Portfolio Spillovers and a Limit to Diversification

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Abstract

Firms are exposed to the idiosyncratic shocks to the returns of other firms. Looking at mutual fund portfolios and instrumenting to address flow/return endogeneity, I find that the shocks to other firms induce portfolio flows, which induce rebalancing and result in temporary price pressure on a given firm. A one standard deviation increase in the flow-induced price pressure corresponds to a .15-.6% increase in daily abnormal firm returns. This pressure fully reverses in 5-6 days, and the magnitude is larger if funds experience a net outflow than if they experience a net inflow. There is evidence that liquid firms are more sensitive than illiquid firms to this price pressure. These findings are consistent with the hypothesis that managers experiencing a portfolio return shock adjust the most liquid assets in expectation of fund flows. If investors are unable to properly estimate the correlations induced by being in common portfolios, they are unable to fully diversify away idiosyncratic risk.

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I Introduction

Are idiosyncratic shocks to the returns of a firm really "idiosyncratic"? An idiosyncratic shock is, by definition, specific to a firm and is uncorrelated with the returns of other firms; the idiosyncratic information is firm-specific and in theory is not linked to the fundamentals of other firms.

A major branch of financial research has been dedicated to portfolio formation and management, but research on the linkage effects induced by being in common peer groups is still developing. These linkage effects could result from peer groups defined in diverse ways (industry, sector, geographical location, common supplier, portfolio similarity[1]); however, I examine a potential spillover via firms being in common mutual fund portfolios. These portfolio-induced peer effects are interesting because, unlike many other potential peer groups (industry, location, etc.), a firm cannot dictate the other firms that are in common portfolios (given a liquid secondary market) and is thus far less able (if at all) to mitigate these spillover effects. From the portfolio manager and investor's perspective, being unable to accurately estimate the other holdings of fellow shareholders implies that these spillover effects are a meaningful limit to the hedging of idiosyncratic risk.

I examine the possibility that the abnormal returns of a given firm are affected by the idiosyncratic shocks to other firms in a common mutual fund portfolio through expected fund flows at the daily frequency. Using the residual from a five-factor regression model (including the Fama-French three factors, the momentum factor, and the industry return) as a proxy for idiosyncratic information shocks, these shocks to the returns of firms mechanically affect the returns of portfolios holding these firms. These portfolio returns affect future fund flows. If there is a net outflow, for example, in order to satisfy these flow demands, portfolio managers may reduce positions in other firms, not directly affected by the original idiosyncratic shocks. If a firm is in many portfolios with firms who experience negative idiosyncratic shocks, this can induce a systematic pressure on the returns of that firm. Conversely, if a firm is in many mutual fund portfolios whose other holdings experience positive idiosyncratic shocks, this can induce positive fund inflows. These positive inflows can translate into increasing other positions (not just in those firms experiencing positive idiosyncratic shocks) implying positive price pressure on an originally "unshocked" firm.

I find that this price pressure significantly affects daily firm returns; a one standard devi-

[1] Cohen & Frazzini (2008) find predictable linkage effects between the idiosyncratic shocks of supplier and customer companies. Leary & Roberts (2012) find that firm leverage is significantly affected by the average leverage of the peer group (defined as the 3 digit SIC code). Lang & Stulz (1992) find an industry spillover when firms file for bankruptcy. Sun (2008) groups securities by the similarity of the portfolios of their institutional owners and finds that these securities have abnormal comovement.

ation increase in flow-induced price pressure implies a .15-.6% increase in daily idiosyncratic returns. The standardized magnitude of this effect is on the same order as the canonical Fama-French three factors. In addition, consistent with previous literature[2], I find that this price pressure affects liquid firms more than illiquid firms, and that it fully reverses over the course of approximately one week. Though investment horizons of many investors may be longer than the duration of this pressure, week-long deviations from fundamental value can have significant effects on arbitrageurs and on the portfolios of investors with shorter investment horizons.

There is an endogeneity issue concerning the causal link between the flow-induced price pressure and the returns of a firm - i.e. firms may perform poorly as a result of selling pressure, but funds may also sell off firms because the firm is performing poorly. There is strong evidence that returns are driven by flow pressure, implying the former relationship.[3] However, there is also strong evidence that many funds are momentum traders, implying the latter causal relationship.[4]

To resolve this, I use both i) a measure of the lagged idiosyncratic returns of other firms in the same portfolios, and also ii) a measure of the legal case announcements against other firms in different industries in the same portfolios, as instruments for the flow-induced price pressure (FIPP) for a given firm. The legal case-based instrument represents a novel contribution of this work to the literature. I control for industry wide shocks in all specifications. Both of these instruments are very significant in the first stage, and the usage of the second instrument produces qualitatively consistent results.

By instrumenting for flow-induced price pressure, I identify both the magnitude and a plausible mechanism for a common portfolio spillover effect. In addition, the reduced form regressions will allow a direct test of the hypothesis that firm abnormal returns are significantly impacted by the shocks to other firms in common portfolios, controlling for other factors. Further, I test this hypothesis directly by forming capital neutral long - short portfolios, constructed by exploiting this price pressure, which generate ex post annual abnormal returns of 6 - 7%.

I motivate and build an explanation of this spillover effect by first demonstrating the link between fund flows and a fund's changes in daily holdings. Edelen and Warner (2001), using aggregate market return and mutual fund flow data, find that aggregate flows are significantly

[2]Johnson (2004) concludes that mutual funds face persistent "liquidity-related" costs that vary with the characteristics of the funds' investors. Massa & Phalippou (2005) find that unpredictable changes in market liquidity affect mutual fund performance and that portfolio liquidity is actively managed. Koch et al. (2010) find that liquid firms are most exposed to mutual fund ownership.

[3]See Coval and Stafford (2007).

[4]See Grinblatt, Titman, and Wermers (1995).

driven by one-day lagged market returns (I find a similar dependence between fund level flows and lagged idiosyncratic fund returns). However, examining daily flow-induced pressure at the individual firm level requires daily fund holdings.

I demonstrate a novel technique for estimating the daily holdings of a mutual fund. Much of the previous literature has assumed that holdings are constant throughout the quarter (implying either exclusive first-day-of-quarter or last-day-of-quarter rebalancing); the proprietary nature of mutual fund holdings data has given researchers no other choice. However, there is strong evidence that mutual fund managers time markets and volatility on a daily basis.[5] I demonstrate a new technique in which quarterly estimates are extrapolated to the daily frequency and then tested by comparing estimated portfolio returns with reported portfolio returns. This technique will be fully explained in section II.C.

I then show that daily fund flows are effected by daily fund returns (consistent with Ippolito (1992), Chevalier & Ellison (1995), and Sirri & Tufano (1998)). And finally, fund flows produce price pressure on firms exposed to these fund flows (see Coval & Stafford (2007) and Lou (2012)). Previous literature has omitted identifying the source of the price pressure, and with few exceptions, has focused predominantly on flow-related price pressure at the quarterly horizon. Previous research had neither the data nor the motivation to examine shorter horizon (daily) spillover effects and has not addressed the endogeneity issue of returns *inducing* holding level flows - e.g. fund managers reduce fund holdings of poorly performing companies and increase holdings of well-performing companies. Controlling for industry effects, I argue that the instruments satisfy the exclusion restriction and overcome this endogeneity. Given data on firm returns, legal cases, and fund flows at the daily horizon, I can accurately identify one (possible) channel in which idiosyncratic shocks can spill onto the returns of another firm.

This work is most closely aligned with the research of Anton & Polk (2013), Hau & Lai (2011), and Blocher (2011). Anton & Polk examine the correlation between returns as a function of the number of funds in common. They find that the covariance of returns, controlling for a number of other factors, significantly loads on the number of funds that are holding both firms. Hau & Lai examine the effect on non-financial firms that are in common portfolios with distressed financial firms during the 2008 financial crisis. They find that non-financial firms exposed to financial firms through common portfolios performed significantly worse during the financial crisis of 2008. Blocher constructs a measure of fund similarity and uses second neighbors to instrument for contagion capital flow effects across similar portfolios. Using a Spatial Auto-Regression (SAR), he finds that network effects magnify

[5] See Busse (1999), Bollen & Busse (2001), Green & Hodges (2002), and Bobson, Cavenaile, & Sougné (2012).

portfolio shocks - specifically, accounting for network effects implies returns that are 52% higher and cash holdings effects that are 76% higher than "non-networked" effects. Blocher's work is similar to Sun (2008) which categorizes institutional portfolios into "clusters" based on portfolio similarity and finds that stock turnover, return, and liquidity depend significantly on the cluster level turnover, return, and liquidity.

Flow-based price pressure, essentially linking fund flows to correlated price movements, has been examined in several notable papers. Coval and Stafford (2007) show that firms held in common by distressed funds experience negative abnormal returns as the common outflows create widespread price pressure.[6] In a corporate finance vein, Edmans et al. (2012) examine the effects of outflow related price pressure on the probability of a takeover, and Hau & Lai (2012) examine corporate investment and employment. Hua & Lai (2011) point out that such work can suffer from a flow-based endogeneity bias as there may be reverse causality in the price pressure/flow relationship as noted above. My research essentially instruments for the realized flow pressure and allows for broader conclusions beyond the financial/non-financial sector relations. Furthermore, I go beyond simply documenting the empirical existence of this channel and establish a viable mechanism for its transmission, i.e. fund flows induced by idiosyncratic shocks.

Also, and perhaps most significantly, my results represent a limitation to the benefits of diversification. To the extent that an investor is unable to accurately distill the complex network of firm ownership, though publicly available, she is unable to accurately construct the covariance matrix of security returns. Omitting important information concerning common portfolio risk implies that she is unable to hedge the risk induced from common portfolio-derived linkages. She is unable to accurately forecast this price pressure and is thus exposed to, and cannot diversify away, the idiosyncratic shocks of seemingly unrelated firms. Previous flow-induced price pressure research abstracts away from the cause of the flow and thus misses this direct limit to diversification.

This inquiry into flow-induced portfolio spillover risk is also broadly connected with several other strands of literature relating to the pricing of idiosyncratic risk[7] and mutual fund family structure.[8] However, the former literature has said very little on peer group effects

[6] Jotikasthira et al. (2011) show that a similar effect holds internationally.

[7] There is a large stock of empirical work which supports the relation between idiosyncratic characteristics and stock returns in various contexts. See Lehmann (1990), Goyal et al. (2003), Bessembinder (1992), Fu (2009), and Storesletten et al. (2001). Theoretical models have implied the pricing of idiosyncratic characteristics due to incomplete markets (Merton (1987)), lack of diversification (Levy (1978)), exclusionary exogenous market factors (Malkiel et al. (2002)), nontradeable human capital (Mayers (1976)), costly trading (Hirschleifer, (1988)), and loss-aversion towards owned stocks based on prospect theory (Barberis et al. (2001)).

[8] Nanda, Wang, and Zheng (2004), in their seminal star phenomenon paper, show that within a fund family, the outperformance of a single firm can increase not only the cash inflows into the star fund but

and idiosyncratic characteristics, and the latter has focused mostly on volatility spillovers and effects at the mutual fund company level. Finally, theoretical equilibrium models have also been built that link fund flows and asset prices, as in Vayanos & Woolley (2011) and a simpler breadth of ownership model, as in Chen, Hong, & Stein (2002). Brunnermeier & Sannikov (2011) claim that common holdings can destabilize markets. Our results are consistent with many of the predictions of this theoretical work.

The rest of this paper is organized as follows. Section II discusses the empirical strategy. Section III provides results. Section IV extends the model along several dimensions, and Section V explores the robustness of our findings to some of the modelling assumptions. Section VI concludes.

II Empirical Strategy

II.A Model Development

There are both anecdotal sources and empirical work that suggest the existence of a common portfolio spillover effect. In an article in the Wall Street Journal, Ip (1997) quotes a notable money manager as saying:

> "Before I look at a stock, I take a look at the (SEC) filings to see who the major shareholders are. If you see a large amount of momentum money in there, you have to accept that there's a high risk."

The manager is worried that the momentum strategies of other shareholders may induce trading that will affect the value of the considered position. These comments highlight, albeit anecdotally, a concern that an investor considering a position in, say, Apple Inc. (AAPL), may be exposed to more than simply the idiosyncratic shocks affecting AAPL (or the shocks affecting AAPL's industry). His comments suggest that an investor is exposed (and concerned about the exposure) to the idiosyncratic shocks of *other* firms that are in the portfolios of the current shareholders of AAPL. If some of the other firms that are in common portfolios with AAPL experience, say, negative return shocks that are not directly related to AAPL, this may illicit redemption-pressure on the managers of those portfolios to sell off other holdings to meet these redemption requests. The redemption-pressure may significantly affect the share price of AAPL.

also into *other* funds within the same family. Gaspar, Massa, & Matos (2006) find that fund families go further than this, transferring performance from low value funds (those with low fee structures or who are unlikely to generate high investor inflows) to high value funds (those funds with high fee structures or a high probability of generating inflows).

Koch et al. (2010) hint at such a possibility in a concluding remark where their findings suggest that "fund managers might consider avoiding stocks ... whose ownership is dominated by other mutual funds, particularly if they are concerned about the effects of liquidity shocks hitting themselves in the form of investor flows." Edelen (1999) suggests a price pressure channel similar to the one proposed by my research in that he finds that the detrimental portfolio performance effects of fund flows are due to transaction costs induced by changing portfolio holdings and the need to carry cash to cover unforeseen redemptions. Khandani & Lo (2007) discuss a similar hypothesis for explaining the "quant meltdown" of 2007, essentially arguing that the liquidity shock to several large hedge funds caused them to unwind their positions, unwinding which reverberated through the network of ownership causing the large volatility spike in August 2007 and record losses for many of the previously most successful equity hedge funds. This suggests that a portfolio spillover channel could be partially explained by return-induced flow pressure.

In a fully efficient market, investors can diversify away idiosyncratic risk, and the market properly compensates any strategy according to the systematic risk of the portfolio. Consider, however, a simplified universe in which there is a single fund ABC and two firms i and j that are both held by fund ABC at time t. Assume that firm j experiences an idiosyncratic shock, and assume, for the sake of explanation, that this shock is significantly negative and unexpected - if the shock is positive, the pressure will be in the opposite direction. In an efficient market, since the shock is idiosyncratic to firm j, it is by definition orthogonal to the returns to firm i, and thus the returns of firm i are unaffected by this shock. However, given that both firm i and j are in a common portfolio, it is possible that the idiosyncratic shock to firm j elicits a flow response that forces the manager of the common portfolio (fund ABC) to liquidate positions, which affects firm i. The heuristic mechanism of this story, including the instrument, is shown schematically in panel A of Figure 1. A schematic using the legal case instrument is shown in panel B.

[Insert Figure 1 about here]

Assuming a less simplified universe by allowing many firms and many funds, if these two firms are in many common portfolios, the idiosyncratic shock affecting firm j may systematically affect the price of firm i. Though this "single-firm spillover" is possible, given the diversified portfolios of mutual funds, I test the more realistic relationship between the abnormal returns of firm i and a value-weighted measure of the lagged portfolio idiosyncratic returns of all other firms in common portfolios with firm i.

The model will be fully specified in the next section, but it can be summarized in the following manner. The idiosyncratic shocks of firms other than firm i (either directly or as a result of a legal case announcement against firms in common portfolios) are an exogenous shock (properly controlling for industry channels as emphasized by Gande & Lewis (2009)) to the flow-induced price pressure of firm i. The shocks to these other firms imply a shock to fund returns which then implies flow-induced selling off (purchasing) of portfolio holdings, if the net shock is negative (positive). If an unrelated firm i is exposed to the idiosyncratic shock of these firms through many common portfolios, the idiosyncratic shocks may significantly affect the returns of firm i through widespread flow-induced price pressure. Thus, though the news that precipitated the return shock is idiosyncratic to the other firms (or, more precisely, contains no information regarding the fundamentals of firm i), the returns of firm i are affected. I examine this possibility using both event study and regression frameworks.

II.B Data

The model posits that funds holding firms that experience a net negative (positive) idiosyncratic shock will face redemptions (deposits) in the future; these future redemptions (deposits) lead managers to reduce (expand) other holdings. These other holdings, those that are in common portfolios with firms experiencing the negative (positive) shock, but do not necessarily experience a shock themselves, experience negative (positive) price pressure as managers meet, and potentially smooth out, oncoming redemptions (deposits).

To test this hypothesis, I connect data from four sources. First, mutual fund holdings data are obtained from the CRSP Survivor-Bias-Free US Mutual Fund Database available via WRDS. These data include reported quarterly holdings for open-end mutual funds. Second, daily stock information, including daily returns and market capitalization, is obtained from the CRSP Daily Stock File. Third, legal disclosure data are obtained from the Legal Case and Legal Parties database from AuditAnalytics. This database contains meticulous case details for all federal securities class action claims, SEC actions, and material federal civil litigation. In our work, since the legal case disclosure is essentially an idiosyncratic shock generator, I do not differentiate between different types of cases. Fourth, daily fund flows are obtained from TrimTabs who surveys daily 20-30% of the mutual fund universe to obtain Total Net Assets (TNA) and change in Net Asset Value (ΔNAV). I perform several robustness checks to ensure the reliability of the TrimTabs data; these checks can be found in the appendix. Because of data constraints on daily fund flow data, I use a relatively recent portion of the CRSP Mutual Fund Holdings Database (2003-2010), sidestepping criticisms of the accuracy of the early data.[9] Thus, all of these data span 2003 - 2010, inclusively.

Summary statistics of the merged datasets are given in Table 1. I cut out very small and

[9] See Elton, Gruber, & Blake (2002).

very illiquid stocks as recommended by Bali et al. (2005). I rescale the Amihud measure of illiquidity by multiplying by 1×10^6. I also only include firms that are held in at least 5 funds and that have return data for at least 200 days. These filters affect an insignificant portion of the data.

A limitation to the mutual fund holdings data is the quarterly frequency. Much of the research utilizing this dataset has assumed constant holdings in the reporting quarter[10]; however, as cited previously, a wide body of work has used daily fund returns to demonstrate mutual fund manager's ability to time market volatility at a daily frequency. Also, Puckett and Yan (2011) report that intraquarterly trading accounts for 20 to 26 basis points of a fund's annual abnormal return. Since daily holdings data are not publicly available, I proxy for changes in daily holdings by examining a model of holding rebalancing at the quarterly frequency that is similar to Lou (2012), but I then use the coefficients estimated at this quarterly frequency to estimate the daily holdings. Coval and Stafford (2007) report that quarter-to-quarter fund holdings for individual firms are maintained, expanded, or reduced (but not eliminated) for 86% of fund positions, which lends credence to this approach since I will be extrapolating from the holdings reported at the end of every quarter onto the next quarter. I test this model by comparing the daily portfolio returns derived from the estimated holdings with the daily returns reported by the funds themselves (via TrimTabs). This construction will be fully specified in the next section.

[Insert Table 1 about here]

II.C Model

The process underlying this analysis is that security price changes are affected by the price pressure induced by mutual fund selling or buying of the security, that is

$$\mathrm{r}_{i,t}^{idio} = \beta_0 + \beta_1 \mathrm{FIPP}_{i,t} + \epsilon_{i,t} = \beta_0 + \beta_1 \sum_{n=1}^{N} \mathrm{flow}_{i,n,t} \frac{V_{i,n,t-1}}{MV_{i,t-1}} + \epsilon_{i,t} \tag{1}$$

where $\mathrm{r}_{i,t}^{idio}$ is the idiosyncratic return of firm i, N is the number of funds in the universe, and I definite the flow-induced price pressure ($\mathrm{FIPP}_{i,t}$) as the value-weighted flow pressure across all funds; that is, $\mathrm{flow}_{i,n,t}$ represents the % change in holdings for fund n of security i from time $t-1$ to t, $V_{i,n,t-1}$ is the (\$) value of firm i held in fund n at time $t-1$, and

[10]See Cohen & Frazzini (2008), Anton & Polk (2013), and Hau & Lai (2012).

$MV_{i,t-1}$ is the market capitalization of firm i at time $t-1$, such that:

$$\text{FIPP}_{i,t} = \sum_{n=1}^{N} \text{flow}_{i,n,t} \frac{V_{i,n,t-1}}{MV_{i,t-1}}. \tag{2}$$

This is similar to the flow-induced price pressure measure constructed elsewhere in the literature; see Lou (2012) and Edmans et al. (2012). Essentially, this definition is a value-weighted sum of the estimated flow pressure of every fund that is holding firm i. This specification is subject to endogeneity as the flows into funds that hold security i are driven by fund performance, which is mechanically connected to the returns of firm i, as discussed in Frazzini & Lamont (2008) and Chevalier & Ellison (1995). To sidestep this issue and to identify a channel for this pressure, I use two instruments: the first is the lagged value-weighted portfolio idiosyncratic returns excluding firm i, and the second is a measure of the legal case announcements of other firms in different industries in the same portfolios.

The first class of instruments is built by first substituting for the change in holdings, $\text{flow}_{i,n,t}$, the lagged value-weighted idiosyncratic returns of all of the other firms in fund n, excluding firm i :

$$\sum_{j \in H_{n,t-k}, i \neq j} \frac{V_{j,n,t-k}}{\text{TNA}_{n,t-k}} r^{idio}_{j,t-k} \tag{3}$$

where $H_{n,t-k}$ are the holdings of the nth fund at time $t-k$, $V_{i,n,t-k}$ is the value of firm i in firm n at time $t-k$, $r^{idio}_{j,t-k}$ is the idiosyncratic return at $t-k$ of firm j, and $\text{TNA}_{n,t-k}$ is the Total Net Assets for fund n at time $t-k$. I will motivate this substitution by looking at how, for a fund n at time t, short horizon fund flows are affected by the k-lagged portfolio idiosyncratic return. That is:

$$\begin{aligned} \text{flow\_daily}_{n,t} \quad &= \quad \beta_0 + \beta_k \text{idio\_ret}_{n,t-k} + \gamma_k \delta^{inflow}_{n,t-k} * \text{idio\_ret}_{n,t-k} \\ &\quad +F_k \delta^{inflow}_{n,t-k} + G \text{flow\_daily}_{n,t-1} + \delta_t + \delta_n + \epsilon_{n,t} \end{aligned} \tag{4}$$

where $\text{idio\_ret}_{n,t-k}$ is the value-weighted portfolio idiosyncratic return on day $t-k$ constructed by first calculating idiosyncratic returns (as outlined below) for all firms in the fund and then value weighting these idiosyncratic returns:

$$\text{idio\_ret}_{n,t-k} = \sum_{j \in H_{n,t-k},} \frac{V_{j,n,t-k}}{\text{TNA}_{n,t-k}} r^{idio}_{j,t-k}. \tag{5}$$

This is similar to Equation (3), but I do not exclude firm i from the construction. $\text{flow\_daily}_{n,t}$

represents the fund flows from day $t-1$ to day t, i.e.

$$\text{flow\_daily}_{n,t} = \frac{\text{TNA}_{n,t} - \text{TNA}_{n,t-1}(1 + \text{fund\_ret}_{n,t})}{\text{TNA}_{n,t-1}} \tag{6}$$

where $\text{fund\_ret}_{n,t}$ is the return per share of fund n on day t. To better capture the concave relationship between redemptions and returns, I include interaction terms with an inflow dummy $\delta^{inflow}_{n,t-k}$, which is equal to 1 if the net flow for quarter $t-k$ is positive and zero otherwise. However, the primary goal is to motivate the construction of the instrument, and I am less concerned with pinning down the precise relationship between fund flow and past fund idiosyncratic returns. Thus, I focus on the significance of the coefficients β_k. I construct the first class of instruments, which I label as $\text{Port\_ret}_{-i,t-k}$, by putting this substitution into the definition of the flow-induced price pressure ($\text{FIPP}_{i,t}$):

$$\text{Port\_ret}_{-i,t-k} = \sum_{n=1}^{N} \left[\sum_{j \in H_{n,t-k}, i \neq j} \frac{V_{j,n,t-k}}{\text{TNA}_{n,t-k}} r^{idio}_{j,t-k} \right] \frac{V_{i,n,t-1}}{MV_{i,t-1}}. \tag{7}$$

The exclusion restriction for this first instrument (lagged portfolio idiosyncratic returns excluding firm i of funds holding firm i) requires that these lagged returns: 1) do not have a causal affect on the idiosyncratic returns of firm i, and 2) do not have a common dependency with the idiosyncratic returns of firm i. These lagged returns only affect the idiosyncratic returns of firm i indirectly through affecting fund flows.

As a robustness check, I also instrument for the flow-induced price pressure ($\text{FIPP}_{i,t}$) directly by using an instrument that is built around a firm's exposure to the legal case announcements of other firms in common portfolios. I construct the alternate instrument $\text{Normalized\_Cases}_{i,t}$ where:

$$\text{Normalized\_Cases}_{i,t} = \frac{\sum_{n=1}^{N} \sum_{j \in H_{n,t}, i \neq j} \delta_{i,j,t}}{S_{i,t}} \tag{8}$$

and

$$\delta_{i,j,t} = \begin{cases} 1 & \text{if firm } i \text{ and } j \text{ are in the same fund at time } t \text{ but different industries} \\ & \text{and } j \text{ is the subject of a legal case announcement} \\ & \text{at any time from time } t \text{ to } t+3 \\ 0 & \text{otherwise} \end{cases}.$$

H_n are the holdings of the nth fund at time t. N is the number of funds, and $S_{i,t}$ is the number of funds holding firm i at time t. Intuitively, we are instrumenting for the fund flow pressure of firm i by using the number of unrelated legal case announcements to which firm i is exposed (via a common mutual fund portfolio). The numerator dummy variable is equal to 1 for any case announced in the next 3 days; this is because the news of the legal case announcement seems to be most severe during the 3 days directly before the legal case announcement (discussed in section V). I normalize this sum by the number of funds estimated to be holding firm i at time t (in any amount). This instrument could be expanded by weighting the legal case exposure of firm i by both the amount of firm i held in the fund and also by the amount of the firm held by the fund that is the subject of the legal case. I favor the parsimonious definition above.

The exclusion restriction for the second instrument (this measure of the legal cases announced against firms in different industries in common fund portfolios) requires that the announcement: 1) does not directly affect the idiosyncratic returns of firm i, and 2) does not have a common dependency with the idiosyncratic returns of firm i. The announcement only affects the idiosyncratic returns of firm i indirectly by affecting fund flows.

Thus, the first stage regressions for the first class of instruments are given by:

$$\text{FIPP}_{i,t} = \alpha + \beta \text{Port\_ret}_{-i,t-k} + \epsilon_{i,t} \tag{9}$$

and the first stage regression for the second instrument class is given by:

$$\text{FIPP}_{i,t} = \alpha + \beta \text{Normalized\_Cases}_{i,t} + \epsilon_{i,t} \tag{10}$$

I want to examine this pressure at the daily frequency which necessitates having data on the holdings of mutual funds at the daily frequency. Given that we do not have daily flows at the firm level, but we do have daily fund flow data for some funds and corresponding quarterly holdings and flow data, I propose a novel technique to estimate daily fund holdings. Lou (2012) shows we cannot simply assume the uniform rebalancing of holdings as a result of fund flow because there is significant cross-sectional variation across security and fund characteristics; thus, I first construct a simple model relating flows and firm characteristics to changes in holdings at the quarterly frequency:

$$\begin{aligned} \Delta\text{Fund\_Holdings\_quarterly}_{i,n,t} \quad = \quad & \gamma_0 + \gamma_1 \text{flow\_quarterly}_{n,t} * \text{illiquidity}_{i,t} \\ & + \gamma_2 \text{flow\_quarterly}_{n,t} * \text{size}_{i,t} \\ & + \gamma_3 \text{flow\_quarterly}_{n,t} \\ & + \gamma_4 \text{illiquidity}_{i,t} + \gamma_5 \text{size}_{i,t} + \delta_{i,n} + \delta_t + \epsilon_{i,n,t} \end{aligned} \tag{11}$$

where $\Delta\text{Fund\_Holdings\_quarterly}_{i,n,t}$ is the percentage change in the number of shares of security i in fund n from time $t-1$ to time t, $\text{flow\_quarterly}_{n,t}$ is the quarterly fund flow from quarter $t-1$ to time t, $\text{illiquidity}_{i,t}$ is the Amihud measure of illiquidity calculated over the trailing 90 days of security i, and $\text{size}_{i,t}$ is the market capitalization of firm i. I then assume that the relationship between rebalancing and the covariates at the quarterly frequency is an accurate model for rebalancing at the daily frequency. I extrapolate the coefficient estimates from the quarterly regressions to estimate changes in holdings at the daily frequency:

$$\begin{aligned}\Delta\text{Fund\_}\widehat{\text{Holdings}}\text{\_daily}_{i,n,t} &= \widehat{\gamma}_0 + \widehat{\gamma}_1\text{flow\_daily}_{n,t} * \text{illiquidity}_{i,t} \\ &\quad + \widehat{\gamma}_2\text{flow\_daily}_{n,t} * \text{size}_{i,t} + \text{main\_effects}_{i,t} + \frac{\delta_t}{63} + \frac{\delta_{i,n}}{63}\end{aligned} \tag{12}$$

where I perform the necessary normalization on the quarterly covariates by dividing by the number of trading days in a quarter. I check the robustness of this assumption by comparing the daily portfolio returns generated by using the estimated holdings, with the daily fund returns reported by TrimTabs. I will show significant improvement over several alternative assumptions, including constant quarterly holdings. The specifics of these comparisons are shown in the next section. Given these estimates of the daily fund holdings, I construct the $\text{FIPP}_{i,t}$:

$$\text{FIPP}_{i,t} = \sum_{n=1}^{N} \Delta\text{Fund\_}\widehat{\text{Holdings}}\text{\_daily}_{i,n,t} \frac{\widehat{V}_{i,n,t-1}}{MV_{i,t-1}} \tag{13}$$

and the $\text{Port\_ret}_{-i,t-k}$ instrument:

$$\text{Port\_ret}_{-i,t-k} = \sum_{n=1}^{N} \left[\sum_{j \in H_{n,t-k}, i \neq j} \frac{\widehat{V}_{j,n,t-k}}{\text{TNA}_{n,t-k}} \hat{r}^{idio}_{j,t-k} \right] \frac{\widehat{V}_{i,n,t-1}}{MV_{i,t-1}} \tag{14}$$

where N is the number of funds, $\Delta\text{Fund\_}\widehat{\text{Holdings}}\text{\_daily}_{i,n,t}$ are the estimated changes in daily holdings derived from using daily data and the quarterly coefficients, $\hat{r}^{idio}_{j,t-k}$ are the idiosyncratic returns of firm j at time $t-k$, $\widehat{V}_{i,n,t-k}$ is the estimated value of firm i held in fund n at time $t-k$, and $MV_{i,t-k}$ is the market capitalization of firm i at time $t-k$.

Idiosyncratic returns, when used, are obtained in the following manner. I control for canonical risk factors by constructing the following time series regressions for each firm i similar to Brennan et al. (2011):

$$r_{i,t} = \alpha^i + \beta_1^i\text{MKTRF}_t + \beta_2^i\text{SMB}_t + \beta_3^i\text{HML}_t + \beta_4^i\text{UMD}_t + \beta_5^i\text{Ind\_ret}_{i,t} + \epsilon_{i,t}. \tag{15}$$

MKTRF, SMB, and HML are the standard Fama-French 3 factors. UMD is the Carhart momentum factor, and $\text{Ind\_ret}_{i,t}$ is the value-weighted return of the industry to which firm

i belongs at time t. Idiosyncratic returns for firm i are obtained for day t by performing the previous regression for the past 90 days (time $t-91$ to $t-1$), rolling these coefficient estimates forward to get a residual and adding the constant term (α^i):

$$\hat{r}_{i,t}^{idio} = r_{i,t} - \left[\hat{\beta}_1^i \text{MKTRF}_t + \hat{\beta}_2^i \text{SMB}_t + \hat{\beta}_3^i \text{HML}_t + \hat{\beta}_4^i \text{UMD}_t + \hat{\beta}_5^i \text{Ind\_ret}_{i,t}\right]. \tag{16}$$

Our analysis is focused on these idiosyncratic returns and the raw returns controlling for these 5 factors. The results are qualitatively unchanged if the constant term in the construction of the idiosyncratic returns is excluded, as well as using the 49 Fama-French industry returns, 2-digit SIC code industry returns, or 3-digit SIC code industry returns. The results discussed in the next section use the more conservative 3-digit SIC code construction of the industry returns.

There is reason to believe that this exposure may not affect all firms in the same manner - Chen, Hong, & Stein (2002), for example, find a larger breadth of ownership effect on small firms relative to large firms. Phalippou & Massa (2005) find that funds target a level of liquidity, and, as has already been cited, Lou (2012) shows that the effects of flow-induced rebalancing vary significantly across firm liquidity. I examine a differential effect along these two proposed dimensions by looking at idiosyncratic returns as a function of the instrument and interactions with the instruments at the daily frequency in the reduced form regressions:

$$\begin{aligned} \hat{r}_{i,t}^{idio} &= \alpha + \beta_0 \text{Port\_ret}_{-i,t-k} * \text{size}_{i,t} + \beta_1 \text{Port\_ret}_{-i,t-k} \qquad (17) \\ &\quad + \beta_2 \text{size}_{i,t} + \delta_i + \delta_t + \epsilon_{i,t}, \end{aligned}$$

and

$$\begin{aligned} \hat{r}_{i,t}^{idio} &= \alpha + \beta_0 \text{Port\_ret}_{-i,t-k} * \text{illiquidity}_{i,t} + \beta_1 \text{Port\_ret}_{-i,t-k} \qquad (18) \\ &\quad + \beta_3 \text{illiquidity}_{i,t} + \delta_i + \delta_t + \epsilon_{i,t}. \end{aligned}$$

The main effects in these regressions, namely the significance of the β_0 coefficients, are important for establishing both the credibility of the instrument and also the credibility of the spillover story in general. Extensions and modifications to the basic framework outlined in this section are specified and discussed in section IV.

III Results

I first establish the relationship between daily fund flows and lagged value-weighted idiosyncratic returns. Given the strong link between these fund flows and raw returns at the quarterly horizon, it seems natural to examine a similar flow-return relationship at shorter horizons. Though funds may charge redemption fees to mitigate short-term market-timing (or redemption in general), Greene et al. (2007) argue that the fact that daily fund flows are nonzero implies that these fees are not completely effective at discouraging redemptions. The main specification is daily fund redemptions as a function of idiosyncratic fund returns. Daily fund flows are obtained from TrimTabs where they are calculated according to Equation 6. Results from the specification in Equation (4) are shown in Table 2. I trace out the impulse response of flows to idiosyncratic portfolio returns by regressing over lagged returns in three different specifications. Standard errors are clustered at the fund level. I follow the econometric approach of Cochrane & Piazzesi (2002). Panel A is the baseline regression with only panel fixed effects and time controls. Panel B adds lagged flows, and Panel C adds an indicator variable for inflows and corresponding interaction terms. Even controlling for inflows and past flows, current flows are significantly determined by past idiosyncratic returns in the last one to five days. In all three models, the idiosyncratic returns from the previous five days significantly predict future flows at the 1% level. I will construct the instrument of lagged portfolio idiosyncratic returns ($\text{Port\_ret}_{-i,t-k}$) for $k = 1$ and $k = 2$ corresponding to one and two day lags (coefficient estimates are qualitatively similar for k values from 3 to 5 but the economic and statistical significance is diminished).

[Insert Table 2 about here.]

Next, in order to construct the daily flow-induced price pressure, I examine changes in holdings as a function of flows, illiquidity, size, relevant interaction terms and other regressors, at the quarterly frequency, similar to Lou (2012). Results are found in Table 3. Errors are clustered at the fund-holding level. The first five regressions include both positive and negative netflows. The next four isolate the net inflows (regressions 6 - 9), and the last four (10 - 13) isolate the net outflows. Regression 4 demonstrates the strong relationship between changes in portfolio holdings, flow, liquidity, and size. I find that liquid firms are more sensitive to flows, which is consistent with previous research; differences with Lou (2012) may be driven by my different dataset that includes the recent economic recession and also our different definition of liquidity - I use the lagged 90 day Amihud measure of illiquidity instead of a bid-ask measure. The expanded list of regressors in regressions 5, 9, & 13 include lagged quarterly flow and a lagged interaction between quarterly flow and illiquidity. I find that lagged quarterly flow is statistically significant though not economically significant, and I find the interaction term to not be statistically different from zero. I will use the coefficient estimates from regressions 8 & 12 in our daily construction, arguing for parsimony and consistency with the literature. Using estimates derived from regressions 7

& 11 (which is more true to Lou's original work and excludes the size characteristic and size interaction terms) produces similar results and are reported later.

[Insert Table 3 about here.]

Given the effect that daily portfolio returns have on fund flows, and the effect of quarterly portfolio flow on fund holdings, I now construct the flow-induced price pressure $\text{FIPP}_{i,t}$. To do this at a daily frequency requires estimates of the daily holdings of the mutual funds in our sample. Using the coefficient estimates from the quarterly regression 8 and 12 from Table 3, I estimate daily changes in holdings $\Delta\text{Fund\_}\widehat{\text{Holdings}}\text{\_daily}_{i,n,t}$. The specifics of this step are discussed in the previous section and in the appendix, but in summary, I form estimates by using the quarterly regression coefficients, replacing quarterly flow data with daily flow data, and performing necessary normalization - some of the coefficients must be multiplied by $\frac{1}{63}$ (to go from quarterly changes in holdings to daily changes in holdings).

A first-order check for the robustness of this model is to compare the daily portfolio returns calculated using the estimated daily holdings with the reported daily portfolio returns from TrimTabs. As a benchmark, if I assume that the holdings remain constant for every day during quarter t except the last day and are equal to the holdings reported at the end of quarter $t-1$, the average correlation across funds between estimation-derived idiosyncratic returns and reported idiosyncratic returns is .297; the idiosyncratic returns, as outlined previously, are the one-day forward residuals of regressing either the reported or the estimated fund returns onto the 3 Fama-French factors and the momentum factor using a 90-day rolling window. I find similar results if alternatively I assume that the holdings are constant but equal to the holdings reported on the last day of the quarter, i.e. first-day-of-quarter rebalancing. Using the estimated holdings derived from the above model (regressions 8 and 12), and removing funds whose daily returns differ by more than 10% from the estimated returns, the correlation between the risk-adjusted estimated returns and the risk-adjusted reported returns jumps to .749, which I argue lends strong credence to the daily-holdings model. If I perform the same analysis using raw returns, I find a similar improvement. Alternatively, I check the added value of my model directly by examining the average R^2 and coefficient significance of the following regression:

$$\text{fund\_ret}_{n,t} - w_{n,t}^{\intercal} r_t = \alpha + \beta_n \left(w_{n,t}^{pred} - w_{n,t}\right)^{\intercal} r_t + \epsilon_{n,t}$$

where $w_{n,t}$ is the $(N \times 1)$ vector of holdings on day t of fund n assuming fund rebalancing only at the end of every quarter. This is the baseline for our comparison. $w_{n,t}^{pred}$ is the estimated $(N \times 1)$ vector of holdings on day t of fund n using the model above - i.e. coefficients are estimated from quarterly data and then used to estimate daily holdings. r_t is the $(N \times 1)$

vector of $r_{i,t}$, i.e. the vector of daily security returns, and $\text{fund\_ret}_{n,t}$ is the raw reported return of fund n on day t. The left-hand side is thus the difference between the reported returns and the returns if the holdings were held constant from the end of last quarter, and the right-hand side regressor is the predicted difference in the fund's holdings between model-derived holdings and constant holdings. The average R^2 across all funds is equal to .21 with an average $B_n = .63$, significant at the 1% level. As a baseline contrast, assume linear rebalancing between reporting quarters - that is, daily holdings of firm i for day d of quarter t are estimated as $\text{holdings}_{i,d} = \text{holdings}_{i,t-1} + \left(\text{holdings}_{i,t} - \text{holdings}_{i,t-1}\right)\left(\frac{d}{63}\right)$ where d counts through the days of the quarter as $d = 1$ to 63. Performing the previous regression but replacing the predicted holdings $w_{n,t}^{pred}$ with the linear estimates results in an average R^2 of less than .01 and a B_n that is on average statistically insignificant. I interpret these results as strong evidence for the quality of the estimates of daily holdings compared to assuming one-day or linear rebalancing.

[Insert Table 4 about here.]

The flow-induced price pressure $\text{FIPP}_{i,t}$ is formed according to Equation (13) for every security i at the daily frequency. Table 4 shows first stage regressions of $\text{FIPP}_{i,t}$ onto 1) a measure of the lagged value-weighted portfolio idiosyncratic returns excluding firm i, and then onto 2) a measure of the number of legal cases announced against firms in a different industry in the same portfolio as firm i. The exact construction of these instruments is explained in the previous section. All regressions include fixed effects and time dummies and errors are clustered at the industry level. I see strong first-stage results for the instruments based both on lagged idiosyncratic portfolio returns and the measure of legal case exposure.

Given that first-stage validity of these instruments, and arguing that the exclusion restriction is satisfied for both of these sets of instruments, I examine the structural model of idiosyncratic returns regressed on the flow-induced price pressure, properly instrumenting for the daily FIPP by using $\text{Port\_ret}_{i,t-1}$ and $\text{Port\_ret}_{i,t-2}$, separately. Results are shown in Table 5. In the next section, I will instead use the legal case instrument; results are consistent with those presented here.

[Insert Table 5 about here.]

We see clearly in regression 1, using two stage least squares, that idiosyncratic returns are strongly driven by flow-induced price pressure induced from the idiosyncratic shocks of other firms in common portfolios. Using a two day lag ($k = 2$) for the portfolio idiosyncratic returns produces qualitatively similar results (regression 2), as does including lagged returns and a measure of turnover as controls (regression 3) where flow-induced price pressure has a standardized coefficient of .221 and a t statistic of greater than 6. This implies that a one standard deviation increase in the flow-induced price pressure measure corresponds to a .6% increase in abnormal daily return. Similarly, if I use the raw returns directly and add factor controls (including the industry return $\text{Ind\_ret}_{i,t}$), regression 4 (without controls) and regression 5 (with controls) show qualitatively identical and quantitatively similar results, with the lowest estimates finding a one standard deviation change in the flow-induced price pressure corresponding to a .15% abnormal daily return (regression 5).

These findings are supported by the reduced form regressions of returns regressed onto the instrument directly; see Figure 6. The standardized coefficients are smaller than the canonical Fama-French 3 factors and also the coefficient on industry returns, but they are on the same order of magnitude with the momentum factor and the control variables of lagged cumulative returns and turnover.

[Insert Table 6 about here.]

To examine cross-sectional variation along liquidity and size dimensions I examine the reduced form regressions specified in Equations (17) and (18). Results are shown in Table 7. I regress idiosyncratic returns onto lagged weighted portfolio idiosyncratic returns as well as interactions between this measure and illiquidity (in regressions 1 and 2) and size (in regressions 3 & 4). We see that the coefficient on the instrument is significant and positive as we would expect. Further, the interaction term between the instrument and illiquidity is highly significant, implying that liquid firms are more sensitive to this price pressure than illiquid firms. These results are unaffected by the inclusion of the lagged returns and the stock turnover (regression 2). The interaction with size regressions (3 & 4) show similar significance for the instrument itself; the interactions are negative (implying small firms are more sensitive) but are not statistically significant.

[Insert Table 7 about here.]

IV Extensions

There are several other explanations for why the idiosyncratic shocks of firms other than a given firm i could induce a response from the fund manager that would systematically effect firm i. It may be volatility targeting (fund managers retreat after a return spike by reducing positions in high-volatility securities). It may be window dressing (funds experiencing a negative shock through firm j reduce their holdings of low return firms - potentially firm i, and increase their holdings of high returns firms to embellish fund performance). Lakonishok et al. (1991) find such window dressing in pension funds. Though it is possible that these other temporary pressure channels are present (volatility targeting and window dressing), my framework has the primary goal of identifying a flow-induced price pressure channel, and I do not formally examine these related alternatives.

There is also an information story. The market observes the poor performance of firm j and lowers its opinion of the quality of the manager of the funds holding firm j, say fund ABC, and thus reduces its outlook for the other firms in ABC's portfolio, i.e. firm i. Essentially, the poor performance of fund j causes the market to discount the quality of any investor that holds firm j, and the other firms in the portfolios of these downgraded investors are penalized. I can differentiate between this hypothesis and the flow-induced price pressure by examining the impulse response of returns to this flow-induced price pressure, since the above information story implies permanent price changes to the other firms in a portfolio (information about the fundamentals of other firms has been revealed), and the flow-induced price pressure story implies an eventual reversal (since the price pressure was caused by fund flows and not by new information).

[Insert Figure 2 about here.]

To this end, I examine the impulse response of the idiosyncratic returns to the FIPP. That is, I examine

$$\hat{r}_{i,t}^{idio} = \alpha + \beta_k \mathrm{FIPP}_{i,t-k} + \delta_i + \delta_t + \epsilon_{i,t},$$

where I examine k from 0 to 6, i.e. 6 days worth of lagged FIPP. The coefficient of the lagged value of the FIPP is shown, as well as the cumulative coefficient, in Figure (2). I find qualitatively similar results if I include all lagged regressors simultaneously, i.e. $\mathrm{r}_{i,t}^{idio} = \alpha + \sum_{k=1}^{k=6} \beta_k \mathrm{FIPP}_{i,t-k} + \delta_i + \delta_t + \epsilon_{i,t}$, or alternatively includ the controls from the previous regressions $\mathrm{r}_{i,t-7,t-2}$ and $\ln(\mathrm{Turnover})$. The spillover from the idiosyncratic returns of other firms is temporary and is insignificantly different from zero after one week (5 trading days) and beyond. This is evidence against the information story discussed previously as an alternative explanation of the spillover of idiosyncratic shocks across common portfolios.

A natural extension of this specification is to examine whether this effect is symmetric - i.e. do firms experience positive price pressure when firms in common portfolios experience positive idiosyncratic shocks and negative price pressure when firms in common portfolios experience negative idiosyncratic shocks? In order to answer this question, I reconstruct the flow-induced price pressure variable in order to capture only those funds experiencing a net infow (daily_flow > 0), $\mathrm{FIPP\_inflow}_{i,t}$, and then again including only funds experiencing a net outflow (daily_flow ≤ 0), $\mathrm{FIPP\_outflow}_{i,t}$. I repeat the regression analysis (I only use the $k = 1$ lagged portfolio idiosyncratic returns, i.e. the one day lagged portfolio idiosyncratic returns excluding the ith firm). Results of this examination are shown in Tables 8 and 9, respectively.

[Insert Table 8 about here.]

[Insert Table 9 about here.]

We see that the coefficients for the flow-induced price pressure are higher when we only include funds experiencing a net outflow. Standardizing the coefficients, we find that the coefficient in the case of only including funds experiencing net outflows is 13-34% bigger than in the case of only including funds experiencing net inflows. This suggests that this price pressure is not symmetric but is more pronounced when funds are forced to liquidate positions to meet outflow demands. Though a prior expectation would be that funds hold adequate amounts of slack, i.e. cash and cash equivalents, in order to meet these outflow demands, this does not appear to be the case. This conclusion is further supported by examining the change in cash holdings of a fund as a function of its net flow. It would be consistent with our findings if the changes in cash holdings are more sensitive to fund flows for funds experiencing net inflows than those experiencing net outflows (implying that liquidation of holdings is used to meet outflow demands as opposed to using a war chest of cash and liquid cash equivalents). Using cash holdings data at the quarterly frequency, I examine the following regression:

$$\Delta \text{Cash}_{n,t} = \alpha + \beta_1 \text{flow\_quarterly}_{n,t} + \delta_t + \delta_n + \epsilon_{n,t} \tag{19}$$

where $\Delta\text{Cash}_{n,t}$ is the percentage change in the cash holdings of fund i from time $t-1$ to time t. I include time and fund fixed effects, and compare coefficient estimates for β_1 when I look at funds experiencing net inflows ($\text{flow\_quarterly}_{n,t} > 0$) and net outflows ($\text{flow\_quarterly}_{n,t} \leq 0$). Results are shown in Table 10. The number of observations is reduced because of merging constraints and cash holdings data availability in the CRSP database. From these regressions, we see that for both cases (positive and negative net fund flow), the coefficient is positive, as we would expect. Including all flows, we see that a one standard deviation change in quarterly flow implies a .086 standard deviation change in the percentage change in cash holdings. However, the standardized coefficient is three times larger in the net inflow case, implying that cash holding sensitivity is higher when cash flows into a fund rather than when cash flows out. This is consistent with the above findings that the spillover price pressure caused by liquidating holdings is more significant when there is a net outflow, implying that funds do not entirely "mop up" outflow demands using cash. This is further supported by the results in Table 3 and the results of Lou (2012), which show that changes in holdings are more (less) dependent on flows when the net fund flows are negative (positive).

Though managers may foresee abnormal negative returns and seek to smoothly reduce holdings to meet liquidity needs and avoid slippage costs, this would imply that our observed effect is a lower bound of the actual spillover effect, i.e. I may only be capturing a part of the managers overall rebalancing. To the extent that flows are affected by returns (Chevalier & Ellison (1995)), managers cannot keep investors from redemptions as a result of negative abnormal returns.

[Insert Table 10 about here.]

As a final examination of this price pressure, I examine a trading strategy based on sorting firms by the $\text{Port\_ret}_{-i,t-1}$ variable, which is the weighted portfolio idiosyncratic returns excluding firm i for funds holding firm i at time $t-1$. I regenerate the estimates of daily holdings using only past data in order to mitigate look-ahead bias. I then form a zero-investment, long-short portfolio that is long the decile of firms with the highest $\text{Port\_ret}_{-i,t-1}$ values and short the decile of firms with the lowest $\text{Port\_ret}_{-i,t-1}$ value. Annualized results of this investment strategy are shown in Table 11. I include raw returns as well as alphas of the CAPM, the Fama-French 3-factor model, and the Carhart 4-factor model.

[Insert Table 11 about here.]

We see in all of these cases (in the annualized raw returns as well as the alphas of the factor models), that the annualized average return for this strategy is around 6.8%. This strategy implies daily rebalancing which may incur substantial transaction costs. However, these findings are evidence that portfolio spillover pressures are significant and are priced in the market.

V Robustness

I examine the robustness of the above findings by using an alternative instrument; this second instrument requires some background work. Starting within an event study framework, I first replicate a result of the literature, showing that firms that experience legal case announcements experience significantly negative abnormal returns around the time of the announcement.[11] As argued earlier, the return of the fund is mechanically derived from the returns of firms in its portfolio; thus, a legal case announcement affects the firm that is

[11] See Gande & Lewis (2009), Romano (1991), and Karpoff et al. (2008).

the subject of the case (i.e. the "subject firm") which in turn mechanically affects the fund returns of funds holding the subject firm, and these returns affect flows. Other firms may inadvertently suffer from this *induced* price pressure.

The proper first stage regression when using legal case announcements as an instrument is to examine the relationship between the flow-induced price pressure for firm i and the legal case announcements against firms in common portfolios with firm i. To support the construction of the Normalized_Cases$_{i,t}$ instrument, I first examine the relationship between returns and legal case announcements for a subject firm (a firm that is the subject of a legal case announcement).

Figure 3 shows an event study of the abnormal returns (adjusted by the Fama-French 3 risk factors and the UMD momentum factor) of firms that are the subject of a legal case announcement one week before and one week after the case filing date. Abnormal returns are averaged across all firms experiencing a legal case announcement in our sample. Legal case announcements are a significant and surprising shock to the returns of the subject firm. A legal case announcement implies daily negative abnormal returns in excess of -1%. Further, the market sees the filing coming before the filing date, as the average firm has significantly negative daily returns of -.5% five days before the legal case announcement. The average firm continues to experience negative abnormal returns until 3 days after the legal case filing. These results are similar to Gande & Lewis (2009) who report daily negative abnormal returns of around -1%[12]. Summing the average returns shown in Figure 3, a portfolio manager holding the average firm will experience cumulative average abnormal returns (CAAR) for holdings in firms with legal case announcements of less than -7% in the 10 days around the filing (from one trading week before the filing date to one trading week after the filing date). Though I only show abnormal returns one week before and after the filing date, the abnormal returns are significantly different from zero well before this time (1-2 months before the filing date), and the (CAAR) is close to -30%.

[Insert Figure 3 about here.]

It is important to note that the flow-induced pressure is a result of the portfolio returns, not necessarily the information released on the date of the case filing. In other words, it is not the filing itself that elicits the response from portfolio managers. It is the abnormal returns surrounding the legal case announcement that are significant and unexpected, and thus cause outflows. The returns of the average firm experiencing a legal case announcement slowly reverse following the legal case announcement, but given that a legal case announcement

[12] Gande & Lewis (2009) find significant abnormal returns on event days before day 5. They also find that abnormal returns are insignificant after 3 days from the case filing.

is an idiosyncratic return shock to the subject firm (as shown in Figure 3), the abnormally negative returns mechanically affect portfolio returns of funds holding the subject firm around the legal case announcement, and despite the long term reversal the machinery outlined in the previous section still holds.

[Insert Table 12 about here.]

Results of the first stage regression were reported in Table 4; I use this instrument, $\text{Normalized\_Cases}_{i,t}$, instead of the first set of portfolio idiosyncratic return based instruments and replicate the two stage least squares regressions from the previous section. Results are shown in Table 12. We see results very similar to the results discussed in the previous section, though the standard errors are different. The bigger standard errors are unsurprising given that the limited number of legal cases reduces the power of this instrument relative to the portfolio returns. The usage of the legal case instrument provides similar qualitative findings - highly significant dependence of idiosyncratic returns on the daily FIPP - that are consistent with the results generated using the lagged idiosyncratic portfolio return instruments from the previous section.

I explore the robustness of these results to different assumptions about the daily rebalancing, at the holdings level, of funds. The above analysis, and the analysis in the previous section, assumed that a good representation of the daily rebalancing could be obtained by extrapolating a model of quarterly rebalancing that included flow, illiquidity, size, and relevant interaction terms. Previous literature, as in Lou (2012), has omitted size, and focused simply on flow, illiquidity, and flow-illiquidity interactions in order to explain quarterly rebalancing. I examine the structural model, using both instruments, where the daily rebalancing estimates are derived from this simpler model (corresponding to regressions 6 and 10 of Table 3). Second-stage regressions built with this underlying model, using both flavors of instruments are shown in Table 13.

[Insert Table 13 about here.]

Again, we see similar results as in the other models; notably, we find that idiosyncratic returns are strongly driven by the flow-induced price pressure where a one standard deviation increase in daily flow corresponds to a .31% increase in daily returns (using the portfolio return instruments) and .2% (using the legal case instrument).

VI Conclusions

Asset pricing literature has held that the idiosyncratic shocks to a firm are, by definition, idiosyncratic to that firm. If the shock is really driven by news that is only relevant to a single firm then the prices of other firms' securities should not be affected by this shock. I have proposed one channel in which this classic conclusion is violated and news that is not informative for the fundamentals of a firm can, in fact, affect its share price.

This work contributes directly to our understanding of flow-induced pressure by identifying a source of the flow pressure. Idiosyncratic shocks to the returns of a given firm are mechanically connected to the returns of mutual funds that hold these securities. Fund returns drive fund flows, and these fund flows can then affect individual firms. This flow-induced price pressure links seemingly unlinked firms and is a channel for the temporary spillover of idiosyncratic news. Similarly, this channel can help us understand the abnormal comovement found between firms in similar portfolios.

Reduced-form regressions of firm returns onto lagged value-weighted portfolio returns produce results in line with this hypothesis. I found strong evidence that this pressure is more pronounced when it is the result of negative idiosyncratic shocks (leading to net fund outflows) and that liquid firms are more sensitive to this pressure. This is consistent with a story in which fund managers, facing redemption demands because of the negative performance of a majority of their portfolio, liquidate those holdings that will have the smallest price impact, i.e. that are most liquid. The price pressure reverses within 5-6 trading days, which supports a temporary flow-induced price pressure explanation as opposed to an information-based explanation.

In order to test the model, I also introduced a novel method for estimating mutual fund daily holdings which can allow econometricians and practitioners deeper insights into many avenues of mutual fund behavior. There are limitations to this practice, but by checking estimated daily returns against reported daily returns, the econometrician can examine the estimation accuracy of any model of fund portfolio rebalancing.

This mechanism for idiosyncratic spillover underlines the importance of the ownership network of a firm. Knowing the portfolios of the shareholders of a given firm is an important piece of information for understanding price fluctuations, and if investors are unable to ascertain this information, they are unable to fully hedge idiosyncratic risk. Higher order ownership spillovers may also be relevant, but this research points out that a canonical factor-based analysis of price movements, omitting a measure of ownership network-induced pressure, can be misguided.

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Appendix

TrimTabs Data Integrity

Though the TrimTabs data has been used extensively[13], I test the data integrity by first comparing both: i) monthly Total Net Assets (TNA) obtained from aggregating the TrimTabs data with monthly TNA data from CRSP monthly mutual fund data, and ii) monthly returns generated by compounding TrimTabs daily returns data with monthly returns data as reported by CRSP. These are the constituent pieces of the flow construction. These comparative plots are shown in Figure VI. Correlations of both of these comparisons are greater than .99.

Second, it is possible that funds, fearing front running by hedge funds that subscribe to TrimTabs data, misrepresent flow data in all days of the month (or the quarter), but do so in such a fashion that monthly CRSP data are accurate (or quarterly SEC filings are accurate). Though complex gaming may occur, I examine a simple version of this possibility by comparing the autocorrelation of flows in the first half of every month to the autocorrelation of flows in the second half of the month. If this type of gaming is occurring, the autocorrelation would be different between the two halves. Results are shown in Panel A of Table 14. We see that the autocorrelations are not significantly different from each other (with a t statistic of .8204), and we assume that such gaming is not occurring.

Third, I examine the representativeness of the reporting funds by comparing summary statistics with the CRSP Mutual Fund Universe. Results are shown in Panel B of the same table. We see that the average firm's total net assets (TNA) and net asset value (NAV) is very similar between the CRSP dataset and the TrimTabs subset.

Estimating Daily Holdings from Quarterly Data

I construct the estimates of daily changes in holdings by using the coefficient estimates reported in Table 3, but using daily flow in place of quarterly flow. For example, using regressions 8 and 12, the estimated change in daily holdings would be constructed in the following manner:

$$\Delta \text{Fund\_}\widehat{\text{Holdings}}\text{\_daily}_{i,n,t} = \begin{cases} (.7794)\text{flow\_daily}_{n,t} - (1.5840)\text{flow\_daily}_{n,t} * \text{illiquidity}_{i,t} & \\ -(\frac{.656}{63})\text{size}_{i,t} + \frac{\delta_t}{63} + \frac{\delta_i}{63} & \text{if flow\_daily}_{n,t} > 0 \\ (.8356)\text{flow\_daily}_{n,t} - (1.9535)\text{flow\_daily}_{n,t} * \text{liquidity}_{i,t} & \text{if flow\_daily}_{n,t} \leq 0 \\ -(3.15)\text{flow\_daily}_{n,t} * \text{size}_{i,t} - (\frac{.714}{63})\text{size}_{i,t} + \frac{\delta_t}{63} + \frac{\delta_i}{63} & \end{cases}.$$

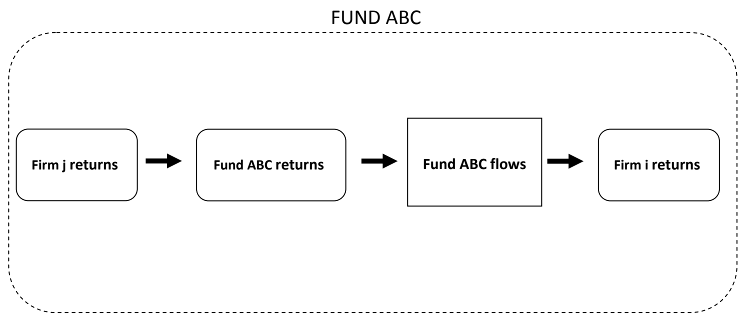
The coefficient estimates of the time dummies, the panel dummies, and regressors that do not include flow, must be normalized by dividing by 63 (the number of trading days assumed to

[13] See Zitzewitz (2006), Greene & Hodges (2002), Edelen & Warner (2001), Brown et al. (2003), Rakowski (2010), and Cao et al. (2008).

be in a quarter). Further, I exclude insignificant regressors; the inclusion of these regressors slightly changes the quantitative results but the qualitative results are unchanged.

Figures

Panel A



Panel B

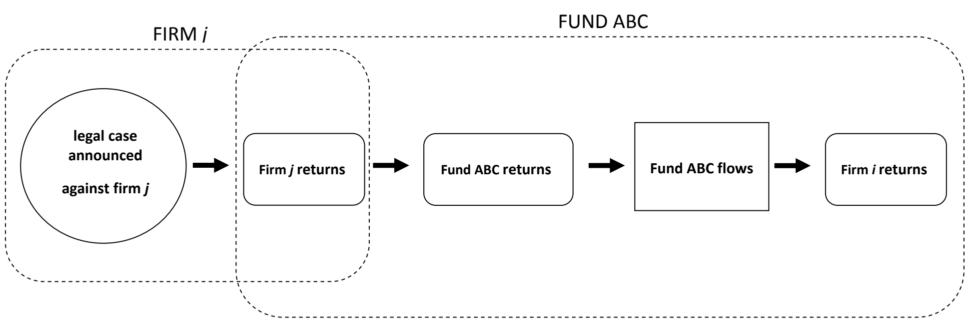


Figure 1: Schematic of the flow-induced spillover mechanism.

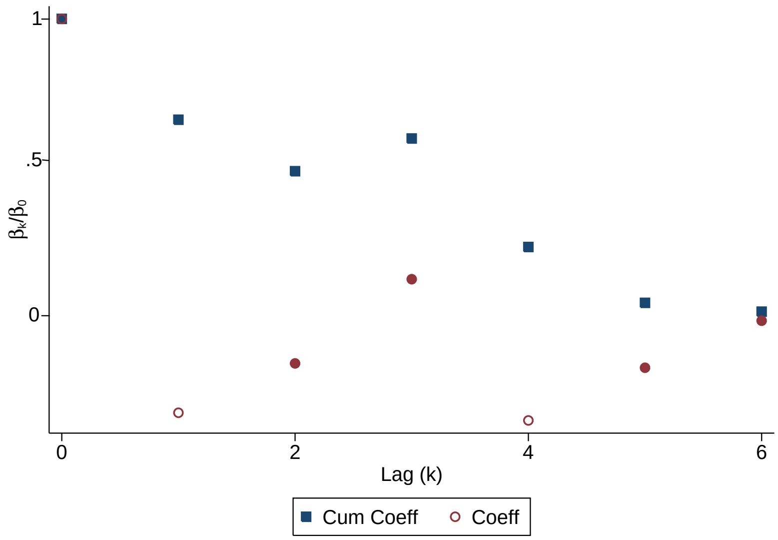


Figure 2: Cumulative coefficient β_k of $\mathrm{r}_{i,t}^{idio} = \alpha + \beta_k \mathrm{FIPP}_{i,t-k} + \mathrm{Controls} + \delta_t + \delta_i + \epsilon_{n,t}$ for $k = 0$ to 6, i.e. six days, normalized by β_0. Controls are lagged cumulative return and turnover. The individual coefficients are circles; hollow circles are significantly different from zero at the 1% level. Solid circles are not significantly different from zero at the 10% level.

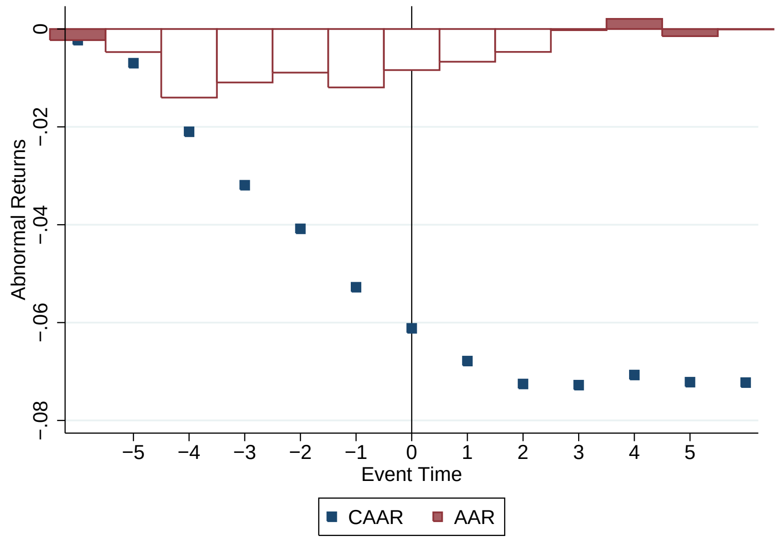
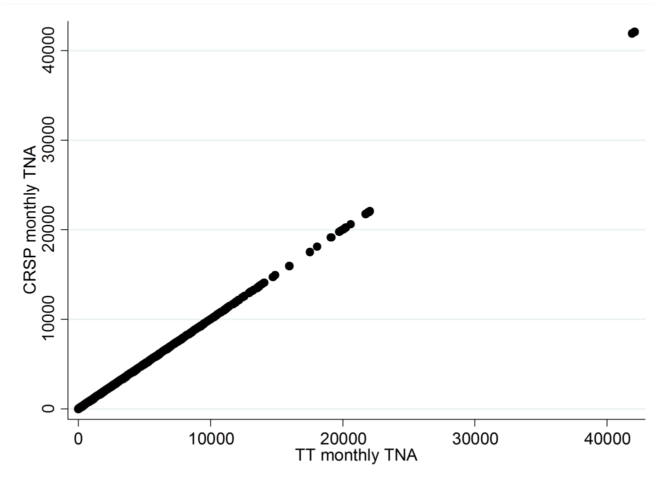


Figure 3: Event study of average abnormal returns (AAR) and cumulative average abnormal returns (CAAR) around a legal case announcement. Abnormal (or idiosyncratic) returns are constructed by performing the following regression: $r^e_{i,t} = \alpha^i + \beta^i_1 \mathrm{MKTRF}_t + \beta^i_2 \mathrm{SMB}_t + \beta^i_3 \mathrm{HML}_t + \beta^i_4 \mathrm{UMD}_t + \epsilon_{i,t}$, rolling the coefficients forward one day, and then constructing the abnormal return as the residual plus the constant: $\hat{r}^{idio}_{i,t} = r^e_{i,t} - \hat{r}^e_{i,t} + \alpha^i$. Event time is constructed from the date the legal case was officially filed. Abnormal returns are averaged across all firms experiencing an event. CAAR are depicted as the blue squares. Outlined bars are significantly different from zero at the 1% level; solid bars are not significantly different from zero at the 10% level.

Panel A



Panel B

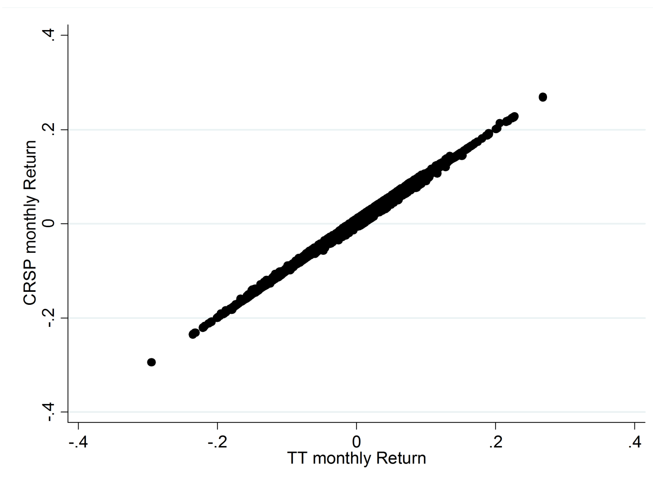


Figure 4: Comparison of TrimTabs data to Crsp data. Panel A compares TrimTabs reported TNA with CRSP reported TNA. Panel B compares monthly returns, generated by compounding the daily returns reported to TrimTabs, with the monthly returns reported by CRSP. Correlations are above .99 for both panels.

Variable	Level	N	mean	sd	p25	p50	p75
TNA (Millions USD)	Fund-quarter	22214	615.458	928.91	99.7	269.44	723.7
Daily Flow	Fund-daily	319772	0.000004	0.0042	-0.00081	-0.00022	0.00038
# of shares	Holding-quarter	2176514	176597.5	278323	20700	67800	199588
Market Value (1000s USD)	Holding-quarter	2176514	5438970	10100000	628620.5	2078000	5895090
Size (Millions USD)	Firm-daily	5349836	7274.3	14450.59	1154.3	2463.7	12478.5
Shares Outstanding (1000s)	Firm-daily	5349836	213005.8	437274.8	42954	83131	195311
Share Price	Firm-daily	5349836	37.91	43.11	20.73	31.84	46.11
r_t	Firm-daily	5349836	0.0005	0.0264	-0.0091	0.00028	0.010
$\mathrm{illiquidity}_{i,t}$	Firm-daily	5349836	0.001132	0.0175	0.00024	0.00070	0.0019
$\hat{r}_t^{idio}$	Firm-daily	5097607	-0.000060	0.0272	-0.0076	-0.00031	0.0072
$\mathrm{r}_{t-7,t-2}$	Firm-daily	5332910	.00412	.0778	-0.0199	0.00251	0.025
ln [Daily Turnover]	Firm-daily	5349832	-3.96	.57	-4.37	-4.10	-3.71
$\mathrm{Normalized\_Cases}_{i,t}$	Firm-daily	4514007	1.731	3.50	0.25	1	2.077
$\mathrm{Port\_ret}_{-i,t-1}$	Firm-daily	4514007	0.0261	0.181	-0.028	0.0112	0.067
$\mathrm{Port\_ret}_{-i,t-2}$	Firm-daily	4514007	0.0267	0.156	-0.0240	0.0109	0.064
$\mathrm{Port\_ret}_{-i,t-3}$	Firm-daily	4514007	0.0269	0.147	-0.0205	0.0107	0.061
$\mathrm{Port\_ret}_{-i,t-4}$	Firm-daily	4514007	0.0272	0.134	-0.018	0.0102	0.059

Table 1: Summary statistics. Data is coordinated between four datasets: 1) CRSP Survivor-Bias-Free Mutual Fund Database, 2) the CRSP Daily Stock File, 3) AuditAnalytics' Legal Case and Legal Parties Database, and 4) the TrimTabs Daily Fund Flow Database. Data are from 2003:2010, inclusive. The "Level" column refers to the level of the statistic calculation, i.e. statistics at the "Fund" level are "per Fund", statistics at the "Holding" level are "per Holding", and "Firm" level statistics are calculated "per Firm". *TNA* is the Total Net Assets. *Daily Flow* is the daily level flow in (or out) of the fund from time day $t-1$ to day t, normalized by the TNA of day $t-1$. *# of shares* is the number of shares of the average holding in the average fund. *Market Value* is the market value in USD of the average holding in the average fund. *Size* is the market capitalization (shares outstanding * Share Price) in $Billions. *Share Price* is the stock price at the end of day t. ret_t is the daily holding period return. *Amihud Illiquidity* is the Amihud measure of illiquidity calculated over the past 90 days multiplied by 1e6. $\hat{r}_t^{idio}$ is the idiosyncratic daily return calculated from a five factor model (Fama-French three factors, momentum, and an average industry return). $\mathrm{r}_{t-7,t-2}$ is the cumulative daily return from $t-7$ to $t-2$. *ln[Daily Turnover]* is the natural log of daily turnover (shares outstanding (in 1000s) divided by the daily volume). $\mathrm{Normalized\_Cases}_{i,t}$ is the number of legal cases announced against firms in common portfolios with firm i in the next 3 days, normalized by the number of funds holding firm i. $\mathrm{Port\_ret}_{-i,t-k}$ is the value-weighted (by holdings in firm i) at time t value-weighted idiosyncratic return (excluding firm i) of portfolios holding firm i at time $t-k$.

Panel A

$k =$	1	2	3	4	5	6	7	8	9	10
	flow_daily$_{n,t}$									
idio_ret$_{n,t-k}$	**0.0042**	**0.0053**	**0.0024**	**0.0030**	**0.0019**	**0.0013**	**0.0018**	0.0010	**0.0014**	**0.0013**
	(7.04)	(8.35)	(4.28)	(5.18)	(3.47)	(2.09)	(3.25)	(1.90)	(2.54)	(2.57)
Time & Panel Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	185648	184169	183251	182542	181927	181103	180529	179740	179037	178432
R^2	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003

Panel B

$k =$	1	2	3	4	5	6	7	8	9	10
	flow_daily$_{n,t}$									
idio_ret$_{n,t-k}$	**0.0042**	**0.0051**	**0.0023**	**0.0027**	**0.0019**	**0.0014**	**0.0013**	0.0009	**0.0013**	0.0009
	(7.04)	(8.29)	(4.18)	(4.77)	(3.36)	(2.26)	(2.48)	(1.71)	(2.34)	(1.76)
flow_daily$_{n,t-1}$	0.0075	0.0026	0.0034	0.0058	0.0014	0.0061	0.0063	0.0067	0.0042	0.0044
	(0.86)	(0.29)	(0.39)	(0.67)	(0.17)	(0.71)	(0.72)	(0.77)	(0.48)	(0.51)
Time & Panel Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	185648	175511	173799	173070	172430	171736	170980	170318	169551	169013
R^2	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003

Panel C

$k =$	1	2	3	4	5	6	7	8	9	10
	flow_daily$_{n,t}$									
idio_ret$_{n,t-k}$	**0.0027**	**0.0046**	**0.0017**	**0.0022**	**0.0018**	**0.0006**	**0.0015**	0.0010	0.0007	0.0006
	(3.84)	(6.42)	(2.67)	(3.25)	(2.67)	(0.88)	(2.32)	(1.52)	(1.01)	(0.86)
$\delta^{inflow}_{n,t-k}$*idio_ret$_{n,t-k}$	**0.0040**	**0.0014**	**0.0019**	**0.0018**	**0.0006**	0.0021	-0.0004	-0.0002	0.0019	0.0011
	(3.76)	(6.51)	(2.69)	(3.26)	(3.07)	(0.86)	(-2.27)	(-1.89)	(0.94)	(0.78)
$\delta^{inflow}_{n,t-k}$	**-0.0039**	-0.0010	-0.0016	-0.0015	-0.0002	-0.0018	0.0007	0.0005	-0.0016	-0.0008
	(-3.29)	(-0.90)	(-1.41)	(-1.31)	(-0.19)	(-1.42)	(0.61)	(0.39)	(-1.40)	(-0.63)
flow_daily$_{n,t-1}$	-0.0135	0.0001	-0.0031	0.0001	-0.0041	0.0010	0.0018	0.0027	0.0003	0.0003
	(-1.46)	(0.01)	(-0.38)	(0.01)	(-0.49)	(0.12)	(0.22)	(0.32)	(0.04)	(0.04)
Time & Panel Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	185648	175511	173799	173070	172430	171736	170980	170318	169551	169013
R^2	0.004	0.011	0.009	0.009	0.008	0.008	0.007	0.007	0.007	0.007

Table 2: Dependent variable is daily mutual fund portfolio flows. Flow for mutual fund n in period t is calculated as flow$_{n,t}$ = $\frac{\text{TNA}_{n,t}-\text{TNA}_{n,t-1}(1+\text{fund\_ret}_{n,t})}{\text{TNA}_{n,t-1}}$ where TNA$_{n,t}$ is the Total Net Asset for fund n on day t and fund_ret$_{n,t}$ is the Return Per Share of fund n on day t. Inflow dummy $\delta^{inflow}_{n,t-k}$ is equal to 1 if the net flow is positive and zero otherwise. idio_ret$_{n,t-k}$ is the value-weighted average idiosyncratic return for fund n at time $t-k$. Time dummies are constructed monthly. Errors are clustered at the fund level.

	(1)	(2)	(3)	(4)	(5)
	ALL FLOWS ΔFund_Holdings_quarterly$_{i,n,t}$				
flow_quarterly$_{n,t}$	**0.8237**	**0.8278**	**0.8343**	**0.8409**	**0.8408**
	(28.21)	(26.99)	(25.19)	(23.86)	(23.86)
illiquidity$_{i,t}$		**-0.0276**		**-0.0230**	**-0.0230**
		(-3.20)		(-2.66)	(-2.66)
flow_quarterly$_{n,t}$ * illiquidity$_{i,t}$		**-0.8510**		**-1.0823**	**-1.0807**
		(-4.31)		(-5.41)	(-5.41)
flow_quarterly$_{n,t}$ * size$_{i,t}$			**-1.723**	**-1.96**	**-1.94**
			(-6.64)	(-7.42)	(-7.41)
size$_{i,t}$			**-0.643**	**-0.641**	**-0.637**
			(-16.46)	(-16.38)	(-16.38)
flow_quarterly$_{n,t-1}$					**-0.0000**
					(-2.28)
flow_quarterly$_{n,t-1}$ * illiquidity$_{i,t-1}$					136.0814
					(0.39)
Time & Panel Effects	YES	YES	YES	YES	YES
Observations	1896250	1896250	1896250	1896250	1896250
R^2	0.053	0.053	0.053	0.053	0.053

	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	flow_quarterly$_{n,t} \leq 0$ ΔFund_Holdings_quarterly$_{i,n,t}$				flow_quarterly$_{n,t} > 0$ ΔFund_Holdings_quarterly$_{i,n,t}$			
flow_quarterly$_{n,t}$	**0.8212**	**0.8114**	**0.8356**	**0.8349**	**0.7722**	**0.7804**	**0.7794**	**0.7795**
	(10.93)	(10.34)	(9.25)	(9.23)	(15.06)	(14.63)	(12.63)	(12.64)
illiquidity$_{i,t}$		-0.0121	-0.0153	-0.0152		**-0.0222**	**-0.0213**	**-0.0213**
		(-0.70)	(-0.89)	(-0.88)		(-1.89)	(-1.81)	(-1.81)
flow_quarterly$_{n,t}$ * illiquidity$_{i,t}$		**-2.7094**	**-1.9535**	**-1.9612**		**-1.6489**	**-1.5840**	**-1.5842**
		(-4.48)	(-3.19)	(-3.20)		(-5.68)	(-5.39)	(-5.39)
flow_quarterly$_{n,t}$ * size$_{i,t}$			**-3.15**	**-3.14**			0.0000	0.0000
			(-4.69)	(-4.66)			(0.06)	(0.06)
size$_{i,t}$			**-0.714**	**-0.712**			**-0.656**	**-0.657**
			(-13.44)	(-13.43)			(-8.34)	(-8.34)
flow_quarterly$_{n,t-1}$				**-0.0000**				**0.0000**
				(-2.90)				(1.74)
flow_quarterly$_{n,t-1}$ * illiquidity$_{i,t-1}$				258.3104				309.9249
				(0.71)				(0.20)
Time & Panel Effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1001002	1001002	1001002	1001002	895248	895248	895248	895248
R^2	0.021	0.021	0.021	0.021	0.038	0.038	0.038	0.038

Table 3: Panel regressions at the fund-holding level of percentage change in quarter holdings. flow_quarterly$_{n,t}$ is the net flow of the fund during quarter t normalized by the Total Net Assets (TNA) in quarter $t-1$. illiquidity$_{i,t}$ is the Amihud measure of illiquidity calculated over the previous 90 days. size$_{i,t}$ is the market cap in \$ US Billions. All regressions are clustered at the fund-holding level and include time and panel fixed effects.

	FIPP$_{i,t}$			
	(1)	(2)	(3)	(4)
Port_ret$_{-i,t-1}$	**0.059**	**0.059**		
	(13.64)	(17.65)		
Port_ret$_{-i,t-2}$	**0.058**		**0.061**	
	(10.88)		(24.91)	
Normalized_Cases$_{i,t}$				**-0.025**
				(-16.19)
FIRM FIXED EFFECTS	YES	YES	YES	YES
TIME DUMMIES	YES	YES	YES	YES
Observations	4064873	4064873	4064873	3821974
R^2	0.023	0.02	0.02	0.036

Table 4: First stage panel regressions of FIPP$_{i,t}$ onto five different instruments, Port_ret$_{-i,t-1}$ and Port_ret$_{-i,t-2}$ and Normalized_Cases$_{i,t}$. Panel unit is at the firm level, and all regressions include time dummies and fixed effects. Port_ret$_{-i,t-k}$ is the value weighted, according to firm i, measure of the value-weighted portfolio returns, excluding firm i, of portfolios holding i at time $t-k$. Normalized_Cases$_{i,t}$ is a measure of a firm's exposure to the legal case announcements of other firms that are in the same portfolio as firm i. The specifics of these constructions and the normalization are given in section II.C. Errors are clustered at the industry level.

	(1)	(2)	(3)	(4)	(5)
	k=1	k=2	k=1	k=1	k=1
	$\hat{r}_{i,t}^{idio}$	$\hat{r}_{i,t}^{idio}$	$\hat{r}_{i,t}^{idio}$	$r_{i,t}$	$r_{i,t}$
	2SLS	2SLS	2SLS	2SLS	2SLS
$\text{FIPP}_{i,t}$	**0.129**	**0.177**	**0.221**	**0.151**	**0.059**
	(6.33)	(3.93)	(6.05)	(6.51)	(3.46)
MKTRF_t				**0.155**	**0.154**
				(8.98)	(8.93)
SMB_t				**0.127**	**0.127**
				(24.91)	(24.79)
HML_t				**0.021**	**0.023**
				(4.44)	(4.82)
UMD_t				-0.002	0.001
				(-0.45)	(0.12)
$\text{Ind\_ret}_{i,t}$				**0.400**	**0.407**
				(17.73)	(17.97)
$\text{r}_{i,t-7,t-2}$			**-0.012**		**-0.006**
			(-7.35)		(-7.15)
$\ln(\text{Turnover}_{i,t})$			-0.002		**-0.002**
			(-1.46)		(-2.87)
FIRM FIXED EFFECTS	YES	YES	YES	YES	YES
TIME DUMMIES	YES	YES	YES	YES	YES
Observations	3988113	3988113	3988110	4822464	4808939

Table 5: Second stage regressions of $\hat{r}_{i,t}^{idio}$ and $r_{i,t}$ onto $\text{FIPP}_{i,t}$. I instrument for $\text{FIPP}_{i,t}$ with the lagged portfolio idiosyncratic returns $\text{Port\_ret}_{i,t-k}$ for $k = 1$ and $k = 2$. $\text{r}_{i,t-7,t-2}$ is the cumulative lagged return. $\ln(\text{Turnover}_{i,t})$ is the natural log of turnover. All coefficients are standardized. Errors are clustered at the industry level. For all of the regressions, the KP LM statistic rejects the null hypothesis of weak instruments at the 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$\hat{r}^{idio}_{i,t}$	$\hat{r}^{idio}_{i,t}$	$\hat{r}^{idio}_{i,t}$	$\hat{r}^{idio}_{i,t}$	$\hat{r}^{idio}_{i,t}$	$\hat{r}^{idio}_{i,t}$	$r_{i,t}$	$r_{i,t}$	$r_{i,t}$	$r_{i,t}$	$r_{i,t}$	$r_{i,t}$
Normalized_Cases$_{i,t}$	**-0.001**	**-0.001**					**-0.002**	**-0.002**				
	(-2.63)	(-2.64)					(-4.69)	(-5.16)				
Port_ret$_{-i,t-1}$			**0.004**	**0.004**					**0.002**	**0.002**		
			(4.36)	(4.39)					(4.00)	(3.98)		
Port_ret$_{-i,t-2}$					**0.002**	**0.002**					0.001	0.001
					(2.27)	(2.38)					(1.35)	(1.38)
MKTRF$_t$							**0.149**	**0.149**	**0.151**	**0.151**	**0.151**	**0.151**
							(8.52)	(8.52)	(8.69)	(8.68)	(8.69)	(8.68)
SMB$_t$							**0.123**	**0.123**	**0.125**	**0.125**	**0.125**	**0.125**
							(23.61)	(23.62)	(23.83)	(23.84)	(23.83)	(23.85)
HML$_t$							**0.024**	**0.025**	**0.024**	**0.024**	**0.024**	**0.024**
							(5.05)	(5.07)	(4.99)	(5.01)	(5.00)	(5.01)
UMD$_t$							0.002	0.002	0.001	0.001	0.001	0.001
							(0.35)	(0.32)	(0.25)	(0.23)	(0.25)	(0.23)
Ind_ret$_{i,t}$							**0.406**	**0.406**	**0.397**	**0.397**	**0.397**	**0.397**
							(17.43)	(17.43)	(17.15)	(17.15)	(17.15)	(17.15)
r$_{i,t-7,t-2}$		**-0.006**		**-0.006**		**-0.006**		**-0.005**		**-0.005**		**-0.005**
		(-4.48)		(-4.74)		(-4.76)		(-5.60)		(-5.89)		(-5.92)
ln (Turnover$_{i,t}$)		**-0.002**		**-0.002**		**-0.002**		**-0.002**		**-0.002**		**-0.002**
		(-2.43)		(-1.48)		(-1.48)		(-3.29)		(-2.40)		(-2.40)
FIRM FIXED EFFECTS	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
TIME DUMMIES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	4117875	4117871	4391434	4391430	4391434	4391430	4217239	4213796	4498216	4494735	4498216	4494735

Table 6: Reduced form regressions of $\hat{r}^{idio}_{i,t}$ and $r_{i,t}$ onto the instruments:Port_ret$_{i,t-1}$, Port_ret$_{i,t-2}$, and Normalized_Cases$_{i,t}$. r$_{i,t-7,t-2}$ is the cumulative lagged return. ln (Turnover$_{i,t}$) is the natural log of turnover. All coefficients are standardized. Errors are clustered at the industry level. For all of the regressions, the KP LM statistic rejects the null hypothesis of weak instruments at the 1% level.

	(1)	(2)	(3)	(4)
	$r_{i,t}$	$r_{i,t}$	$r_{i,t}$	$r_{i,t}$
$\text{Port\_ret}_{-i,t-1}$	**0.003**	**0.003**	**0.003**	**0.003**
	(5.00)	(5.00)	(3.62)	(3.63)
$\text{Port\_ret}_{-i,t-1} * \text{illiquidity}_{i,t}$	**-0.002**	**-0.002**		
	(-3.09)	(-3.10)		
$\text{Port\_ret}_{-i,t-1} * \text{size}_{i,t}$			-1.1	-1.1
			(-0.72)	(-0.85)
MKTRF_t	**0.151**	**0.151**	**0.151**	**0.151**
	(8.69)	(8.68)	(8.69)	(8.68)
SMB_t	**0.125**	**0.125**	**0.125**	**0.125**
	(23.83)	(23.85)	(23.82)	(23.85)
HML_t	**0.024**	**0.024**	**0.024**	**0.024**
	(4.97)	(4.99)	(4.98)	(5.01)
UMD_t	0.001	0.001	0.001	0.001
	(0.25)	(0.21)	(0.25)	(0.21)
$\text{Ind\_ret}_{i,t}$	**0.397**	**0.397**	**0.397**	**0.397**
	(17.14)	(17.14)	(17.14)	(17.14)
$\text{illiquidity}_{i,t}$	-0.000	-0.001		
	(-0.49)	(-0.83)		
$\text{size}_{i,t}$			**0.019**	**0.019**
			(6.47)	(6.49)
$\text{r}_{i,t-7,t-2}$		**-0.007**		**-0.007**
		(-7.79)		(-7.83)
$\ln(\text{Turnover}_{i,t})$		**-0.002**		**-0.002**
		(-2.44)		(-2.43)
FIRM FIXED EFFECTS	YES	YES	YES	YES
TIME DUMMIES	YES	YES	YES	YES
Observations	4498216	4494735	4498216	4494735

Table 7: Second stage regressions of $\hat{r}_{i,t}^{idio}$ and $r_{i,t}$ onto $\text{FIPP}_{i,t}$. I instrument for $\text{FIPP}_{i,t}$ with the lagged portfolio idiosyncratic returns $\text{Port\_ret}_{i,t-1}$. $\text{illiquidity}_{i,t}$ is the Amihud measure of illiquidity calculated over the previous 90 days. $\text{size}_{i,t}$ is the market cap in \$ US Billions. $\text{r}_{i,t-7,t-2}$ is the cumulative lagged return. $\ln(\text{Turnover}_{i,t})$ is the natural log of turnover. All coefficients are standardized. Errors are clustered at the industry level. For all of the regressions, the KP LM statistic rejects the null hypothesis of weak instruments at the 1% level.

	daily_flow > 0			
	$\hat{r}^{idio}_{i,t}$	$\hat{r}^{idio}_{i,t}$	$r_{i,t}$	$r_{i,t}$
	2SLS	2SLS	2SLS	2SLS
FIPP_inflow$_{i,t}$	**4.6736**	**4.6696**	**2.7743**	**2.7695**
	(2.65)	(2.65)	(2.61)	(2.60)
MKTRF$_t$			**0.3002**	**0.2998**
			(8.69)	(8.68)
SMB$_t$			**0.5651**	**0.5659**
			(23.92)	(23.93)
HML$_t$			**0.0976**	**0.0982**
			(4.87)	(4.90)
UMD$_t$			0.0008	0.0003
			(0.07)	(0.03)
Ind_ret$_{i,t}$			**0.6310**	**0.6307**
			(17.15)	(17.14)
$\mathrm{r}_{i,t-7,t-2}$		**-0.0035**		**-0.0027**
		(-6.82)		(-8.61)
$\ln(\mathrm{Turnover}_{i,t})$		-0.0000		**-0.0000**
		(-1.38)		(-2.46)
FIRM FIXED EFFECTS	YES	YES	YES	YES
TIME DUMMIES	YES	YES	YES	YES
Observations	4391430	4391430	4498216	4494735

Table 8: Second stage regressions of $\hat{r}^{idio}_{i,t}$ and $r_{i,t}$ onto FIPP$_{i,t}$ where I construct FIPP$_{i,t}$ using only funds experiencing a net inflow - i.e. daily_flow > 0. I instrument for FIPP$_{i,t}$ with the lagged portfolio idiosyncratic returns Port_ret$_{i,t-1}$. $\mathrm{r}_{i,t-7,t-2}$ is the cumulative lagged return over the past 6 days. $\ln(\mathrm{Turnover}_{i,t})$ is the natural log of trading turnover. Errors are clustered at the industry level. For all of the regressions, the KP LM statistic rejects the null hypothesis of weak instruments at the 1% level.

	daily_flow ≤ 0			
	$\hat{r}_{i,t}^{idio}$	$\hat{r}_{i,t}^{idio}$	$r_{i,t}$	$r_{i,t}$
	2SLS	2SLS	2SLS	2SLS
FIPP_outflow$_{i,t}$	**7.5610**	**7.5574**	**4.6572**	**4.6533**
	(2.97)	(2.98)	(2.68)	(2.69)
MKTRF$_t$			**0.2971**	**0.2968**
			(8.48)	(8.48)
SMB$_t$			**0.5674**	**0.5680**
			(23.94)	(23.96)
HML$_t$			**0.0975**	**0.0979**
			(4.92)	(4.94)
UMD$_t$			0.0006	0.0003
			(0.06)	(0.03)
Ind_ret$_{i,t}$			**0.6312**	**0.6310**
			(17.15)	(17.15)
$\mathrm{r}_{i,t-7,t-2}$		**-0.0024**		**-0.0021**
		(-5.11)		(-6.90)
$\ln(\mathrm{Turnover}_{i,t})$		-0.0000		**-0.0000**
		(-1.37)		(-2.43)
FIRM FIXED EFFECTS	YES	YES	YES	YES
TIME DUMMIES	YES	YES	YES	YES
Observations	4391434	4391430	4391430	4494735

Table 9: Second stage regressions of $\hat{r}_{i,t}^{idio}$ and $r_{i,t}$ onto FIPP$_{i,t}$ where I construct FIPP$_{i,t}$ using only funds experiencing a net outflow - i.e. daily_flow ≤ 0. I instrument for FIPP$_{i,t}$ with the lagged portfolio idiosyncratic returns Port_ret$_{i,t-1}$. $\mathrm{r}_{i,t-7,t-2}$ is the cumulative lagged return over the past 6 days. $\ln(\mathrm{Turnover}_{i,t})$ is the natural log of trading turnover. For all of the regressions, the KP LM statistic rejects the null hypothesis of weak instruments at the 1% level.

	All Flows	$\text{flow\_quarterly}_{n,t} > 0$	$\text{flow\_quarterly}_{n,t} \leq 0$
	$\Delta\text{Cash}_{n,t}$	$\Delta\text{Cash}_{n,t}$	$\Delta\text{Cash}_{n,t}$
$\text{flow\_quarterly}_{n,t}$	**.086**	**.081**	**.027**
	(8.52)	(4.53)	(1.89)
FIRM FIXED EFFECTS	YES	YES	YES
TIME DUMMIES	YES	YES	YES
Observations	18445	10154	6960

Table 10: Regressions of the percentage change in cash holdings as a function of quarterly flow including quarter and fund fixed effects. Coefficients have been standardized. Errors are clustered at the industry level.

Annualized Average return of 10th decile of Port_ret$_{-i,t-1}$	.2605
Annualized Average return of 1st decile of Port_ret$_{-i,t-1}$	.2047
Annualized Average Long-Short raw return	.0684
Annualized CAPM α	**.0683**
	(1.78)
Annualized FF3 factor α	**.0678**
	(1.77)
Annualized Carhart 4 factor α	**.0668**
	(1.74)
Observations	1511

Table 11: Zero-investment portfolio returns (and factor model alphas) for a portfolio that is long the firms in the highest decile of Port_ret$_{-i,t-1}$ and short the firms in the lowest decile. Daily returns have been annualized by multiplying by 252. Factor model alphas are calculated by regressing the long-short portfolio returns onto the appropriate factors and extracting the α.

	$\hat{r}^{idio}_{i,t}$	$\hat{r}^{idio}_{i,t}$	$r_{i,t}$	$r_{i,t}$
	(1)	(2)	(3)	(4)
	2SLS	2SLS	2SLS	2SLS
$\text{FIPP}_{i,t}$	**0.036**	**0.037**	**0.047**	**0.048**
	(2.46)	(2.48)	(3.49)	(3.48)
MKTRF_t			**0.149**	**0.149**
			(8.51)	(8.51)
SMB_t			**0.123**	**0.123**
			(23.63)	(23.64)
HML_t			**0.024**	**0.024**
			(4.99)	(5.01)
UMD_t			0.001	0.001
			(0.23)	(0.19)
$\text{Ind\_ret}_{i,t}$			**0.406**	**0.406**
			(17.45)	(17.44)
$\text{r}_{i,t-7,t-2}$		**-0.008**		**-0.007**
		(-6.18)		(-7.74)
$\ln(\text{Turnover}_{i,t})$		**-0.002**		**-0.001**
		(-2.18)		(-2.51)
FIRM FIXED EFFECTS	YES	YES	YES	YES
TIME DUMMIES	YES	YES	YES	YES
Observations	4117875	4117871	4217239	4213796

Table 12: Second stage regressions of $\hat{r}^{idio}_{i,t}$ onto $\text{FIPP}_{i,t}$. I instrument for $\text{FIPP}_{i,t}$ using $\text{Normalized\_Cases}_{i,t}$. $\text{illiquidity}_{i,t}$ is the Amihud measure of illiquidity calculated over the previous 90 days. $\text{size}_{i,t}$ is the market cap in \$ US Billions. $\text{r}_{i,t-7,t-2}$ is the cumulative lagged return. $\ln(\text{Turnover}_{i,t})$ is the natural log of turnover. All coefficients are standardized. Errors are clustered at the industry level. For all of the regressions, the KP LM statistic rejects the null hypothesis of weak instruments at the 1% level.

	$\hat{r}^{idio}_{i,t}$	$\hat{r}^{idio}_{i,t}$	$r_{i,t}$	$r_{i,t}$	$\hat{r}^{idio}_{i,t}$	$\hat{r}^{idio}_{i,t}$	$r_{i,t}$	$r_{i,t}$
Instruments	Port_ret$_{-i,t-1}$				Normalized_Cases$_{i,t}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FIPP$_{i,t}$	**0.114**	**0.114**	**0.096**	**0.096**	**0.043**	**0.044**	**0.065**	**0.065**
	(2.15)	(2.15)	(1.96)	(1.96)	(2.27)	(2.29)	(3.33)	(3.30)
MKTRF$_t$			**0.152**	**0.152**			**0.150**	**0.150**
			(8.68)	(8.68)			(8.61)	(8.60)
SMB$_t$			**0.124**	**0.125**			**0.123**	**0.123**
			(24.04)	(24.05)			(23.68)	(23.70)
HML$_t$			**0.024**	**0.024**			**0.024**	**0.024**
			(4.96)	(4.98)			(5.06)	(5.08)
UMD$_t$			0.001	0.001			0.002	0.002
			(0.24)	(0.20)			(0.36)	(0.33)
Ind_ret$_{i,t}$			**0.397**	**0.397**			**0.406**	**0.406**
			(17.19)	(17.18)			(17.50)	(17.49)
$r_{i,t-7,t-2}$		**-0.011**		**-0.008**		**-0.008**		**-0.007**
		(-6.58)		(-7.55)		(-6.47)		(-7.79)
ln (Turnover$_{i,t}$)		-0.001		**-0.002**		**-0.002**		**-0.001**
		(-1.38)		(-2.47)		(-2.14)		(-2.55)
FIRM FIXED EFFECTS	YES	YES	YES	YES	YES	YES	YES	YES
TIME DUMMIES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	4393052	4393049	4496339	4496335	4119419	4119416	4218836	4215390

Table 13: Second stage regressions of $\hat{r}^{idio}_{i,t}$ onto FIPP$_{i,t}$. I instrument for FIPP$_{i,t}$ first with Port_ret$_{i,t-k}$ for $k = 1$ and then with Normalized_Cases$_{i,t}$. illiquidity$_{i,t}$ is the Amihud measure of illiquidity calculated over the previous 90 days. size$_{i,t}$ is the market cap in \$ US Billions. $r_{i,t-7,t-2}$ is the cumulative lagged return. ln (Turnover$_{i,t}$) is the natural log of turnover. FIPP$_{i,t}$ is constructed by extrapolating to daily data the quarterly coefficients found in regressions 6 and 10 of Table 3. All coefficients are standardized. Errors are clustered at the industry level. For all of the regressions, the KP LM statistic rejects the null hypothesis of weak instruments at the 1% level.

Panel A	Autocorrelation of $flow_t$	
	Days 1-15	Days 16-30
AVE Corr $[flow_t, flow_{t-1}]$	-.0673	-.0733
Sample Size	1945	1945
	Two-sample t-test	
	t-stat	
H_0 : AVE Corr is the same in both periods	(.8204)	

Panel B: Summary Statistics	TrimTabs	CRSP
mean[TNA]	615.458	615.4625
mean[NAV]	15.97	16.07

Table 14: Panel A: comparison of the autocorrelation of flows between the first half and the second half of the month. 1 day flow autocorrelations are calculated for each fund for calendar days between 1 and 15 and then separately for calendar days between 16 and 31. A two sample t-test is performed between these two samples of flow autocorrelation. Panel B: comparison of summary statistics of the TrimTabs and CRSP data.