NBER WORKING PAPER SERIES

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Working Paper 25104
http://www.nber.org/papers/w25104

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
September 2018

We are grateful to Carter Anthony, Jules van Binsbergen, Charles Calomiris, Jaewon Choi, Lauren Cohen, Andrew Ellul, Robin Greenwood, Sam Hanson, Johan Hombert, Zoran Ivkovic, Marcin Kacperczyk, Xuewen Liu, Toby Moskowitz, Stefano Rossi, Alexi Savov, Jeremy Stein, Rene Stulz, Robert Turley, Jeff Wang, Zhi Wang, Michael Weisbach, Russ Wermers, Yao Zeng, and seminar participants at Yale University and the SEC for helpful comments and suggestions. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 25104
September 2018
JEL No. G11,G12,G18,G23

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 provide evidence of meaningful fire sale externalities in the mutual fund industry.

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An internet appendix is available at
https://www.dropbox.com/s/cvrjtg3jhh46lwh/fireSalesInternetAppendix.pdf?dl=0

Fire sales are at the center of our understanding of financial stability problems in securities markets. Instability arises because there are spillover effects: 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, amplifying the initial shock. The key conceptual feature of such amplification cycles is that they can generate externalities: if funds internalized the effect of their sales on other funds, they would change their flow management policies to dampen the feedback effects that arise from their forced trading.

A large empirical literature documents the existence of some of the main ingredients of the fire sales mechanism. In instances when forced sales happen, they can result in depressed security prices (e.g., Coval and Stafford, 2007; Ellul, Jotikasthira and Lundblad, 2011; Greenwood and Thesmar, 2011; Merrill et. al., 2012; Hau and Lai, 2017; Choi and Shin, 2018). Furthermore, in these instances, there can be spillovers: depressed prices created by one fund's sales can affect other funds holding the same securities (Lou, 2012; Falato et. al., 2016).

However, the empirical literature has yet to directly address the main conceptual question about fire sales: is there an externality? In other words, would funds act differently if they cared more about the spillover effects of their trading? This need not be the case – if spillovers are infrequent or mild, individual funds will act the same whether they care about other funds or not. Although the question of whether there are externalities has important implications for both our conceptual understanding of fire sales and for the regulation of asset managers, it cannot be answered from the existing literature.

In this paper, we take on this empirical challenge and provide evidence that mutual funds do indeed manage their flows differently when they care more about the impact of their trading on other funds. 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 funds' liquidity management policies, the volatility of the securities they hold, and the spillover effects they impose on each other. We find that funds that internalize more of the price impact of their trading, which we refer to as high internalization funds, do behave differently from those that do not, suggesting that there are indeed meaningful fire sale externalities in the mutual fund industry.

We begin by writing down a simple model of funds choosing optimal cash buffers and flow management policies. The model motivates our empirical tests, which we implement by introducing three new empirical measures of internalization of price impact. These measures are based on a fund's incentive to care about the performance of other funds. The first measure leverages the fact that many portfolio managers manage multiple funds, and therefore care about the adverse price pressure that trading by one of their funds exerts on their other funds. Our second measure exploits the idea that a fund may be cautious about exerting price impact when it would adversely affect other funds managed by the same investment adviser.[1] Our third measure is similar to the second one, but excludes funds managed by the same portfolio manager to focus on incentives at the investment adviser level. Throughout our analysis, we use all three internalization measures, with all three delivering similar results.

To test the predictions of our model, we use SEC form N-SAR filings to build a novel data set on the cash holdings of open-end domestic equity mutual funds over the 1994 – 2016 period. Our first main result concerns how a fund's management of the inflows and outflows it receives varies with its internalization. We find that high internalization funds use their cash buffers more aggressively to accommodate flows. The economic magnitudes are significant. Going from the 25^{th} to 75^{th} percentile of internalization is associated with being 50% more aggressive in using cash to accommodate fund flows. The magnitude of the effect of internalization is similar to the impact of asset liquidity on flow management. Our evidence suggests that there are significant price impact externalities: when a fund internalizes more of the price impact of its trading on other funds, it follows a different strategy for accommodating inflows and outflows.

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, fund strategy, variation in investor clienteles across funds, or manager characteristics.

To further rule out alternative explanations, we use variation in internalization driven by two types of structural changes: one at the portfolio manager and one at the investment adviser

[1] Throughout the paper, the phrase "investment adviser" refers to the firm providing investment management services to the fund, while the phrase "portfolio managers" refers to employees of the investment adviser who are actually managing the fund.

level. First, we examine cases in which a fund's portfolio manager is assigned an additional fund to manage. The idea is that because fund managers internalize the impact of decisions to trade across all of their funds, being assigned an additional fund increases internalization. We examine variation in flow management within the same fund before and after the assignment of the new fund. After fund managers are assigned a new fund, they become more aggressive in using cash to accommodate flows into the old fund, consistent with them caring more about the price impact of their trading because it impacts their new fund.

The second structural change we investigate is mergers of investment advisers, which increase our adviser-level measures of internalization. We examine variation in flow management within target and acquirer funds before and after the merger. After a merger, the same fund becomes more aggressive in using cash to manage flows, consistent with it caring more about the price impact of its trading on the funds added through the merger. Our analyses of these two structural changes give us confidence that we are capturing differences in flow management due to internalization, not alternative explanations.

Our second main result is at the stock level. We show that when the same stock is held by high internalization funds, its realized volatility is lower over the following quarter. High internalization funds trade less in response to flows, thus reducing the volatility in the stock that is induced by trade. The magnitude of the effect of internalization is modest in absolute terms, but significant relative to the total excess volatility that is induced by trading in response to flows (Greenwood and Thesmar, 2011). Our stock-level analysis 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. 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 *f*'s securities are held by other funds that internalize more of their price impact, the relationship between flows into these other funds and *f*'s returns is diminished because the other funds trade less in response to flows. In addition, we show that the internalization of other funds holding the same securities impacts fund *f*'s overall performance. When holders of the same securities are high internalization funds, fund *f*'s returns tend to be higher and less volatile. Thus, the internalization of other funds holding the same securities aggregates to affect *f*'s average performance.

Finally, we examine the relationship 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 and comparable to the variation in the cash-to-assets ratios induced by variation in asset liquidity.

Overall, our results provide evidence that fire sale externalities operate across equity mutual funds. 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), Merrill et. al. (2012), Hau and Lai (2017), and Choi and Shin (2018).[2] These studies, which frequently examine specific events to causally identify fire sales, show that funds' liquidation policies create spillovers: they affect asset prices and the performance of other funds. For instance, Hau and Lai (2017) show that during the 2007-2009 financial crisis, funds with high exposure to financial stocks sold nonfinancial stocks, depressing their prices. In contrast, we are interested in how equilibrium forces determine liquidation policies in the first place. In particular, we show that when funds internalize more of their price impact, spillovers are smaller because funds choose different liquidation policies: they rely more on cash and less on sales of non-cash assets. These results show us that, on average across our 1994-2016 sample, funds perceive fire sale risk to be significant enough that they act differently when they internalize their price impact.

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). This literature focuses primarily on funds' market timing ability and the impact of cash holdings on a fund's own returns. In contrast, we use cash holdings along with our internalization measures to empirically explore the extent to which a fund internalizes the price impact it exerts on security prices and other funds.

[2] 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), Pastor and Stambaugh (2003), Longstaff (2004), Acharya and Pedersen (2005), Bao, Pan, and Wang (2011), Dick-Nielsen, Feldhütter, and Lando (2012), Feldhütter (2012), and many others.

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

I. Framework

This section outlines the economic logic behind our empirical tests.

A. Model

We present a stylized model that highlights the intuition behind our empirical tests. For expositional simplicity, the benchmark model focuses on how funds manage liquidity to deal with outflows. In the appendix, we show that similar comparative statics apply when we write down a similar model of how funds deal with inflows.[3]

Suppose there are $f = 1,\ldots, F$ funds, which invest in an illiquid asset and hold some cash reserves. Fund f faces uncertain redemptions x_f. To obtain simple closed form solutions, we begin by assuming that redemptions are perfectly correlated across funds so that $x_f = x$ for all f, and that redemptions follow an exponential distribution with probability distribution function $g(x) = \lambda^{-1}\exp\left(-\lambda^{-1}x\right)$. The cumulative distribution function is then $G(x) = 1 - \exp\left(-\lambda^{-1}x\right)$, so larger values of λ are associated with a longer right tail for the distribution of redemptions.

Funds may accommodate redemptions in two ways. First, they may choose to hold cash reserves c_f. These reserves are liquid claims that are available in elastic supply and that can be sold costlessly to meet outflows. Each dollar of cash reserves is associated with carrying cost i. One may think of i as the cost to the fund of the tracking error generated by not being fully invested in the illiquid asset.

Second, if it does not have sufficient cash reserves, the fund meets outflows by selling quantity $s_f = x_f - c_f$ of its illiquid asset holdings.[4] When it does so, the fund incurs liquidation costs that depend on the aggregate sales of the illiquid asset by all funds. We think of these

[3] The two problems differ in that the treatment of inflows in a purely ex-post problem: once a fund receives an inflow of cash, it must decide what to do with it. In contrast, the treatment of outflows requires an ex-ante choice of a cash buffer.

[4] Because this is a simple one-shot model, where cash serves no other purpose, the policy of first using cash reserves to meet redemptions and then selling the illiquid asset is optimal.

liquidation costs as arising from the fact that sales temporarily move prices – that is, we think of the fundamental value of the illiquid asset as being fixed, but its market price as depending on aggregate sales by funds. For simplicity, we assume that the liquidation cost per dollar is $l\left(\sum_f s_f\right)/F$, where l indexes the illiquidity of the asset.[5] This formulation implies that there are spillovers for $l > 0$. When $l > 0$, sales by one fund affect the liquidation costs of other funds. As we will see, however, $l > 0$ is not sufficient for funds that internalize more of their price impact to act differently than other funds. We normalize liquidation costs by the total number of funds F so that aggregate liquidation costs across funds do not mechanically change with F.

We start by solving for optimal cash holdings in two settings. First, we consider the private market equilibrium, in which each individual fund wishes to minimize its total liquidity management costs, including the carrying costs of cash, taking as given the actions of other funds:

$$
\begin{aligned}
E\left[L_f\right] &= ic_f + E_x\left[s_f \frac{l}{F}\left(\sum_h s_h\right)\right] \\
&= ic_f + \int_{c_f}^{\infty} s_f \frac{l}{F}\left(\sum_h s_h\right) dG(x).
\end{aligned}
$$

Second, we consider the solution that would be chosen by a planner coordinating across funds. The planner's objective is to minimize the sum of the expected liquidity management costs across all funds:

$$
E\left[\sum_f L_f\right] = F\left(ic_f + \int_{c_f}^{\infty} s_f \frac{l}{F}\left(Fs_f\right) dG(x)\right).
$$

Note that this formulation of the planner's problem does not imply a welfare statement. For there to be a welfare loss from the behavior of low internalization funds in general equilibrium, the liquidation costs borne by mutual funds when they sell illiquid assets must not simply be a transfer to an outside liquidity provider.[6] Moreover, our formulation of both the individual fund's problem and the planner's problem only focuses on the costs of liquidity management. In reality, a fund's

[5] Funds can be liquidity demanders or liquidity suppliers (Anand et. al., 2018); we are focused on liquidity demand.

[6] For example, 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).

behavior is determined by many other considerations, most notably the risk and return of the illiquid securities it holds.

Proposition 1 characterizes the symmetric equilibrium, obtained by taking the first order condition with respect to c_f and imposing symmetry across funds so that $c_f = c_h = c^*$ for all *f, h.*

Proposition 1. *Optimal cash holdings in the symmetric private market equilibrium are given by*

$$c^* = \begin{cases} -\lambda \ln\left(\frac{i}{\lambda l}\frac{F}{F+1}\right) & \text{if } \; i < \lambda l\left(F+1\right)/F \\ 0 & \text{if } \; i \geq \lambda l\left(F+1\right)/F \end{cases}.$$

The planner chooses cash holdings of

$$c^{**} = \begin{cases} -\lambda \ln\left(\frac{i}{2\lambda l}\right) & \text{if } \; i < 2\lambda l \\ 0 & \text{if } \; i \geq 2\lambda l \end{cases}.$$

Proof: *All proofs are given in the Appendix.*

Intuitively, in both cases, there is a tradeoff between the carrying costs of cash reserves and the expected liquidation costs of selling the illiquid asset. Cash holdings are zero if the carrying costs of cash are high relative to liquidation costs, which are determined by the size of the right tail of redemptions (λ) and the illiquidity of the asset (l). In the limit, as redemptions become large ($\lambda \to \infty$) or the asset becomes very illiquid ($l \to \infty$), cash holdings become large. In contrast, for small values of λ and l, cash holdings go to zero in both the private market and planner solutions.

The key difference between the individual fund's problem and the planner's problem is the following. In the private market equilibrium, an individual fund does not internalize the positive effect its cash holdings have on the marginal liquidation costs faced by other funds, while the planner does. As such, funds hold more cash in the planner's solution: $c^{**} \geq c^*$.

The extent to which the planner's solution differs from the private market's depends on the parameters. There is no difference between the planner's solution and the private market solution when λ and l are sufficiently small – when the probability of large redemptions is small or the non-cash asset is very liquid, both solutions involve no cash holdings. If $l > 0$, $\lambda > 0$, and $2\lambda l \leq i$, there will be spillovers across funds – funds will sell the illiquid asset when faced with redemptions and their sales will affect the liquidation costs of other funds. However, there will not be an externality – the spillovers are small enough that the planner chooses the same outcome as the private market.

In contrast, when λ and l are large (i.e., $2\lambda l > i$), so that spillovers across funds are frequent and costly, the planner's solution involves larger cash holdings than the private market's. In addition, the difference between the planner's problem and the private market solution is large when F is large. Intuitively, when there are many funds, none of the funds internalize the effect that their forced sales will have on the other funds.

Our empirical internalization measures aim to capture the idea that some funds put a positive weight on the price impact of their trading on other funds. A simple way to capture this in the model is to think of fund f as minimizing an objective that puts weight α on the planner's objective and weight ($1-\alpha$) on the objective in the fully private market:

$$(1-\alpha)E\left[L_f\right]+\alpha E\left[\sum_h L_h\right]=\left((1-\alpha)+aF\right)ic_f+\frac{l}{F}\int_{c_f}^{\infty}s_f\left[(1-\alpha)\left(\sum_h s_h\right)+\alpha F^2 s_f\right]dG(x).$$

For $0 < \alpha < 1$, the fund internalizes the positive effect its cash holdings have on the liquidation costs faced by other funds, but not as much as the planner. Proposition 2 shows that the properties of the symmetric equilibrium vary intuitively with the level of internalization.

Proposition 2. *Optimal cash holdings in the internalization equilibrium are given by*

$$c^{***}=\begin{cases}-\lambda\ln\left(\dfrac{i}{\lambda l}\eta\right) & \text{if } \; i<\lambda l/\eta \\ 0 & \text{if } \; i\geq \lambda l/\eta\end{cases} \qquad \text{where}$$

$$\eta=\frac{\left((1-\alpha)+\alpha F\right)F}{(1-\alpha)(F+1)+2\alpha F^2}.$$

We have $c^{***}=c^{*}$ *when* $\alpha = 0$ *and* $c^{***}=c^{**}$ *when* $\alpha = 1$. *In addition, we have* $dc^{***}/d\alpha \geq 0$.

Cash holdings are lowest in the private market equilibrium where $\alpha = 0$ and highest in the planner's solution where $\alpha = 1$. In between, they increase monotonically with α. The extent to which the solution with $\alpha > 0$ differs from the private market equilibrium with $\alpha = 0$ again depends on the parameters λ and l. When large redemptions are infrequent and the illiquid asset is relatively liquid (i.e., λ and l are sufficiently small), both solutions again involve no cash holdings.

With this set up in place, we can now derive the comparative statics that motivate our empirical tests. We first show that the sensitivity of the change in cash holdings to flows is increasing in internalization. The change in cash holdings in response to redemptions x is given by $\Delta c = \max\left\{c^{***} - x, 0\right\}$. The proposition then characterizes the covariance between the change in cash and flows, which are the negative of redemptions -x.

Proposition 3. *The covariance between the change in cash holdings and flows is given by*

$$Cov\left(-x, \Delta c\right) = -\exp\left(-c^{***}\right)\left(1 + c^{***}\right) + 1 > 0$$

if $i < \lambda l/\eta$ and is zero otherwise. This covariance is increasing with internalization: $dCov\left(-x, \Delta c\right)/d\alpha > 0$ *if $i < \lambda l/\eta$.*

Intuitively, redemptions x are negatively correlated with the change in cash holdings: the larger the redemption, the more that cash holdings fall. Thus, flows $-x$ are positively correlated with cash holdings, and the strength of this correlation increases with internalization. Funds that internalize more of their price impact will meet redemptions with more cash and fewer sales of the illiquid asset. This is a key prediction of the model that we will test in our empirical work.[7] Again, this is only the case when λ and l are large (i.e., $\lambda\ l/\eta > i$), so that spillovers across funds are sufficiently frequent and costly. If λ and l are small but nonzero, there are spillovers across funds, but they are too rare and infrequent for high internalization funds to behave differently.

Next, we compute the impact of flows faced by other funds on fund f's liquidation costs. To vary other funds' flows without varying f's, we loosen the assumption that redemptions are perfectly correlated across funds. We instead assume that redemptions for each fund h are independently exponentially distributed: $g\left(x_h\right) = \lambda^{-1}\exp\left(-\lambda^{-1}x_h\right)$. Let $-x_{-f} = \sum_{h \neq f} -x_h$ be the total flows out of all funds except fund f. In addition, let

$$L_f^{***} = ic^{***} + \int_{c^{***}}^{\infty}\int_{c^{***}}^{\infty} \ldots s_f \frac{l}{F}\left(\sum_h s_h\right) dG\left(x_1\right)\ldots dG\left(x_F\right)$$

[7] It is also the case that the sensitivity of cash to flows increases with illiquidity ($dCov\left(-x, \Delta c\right)/dl > 0$), consistent with what we find in the data.

be the liquidation costs incurred by fund f in the internalization equilibrium. Proposition 4 characterizes the covariance between f's liquidation costs and flows into other funds.

Proposition 4. *The covariance between flows into other funds and fund f's liquidation costs is negative:* $Cov\left(-x_{-f}, L_f^{***}\right) < 0$ *if* $i < \lambda l/\eta$. *Because liquidation costs lower fund returns, the covariance between flows into other funds and fund f's returns is positive. This covariance gets weaker with internalization:* $dCov\left(-x_{-f}, L_f^{***}\right)/d\alpha > 0$ *if* $i < \lambda l/\eta$. *Moreover, this comparative static obtains holding fixed f's own cash holdings.*

Intuitively, larger redemptions from other funds x_{-f} cause them to sell more of the illiquid asset, raising liquidation costs for fund f. Thus, flows $-x_{-f}$ are negatively correlated with liquidation costs for fund f. If λ and l are sufficiently large, the more other funds internalize their price impact, the less they sell the illiquid asset when faced with flows $-x_{-f}$, weakening this correlation. These comparative statics obtain holding fixed fund f's cash holdings, showing that they are driven by the behavior of other funds, not by the way f's behavior changes as we change internalization.

Finally, we relate internalization to overall measures of fund performance: the mean and variance of the liquidation costs the fund incurs. Again, let L_f^{***} be the liquidation costs incurred by fund f in the internalization equilibrium.

Proposition 5. *The expected liquidation costs faced by fund f are decreasing in internalization:* $dE\left[L_f^{***}\right]/d\alpha < 0$ *if* $i < \lambda l/\eta$. *In addition, the variance of liquidation costs is decreasing in internalization:* $dVar\left[L_f^{***}\right]/d\alpha < 0$ *if* $i < \lambda l/\eta$. *Because liquidation costs lower fund returns, fund f's expected return is increasing in internalization and the volatility of its returns is decreasing in internalization. Moreover, these comparative statics obtain holding fixed f's own cash holdings.*

Intuitively, if λ and l are sufficiently large, when other funds internalize their price impact more, they use cash to meet redemptions rather than selling the illiquid asset. As a result, fund f faces lower and less volatile costs when it sells its holdings of the illiquid asset. Again, these comparative statics are driven by the behavior of other funds, not by the way f's behavior changes as we change internalization.

B. *Measures of Internalization*

Throughout the paper, we use three empirical proxies for 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. The common thread in our measures is that they capture cases where funds face incentives to care about the price impact they exert on other funds.

Our first internalization measure leverages the fact that many mutual fund managers manage multiple funds. Our *Manager internalize* 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 of 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 manager's funds. In the model, this overlap is assumed, since there is only one illiquid asset.

Our two other measures of internalization are based on the idea that investment advisers may create incentives for funds to partially internalize their price impact on other funds and accounts under their management. This kind of internalization is sometimes incentivized by the compensation contracts of fund managers.[8] 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 the Adviser's parent company."[9] 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." [10] Thus, if a fund holds assets that are also held by other funds run by the same investment adviser, then the fund may be more likely to internalize the price impact of its trading on those funds, than on funds run by other investment advisers. Our *Adviser internalize* measures capture the overlap in portfolio holdings across multiple funds managed by the same investment adviser.

[8] Ibert et. al. (2017) show the importance of firm-level revenues and profit for the compensation of mutual fund managers in Sweden, and Gaspar et. al. (2006) show evidence of coordination within fund families.
[9] https://www.sec.gov/Archives/edgar/data/1028621/000119312516656538/d204146d485bpos.htm
[10] https://www.sec.gov/Archives/edgar/data/312555/000072888916004375/risingdividends485bpos.htm

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.[11] These forms are filed semi-annually by all mutual funds and, among other things, provide data on asset composition, including 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),[12] 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 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 inflate our standard errors, biasing us against finding statistically significant results.[13]

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[11] We discuss parsing of N-SAR filings in the Internet Appendix.

[12] 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.

[13] 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

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

We link our N-SAR data to the CRSP Mutual Fund and Thomson Reuters Mutual Fund Holdings Databases for additional fund characteristics and security-level holdings data that we use to construct our measures of internalization. Our matching algorithm is described in detail in the Internet Appendix; here we provide a brief overview. In linking N-SAR data with CRSP, we leverage the CRSP_CIK_MAP file provided by WRDS. This file maps CRSP share class identifiers (crsp_fundno) to the CIK of the trust offering the fund and, for a subset of funds, to the fund's SEC series identifier that is used after 2006. Given that the series identifier is not used prior to 2006, our matching algorithm proceeds in two main steps. First, we try to match funds based on their series identifier. Second, prior to 2006 or when matching based on series identifier is not successful, we match based on the trust's CIK and fund's TNA. Specifically, we first link each fund-date observation in N-SAR to all fund-date observations in CRSP that share the same trust CIK as the fund in N-SAR. We then keep the closest match in CRSP in terms of TNA provided that the difference in TNA is less than 1% or the difference in TNA is less than 10% and fund names in CRSP and N-SAR match exactly. The advantage of matching based on TNA as opposed

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.

to fund names is that we do not have to deal with alternative abbreviations and conventions about the reporting of fund names in CRSP versus SEC. Finally, we use MFLINKS to link N-SAR to Thomson Reuters.

After linking N-SAR data to CRSP and Thomson Reuters, we limit the sample to open-end domestic equity funds.[14] These are the funds for which we can fairly accurately measure internalization and portfolio illiquidity. The effect of internalization on flow management should be even stronger for funds that invest in less liquid securities, such as emerging market equity funds and corporate bond funds. However, there is less data available on the security holdings of these funds and their liquidity.

C. *Portfolio Holdings*

Our key explanatory variables of interest are measures of internalization that are based on the overlap in holdings between a given fund and either (i) other funds managed by the same portfolio manager or (ii) aggregate assets under management of the fund's investment adviser. To make sure that we have the most comprehensive and up-to-date data on portfolio holdings, we combine mutual fund holdings data from Thomson Reuters and CRSP. For each fund-quarter observation, we first check if one source has more recent data. If for a given fund-quarter, both sources report as of the same date, we use the source with the larger number of positions; otherwise we default to Thomson Reuters. Overall, 59% of our fund-quarter observations of portfolio holdings are from Thomson Reuters, and 41% are from CRSP.

D. *Internalization*

Using our combined CRSP/Thomson Reuters holdings data, we construct three measures of fund internalization, referred to in the tables as *Fund Internalize.* All three measures are value-weighted portfolio averages of the product of a) a fund's holdings of a security scaled by the security's average daily dollar trading volume, and b) holdings of the security by the fund's affiliates, also scaled by the security's trading volume:

$$\sum_{s} w_{f,s} \times \frac{V_{f,s}}{Volume_s} \times \frac{V_s^{affiliates}}{Volume_s}.$$

[14] Domestic equity funds are identified based on CRSP objective codes that begin with ED.

where f indexes funds, s indexes securities, $V_{f,s}$ is the value of fund f's holdings of security s, $V_s^{affiliates}$ is the value of holdings of security s by affiliates of f that f has an incentive to care about, and $Volume_s$ is the trading volume.[15]

Internalization thus depends both on the liquidity of the fund's holdings, measured as position size relative to trading volume, and the overlap in holdings with affiliated entities. Where the three internalization measures differ is in the definition of the affiliates that may be affected by the fund's trading decisions.

The first measure, *Manager internalize*, defines affiliates as other funds managed by the same portfolio manager:

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

The measure thus captures the overlap in portfolio holdings across multiple funds managed by the same portfolio manager. Information on the identity of fund portfolio managers is from Morningstar. For funds with multiple portfolio managers, we split total holdings of each security equally among the fund's managers.

The other two measures of internalization define affiliates at the investment adviser level. Investment advisers' aggregate holdings are from the Thomson Reuters 13F database.[16] The 13F filings include holdings of stocks both by other mutual funds managed by the same investment adviser, and by hedge funds, separate accounts, and any other affiliates managed by the fund's investment adviser.

Our second measure, *Adviser internalize,* uses the difference between adviser's 13F holdings of a security and fund holdings to measure the scope for fund trading to impose price impact externalities on the affiliated entities:

[15] Because it requires data on trading volume, which we measure as average daily trading volume over the quarter, calculation of internalization is limited to CRSP stocks. We therefore restrict the sample to observations for which the ratio of the value of stocks in CRSP to the fund's TNA (from form N-SAR) is within the [3/4, 4/3] interval.

[16] To help address the data quality issues with the recent updates of the Thomson Reuters 13F data, after June 2013 we supplement Thomson Reuters 13F data with WRDS 13F holdings data. See WRDS Research Note Regarding Thomson-Reuters Ownership Data Issues: https://wrds-www.wharton.upenn.edu/pages/support/research-wrds/research-guides/research-note-regarding-thomson-reuters-ownership-data-issues

$$Adviser\ internalize_f = \sum_s w_{f,s} \times \frac{V_{f,s}}{Volume_s} \times \frac{V^{13F}_{adviser(f),s} - V_{f,s}}{Volume_s}$$

where $V^{13F}_{adviser(f),s}$ are the fund adviser's 13F holdings of security *s*.

The third measure of internalization takes the difference between the investment adviser's 13F holdings of a security and aggregate holdings of the security by all mutual funds managed by the fund's portfolio manager:

$$Adviser\ internalize\ without\ manager_f = \sum_s w_{f,s} \times \frac{V_{f,s}}{Volume_s} \times \frac{V^{13F}_{adviser(f),s} - \sum_{j,mgr(j)=mgr(f)} V_{j,s}}{Volume_s}$$

By excluding holdings by all funds managed by the same portfolio manager, this measure zeroes in on adviser-level internalization that is incentivized through compensation linked to the investment adviser's overall performance.

Because the distribution of raw internalization measures is highly skewed and can be affected by time series changes in data quality, we convert raw internalization measures into decile ranks within each quarter. This has the further advantage of easing the interpretation of the economic magnitudes.

To analyze the effect of internalization on stock price volatility, we construct stock-level versions of our internalization measures. Referred to as *StockInternalize*, these measures are value-weighted averages of *Fund Internalize*, calculated across all funds holding a given stock. Since fund internalization is expressed as decile rank within each quarter, a unit change in stock internalization indicates that all funds holding the stock belong to a higher decile of fund internalization. Finally, to analyze spillovers across funds, we construct a fund-level measure of co-holder internalization, *CoHolderInternalize.* This is the value-weighted average of *StockInternalize* across all stocks in a fund's portfolio, where *StockInternalize* is calculated while excluding the fund in question. Thus, *CoHolderInternalize* measures the propensity of other funds holding the same securities to internalize price impact. In constructing both *StockInternalize* and *CoHolderInternalize*, we set the internalization of index funds to zero because these funds are constrained to holding the index and cannot use cash to accommodate fund flows.

Where does variation in our measures come from? Our measures 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 expectations of risk and return for each stock. If a manager manages two funds and has strong, positive expectations for a stock, they will likely hold the stock in both funds, driving up their *Manager internalize*. In addition, 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 subjective 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. Furthermore, in Tables 5 and 6 we exploit variation in internalization due to a) portfolio managers being assigned an additional fund to manage and b) mergers of investment advisers.

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, portfolio holdings from CRSP and Thomson Reuters, portfolio manager identities from Morningstar, and investment adviser holdings from Thomson Reuters 13F data. The sample period is January 1994 – December 2016. To make sure that our results are not affected by fund incubation (Evans 2010), we restrict the sample to funds that are at least two years old and that have real TNA of at least $10 million, measured in 2016 dollars.

Figure 1 plots the number of funds and their TNA over time. The average half-year period has 945 funds with aggregate TNA of $1,748 billion. Table 1 reports basic summary statistics for funds in our data. Actively managed funds are in Panel A, index funds are in Panel B. Our sample consists of 37,707 observations on actively managed funds and 5,402 observations on index funds, which we use for placebo tests. The median actively managed has TNA of almost $350 million, of which about 2.76% is held in cash and equivalents.

There is significant variation across funds in the cash-to-assets ratio: the interquartile range for actively managed funds is 1.15%-5.26%. Index funds hold significantly less cash (the median is 0.36%) and have a significantly narrower interquartile range of 0.10%-1.79%. Consistent with an aggregate shift towards index funds, the median actively managed fund in our data experiences quarterly fund flows of -1.38%, while the median index fund experiences quarterly fund flows of 0.76%. Figure 2 shows the distribution of the cash-to-assets ratio for funds in our sample. The distribution has shifted to the left and compressed over time. The 50th percentile has declined from

5.62% in 1994H1 to 1.68% in 2016H2, while the interquartile range has shrank from 8.90% to 3.50% over the same period.

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

III. Results

We now present tests of the empirical predictions outlined above.

A. Liquidity Management through Cash Holdings

To ensure that our 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 2 we estimate regressions of the change in a fund's cash-to-assets ratio over a six-month reporting period on the net flows received during each of those six months:

$$\left(\frac{Cash}{TNA}\right)_{f,m} - \left(\frac{Cash}{TNA}\right)_{f,m-6} = \alpha_{obj(f),m} + \sum_{s=0}^{5} \beta_s \cdot Flows_{f,m-s} + \varepsilon_{f,m} \tag{1}$$

Fund flows are winsorized at the 5th and 95th percentiles; results are similar when winsorizing at the 1st and 99th percentiles.

Columns (1)-(3) examine actively managed funds. In Column (1), the coefficient $\beta_0 = 18.51$ is statistically and economically significant. Flows equal to 100% of assets increase the fund's cash-to-assets ratio by 18.51% (percentage points). For reference, the standard deviation of monthly fund flows is 2.5%. The coefficient β_0 shows that an economically significant portion of flows is accommodated through cash holdings. Even though stocks are fairly 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 portfolios is changing, becoming more cash-heavy when funds receive inflows and less cash-heavy when they suffer outflows.[17] At higher

[17] Massa and Phalippou (2005) and Hahouna et. al. (2015) show that mutual funds' portfolio liquidity decreases following outflows. This suggests that funds respond to outflows by both drawing down their cash balances and selling more liquid securities.

frequencies (e.g., daily or weekly), cash presumably 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 0.22. The coefficients then turn negative, indicating that over the full six-month period, the total effect of flows on the cash-assets ratio is essentially zero.

The second column of Table 3 shows that the results are similar if we include fixed effects for Lipper objective codes and time, indicating the results are not driven by common trends over time in cash and flows or by a correlation between average changes in cash and flows across objectives. Finally, the third column shows that the results remain essentially unchanged if we include Lipper objective code-by-time fixed effects, indicating that the results are not driven by relationships between flows and cash holdings in particular fund objectives.

Columns (4)-(6) examine index funds. These funds are constrained to hold the index, and therefore have much less scope for managing flows using cash buffers. Consistent with this, the relationship between changes in cash holds and flows is much weaker for index funds than for actively managed funds. For instance, in Column (4) we find $\beta_0 = 2.58$, as compared to $\beta_0 = 18.51$ for actively managed funds in column (1). The reason the coefficient β_0 is not zero is that some index funds achieve their exposure through derivatives, which require cash collateral. When these funds receive inflows and outflows, they scale their derivative positions, which in turn affects the cash collateral that they hold.

B. Internalization and Flow Management

We next examine how the propensity to accommodate fund flows using cash holdings varies with our internalization measures. Table 3 estimates specifications that allow flow management practices to differ in the cross section of funds based on our internalization measures:

$$\begin{aligned}\Delta\left(\frac{Cash}{TNA}\right)_{f,t-2:t} = {} & \alpha_{obj(f),t} + \beta_1 Flows_{f,t} + \beta_2 Flows_{f,t} \times Fund\ Internalize_{f,t-2} + \beta_3 Flows_{f,t} \times Illiq_{f,t-2} \\ & + \beta_4 Flows_{f,t-1} + \beta_5 Flows_{f,t-1} \times Fund\ Internalize_{f,t-2} + \beta_6 Flows_{f,t-1} \times Illiq_{f,t-2} \\ & + \beta_7 Fund\ Internalize_{f,t-2} + \beta_8 Illiq_{f,t-2} + \varepsilon_{f,t}.\end{aligned} \tag{2}$$

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 the fund internalizes its price impact? As Proposition 3 of Section I suggests, if large outflows are frequent enough and the fund's non-cash assets are illiquid enough, high internalization funds should behave differently.

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). Controlling for illiquidity helps us separate liquidity from internalization. Liquidity is essentially independent of who holds the security: l in the notation of the model we presented in Section I. Any fund holding a given illiquid security will 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; α in the notation of the model in Section I. 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 the other funds.

The dependent variable in Eq. (2) is once again the change in the fund's cash-to-assets ratio. We convert raw values of our internalization measures into decile rankings within each quarter, so that their coefficients can be interpreted as the effect of a one-decile change in each variable. Again, all specifications include Lipper objective-by-time fixed effects.

The first column of Table 3 examines actively managed funds. The coefficient β_2 on the interaction between flows and *Manager internalize* is positive and significant. To give a sense of the magnitudes, for a fund in the 25th percentile of *Manager internalize*, flows equal to 100% of assets over the most recent quarter t change the cash-to-assets ratio by 4.52 percentage points.[18] For a fund in the 75th percentile of *Manager internalize*, the same flows change the cash-to-assets ratio by 6.98 percentage points, a 54% larger effect. The effect is comparable to the impact on flow management of going from the 25th percentile to the 85th percentile of asset illiquidity. Thus, the impact of our internalization measures is economically sizeable. The reduction in trading we would observe if funds internalized more of the price impact of their trading is similar to the reduction we would observe if their assets were substantially less liquid.

[18]A fund in the 25th percentile is in the 3rd decile of *Manager internalize*, so the total effect of flows is $\beta_1 + \beta_2 * 3 = 4.52$.

Column (2) examines index funds as a placebo test. Here we find no impact of *Manager internalize* on flow management, consistent with the idea that index funds have limited discretion.[19] If anything *Manager internalize* is associated with slightly less aggressive use of cash in flow management.[20]

Columns 3—6 of Table 3 show that similar results obtain using our other measures of internalization: *Adviser internalize with manager* and *Adviser internalize without manager.* These measures are associated with more aggressive use of cash in flow management for actively managed funds, but not for index funds.

Our *Adviser internalize* 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 fund family increase their positions in the fire sold securities. This kind of cross trading among family funds should be positively correlated with our measures of internalization, and thus should bias us against finding our results: if funds can cross-trade with their families, they do not need to use as much cash for flow management. Nonetheless, funds with high *Adviser internalize* do manage fund flows more aggressively using cash.

Overall, all three measures of internalization deliver similar results. 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 3 show that our measures of internalization strongly affect funds' flow management strategies. Funds that score highly on our internalization measures use cash more

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[19] Note that though the coefficient β_1 is similar for index funds and actively managed funds, the average effect of flows is quite different. The average fund is in the 5[th] decile of internalization, and we have $\beta_1 + \beta_2 * 5 = 5.5$ for active funds in column (1) and $\beta_1 + \beta_2 * 5 = 0.7$ for index funds in column (2).

[20] This may be capturing the fact that index funds that rely more heavily on derivatives to maintain exposure to the index tend to be somewhat smaller funds with lower levels of internalization.

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 4 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, 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 for all three measures of internalization. All specifications include Lipper objective by time fixed effects. Row (1) replicates our baseline results from columns (1), (3), and (5) of Table 3. For compactness, we only report the coefficient on our variable of interest, the interaction of fund flows during the most recent quarter with lagged values of our internalization measures.[21] 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 higher internalization is associated with a greater propensity to accommodate fund flows through cash holdings.

In Row (2) of Table 4, 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 could 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, 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 4 shows that controlling for past returns has no impact on our results.

Whether funds accommodate fund flows through changes in cash or by trading in their portfolio securities could depend on fund managers' expectations of future returns. For instance, if the manager expects future returns to be high, they may want to satisfy redemption requests using the fund's cash buffer rather than selling portfolio securities. If our internalization measures are correlated with expected returns, this could help explain the stronger sensitivity of cash to fund flows for high internalization funds. Row (3) of Table 4 uses future returns realized over the

[21] The full regression output is reported in the Internet Appendix.

following one, three, six, and twelve months as proxies for expected returns. These controls do 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 3 controls for the interaction of flows and illiquidity, the effect of illiquidity on cash holdings may be non-linear. Rows (4), (5), and (6) of Table 4 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.

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 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 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 4 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 variables with fund flows. Overall, rows (4), (5), and (6) of Table 4 are strong evidence that our internalization measures are not simply proxies for the illiquidity of fund holdings.

We next consider the idea that our internalization measures could be correlated with fund strategies. For instance, a fund manager who tends to make big bets may manage liquidity differently. We explore this alternative in rows (7), (8), and (9) of Table 4. 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, and our results are again unaffected. Overall, rows (7), (8), and (9) of Table 4 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 that some clienteles are subject to stronger strategic complementarities than others. For instance, Chen, Goldstein, and Jiang (2010) and Goldstein, Jiang, and Ng (2016) argue that retail investors are subject to stronger strategic complementarities. Thus, funds catering to retail investors may want to be less aggressive in using cash to manage fund flows, since doing otherwise risks incentivizing shareholder runs (Zeng, 2016). Correlation between our internalization measures and fund clienteles could therefore 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. 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 manager's years of experience, 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: smaller (below median TNA) versus larger (above median) funds,[22] and the first versus second half of our sample period. Given the smaller sample sizes, the standard errors here are larger, and statistical significance is weaker. Overall, however, we find broadly similar results across the sample splits.

Overall, Table 4 provides strong evidence that we are picking up the impact of internalization on flow management. Table 4 is inconsistent with a wide variety of plausible alternative explanations for our results.

[22] While fund size and internalization are positively correlated (0.38-0.56), there is meaningful variation in internalization within both small and large funds. The standard deviation of *Manager internalize* for example is 2.36 for small funds and 2.70 for large funds. Small funds can be high internalization if they hold concentrated positions in illiquid securities and have significant overlap with affiliates who themselves are large.

D. *Evidence from Structural Changes*

Despite the battery of robustness tests in Table 4, one might still worry that our internalization variables are endogenous and that our results are thus picking up factors other than internalization. In this section, we examine whether changes in internalization driven by structural changes at the portfolio manager or investment adviser level affect the fund's propensity to use cash to accommodate fund flows.

First, we examine cases in which the fund's portfolio managers are assigned an additional fund to manage. The basic idea is that the fund manager internalizes the impact of decisions to trade across all of their funds. Thus, being assigned an additional fund means that *Manager internalize* increases, and that the propensity to use cash to manage flows should increase as well.

To isolate the set of new fund management assignments that are likely to have a sizable effect on a portfolio manager's internalization, we focus on cases where the manager initially manages a single fund and where the size of the new fund is at least 5%, 15%, or 25% of the size of the existing fund. We identify 454, 411, 389 funds that satisfy these criteria, respectively.

In Panel A of Table 5, we show *Manager internalize* increases significantly for the manager's existing fund after being assigned a new fund to manage. Treated funds are typically in the third decile of internalization prior to treatment and increase by two deciles once their portfolio manager is assigned a new fund.[23] The fact that treated funds are in the middle of the distribution of internalization suggests that our results are not driven by a small set of funds with very high values of internalization. Columns (2), (4), and (6) include fund fixed effects, so we are only identifying off changes in *Manager internalize* within a fund after the manager is assigned a new fund to manage. The results are nearly identical when we include fund fixed effects.

Panel B of Table 5 then reports the results of regressions where we allow the sensitivity of cash to flows to vary before and after the new fund assignment:

$$\begin{aligned}\Delta\left(\frac{Cash}{TNA}\right)_{f,t} &= \alpha_{obj(f),t} + \beta_1 Flows_{f,t} + \gamma_1 Flows_{f,t} \times Post_{f,t} \\ &\quad + \beta_2 Flows_{f,t-1} + \gamma_2 Flows_{f,t-1} \times Post_{f,t} + \delta Post_{f,t} + \varepsilon_{f,t}.\end{aligned} \tag{3}$$

[23] By construction, the raw value of *Manager internalize* is zero for treated funds prior to treatment.

The sample is limited to the funds the manager managed before being assigned the new fund. Thus, the results are not driven by newly assigned funds having different flow management practices. In addition, we limit the sample to a window of [-24, +24] months around treatment to help ensure that we are capturing changes due to the new fund assignment. Note that the coefficient β_1 on flows is similar to what we found in Table 3, indicating that the funds we are studying have average flow management policies before the new fund assignment.

The coefficient γ_1 on the interaction of flows with the post treatment dummy is positive and significant, indicating that once managers are assigned a new fund to manage and begin to internalize the price impact of their trading, not only on their old fund but also on the new fund, their propensity to accommodate fund flows using cash increases. Again, columns (2), (4), and (6) include fund fixed effects, so we are only identifying off within fund variation. In addition, it is worth noting that the magnitude of the interaction term increases as we increase the relative size cutoff for the new fund, consistent with the idea that managers internalize more of their price impact when the new fund they are managing is larger. However, given the limited sample size, the difference in the coefficients is not statistically significant.

In Table 6, we examine a second type of structural change – mergers of investment advisers. Such mergers have the potential to increase investment adviser internalization. We search SDC and Capital IQ for mergers of investment adviser firms during the 1994-2016 period. To focus on mergers that are likely to increase adviser internalization, we a) focus on cases where the target is initially a stand-alone entity[24] and b) require both the target and acquirer to be sizable relative to the combined firm. Specifically, the target's funds are considered to be treated as long as the acquirer accounts for at least 50% (columns 1-4) or 25% (columns 5-8) of combined pre-merger 13F assets, i.e., acquirer is relatively large compared to the target. Symmetrically, the acquirer's funds are considered to be treated as long as the target accounts for at least 50% (columns 1-4) or 25% (columns 5-8) of combined 13F assets. We identify 56 mergers affecting 133 target and acquirer funds using the 50% criterion, and 61 mergers affecting 185 target and acquirer funds using the 25% criterion.[25]

[24] In other words, we want to avoid acquisitions of subsidiaries as these transactions have an ambiguous effect on the internalization of the target's funds.
[25] The sample is fairly small because we look at mergers of investment advisers where target's and acquirer's mutual funds themselves do not merge but continue to maintain their separate legal and economic identities.

Panel A of Table 6 shows that our *Adviser internalize* measure increases by between 0.5 and 1 decile after a merger. In columns (1)-(4) we restrict the sample to cases where the merger counterparty accounts for at least 50% of combined 13F assets. Columns (1) and (2) examine only funds managed by targets, while columns (3) and (4) examine funds managed by both targets and acquirer. In columns (5)-(8), we repeat the exercise, restricting the sample to cases where the merger counterparty accounts for at least 25% of combined 13F assets. Columns (2), (4), (6), and (8) include fund fixed effects, so we are only identifying off changes in *Adviser internalize* within fund after the merger. Given the significantly smaller sample size – we have roughly 500-1000 observations in Table 6 versus 2400-2800 observations in Table 5 – the statistical significance is slightly weaker. Nonetheless, of the eight specifications in Table 6 Panel A, five are significant at the 5% level and one is significant at the 10% level. The effect of mergers on *Adviser internalize* is always significant once we include fund fixed effects.

Panel B of Table 6 then reports the results of regressions, where we interact fund flows with a post-merger dummy, limiting the sample to treated funds within a window of [-24, +24] months around treatment as in Table 5. The interaction of fund flows with the post treatment dummy is positive and significant, indicating that after the merger, funds' propensity to accommodate fund flows using cash increases. Again, columns (2), (4), (6), and (8) include fund fixed effects, so we are only identifying off within fund variation.

These results give us confidence that we are in fact identifying differences in flow management practices driven by internalization rather other than factors.

E. Stock-Level Implications of Internalization

We next turn to the effects of internalization on market prices and other funds holding the same securities. We start by examining how differences in flow management practices across funds with different levels of internalization impact the price behavior of the assets they 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 response to flows. To test this prediction, we estimate the regression

$$Vol_{s,t+1} = \alpha_s + \alpha_{t+1} + \beta \cdot StockInternalize_{s,t} + \gamma' X_{s,t} + \varepsilon_{s,t+1}, \tag{4}$$

where $Vol_{s,t+1}$ is the realized volatility of stock s in quarter t+1, calculated in daily data and annualized. $StockInternalize_{s,t}$ is the average of one of our internalization measures across all funds holding stock s at the end of quarter t, weighted by the share of each fund in total mutual fund holdings of the security. To ensure we focus on stocks where our measures are meaningful, we exclude stocks where the total holdings of mutual funds as a fraction of total shares outstanding are less than 10%. 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.[26] We follow Greenwood and Thesmar (2011) and restrict the sample to stocks above the NYSE median size. Thus, our specification asks whether a stock held by high internalization funds experiences lower volatility, controlling for the volatility of flows into funds holding that stock.[27]

Table 7 reports the results, with the dependent variable expressed in percentage points and annualized. In the first two columns, we use our *Manager internalize* measure. The first column shows that a one-decile increase in the average level of internalization across holders of a given stock is associated with a 1.1 percentage point reduction in the stock's annual volatility. Given that mean volatility for the stocks in our sample is 36.1%, 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

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[26] 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.

[27] Controlling for fragility does not affect the coefficient on *StockInternalize*. We include it in the regression to have a benchmark for comparison.

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. In the first column of Table 7, the effect of fragility is similar to what Greenwood and Thesmar (2011) find. The effect of a one-decile increase in *Manager internalize* is equivalent to decreasing fragility from the median to the 33rd percentile. Compared to this benchmark, the effect of internalization is significant.

In the second column of Table 7, we add stock fixed effects. The effect of a one-decile increase in *Manager internalize* is now a 0.9-percentage point decrease in volatility, and it is equivalent to decreasing fragility from the median to the 29th percentile. The remaining columns of Table 7 show that we get similar results for our other internalization measures. For our measures of *Adviser internalize*, a one-decile increase in internalization is associated with a decrease in volatility of 0.6 to 1.8 percentage points. In these specifications, our results generally get stronger once we add stock fixed effects.

In summary, Table 7 shows that when high internalization funds hold the same stock, that stock's volatility is lower.

F. *Internalization and Spillovers on Fund Performance*

Having demonstrated that the price behavior of individual stocks is affected by the internalization of funds holding those stocks, we now turn to how funds are affected by the internalization of other funds holding the same securities. As suggested by Proposition 4 of the model, sales by some funds can exert negative price pressure, thereby driving down the returns of other funds, an effect that should be mitigated if funds internalize more of their price impact. We now empirically 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 sales of 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, they will trade less, and the effect on *f*'s returns will be smaller. To examine this prediction, we estimate the regression

$$R_{f,m} = \alpha_m + \beta_1 \cdot Pressure_{f,m} + \beta_2 \cdot Pressure_{f,m} \times CoHolderInternalize_{f,m-1} + \beta_3 \cdot CoHolderInternalize_{f,m-1} + \beta_4 \cdot Flows_{f,m} + \varepsilon_{f,m}, \tag{5}$$

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 the share of each security in *f*'s portfolio and the share of each other fund in total mutual fund holdings of the security. To ensure that we focus on funds for which $Pressure_{f,m}$ is economically relevant, we exclude funds that hold stocks with an average mutual fund share of less than 10%. Even if the mutual funds holding such stocks experience large fund flows, their trading is likely to be small compared to the other investors holding the stocks. $CoHolderInternalize_{f,m}$ is the average over securities that fund *f* holds of our internalization measure for other funds that hold the same security. In addition, we control directly for the flows into fund *f* and include time fixed effects in all specifications.

Table 8 shows the results. The first column reports the results for *Manager internalize*. The coefficient β_1 on $Pressure_{f,m}$ is positive: when funds that have holdings overlapping with *f* have outflows, fund *f* has lower returns. When the other funds holding the same stocks as *f* experience outflows equal to 1% of their TNA, fund *f* experiences about 1.4% lower returns, a magnitude comparable to Lou (2012).[28] However, the coefficient β_2 on the interaction $Pressure_{f,m} \times CoHolderInternalize_{f,m-1}$ is negative, so the effect of outflows from funds with overlapping holdings is muted when those funds internalize more of their price pressure. A one-decile increase in the average level of internalization across all funds with overlapping holdings reduces the effect of a 1% outflow on returns by 0.2 percentage points, a 14% reduction. Column (2) shows that the results are unchanged when we add fund fixed effects.

Columns (3)-(6) of Table 8, show that similar results obtain with our *Adviser internalize* measures. For these measures, a one-decile increase in the average level of internalization across all funds with overlapping holdings reduces the effect of a 1% outflow on returns by about 0.1 percentage points.

[28] The main difference between our results here and Lou (2012) is that 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 ex-post behavior: how does internalization moderate the effect of flow-induced trading on other funds?

These results show that when other funds holding the same securities experience flows, how much they internalize their price pressure affects fund *f*. We next ask whether fund *f*'s unconditional performance is affected by the internalization of other funds holding the same securities. In other words, do the effects we document in Table 8 aggregate up once we average across the flows experienced by other funds holding the same securities? Proposition 5 in Section I suggests they should. If other funds holding the same securities as *f* internalize more of their price pressure, they use more cash and less non-cash asset sales to accommodate flows. As a result, fund *f* faces lower and less volatile costs when it sells its holdings of illiquid assets, so it has higher and less volatile returns.

Table 9 shows the results. In Panel A, we examine fund *f*'s return volatility, running the quarterly regression:

$$Vol_{f,t+1} = \alpha_{obj(f),t} + \alpha_f + \beta \cdot CoHolderInternalize_{f,t} + \gamma' X_{f,t} + \varepsilon_{s,t+1}, \tag{6}$$

where $Vol_{f,t+1}$ is the volatility of *f*'s return over quarter t+1, calculated in daily data and annualized. We include objective-time fixed effects in column (1) and objective-time and fund fixed effects in column (2). The results show that higher *CoHolderInternalize* is associated with lower return volatility for fund *f*. A one-decile increase in *CoHolderInternalize* is associated with annual volatility that is 1-2 percentage points lower. Columns (3)-(6) of Table 9, show that similar results obtain when we measure internalization using our *Adviser internalize* measure.

In Panel B of Table 9, we run similar regressions with fund *f*'s return over quarter t+1 as the dependent variable. Returns are annualized, and the analysis again includes both objective-time and fund fixed effects. The results show that higher *CoHolderInternalize* is associated with higher average returns for fund *f*. A one-decile increase in *CoHolderInternalize* is associated with annual returns that are 0.3 to 0.5 percentage points higher.

G. Internalization and Cash Holdings

We have shown that high internalization funds use cash more aggressively to accommodate fund flows. This decreases the volatility of the stocks they hold and reduces the price pressure exerted on other funds holding the same stocks. We close by examining the relationship between internalization and the level of cash holdings. A basic prediction of our model (Proposition 2 in Section I) is that the level of cash holdings should be positively related to internalization. These results are also interesting because they speak to the design of regulation. Regulations typically do not mandate the exact flow management practices of individual financial institutions; they instead tend to focus on ensuring that the level of liquid assets financial institutions hold is sufficient.[29] While evaluating the effects of such rules is beyond the scope of this paper, this subsection provides some evidence on the funds' ex-ante choice of the cash-to-assets ratio and its relation to internalization.

Table 10 estimates regressions of the cash-to-assets ratio on our internalization measures:

$$\frac{Cash_{f,t}}{TNA_{f,t}} = \alpha + \beta \cdot FundInternalize_{f,t} + \gamma' X_{f,t} + \varepsilon_{f,t}. \tag{7}$$

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 and the volatility of fund flows. 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 10 shows that our internalization measures have a substantial impact on cash holdings. Going from the 25th percentile to the 75th percentile of our *Manager internalize* measures is associated with a 0.40-percentage point higher cash-to-assets ratio. The effect is comparable to the impact on cash holdings of going from the 25th percentile to the 65th percentile of asset illiquidity. The specification includes objective-time fixed effects, indicating that the results are not driven by common time variation in internalization and cash holdings within fund objectives. 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.

[29] For instance, the SEC adopted new liquidity rules for open end mutual funds in 2017: https://www.sec.gov/rules/final/2016/33-10233.pdf

The remaining columns of Table 10 show that results are similar for our other internalization measures. Overall, these results show that internalization impacts cash holdings.

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 sometimes spill over, adversely affecting other investors. However, there is no direct empirical evidence of externalities: are the frequency and severity of spillovers significant enough that funds would act differently if they cared more about their impact on other funds?

We construct three novel, theoretically-motivated measures of how much of the price impact of their trading different mutual funds are likely to internalize. 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. Overall, these results suggest that there are indeed meaningful price impact externalities in the mutual fund industry.

Our results speak to the policy debate among academics, practitioners, and regulators about liquidity transformation in asset management (e.g., Goldstein et al, 2016; International Monetary Fund, 2015; Financial Stability Oversight Council, 2014; Feroli et al, 2014; Chen, Goldstein, and Jiang, 2010). Our results suggest that because individual mutual funds do not fully internalize the price impact of their trading, giving funds a stronger incentive to care about the spillover effect of their trading on other funds may lead to changes in liquidity management practices. This in turn may result in lower volatility at the stock and fund level.

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.

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Appendix A. Proofs

A.1. Proof of Proposition 1

We start with the private market equilibrium. Writing out fund f's objective in terms of c_f, we have

$$E\left[L_f\right] = ic_f + \frac{l}{F}\int_{c_f}^{\infty}\left(x - c_f\right)\left(x - c_f + \sum\nolimits_{h \neq f} x - c_h\right)dG\left(x\right).$$

Differentiating with respect to c_f, by Leibniz's rule, the first order condition is

$$i - \frac{l}{F}\int_{c_f}^{\infty}\left[\left(x - c_f\right) + \left(x - c_f + \sum\nolimits_{h \neq f}\left(x - c_h\right)\right)\right]dG\left(x\right) = 0.$$

Imposing symmetry so that $c_f = c_h = c^*$ for all f, h, we have

$$\begin{aligned} 0 &= i - l\frac{F+1}{F}\int_{c^*}^{\infty}\left(x - c^*\right)dG\left(x\right) \\ 0 &= i - l\frac{F+1}{F}\lambda\exp\left(-\lambda^{-1}c^*\right) \\ c^* &= -\lambda\ln\left(\frac{i}{l\lambda}\frac{F}{F+1}\right), \end{aligned}$$

where the second line follows from integration by parts with the exponential distribution. When the term inside the logarithm is greater than 1, $c^* = 0$.

For the planner's problem, writing out the objective in terms of c_f, we have

$$Fic_f + \frac{l}{F}\int_{c_f}^{\infty}\left[F\left(x - c_f\right)F\left(x - c_f\right)\right]dG\left(x\right) = 0.$$

The first order condition is

$$\begin{aligned} 0 &= Fi - \frac{2l}{F}\int_{c^{**}}^{\infty}F^2\left(x - c^{**}\right)dG\left(x\right) \\ 0 &= i - 2l\int_{c^{**}}^{\infty}\left(x - c^{**}\right)dG\left(x\right). \\ c^{**} &= -\lambda\left(\frac{i}{2\lambda l}\right). \end{aligned}$$

When the term inside the logarithm is greater than 1, $c^{**} = 0$.

A.2. Proof of Proposition 2

Writing out the objective in terms of c_f, we have

$$\left((1-\alpha)+\alpha F\right)ic_f+\frac{l}{F}\int_{c_f}^{\infty}\left[(1-\alpha)\left(x-c_f\right)\sum_h\left(x-c_h\right)+\alpha F\left(x-c_f\right)F\left(x-c_f\right)\right]dG(x).$$

The first order condition is

$$\left((1-\alpha)+\alpha F\right)i-\frac{l}{F}\int_{c_f}^{\infty}\left[\begin{array}{c}(1-\alpha)\left(x-c_f\right)+(1-\alpha)\sum_h\left(x-c_h\right)\\ +2\alpha F^2\left(x-c_f\right)\end{array}\right]dG(x)=0.$$

Imposing symmetry $c_f=c_h=c^{***}$ for all f, h, we have

$$0=\left((1-\alpha)+\alpha F\right)i-l\frac{\left((1-\alpha)(F+1)+2\alpha F^2\right)}{F}\int_{c^{***}}^{\infty}\left(x-c^{***}\right)dG(x).$$

$$c^{***}=-\lambda\ln\left(\frac{i}{\lambda l}\eta\right).$$

Differentiating c^{***} with respect to α, we have

$$\begin{aligned}\frac{dc^{***}}{d\alpha}&=-\lambda\left[\frac{1}{(1-\alpha)+\alpha F}(F-1)+\frac{1}{(1-\alpha)(F+1)+2\alpha F^2}\left(2F^2-F-1\right)\right]\\ &=\lambda(F-1)\left[\frac{(2F+1)\left(1+\alpha(F-1)\right)-1}{\left((1-\alpha)+\alpha F\right)\left((1-\alpha)(F+1)+2\alpha F^2\right)}\right].\end{aligned}$$

The numerator in brackets is increasing in α and is equal to $2F>0$ when $\alpha=0$. Thus, we have $dc^{***}/d\alpha>0$.

A.3. Proof of Proposition 3

We have

$$Cov(-x,\Delta c)=\int_0^{c^{***}}-x\left(c^{***}-x\right)dG(x)+\int_0^{\infty}xdG(x)\int_0^{c^{***}}\left(c^{***}-x\right)dG(x).$$

For simplicity, we work with the $\lambda=1$ case, which will not alter the signs of any of the comparative statics. Computing the right hand side of the equation for the exponential distribution gives

$$Cov(-x,\Delta c) = -\left(c^{***} - 2 + \exp\left(-c^{***}\right)\left(c^{***}+2\right)\right) + 1\cdot\left(c^{***} + \exp\left(-c^{***}\right) - 1\right)$$
$$= -\exp\left(-c^{***}\right)\left(1+c^{***}\right)+1.$$

This is positive so long as $1+c^{***} < \exp\left(c^{***}\right)$, which is true so long as $c^{***} > 0$. We have

$$\frac{dCov(-x,\Delta c)}{d\alpha} = \frac{dCov(-x,\Delta c)}{dc^{***}}\frac{dc^{***}}{d\alpha}$$
$$\frac{dCov(-x,\Delta c)}{dc^{***}} = c^{***}\exp\left(-c^{***}\right) > 0.$$

From Proposition 2, we know that $dc^{***}/d\alpha > 0$, so we have $dCov(-x,\Delta c)/d\alpha > 0$.

A.4. Proof of Proposition 4

With independent flows, the objective of an individual fund in the private market equilibrium is

$$E\left[L_f\right] = ic_f + \frac{l}{F}\int_{c_1}^{\infty}\ldots\int_{c_F}^{\infty}\left(x_f - c_f\right)\sum\nolimits_h\left(x_h - c_h\right)dG\left(x_F\right)\ldots dG\left(x_1\right).$$

The planner's objective is

$$E\left[\sum\nolimits_f L_f\right] = Fic + \frac{l}{F}\int_{c}^{\infty}\ldots\int_{c}^{\infty}F\left(x_1 - c\right)\left(\sum\nolimits_h x_h - c\right)dG\left(x_F\right)\ldots dG\left(x_1\right).$$

The internalization objective is a weighted average of the two. Optimal cash holdings are:

$$c^{*} = -\frac{1}{F}\lambda\ln\left(\frac{i}{\lambda l}\frac{F}{F+1}\right)$$
$$c^{**} = -\frac{1}{F}\lambda\ln\left(\frac{i}{2\lambda l}\right)$$
$$c^{***} = -\frac{1}{F}\lambda\ln\left(\frac{i}{\lambda l}\eta\right).$$

That is, cash holdings are equal to the expressions we had with perfectly correlated flows in Propositions 1 and 2, divided by *F*.

With these basics in hand, we can express the covariance between fund *f*'s liquidation costs and flows into other funds as

$$Cov\left(-x_{-f},L_f\right)=\int_{c_1}^{\infty}...\int_{c_F}^{\infty}\overbrace{\left(\sum\nolimits_{h\neq f}-x_h\right)}^{-x_{-f}}\overbrace{\left(x_f-c_f\right)\frac{l}{F}\left(\sum\nolimits_h x_h-c_h\right)}^{L_f}d\left(Gx_F\right)...d\left(Gx_1\right)$$
$$-\left(\int_{c_1}^{\infty}...\int_{c_F}^{\infty}\left(\sum\nolimits_{h\neq f}-x_h\right)d\left(Gx_F\right)...d\left(Gx_1\right)\right)\left(\int_{c_1}^{\infty}...\int_{c_F}^{\infty}\left(x_f-c_f\right)\frac{l}{F}\left(\sum\nolimits_h x_h-c_h\right)d\left(Gx_F\right)...d\left(Gx_1\right)\right)$$

For simplicity, we work with the $\lambda = 1$ case, which will not alter the signs of any of the comparative statics. Computing the right hand side of the equation for the exponential distribution gives

$$Cov\left(-x_{-f},L_f\right)=\frac{l}{F}\exp\left(-\sum\nolimits_h c_h\right)\left[(F+1)\left(\sum\nolimits_{h\neq f}c_h+F-1\right)\exp\left(-\sum\nolimits_{h\neq f}c_h\right)\left(1-\exp\left(\sum\nolimits_{h\neq f}c_h\right)\right)-1\right].$$

Imposing symmetry of cash holdings across funds we have

$$Cov\left(-x_{-f},L_f\right)=\frac{l}{F}\exp\left(-Fc^{***}\right)\left[\left(F^2-1\right)\left(c^{***}+1\right)\exp\left(-\left(F-1\right)c^{***}\right)\left(1-\exp\left(\left(F-1\right)c^{***}\right)\right)-1\right].$$

The first term in the square bracket is negative because $1-\exp\left(\left(F-1\right)c^{***}\right)$ is negative so long as $c^{***}>0$. The remaining parts of the first term in the square brackets are positive, so the first term is negative. Thus, the overall covariance is negative.

We have

$$\frac{dCov\left(-x_{-f},L_f\right)}{d\alpha}=\frac{dCov\left(-x_{-f},L_f\right)}{dc^{***}}\frac{dc^{***}}{d\alpha}$$
$$\frac{dCov\left(-x_{-f},L_f\right)}{dc^{***}}=\left(F^2-1\right)\exp\left(-Fc^{***}\right)\left[\exp\left(-\left(F-1\right)c^{***}\right)-1\right]\left[\left(1+c^{***}\right)\left(-2F+1\right)+1\right]+F\exp\left(-Fc^{***}\right)$$

The two terms in square brackets in the expression for $dCov\left(-x_{-f},L_f\right)/dc^{***}$ are both negative so long as $c^{***}>0$ and $F > 1$. Thus, $dCov\left(-x_{-f},L_f\right)/dc^{***}$ is positive. We know that $dc^{***}/d\alpha>0$ so $dCov\left(-x_{-f},L_f\right)/d\alpha$ is positive.

We can also compute the covariance of fund *f*'s liquidation costs and flows into other funds holding fixed fund *f*'s choices. Writing the covariance as a function of fund *f*'s choices (c_f) and all other funds' choices (c_{-f}), we have

$$Cov\left(-x_{-f},L_f\right)=\frac{l}{F}\exp\left(-c_f-\left(F-1\right)c_{-f}\right)\left[\left(F^2-1\right)\left(c_{-f}+1\right)\exp\left(-\left(F-1\right)c_{-f}\right)\left(1-\exp\left(\left(F-1\right)c_{-f}\right)\right)-1\right].$$

Differentiating with respect to c_{-f}, we have

$$\frac{dCov\left(-x_{-f},L_f\right)}{dc_{-f}}=\left(F^2-1\right)\exp\left(-c_f-\left(F-1\right)c_{-f}\right)\left[\exp\left(-\left(F-1\right)c_{-f}\right)-1\right]\left[-2\left(1+c_{-f}\right)\left(F-1\right)+1\right]$$
$$+\left(F-1\right)\exp\left(-c_f-\left(F-1\right)c_{-f}\right).$$

The two terms in square brackets are both negative so long as $c_{-f}>0$ and $F>1$, so the overall expression is positive.

A.5. Proof of Proposition 5

We start by allowing all funds' cash to adjust with α. Expected liquidation costs are

$$E\left[L_f^{***}\right]=ic_f^{***}+\frac{l}{F}\int_{c_f^{***}}^{\infty}\left(x-c_f^{***}\right)F\left(x-c_f^{***}\right)dG\left(x\right).$$

For simplicity, we work with the $\lambda=1$ case, which will not alter the signs of any of the comparative statics. We have

$$\frac{dE\left[L_f^{***}\right]}{d\alpha}=\frac{dE\left[L_f^{***}\right]}{dc_f^{***}}\frac{dc_f^{***}}{d\alpha}$$
$$\frac{dE\left[L_f^{***}\right]}{dc_f^{***}}=i-2l\int_{c_f^{***}}^{\infty}\left(x-c_f^{***}\right)dG\left(x\right)$$
$$=i-2l\exp\left(c_f^{***}\right)<0$$

when $c_f^{***}>0$, since $c_f^{***}>0$ implies $i<2l$. Since $dc_f^{***}/d\alpha>0$, $dL_f^{***}/d\alpha<0$.

We can also compute the expected loss holding fixed fund f's choices. Writing the expected liquidation cost as a function of fund f's choices and all other funds' choices, we have

$$E\left[L_f\left(c_f,c_{-f}\right)\right]=ic_f+\frac{l}{F}\int_{c_f}^{\infty}\left(x-c_f\right)\left(\sum\nolimits_{h\neq f}x-c_{-f}\right)dG\left(x\right).$$

Differentiating with respect to c_{-f} we have

$$\frac{dE\left[L_f\left(c_f,c_{-f}\right)\right]}{dc_{-f}}=-l\frac{F-1}{F}\int_{c_f}^{\infty}\left(x-c_f\right)dG\left(x\right)$$
$$=-l\frac{F-1}{F}\exp\left(-c_f\right)<0.$$

For the variance comparative static, we have

$$Var\left[L_f^{***}\right] = l^2 \int_{c_f^{***}}^{\infty} \left(x - c_f^{***}\right)^4 dG(x) - \left(l \int_{c_f^{***}}^{\infty} \left(x - c_f^{***}\right)^2 dG(x)\right)^2$$
$$= 20 l^2 \exp\left(-c_f^{***}\right).$$

This is clearly decreasing in c_f^{***} and therefore in internalization.

We can also compute the variance holding fixed fund f's choices. Writing the variance as a function of fund f's choices and all other funds' choices, we have

$$Var\left[L_f\left(c_f, c_{-f}\right)\right] = \left(\frac{l}{F}\right)^2 \int_{c_f}^{\infty} \left(x - c_f\right)^2 \left(x - c_f + \sum_h x - c_{-f}\right)^2 dG(x)$$
$$- \left(\frac{l}{F} \int_{c_f}^{\infty} \left(x - c_f\right)\left(x - c_f + \sum_h x - c_{-f}\right) dG(x)\right)^2$$
$$= 2\left(\frac{l}{F}\right)^2 \exp\left(-c_f\right)\left(\left(\left(F-1\right)\left(c_f - c_{-f}\right) + 3F^2\right) + 3F\right)$$
$$- \left(\frac{l}{F}\right)^2 \exp\left(-2c_f\right)\left(\left(F-1\right)\left(c_f - c_{-f}\right) + 2F\right).$$

Differentiating with respect to c_{-f} we have

$$-2 \frac{\left(F-1\right)\left(c_f - c_{-f}\right) + 3F}{\left(F-1\right)\left(c_f - c_{-f}\right) + 2F} \exp\left(c_f\right) + 1 < 0$$

in the neighborhood of the symmetric equilibrium we study where $c_f = c_{-f}$ when $c_f > 0$.

Appendix B. Model of Inflows

In the main text, we present a model of how a fund manages redemptions. In this section, we show how to write down a very similar model of how a fund manages inflows. The key difference between the problems is that redemption management requires an ex ante decision of how much cash to hold before the redemptions happen. Inflow management is an ex post decision, made after the quantity of inflows is known.

Suppose fund f receives inflows x_f, which are public information. The fund must choose between investing in the illiquid asset and holding cash. In buying the illiquid asset, the fund incurs an accumulation cost. Think of this accumulation cost as reflecting the temporary price pressure that will revert. In other words, the fund is paying more than fundamental value for the asset. We assume that the accumulation cost depends on the total purchases by all funds, and parametrize it as $b_f \frac{l}{F}\left(\sum_h b_h\right)$ where b_f is the quantity purchased by fund f. As in the model in the main text, l indexes the illiquidity of the asset and we normalize accumulation costs by F, the total number of funds, so that aggregate accumulation costs do not change as we vary F.

Holding cash has carrying cost i. A complete model of inflow management would be dynamic: a fund would hold cash today, planning to invest it in the illiquid asset tomorrow with lower accumulation costs. For simplicity, we abstract from the dynamic aspects of the problem and assume that the carrying cost of cash includes expected future accumulation costs.

The problem of fund f in the private market equilibrium is to pick cash holdings $c_f = x_f - b_f$ to minimize total liquidity management costs:

$$ic_f + b_f \frac{l}{F}\left(\sum_h b_h\right).$$

The first order condition for c_f is

$$0 = i - \frac{l}{F}\left(x_f - c_f + \sum_h \left(x_h - c_h\right)\right).$$

As in the main text, to simplify the analysis, we assume flows are perfectly correlated so that $x_f = x$ and solve for the symmetric equilibrium. Doing so, we find that

$$c^* = x - \frac{i}{l}\frac{F}{F+1}.$$

The planner's problem is to minimize total liquidity management costs of all funds:

$$Fic + F\left(x-c\right)\frac{l}{F}F\left(x-c\right).$$

The first order condition is

$$c^{**} = x - \frac{i}{2l}.$$

The internalization objective puts weight α on the planner's objective and weight $(1-\alpha)$ on the private market objective. Taking the first order condition and imposing symmetry we have

$$c^{***} = x - \frac{i}{l}\eta,$$

where

$$\eta = \frac{\left(\left(1-\alpha\right)+\alpha F\right)F}{\left(1-\alpha\right)\left(F+1\right)+2\alpha F^2},$$

the same expression for η that arises in the main text.

Clearly, the expressions here are similar to those in the main model and thus similar comparative statics go through. The key difference is that the problem is ex post as opposed to ex ante: inflows are known before the decision is made. Thus, we do not need to take expectations.

Appendix C. Variable Definitions

Table A1
Variable definitions

Variable	Definition
Active share	The percentage of fund holdings that is different from the benchmark holdings. Minimum active share across all U.S.-equity benchmarks (activeshare_min) is from Martijn Cremers's website http://activeshare.nd.edu. Active share is generally reported as of December of each year. Observations in N-SAR data are matched (based on wficn fund identifier) to the most recent value of active share, assuming the latter is within eleven months of the N-SAR reporting date.
Adviser overlap	Value-weighted average of the overlap in fund holdings with the aggregate 13F holdings by the fund's investment adviser: $$Adviser\ overlap_f = \sum_s w_s \times \frac{V_{f,s}}{Volume_s} \times \frac{V^{13F}_{adviser(f),s} - V_{f,s}}{Volume_s},$$ where $V_{f,s}$ is the value of fund f holdings of security s, $V^{13F}_{adviser(f),s}$ is the value of the 13F holdings of security s by the fund's investment adviser, and $Volume_s$ is the average daily trading volume calculated over the last quarter. Raw values of *Adviser overlap* are converted into decile ranks within each quarter.
Adviser overlap without manager	Same as *Adviser overlap*, except that instead of subtracting fund holdings of security s, we subtract aggregate holdings of security s by all funds managed by fund f's portfolio manager. Formally, $Adviser\ overlap\ without\ manager_f = \sum_s w_s \times \frac{V_{f,s}}{Volume_s} \times \frac{V^{13F}_{adviser(f),s} - \sum_{j,mgr(j)=mgr(f)} V_{j,s}}{Volume_s}$. Raw values of *Adviser overlap without manager* are converted into decile ranks within each quarter.
$\frac{Cash}{TNA}$	Cash is cash (item 74A) + repurchase agreements (74B) + short-term debt securities other than repurchase agreements (74C) + other investments (74I) − securities lending collateral. For domestic equity funds, other investments (74I) consist mostly of money market mutual funds. Value of securities lending collateral is collected from the 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.

Table A1—*Continued*

Variable	Definition
Clientele	In Table 4, 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. Beginning of semi-annual period values are interacted with fund flows during the period.
CoHolderInternalize	Value-weighted average of the propensity of other funds holding the same securities as fund f to internalize price impact: $$\sum_s w_{f,s} \times \left(\sum_{j \neq f} \frac{V_{j,s}}{\sum_{k \neq f} V_{k,s}} \times FundInternalize_{j,s} \right)$$ Internalization of index funds is set to zero.
Experience	Number of years managing mutual funds. Using Morningstar data on the identity of mutual fund managers, we count the number of years since the portfolio manager started managing mutual funds. For team-managed funds, *Experience* is the average across individual portfolio managers.
Family size	Log of aggregate TNA across all CRSP mutual funds within the same family, with family defined based on mgmt_cd in CRSP.
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 Redeemed and Repurchased (Incl. Exchanges)*. We exclude the *Total NAV of Shares Sold: Other* as these generally capture share activity due to mergers. *Total NAV of Shares Sold: Reinv. of Dividends & Distributions* is excluded to focus on the less predictable component of flows. *Flows* are winsorized at the 5th and 95th percentiles.
$\sigma(Flows)$	Standard deviation of monthly fund flows (N-SAR item 28) over the preceding six months. Fund flows are scaled by TNA as of the beginning of the semi-annual reporting period.

Table A1—*Continued*

Variable	Definition
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 within each period at the 1st and 99th percentiles before calculating fund flow volatility.
FundInternalize	Fund-level version of one of our three internalization measures. We calculate the value-weighted average of raw internalization measures across portfolio securities, with the weights defined relative to the aggregate holdings of securities with valid values of internalization. Raw values of fund-level internalization are converted into decile ranks within each quarter.
Fund manager chars	In Table 4, 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 managers, and (d) CFA credential. Fund manager data are from Morningstar. Beginning of semi-annual period values of fund manager characteristics are interacted with fund flows during the period.
Future returns	In Table 4, we include controls for average monthly returns over the subsequent 1, 3, 6, and 12 months.
Illiq	The illiquidity of portfolio holdings. We first calculate the square-root version of Amihud (2002) liquidity measure for each stock in a fund's portfolio. Stock-level illiquidity is calculated using daily data for the preceding six months. We then calculate the value-weighted average across all stocks held by the fund. 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.

Table A1—*Continued*

Variable	Definition
Institutional share	Fraction of institutional share classes, identified following Chen, Goldstein, and Jiang (2010). A share class is considered to be institutional if a) CRSP's 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.
Manager overlap	Value-weighted average of the overlap in fund holdings with the aggregate holdings by other funds manager by the fund's portfolio manager: $Manager\ overlap_f = \sum_s w_s \times \frac{V_{f,s}}{Volume_s} \times \frac{\sum_{j,mgr(j)=mgr(f),j\neq f} V_{j,s}}{Volume_s}$, where $V_{f,s}$ is the value of fund f holdings of security s, and $Volume_s$ is the average daily trading volume calculated over the last quarter. Identity of fund portfolio managers is from Morningstar. For team-managed funds, we split the fund's holdings equally across the portfolio managers. Raw values of *Manager overlap* are converted into decile ranks within each quarter.
Mutual funds share	For each stock, 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).

Table A1—*Continued*

Variable	Definition
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 $m-1$.
$Pressure$ $\times CoHolderInternalize$	Calculated similarly to $Pressure$ except that flows into fund j are multiplied by the fund's propensity to internalize price impact: $$\sum_s \left(w_{f,s,m-1} \times \left(\sum_{j \neq f} \frac{V_{j,s,m-1}}{\sum_{k \neq f} V_{k,s,m-1}} \times Internalize_{j,s,m-1} \times \frac{Flows_{j,m}}{TNA_{j,m-1}} \right) \right).$$ Internalization of index funds is set to zero.
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).
Short selling	Binary variable equal to one for funds that engage in short selling (70R).
$StockInternalize$	Value-weighted average of the propensity of funds holding stock s to internalize price impact $$\sum_f \frac{V_{f,s}}{\sum_j V_{j,s}} \times FundInternalize_{f,s}$$ Internalization of index funds is set to zero.
$Tenure$	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.

Figure 1
Number of Funds

This figure shows the number of domestic equity open-end funds in the merged N-SAR/CRSP/Thomson Reuters data. Funds are required to be at least two years old, to have valid values of holdings illiquidity and of all three measures of internalization, to have TNA of at least \$10 million in 2016 dollars, and to have the ratio of portfolio holdings to TNA in the $[\frac{3}{4}, \frac{4}{3}]$ interval.

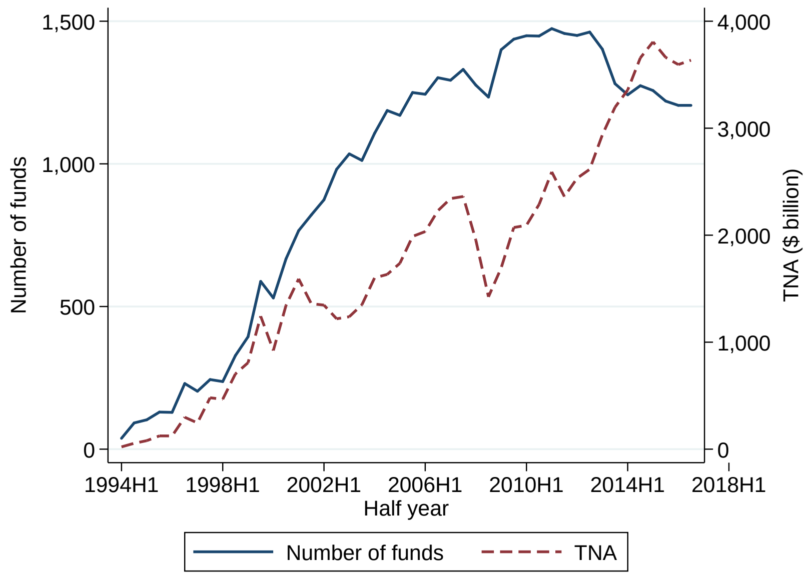

Figure 2
Distribution of the Cash-to-Assets Ratio

This figure shows the distribution of the cash-to-assets ratio for funds in the sample.

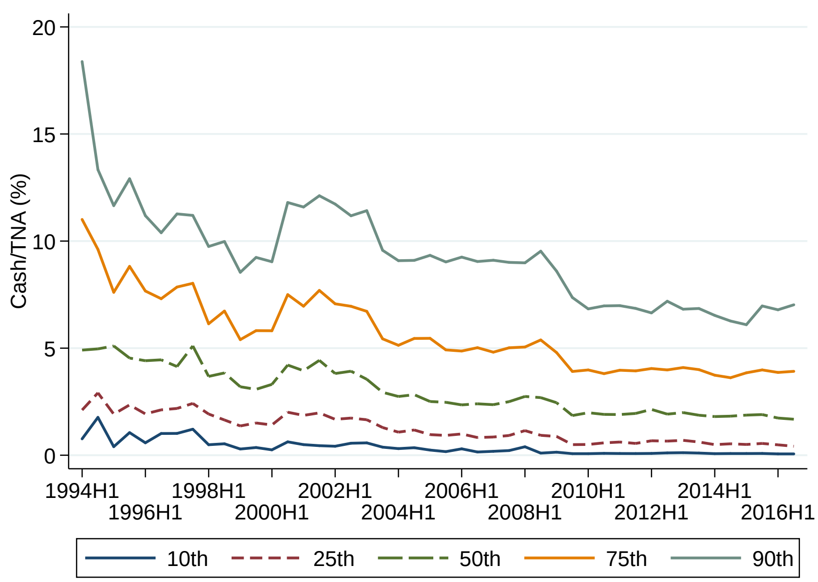

Table 1
Summary Statistics

This table reports summary statistics for the sample of domestic equity open-end mutual funds studied in the paper. The sample period is 1994–2016. *Illiq* is the weighted-average of the square-root version of Amihud (2002) across all stocks in the fund's portfolio (Chen et al 2010). *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. Internalization proxies are value-weighted averages across fund positions of the product of a) the fund holdings of a security, divided by its average daily dollar trading volume, and b) holdings of the security by either other funds managed by the same portfolio manager or other funds in the same family, also divided by the security's average trading volume. For funds with multiple portfolio managers, holdings are split evenly across individual portfolio managers. In calculating *Family internalization without manager*, we add up holdings by all other family funds, excluding funds managed by the fund's portfolio managers.

				Percentile		
	N	Mean	SD	25	50	75
Panel A: Actively Managed Funds						
TNA	37707	1601.70	4966.32	97.25	342.16	1186.92
$Size$	37707	5.87	1.72	4.58	5.84	7.08
Family size	36461	9.38	2.52	7.71	9.70	11.06
$Cash/TNA$ (%)	37707	3.97	4.10	1.15	2.76	5.26
$\Delta(Cash/TNA)$ (%)	37707	−0.16	3.51	−1.43	−0.03	1.25
$Flows_t$ (%)	37707	−0.23	6.87	−4.15	−1.38	2.15
$Flows_{t-1}$ (%)	37707	−0.09	7.12	−4.10	−1.21	2.51
Illiq ($\times 10^4$)	37707	0.24	0.22	0.09	0.15	0.33
$\sigma(Flows)$ (%)	37707	7.56	9.71	2.07	4.14	8.66
Institutional share (%)	36899	26.73	37.39	0.00	2.08	52.96
$Turnover$ (%)	36550	78.99	66.96	33.00	61.00	103.00
Shorting	36311	0.02	0.14	0.00	0.00	0.00
Options	36320	0.03	0.06	0.00	0.00	0.00
Other practices	36316	0.32	0.18	0.12	0.25	0.50
Manager internalization	37707	6.64	107.19	0.00	0.01	0.13
Adviser internalization with manager	37707	34.42	640.90	0.03	0.31	2.70
Adviser internalization without manager	37707	29.04	623.77	0.02	0.25	2.28
Holdings HHI	37707	0.02	0.02	0.01	0.02	0.03
Panel B: Index Funds						
TNA	5402	3460.37	9365.87	160.22	556.70	2359.72
$Size$	5402	6.44	1.87	5.08	6.32	7.77
Family size	5303	11.17	2.09	9.90	11.15	12.96
$Cash/TNA$ (%)	5402	1.33	2.24	0.10	0.36	1.79
$\Delta(Cash/TNA)$ (%)	5402	−0.05	1.76	−0.23	−0.00	0.18
$Flows_t$ (%)	5402	2.06	8.09	−2.70	0.76	5.99
$Flows_{t-1}$ (%)	5402	2.20	8.10	−2.38	0.85	6.02
Illiq ($\times 10^4$)	5402	0.20	0.19	0.07	0.12	0.25
$\sigma(Flows)$ (%)	5402	13.97	15.50	3.24	7.52	18.90
Institutional share (%)	5319	69.17	42.11	18.39	100.00	100.00
$Turnover$ (%)	5266	39.19	59.18	9.00	20.00	43.00
Shorting	5188	0.05	0.22	0.00	0.00	0.00
Options	5188	0.06	0.06	0.00	0.00	0.12
Other practices	5188	0.23	0.11	0.12	0.25	0.25
Manager internalization	5402	0.60	4.21	0.00	0.01	0.12
Adviser internalization with manager	5402	1.78	4.91	0.01	0.08	0.90
Adviser internalization without manager	5402	1.25	3.27	0.00	0.06	0.72
Holdings HHI	5402	0.02	0.02	0.00	0.01	0.02

Table 2
Flow Management using Cash

This table reports the results of regressions of the change in the cash-to-assets ratio over the semi-annual reporting period on monthly fund flows during the period:

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

where f indexes funds and m indexes months. Cash-to-assets ratio is expressed in percent. Independent variables are monthly net fund flows, scaled by TNA at the beginning of the semi-annual reporting period. Fund flows are winsorized at the 5th and 95th percentiles. The sample period is 1994–2016. Objective fixed effects are based on Lipper objective codes. Time fixed effects are based on quarter dates. Standard errors are adjusted for clustering by fund. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Active			Index		
	(1)	(2)	(3)	(4)	(5)	(6)
$Flows_{f,m}$	18.507***	18.645***	18.281***	2.581***	2.236***	2.481***
	(1.075)	(1.076)	(1.090)	(0.676)	(0.675)	(0.781)
$Flows_{f,m-1}$	4.893***	4.778***	5.132***	1.005*	0.804	1.080
	(1.070)	(1.066)	(1.092)	(0.601)	(0.622)	(0.694)
$Flows_{f,m-2}$	0.219	0.118	−0.106	−0.830	−0.543	−0.587
	(1.093)	(1.094)	(1.130)	(0.769)	(0.787)	(0.839)
$Flows_{f,m-3}$	−3.118***	−3.235***	−3.471***	0.891	0.763	0.507
	(1.083)	(1.085)	(1.104)	(0.677)	(0.702)	(0.815)
$Flows_{f,m-4}$	−3.597***	−3.397***	−3.030***	−0.507	−0.498	−0.678
	(1.093)	(1.089)	(1.097)	(0.735)	(0.781)	(0.836)
$Flows_{f,m-5}$	−12.630***	−12.379***	−12.208***	−1.602**	−1.480**	−1.026
	(1.119)	(1.121)	(1.117)	(0.699)	(0.673)	(0.739)
$Constant$	−0.143***			−0.061***		
	(0.011)			(0.014)		
N	37,707	37,706	37,628	5,402	5,401	5,173
R^2	0.02	0.03	0.06	0.00	0.04	0.17
Objective FEs		✓			✓	
Time FEs		✓			✓	
Objective-time FEs			✓			✓

Table 3
Flow Management and Propensity to Internalize Price Impact

This table reports the results of regressions of the change in the cash-to-assets ratio over the semi-annual reporting period on quarterly fund flows interacted with internalization proxies:

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

where f indexes funds and t indexes quarters. Cash-to-assets ratio is expressed in percent. *Fund Internalize* captures the fund's propensity to internalize the price impact it may impose on either the other funds managed by the fund's portfolio manager (columns 1–2) or other funds within the same fund family (columns 3–6). Columns 3–4 consider all funds within the family, while columns 5–6 restrict the calculation of internalization to family funds that are not managed by the same portfolio managers. Raw values of *Fund Internalize* are converted into decile rankings within each quarter. *Illiq* is the weighted-average of the square-root version of Amihud (2002) across all stocks in the fund's portfolio (Chen et al 2010). Raw values of *Illiq* are standardized so that the coefficients represent the effect of a one standard deviation change in portfolio illiquidity. Standard errors are adjusted for clustering by fund. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

			Investment adviser			
	Portfolio manager		with manager		without manager	
	Active	Index	Active	Index	Active	Index
	(1)	(2)	(3)	(4)	(5)	(6)
$Flows_{f,t}$	3.046***	1.993**	2.396***	1.683**	2.703***	1.598**
	(0.922)	(0.965)	(0.829)	(0.656)	(0.841)	(0.655)
$Flows_{f,t} \times Fund\ Internalize_{f,t-2}$	0.492***	−0.252*	0.648***	−0.251***	0.584***	−0.239**
	(0.157)	(0.130)	(0.146)	(0.097)	(0.147)	(0.098)
$Flows_{f,t} \times Illiq_{f,t-2}$	1.373***	0.249	0.928**	0.277	1.009**	0.269
	(0.407)	(0.443)	(0.421)	(0.439)	(0.421)	(0.442)
$Flows_{f,t-1}$	−2.161**	−0.755	−1.710**	−0.594	−1.904**	−0.475
	(0.860)	(1.037)	(0.787)	(0.735)	(0.787)	(0.710)
$Flows_{f,t-1} \times Fund\ Internalize_{f,t-2}$	−0.389***	0.127	−0.506***	0.121	−0.464***	0.096
	(0.148)	(0.136)	(0.138)	(0.112)	(0.137)	(0.108)
$Flows_{f,t-1} \times Illiq_{f,t-2}$	−0.336	0.172	0.020	0.163	−0.039	0.170
	(0.392)	(0.526)	(0.409)	(0.523)	(0.407)	(0.523)
$Illiq_{f,t-2}$	−0.062**	−0.036	−0.056*	−0.036	−0.055*	−0.038
	(0.029)	(0.042)	(0.029)	(0.041)	(0.029)	(0.041)
$Fund\ Internalize_{f,t-2}$	−0.008*	0.005	−0.007	0.002	−0.008*	0.001
	(0.004)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)
Constant	−0.108***	−0.093**	−0.114***	−0.072**	−0.109***	−0.068**
	(0.028)	(0.042)	(0.031)	(0.035)	(0.030)	(0.034)
N	37,707	5,402	37,707	5,402	37,707	5,402
R^2	0.06	0.21	0.06	0.21	0.06	0.21
Objective-time FEs	✓	✓	✓	✓	✓	✓

Table 4
Flow Management: Alternative Explanations

This table shows the robustness of the results in Table 3 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%.

				Investment adviser			
		Portfolio manager		with manager		without manager	
	N	β	R^2	β	R^2	β	R^2
(1) Baseline	37,707	0.492***	0.058	0.648***	0.059	0.584***	0.059
		(0.157)		(0.146)		(0.147)	
Additional controls:							
(2) Past returns	37,693	0.477***	0.059	0.635***	0.060	0.572***	0.059
		(0.157)		(0.146)		(0.147)	
(3) Future returns	35,273	0.522***	0.061	0.658***	0.061	0.581***	0.061
		(0.161)		(0.149)		(0.150)	
(4) Powers of illiquidity	37,707	0.499***	0.059	0.675***	0.059	0.608***	0.059
		(0.157)		(0.148)		(0.149)	
(5) Deciles of illiquidity	37,707	0.506***	0.059	0.690***	0.059	0.624***	0.059
		(0.158)		(0.147)		(0.148)	
(6) Layers of liquidity	37,707	0.506***	0.061	0.677***	0.061	0.623***	0.061
		(0.153)		(0.145)		(0.146)	
(7) Holdings HHI	37,707	0.497***	0.059	0.654***	0.059	0.589***	0.059
		(0.156)		(0.147)		(0.148)	
(8) Top share	37,707	0.486***	0.059	0.682***	0.059	0.617***	0.059
		(0.157)		(0.148)		(0.149)	
(9) Active share	33,889	0.511***	0.063	0.590***	0.063	0.511***	0.063
		(0.167)		(0.160)		(0.162)	
(10) Clientele	36,899	0.547***	0.057	0.681***	0.057	0.612***	0.057
		(0.160)		(0.150)		(0.151)	
(11) Fund managers	37,480	0.369**	0.060	0.563***	0.060	0.512***	0.060
		(0.162)		(0.149)		(0.150)	
Sample splits:							
(12) Small funds	19,162	0.451*	0.086	0.444*	0.086	0.391	0.086
		(0.237)		(0.239)		(0.239)	
(13) Large funds	18,545	0.190	0.104	0.631**	0.104	0.494*	0.104
		(0.242)		(0.269)		(0.268)	
(14) 1994–2007	17,816	0.395	0.064	0.708***	0.065	0.636**	0.065
		(0.272)		(0.254)		(0.254)	
(15) 2008–2016	19,891	0.542***	0.049	0.618***	0.049	0.555***	0.049
		(0.184)		(0.162)		(0.161)	

Table 5
Changes in Flow Management when Portfolio Managers Start Managing Multiple Funds

This table reports the results of the analysis of how the propensity to accommodate fund flows using cash changes when portfolio managers start managing multiple funds:

$$\Delta\left(\frac{Cash}{TNA}\right)_{f,t} = \alpha_f + \sum_{s=0}^{1}\left(\beta_s \cdot Flows_{f,t-s} + \gamma_s \cdot Flows_{f,t-s} \times Post_{f,t}\right) + \delta \cdot Post_{f,t} + \varepsilon_{f,t},$$

where f indexes funds and t indexes quarters. The sample consists of funds whose portfolio managers go from managing a single fund to managing multiple funds. The sample is limited to observations within 24 months of the fund manager getting a new fund to manage. *Post* is a dummy variable equal to one for months after the fund's portfolio manager is appointed in charge of another fund. TNA of the new fund is required to be at least 5% (columns 1–2), 15% (columns 3–4), or 25% (columns 5–6) of the TNA of the original fund. For funds with multiple portfolio managers, fund assets are split equally across the fund's managers. For each fund we keep the first treatment event during the 1994–2016 period. Standard errors are adjusted for clustering by fund. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	New fund size cutoff					
	5%		15%		25%	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Changes in Manager Internalization						
$Post_{f,t}$	2.260***	2.169***	2.257***	2.198***	2.241***	2.190***
	(0.109)	(0.119)	(0.116)	(0.127)	(0.122)	(0.132)
Constant	3.273***	3.321***	3.225***	3.256***	3.224***	3.251***
	(0.048)	(0.063)	(0.050)	(0.067)	(0.052)	(0.070)
N	2,739	2,739	2,490	2,490	2,350	2,350
R^2	0.26	0.67	0.26	0.66	0.26	0.66
Fund FEs		✓		✓		✓
Panel B: Changes in Flow Management						
$Flows_{f,t}$	4.517**	7.117***	3.378*	5.577**	3.322*	5.673**
	(1.763)	(2.332)	(1.871)	(2.462)	(1.926)	(2.582)
$Flows \times Post_{f,t}$	7.386***	7.766**	8.680***	9.064**	9.029***	9.671**
	(2.747)	(3.481)	(2.899)	(3.627)	(2.990)	(3.773)
$Flows_{f,t-1}$	−2.181	−2.089	−0.582	−0.617	−0.946	−1.590
	(1.898)	(2.592)	(2.087)	(2.882)	(2.088)	(2.938)
$Flows \times Post_{f,t-1}$	−4.550	−3.521	−6.205**	−5.325	−5.710*	−4.388
	(2.771)	(3.580)	(3.068)	(3.941)	(3.117)	(3.999)
$Post_{f,t}$	−0.032	0.063	−0.071	−0.003	−0.019	0.042
	(0.113)	(0.143)	(0.119)	(0.149)	(0.123)	(0.158)
Constant	−0.088	−0.136*	−0.063	−0.089	−0.075	−0.093
	(0.073)	(0.075)	(0.078)	(0.078)	(0.080)	(0.082)
N	2,739	2,739	2,490	2,490	2,350	2,350
R^2	0.02	0.10	0.02	0.10	0.02	0.11
Fund FEs		✓		✓		✓

Table 6
Changes in Flow Management around Mergers of Investment Advisers

This table reports the results of the analysis of how the propensity to accommodate fund flows using cash changes around mergers of fund investment advisers:

$$\Delta\left(\frac{Cash}{TNA}\right)_{f,t} = \alpha_{obj(f)} + \alpha_t + \beta_1 \cdot Flows_{f,t} + \beta_2 \cdot Flows_{f,t} \times Post\ merger_{f,t}$$
$$+ \beta_3 \cdot Flows_{f,t-1} + \beta_4 \cdot Flows_{f,t-1} \times Post\ merger_{f,t} + \beta_5 \cdot Post\ merger_{f,t} + \varepsilon_{f,t},$$

where f indexes funds and t indexes quarters. In columns 1–4, for target's or acquirer's funds to be considered treated, the other party has to account for at least 50% of the combined pre-merger 13F assets. In other words, target's funds are included for mergers in which the acquirer accounts for at least 50% of the combined 13F assets. Symmetrically, acquirer's funds are included for mergers in which the target accounts for at least 50% of the combined 13F assets. In columns 5–8, the relative cutoff is 25%. In columns 1–2 and 5–6, the sample consists of target's funds only. In columns 3–4 and 6–8, the sample consists of both target and acquirer funds from qualifying mergers. For each merger, we include observations within 24 months of the merger closing date. Standard errors are adjusted for clustering by investment adviser. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Minimum share of the other party in combined 13F assets							
	50%				25%			
	Target only		Target & Acquirer		Target only		Target & Acquirer	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Changes in Family Internalization							
$Post\ merger_{f,t}$	0.455	0.503**	0.981*	0.843***	0.535	0.538**	0.872**	0.616**
	(0.628)	(0.250)	(0.506)	(0.282)	(0.599)	(0.239)	(0.386)	(0.255)
$Constant$	5.841***	5.815***	4.895***	4.971***	5.684***	5.683***	4.758***	4.897***
	(0.491)	(0.174)	(0.539)	(0.177)	(0.473)	(0.168)	(0.457)	(0.161)
N	461	461	749	749	494	494	1,022	1,022
R^2	0.01	0.85	0.03	0.83	0.01	0.84	0.02	0.84
Fund FEs		✓		✓		✓		✓
	Panel B: Changes in Flow Management							
$Flows_{f,t}$	3.129	4.808	5.618*	7.546	3.518	4.996	4.905*	6.811*
	(4.253)	(5.559)	(3.362)	(4.701)	(3.959)	(5.054)	(2.913)	(4.037)
$Flows_{f,t} \times Post\ merger_{f,t}$	9.592**	11.459*	7.709**	7.912*	8.427*	9.770*	7.553**	8.320*
	(4.632)	(6.122)	(3.445)	(4.745)	(4.478)	(5.712)	(3.311)	(4.460)
$Flows_{f,t-1}$	−0.683	0.480	−4.873	−5.160	−1.527	−1.115	−4.214	−3.898
	(5.975)	(7.631)	(4.576)	(6.085)	(5.603)	(6.992)	(3.433)	(4.580)
$Flows_{f,t-1} \times Post\ merger_{f,t}$	−9.661	−10.518	−4.915	−3.919	−8.580	−9.244	−7.002*	−6.353
	(6.304)	(8.004)	(5.199)	(6.768)	(5.960)	(7.452)	(4.022)	(5.326)
$Post\ merger_{f,t}$	−0.832***	−0.934***	−0.638***	−0.754***	−0.839***	−0.925***	−0.562***	−0.576**
	(0.217)	(0.257)	(0.191)	(0.238)	(0.207)	(0.248)	(0.163)	(0.222)
$Constant$	0.294	0.341*	0.271*	0.341**	0.271	0.311*	0.151	0.178
	(0.178)	(0.181)	(0.140)	(0.156)	(0.168)	(0.167)	(0.105)	(0.127)
N	461	461	749	749	494	494	1,022	1,022
R^2	0.04	0.11	0.04	0.12	0.04	0.11	0.03	0.14
Fund FEs		✓		✓		✓		✓

Table 7
Internalization and Stock Volatility

This table reports the results of regressions of stock volatility during quarter $t + 1$ on stock-level measures of internalization:

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

where s indexes stocks and t indexes quarter dates. *StockInternalize* is the value-weighted average of fund-level internalization calculated over all funds holding stock s. *Fragility* is the diagonal version of Greenwood and Thesmar (2011) stock fragility measure. Following Greenwood and Thesmar (2011), the sample consists of stocks with market capitalization above the NYSE median. Stocks with a mutual fund share of less than 10% are excluded. The sample period is 1994–2016. Continuous variables other than internalization 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%.

			Investment adviser			
	Portfolio manager		with manager		without manager	
	(1)	(2)	(3)	(4)	(5)	(6)
$StockInternalize_{s,t}$	-1.118^{***}	-0.886^{***}	-0.648^{***}	-1.798^{***}	-0.623^{***}	-1.522^{***}
	(0.162)	(0.114)	(0.218)	(0.155)	(0.200)	(0.144)
$Fragility_{f,t}$	1.914^{***}	0.796^{***}	1.896^{***}	0.699^{***}	1.890^{***}	0.699^{***}
	(0.184)	(0.146)	(0.187)	(0.145)	(0.187)	(0.145)
$Ln(Marketcap)_{s,t}$	-2.647^{***}	-3.280^{***}	-2.757^{***}	-3.241^{***}	-2.749^{***}	-3.180^{***}
	(0.203)	(0.414)	(0.204)	(0.414)	(0.204)	(0.415)
$MF\ Share_{s,t}$	2.914^{***}	1.705^{***}	2.908^{***}	2.356^{***}	2.900^{***}	2.203^{***}
	(0.216)	(0.181)	(0.236)	(0.196)	(0.230)	(0.192)
N	82,592	82,272	82,592	82,272	82,592	82,272
Adjusted R^2	0.399	0.664	0.397	0.665	0.397	0.665
Date FEs	✓	✓	✓	✓	✓	✓
Stock FEs		✓		✓		✓

Table 8
Fund Returns, Flow Pressure, and Internalization

This table reports the 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. $Press_{f,m}$ 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 the security's market capitalization. Second, we calculate the weighted-average across all securities held by fund f. $Press \times CoHolderInternalize_{f,m}$ is constructed similarly to $Press_{f,m}$ except that each fund's flow is multiplied by the fund's internalization, expressed as the decile rank of the distribution of internalization for that quarter. The sample period is 1994–2016. Standard errors are adjusted for clustering by fund. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

			Investment adviser			
	Portfolio manager		with manager		without manager	
	(1)	(2)	(3)	(4)	(5)	(6)
$Press_{f,m}$	2.520***	2.649***	2.002***	2.062***	1.846***	1.894***
	(0.085)	(0.086)	(0.093)	(0.093)	(0.091)	(0.091)
$Press \times CoHolderInternalize_{f,m}$	−0.203***	−0.218***	−0.091***	−0.096***	−0.067***	−0.070***
	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)
$CoHolderInternalize_{f,m-1}$	0.317***	0.298***	0.306***	0.344***	0.359***	0.416***
	(0.023)	(0.033)	(0.020)	(0.034)	(0.019)	(0.031)
$Flows_{f,m}$	0.013***	0.008***	0.013***	0.007***	0.013***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
N	334,340	334,299	334,340	334,299	334,340	334,299
R^2	0.88	0.88	0.88	0.88	0.88	0.88
Objective × Date FEs	✓	✓	✓	✓	✓	✓
Fund FEs		✓		✓		✓

Table 9
Coholder Internalization and Fund Performance

This table reports the results of regressions of buy-and-hold returns and volatility of daily fund returns on coholder internalization:

$$R_{f,t+1} = \alpha_{obj(f),t} + \alpha_f + \beta \cdot CoHolderInternalize_{f,t} + \gamma' \mathbf{X}_{f,t} + \varepsilon_{f,t+1},$$

where f indexes stocks and t indexes quarter dates. In Panel A, the dependent variable is the volatility of daily fund returns during the quarter. Volatility is annualized and expressed in percent. In Panel B, the dependent variable is the buy-and-hold return during the quarter, expressed in percent. $CoHolderInternalize$ is the value-weighted average of $StockInternalize$ for all stocks in the fund's portfolio. $StockInternalize$ is the value-weighted average of $FundInternalize$ across all funds holding a given stock. Raw values of $FundInternalize$ are converted into decile ranks within each quarter. All other 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%.

			Investment adviser			
	Portfolio manager		with manager		without manager	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Daily return volatility (%)						
$CoHolderInternalize_{f,t}$	-1.831^{***}	-1.079^{***}	-1.591^{***}	-1.593^{***}	-1.699^{***}	-1.981^{***}
	(0.190)	(0.167)	(0.206)	(0.205)	(0.216)	(0.213)
$Size_{f,t}$	-0.120^{***}	0.630^{***}	-0.135^{***}	0.607^{***}	-0.135^{***}	0.599^{***}
	(0.037)	(0.069)	(0.038)	(0.069)	(0.038)	(0.069)
$Portfolio\ HHI_{f,t}$	0.338^{***}	0.142^{**}	0.338^{***}	0.131^{**}	0.339^{***}	0.129^{**}
	(0.072)	(0.063)	(0.073)	(0.062)	(0.073)	(0.061)
$Illiq_{f,t}$	-0.339^{***}	-0.569^{***}	-0.307^{***}	-0.517^{***}	-0.316^{***}	-0.506^{***}
	(0.092)	(0.109)	(0.091)	(0.105)	(0.091)	(0.104)
$Mutual\ fund\ share_{f,t}$	1.545^{***}	0.916^{***}	1.693^{***}	1.001^{***}	1.700^{***}	1.027^{***}
	(0.090)	(0.086)	(0.105)	(0.094)	(0.106)	(0.094)
$Fragility_{f,t}$	0.226^{***}	-0.046	0.244^{***}	-0.048	0.243^{***}	-0.046
	(0.063)	(0.037)	(0.067)	(0.036)	(0.067)	(0.036)
N	115,774	115,700	115,774	115,700	115,774	115,700
R^2	0.87	0.92	0.87	0.92	0.87	0.92
Objective × Date FEs	✓	✓	✓	✓	✓	✓
Fund FEs		✓		✓		✓
Panel B: Buy-and-hold return (%)						
$CoHolderInternalize_{f,t}$	0.495^{***}	0.447^{***}	0.329^{***}	0.291^{**}	0.395^{***}	0.538^{***}
	(0.077)	(0.115)	(0.070)	(0.123)	(0.071)	(0.126)
$Size_{f,t}$	-0.022	-1.236^{***}	-0.016	-1.236^{***}	-0.017	-1.230^{***}
	(0.013)	(0.047)	(0.013)	(0.047)	(0.013)	(0.047)
$Portfolio\ HHI_{f,t}$	-0.093^{***}	-0.076^{*}	-0.088^{***}	-0.072^{*}	-0.090^{***}	-0.071^{*}
	(0.024)	(0.042)	(0.025)	(0.041)	(0.025)	(0.041)
$Illiq_{f,t}$	0.208^{***}	0.317^{***}	0.206^{***}	0.319^{***}	0.205^{***}	0.307^{***}
	(0.044)	(0.069)	(0.044)	(0.069)	(0.044)	(0.069)
$Mutual\ fund\ share_{f,t}$	0.136^{***}	0.313^{***}	0.116^{***}	0.315^{***}	0.107^{***}	0.294^{***}
	(0.037)	(0.053)	(0.039)	(0.054)	(0.039)	(0.054)
$Fragility_{f,t}$	0.093	0.222^{***}	0.087	0.223^{***}	0.088	0.222^{***}
	(0.085)	(0.084)	(0.084)	(0.084)	(0.084)	(0.084)
N	115,774	115,700	115,774	115,700	115,774	115,700
R^2	0.86	0.87	0.86	0.87	0.86	0.87
Objective × Date FEs	✓	✓	✓	✓	✓	✓
Fund FEs		✓		✓		✓

Table 10
Cash Holdings

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

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

where f indexes funds and t indexes time. Cash-to-assets ratio is expressed in percent. Raw values of *Fund Internalize* are converted into decile ranks within each quarter. All other continuous variables are standardized so that their coefficients represent the effect of a one-standard deviation change in each variable. *Illiq* is the weighted-average of the square-root version of Amihud (2002) across all stocks in the fund's portfolio (Chen et al 2010). Standard errors are adjusted for clustering by fund. $*$, $**$, and $***$ indicate statistical significance at 10%, 5%, and 1%.

	Portfolio manager		Investment adviser with manager		Investment adviser without manager	
	Active	Index	Active	Index	Active	Index
	(1)	(2)	(3)	(4)	(5)	(6)
$\textit{Fund Internalize}_{f,t}$	0.082^{***}	-0.101^{**}	0.119^{***}	0.021	0.109^{***}	0.051
	(0.021)	(0.050)	(0.027)	(0.055)	(0.027)	(0.048)
$Illiq_{f,t}$	0.480^{***}	0.089	0.349^{***}	0.039	0.372^{***}	0.033
	(0.109)	(0.154)	(0.111)	(0.157)	(0.111)	(0.154)
$\sigma(Flows)_{f,t}$	0.178^{***}	-0.078^{***}	0.171^{***}	-0.074^{**}	0.170^{***}	-0.075^{**}
	(0.039)	(0.029)	(0.039)	(0.029)	(0.039)	(0.029)
$Size_{f,t}$	0.117^{*}	-0.180^{*}	0.004	-0.327^{**}	0.022	-0.365^{***}
	(0.071)	(0.105)	(0.081)	(0.134)	(0.081)	(0.128)
$\textit{Family size}_{f,t}$	-0.673^{***}	-0.135	-0.680^{***}	-0.266^{**}	-0.675^{***}	-0.302^{**}
	(0.078)	(0.140)	(0.080)	(0.130)	(0.080)	(0.124)
$\textit{Institutional share}_{f,t}$	-0.287^{***}	-0.083	-0.271^{***}	-0.113	-0.271^{***}	-0.121
	(0.055)	(0.096)	(0.054)	(0.095)	(0.054)	(0.094)
$Turnover_{f,t}$	-0.167^{***}	-0.144^{**}	-0.131^{**}	-0.164^{**}	-0.135^{**}	-0.169^{***}
	(0.053)	(0.067)	(0.053)	(0.065)	(0.053)	(0.065)
$\textit{Short selling}_{f,t}$	1.052^{***}	-0.165	1.032^{***}	-0.251^{*}	1.045^{***}	-0.275^{*}
	(0.355)	(0.139)	(0.359)	(0.142)	(0.361)	(0.143)
$Options_{f,t}$	3.743^{***}	10.589^{***}	4.078^{***}	11.289^{***}	4.044^{***}	11.348^{***}
	(0.809)	(1.687)	(0.814)	(1.691)	(0.813)	(1.688)
$\textit{Other practices}_{f,t}$	0.447	-0.848	0.266	-0.631	0.282	-0.567
	(0.302)	(0.634)	(0.306)	(0.678)	(0.306)	(0.678)
$Constant$	3.158^{***}	1.679^{***}	2.992^{***}	1.030^{***}	3.045^{***}	0.917^{**}
	(0.160)	(0.380)	(0.179)	(0.395)	(0.178)	(0.373)
N	34,879	5,045	34,879	5,045	34,879	5,045
R^2	0.117	0.430	0.117	0.427	0.117	0.428
Objective-time FEs	✓	✓	✓	✓	✓	✓