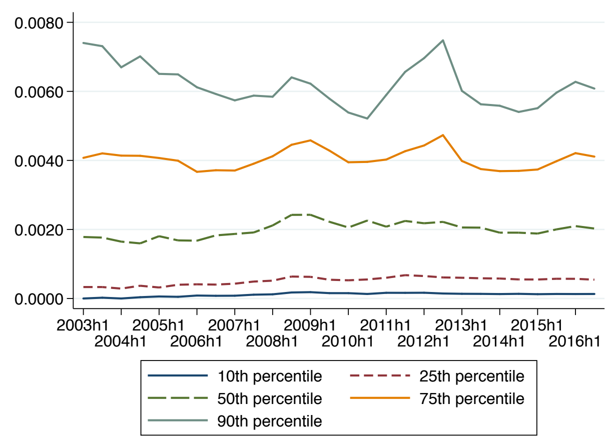
Figure 2
Distribution of Internalization Measures

This figure shows how the distribution of internalization measures has evolved over time. *Manager overlap* is the value-weighted average of the ratio of aggregate holdings of each security s in fund f's portfolio by all other funds managed by the same portfolio manager to the aggregate portfolio value of all funds managed by fund f's portfolio manager. *Family overlap* is the value-weighted average of the ratio of aggregate holdings of each security s in fund f's portfolio by all other funds that belong to the same fund family to the aggregate portfolio value of all funds in the family. *Share outstanding* is the value-weighted average of holdings of each portfolio security relative to the security's market cap.

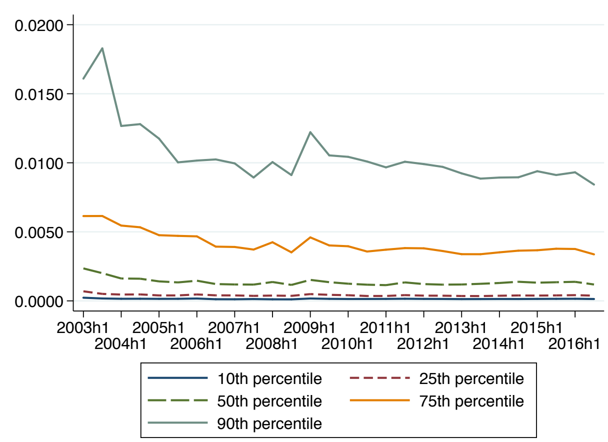
(a) Manager overlap



(b) Family overlap



(c) Share outstanding



Appendix

A1 N-SAR Filings

A1.1 Parsing N-SAR Filings

Each N-SAR filing can cover multiple funds offered by a given *Registrant*. For example, the December 31, 2016 filing by Fidelity Contrafund Trust covers four funds:

1. Fidelity Contrafund,
2. Fidelity Advisor New Insights Fund,
3. Fidelity Series Opportunistic Insights Fund,
4. Fidelity Advisor Series Opportunistic Insights Fund.

The names of the funds are reported in Item 7.C.2. Furthermore, within an N-SAR filing, each fund is assigned a series number, which is reported in Item 7.C.1 and which we refer to as `SeriesNum`. Funds are instructed to continue using the same `SeriesNum` for a given fund over time.

We parse raw N-SAR filings using a Python script. Each line in an N-SAR filing reports the answer of one of the funds identified in Item 7.C to a given question. Below is a sample line from the N-SAR filing mentioned above:

```
074 T000200 24397997
```

In this line, the first seven characters encode the question number: “`074 T00`” corresponds to Item 74.T: *Net assets of common shareholders.* The next four characters in positions 8–11 encode the fund’s `SeriesNum`. The remaining characters are used to encode the fund’s answer. In this case, since answers to Item 74 are reported in thousands, the TNA of Fidelity Advisor New Insights Fund is about $24.4 billion.

For questions that apply to all funds within a filing, such as *Registrant Information* Items 1–7, 27, 58–61, 78–79, the characters that encode the fund’s `SeriesNum` are generally set to “`0000` or “`AA00`”. Our script matches answers to such questions to all funds covered by the filing.

In addition to occasional typos and encoding errors, whereby for example answers to multiple questions appear on a single line, N-SAR filings have three systematic limitations:

1. The electronic system used by funds to submit their N-SAR filings imposes limits on the lengths of answers to certain questions. In particular the system generally does not allow funds to report values of TNA, or of other balance sheet variables in Item 74, greater than `99999999` thousand. As a result, whenever the answer is equal to or greater than $100 billion, funds report either `99999999` or `0`. In the N-SAR filing mentioned above, Fidelity Contrafund reports its TNA as of December 31, 2016 as `99999999`. The actual value was $102,065,141 thousand. We drop observations with TNA equal to 0 or `99999999`. We also drop six observations that report TNA greater than $100 billion.

2. N-SAR filings are generally limited to 99 funds. If a given trust offers more than 99 funds, information on funds with series numbers greater than 99 is not reported in a systematic manner.[1] The names of these funds are listed in a separate exhibit, which refers to the latest shareholder reports for additional information on these funds. During the 2003–2016 period, 70 filings indicate in Item 7.B that they had more than 99 funds at the end of the reporting period. In total, we are missing 1,051 fund-semi-annual-period observations as a result of this limit.

   Generally, it is the same funds whose answers are missing from one filing to another.

   A handful of filers with more than 99 funds reuse `SeriesNum` within the same filing. We discard such filings. The vast majority of funds affected by this issue are ETF and index fund families that offer many funds. Since our analysis focuses on actively managed funds, this issue should not have much effect on our sample.

3. We use only original filings and ignore amendments. As a result, if an amended filing corrects a missing or incorrect value in the original filing, our algorithm would not pick this up.

A1.2 Linking N-SAR Filings to CRSP

We link N-SAR filings to CRSP Mutual Fund Database using the following algorithm.

1. The first step in our algorithm relies on the fact that starting in 2006, mutual fund filing detail in EDGAR includes fund ticker symbols and `SeriesID`. The latter consists of letter "S" followed by nine numbers and uniquely identify funds within EDGAR. Specifically, the SEC prepends a header to each filing that among other things includes the following information on each fund covered by the filing:

```
<SERIES-ID>S000011202
<SERIES-NAME>Dodge & Cox Stock Fund
<CLASS-CONTRACT>
<CLASS-CONTRACT-ID>C000030875
<CLASS-CONTRACT-NAME>Dodge & Cox Stock Fund
<CLASS-CONTRACT-TICKER-SYMBOL>DODGX
</CLASS-CONTRACT>
```

   Within each N-SAR filing, we link a fund's `SeriesNum` to its `SeriesID` by matching fund names as reported in the header and in Item 7.C. Fund names in Item 7.C often use abbreviations, such as "intl" for "international," and omit the name of the family. For example, "RidgeWorth Silvant Large Cap Growth Stock Fund" reports its name as "Silvant Large

[1] Note that a trust is different from a fund family. For example, Fidelity has 509 registered investment companies reported on form N-SAR during 2016H2. These funds were offered by 60 separate trusts (CIKs), with no trust offering more than 99 funds.

Cap Growth Stock Fund" in Item 7.C and as "RidgeWorth Silvant Large Cap Growth Stock Fund" in the SEC filing header. To handle such cases, when unsuccessful in matching raw names, our algorithm attempts to match the names after removing the brand name, reported in Item 1.A *Registrant Name*. In this example, Registrant Name is *RidgeWorth Funds*. After discarding the *Funds* part, our algorithm attempts to remove the *RidgeWorth* part from both the header name and the name of the fund as reported in Item 7.C.

2. For filings before 2006, filing header does not include `SeriesID` or share class ticker symbols. For these filings, we backfill the link between `SeriesNum` and `SeriesID` as long as the following two conditions are met:

   (a) All `CIK-SeriesNum` observations that do match to a `SeriesID` match to the same `SeriesID`.

   (b) The maximum gap between two consecutive filings for a given `CIK-SeriesNum` pair is less than 12 months. This allows for changes in the fiscal year but rules out most cases where a `SeriesNum` is reused by different funds offered by the same registrant (CIK).

3. We next construct a link between `SeriesID` in EDGAR and `CRSP_CL_GRP` fund identifiers in CRSP. We do so by matching share class ticker symbols. For a link to be considered valid, we require that all of a fund's tickers in N-SAR match to the same fund in CRSP.

4. We next match the unmatched funds in N-SAR with unmatched funds in CRSP based on their name. The name-based merge 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. 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.

5. If a given fund in N-SAR, as defined by `SeriesID`, matches to the same fund in CRSP, as defined by `CRSP_CL_GRP`, we fill in any missing values of `CRSP_CL_GRP` with the value in the other periods.

6. Finally, we check that the ratio of TNA in N-SAR relative to TNA in CRSP lies in the $[0.5, 1.5]$ interval and discard any observations outside this interval.

A2 Model

This section presents a simple model of fund cash holdings.

A2.1 Setup

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 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

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

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

$$iR + \int_R^\infty c(x - R)dF(x), \tag{2}$$

where F is the cumulative distribution function of x.

A2.2 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.

A2.3 Optimal cash reserves for a single fund

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

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

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.

Let $r^* = \frac{R^*}{M}$ be the fund's optimal cash-to-assets ratio. Proposition 2 derives some simple comparative statics.

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

- $\frac{\partial r^*}{\partial c} > 0$: The optimal cash-to-assets ratio increases with asset illiquidity.
- $\frac{\partial r^*}{\partial \sigma} > 0$: The optimal cash-to-assets ratio increases with the volatility of fund flows.

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

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

- $\frac{\partial^2 r^*}{\partial M\partial\rho} > 0$: 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.

A2.4 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

$$iR + \int_R^\infty c\left(x - R + \sum_{k\neq j}(x_k - R_k)\right)(x - R)\,dF(x). \tag{3}$$

Eq. (3) is the same as Eq. (2), 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:

$$i - \int_{R^*}^\infty \big(c\,(G\,(x - R^*)) + (x - R^*)\,c'\,(G\,(x - R^*))\big)\,dF(x) = 0. \tag{4}$$

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

$$G\left[iR + \int_{R}^{\infty} c\left(G(x-R)\right)(x-R)dF(x)\right]. \tag{5}$$

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:

$$i - \int_{R^{**}}^{\infty} \left(c\left(G(x-R^{**})\right) + G(x-R^{**})c'(G(x-R^{**})\right) dF(x) = 0. \tag{6}$$

Eq. (6) is the same as the private market first order condition in Eq. (4), 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 3 says that this leads the planner to a higher level of reserves than the private market outcome.

Proposition 3: 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 equilibrium cash holdings R^{*} lower than R^{**}, the level of cash chosen by the planner coordinating among the funds, 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 the fraction of the underlying assets owned by a given fund, the more the fund will 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.

Table A1
Variable definitions

Variable	Definition
Active share	The percentage of fund holdings that is different from the benchmark holdings. Active share is from Martijn Cremers's website http://activeshare.nd.edu. Active share is generally reported as of December of each year. We match observations in N-SAR to the most recent values of active share assuming the latter is within six months of the N-SAR reporting date.
$\frac{Cash}{TNA}$	Cash is cash (74A) + repurchase agreements (74B) + short-term debt securities other than repurchase agreements (74C) + other investments (74I) − securities lending collateral. Other investments consist mostly of money market mutual funds. Value of securities lending collateral is collected from N-CSR filings. Cash is scaled by total net assets (74T). Winsorized at the 1st and 99th percentiles.
$\Delta\left(\frac{Cash}{TNA}\right)$	The change in the cash-to-assets ratio between two semi-annual reporting periods. Winsorized at the 1st and 99th percentiles.
Clientele	In Tables 5 and 9, we control for (a) the number of share classes, (b) HHI of assets across share classes, (c) the fraction of assets in share classes with front load fees, and (d) fraction of TNA in institutional share classes.
Experience	Number of years managing mutual funds. Using Morningstar data on the identity of mutual fund managers, we identify when each manager first started managing mutual funds and measure the number of years since then. For team-managed funds, *Experience* is the average across individual portfolio managers.
Family overlap	For each security s held by fund f, we calculate aggregate holdings of the security by all other funds in the same family and divide this by the aggregate portfolio value of the family's fund. We then calculate the value-weighted average across all securities held by fund f. Specifically, $Family\ overlap_f = \sum_s \frac{V_{f,s}}{\sum_s V_{f,s}} \times \frac{\sum_{j,fam(j)=fam(f),j\neq f} V_{j,s}}{\sum_{j,fam(j)=fam(f)} \sum_s V_{j,s}}$, where f and j index funds and s indexes securities.
Family size	Log of aggregate TNA across all CRSP mutual funds within the same family.
Flows	Net fund flows during each of the preceding six months (N-SAR item 28) are scaled by TNA at the end of the previous semi-annual reporting period. Net flows are calculated as *Total NAV of Shares Sold: New Sales (Incl. Exchanges) + Total NAV of Shares Sold: Reinv. of Dividends & Distributions − Total NAV of Shares Redeemed and Repurchased (Incl. Exchanges)*. We exclude the *Total NAV of Shares Sold: Other* as these capture share activity due to mergers. *Flows* are winsorized at the 5th and 95th percentiles.

Table A1—*Continued*

Variable	Definition
$\sigma(Flows)$	Standard deviation of monthly fund flows (28) over the preceding six months. Fund flows are scaled by TNA as of the beginning of the semi-annual reporting period.
$Fragility$	Greenwood and Thesmar (2011) measure of fragility. We calculate the "diagonal" version of fragility that ignores correlation in fund flows across funds. Column (4) of Table 3 in Greenwood and Thesmar (2011) shows that the diagonal version of fragility generates similar results to the full version that accounts for cross-correlation. For each fund holding security s at time t, we calculate the volatility of fund flows over the previous five years, requiring each fund to have at least 12 monthly observations. Fund flows are winsorized at the 1st and 99th percentiles before calculating fund flow volatility.
FundInternalize	Fund-level version of one of our three internalization measures: *Share outstanding*, *Manager overlap*, and *Family overlap.*
Fund manager chars	In Table 5 and 9, we include controls for (a) team managed funds, (b) the number of portfolio managers in charge of the fund, (c) mean experience of the fund's manager, and (d) CFA credential. Fund manager data are from Morningstar.
Future returns	In Tables 5 and 9, we include controls for average monthly returns over the subsequent 1, 3, 6, and 12 months.
$Illiq$	We first calculate the square-root version of Amihud (2002) liquidity measure for each stock in a fund's 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. Portfolio holdings are from the CRSP Mutual Fund Database. For an N-SAR reporting period ending in month t, we use holdings data from the last of months t, $t-1$, and $t-2$. Illiquidity is winsorized at the 1st and 99th percentiles.
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 J, K, and R suffixes are considered to be retail.
Layers of liquidity	We sort portfolio securities by their liquidity and measure average liquidity of each decile of the portfolio.

Table A1—*Continued*

Variable	Definition
Manager overlap	For each security s held by fund f, we calculate aggregate holdings of the security by all other funds managed by the same portfolio manager and divide this by the aggregate portfolio value of all funds managed by the portfolio manager. We then calculate the value-weighted average across all securities held by fund f. Specifically, *Manager overlap*$_f = \sum_s \frac{V_{f,s}}{\sum_s V_{f,s}} \times \frac{\sum_{j,mgr(j)=mgr(f),j\neq f} V_{j,s}}{\sum_{j,mgr(j)=mgr(f)} \sum_s V_{j,s}}$, where f and j index funds and s indexes securities. For funds managed by multiple portfolio managers, we split their total holdings of each security equally among the fund's managers.
Mutual funds share	For each stock, we calculate the share of outstanding owned by mutual funds.
Options	Average of eight 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).
Other practices	Average of seven 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) investment 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).
Pressure	Weighted average of fund flows experienced by other funds holding the same securities as fund f: $$Pressure_{f,m} = \sum_s \left(w_{f,s,m-1} \times \left(\sum_{j\neq f} \frac{V_{j,s,m-1}}{\sum_{k\neq f} V_{k,s,m-1}} \times \frac{Flows_{j,m}}{TNA_{j,m-1}} \right) \right)$$ where f, j, and k index funds, s indexes securities, and m indexes (month) dates. $V_{j,s,m-1}$ is the dollar holdings of security s by fund j at time $m-1$. $w_{f,s,m-1}$ is the fraction of fund f's portfolio invested in security s at time $m-1$. The set of securities is limited to valid PERMNOs.

Table A1—*Continued*

Variable	Definition
$Pressure$ $\times CoHolderInternalize$	Calculated similarly to $Pressure$ except that flows into fund j are multiplied by the fund's propensity to internalize price impact: $$\sum_s \left(w_{f,s,m-1} \times \left(\sum_{j \neq f} \frac{V_{j,s,m-1}}{\sum_{k \neq f} V_{k,s,m-1}} \times Internalize_{j,s,m-1} \times \frac{Flows_{j,m}}{TNA_{j,m-1}} \right) \right).$$ Because index funds cannot use cash holdings to accommodate fund flows, their propensity to $Internalize$ is set to zero. The set of securities is limited to valid PERMNOs. Propensity measures are winsorized year-by-year at the 1st and 99th percentiles.
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).
Sec lending	Binary variable equal to one for funds that engage in loaning portfolio securities (70N).
Share outstanding	Weighted average of the fund's 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.
Short selling	Binary variable equal to one for funds that engage in short selling (70R).
$StockInternalize$	To construct stock-level versions of our internalization measures, we calculate the value-weighted average of the propensity of funds holding stock s to internalize price pressure in stock s.
$Tenure$	Number of years managing the fund. For team managed funds, $Tenure$ is the average across individual managers. Manager identities and characteristics are from Morningstar.
$Turnover$	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.

Table A2
Cash Response to Subscriptions versus Redemptions

This table shows the response of the cash-to-assets ratio to subscriptions versus redemptions:

$$\Delta\left(\frac{Cash}{TNA}\right)_{f,m} = \alpha + \sum_{s=0}^{5}\left(\beta_s^+ Subscriptions_{f,m-s} + \beta_s^- Redemptions_{f,m-s}\right) + \varepsilon_{f,m},$$

where f indexes funds and m indexes months. Independent variables are monthly subscriptions and redemptions, scaled by net assets six months ago. Redemptions are expressed as a nonnegative number. Subscriptions and redemptions are winsorized at the 5th and 95th percentiles. The sample period is January 2003 to December 2016. Standard errors are adjusted for clustering by fund. The table reports the p-values from two-sided tests that the coefficients on subscriptions and redemptions are equal in magnitude and opposite in sign. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	(1)	(2)	(3)
$Subscriptions_{f,m}$	0.095***	0.100***	0.110***
	(0.010)	(0.012)	(0.012)
$Redemptions_{f,m}$	−0.109***	−0.128***	−0.127***
	(0.019)	(0.022)	(0.021)
$Subscriptions_{f,m-1}$	0.051***	0.035**	0.039***
	(0.012)	(0.014)	(0.014)
$Redemptions_{f,m-1}$	−0.062***	−0.067***	−0.065***
	(0.021)	(0.024)	(0.023)
$Subscriptions_{f,m-2}$	0.038***	0.046***	0.050***
	(0.012)	(0.015)	(0.014)
$Redemptions_{f,m-2}$	−0.048**	−0.052**	−0.060**
	(0.022)	(0.026)	(0.025)
$Subscriptions_{f,m-3}$	−0.032***	−0.040***	−0.042***
	(0.010)	(0.013)	(0.012)
$Redemptions_{f,m-3}$	0.041**	0.038	0.034
	(0.020)	(0.023)	(0.023)
$Subscriptions_{f,m-4}$	−0.041***	−0.044***	−0.048***
	(0.011)	(0.013)	(0.013)
$Redemptions_{f,m-4}$	−0.024	−0.043*	−0.041*
	(0.022)	(0.025)	(0.024)
$Subscriptions_{f,m-5}$	−0.105***	−0.129***	−0.118***
	(0.013)	(0.015)	(0.015)
$Redemptions_{f,m-5}$	0.085***	0.060**	0.063**
	(0.022)	(0.025)	(0.025)
N	23,635	23,635	23,474
R^2	0.025	−0.018	−0.013
p0	0.485	0.240	0.470
p1	0.600	0.191	0.273
p2	0.657	0.838	0.699
p3	0.648	0.923	0.745
p4	0.004	0.001	0.001
p5	0.382	0.012	0.044
poverall	0.000	0.000	0.000
Objective-time FEs	✓		✓
Fund FEs		✓	✓