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Asset fire sales (and purchases) in equity markets ☆

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Abstract

This paper examines institutional price pressure in equity markets by studying mutual fund transactions caused by capital flows from 1980 to 2004. Funds experiencing large outflows tend to decrease existing positions, which creates price pressure in the securities held in common by distressed funds. Similarly, the tendency among funds experiencing large inflows to expand existing positions creates positive price pressure in overlapping holdings. Investors who trade against constrained mutual funds earn significant returns for providing liquidity. In addition, future flow-driven transactions are predictable, creating an incentive to front-run the anticipated forced trades by funds experiencing extreme capital flows.

JEL classifications: G11; G12; G14

Keywords: Mutual fund flows; Liquidity; Price pressure

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1. Introduction

This paper investigates the costs of asset fire sales in equity markets. Financial distress is costly whenever a firm's past financing decisions interfere with current operations. This can arise when capital providers force a firm to quickly sell specialized assets. Because the sale is immediate, the liquidity premium can be large, resulting in transaction prices that are substantially below their fundamental values. The high liquidity of equity markets prompts many firms that specialize in equity investing to be willing to allow capital providers to withdraw their capital on demand. Nonetheless, equity market are not perfectly liquid, and evidence presented in this paper suggests that even in the most liquid of markets, assets sometimes sell at fire sale prices.

Shleifer and Vishny (1992) analyze the equilibrium aspect of asset sales and describe how liquidity can disappear, making it very costly for someone who is forced to sell. They essentially argue that asset fire sales are possible when financial distress clusters through time at the industry level and firms within an industry have specialized assets. When a firm must sell assets because of financial distress, the potential buyers with the highest valuation for the specialized asset are other firms in the same industry, who are likely to be in a similarly dire financial situation and therefore will be unable to supply liquidity. Instead, liquidity comes from industry outsiders, who have lower valuations for specialized assets, and thus bid lower prices.

This story can easily be recast in a capital market setting. Here, the firms are professional investors, who follow somewhat specialized investment strategies. In this context, specialization refers to concentrated positions in securities that have limited breadth of ownership and, importantly, have significant overlap with others following a similar strategy. For example, merger arbitrage is a specialized investment strategy followed by many professional investors, requiring relatively large positions in stocks that eventually are held mainly by merger arbitrageurs. Specialization is common in investment management, with many professional investors focusing on a single or limited number of investment strategies. Merton (1987) and Shleifer and Vishny (1997) present models of investment management that rely on specialization to derive limited arbitrage.

Accurate assessment of asset fire sale costs requires considerable transparency in the decisions of the firm and its investors, whereas most settings in which asset fire sales are costly are likely to be highly opaque. The primary challenge in measuring the costs of asset fire sales is that distinguishing financial from economic distress requires identifying asset sales that are a direct consequence of the financing decisions of the firm. In many corporate settings, financial difficulties and economic difficulties coincide over multi-year periods, making causality difficult to assign. Additionally, efficient estimation of costs requires precise measurement of fair asset value, which can be a challenge in environments characterized by illiquidity and declining prices.

The focus of this paper is on the assets held by open-ended mutual funds. The open-ended mutual fund structure produces a highly transparent firm with investment decisions that are easy to identify and monitor. The open-ended mutual fund is also extremely reliant on outside capital to fund its investment opportunities—only the occasional back-end load stands between outside capital providers and their capital. When capital is immediately demandable, a poorly performing mutual fund without significant cash reserves has no choice but to sell holdings quickly. Regulations and self-imposed constraints effectively prevent mutual funds from raising funds by short selling other securities (Almazan, Brown, Carlson, and Chapman, 2004), and binding margin constraints are likely to restrict short selling by severely underperforming hedge funds. Monthly reporting of total net assets allows real-time measurement of the pressures that outside capital providers place on the firm. Moreover, because of high trading frequency in public markets, deviations in transaction prices from fair values can be accurately assessed via the tracking of post-sale returns. On the other hand, the stock market environment is a relatively hospitable one for asset sales. With high transaction volumes and low execution costs, a distressed seller of a listed equity might expect to find many willing buyers. In addition, mutual funds that select the open-ended organizational form do so precisely because they view the potential costs of this structure to be low.[1] Thus, our focus is on a setting where asset fire sales are unlikely, but where high transparency permits them to be properly detected should they occur.[2]

The asset fire sale story is similar to the price pressure hypothesis of Scholes (1972), where stock prices can diverge from their information-efficient values because of uninformed shocks to excess demand to compensate those who provide liquidity. Although a variety of evidence exists in support of the price pressure hypothesis,[3] the documented effects rarely last for more than several days. The asset fire sale story identifies forced selling by distressed mutual funds as one particular type of uninformed shock, explains why those who provide liquidity are likely to demand additional compensation, and accounts for why the supply of liquidity can be constrained in the short run and result in more persistent mispricing.

To empirically examine asset fire sales in equity markets and the effects of institutional price pressure more generally, we construct a sample of situations where widespread mutual fund selling in response to capital outflows is concentrated in a limited number of securities. Fundamental value is not immediately observable, but by studying systematic patterns in abnormal returns over time, we can identify deviations between transaction prices and fundamental value ex post if we find evidence of significant price reversals following forced transactions. We attempt to disentangle price pressure from information effects by focusing on situations where the fire sale story predicts that mutual fund sales are motivated by necessity, as opposed to opportunistic information-based trading. In particular, we focus on mutual fund stock transactions that are forced by financial distress and therefore unlikely to reveal much new information about the individual securities being sold, and where there is considerable overlap in the holdings among poorly performing funds.

The empirical results provide considerable support for the view that concentrated mutual fund sales forced by capital flows exert significant price pressure in equity markets, often resulting in transaction prices far from fundamental value. We find that poor performance leads to capital outflows for mutual funds, the most serious of which we consider financial distress. This corroborates previous research, which finds a strong

[1] Stein (2005) presents a model where competition pushes mutual funds toward the open-end form even though this severely constrains their ability to conduct arbitrage trades. Edelen (1999) finds that liquidity-motivated trading caused by fund flows has a negative impact on the performance of open-end mutual funds.

[2] See Andrade and Kaplan (1998), Asquith, Gertner, and Scharfstein (1994), and Gilson (1997) for studies of financially distressed firms. See Pulvino (1998) for a study focusing on asset fire sales in the used aircraft market, and Eckbo and Thorburn (2004) for one on those in Swedish bankruptcy auctions.

[3] Early empirical evidence of short-term price pressure comes from studies around S&P index inclusions (e.g., Harris and Gurel, 1986; Shleifer, 1986) and large-block transactions (e.g., Kraus and Stoll, 1972; Scholes, 1972).

relation between mutual fund flows and past performance (e.g., Ippolito, 1992; Chevalier and Ellison, 1997; Sirri and Tufano, 1998). The analysis also indicates that flows into and out of mutual funds do indeed force trading. Mutual funds in the bottom decile of capital flows are roughly twice as likely to reduce, or eliminate holdings, as funds experiencing normal flows. This forced trading can be especially costly when there is significant overlap with the securities held by other funds experiencing outflows, as transactions appear to occur far from fundamental value. We estimate that investors providing liquidity to the distressed funds earn significant abnormal returns over the subsequent months. Somewhat surprisingly, we also find that extreme *inflows* can be costly for mutual funds. Funds experiencing large inflows tend to increase their existing positions, creating significant price pressure in the stocks held in common by these funds. Like the asset fire sales, these inflow-driven purchases produce trading opportunities for outsiders. Finally, we show that forced transactions are predictable, which creates an opportunity for front-running. An investment strategy that short sells stocks most likely to be the subject of widespread flow-induced selling, and buys ahead of anticipated forced purchases, earns average annual abnormal returns well over 10%.

This paper is organized as follows. Section 2 describes the data. Section 3 presents evidence on the existence and magnitudes of flow-induced price pressure in equity markets. Section 4 investigates the strategic trading behavior of funds in response to extreme flows. Section 5 examines the incentives for providing liquidity during crisis periods and for front-running. Section 6 discusses the persistence of institutional price pressure, and Section 7 concludes.

2. Data description

2.1. Mutual fund holdings, returns, and flows

Most of our analysis relies on a merger of the two major mutual fund databases that have been used extensively in the literature: the Spectrum mutual fund holdings database and the Center for Research in Security Prices (CRSP) mutual fund monthly net returns database. Comprehensive descriptions of both can be found in Wermers (1999), who conducts a similar merge.

Our merge procedure is as follows. First, funds are matched by name. To make sure we have identified the timing of changes in holdings accurately, we only include fund-quarter observations reported across adjacent quarters when holdings changes are required. We remove fund-quarter observations when the value of the holdings differs substantially from that reported in the CRSP database net of the cash position. Because our focus is on US equity funds, we exclude funds with an investment objective code indicating any of the following: international, municipal bonds, bonds and preferred, or metals. Finally, because the number of matched funds is significantly lower in the 1980s than in the 1990s, we often emphasize the subperiod from 1990 to 2004 in our analysis.

Mutual fund flows are estimated using the CRSP series of monthly total net assets (*TNA*) and returns. The net flow of funds to mutual fund j during month t is defined as

$$FLOW_{j,t} = TNA_{j,t} - TNA_{j,t-1} \cdot (1 + R_{j,t}), \tag{1}$$

$$flow_{j,t} = \frac{FLOW_{j,t}}{TNA_{j,t-1}}, \tag{2}$$

where $TNA_{j,t}$ is the CRSP TNA value for fund j at the end of month t and $R_{j,t}$ is the monthly return for fund j over month t. In order to match with the quarterly holdings data, we sum monthly flows over the quarter to calculate quarterly flows. Most of the analysis involving mutual fund flows uses the dollar value of $FLOW$ as a percentage of beginning-of-period TNA as in Eq. (2).

2.2. Measuring the relation between fund performance and flows

It is well documented that capital flows to and from mutual funds are strongly related to past performance (e.g., Sirri and Tufano, 1998). We use a simple Fama and MacBeth (1973) style regression model to forecast fund flows based on past returns and lagged flows.

$$flow_{j,t} = a + \sum_{k=1}^{K} b_k \cdot flow_{j,t-k} + \sum_{h=1}^{H} c_h \cdot R_{j,t-h}. \tag{3}$$

In particular, for each quarter or month t we estimate a cross-sectional regression as in (3). For quarterly regressions, we include lagged flows and fund returns from the previous two years, while the monthly regressions include lagged flows and fund returns from the previous year. We then calculate the time-series average of the coefficients and report t-statistics using the time-series standard error of the mean. Expected flows are calculated as the fitted values using the time-series average of the coefficients.

We estimate the regression coefficients using a subsample of the quarterly mutual fund observations that we view as having the most reliable data. In particular, we impose the following data requirements:

- Fund must have had, at some point in the past, $TNA_{j,t} < \$1$ billon (2004 dollars)[4]
- At some point in the past, the fund must have had at least 20 holdings
- Changes in TNA cannot be too extreme:

  $$-0.50 < \Delta TNA_{j,t}/TNA_{j,t-1} < 2.0.$$
- Data from CRSP and Spectrum cannot be too different:

  $$1/1.3 < TNA_{j,t}^{\text{CRSP}}/TNA_{j,t}^{\text{Spectrum}} < 1.3.$$

Table 1 reports the regression results. As expected from previous research, there is a strong relation between mutual fund flows and both lagged flows and lagged returns. Quarterly mutual fund flows are highly significant in explaining future flows for up to a full year, while quarterly fund returns are important determinants of future flows for two years. The results are largely consistent with pooled regression results. The main distinction is that the explanatory variables in the Fama–MacBeth regression focus on explaining cross-sectional differences in flows, whereas the pooled regression coefficients must also account for time-series variation in overall flows. As a result, the Fama–MacBeth coefficients are estimated more precisely, relative to the number of observations.

[4]The \$1 billion cutoff is based on constant 2004 dollars with the CRSP value-weight market index as the deflator. Results are largely unchanged when lower thresholds are used. Results are similar if we include only those event-quarters in which TNA exceeds the minimum size threshold.

Table 1

Regressions explaining mutual fund flows (1980–2004)

This table reports results from regressions of mutual fund flows on lagged fund flows and lagged fund returns. Mutual fund flows are measured as a percentage of beginning-of-period total net assets (*TNA*). Mutual fund flows are estimated as the percentage change in *TNA* over the quarter controlling for capital gains and losses of the initial holdings: $[TNA_t - TNA_{t-1} \times (1 + Return_t)]/TNA_{t-1}$. Quarterly regressions use quarterly observations on flows and returns, while monthly regressions use monthly observations of flows and returns. Fama-MacBeth regression coefficients are the time-series average of periodic cross-sectional regression coefficients, with *t*-statistics calculated using the time-series standard error of the mean. The reported R^2 is the average across all cross-sectional regressions. The pooled regression results are based on OLS coefficients, where the mean of each variable has been subtracted. The number of observations is denoted by *N*, and *t*-statistics are in parentheses.

	Quarterly		Monthly	
	Fama–MacBeth	Pooled	Fama–MacBeth	Pooled
Intercept	−0.0211	0.0000	−0.0069	0.0000
	(−5.61)	(0.00)	(−7.25)	(0.00)
flow(*t*-1)	0.2499	0.2887	0.1329	0.1673
	(9.35)	(40.22)	(9.27)	(37.31)
flow(*t*-2)	0.1762	0.1494	0.1684	0.1672
	(9.55)	(20.52)	(15.95)	(36.97)
flow(*t*-3)	0.1264	0.0979	0.1617	0.1322
	(6.50)	(13.39)	(14.33)	(28.94)
flow(*t*-4)	0.0852	0.0584	0.0711	0.0605
	(5.15)	(8.17)	(6.54)	(13.23)
flow(*t*-5)	0.0032	0.0311	0.0682	0.0714
	(0.19)	(4.38)	(6.77)	(15.72)
flow(*t*-6)	−0.0079	−0.0089	0.0473	0.0346
	(−0.58)	(−1.31)	(4.64)	(7.69)
flow(*t*-7)	−0.0218	0.0032	0.0243	0.0258
	(−1.48)	(0.49)	(2.55)	(5.79)
flow(*t*-8)	0.0659	0.0513	0.0276	0.0196
	(5.15)	(8.79)	(2.98)	(4.47)
flow(*t*-9)			0.0391	0.0352
			(4.47)	(8.12)
flow(*t*-10)			0.0150	0.0104
			(1.72)	(2.45)
flow(*t*-11)			0.0067	0.0136
			(0.80)	(3.31)
flow(*t*-12)			0.0179	0.0180
			(2.05)	(4.60)
Return(*t*-1)	0.2867	0.1909	0.1196	0.0736
	(12.82)	(23.04)	(12.97)	(23.88)
Return(*t*-2)	0.1795	0.0579	0.0845	0.0369
	(7.74)	(7.08)	(7.96)	(12.13)
Return(*t*-3)	0.1794	0.0760	0.0814	0.0334
	(7.21)	(9.50)	(7.43)	(11.04)

Table 1 (*continued*)

	Quarterly		Monthly	
	Fama–MacBeth	Pooled	Fama–MacBeth	Pooled
Return(*t*-4)	0.0961	0.0383	0.0679	0.0241
	(3.52)	(4.82)	(6.56)	(7.99)
Return(*t*-5)	−0.0169	0.0488	0.0621	0.0150
	(−0.81)	(6.36)	(5.73)	(4.98)
Return(*t*-6)	−0.0313	0.0036	0.0324	0.0132
	(−1.22)	(0.49)	(3.51)	(4.38)
Return(*t*-7)	0.0552	0.0077	0.0504	0.0060
	(2.66)	(1.04)	(4.86)	(2.01)
Return(*t*-8)	0.0387	−0.0024	0.0240	0.0037
	(1.53)	(−0.34)	(2.20)	(1.24)
Return(*t*-9)			0.0263	0.0029
			(2.52)	(0.99)
Return(*t*-10)			0.0287	0.0073
			(2.89)	(2.48)
Return(*t*-11)			0.0186	0.0004
			(1.71)	(0.13)
Return(*t*-12)			0.0206	−0.0087
			(2.06)	(−3.02)
R^2	0.5288	0.3589	0.5345	0.3673
N	100	19,278	300	50,181

2.3. Fund behavior in response to financial pressure

Our notion of a stock fire sale requires that several different owners, who are each experiencing financial distress, contemporaneously sell the security. Mutual funds experiencing significant outflows have no choice but to sell some of their holdings to cover redemptions, unless they have excess cash or can borrow. Typically, borrowing is difficult and, because most funds are evaluated against all-equity benchmarks, few maintain significant cash balances. Moreover, short selling other securities is usually not feasible.[5] Therefore, the immediate selling of some existing holdings is the only option. In addition, it is important that there are many sellers relative to potential buyers. A single fund selling when others are willing and able to provide liquidity is unlikely to produce a fire sale price. A large investor can liquidate a large position in an orderly way, but a large number of small investors cannot easily liquidate a similar size aggregate position. Thus, only when many funds are forced to sell the same security should we expect to see significant price pressure.

[5]The Investment Company Act of 1940 impedes mutual funds ability to short sell and purchase securities on margin. In addition, mutual funds tend to voluntarily refrain from engaging in these activities (see Almazan, Brown, Carlson, and Chapman, 2004).

Table 2 provides an overview of fund characteristics and their behavior in response to financial pressure. In Panels A and B, funds are sorted into deciles according to actual quarterly flows. In Panel C, funds are sorted into deciles according to expected quarterly flows determined from the model in (3). Panel A reports average fund and fund holding characteristics by flow decile. Panels B and C report summaries of fund trading behavior in response to actual (Panel B) and expected (Panel C) flows. Panel B takes the fraction of a given fund's positions that are maintained, expanded, reduced, or eliminated during the given quarter and averages these values across funds within each decile. Panel B also calculates the average percent change in a given fund's positions during the quarter and averages these across all funds in the decile. The percent change is calculated as the split-adjusted percent change in the number of shares held and is calculated for all fund holdings that existed at the start of the quarter. Panel C repeats the averages of Panel B but uses expected flows to determine fund deciles.

A variety of interesting patterns emerge from Table 2. First, funds experience a wide range of quarterly flows. Funds in the top decile experience an average inflow of 23.7% whereas funds in the bottom decile experience outflows of 12.5%. As documented in Table 1 and elsewhere in the literature, a reasonable fraction of these flows can be anticipated. Funds in the top decile were expected to experience inflows of 6.9% whereas those in the bottom decile had anticipated outflows of 5.1%. Also consistent with Table 1 and the literature, past one-year fund returns line up closely with expected and actual flows, ranging from 18.7% for the top decile to 2.8% for the bottom decile. Column 5 reports that funds experiencing extreme flows and returns appear to be somewhat less diversified than funds with more moderate flows and returns. Funds in the top decile hold over 50% more cash (5.7% vs. 3.6%) than those in the bottom decile, which is consistent with the notion that these funds will have more flexibility in their trading and is also consistent with Warther (1995), who finds a similar pattern in aggregate performance and cash holdings. The final columns indicate that our sample of mutual funds tends to invest in firms that are relatively large and liquid.[6]

Panel B presents our most fundamental evidence relating fund flows to fund trading behavior. Funds experiencing large outflows are far more likely to reduce or eliminate positions than funds experiencing inflows. A fund that ranks in the bottom decile of fund flows will reduce or eliminate 54% of its existing positions, whereas a fund in the top decile reduces or eliminates only 26% of its positions. Perhaps somewhat surprisingly, a fund experiencing high inflows is far more likely than other funds to expand existing positions (as opposed to using the inflows to initiate new positions). Funds in the top decile expand 46% of their existing positions, which is more than double the rate for funds not experiencing inflows. These patterns are confirmed in the final column of Panel B. A fund in the top decile of fund flows increases the number of shares in its average position by 0.8%. On the other hand, a fund in the bottom decile reduces its average position by 20.5%. Since turnover is positive, the average fund decreases its number of shares in existing positions by roughly 10% each quarter.

Panel C indicates that many of the above patterns are predictable. When funds are sorted according to expected flows, during the subsequent quarter those in the bottom decile reduce or eliminate 50% of their holdings as compared to 26% for funds in the top

[6]We use NYSE breakpoints for our size decile (as reported on Ken French's website) and CRSP universe breakpoints for our volume deciles.

Table 2

Mutual fund trading associated with actual and predicted flows (1980–2004)

This table reports how quarterly mutual fund holdings change conditional on actual and expected fund flows. Mutual fund flows are measured as a percentage of beginning-of-period total net assets (*TNA*). Mutual fund flows are estimated as the percentage change in *TNA* over the quarter controlling for capital gains and losses of the initial holdings: $[TNA_t - TNA_{t-1} \times (1 + Return_t)]/TNA_{t-1}$. Expected flow is estimated via Fama–MacBeth regressions of quarterly flows on lagged flows and returns, where coefficients are the time-series average of periodic cross-sectional regression coefficients. Fund-quarter observations with available flow data ($N = 142{,}720$) are sorted according to actual quarterly fund flow (Panels A and B) and expected quarterly flow (Panel C). Within each *flow* decile, Panel A reports the fund flow, expected flow, number of holdings, past 12-month fund return, and cash holdings averaged across all funds in the decile. The final two columns of Panel A report for each flow decile the average fund's size decile of its holdings (using the NYSE break-points reported on Ken French's website) and the average volume decile. Panels B and C report for the average fund the fraction of positions that were maintained, expanded, reduced, or eliminated. The final column reports the average fund's percent change in positions held at the start of the quarter.

Decile	Flow (%)	E[Flow] (%)	Prior fund return (%)	Average number of holdings	Average Cash/TNA (%)	Average holding size decile	Average holding volume decile
Panel A: Fund and holding characteristics (sorted on actual flows)							
1 (Inflow)	23.7	6.9	18.7	124.3	5.7	4.4	2.3
2	8.1	4.3	14.9	143.8	5.5	3.9	2.0
3	3.6	2.3	12.9	167.1	5.7	3.6	1.9
4	1.0	0.6	9.9	160.4	5.2	3.5	1.8
5	−0.6	−0.6	8.1	143.6	5.1	3.3	1.8
6	−2.0	−1.6	6.0	134.3	4.7	3.4	1.8
7	−3.4	−2.6	3.3	130.8	4.3	3.3	1.7
8	−4.9	−3.4	1.4	130.4	3.7	3.1	1.6
9	−7.0	−4.4	0.7	134.1	3.3	3.4	1.7
10 (Outflow)	−12.5	−5.1	2.8	117.1	3.6	3.5	1.8

Decile	Flow (%)	Fraction of positions				Average change in holding (%)
		Maintained	Expanded	Reduced	Eliminated	
Panel B: Fund trading behavior (sorted on actual flow)						
1 (Inflow)	23.7	0.28	0.46	0.11	0.15	0.8%
2	8.1	0.36	0.38	0.14	0.13	−5.0%
3	3.6	0.41	0.32	0.15	0.12	−5.4%
4	1.0	0.41	0.27	0.18	0.13	−7.9%
5	−0.6	0.45	0.23	0.19	0.12	−8.2%
6	−2.0	0.42	0.21	0.23	0.13	−9.9%
7	−3.4	0.41	0.19	0.24	0.14	−13.2%
8	−4.9	0.36	0.20	0.31	0.14	−14.1%
9	−7.0	0.29	0.20	0.33	0.17	−16.8%
10 (Outflow)	−12.5	0.27	0.18	0.37	0.17	−20.5%

Decile	E[Flow] (%)	Fraction of positions				Average change in holding (%)
		Maintained	Expanded	Reduced	Eliminated	
Panel C: Fund trading behavior (sorted on expected flow)						
1 (Inflow)	9.6	0.35	0.39	0.13	0.13	−1.9%
2	3.9	0.41	0.31	0.17	0.12	−6.1%
3	1.7	0.43	0.27	0.18	0.12	−7.3%

Table 2 (*continued*)

Decile	E[Flow] (%)	Fraction of positions				Average change in holding (%)
		Maintained	Expanded	Reduced	Eliminated	
Panel C: Fund trading behavior (sorted on expected flow)						
4	0.2	0.43	0.25	0.22	0.12	−8.0%
5	−1.1	0.42	0.23	0.23	0.13	−10.6%
6	−2.3	0.40	0.23	0.25	0.14	−11.8%
7	−3.3	0.37	0.20	0.28	0.15	−15.0%
8	−4.5	0.32	0.21	0.31	0.17	−17.6%
9	−5.9	0.29	0.20	0.33	0.16	−17.3%
10 (Outflow)	−9.6	0.26	0.19	0.33	0.17	−20.1%

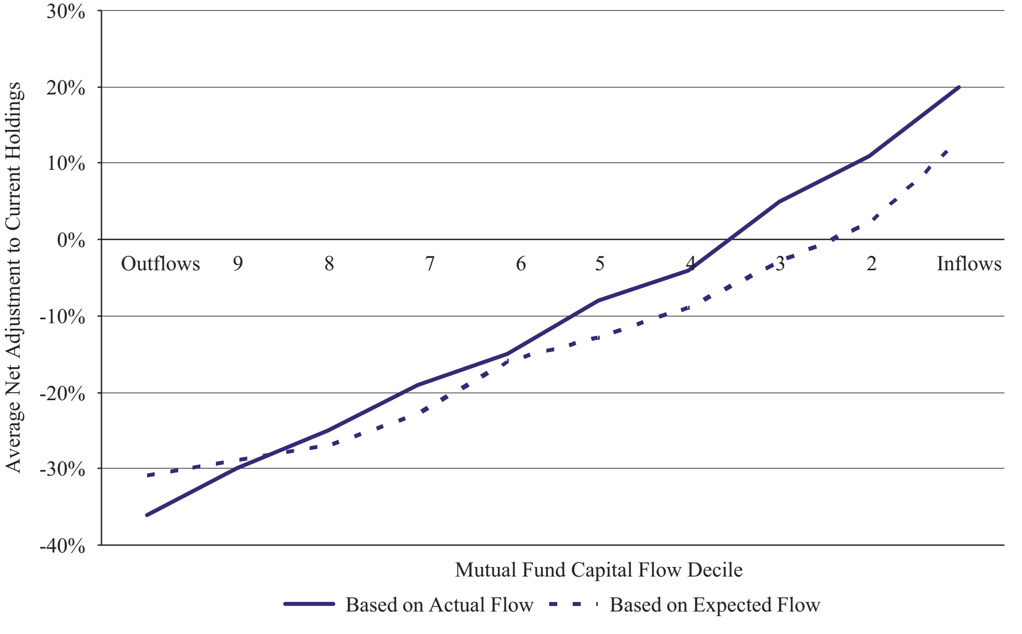

Fig. 1. Relation between mutual fund flows and average tendency to adjust current holdings. Mutual fund flows are measured as a percentage of beginning-of-period total net assets (*TNA*). Mutual fund flows are estimated as the percentage change in *TNA* over the quarter controlling for capital gains and losses of the initial holdings: $[TNA_t – TNA_{t-1} \times (1+Return_t)]/TNA_{t-1}$. Expected flow is estimated via Fama–MacBeth regressions of quarterly flows on lagged flows and returns, where coefficients are the time-series average of periodic cross-sectional regression coefficients. For each fund, in each quarter, the fraction of a fund's positions that are expanded minus the fraction of positions reduced or eliminated is calculated. Each of these fund-quarter observations is then sorted into deciles according to the fund's actual and expected quarterly flows. Averages are reported for each mutual fund capital flow decile.

decile. Funds expected to experience inflows among the top decile expand 39% of their existing positions during the subsequent quarter. Funds expected to experience outflows expand only 20% of existing positions. Evaluated according to the average change in holdings, funds in the top decile of expected flows reduce their average position by 1.9%

whereas those in the bottom decile reduce their positions by 20.1% over the subsequent quarter.

Fig. 1 displays the average tendency of net adjustments to existing positions as a function of capital flows. This is merely a graphical representation of some of the data from Table 2. Consistent with the fire sale story, the funds with the most significant outflows are very likely to reduce their existing positions. However, the figure clearly shows that there is a similar effect caused by inflows. Funds in the top decile of capital flows tend to increase a large fraction of their existing positions. This is interesting, because unlike the firms who must sell in the face of outflows, these funds have more options: they can accumulate cash, purchase securities that they do not currently own, or simply invest in their benchmark, none of which is feasible for firms facing outflows.

2.4. Identifying fire sales

Our tests identify fire sale stocks in the simplest terms possible: stocks where large fractions of volume are accounted for by mutual funds experiencing significant outflows. We sum the difference between flow-induced purchases and flow-induced sales in a given quarter and then divide this difference by the average trading volume of the stock from prior quarters. Flow-induced sales (purchases) are identified as reductions (increases) in shares owned by funds experiencing severe outflows (inflows). Severe flows are those below/above the 10th/90th percentile of *flow*. We label the fraction of average volume from flow-motivated trading in a given stock as the variable *PRESSURE_1*[7]:

$$PRESSURE\_1_{i,t} = \frac{\sum_j \left(\max(0, \Delta Holdings_{j,i,t}) | flow_{j,t} > Percentile(90th)\right) - \sum_j \left(\max(0, -\Delta Holdings_{j,i,t}) | flow_{j,t} < Percentile(10th)\right)}{AvgVolume_{i,t-12:t-6}}. \tag{4}$$

In the tests that follow, stocks with *PRESSURE*_1 below the 10th percentile are considered fire sale stocks. We also pay particular attention to stocks with *PRESSURE*_1 above the 90th percentile, as they appear to be stocks with significant inflow-driven purchases.[8]

To check robustness, we also identify stocks involved in flow-motivated trading using two additional "pressure" variables,[9] again to identify extreme situations of flow-motivated trading. A flow-motivated purchase of stock i by fund j is defined as the product of the fund's inflow and its increase in holdings of the stock. Similarly, a flow-motivated sale of stock i by fund j is defined as the product of the fund's outflow and its decrease in shares held of that stock. The sum across funds of all flow-motivated sales of the stock is subtracted from the sum across funds of all flow-motivated purchases of the stock and the result is scaled by the average volume of the stock to

[7]We thank the referee for suggesting this measure of pressure. We require a minimum of at least ten mutual fund owners before we calculate the *PRESSURE* variable.

[8]Earlier drafts of this paper used a pressure variable based on counts of forced sales and purchases, scaled by number of mutual fund owners; the results are qualitatively similar to those presented here.

[9]We thank Tuomo Vuolteenaho for discussions on this issue.

calculate $PRESSURE\_2$:

$$PRESSURE\_2_{i,t} = \frac{\sum_j \left(\max(0, flow_{j,t}) \cdot \max(0, \Delta Holdings_{j,i,t})\right) - \sum_j \left(\max(0, -flow_{j,t}) \cdot \max(0, -\Delta Holdings_{j,i,t})\right)}{Avg\ Volume_{i,t-12:t-6}}. \tag{5}$$

This variable has the properties that both the severity of the flows (amount of duress the fund is facing) and larger transaction sizes (relative to the average volume of the stock) will each create more "pressure."

The third pressure variable scales the original variable by shares outstanding rather than average volume to make sure that the denominator is not driving the results. This modification leads to the variable $PRESSURE\_3$:

$$PRESSURE\_3_{i,t} = \frac{\sum_j \left(\max(0, \Delta Holdings_{j,i,t}) | flow_{j,t} > Percentile(90th)\right) - \sum_j \left(\max(0, -\Delta Holdings_{j,i,t}) | flow_{j,t} < Percentile(10th)\right)}{SharesOutstanding_{i,t-1}}. \tag{6}$$

As with $PRESSURE\_1$, we use the 10th and 90th percentiles of these pressure measures to identify firms facing extreme flow-induced trading.

Table 3 displays the distribution of the sample firms according to size and book-to-market quintiles using NYSE breakpoints (see Fama and French, 1992, 1993). Both flow-motivated sales and purchases have size distributions that are tilted towards large firms relative to the population of CRSP firms. More than 60% of all common stocks listed in

Table 3
Characteristics of stocks Involved in flow-motivated trading by mutual funds

Distribution of sample firms by various characteristics. All quintiles are defined using annual NYSE breakpoints. Stocks with $PRESSURE\_1$ below the 10th percentile are determined to be fire sale stocks. Stocks with $PRESSURE\_1$ above the 90th percentile are determined to be flow-motivated purchase stocks. $PRESSURE\_1$ is a stock-level variable calculated as the quantity of shares purchased by mutual funds experiencing significant inflows, minus the quantity of shares sold by mutual funds with significant outflows, scaled by the average volume of the stock, requiring at least ten owners.

Sample	Quintile 5 (low) (%)	Quintile 4 (%)	Quintile 3 (%)	Quintile 2 (%)	Quintile 1 (high) (%)
A: Market capitalization					
Universe	61.2	14.4	9.5	7.6	7.2
Forced sales	3.2	10.8	21.2	33.5	31.2
Forced buys	3.2	9.7	17.7	32.6	36.8
B: Book-to-Market Equity					
Universe	29.1	19.7	17.4	15.4	18.4
Forced Sales	32.0	27.6	21.0	12.4	6.9
Forced Buys	38.4	25.6	18.8	12.2	5.0
C: Dividend Yield					
Universe	68.6	7.2	7.1	7.6	9.5
Forced sales	50.4	14.6	13.8	13.0	8.2
Forced buys	54.1	13.8	14.2	11.2	6.7

CRSP fall into the bottom size quintile based on NYSE breakpoints. Stocks identified as flow-motivated sales or purchases are distributed across dividend yield quintiles in roughly the same way as the universe of publicly traded stocks. Finally, the event firms have book-to-market distributions that are tilted towards growth firms relative to the CRSP universe.

3. Price effects of mutual fund transactions and forced transactions

Berk and Green (2004) develop a theory for why we should expect flows to chase performance to the point where predictability is eliminated. While there are strong reasons why fund flows should have modest impact on subsequent abnormal *fund* returns, if extreme flows prompt many funds to simultaneously trade the same stocks there could be a significant impact on subsequent abnormal *stock* returns. Relying on a similar insight, Frazzini and Lamont (2006) use aggregate stock-level flows as a measure of investor sentiment for particular stocks.

In general, detecting price pressure effects around mutual fund stock transactions is problematic because of the simultaneous effects of price pressure and information revelation. In an attempt to disentangle price pressure and information effects, we examine stock price changes around widespread forced and unforced mutual fund sales, and look for evidence of stock price drops followed by a significant price reversal. This empirical approach is similar to the one used by Mitchell, Pulvino, and Stafford (2004) who study price pressure around mergers. If mutual funds bring information into prices through their trading, then we should see a price drop in the period when they are selling heavily, and then no drift in abnormal returns following the trades. However, if mutual fund trading is driven by necessity rather than information, and if this forced trading results in fire sale prices, then we should see a significant price drop over the period when they are being forced to sell, followed by a period of positive abnormal returns compensating those who provided liquidity in the crisis period.

Table 4 displays monthly abnormal returns around various types of mutual fund stock transactions. At this point, our interest is whether this subset of firms exhibits unusual returns relative to the average firm held by mutual funds. In the analysis that follows, we investigate whether these returns are unusual relative to single- and four-factor asset pricing models. Abnormal returns during a given month are calculated by subtracting the equal-weighted return of the universe of firms held by mutual funds in that month. In the spirit of Fama and MacBeth (1973), we calculate average abnormal returns each month and then use the time-series of mean abnormal returns for statistical inference to control for potential cross-sectional dependence in the monthly abnormal returns. This procedure gives equal weight to each monthly observation, rather than to each individual observation. To prevent quarters with a small number of firms from dominating the results, we require at least 25 firms in a quarter for the firm average return to be included as an observation. When individual observations are given equal weight and assumed to be independent, the patterns are somewhat more pronounced, with highly significant test statistics. Table 4 also reports the average quarterly abnormal value of our pressure variable for easy comparison to the associated monthly abnormal returns.

In Panel A, the pattern in average abnormal returns around the widespread selling of stocks held by distressed mutual funds is striking (see Fig. 2 for a graphical representation). We find significantly negative abnormal returns in the months of forced selling and the months immediately preceding. Over the two quarters (t-3 through the event quarter) with

Table 4
Monthly cumulative average abnormal returns for stocks around mutual fund sales

Cumulative average abnormal returns (*CAAR*s) are measured monthly returns in excess of the equal-weighted average return of all stocks held by mutual funds at the start of the month. Panel A reports results for "fire sale" stocks. Stocks with *PRESSURE_1* below the 10th percentile are determined to be fire sale stocks. *PRESSURE_1* is a stock-level variable calculated as the quantity of shares purchased by mutual funds with inflows above the 10th percentile of flows, minus the quantity of shares sold by mutual funds with outflows below the 10th percentile of flows, scaled by the average monthly trading volume for the stock, requiring at least ten owners. Panel B reports results for stocks with significant net selling by funds that are unconstrained by capital flows. These stocks are identified using a "pressure" variable that is calculated as the net change in mutual fund holdings, scaled by the average monthly trading volume for the stock. Abnormal *PRESSURE* is calculated by subtracting the monthly average from each observation. All reported statistics are calculated from the time series of monthly averages of abnormal returns and abnormal *PRESSURE*, requiring at least 25 firms during the event quarter. Test statistics are calculated using the standard error of the mean, and are in parentheses. The number of quarterly observations is denoted by *N*.

T	AAR (%)	*t*-statistic	*CAAR* (%)	*t*-statistic	Avg. abnormal *PRESSURE* (%)	*t*-statistic	*N*
A: Flow-induced selling by mutual funds ("fire sales")							
−12	−1.19	(−1.54)	−1.19	(−1.54)	−0.08		
−11	−0.21	(−0.33)	−1.40	(−1.32)	−0.08		
−10	−0.74	(−0.89)	−2.14	(−1.59)	−0.08	(−1.21)	18
−9	−1.10	(−1.41)	−3.24	(−2.08)	−0.35		
−8	−0.92	(−0.90)	−4.16	(−2.26)	−0.35		
−7	−0.76	(−0.88)	−4.92	(−2.43)	−0.35	(−2.12)	18
−6	−0.80	(−1.24)	−5.72	(−2.72)	−0.33		
−5	−0.86	(−0.85)	−6.58	(−2.84)	−0.33		
−4	−0.51	(−0.51)	−7.09	(−2.85)	−0.33	(−1.84)	18
−3	−0.38	(−0.71)	−7.47	(−2.92)	−0.55		
−2	−1.94	(−2.04)	−9.41	(−3.40)	−0.55		
−1	−1.60	(−1.62)	−11.01	(−3.73)	−0.55	(−2.30)	18
Event 1	−2.17	(−2.26)	−13.18	(−4.21)	−2.15		
Event 2	−1.28	(−1.20)	−14.46	(−4.38)	−2.15		
Event 3	−0.53	(−0.63)	−14.99	(−4.39)	−2.15	(−13.66)	18
1	1.13	(1.84)	−13.86	(−3.79)	0.33		
2	0.67	(0.84)	−13.19	(−3.47)	0.33		
3	0.31	(0.39)	−12.88	(−3.28)	0.33	(2.33)	18
4	0.42	(0.65)	−12.46	(−3.05)	−0.06		
5	0.66	(0.65)	−11.80	(−2.82)	−0.06		
6	0.45	(0.79)	−11.35	(−2.58)	−0.06	(-0.56)	18
7	−0.37	(−0.62)	−11.72	(−2.66)	−0.07		

8	1.34	(1.55)	−10.38	(−2.28)	−0.07		
9	0.72	(0.96)	−9.66	(−2.03)	−0.07	(−1.09)	18
10	−1.24	(−1.39)	−10.90	(−2.27)	−0.16		
11	0.97	(1.39)	−9.93	(−1.95)	−0.16		
12	1.07	(1.53)	−8.86	(−1.62)	−0.16	(−0.80)	18
13	−1.42	(−1.62)	−10.28	(−1.90)	−0.06		
14	0.65	(0.97)	−9.63	(−1.69)	−0.06		
15	1.38	(2.68)	−8.25	(−1.17)	−0.06	(−1.04)	18
16	0.01	(0.01)	−8.24	(−1.15)	0.03		
17	1.47	(1.99)	−6.77	(−0.78)	0.03		
18	1.43	(2.11)	−5.34	(−0.40)	0.03	(0.46)	18
	Event Period [*t*-6, *t*]		−10.07	(−3.68)			
	Event Period [*t*-3, *t*]		−7.90	(−3.45)			
	Post Event [$t+1$, $t+3$]		2.11	(1.77)			
	Post Event [$t+1$, $t+12$]		6.13	(2.47)			
	Post Event [$t+1$, $t+18$]		9.65	(3.47)			

B: Discretionary selling by mutual funds

−12	−0.33	(−0.69)	−0.33	(−0.69)	0.07		
−11	−0.18	(−0.36)	−0.51	(−0.75)	0.07		
−10	−0.40	(−0.97)	−0.91	(−1.17)	0.07	(1.03)	27
−9	−0.72	(−1.71)	−1.63	(−1.87)	−0.01		
−8	−0.84	(−1.46)	−2.47	(−2.33)	−0.01		
−7	0.04	(0.08)	−2.43	(−2.09)	−0.01	(−0.17)	27
−6	−1.02	(−1.93)	−3.45	(−2.66)	0.01		
−5	0.21	(0.36)	−3.24	(−2.36)	0.01		
−4	−1.20	(−2.02)	−4.44	(−2.90)	0.01	(0.07)	27
−3	−3.04	(−6.29)	−7.48	(−4.74)	−0.02		
−2	−1.20	(−2.02)	−8.68	(−5.13)	−0.02		
−1	−1.71	(−2.68)	−10.39	(−5.69)	−0.02	(−0.26)	27
Event 1	−2.77	(−4.80)	−13.16	(−6.80)	−0.07		
Event 2	−0.66	(−1.49)	−13.82	(−6.95)	−0.07		
Event 3	−0.82	(−1.56)	−14.64	(−7.11)	−0.07	(−1.11)	27
1	0.02	(0.05)	−14.62	(−6.88)	−0.07		
2	0.53	(0.96)	−14.09	(−6.44)	−0.07		
3	−0.02	(−0.03)	−14.11	(−6.26)	−0.07	(−0.61)	27
4	−0.64	(−1.20)	−14.75	(−6.37)	−0.13		
5	0.79	(1.53)	−13.96	(−5.87)	−0.13		

Table 4 (*continued*)

T	AAR (%)	t-statistic	*CAAR* (%)	*t*-statistic	Avg. abnormal *PRESSURE* (%)	*t*-statistic	*N*
6	−0.42	(−1.16)	−14.38	(−5.98)	−0.13	(−2.53)	27
7	0.08	(0.13)	−14.30	(−5.82)	−0.13		
8	0.31	(0.55)	−13.99	(−5.57)	−0.13		
9	−0.10	(−0.25)	−14.09	(−5.51)	−0.13	(−1.11)	27
10	−0.36	(−0.64)	−14.45	(−5.53)	−0.04		
11	−0.03	(−0.07)	−14.48	(−5.43)	−0.04		
12	0.21	(0.51)	−14.27	(−5.23)	10.04	(−0.42)	27
13	−0.81	(−1.28)	−15.08	(−5.38)	−0.11		
14	0.19	(0.37)	−14.89	(−5.22)	−0.11		
15	1.11	(1.84)	−13.78	(−4.80)	−0.11	(−1.48)	27
16	−0.65	(−1.21)	−14.43	(−4.93)	−0.16		
17	0.29	(0.53)	−14.14	(−4.76)	−0.16		
18	0.14	(0.32)	−14.00	(−4.63)	−0.16	(−1.19)	27
	Event Period [*t*-6, *t*]		−12.21	(−7.48)			
	Event Period [*t*-3, *t*]		−10.20	(−7.69)			
	Post Event [$t+1$, $t+3$]		0.53	(0.56)			
	Post Event [$t+1$, $t+12$]		0.37	(0.11)			
	Post Event [$t+1$, $t+18$]		0.64	(0.22)			

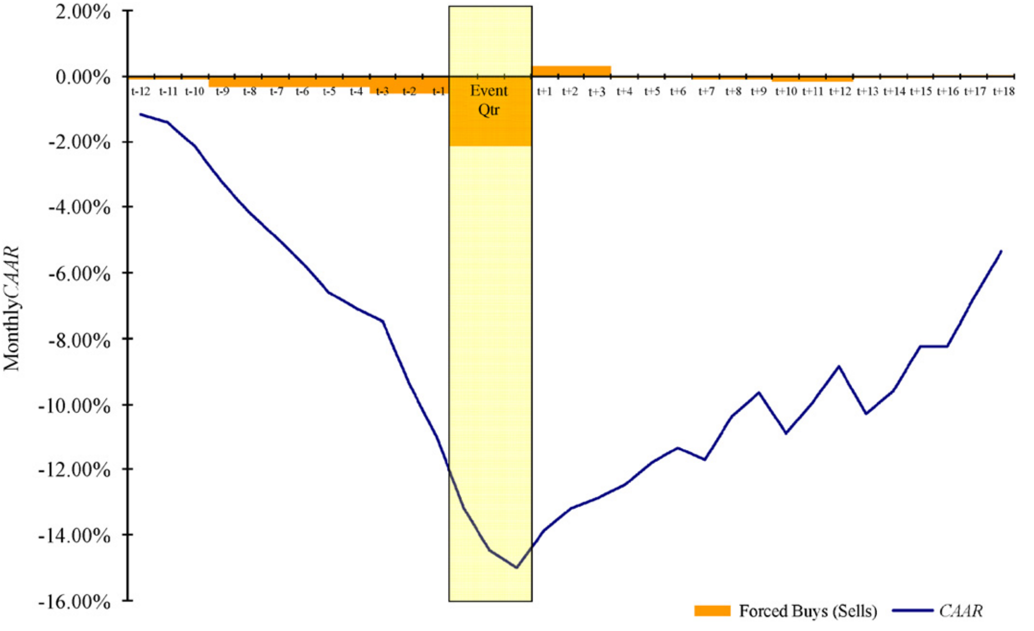

Fig. 2. Cumulative average abnormal returns around mutual fund fire sales. Cumulative average abnormal returns (*CAAR*s) are measured monthly returns in excess of the equal-weighted average return of all stocks held by mutual funds at the start of the month. Each month the average of monthly abnormal return is calculated, and then the time-series mean and standard error of the mean are used for statistical inference. Transactions are identified as "forced" based on their capital flows as a percentage of their beginning-of-period total net assets. Fire sales are identified at the stock level based on net selling pressure below the 10th percentile.

$$PRESSURE\_1_{i,t} = \frac{\sum_j \left(\max(0, \Delta Holdings_{j,i,t}) | flow_{j,t} > Percentile(90th)\right) - \sum_j \left(\max(0, -\Delta Holdings_{j,i,t}) | flow_{j,t} < Percentile(10th)\right)}{Avg\ Volume_{i,t-12:t-6}}.$$

severe distressed selling of the same stock, the average abnormal stock return is −7.9% with a *t*-statistic of −3.45. Over the quarter in which fire sales are occurring, the net forced selling pressure accounts for roughly 2% of average volume.

Importantly, the downward pattern in abnormal returns eventually reverses once the net forced sales dissipate. Over the 12 months that follow the fire sale quarter, average abnormal net forced selling pressure retreats to roughly 0%, and stock prices for the fire sale stocks rebound 6.13% over this period, with a *t*-statistic of 2.47. The modest statistical significance of the result is due to our conservative approach to measuring standard errors. By grouping all firms that share an event quarter, averaging the returns if at least 25 firms share the same quarter, and treating their average return as a single observation, we end up with only 18 quarters with firms with extreme flow-induced selling. Nevertheless, the high economic significance of the result suggests that flow-induced transactions can be quite costly. This evidence suggests that widespread forced selling by distressed mutual funds exerts significant downward price pressure on the individual stocks sold, well beyond any contemporaneous information effects.

Panel B repeats the calculations of Panel A, but on the subsample of firms subject to widespread selling by unconstrained funds. In particular, the sample is identified by using a version of Eq. (4) that has been altered by removing the condition on *flow* from the calculation. This measure is quite similar to those used by Lakonishok, Shleifev, and Vishny (1992) and Wermers (1999) to identify firms subject to mutual fund trading imbalances. When there is widespread selling by unconstrained funds, the fire sale pattern in abnormal returns is not present. Again, there is a significant price drop over the quarter of widespread selling and the previous quarter. However, this time there is virtually no reversal. This is consistent with voluntary mutual fund trading bringing information into prices and, perhaps more commonly, mutual funds eliminating underperforming holdings Fig. 3.

In Table 5, we report a summary of the results using the samples identified with the alternative share-based pressure measures, along with the original results for easy comparison. As can be seen, the results for the fire sale sample are remarkably similar across the different pressure variables. This suggests that the results are not driven by abnormally low trading volume or by the cutoffs used to identify extreme outflows.

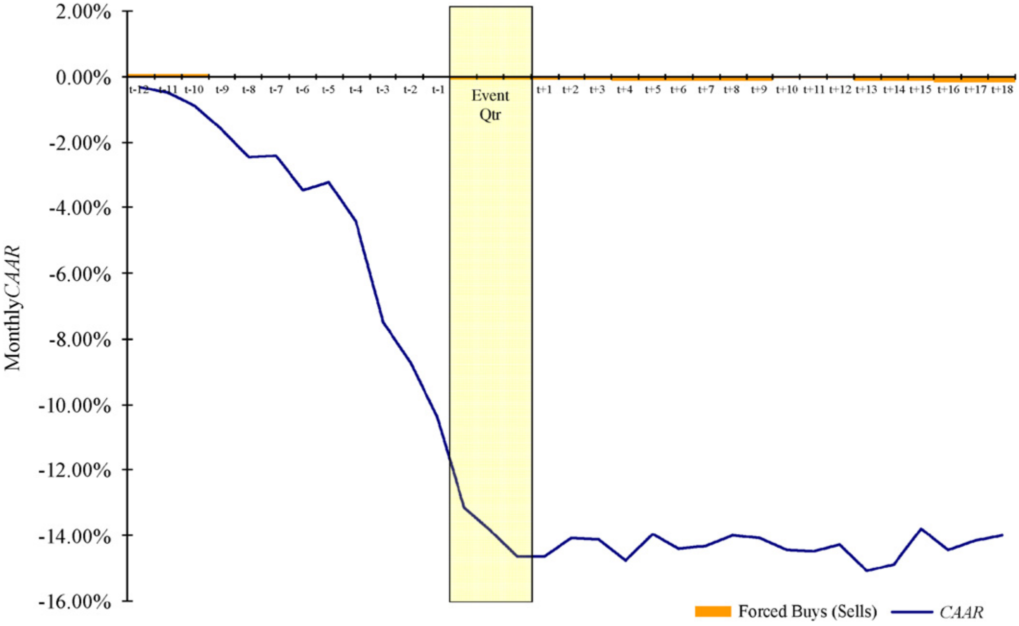

Fig. 3. Cumulative average abnormal returns around voluntary mutual fund sales. Cumulative average abnormal returns (*CAAR*s) are measured monthly returns in excess of the equal-weighted average return of all stocks held by mutual funds at the start of the month. Each month the average of monthly abnormal return is calculated, and then the time-series mean and standard error of the mean are used for statistical inference. Transactions are not conditioned on the capital flows into the fund. Voluntary sales are identified at the stock level based on net selling pressure below the 10th percentile.

$$Unforced\_PRESSURE_{i,t} = \frac{\sum_j \Delta Holdings_{j,i,t}}{Avg\ Volume_{i,t-12:t-6}}.$$

Table 5
Monthly cumulative average abnormal returns for stocks around flow-motivated trading by mutual funds identified with alternative measures

Cumulative average abnormal returns (*CAARs*) are measured monthly returns in excess of the equal-weighted average return of all stocks held by mutual funds at the start of the month. Flow-motivated buys and sales are identified as stocks with extreme values of one of three *PRESSURE* variables.

$$PRESSURE\_1_{i,t} = \frac{\sum_j \big(\max(0, \Delta Holdings_{j,i,t}) | flow_{j,t} > Percentile(90th)\big) - \sum_j \big(\max(0, -\Delta Holdings_{j,i,t}) | flow_{j,t} < Percentile(10th)\big)}{Avg\ Volume_{i,t-12:t-6}},$$

$$PRESSURE\_2_{i,t} = \frac{\sum_j \big(\max(0, flow_{j,t}) \cdot \max(0, \Delta Holdings_{j,i,t})\big) - \sum_j \big(\max(0, -flow_{j,t}) \cdot \max(0, -\Delta Holdings_{j,i,t})\big)}{Avg\ Volume_{i,t-12:t-6}},$$

$$PRESSURE\_3_{i,t} = \frac{\sum_j \big(\max(0, \Delta Holdings_{j,i,t}) | flow_{j,t} > Percentile(90th)\big) - \sum_j \big(\max(0, -\Delta Holdings_{j,i,t}) | flow_{j,t} < Percentile(10th)\big)}{Shares\ Outstanding_{i,t-1}},$$

$$Unforced\_PRESSURE_{i,t} = \frac{\sum_j \Delta Holdings_{j,i,t}}{Avg\ Volume_{i,t-12:t-6}},$$

*PRESSURE*_1 corresponds to the measure defined in Table 4. Flow-motivated transactions are identified at the stock level based on net buying pressure above the 90th percentile for buys and below the 10th percentile for sales. All measures require at least ten owners. All reported statistics are calculated from the time series of monthly averages of abnormal returns, requiring at least 25 events during the month. Test statistics are calculated using the standard error of the mean, and are in parentheses

	PRESSURE_1		*PRESSURE_2*		*PRESSURE_3*		*Unforced*	
	CAAR (%)	*t*-statistic	*CAAR* (%)	*t*-statistic	*CAAR*	*t*-statistic	*CAAR* (%)	*t*-statistic (%)
Flow-motivated sales								
Event Period [*t*-6, *t*]	−10.07	(−3.68)	−13.25	(−5.22)	−10.69	(−3.35)	−12.21	(−7.48)
Event Period [*t*-3, *t*]	−7.90	(−3.45)	−9.77	(−4.64)	−9.72	(−3.66)	−10.20	(−7.69)
Post Event [$t+1$, $t+3$]	2.11	(1.77)	3.28	(2.65)	5.70	(2.85)	0.53	(0.56)
Post Event [$t+1$, $t+12$]	6.13	(2.47)	5.76	(2.18)	8.10	(1.94)	0.37	(0.11)
Post Event [$t+1$, $t+18$]	9.65	(3.47)	7.14	(2.39)	12.40	(2.44)	0.64	(0.22)
Flow-motivated buys								
Event Period [*t*-6, *t*]	6.10	(3.93)	12.59	(6.62)	11.68	(3.58)	10.64	(8.79)
Event Period [*t*-3, *t*]	3.64	(2.58)	8.83	(5.07)	6.42	(2.13)	8.25	(8.08)
Post Event [$t+1$, $t+3$]	0.02	(0.10)	0.28	(0.07)	−2.33	(−1.56)	−0.01	(0.98)
Post Event [$t+1$, $t+12$]	−0.73	(−0.23)	−1.95	(−1.04)	−6.26	(−2.52)	−0.49	(0.41)
Post Event [$t+1$, $t+18$]	−3.86	(−1.87)	−5.46	(−2.21)	−9.53	(−3.00)	−2.80	(−0.99)

We are also interested in any price effects associated with widespread flow-motivated purchasing by mutual funds. The evidence in Table 2 and Fig. 1 suggests that funds with significant capital inflows tend to increase their existing holdings much like the funds experiencing significant outflows tend to reduce their existing positions. In other words, funds facing significant inflows behave as if they too are constrained. As in the fire sale story, if many funds are simultaneously forced to buy the same securities when few others are able to sell—what we will call inflow-driven purchases—transaction prices can occur at a price significantly above fundamental value. We identify inflow-driven purchases using the *PRESSURE* variable. In particular, when *PRESSURE* exceeds the 90th percentile, we consider the stock to be involved in an inflow-driven purchase.

Table 5 reports cumulative abnormal returns for the sample generated by our three pressure variables. On average, these firms have highly significant positive abnormal returns prior to the event quarter. This positive stock price momentum increases over the event quarter as inflow-driven buying increases. The six-month cumulative annual abnormal returns (CAARs), ending at the close of the event quarter, range from 3.6% (t-statistic $= 2.58$) to 8.8% (t-statistic $= 5.07$). As with the fire-sale sample, inflow-driven purchase stocks see their returns reverse during the months that follow the event quarter. The reversal pattern shows more variability using the different pressure variables, ranging from -3.8% (t-statistic $= -1.87$) to -9.5% (t-statistic $= -3.00$) over the next 18 months, and exhibiting the greatest significance in the *PRESSURE_3* sample.

4. Mitigating the costs of fire sales

An important question raised by the above results raise is whether mutual funds take steps to mitigate the costs of flow-motivated trading. A variety of possibilities are available for distressed funds. First, because a portion of their flows is predictable, funds expected to experience outflows could accumulate cash holdings. Because our data on cash holdings are only at an annual frequency, we are unable to investigate this possibility very closely. However, the evidence from Table 2 suggests that little, if any, of this activity takes place. When funds are sorted according to expected flow, funds in the lowest decile of expected flows exhibit slightly higher cash holdings than other funds expecting outflows, but their cash holdings are still below those of the average fund. A second option is to transact in holdings in which the fund expects to face relatively low costs of demanding liquidity. Such holdings might be relatively large firms, more liquid firms, or firms whose past performance has been reasonably favorable. These possibilities are investigated in Table 6.

Table 6 repeats the analysis of Panel B in Table 2, in which funds are sorted according to quarterly flows, and investigates the tendency to maintain, expand, reduce, or eliminate existing positions. Here, we ask whether funds exhibit systematic differences in their selection of positions to maintain, adjust, or eliminate. Panel A measures the average relative size of various holdings. Specifically, we take the ratio of each holding's size to the fund's average holding size and calculate a fund-specific average for holdings that the fund maintains, expands, reduces, and eliminates. Funds are then sorted according to realized flows and the fund-specific averages are then averaged across all funds within each flow decile. Panel B repeats this procedure to assess relative trading volume, measured in dollar terms over the previous quarter. Panel C calculates the difference between each position's return and the return of the fund's average position and then calculates decile averages as above.

Table 6
Mutual fund trading response to actual flows (1980–2004)

This table reports how quarterly mutual fund holdings change conditional on actual fund flows. Mutual fund flows are measured as a percentage of beginning-of-period total net assets (TNA). Mutual fund flows are estimated as the percentage change in TNA over the quarter controlling for capital gains and losses of the initial holdings: $[TNA_t - TNA_{t-1} \times (1 + Return_t)]/TNA_{t-1}$. Fund-quarter observations with available flow data ($N = 142{,}720$) are sorted according to actual quarterly fund flow. Within each decile, Panel A reports the average relative size of fund holdings maintained, expanded, reduced, or eliminated. A holding's relative size is measured as the ratio of its market capitalization to the average market capitalization of the fund's current positions. Panel B reports the average relative trading volume of fund holdings maintained, expanded, reduced, or eliminated, with relative trading volume measured likewise. Panel C reports the average relative return of fund holdings maintained, expanded, reduced, or eliminated. Relative return is measured as the difference between the holding's return over the past year and the average fund holding's return over the past year.

Decile	Maintained (%)	Expanded (%)	Reduced (%)	Eliminated (%)
Panel A: Relative size of holdings				
1 (Inflow)	0.88	1.09	1.06	0.86
2	0.92	1.10	1.16	0.78
3	0.92	1.11	1.13	0.77
4	0.96	1.14	1.11	0.68
5	0.94	1.11	1.14	0.70
6	0.95	1.09	1.12	0.71
7	0.96	1.09	1.18	0.68
8	0.94	1.09	1.18	0.69
9	0.90	1.08	1.15	0.69
10 (Outflow)	0.91	1.03	1.18	0.78
Panel B: Relative trading volume of holdings				
1 (Inflow)	0.90	1.11	1.21	0.80
2	0.86	1.13	1.19	0.85
3	0.96	1.19	1.18	0.82
4	0.91	1.16	1.18	0.79
5	0.91	1.17	1.19	0.74
6	0.92	1.14	1.24	0.75
7	0.92	1.19	1.17	0.75
8	0.96	1.16	1.21	0.76
9	0.90	1.18	1.18	0.80
10 (Outflow)	0.92	1.21	1.17	0.81
Panel C: Relative past return of holdings				
1 (Inflow)	−2.9	1.1	9.5	−9.9
2	−3.6	0.8	8.9	−7.6
3	−3.0	1.8	5.7	−7.9
4	−2.8	1.1	5.2	−6.8
5	−2.8	2.6	4.8	−8.3
6	−2.1	2.0	4.3	−6.3
7	−1.7	1.5	2.6	−7.2
8	−2.5	2.8	1.4	−7.6
9	−1.4	3.7	1.9	−6.3
10 (Outflow)	−2.5	4.0	1.2	−7.2

Several features of this analysis are worth noting. First, funds tend to expand or reduce holdings that are large and liquid compared to those maintained or eliminated. However, there appears to be little evidence that funds experiencing severe flows are more judicious in their selection of holdings to adjust or eliminate. Funds in the top and bottom deciles of flows transact in holdings that are of similar relative size and trading volume as those in the middle deciles. In Panel C, we see that funds tend to eliminate severely underperforming positions, regardless of their experience with flows. In addition, across all flow deciles, funds adjust their positions in firms that have performed relatively well. Funds experiencing inflows tend to reduce their top-performing positions, whereas funds experiencing outflows tend to expand their top performers.

Taken as a whole, the evidence in Table 6 suggests that while funds tend to prefer to transact in larger, more liquid, and better-performing holdings, and to maintain or eliminate other positions, this preference is relatively uniform across flow deciles. Funds experiencing extreme inflows or outflows do not appear to transact with any greater frequency in larger, more liquid, or better-performing holdings than funds that are subject to moderate flows. This suggests that funds experiencing extreme inflows or outflows do not mitigate the costs of their liquidity demands by transacting selectively in holdings. In unreported analysis, we ran the calculations of Table 2 for the subset of funds reported by Almazan, Brown, Corlson, and Chapman (2004) as being unconstrained with respect to the use of margin, short sales, or derivatives. The results are highly similar, consistent with the Almazan et al. findings that, conditional on being unconstrained in the use of margin, short sales, or derivatives, fewer than 10% of funds engage in such activities.

5. Incentives for front-running and providing liquidity

The event-time analysis presented in Section 3 suggests that there is a strong incentive to provide liquidity at times of widespread selling by financially distressed mutual funds. In other words, the buyers in asset fire sales are receiving attractive prices for providing liquidity when few others are able or willing. In addition, because capital flows are predictable, there could also be an incentive to remove liquidity in anticipation of forced sales by front-running the distressed mutual funds. We investigate both of these incentives by studying the portfolio returns to investors following these investment strategies.

5.1. Investment returns following asset fire sales and inflow-driven purchases

The results in Tables 4 and 5 suggest that the buyer in an asset fire sale will, on average, be compensated for providing liquidity. The compensation is realized as prices return to their information-efficient values in subsequent months, and can be detected in the form of positive abnormal returns. To measure the investment performance of buyers in asset fire sales, we calculate the calendar-time portfolio returns to an investment strategy that buys all stocks identified as fire sale stocks within the past year, but not within the most recent quarter. These stocks are identified as those in the bottom decile of one-year average pressure, lagged by one quarter. The restriction that the fire sale has not occurred within the most recent quarter ensures that this is a feasible investment strategy in terms of all required information being publicly available. We measure the investment performance of sellers in inflow-driven purchases in a similar way (i.e., stocks in the top decile of one-year average pressure, lagged by one quarter).

Measuring abnormal returns requires a model of expected returns. We report results using three different models: the CAPM, the Fama-French three-factor model, and a four-factor model that includes momentum; see Fama and French (1993) and Carhart (1997)

Table 7
Calendar-time portfolio regressions of flow-induced mutual fund transactions (1990–2004)

Dependent variables are event portfolio returns, *Rp*, in excess of the one-month Treasury bill rate, *Rf*, observed at the beginning of the month. Each month we form equal- and value-weighted portfolios of all sample firms that have completed the event within a one-year window, lagged one quarter. The event portfolio is rebalanced quarterly to drop all stocks that reach the end of their event period and add all companies that have recently been involved in a flow-driven transaction. The three Fama–French factors are zero-investment portfolios representing the excess return of the market, *Rm– Rf*; the difference between a portfolio of "small" stocks and "big" stocks, SMB; and the difference between a portfolio of "high" book-to-market stocks and "low" book-to-market stocks, HML. The fourth factor, UMD, is the difference between a portfolio of stocks with high past one-year returns minus a portfolio of stocks with low past one-year returns. Stocks recently experiencing outflow-induced sales are identified as those with an average *PRESSURE*_1 below the 10th percentile. Stocks recently experiencing inflow-induced purchases are identified as those with an average *PRESSURE*_1 above the 90th percentile. The firm average of *PRESSURE*_1 is calculated over the previous year, skipping the most recent quarter. A minimum of ten firms in the event portfolio is required. *N* denotes the number of monthly observations and *t*-statistics are in parentheses.

$$Rp_{t+1}\text{-}Rf_{t+1} = a + b(Rm_{t+1}\text{-}Rf_{t+1}) + sSMB_{t+1} + hHML_{t+1} + uUMD_{t+1} + e_{t+1}$$

Equally-weighted						Value-weighted					
Intercept	Rm –Rf	SMB	HML	UMD	R^2/N	Intercept	Rm – Rf	SMB	HML	UMD	R^2/N
A: Recent outflow-induced sales											
0.47%	0.9875				0.6762	0.29%	0.8091				0.6547
(2.11)	(19.28)				180	(1.49)	(18.37)				180
0.05%	1.1765	0.4123	0.6317		0.8078	−0.03%	0.9886	0.1489	0.4990		0.7557
(0.28)	(25.56)	(8.13)	(10.12)		180	(−0.16)	(22.87)	(3.13)	(8.51)		180
0.13%	1.1533	0.4221	0.6159	−0.0712	0.8122	−0.03%	0.9898	0.1484	0.4998	0.0038	0.7557
(0.72)	(24.50)	(8.36)	(9.87)	(−2.01)	180	(−0.18)	(22.14)	(3.09)	(8.44)	(0.11)	180

B: Recent inflow-induced purchases											
−0.50%	1.3028				0.7775	−0.49%	1.1059				0.7846
(−2.20)	(24.94)				180	(−2.58)	(25.47)				180
−0.66%	1.3444	0.2681	0.2129		0.7989	−0.62%	1.1883	0.0243	0.2107		0.7972
(−2.94)	(23.20)	(4.20)	(2.71)		180	(−3.25)	(24.17)	(0.45)	(3.16)		180
−0.32%	1.2487	0.3087	0.1476	−0.2937	0.8476	−0.44%	1.1369	0.0461	0.1757	−0.1576	0.8169
(−1.61)	(23.93)	(5.52)	(2.14)	(−7.48)	180	(−2.35)	(23.52)	(0.89)	(2.74)	(−4.33)	180
C: Long recent outflow-induced sales and short recent inflow-induced purchases											
0.97%	−0.3153				0.1516	0.77%	−0.2968				0.1535
(3.98)	(−5.64)				180	(3.40)	(−5.68)				180
0.71%	−0.1679	0.1442	0.4188		0.2596	0.59%	−0.1997	0.1246	0.2883		0.2128
(3.01)	(−2.76)	(2.15)	(5.07)		180	(2.60)	(−3.40)	(1.92)	(3.62)		180
0.45%	−0.0954	0.1135	0.4682	0.2225	0.3528	0.41%	−0.1471	0.1023	0.3241	0.1613	0.2687
(2.00)	(−1.62)	(1.80)	(6.00)	(5.02)	180	(1.81)	(−2.51)	(1.63)	(4.17)	(3.66)	180

for a description of the construction of the factors.

$$Rp_t - Rf_t = a + b \cdot [Rm_t - Rf_t] + s \cdot SMB_t + h \cdot HML_t + u \cdot UMD_t + e_t. \tag{5}$$

Panel A of Table 7 reports calendar-time portfolio regressions of the investment strategy described above for both equal-weighted and value-weighted portfolios. The intercept from these regressions represents the average monthly abnormal return, given the model. The intercepts range from -0.03% per month (t-statistic $= -0.15$) to 0.47% per month (t-statistic $= 2.11$). Although the alphas are, for some of the models, economically attractive, the strategy is a highly volatile stand-alone investment strategy. The positive loadings on size and HML are interesting, suggesting that the stocks covary significantly with small growth firms.

The second panel in Table 7 displays performance results for an investment strategy that sells stocks involved in an inflow-driven purchase during the past year but not the past quarter. Here again, the average abnormal returns are economically large but of mixed statistical significance, ranging from -0.32% per month (t-statistic $= -1.61$) to -0.66% per month (t-statistic $= -2.94$). Again, loadings on SMB and HML are positive and highly significant. The final panel in Table 7 shows the results from combining the two strategies described above into a long-short investment strategy. The same basic pattern emerges. The returns are similar for both the equal-weighted and value-weighted portfolios: large in economic terms, with monthly abnormal returns ranging from 0.41% (t-statistic $= 1.81$) to 0.97% (t-statistic $= 3.98$), and reasonable statistical reliability. These results verify that those of the event study setting are not merely artifacts of a failure to properly control for risk.

5.2. Investment returns to those anticipating asset fire sales and inflow-driven purchases

The evidence presented thus far suggests that there is a powerful incentive to try to anticipate widespread forced buying and selling by constrained mutual funds. There is a real possibility that this is feasible because capital flows to mutual funds are reasonably well explained by lagged flows and returns. Using the regression model presented in Table 1, we forecast expected flows to mutual funds and identify anticipated fire sale and inflow-driven purchase stocks using the procedure described in Section 3, substituting expected flows for actual flows:

$$\mathrm{E}_t\left[PRESSURE_{i,t+1}\right] = \frac{\sum_j \left(Holdings_{j,i,t} | \mathrm{E}_t[flow_{j,t+1}] > Percentile(90th)\right) - \sum_j \left(Holdings_{j,i,t} | \mathrm{E}_t[flow_{j,t+1}] < Percentile(10th)\right)}{\sum_j Holdings_{j,i,t}}. \tag{6}$$

Table 8 reports calendar-time portfolio regressions for an investment strategy that invests in stocks when a fire sale or inflow-driven purchase is anticipated. Specifically, anticipated fire sale stocks are identified as those with an expected pressure below the 10th percentile (reported in Panel B), while anticipated inflow-driven purchase stocks are those with an expected pressure above the 90th percentile (reported in Panel A). The predictability of flows offers non-trivial compensation to those that trade in anticipation of severe flows. Stocks whose owners are expected to experience severe outflows lose between 0.16% (t-statistic $= 0.64$) and 0.68% (t-statistic $= 2.82$) over the subsequent

Table 8

Calendar-Time Portfolio Regressions of Anticipated Mutual Fund Forced Transactions (1990–2004)

Dependent variables are event portfolio returns, *Rp*, in excess of the one-month Treasury bill rate, *Rf*, observed at the beginning of the month. Each month we form equal- and value-weighted portfolios of all sample firms that are expected to complete the event within the next month. The three Fama-French factors are zero-investment portfolios representing the excess return of the market, *Rm-Rf*; the difference between a portfolio of ''small'' stocks and ''big'' stocks, SMB; and the difference between a portfolio of ''high'' book-to-market stocks and ''low'' book-to-market stocks, HML. The fourth factor, UMD, is the difference between a portfolio of stocks with high past one-year returns minus a portfolio of stocks with low past one-year returns. Anticipated fire sales are identified each month as stocks with $E_t[PRESSURE_{t+1}]$ in the bottom decile. Anticipated inflow-driven purchases are identified each month as stocks with $E_t[PRESSURE_{t+1}]$ in the top decile. $E_t[PRESSURE_{t+1}]$ is a stock-level variable, calculated each month as the number of shares held by mutual funds with expected flows above the 90th percentile, minus the number of shares held by mutual funds with flows below the 10th percentile, scaled by the average monthly volume of the stock, requiring at least ten owners. A minimum of ten firms in the event portfolio is required. The number of monthly observations is denoted by *N* and *t*-statistics are in parentheses.

$$Rp_{t+1}\text{-}Rf_{t+1} = a + b(Rm_{t+1}\text{-}Rf_{t+1}) + sSMB_{t+1} + hHML_{t+1} + uUMD_{t+1} + e_{t+1}$$

Equally-weighted						Value-weighted					
Intercept	Rm–Rf	SMB	HML	UMD	R^2/N	Intercept	Rm–Rf	SMB	HML	UMD	R^2/N
A: Stocks expected to be in an inflow-driven purchase over the next month											
0.74%	0.8930				0.6502	0.55%	0.8894				0.6722
(3.31)	(16.92)				156	(2.59)	(17.77)				156
0.39%	0.9536	0.5243	0.3322		0.8027	0.35%	0.9139	0.3405	0.1830		0.7391
(2.17)	(20.33)	(10.82)	(5.52)		156	(1.73)	(17.30)	(6.24)	(2.70)		156
0.29%	0.9848	0.5062	0.3484	0.0861	0.8109	0.08%	1.0005	0.2905	0.2276	0.2385	0.8044
(1.62)	(20.66)	(10.52)	(5.86)	(2.55)	156	(0.45)	(21.07)	(6.06)	(3.84)	(7.10)	156
B: Stocks expected to be in a fire sale over the next month											
−0.20%	1.0011				0.6277	−0.16%	0.9017				0.5967
(−0.74)	(16.11)				156	(−0.64)	(15.09)				156
−0.68%	1.1763	0.3609	0.5230		0.7182	−0.51%	1.1081	−0.0509	0.4355		0.6859
(−2.82)	(18.39)	(5.46)	(6.37)		156	(−2.16)	(17.76)	(−0.79)	(5.44)		156
−0.36%	1.0711	0.4216	0.4687	−0.2899	0.7892	−0.27%	1.0288	−0.0052	0.3946	−0.2184	0.7331
(−1.68)	(18.66)	(7.28)	(6.54)	(−7.14)	156	(−1.19)	(17.24)	(−0.09)	(5.30)	(−5.17)	156

Table 8 (*continued*)

Equal-weighted						Value-weighted					
Intercept	Rm–Rf	SMB	HML	UMD	R^2/N	Intercept	Rm–Rf	SMB	HML	UMD	R^2/N
C: Long stocks expected to be in an inflow-driven purchase over the next month and short stocks expected to be in a fire sale over the next month											
0.94%	−0.1081				0.0155	0.71%	−0.0123				0.0001
(3.18)	(−1.56)				156	(1.96)	(−0.14)				156
1.07%	−0.2228	0.1634	−0.1907		0.0988	0.86%	−0.1942	0.3914	−0.2525		0.2041
(3.59)	(−2.84)	(2.01)	(−1.89)		156	(2.50)	(−2.15)	(4.20)	(−2.18)		156
0.65%	−0.0863	0.0846	−0.1203	0.3760	0.3524	0.35%	−0.0283	0.2957	−0.1670	0.4569	0.4553
(2.51)	(−1.25)	(1.21)	(−1.40)	(7.69)	156	(1.20)	(−0.37)	(3.79)	(−1.73)	(8.34)	156

month. Stocks with many owners anticipating inflows outperform by 0.08% (t-statistic = 0.45) to 0.74% (t-statistic = 3.31) during the following month. However, both sets of results are of mixed statistical reliability. Finally, the long-short strategy that combines these two strategies produces fairly large abnormal returns, ranging from 0.35% per month (t-statistic = 1.20) to 1.07% per month (t-statistic = 3.59). Controlling for momentum reduces the abnormal returns by roughly half, but leaves 0.35–0.65% per month abnormal return unexplained. The coefficients on the momentum portfolio are around 0.4, which highlights how, because mutual fund flows are highly sensitive to past performance, the transactions (and forecasted transactions) of mutual funds due to these flows tend to overlap with the stocks identified by a momentum strategy. Finally, given that the above strategies require roughly quarterly turnover and do not entail trading in stocks that are small or illiquid, it is unlikely that our return estimates will be severely moderated by transaction costs.

5.3. Robustness

The 10% and 90% cutoffs we employ for most of our results are somewhat arbitrary. Indeed, many of our results should be continuous and increasing in the severity of our pressure variables. In Table 9, we investigate whether this predicted cross-sectional relation holds. Following Fama and MacBeth (1973), we regress monthly returns on a variety of variables known to explain return differences and include in these month-by-month regressions our actual and expected pressure variables, and then use the time-series mean and standard error for statistical inference. Specifically, we regress a stock's monthly return on the market, its size, its book-to-market ratio, its lagged one-month return, its lagged 11-month return ending one month prior, its 24-month return ending 12 months prior, and its three-year net equity issuance variable as defined in Daniel and Titman (2006). We also include pressure expected at the start of the month ($E_t[Pressure_{t+1}]$) and the average value of the pressure experienced over the past year.

As Table 9 reveals, the coefficient on past pressure is negative and significant across all specifications, verifying once again the transitory price impact caused by flow-induced transactions. The coefficients on expected pressure are also in the predicted direction, although statistical significance is somewhat mixed, particularly in the presence of the seven controls.

6. Persistence of institutional price pressure

6.1. The role of information and agency costs

Care must be taken in interpreting the calendar-time portfolio regression analysis. The estimates of average abnormal returns ignore two important costs (Merton, 1987). The first is the cost of generally becoming informed about the investment strategy. Our estimates are based on the period from 1980 to 2004, coinciding with the availability of the necessary data. Importantly, prices over this period were set by investors who did not have access to these data and whose assessments of the risks and returns associated with the strategy were surely less precise than those presented in the tables. Even now, the results, while economically enticing, are only marginally significant when taken as a whole. Second, once the general strategy is recognized as potentially profitable, there are the

Table 9

Fama-macbeth cross-sectional regressions of monthly stock returns (1990–2004)

Dependent variables are monthly stock returns, $R_{i,t+1}$, in excess of the one-month Treasury bill rate, Rf, observed at the beginning of the month. $\mathrm{E}_t[PRESSURE_{t+1}]$ is a stock-level variable, calculated each month as the number of shares held by mutual funds with expected flows above the 90th percentile, minus the number of shares held by mutual funds with flows below the 10th percentile, scaled by the average monthly volume of the stock, requiring at least ten owners. *Average Pressure*$_t$ is the one-year average value of *PRESSURE*, lagged one-quarter. Beta is the slope coefficient from a 36-month market model regression, using the CRSP value-weighted portfolio as the market proxy. BE/ME is the ratio of book equity to market equity following the definition in Fama-French (1993). R_t is the one-month lagged return; $R_{t-12:t-1}$ is the 11-month lagged return ending one month prior; $R_{t-36:t-13}$ is the 24-month lagged return ending 12 months prior. Net Equity Issuance measures the three-year composite share issuance variable defined by Daniel and Titman (2006). The table reports average coefficients from 151 monthly cross-sectional regressions. The averages are time-series means with t-statistics (in parentheses) corresponding to the standard error of the mean. R^2 is the average cross-sectional R^2. N denotes the average number of cross-sectional observations.

Int	E_t[Pressure$_{t+1}$]	Average pressure$_{t-3}$	Beta	Size	BE/ME	R_t	$R_{t-12:t-1}$	$R_{t-36:t-13}$	Net equity issuance	R^2 [N]
PRESSURE_1										
0.0096	0.0096	−0.0257								0.0085
(2.30)	(2.30)	(−2.34)								[1,017]
0.0178	0.0026	−0.0171	0.0022	−0.0006	0.0010	−0.0278	0.0086	−0.0019	−0.0042	0.1060
(1.36)	(0.98)	(−2.46)	(0.86)	(−0.79)	(1.05)	(−3.50)	(2.50)	(−1.16)	(−3.54)	[1,017]
PRESSURE_2										
0.0095	0.1281	−0.1595								0.0149
(2.51)	(2.00)	(−2.89)								[1,017]
0.0159	0.0689	−0.0991	0.0022	−0.0005	0.0010	−0.0281	0.0086	−0.0018	−0.0044	0.1074
(1.23)	(1.93)	(−2.60)	(0.86)	(−0.66)	(1.08)	(−3.55)	(2.55)	(−1.10)	(−3.69)	[1,017]
PRESSURE_3										
0.0095	0.1232	−0.0004								0.0186
(2.51)	(1.98)	(−2.44)								[1,017]
0.0157	0.0655	−0.0002	0.0024	−0.0005	0.0010	−0.0282	0.0086	−0.0015	−0.0043	0.1075
(1.22)	(1.84)	(−2.23)	(0.93)	(−0.67)	(1.11)	(−3.56)	(2.52)	(−0.95)	(−3.54)	[1,017]

information acquisition costs associated with the individual securities, which have not yet been borne by the eventual liquidity providers. These costs, too are not included in the measured abnormal returns.

In some sense, we have documented that equities are in fact specialized assets. The fire sale story begins with the idea that assets are specialized which, in the short run, fixes the pool of potential buyers and sellers who fully value the asset. In the case of stocks, where the information relevant for pricing is costly to obtain, specialization will arise around who has and regularly collects this information. In extreme situations, when a majority of the funds that are informed about an individual stock are unable to voluntarily trade, price setting could fall on funds that have not yet invested in the relevant information. These costs are surely positive, and potentially quite large. The evidence on funds experiencing significant inflows behaving as if they are constrained is consistent with these costs being large. The fact that these additional costs occasionally apply produces time variation in transaction costs. Market prices might not be perfectly efficient, in that prices do not reflect all available information at every point in time, but they could well be within the bounds of time-varying transaction and information costs in a dynamic version of Grossman and Stiglitz (1980).

An interesting consequence of significant institutional price pressure in conjunction with a strong fund performance-flow relation is that the price pressure can spill over into subsequent periods (Shleifer and Vishny, 1997; Shleifer, 2000). There are actually two spillover effects. One is the own-fund spillover, where a fund's buying or selling of its existing positions mechanically improves or degrades its own performance, which affects capital flows in the subsequent period. Another spillover occurs across funds when the initial institutional price pressure affects marginal funds that would not face capital flows in the absence of this price pressure. However, their performance is sufficiently affected by institutional price pressure, that their capital flows are altered the subsequent quarter, forcing them to transact with a lag. This sequence of events results in persistent mispricing, which can get worse before being eliminated.

6.2. Economic significance

The economic significance of these results can be interpreted from two distinct perspectives. Conditional on occurring, forced transactions appear to be fairly costly for funds invested in these stocks. The average holding in our baseline flow-induced trading sample experiences a maximum mispricing of roughly 10%. If transactions are uniformly spread across this price decline, the average fund is forced to sell at a 5% discount to fair value, representing a relatively significant hit to fund performance. On the other hand, considering that less than one percent of the stocks in our sample are subject to widespread flow-induced selling during a given quarter, a fund faces relatively trivial ex ante expected costs from the possibility of being forced by fund outflows to sell holdings at discounted prices. To the extent that flow-induced selling occurs much more frequently but to a lesser degree than documented here, integrating over such unmeasured effects could yield results that are more economically important.

6.3. Implications

An interesting implication of the persistent institutional price pressure relates to the performance evaluation of fund managers. Over moderately long periods of several quarters, the evidence suggests that some portion of performance can, at times, be attributed to price pressure, which will eventually reverse. In many applications of performance evaluation, one would want to control for this effect. Additionally, to the extent that fund managers understand these effects, perverse incentives could exist to exploit the own-fund price pressure of trades to "dress," or temporarily enhance, performance, and thereby induce subsequent flows. Since capital flows appear to be more sensitive to good performance than to poor performance,[10] the eventual reversal of the price pressure could not adversely affect capital flows enough to fully offset the initial benefits. The likelihood of a single fund being able to create sufficiently persistent price pressure as to induce meaningful capital inflows is low, but a fund family could well be able to coordinate across its own funds to make such a strategy worthwhile.

Given that mutual funds cannot easily coordinate with other funds, the contemporaneous selling of overlapping holdings, combined with an outsider's ability to predict which funds will be forced to transact, gives rise to an incentive for predatory trading (Brunnermeier and Pedersen, 2005). This can create a situation where arbitrageurs have an incentive to destabilize prices relative to informationally efficient values by exploiting firms that have chosen a capital structure and organizational form that relies on immediately demandable capital.

6.4. Possibilities for future research

The cycle whereby capital flows can force widespread trading in individual securities, resulting in institutional price pressure, which in turn affects fund performance and eventually feeds back into capital flows, is intriguing. Two possible extensions could warrant additional research. First, the relation to the momentum effect is enticing. This cycle could well describe the mechanics of why stocks that do well or poorly continue to do so. The evidence presented here suggests that the simple liquidity-motivated strategies we examine are highly correlated with momentum, but offer abnormal returns beyond the momentum factor. A second research avenue is to examine the role of this cycle in explaining the unusual pricing of technology stocks in the late 1990s. Casual empiricism suggests that focused sector funds holding concentrated positions in technology stocks initially outperformed the broader indices and consequently received large inflows, which they piled into their existing holdings. This, in turn, boosted their performance and led to additional inflows.

7. Conclusion

This paper studies asset fire sales, and institutional price pressure more generally, in equity markets by examining a large sample of stock transactions of mutual funds. We find considerable support for the notion that widespread selling by financially distressed mutual funds leads to transaction prices below fundamental value. Somewhat surprisingly, we find that funds with large inflows behave as if they too are constrained to quickly transact in their existing positions, on average buying more of what they already own. When inflow-driven purchases are widespread relative to the potential sellers of individual securities, these forced purchases also result in persistent institutional price pressure. These findings

[10]See, for example, Chevalier and Ellison (1997) and Sirri and Tufano (1998).

suggest that even in the most liquid markets there can be a significant premium for immediacy. The price effects are relatively long-lived, lasting around two quarters and taking several more quarters to reverse. This evidence adds to previous findings of price pressure effects around index additions and stock-financed mergers. Short-run excess demand curves for stocks appear to be less than perfectly elastic.

Asset fire sales and inflow-driven purchases are probably the most significant cost of financial distress for money management firms. Given that most of these firms have selected an organizational form that allows capital providers to add or withdraw capital on demand, this suggests that the expected costs of liquidity provision are low. However, when many funds are forced to transact the same stocks at the same time, the price impact can be substantial.

The existence of institutional price pressure in equity markets is informative about the organization of money management firms and, in turn, the effect that these organizations have on prices. First, it suggests that the costs associated with being informed about an individual security can be substantial. Merton (1987) argues that large fixed costs of becoming informed about an investment opportunity can initially limit arbitrage investing, and once the costs are borne, it can take a while to learn how best to exploit the opportunity. Moreover, these costs can lead firms to specialize. Specialization limits the ability to diversify, exposing firms to additional risks, which Shleifer and Vishny (1997) describe as limits to arbitrage. It certainly appears that many funds follow highly similar strategies, such that there are times when many face redemptions and are contemporaneously forced to transact the same securities. In addition, it seems that it takes a while for forced transactions to be understood by strategy outsiders, creating time variation in transaction costs, and allowing prices to deviate from their fundamental value for several months. Importantly, the asset fire sale story provides a mechanism for rational mispricing. The market is clearly somewhat inefficient, in that market prices are not perfectly reflective of all available information. However, the basis of this mispricing requires neither irrational investors nor managers. Prices eventually reflect available information, but sometimes with a significant delay.

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