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The Information in Asset Fire Sales

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Abstract

Asset prices remain depressed for years following mutual fund re sales. We show that price pressure from re sales is partly due to asymmetric information. We separate trades into expected trades, which assume fund managers scale down their portfolio, and discretionary trades. We nd that discretionary trades contain information about future returns, while expected trades do not. Moreover, other traders cannot distinguish between discretionary and expected trades. Our ndings help explain the magnitude and persistence of re sale discounts: fund managers *choose* which assets to sell and information asymmetries make it di -cult for arbitrageurs to disentangle price pressure from negative fundamentals.

Keywords: adverse selection, asymmetric information, re sales, slow moving capital

JEL Classi cation Numbers: E22, G01, G12, G14

I. Introduction

counts. In many ways, mutual funds are an ideal setting for examining whether information asymmetries matter during fire sales. Our sample of U.S. equity mutual funds holds liquid assets that are not subject to significant limits to arbitrage.[2] These assets do not have a specialized use; they represent claims on future cash flows. Moreover, mutual fund fire sales occur frequently, not just during periods of financial crisis when many investors are constrained at the same time.[3] Finally, and most importantly, mutual funds allow us to precisely measure whether asset managers use information when determining which asset to liquidate.

While many of the possible explanations for fire sales discounts seem unlikely to explain price pressure in equities, it is also not obvious that information asymmetries matter in this setting. A number of papers document evidence that mutual fund mangers are not skilled (e.g., Carhart (1997)). As such, it is unclear, a priori, whether fire sale discounts in equities are a result of information asymmetries. Indeed, it is somewhat surprising that equity mutual funds experience fire sale discounts at all. Mutual fund fire sales are common knowledge events. Mutual fund holdings are publicly released at regular intervals. Moreover, although mutual fund flows are not instantaneously viewable, a number of papers argue that fire sale price pressure is predictable (e.g., Coval and Stafford (2007), Shive and Yun (2012), Dyakov and Verbeek (2013), Arif, Ben-Rephael, and Lee (2016)). Together, these facts beg an important question: why don't arbitrageurs correct mispricing from fire sales sooner?

Our results provide an explanation for the long-lasting impact of price pressure from mutual fund fire sales. Specifically, we show that mutual fund managers do not randomly sell stocks when they experience a flow shock, but rather, they *choose* to sell those stocks which they believe will perform poorly in the future. Moreover, we find evidence that these

[2] In our setting, mutual fund fire sales are associated with price drops in common U.S. equity securities. To trade on these mispricings, an investors need only purchase the stocks, as such, transaction costs are unlikely to explain the magnitude of the mispricings in our sample.

[3] Consistent with Shleifer and Vishny (1992), we find that times of market stress are associated with significantly stronger fire sale discounts. However, in our main tests, we include date or date industry fixed effects in all of our regression specifications to absorb the impact of macro-economic conditions. As a result, our findings are not driven by aggregate fluctuations in the ability of arbitrageurs to trade on mispricings.

managers are more likely to sell stocks with bad fundamentals: on average, the stocks they sell experience severe price drops that do not subsequently rebound. In other words, part of the observed under-performance of fire sales stocks is due to negative fundamental information: fund managers choose to sell assets that are likely to under-perform going forward, and the resulting information asymmetries makes it difficult for arbitragers to disentangle price pressure from negative fundamental information. Consistent with this, we find that the Sharpe ratio to unconditionally purchasing all fire sale stocks is only 0.02. Thus, while fire sale stocks earn predictably higher future returns, a subset of these stocks perform badly which leads to a high standard deviation in fire sale stock returns; this prevents a natural buyer from stepping in to buy these assets sooner.

We start by examining how managers trade after a flow shock. Following a large negative flow shock, fund managers decrease their positions in 43.2% of their holdings, while 37.2% of their positions remain unchanged. More surprisingly, fund managers actually increase their holdings in 19.6% of securities.[4] In other words, fund managers continue to purchase securities even as their fund is shrinking in size. The results show that fund managers do not simply scale their fund down to meet redemptions, they *choose* which assets to sell.

In order to examine whether fund managers use fundamental information to make trading decisions, we next decompose the trades of fund managers into (i) *expected trading* and (ii) *discretionary trading*. *Expected trading* measures the portion of actual fund manager trades that would be expected if the fund manager simply prorated flow shocks across each asset in her portfolio. The intuition is simple: imagine a fund manager who has 40% of her portfolio allocated to stock A and the remaining 60% allocated to stock B. If the manager has no fundamental information about asset values, then following an outflow of $5 we would expect her to sell $5 × 40% = $2 of stock A and $5 × 60% = $3 of stock B. Put differently, the *expected trading* down so that all assets maintain a constant weight in the portfolio. In contrast, our second measure of trading, *discretionary trading*, measures the portion of actual trades that were not *expected*. As such, it measures the portion of fund manager trades that are discretionary and likely to be motivated by fund manager beliefs.

We show that *discretionary trading* is related to fundamental information, but *expected trading* is not. To do this, we use two proxy variables to measure negative information about a stock: short interest and future earnings surprises.[5] Both variables have been extensively studied in the existing literature. A large literature has shown that short sellers are skilled at identifying overvalued securities; stocks with high short interest today earn lower returns in the future (e.g., Senchack and Starks (1993); Boehmer, Jones, and Zhang (2008)). Similarly, future earnings surprise allows us to measure whether fund managers use information about rm fundamentals when trading in response to a ow shock. We nd that they do.

Following a large negative ow shock, a one-standard deviation increase in short selling is associated with discretionary sales that are 22% larger relative to their unconditional mean. Put di erently, after an out ow, fund managers are signi cantly more likely to sell stocks that have high short interest.[6] Similarly, we nd that a one-standard deviation increase in positive future earnings surprises is associated with discretionary sales that are 9% smaller relative to their unconditional mean. In other words, fund managers choose to sell less shares in stocks that beat earnings expectations in the next quarter, suggesting their trades are motivated by fundamental information. Finally, we examine *expected* sales as a placebo test; we nd no relation between *expected* sales and either short interest or future earnings surprises.

We then examine the stock return implications of *expected* and *discretionary trading*, and relat(rter,lTd [((In)ns)-317ns)-317na-282lna-282lne8tfsale.xaTd [ie27(iar)-27(y)-40465(return)-3 marizes our main result. Panel A displays cumulative average abnormal returns around all re sale stocks, while Panel B decomposes these sales into *expected* and *discretionary* components. In Panel A, the re sale result is immediately apparent: stocks that are sold

However, a number of papers do find evidence that mutual fund managers are skilled.[8] For example, Chen, Jegadeesh, and Wermers (2000) find that stocks purchases by mutual funds outperform stocks sold by mutual funds. Similarly, Alexander, Cici, and Gibson (2007) find that mutual funds tend to substantially outperform when their trades are valuation-motivated, however, they are unable to outperform when their trades are flow-induced. Our work is related to, but distinct from, the findings in Chen et al. (2000) and Alexander et al. (2007). While the existing literature examines trading in general, we focus on fire sales, and

as of the fifteenth of the month and publicly report the data four business days later.[10] We download historical short interest data from Compustat and express short interest as a fraction of shares outstanding.

In addition to the short interest data, we also obtain financial market data from CRSP. We include the bid-ask spread as a fraction of the closing mid-price, shares outstanding, the daily stock return, and trading volume as a fraction of shares outstanding. We calculate market capitalization as the product of the absolute value of CRSP share price and the number of shares outstanding.

To measure institutional ownership in each stock, we use data from the Thomson-Reuters Mutual Fund Holdings database (formerly known as CDA/Spectrum). The Thomson-Reuters Mutual Fund Holdings database provides the quantity of shares held by each fund in a given quarter. To construct capital flows into and out of mutual funds, we use the CRSP mutual fund monthly net returns database. The calculation is discussed in detail in Section II.B, below. We then use the MFLINKS file to match the Thomson-Reuters data with the CRSP mutual fund data. We filter the mutual fund data to include only domestic equity funds using the filters in Khan, Kogan, and Serafeim (2012); we also exclude index funds from our sample.

To mitigate the impact of asset illiquidity, in each period we drop stocks with a price less than $5. We also filter the mutual fund data to exclude funds with fewer than 10 holdings or assets less than $5 million. Similar to Khan et al. (2012) the resulting database includes approximately 300,000 observations at the stock-quarter level over our 25-year sample period.

B. Flow-induced mutual fund sales

To quantify the magnitude of fire sales in each stock, we follow Coval and Stafford (2007) and Khan et al. (2012) to construct fund flow induced trading pressure for each stock held

[10]Starting in September of 2007, the exchanges began reporting short interest data twice a month (at the middle and end of the month). For consistency, we keep only the mid-month short interest value, as in Rapach, Ringgenberg, and Zhou (2016).

by mutual funds during our sample period. Speci cally, we de ne ows for fund j in month s as:

$$Flow_{j;s} = \frac{[TNA_{j;s} \quad TNA_{j;s \;\; 1} \;\; (1 + R_{j;s})]}{TNA_{j;s \;\; 1}}; \tag{1}$$

where $TNA_{j;s}$ is total net assets for fund j as of the end of month s and $R_{j;s}$ is the monthly return for fund j in month s. We measure total net assets and returns using the CRSP mutual fund monthly net returns database.[11] To match our estimated $Flow_{j;s}$ variable with quarterly fund holding data from Thomson Financial, we sum the monthly ows over the quarter to obtain quarterly fund ows $Flow_{j;t} = \sum_{s}^{s+2} (Flow_{j;s})$ for each fund j in quarter t. Then, we calculate ow-induced trading pressure for stock *019552 Tf]TJ2 Tf]TJ2 Tf]TJ2 Tf]TJ2 T*

Specifically, we define:

$$ExpectedTrading_{i,t} = \frac{\sum_j (Holdings_{j,i,t-1} \times flow_{j,t} | flow_{j,t} > 90th\%) + \sum_j (Holdings_{j,i,t-1} \times flow_{j,t} | flow_{j,t} < 10th\%)}{SharesOutstanding_{i,t-1}}. \quad (3)$$

For each stock and each fund that holds the stock (and experiences extreme inflows or outflows) during the quarter, we calculate the expected number of shares to be traded by the fund based on the dollar flow from the fund prorated by its percentage holdings of the stock at the beginning of the quarter. The *expected trading* of the stock is then defined as the sum of the expected number of shares to be traded by all funds with extreme flow shocks.

Our measure of *expected trading* is designed to represent a counter-factual measure of fund trading absent a fire sale. Put differently, it answers the question, "What would we expect fund managers to do if a flow shock had not occurred?" While there is not necessarily one unique answer to this question, our measure has several desirable properties. First, our method is motivated by the idea that funds managers perform an optimization that generates portfolio weights, and as money enters or exits the portfolio, they pro-rate inflows and outflows across their portfolio using these weights. As such, flows do not lead to any change in the portfolio weights. Second, by construction, our approach isolates the passive portion of trading from the active portion of trading. Our measure assumes that the fund manager holds her target portfolio so that, absent flows, she will not trade unless some new information changes her optimal portfolio weights. Third, our calculation does not divide by stock price; as such, we do not build in a mechanical correlation between trading and returns (e.g., Wardlaw (2018)).[13]

Using our *expected trading* measure, we then calculate the discretionary sales and purchases of fund managers experiencing large outflows or inflows. Formally, we define:

$$DiscretionaryTrading_{i,t} = Pressure_{i,t} - ExpectedTrading_{i,t}. \tag{4}$$

Importantly, *expected trading* is defined by conditioning on extreme inflows and outflows in the exact same manner as $Pressure$. As a result, our measures allow us to decompose $Pressure$ into an expected component and a discretionary component.[14] The resulting variables allow us to measure (i) whether fund managers experiencing large outflows (inflows) react by scaling down (up) their portfolio and (ii) whether *discretionary trading* by these fund managers can explain the strong and long-lasting under-performance of fire sale assets.[15]

C. Proxy Variables

If managers use fundamental information when deciding which assets to trade, then our $DiscretionaryTrading$ variable should be related to measures of fundamental value. To test this, we use two different variables to proxy for fundamental information. First, we define the short interest ratio ($ShortInterest_{i,t-1}$) of firm i in quarter $t-1$ as the ratio of shares held short to the number of shares outstanding in the period prior to a fire sale. As

[13]For example, an alternative way to calculate expected trading would define it as $ExpectedTrading_{i,t} = (weight_{j,i,t-1} \times TNA_{j,t})/p_{i,t}$, where $weight_{j,i,t-1}$ is the weight fund j held in stock i last period and $p_{i,t}$ is the end of period price of stock i. While this measure is similar to our measure in equation (3), it builds in a mechanical relation between trading and stock returns. In addition, it implies that managers will need a large amount of re-balancing each period even absent flow shocks: to keep asset weights constant managers should sell recent winners and buy recent losers each period. In contrast, our approach implies that fund managers will not trade absent flow shocks or information that changes their target weights going forward.

[14]Note that a negative value of *discretionary trading* implies the fund manager owns less than expected while a positive value implies the manager owns more than expected. While a fund manager might choose not to trade in some assets following a flow shock, this reflects a *choice* and our *discretionary trading* variable reflects this fact.

[15]We note that our measures are related to the measures constructed in Khan et al. (2012). In many ways, our paper is the complement to theirs. Their measures are designed to focus on purchases by funds that do not have fundamental information; thus, they focus on inflow-driven purchases. In contrast, we specifically focus on sales that are not driven by flows (i.e., *discretionary* sales).

previously discussed, a large literature has found that short sellers are skilled at identifying overvalued securities (e.g., Senchack and Starks (1993)). More recently, Rapach et al. (2016) nd that short interest contains information about aggregate market returns and several papers provide evidence that short sellers are skilled at processing information (e.g., Karpo and Lou (2010), Boehmer et al. (2008); Engelberg, Reed, and Ringgenberg (2012). Accordingly, we use it as a measure of negative fundamental information.[16] Second, we calculate a measure of future earnings surprises ($EarnSurprise_{i;t+1}$) using a rolling seasonally adjusted random walk model as in Livnat and Mendenhall (2006). If fund managers do have negative fundamental information, then we expect their trading decisions to predict future earnings surprises.[17]

By construction, $EarnSurprise$ has a mean of zero, since it measures deviations from papers document robust evidence of front-running (e.g., Shive and Yun (2012), Dyakov and Verbeek (2013), Arif et al. (2016), Barbon, Maggio, Franzoni, and Landier (2019)). Second, it is also possible that negative information jointly leads to high short interest *and* selling by fund managers. We note that these two explanations are not mutually exclusive. However, to help distinguish between these two competing explanations, we also plot our second proxy variable, $EarnSurprise$, in Figure 2. The figure clearly shows that, on average, stocks in the fire sale portfolio tend to experience negative earnings surprises in the quarters immediately following the fire sale. In other words, the results suggest that our proxy variables are measuring negative fundamental information.[19]

D. Summary statistics

Table I provides summary statistics for the combined database. The mean (median) short interest ratio ($ShortInterest$) over our sample is 3% (1.4%), consistent with the existing literature (e.g., Rapach et al. (2016)). As previously mentioned, in our main specifications we use the natural log of short interest, since it is highly right-skewed (the 99th percentile is 24%). In addition, we also take the natural log of our control variables, since they are all highly right-skewed. Finally, we note that the mean of *discretionary trading* is negative, indicating that on average, discretionary sales are more likely to occur than discretionary buys.

III. Results

In this section, we examine whether the magnitude and persistence of price pressure make it di cult for arbitrageurs to disentangle pure price pressure from negative information.

We begin by examining the trading motivations of fund managers to determine which stocks they sell (and why) following re sales. We then examine the risk-adjusted returns to a simple-trading strategy to quantify the value of the information in re sales. Finally, we discuss the implications of our ndings.

A. Trading Motivation of Fund Managers

To investigate the magnitude and persistence of re sale discounts, we rst examine the trading motivation of managers following a ow shock. As previously discussed, the information set of fund managers is latent, which makes it di cult to know why fund managers choose to sell a particular stock. Thus, we use earnings surprises and short interest as proxy variables for negative fundamental information. Speci cally, we examine whether managers are more likely to sell stocks which experienced recently high short interest or have negative future earnings surprises. The null hypothesis is that, absent negative information about the fundamental value of each stock, fund managers experiencing extreme redemptions should sell stocks in proportion to their holdings.[20] For example, if a manager had 40% of her portfolio allocated to stock A and 60% allocated to stock B and she experienced $5 in redemptions, then we would expect her to sell $2 of stock A and $3 of stock B. On the other hand, if the manager has fundamental information that one of these stocks is likely to underperform going forward, we would expect the manager to concentrate her selling in that asset.

We start by examining summary statistics of the trading behavior of distressed funds during a re sale. Consistent with Coval and Sta ord (2007), we de ne distressed funds as those funds in the top 10% of out ows each quarter, and we then examine whether distressed fund managers scale down their portfolio in order to keep the weight on each asset constant.

[20]For example, the output from a Markowitz optimization would keep the weights in each asset xed as money is withdrawn from the portfolio. Of course, more realistically, it is likely that fund managers would sell stocks in proportion to re6(F)832aftn difollo on e832190% TdurpriAcereealisticwould

The results are shown in Panel A of Table II. Interestingly, following large outflows, fund managers do not simply scale down their portfolio. In fact, fund managers decrease their positions in 43.2% of assets and they maintain their position in 37.2% of assets. Moreover, they actually increase their holdings in 19.6% of securities. Thus, the summary statistics provide strong evidence that managers do not scale down their portfolios and rather they choose to concentrate their selling in a subset of assets.

Accordingly, we next whether these selling choices are motivated by fundamental information using linear probability panel regressions of the form:

$$\mathbb{1}_{[Sell]i,t} = \beta_1 StockCharacteristics + FE_i + FE_t + \epsilon_{i,t}, \tag{5}$$

where $\mathbb{1}_{[Sell]i,t}$ is an indicator variable that equals one if a distressed fund manager sells stock i in quarter t, and $StockCharacteristics$ is a vector of firm-level characteristics that includes our two proxy variables for information about the fundamental value of the firm, either: (i) short interest or (ii) future earnings surprises. In addition, $StockCharacteristics$ includes

sell more shares of stocks in which they have negative information. The negative and statistically significant coefficient on $LN(ShortInterest)$ in model (1) indicates that a one standard deviation increase in short interest is associated with a 22% increase in *discretionary* selling relative to the unconditional mean. Similarly, the positive and significant coefficient on $EarnSurprise$ in column (2) suggests that managers liquidate fewer positions that have positive future earnings surprises. A one standard deviation increase in $EarnSurprise$ is associated with a decrease in *discretionary* sales of nearly 9%, relative to the unconditional mean. Overall, the results show fund managers sell more shares of stocks that have negative fundamentals. In addition, we again find evidence that fund managers liquidate more shares of large stocks, consistent with the findings in Strahan and Tanyeri (2014).

In models (3) and (4) we examine the relation between $ExpectedTrading$ and our proxies for fundamental information. This analysis serves as a placebo test: if our measures of *discretionary* and *expected* trading correctly categorize trades, then we would expect to find no relation between *expected* trading and our proxies for fundamental information.[21] Indeed, in columns (3) through (4) we find no relation between *expected* trading and either *short interest* or $EarnSurprise$. In both models the coefficient estimates are economically and statistically insignificant.

In sum, our evidence suggests that managers strategically *choose* which stocks to sell following a flow shock and this choice contains fundamental information. As a result, our results are distinct from existing findings that short sellers front-run mutual fund fire sales (e.g., Shive and Yun (2012), Dyakov and Verbeek (2013), Arif et al. (2016), Barbon et al. (2019)). We find a positive relation between short interest in a *specific* stock and selling behavior by fund managers. However, the front-running hypothesis suggests that short sellers can anticipate which funds will be distressed. But without further fundamental information, short sellers should not be able to identify specific stocks that managers will choose to sell in greater than expected proportion. Importantly, we show that most stocks in a distressed

[21] We thank Vyacheslav Fos for suggesting this test.

fund's portfolio are not sold during a fire sale; on average, distressed funds decrease their holdings in only 43.2% of the stocks in their portfolio. Moreover, our results show that fund managers over-sell stocks that are likely to experience negative future earnings surprises. Thus, while the existing literature has documented significant evidence of front-running, our results document a new fact: following flow shocks, mutual fund managers choose to sell those stocks that have negative fundamental information.

These findings have important implications. As noted in Berger (2018) and Wardlaw (2018), a number of recent papers have used mutual fund fire sales as an exogenous instrument to shock stock prices. Consistent with our results, Berger (2018) and Wardlaw (2018) show that this instrument likely fails to satisfy the exclusion restriction in most settings because fire sales are correlated with firm characteristics. Our results show why: mutual fund managers *choose* which stocks to sell, and they sell stocks that are likely to underperform in the future. Accordingly, our findings show the identification strategy in Edmans et al. (2012) is crucial to identifying the impact of fire sales because managers choose which stocks to sell, and these choices are a function of firm fundamentals.

B. Performance of Selling Decisions

If fund managers are truly selling more of those stocks that, ex-ante, had negative fundamental information then we would expect these assets to perform worse in the future. Accordingly, in this section we examine the performance of *discretionary* and *expected* sales by fund managers.

We start with a simple event study of abnormal returns around fire sales. As in Coval and Stafford (2007), we calculate the abnormal return on stock i as the monthly return on stock i in excess of the equally-weighted average return of all stocks held by mutual funds that month. To examine the performance of discretionary and expected trading decisions by fund managers, we first sort all fire sale stocks into terciles based on *discretionary* trading in quarter t. Stocks in the lowest tercile have more selling pressure than expected (*Sold More*), stocks in the middle tercile have selling pressure approximately equal to the expected selling pressure (*Sold Expected*), and stocks in the highest tercile have less selling pressure than expected (*Sold Less*).[22] We form portfolios at time $t=0$ (when the re sale occurs) and then examine the returns in event time over the subsequent three years.

Figure 1 displays compound abnormal returns in event time over a three-year window around re sales.[23] Table IV contains the corresponding monthly return values as well as *t*-statistics and the cumulative return values. In Panel A of Figure 1, we display the cumulative average abnormal returns for all re sale stocks, similar to the well-known return pattern documented by Coval and Sta ord (2007). While our sample covers a substantially longer time period than Coval and Sta ord (2007), we con-325(2)-346(StEe)1(i502007 -o-c(2007-c t((2d abnormal returns of -5%. Moreover, stocks that are sold in lower than expected quantities exhibit cumulative average abnormal returns of only -2%. These latter two groups begin correcting after approximately one year; in contrast, the rst group never corrects over our event window.

Our results are generally consistent with models of adverse selection in which re sales cause managers to sell a mix of both low-quality and high-quality assets (e.g., Dow and Han the panel. Models (1) and (4) display the baseline relation between returns and fire sales, as measured by *Pressure*. Consistent with prior studies, we find significant evidence of price pressure from fire sales. To aid interpretation, we standardize all independent variables to have a mean of zero and a standard deviation of one. Thus, the coefficient of 0.0040 on *Pressure* in model (1) indicates that a one standard deviation increase in selling pressure is associated with a 40 basis point decrease in abnormal returns during the event month.[26] In models (4) through (6), we test for evidence of return reversals. The coefficient of -0.0058 on *Pressure* in model (4) indicates that a one standard deviation increase in selling pressure is associated with a 58 basis point increase in abnormal returns over the window t=+5 to +12, corresponding to a two-year return starting one year after the file sale. Put differently, the results in models (1) and (4) document strong evidence of fire sale price drops in the event month that reverse over a two year period starting the year after a fire sale.

In models (2), (3), (5), and (6) we examine the relation between returns and *expected* and *discretionary* trading. Because these variables are standardized, it is clear from the table that *discretionary* trading is associated with significantly more price pressure than *expected* trading during the event quarter. In model (3), the results suggest that a one standard deviation increase in *discretionary* trading is associated with a 49 basis point increase in abnormal returns; this effect is approximately seven times larger than the impact of *expected* trading. In models (5) and (6), we again test for evidence of reversals over a two-year window starting one year after the file sale. In both models (5) and (6), the coefficient on *discretionary* trading is statistically insignificant, implying that price pressure from *discretionary* sales does not reverse over the event window. The results suggest that *discretionary* sales are concentrated in low-quality assets; as such, these assets experience price declines that do not later reverse. Finally, the negative and statistically significant coefficients on *expected* trading in models (5) and (6) suggest that these assets slightly

[26] *Pressure*, *Expected Trading*, and *Discretionary Trading* take on positive values for buying pressure and negative values for selling pressure. Thus, a positive coefficient in Table V indicates price pressure in the direction of the trade, while a negative coefficient indicates a reversal.

a function of recent trades by fire sales funds. We then examine whether non-fire sale fund managers respond differently to expected and discretionary trades by fire sale funds. The results are shown in Table VII. The results show that non-fire sale fund managers respond to trades by fire sales funds over the last quarter. Specifically, non-fire sale funds are more likely to sell stocks that were recently sold by funds experiencing a fire sale. Interestingly, they respond similarly to both expected and discretionary trading. The results show that fire sales lead to contagion effects, in part, because of information asymmetries that make it difficult for other traders to separate price pressure from negative fundamental information.

We then test predictions specific to Dow and Han (2018). Dow and Han (2018) model fire sales in a noisy rational expectations equilibrium in which some investors are informed and act as arbitrageurs who buy some (but not all) assets following fire sales. As a result of these informed trades, asset prices are corrected following fire sales; in other words, these specialized arbitrageurs succeed in separating low-quality assets from high-quality assets thereby allowing other, uninformed, investors to buy the remaining supply of fire sale assets at their fundamental value. However, in times of market stress, the informed investors may be unable to buy assets which then prevents uniformed investors from trading due to the classic lemons problem. Thus, market stress causes all fire sale assets to sell at a lower "lemon" price.

We examine whether market stress exacerbates information asymmetries, leading to larger price drops for both *ExpectedTrading* and *DiscretionaryTrading*. To do this, we use data on the Volatility Index (VIX) from the Chicago Board Options Exchange (CBOE). We define an indicator variable for market stress (*Stress*) that takes the value one if VIX exceeds 40, and zero otherwise. This cutoff corresponds to approximately the 98th percentile of all VIX observations.

In addition, we also test the theoretical predictions in Malherbe (2014), who shows that selling decisions by fund managers are more likely to be a result of information if the fund holds a large amount of cash. The intuition for this prediction is simple: if a fund manager has enough cash to meet redemption requests and she still sells a stock, then it is likely that her trade is informationally motivated. As a result, all else equal, cash holdings exacerbate the adverse selection issue around asset re sales. To test this prediction, we construct an indicator variable for cash holdings (*Cash*) that takes the value one if a stock is held by mutual funds that on average have more than 2% of net assets in cash, and zero otherwise.

We then run OLS panel regressions of the form:

$$AbnRet_{i;t} = {}_1 ExpectedTrading_{i;t} + {}_2 DiscretionaryTrading_{i;t} + {}_3 S_{i;t} + X_{i;t} + FE_i + {}_{i;t}; \quad (9)$$

where $AbnRet_{i;t}$ is the abnormal return in quarter t=0, where t=0 is the quarter of the re sale for stock i, $ExpectedTrading_{i;t}$ is the portion of $Pressure$ that equals fund ows

ated to the stock-level using each stock's weight in the portfolio, $DiscretionaryTrading$

e portion of $Pressure$ this is not from $ExpectedTrading$, $S_{i;t}$ is either (i) an indicator

le that takes the value one if a stock is held by funds that have more than 2% of net

in cash and zero otherwise (*Cash*) or (ii) an indicator variables that takes the value

the VIX is above 40 and zero otherwise (*Stress*), and $X_{i;t}$ is a vector of interaction

that contain $ExpectedTrading\, S_{i;t}$ and $DiscretionaryTrading\, S_{i;t}$. The Malherbe

del predicts that $DiscretionaryTrading$ will have a larger impact when funds have

n holdings, while the Dow and Han (2018) model predicts that $ExpectedTrading$

etionaryTrading will have a larger impact when VIX is high.

sults are shown in Table VIII. Models (1), (2), and (5) display the benchmark

out conditioning on whether the trades were *discretionary* or *expected*. In models arbitrageurs to buy assets, and as a result, fire sale assets are sold at larger discounts.[30]

In models (3), (4), and (6), we examine the results for *discretionary* and *expected* trading. In models (3) and (4), the coefficient on *Discretionary Cash* is positive and statistically significant, however the coefficient on *Expected Cash* is insignificant. This result supports the theoretical predictions in Malherbe (2014); cash holdings appear to magnify the impact of information asymmetries on asset prices. When managers have large cash holdings and they still choose to sell an asset following large outflows (i.e., *DiscretionaryTrading* is large), it is more likely that they have negative information about the asset. Moreover, these findings are also consistent with Simutin (2013) who finds that fund managers with abnormally high cash holdings tend to make superior stock selections.

In model (6), we find that the coefficients on *Discretionary Stress* and *Expected Stress* are both positive and statistically significant.[31] In other words, the results are consistent with the predictions in the Dow and Han (2018) model which argues that specialized arbitrageurs help separate low-quality assets and high-quality assets thereby allowing other, uninformed, investors to buy the remaining supply of fire sale assets at the correct price. When combined with our return results in Table IV, which found that *expected* trades sell for a discount that is smaller than the discount on *discretionary* trades, the overall picture becomes clear: specialized arbitrageurs are able to partially determine the trading motivations for some expected sales, such that not all of them sell for the same discount as discretionary trades. However, in times of market stress, these arbitrageurs are prevented from trading and as a result, all fire sale assets sell at a large discount.

[30] Of course, because our market stress variable does not have any cross-sectional variation, we are unable to include time fixed effects in models that contain it. As such, these results could be picking up other aggregate fluctuations that are correlated with fire sale discounts.

[31] In unreported results, available upon request, we find that these results do not hold if we use a continuous measure of VIX, instead of an indicator variable. These findings suggest that the relation between adverse selection and asset prices is non-linear in market stress.

D. The Value of Fire Sale Information

Finally, we explore the *value* of the information in fund manager's selling decisions around re sales. To do this, we examine risk-adjusted portfolio returns to strategies that condition on whether mutual fund re sales are *discretionary*. As a benchmark, we rst note that the Sharpe ratio from unconditionally buying all re sale stocks and holding them from quarter 5 to quarter 8 after the re sale event quarter is only 0.02. Speci cally, even though Figure 1 shows that re sales stock prices are likely to rise from quarter 5 to quarter 8, these returns

We examine two different holding horizons. The evidence in Figure 1 suggests that both *discretionary* and *expected* fire sale trades experience price drops, however *expected* fire sale trades begin to correct after approximately one year. Accordingly, in Panel A of Table IX, we examine returns to a portfolio that begins trading five quarters after the event date (i.e., one year after the fire sale) and holds stocks until the eighth quarter (corresponding to a one-year holding horizon). In Panel B of Table IX, we examine returns to a portfolio that begins trading five quarters after the event date and holds stocks until the twelfth quarter (corresponding to a two-year holding horizon).

The results are shown in Table IX with *t*-statistics, calculated using standard errors clustered by firm, reported next to the coefficient estimates. In Panel A, for holding periods from quarter 5 to quarter 8 after the fire sale event quarter (i.e., over the year following the sale), the annualized 5-factor alpha of the strategy is 1.9%. In Panel B, when we extend the strategy to encompass two years (from quarter 5 to quarter 12 after the event quarter), the annualized 5-factor alpha of the strategy is 2.1%.[34] In sum, these findings further confirm that there is valuable information in asset fire sales.

E. Interpretation of Results

Our results all point to the same conclusion: fund managers selectively choose which stocks to sell following a fire sale and this makes it difficult for arbitrageurs to disentangle pure price pressure from negative information. Thus, the well-documented price drop in fire sale assets is partly attributable to the classic lemons problem and partly attributable to fundamental information that allows fund managers to concentrate their selling in those assets that are likely to experience future price drops. These findings have important implications for academics, practitioners, and regulators. A number of papers show that fire sales have important implications for macro-economic policies. For example, Lorenzoni (2008) argues that inefficient credit booms can occur in an economy where investors do not inter-

[34] These findings are robust to alternate trading horizons.

nalize pecuniary externalities from fire sales. As a result, regulators could increase welfare by reducing aggregate investment ex-ante. However, Kurlat (2018) shows that these findings depend on the reason underlying fire sale price drops: if fire sales are the result of asymmetric information, then the policy prescription is actually reversed. In other words, regulators could increase welfare by increasing aggregate investment ex-ante. Thus, understanding *why* asset prices fall during fire sales is crucial to our understanding of macro-prudential policies regarding investment. Our results provide novel evidence on this point. However, we note that several outstanding issues remain.

First, any statement about the motivation of sales following flow shocks should explain both (i) the choice of assets which are sold and (ii) the timing of those sales. Put differently, if fund managers have negative fundamental information about some of their holdings, why didn't they sell these stocks sooner? Moreover, why didn't they short sell these assets in order to profit from their negative information? There are several possible explanations for this. First, in Table A2 of the Appendix we show that fund managers are significantly more likely to sell stocks with high short interest during *all* periods, not just periods with large outflows. Second, we note that our analyses included firm and time fixed effects, so our proxy variables for negative information focus on new (abnormal) information about a stock. As such, the negative signal largely arrived proximate to the flow shock, which explains both the choice of assets and the timing of the sale. Third, many mutual fund managers are precluded from short selling, which limits their ability to profit from negative fundamental information. Finally, we also note that fund managers likely face portfolio re-balancing costs (both pecuniary and non-pecuniary). Novy-Marx and Velikov (2016) examine optimal trading strategies in the presence of transaction costs. They find that the optimal trading strategy is biased towards holding a current position. In other words, even if a manager receives a signal, it may not be optimal for them to immediately act on it. In our context, this suggests that fund managers may have negative information about some of their holdings, but choose not to trade on this information right away. Following a flow shock, managers are forced to sell and thus it becomes optimal to use their information when making these trades.

A second issue relates to the long-standing short interest puzzle. A number of papers note that high short interest predicts lower future returns. Since short interest data is publicly available, this begs a question: why don't other investors trade on the signal in short interest until it is arbitraged away? Similarly, our results show that *discretionary* trades contain information. Since mutual fund holdings and ows can be publicly observed, it should be possible for arbitrageurs to construct a measure of *discretionary* trading. In our context, these results suggest a question. Since investors face an adverse selection problem when they see price pressure from re sales, why don't they use short interest and/or our measure of *discretionary* trades to separate assets into low-quality and high-quality? One possibility is that, prior to our ndings, investors were unaware of the signal value in these variables within the re sale context. Several paper shows that return predictability diminishes after the publication of academic studies (e.g., Schwert (2003) and McLean and Ponti (2015)). As a result, it is possible that price pressure from re sales will diminish going forward as investors learn to separate low-quality re sale assets from high-quality re sale assets. Future research should continue to explore these issues.

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We provide an explanation for the puzzling persistence of price pressure from fire sales; following a flow shock, mutual fund managers *choose* to sell low-quality stocks. Our finding is surprising in light of the large literature showing that fund managers are not skilled (e.g., Carhart (1997)). We decompose fund manager trades into *expected* and *discretionary* components. Using short interest and future earnings surprises as proxy variables for managers' unobservable negative signals, we confirm that discretionary sales contain more negative information, but we find little evidence that expected trades do. The results help explain the magnitude and persistence of fire sale discounts. We find that discretionary sales experience large price drops and these prices remain low for several years. In contrast, expected sales experience much smaller price drops that quickly reverse. In other words, the results suggest fund managers attempt to sell their worst assets which leads to an adverse selection problem for other investors. Overall, our findings help explain the tendency of asset prices to remain depressed following fire sales: information asymmetries make it difficult for arbitrageurs to disentangle pure price pressure from negative information.

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Figure 1. Cumulative Average Abnormal Returns in Event Time around Fire Sales

The gure plots cumulative average returns (CAARs) in quarterly event time for sub-samples of stocks formed by conditioning on managerial selling decisions. Panel A plots CAARs for all re sale stocks, while Panel B examines this same sample broken into terciles based on whether fund managers: (i) sold more shares than

Figure 2. Negative Information in Event Time around Fire Sales

The figure plots two proxy variables for negative information: (i) *Short Interest* (as a percent of shares outstanding) and (ii) future earnings surprises (*EarnSurprise*) calculated using a seasonally adjusted random walk model. Both variables are plotted in event time for fire sale stocks (i.e., those in the bottom decile of *Pressure*) over the period 1990 through 2015; the vertical gray bar at $t = 0$ indicates the fire sale quarter. Detailed variable definitions are provided in Section II.C of the text.

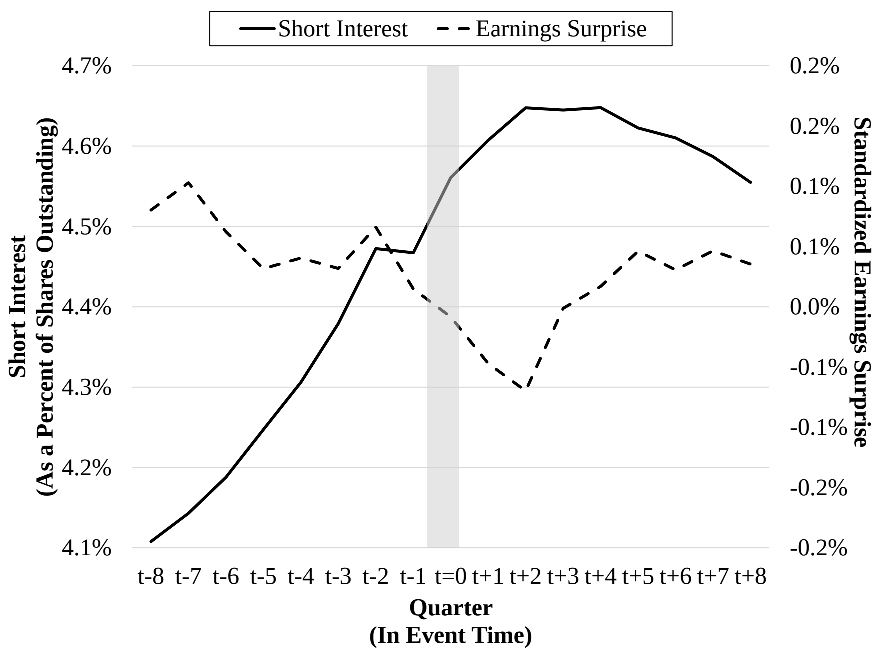

Table I
Summary Statistics

The sample includes all NYSE and NASDAQ common stocks (i.e., share codes 10 and 11) over the period January 1990 to December 2015. The mean, median, 1st percentile, 99th percentile, and standard deviation of the following variables are reported: $Pressure$ is a measure of price pressure as de ned in equation (2) and based on Coval and Sta ord (2007) and Kahn, Kogan, and Serafeim (2012). $ExpectedTrading_{i;t}$ is the portion of $Pressure$ that equals fund ows prorated to the stock-level using each stock's weight in the portfolio, and $DiscretionaryTrading$ is the portion of $Pressure$ this is not from $ExpectedTrading$. *EarnSurprise* is standardized unexpected earnings in the period *after* the re sale calculated using a seasonally adjusted random walk model, *Short Interest %* is short interest as a percentage of shares outstanding, *LN(Short Interest %)* is the natural log of short interest as a percentage of shares outstanding, *LN(Bid-Ask %)* is the natural log of the bid-ask spread as a fraction of the closing mid-point, and *LN(Market Cap.)* is the natural log of market capitalization in millions of U.S. dollars.

Variable	(1) Mean	(2) Median	(3) 1st %	(4) 99th %	(5) St. Dev.
Pressure	0.0005	0.0000	-0.0176	0.0222	0.0068
Expected Trading	0.0009	0.0000	-0.0082	0.0200	0.0051
Discrectionary Trading	-0.0004	0.0000	-0.0237	0.0198	0.0074
EarnSurprise	0.0000	0.0015	-0.1469	0.1307	0.0292
Short Interest %	3.26%	1.43%	0.00%	23.67%	4.97%
LN(Short Interest %)	-4.7019	-4.2333	-11.0303	-1.4391	2.1039
LN(Bid-Ask %)	-5.0337	-4.6396	-8.8069	-2.1785	1.7114
LN(Market Cap.)	19.6611	19.4849	16.3406	24.4744	1.8104

Table II

Trading Decisions of Fire Sale Fund Managers

This table examines the trading decisions of funds during a re sale quarter. Panel A displays the percent of positions within each distressed fund that were (1) decreased, (2) increased, or (3) held constant in the re sale quarter. Panel B examines a linear probability model of the form:

$$\mathbb{1}_{[Sell]i;t} = {}_{1}StockCharacteristics + FE_i + FE_t +$$

Table III

Discretionary and Expected Trading Decisions of Fire Sale Fund Managers

This table examines selling decisions by distressed funds according to an OLS panel model of the form:

$$Holdings_{i;t} = \ _1 StockCharacteristics + Controls + FE$$

Table IV

Table V
Relation between Fire Sales and Returns

We estimate OLS panel regressions of the form:

$$AbnRet_{i;t:t+h} = {}_1 ExpectedTrading_{i;t} + {}_2 DiscretionaryTrading_{i;t} + Controls + FE_i + FE_t + {}_{i;t:t+h};$$

where $AbnRet_{i;t:t+h}$ is the abnormal return from quarter t to quarter $t + h$

Table VI
Duration of Price Pressure Following Fire Sales

The table examines the duration of price pressure following re-sales. Speci cally, we examine the determinants of price corrections following re-sales; a price correction occurs when a stock's market-adjusted return reverts back to zero during the 16 quarters following a re sale. To do this, we examine OLS panel models of the form:

$$Correction_{i;t} = \quad _1$$

Table VII
Discretionary Trading by Non-Fire Sale Funds
This table examines trading decisions by non-distressed funds according to an OLS panel

Table VIII

Test of Theoretical Relation between Adverse Selection and Price Pressure

The table examines the relation between trading, price pressure, and variables that theoretically exacerbate adverse selection using panel regressions of the form:

$$AbnRet_{i;t} = {}_1 ExpectedTrading_{i;t} + {}_2 DiscretionaryTrading_{i;t} + {}_3 S_{i;t} + X_{i;t} + FE_i + {}_{i;t};$$

where $AbnRet_{i;t}$ is the abnormal return in quarter t=0, where t=0 is the quarter of the re sale for stock i, $ExpectedTrading_{i;t}$ is the portion of $Pressure$ that equals fund ows prorated to the stock-level using each stock's weight in the portfolio, $DiscretionaryTrading$ is the portion of $Pressure$ this is not from $ExpectedTrading$, $S_{i;t}$ is either (i) an indicator variable that takes the value one if a stock is held by funds that have more than 2% of net assets in cash and zero otherwise ($Cash$) or (ii) an indicator variables that takes the value one if the VIX is above 40 and zero otherwise ($Stress$), and $X_{i;t}$ is a vector of interaction terms that contain $ExpectedTrading$ $S_{i;t}$ and $DiscretionaryTrading$ $S_{i;t}$. As in Coval and Sta ord (2007), abnormal returns are calculated as monthly returns in excess of the equal-weighted average return of all stocks held by mutual funds that month. Models (1), (2), and (5) display the baseline relation between future returns and re-sales, as measured by $Pressure$, while models (3), (4), and (6) examine the relation between future returns and $ExpectedTrading$ and $DiscretionaryTrading$. We include rm xed e ects in all models, and date (year-quarter) or industry date xed e ects, as indicated at the bottom of the panel. t-statistics calculated using standard errors clustered by rm and date are shown below the estimates. To aid interpretation, all independent variables are standardized to have a mean of zero and standard deviation of one. *, **, *** indicate statistical signi cance at the 10%, 5%, and 1% levels, respectively.

Explanatory Variables	Dependent Variable: Abnormal Announcement Quarter Return					
	(1)	(2)	(3)	(4)	(5)	(6)
Pressure	0.1532	0.1538			0.4624**	
	(0.71)	(0.65)			(2.14)	
Expected Trading			0.3456	0.4178		-0.0799
			(0.69)	(0.66)		(-0.21)
Discretionary Trading			0.0974	0.0887		0.5778**
			(0.39)	(0.34)		(2.59)
Cash Indicator	0.0071	0.0073	0.0071	0.0073		
	(1.51)	(1.56)	(1.50)	(1.54)		
Pressure Cash	0.4693	0.4866				
	(1.57)	(1.57)				
Expected Cash			-0.0743	-0.3261		
			(-0.14)	(-0.51)		
Discretionary Cash			0.5937*	0.6571**		

Expected

Table IX
Five-Factor Alphas from Portfolios formed on Discretionary Trades around Fire Sales

The table examines ve-factor (Fama and French (2015)) alphas from portfolios formed by conditioning on the discretionary selling decisions of stocks that are experiencing re sales. We calculate $ExpectedTrading$ as the portion of $Pressure$ that equals fund ows prorated to the stock-level using each stock's weight in the portfolio, and $DiscretionaryTrading$ as the portion of $Pressure$ this is not from $ExpectedTrading$. We then rank all re sale stocks into terciles based on $DiscretionaryTrading$. Column (2) shows the alpha (intercept) and

V. Appendix

This appendix provides additional empirical evidence to supplement the analyses provided in the main text. Below, we briefly discuss each of the included figures and tables.

In Figure A1 we plot the returns to fire sale stocks split on two proxies for fundamental information: *Short Interest* and *EarnSurprise*. The results show that fire sale stocks with high short interest earn abnormally low returns that do not reverse, while fire sales stocks with low short interest experience small price drops that quickly correct. Similarly, fire sale stocks with negative future earnings surprises earn abnormally low future returns that do not reverse, while fire sales stocks with positive future earnings surprises experience small price drops that quickly correct.

In Table A1 we display a correlation matrix of the variables used in the main text.

In Table A2 we examine whether mutual fund managers use their selling skill during all periods (not just those with fire sales). To do this, we modify equations (3) and (4) in the main text so that they do not condition on the magnitude of flow shocks. Specifically, we calculate a measure of expected trading in each period (regardless of flow magnitude) according to the equation:

$$ExpectedTradingNoFire_{i,t} = \frac{\sum_j (Holdings_{j,i,t-1} \times flow_{j,t})}{SharesOutstanding_{i,t-1}}. \tag{11}$$

We then calculate a measure of discretionary trading by fund managers regardless of flow magnitude according to the equation:

$$DiscretionaryTradingNoFire_{i,t} = ActualTrades_{i,t} - ExpectedTradingNoFire_{i,t}, \tag{12}$$

where $ActualTrades_{i,t}$ is the actual change in holdings by mutual funds between period $t-1$ and t for stock i. The results in Table A2 shows that fund managers are more likely to have *discretionary* sales in stocks with high short interest in all periods regardless of ow shocks (model (1)). Moreover, consistent with the placebo test in the main text, we nd that *expected* trading is never related to stock characteristics (model (2)).

In Table A3 we examine a linear probability model of the determinants of whether or not cumulative average abnormal returns revert to zero during the twelve quarters following re-sales.

In Section V.A, we provide a detailed discussion of the requirements for a valid proxy variable.

Figure A1. Cumulative Average Abnormal Returns in Event Time around Fire-Sales for High and Low Quality Stocks

The gure plots cumulative average returns (CAARs) in quarterly event time for sub-samples of stocks formed using two di erent proxy variables for negative information: (i) *Short Interest* (as a percent of shares outstanding) and (ii) future earnings surprises (*EarnSurprise*) calculated using a seasonally adjusted random walk model. Each quarter, stocks in the bottom decile of *Pressure* are grouped into two portfolios, based on a proxy variable for negative information. In Panel A, we use short interest in the quarter prior to the event quarter as the proxy variable: stocks above the sample median value of short interest are assigned to the *High Short Interest* portfolio (dashed line), and stocks at or below the median value are assigned to the *Low Short Interest* portfolio (solid line). In Panel B, we use earnings surprise in the quarter *after* the event quarter as the proxy variable: stocks with a negative value of *EarnSurprise* are assigned to the *Negative Earnings Surprise* portfolio (dashed line), and stocks with a positive value of *EarnSurprise* are assigned to the *Positive Earnings Surprise* portfolio (solid line). As in Coval and Sta ord (2007), cumulative average abnormal returns (CAARs) are calculated as monthly returns in excess of the equal-weighted average return of all stocks held by mutual funds that month. Detailed variable de nitions are in Section II.C of the text.

Table A1
Correlation Matrix

The table displays a correlation matrix of the variables used in the main paper. Pearson correlations are shown below the diagonal and Spearman correlations are shown above the diagonal. The price pressure measure, $Pressure$, is de ned in equation (2) and based on Coval and Sta ord (2007) and Kahn, Kogan, and Serafeim (2012). $ExpectedTrading_{i;t}$ is the portion of $Pressure$ that equals fund ows prorated to the stock-level using each stock's weight in the portfolio, and $DiscretionaryTrading$ is the portion of $Pressure$ this is not from $ExpectedTrading$. *EarnSurprise* is standardized earnings surprises in the period *after* the re sale calculated using a seasonally adjusted random walk model, *LN(Short Interest %)* is the natural log of short interest as a percentage of shares outstanding, *LN(Bid-Ask %)* is the natural log of the bid-ask spread as a fraction of the closing mid-point, and *LN(Market Cap.)* is the natural log of market capitalization in millions of U.S. dollars.

	Pressure	Expected Trading	Discrectionary Trading	EarnSurprise	LN(Short Interest %	LN(Bid-Ask %)	LN(Market Cap.)
Pressure	**1.00**	0.57	0.58	0.01	0.02	-0.03	-0.02
Expected Trading	0.40	**1.00**	-0.15	0.02	0.04	-0.05	0.01
Discrectionary Trading	0.80	-0.24	**1.00**	-0.01	-0.04	0.02	0.00
EarnSurprise	0.00	0.01	0.00	**1.00**	-0.03	0.00	0.01
LN(Short Interest %)	0.00	0.03	-0.02	-0.01	**1.00**	-0.34	0.01
LN(Bid-Ask %)	0.01	-0.01	0.01	-0.02	-0.40	**1.00**	-0.42
LN(Market Cap.)	-0.03	-0.05	0.00	0.01	0.11	-0.40	**1.00**

Table A2

Table A3
Linear Probability Model of Price Corrections Following Fire Sales

The table examines whether cumulative average abnormal returns revert to zero during the twelve quarters following re-sales. Speci cally, we examine the determinants of price corrections following re sales. To do this, we examine linear probability panel models of the form:

$$\mathbb{1}_{Correction_{i;t}} = {}_1 ExpectedTrading + {}_2 DiscretionaryTrading + FE_i + FE_t + {}_{i;t};$$

where $\mathbb{1}_{Correction_{i;t}}$ is an indicator variable that takes the value one if a stock's cumulative abnormal return reverts to zero within twelve quarters of a re sale, and zero otherwise. $ExpectedTrading_{i;t}$ is the portion of $Pressure$ that equals fund ows prorated to the stock-level using each stock's weight in the portfolio, and $DiscretionaryTrading$ is the portion of $Pressure$ this is not from $ExpectedTrading$. We include xed e ects in all models, as indicated at the bottom of the panel. *t*-statistics calculated using standard errors clustered by rm and year-quarter are shown below the estimates. *, **, *** indicate statistical signi cance at the 10%, 5%, and 1% levels, respectively.

Explanatory Variable	Dependent Variable: Indicator Variable for Price Correction					
	(1)	(2)	(3)	(4)	(5)	(6)
Pressure	0.0099***	0.0034*	0.0029			
	(4.85)	(1.76)	(1.42)			
Expected Trading				0.0034	-0.0006	-0.0010
				(1.62)	(-0.29)	(-0.46)
Discretionary Trading				0.0104***	0.0041**	0.0037*
				(5.03)	(2.13)	(1.76)
Firm FE	No	Yes	Yes	No	Yes	Yes
Date FE	Yes	Yes	No	Yes	Yes	No
Industry Date FE	No	No	Yes	No	No	Yes
Observations	54,628	52,354	50,633	54,628	52,354	50,633
R-squared	2.8%	24.7%	37.6%	2.8%	24.7%	37.6%

A. Formal Requirements for a Valid Proxy Variable

Wooldridge (2010) discusses the requirements for a valid proxy variable. Formally, there are two requirements for a variable, z, to be valid proxy variable for a latent variable q:

1. $\mathrm{E}[y \mid x, q, z] = \mathrm{E}[y \mid x, q]$

2. $\mathrm{L}[q \mid 1, x_1, \ldots, x_K, z] = \mathrm{L}[q \mid 1, z]$,

where E[ ] is the expectations operat47.4orvwoL[

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