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Abstract

Asset prices remain depressed for several years following mutual fund fire sales. We show that price pressure from fire sales is partly due to asymmetric information which leads to an adverse selection problem for arbitrageurs. After a flow shock, fund managers do not scale down their portfolio, rather, they *choose* to sell a subset of low-quality stocks that subsequently under-perform. Our findings help explain the magnitude and persistence of asset prices drops following fire sales: managers try to sell their worst assets and information asymmetries make it difficult for arbitrageurs to disentangle pure price pressure from negative fundamentals.

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

JEL Classification Numbers: E22, G01, G12, G14

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I. Introduction

Fire sales occur when an owner of an asset is forced to sell it at a discounted price in order to meet creditor demands. The sale of assets at fire sale prices may cause similar assets held by other market participants to decline in value, leading to a self-reinforcing process that generates downward spirals in the net worth of firms; in turn, this may generate reductions in real investment and output (Lorenzoni (2008), Diamond and Rajan (2011), Shleifer and Vishny (2011)). To date, fire sales have been documented in a wide variety of asset classes, from financial securities to airplanes and real estate.[1] Yet, despite the importance of fire sales for the economy, there is relatively little empirical evidence on the determinants of fire sale discounts. Put differently, it is clear that asset prices remain depressed for prolonged periods of time following fire sales. What is less clear is *why* these effects persist.

There are several possible explanations for fire sale discounts including: (i) market frictions that limit arbitrage (Shleifer and Vishny (1997), Gromb and Vayanos (2002)), (ii) specialized asset use that generates heterogeneous valuations (Williamson (1988)), (iii) financial constraints that are correlated across market participants (Shleifer and Vishny (1992)), and (iv) information asymmetries (Akerlof (1970), Dow and Han (2018)). Importantly, Kurlat (2018) shows that understanding the cause of fire sales is crucial to developing macroeconomic policies. In particular, he shows that optimal policies regarding aggregate investment depend on whether information asymmetries are a cause of fire sale price discounts. In this paper, we empirically test whether information asymmetries affect fire sale discounts. We find that they do. Specifically, we find that information asymmetries make it difficult for asset purchasers to disentangle pure price pressure from negative information about asset fundamentals. As a result, fire sale assets sell at deep discounts for prolonged periods.

We use mutual funds as a laboratory for examining the determinants of fire sale dis-

[1]Fire sales have been documented in a number of financial asset classes (e.g., Coval and Stafford (2007), Ellul, Jotikasthira, and Lundblad (2011), Jotikasthira, Lundblad, and Ramadorai (2012), and Merrill, Nadauld, Stulz, and Sherlund (2014); Pulvino (1998) documents evidence of fires sale in the aircraft market; Campbell, Giglio, and Pathak (2011) document evidence of fire sales in the real estate market.

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 extremely liquid assets that are not subject to severe 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. As a result, we can use mutual funds to test whether information asymmetries generate fire sale discounts.

It is perhaps surprising that equity mutual funds experience fire sale discounts at all. Mutual fund fire sales are, arguably, 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 fund managers are more likely to sell stocks with bad fundamentals: a subset of 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:

[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.

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. 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 private 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 private information about asset values, then following an outflow of \$5 we would expect her to sell $\$5 \times 40\% = \$2$ of stock A and $\$5 \times 60\% = \$3$ of stock B. Put differently, the *expected trading* measure assumes the portfolio manager simply scales her portfolio 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.[4] 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 firm fundamentals when trading in response to a flow shock. We find that they do.

Following a large negative flow shock, a one-standard deviation increase in short selling is associated with discretionary sales that are 22% larger relative to their unconditional mean. Put differently, after an outflow, fund managers are significantly more likely to sell stocks that have high short interest.[5] Similarly, we find 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 find 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 relate them to the magnitude and persistence of fire sale price effects. Figure 1 summarizes our main result. Panel A displays cumulative average abnormal returns around all fire sale stocks, while Panel B decomposes these sales into *expected* and *discretionary* components. In Panel A, the fire sale result is immediately apparent: stocks that are sold by mutual funds experiencing extreme outflows have significant price drops of 5% and three years later, they still have negative cumulative returns. In contrast, in Panel B, it is clear

[4]Wooldridge (2010) discusses the conditions under which a proxy variable is valid. We discuss our proxy variables in greater detail in Section II.C.

[5]This finding begs an additional question: if fund managers have some selling skill, why don't they use it to sell stocks during periods that do not have extreme outflows? We find that they do. In Table A2 of the Appendix we show that fund managers are significantly more likely to sell high short interest stocks during *all* periods, not just periods with large outflows. We discuss this in greater detail in Section III.E.

that the results in Panel A are driven primarily by *discretionary* sales. Following a large outflow, stocks that are sold in greater than expected quantity experience extreme price drops of 10% that never reverse over our event window. On the other hand, stocks that are sold in the expected quantities experience significantly smaller price drops. Our results show that managers attempt to sell the worst assets in their portfolio and this makes it difficult for arbitrageurs to disentangle pure price pressure from negative information.

The results from multivariate analyses (that account for time-series and cross-sectional heterogeneity in the performance of fire sale stocks) are consistent with the univariate evidence in Figure 1. We find that *discretionary* sales are associated with significant price pressure in the quarter of the sale while *expected* sales experience significantly smaller effects that are not statistically different from zero. Across all trades, stocks that are sold by funds experiencing large outflows experience significant price drops. A one standard deviation increase in selling quantities is associated with a price drop of approximately 40 basis points. However, when we split these trades into *discretionary* and *expected*, we find that most of the price pressure is due to *discretionary* sales. Importantly, our regressions examine the price response per unit of stock traded; as a result, our results are not driven by differential trade sizes between *discretionary* and *expected* sales. In other words, *discretionary* sales have a significantly larger impact *per share traded*. We also find that *discretionary* sales take significantly longer to revert to their pre-fire sale price; indeed many do not ever recover during our sample.

In addition, we examine a simple trading strategy designed to measure the value of the information in asset fire sales. Our findings suggest that asset managers strategically *choose* which assets to liquidate following negative flow shocks. Accordingly, we examine the returns to a trading strategy that buys fire sale stocks with low *discretionary* selling and short sells those stocks with high *discretionary* trading. 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%. If 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%. Put differently, understanding *why* fund managers sold a stock is crucial to understanding return movements around asset fire sales.

Our results are related to a growing theoretical literature on fire sales. We document evidence of the classic "lemons" problem as described in Akerlof (1970). In our setting, fund managers who own a particular stock are likely to have some information advantage about the value of that asset (by revealed preference). In other words, managers choose to buy an asset because they believe they can value it better than other market participants. Following a flow shock, managers must sell some of their holdings and they use their information advantage to make this decision. Specifically, they reevaluate their asset holdings and *choose* to sell the stocks they believe will perform poorly in the future, although the magnitude of the flow shock may lead them to sell other (high quality) stocks at the same time. As a result, following a flow shock, managers will sell a mix of low- and high-quality assets and other market participants may be unable to distinguish between the two types. This causes all fire sale assets to experience price drops.[6]

Our results are broadly consistent with the predictions of Dow and Han (2018) who model fire sales in a noisy rational expectations equilibrium. In their model, 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 correct and this separates 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, all fire sale assets sell at the lower "lemon" price. We test the predictions of this model by examining whether market stress

[6]Our results show that *all* assets experience a significant initial price drop during a fire sale, however, after the initial period we find that *discretionary* stock sales continue to fall in price, while other assets experience flat to increasing prices. This finding suggests that our results are partly due to a "lemons" problem and partly due to an information asymmetry that allows fund managers to concentrate their selling in those assets that are likely to experience future price drops. In other words, our findings are suggestive of a combination of the lemons problem and private information about future price drops.

exacerbates information asymmetries, leading to larger price drops. We find that it does. In times of market stress, both *discretionary* and *expected* trades by fire sale funds are associated with larger price drops.

In addition, our findings are consistent with 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. Empirically, we find that *discretionary* sales by fire sale fund managers have a larger price impact when the fund has a large amount of cash. In other words, cash holdings appear to worsen the adverse selection problem, leading to larger fire sale discounts.

Our results are also related to the large literature on fund manager skill. It is well known that, on average, mutual fund managers do not outperform on a risk-adjusted basis. However, a number of papers do find evidence that mutual fund managers are skilled.[7] 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 we use mutual funds as a laboratory for examining the cause of the large and long-lasting impact of the price pressure. Moreover, while Alexander et al. (2007) do consider flows when examining trades, our paper presents a novel decomposition of trading into expected and

[7] Berk and Green (2004) develop a model of mutual fund flows that shows, in equilibrium, skilled funds managers will have more money allocated to their fund up until their fund no longer outperforms due to diseconomies of scale. As a result, their model predicts that funds will not earn abnormal returns, on average, even if some fund managers are skilled. Consistent with the diseconomies of scale assumption in Berk and Green (2004), J. Chen, Hong, Huang, and Kubik (2004) find that mutual fund returns decline as a function of fund size. Their results imply that some fund managers may in fact be skilled. Moreover, Daniel, Grinblatt, Titman, and Wermers (1997) examine mutual fund performance and they find some evidence that fund managers are skilled at selecting stocks based on their characteristics. More recently, Jiang, Verbeek, and Wang (2014) find that stocks which are heavily overweighted by active funds, relative to their benchmark indexes, tend to significantly outperform stocks that are underweighted by active funds. Their results show that some actively managed mutual funds are informed investors.

discretionary components.

Finally our results complement recent work on the use of price pressure from fire sales as an instrument to shock asset prices. Edmans, Goldstein, and Jiang (2012) develop an identification strategy that controls for the possibility that managers use private information when selling stocks after outflows. Our results suggest the methodology in Edmans et al. (2012) is crucial to identifying the impact of fire sales because managers do choose which stocks to sell. In addition, two recent papers argue that mutual fund fire sales do not satisfy the necessary conditions for a valid instrument. Berger (2018) argues that fire sales are not a valid instrument because they are correlated with firm fundamentals and Wardlaw (2018) shows that scaling by dollar volume induces a mechanical correlation with returns.[8] Our paper does not examine fire sales as an instrument; rather, we examine the reason behind fire sale discounts.

Overall, our primary contribution is that we provide the first evidence that information asymmetries are a significant determinant of the magnitude and persistence of fire sale discounts. Fire sales can generate important real effects (e.g., Lorenzoni (2008), Shleifer and Vishny (2011)), and Kurlat (2018) shows that understanding the cause of fire sale discounts is crucial to developing macro-economic policies. Our paper provides the first empirical evidence on the cause of fire sale discounts. Moreover, while our results examine fire sales in stocks, we note that stocks are arguably the least likely to have information asymmetries (as a result of market efficiency). As such, our results may generalize to other asset classes: anytime an owner is forced to liquidate assets to generate liquidity, it is possible the owner will choose to sell their worst assets.

II. Data

To test whether price pressure from fire sales is a result of information asymmetries, we combine data from the Center for Research in Security Prices ("CRSP"), Compustat, and

[8]As discussed in Section II.B, our analyses avoid this issue.

Thomson Financial, as discussed in detail below.

A. Sample Construction

Our sample consists of all U.S. firms in Compustat over the period 1990 to 2015. We include all common U.S. equities with CRSP share codes of 10 or 11 (i.e., we exclude American Depository Receipts ("ADRs"), Exchange Traded Funds ("ETFs"), and Real Estate Investment Trusts ("REITs")).

We obtain monthly short interest data from Compustat. Short interest is the quantity of open short positions (in shares) with settlements on the last business day on or before the fifteenth of a calendar month. Each month, U.S. stock exchanges calculate short interest as of the fifteenth of the month and publicly report the data four business days later.[9] 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

[9]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).

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 by mutual funds during our sample period. Specifically, we define flows for fund j in month s as:

$$Flow_{j,s} = \frac{[TNA_{j,s} - TNA_{j,s-1} \cdot (1 + R_{j,s})]}{TNA_{j,s-1}}, \tag{1}$$

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.[10] To match our estimated $Flow_{j,s}$ variable with quarterly fund holding data from Thomson Financial, we sum the monthly flows over the quarter to obtain quarterly fund flows $Flow_{j,t} = \sum_{s}^{s+2} (Flow_{j,s})$ for each fund j in quarter

[10]As in Coval and Stafford (2007), we drop funds that experienced extreme changes in TNA that may not be reliably measured. We require -0.50 < $\Delta TNA_{j,s}$ / $TNA_{j,s-1}$ < 2.0 to be included in our sample.

t. Then, we calculate flow-induced trading pressure for stock i in quarter t as:[11]

$$Pressure_{i,t} = \frac{[\sum_j (max(0, \Delta Holdings_{j,i,t}) | flow_{j,t} > 90th\%) - \sum_j (max(0, -\Delta Holdings_{j,i,t}) | flow_{j,t} < 10th\%)]}{SharesOutstanding_{i,t-1}}. \quad (2)$$

As in Coval and Stafford (2007), stocks in the bottom decile of $Pressure_{i,t}$ are considered to be experiencing excess selling demand from mutual funds with large capital outflows. The Coval and Stafford (2007) measure excludes obviously discretionary trades; the measure only includes sales when there is an outflow and purchases when there is an inflow. However, fund managers still have discretion to choose particular stocks to sell when there is an outflow which could help explain the magnitude and duration of fire sale price drops.

To examine this possibility, we calculate a new variable that measures whether fund managers experiencing large outflows (inflows) react by scaling down (up) their portfolio. 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

[11]Khan et al. (2012) scale the *Pressure* variable by shares outstanding, while Coval and Stafford (2007) scale it by average trading volume in their main specification and they scale by shares outstanding in an alternate specification. Both Coval and Stafford (2007) and Khan et al. (2012) show that the two measures lead to nearly identical inferences. Scaling by shares outstanding is also advantageous because Wardlaw (2018) shows that scaling by dollar volume induces a mechanical correlation with returns; our calculation avoids this issue.

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)).[12]

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.[13] The resulting

[12]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.

[13]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.

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.[14]

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 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) find that short interest contains information about aggregate market returns and several papers provide evidence that short sellers are skilled at processing information (e.g., Karpoff and Lou (2010), Boehmer et al. (2008); Engelberg, Reed, and Ringgenberg (2012). Accordingly, we use it as a measure of negative fundamental information.[15] 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 private negative information, then we expect their trading decisions to predict future earnings surprises.[16]

By construction, $EarnSurprise$ has a mean of zero, since it measures deviations from the expected value of earnings. However, short interest does not have a mean of zero, and some stocks have persistently different levels of short interest. We stress that our regression specifications include firm- and time-fixed effects, so our short interest variable effectively

[14]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 private 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).

[15]Because short interest is highly right-skewed, we use the natural log of the short interest ratio.

[16]Because the random walk model generates several observations that are more than 10 standard deviations from the mean, we winsorize $EarnSurprise_{i,t+1}$ at the 1st and 99th percentiles.

measures deviations from the expected value of short interest for each stock and time period. As such, in our analyses we are not simply screening on stocks which always have high short interest, but rather, stocks which likely had recent (unexpected) negative signals.[17]

Figure 2 displays a graph of *ShortInterest* and *EarnSurprise* in event time around fire sale events. For the average fire sale, the results show that short interest tends to rise sharply right before the event quarter, peaking a few periods later, before it subsequently declines. The event time data on short interest is consistent with a number of explanations. First, it is possible that short sellers are skilled at anticipating which funds are likely to experience negative flow shocks which will result in forced selling. As a result, short sellers may front-run stocks that are owned by funds which will soon experience fire sales. Indeed, several 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.[18]

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

[17]Our results are also robust to constructing a measure of abnormal short interest, which projects short interests on a vector of observable firm characteristics and takes the residual as a measure of abnormal short selling, as in Karpoff and Lou (2010).

[18]In the Appendix, we provide a detailed discussion of the requirements for a valid proxy variable.

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 following fire sales can be explained by negative information which leads to selective selling by fund managers. Our findings suggest that price pressure from fire sales can partially be explained by selective selling by fund managers, which leads to information asymmetries that make it difficult 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 fire sales. We then examine the risk-adjusted returns to a simple-trading strategy to quantify the value of the information in fire sales. Finally, we discuss the implications of our findings.

A. Trading Motivation of Fund Managers

To investigate the magnitude and persistence of fire sale discounts, we first examine the trading motivation of managers following a flow shock. As previously discussed, the information set of fund managers is latent, which makes it difficult 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. Specifically, 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.[19] 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 private 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 fire sale. Consistent with Coval and Stafford (2007), we define distressed funds as those funds in the top 10% of outflows each quarter, and we then examine whether distressed fund managers scale down their portfolio in order to keep the weight on each asset constant. 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 two proxies for asset liquidity: (i) the bid-ask spread and (ii) market capitalization. We

[19] For example, the output from a Markowitz optimization would keep the weights in each asset fixed as money is withdrawn from the portfolio. Of course, more realistically, it is likely that fund managers would sell stocks in proportion to their holdings after accounting for the relative liquidity of each asset. Accordingly, we include measures of liquidity in our analyses.

also include firm fixed effects in all models to control for time-invariant firm characteristics. Finally, we control for time-varying macro-economic conditions using industry×date fixed effects. This specification ensures that our estimates are not driven by aggregate events (like a financial crisis) when many investors are constrained at the same time. Moreover, it allows aggregate shocks to exert differential effects across industries. As such, the resulting estimates allow us to examine whether stock-level information affects the trading behavior of fund managers.

The results are shown in Panel B of Table II, with t-statistics calculated using standard errors clustered by firm and date (i.e., year-quarter) shown below the estimates in italics. In all of the specifications we find strong evidence that fund managers are more likely to sell stocks with negative fundamental information. In model (1), the coefficient of 0.0223 on *Short Interest* suggests that a one standard deviation increase in short interest is associated with an 10.0% increase in the probability of sale by a manager (relative to the unconditional mean). In other words, fund managers are significantly more likely to sell stocks with negative information. Similarly, the coefficient of -0.2314 on *EarnSurprise* suggests that a one standard deviation increase in future negative earnings surprises is associated with a 1.4% increase in the probability of sale by a manager. By definition, this result implies that fund managers have fundamental information; their selling decisions are associated with future earnings *surprises*. Put differently, fund managers are not scaling down their portfolio during fire sales; rather, they are strategically selling assets that are likely to under-perform going forward.

Interestingly, we also find that fund managers are significantly more likely to sell larger stocks and they are significantly less likely to sell illiquid stocks, as measured by the bid-ask spread. The results suggest that managers prefer to sell stocks that are easier to liquidate. These findings are consistent with the results in Strahan and Tanyeri (2014) who find that money market fund managers sold their most liquid holdings following the collapse of Lehman brothers.

To show that $DiscretionaryTrading$, but not $ExpectedTrading$, is related to fund managers' information set, we next examine the determinants of trading size for *expected* and *discretionary* trading, respectively. Specifically, in Table III, we repeat the analysis using OLS panel regressions to examine the relation between the magnitude of trading decisions and our proxies for negative information according to the model:

$$\Delta Holdings_{i,t} = \beta_1 StockCharacteristics + Controls + FE_i + FE_t + \epsilon_{i,t}, \tag{6}$$

where $\Delta Holdings_{i,t}$ measures the magnitude of trading using either $DiscretionaryTrading$ in models (1) and (2) or $ExpectedTrading_{i,t}$ in models (3) and (4). $DiscretionaryTrading$ measures the strategic component of managerial trading decisions. A positive value of $DiscretionaryTrading$ indicates that, on average, fund managers sold less than expected, while a negative value indicates that they sold more than expected.

Once again, the results suggest that fund managers *choose* which stocks to sell, and they 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.[20] 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 private 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 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.

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

(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*).[21] We form portfolios at time t=0 (when the fire 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 fire sales.[22] 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 fire sale stocks, similar to the well-known return pattern documented by Coval and Stafford (2007). While our sample covers a substantially longer time period than Coval and Stafford (2007), we confirm their main finding: fire sale

[21]Note that we form the *Sold Expected* tercile by ranking *discretionary* trading, instead of ranking *expected* trading, because the two variables are not orthogonal. Thus, our methodology ensures that the *Sold Expected* tercile contains the portion of *expected* trading that was not correlated with high or low *discretionary* trading.

[22]We thank Malcolm Wardlaw for helpful discussions (and code) regarding the construction of Figure 1.

stocks experience extreme price drops that persist for several years. However, in Panel B of Figure 1, we plot the cumulative average abnormal returns for fire sale stocks, split into terciles based on *discretionary* trading. Our main finding is immediately clear: the magnitude and persistence of fire sale discounts are driven primarily by *discretionary* sales. Following a large outflow, stocks that are sold in greater than expected quantity experience extreme price drops that never reverse over our event window. On the other hand, stocks that are sold in the expected quantities experience significantly smaller price drops. The corresponding numbers in Table IV confirm these findings.[23] Four quarters after a fire sale, stocks that are sold in greater than expected quantities exhibit cumulative average abnormal returns of -10%. However, stocks that are sold as expected experience cumulative average 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 first group never corrects over our event window.

Our results are generally consistent with models of adverse selection in which fire sales cause managers to sell a mix of both low-quality and high-quality assets (e.g., Dow and Han (2015)). Following a flow shock, managers choose to sell the worst stocks in their portfolio; these stocks experience subsequent price drops that do not later reverse. If the flow shock is large enough, fund managers must also sell some high-quality assets, and arbitrageurs may have difficulty distinguishing between the good and bad assets. As a result, all fire sale assets

[23]In Figure A1 of the Appendix, we show that similar results also emerge if we sort fire sale stocks on our proxy variables for fundamental information. Following a fire sale, the *Low Short Interest* portfolio stocks actually increase in value, on average. Over the next two years, they earn a cumulative average return of nearly 20% (around 10% per year). On the other hand, *High Short Interest* stocks experience extreme price drops during the event month and for the next six quarters. Moreover, the prices of these stocks remain low; they do not revert over our sample period. Similarly, Panel B displays results when *EarnSurprise* is our proxy variable. Following a fire sale, the *Positive EarnSurprise* portfolio stocks increase initially, and then remain relatively flat over our sample period. However, *Negative EarnSurprise* stocks experience extreme price drops during the event month and again, their prices continue to fall for approximately six quarters.

sell for a discount.[24]

Of course, univariate sorts do not account for time-series or cross-sectional heterogeneity that could impact our inferences. Thus, we examine OLS panel regressions of the form:

$$\begin{aligned} AbnRet_{i,t:t+h} = \beta_1 ExpectedTrading_{i,t} + \beta_2 DiscretionaryTrading_{i,t} \\ + Controls + FE_i + FE_t + \epsilon_{i,t:t+h}, \end{aligned} \tag{7}$$

where $AbnRet_{i,t:t+h}$ is the abnormal return from quarter t to quarter $t+h$ for stock i, where t=0 in models (1) to (3) and t=+5 to +12 in models (4) through (6), $ExpectedTrading_{i,t}$ is the portion of $Pressure_{i,t}$ that equals fund flows prorated to the stock-level using each stock's weight in the portfolio, and $DiscretionaryTrading_{i,t}$ is the portion of $Pressure_{i,t}$ this is not from $ExpectedTrading_{i,t}$.

The results are shown in Table V with t-statistics calculated using standard errors clustered by firm and date shown below the coefficient estimates. We include firm fixed effects in all models, and either date or industry×date fixed effects, as indicated at the bottom of 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.[25] 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

[24] We note that in a pure adverse selection story with a pooling equilibrium, *discretionary* trades and *expected* trades should initially sell at the same discount. In our setting, *expected* trades initially sell for a large discount, although it is smaller than the discount at which *discretionary* trades sell. These results suggest that arbitrageurs may be able to partially understand the trading motivations for some *expected* sales, such that not all of them sell for the same discount as *discretionary* trades.

[25] *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.

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 outperform by approximately 80 basis points over the two-year period from t+5 to t+12. In other words, these assets initially experienced price drops that were too large, suggesting that arbitrageurs were initially unable to distinguish between price pressure from fire sales and selling due to asymmetric information.[26] Importantly, we note that our regression results account for trade quantity. As such, our results are not driven by differential trades sizes between *discretionary* and *expected* sales. In other words, *discretionary* sales have a significantly larger impact *per share traded*.[27]

[26]These findings are consistent with the results in Jiang et al. (2014) who find that the overweight and underweight decisions of fund managers contain information about future stock returns.

[27]Of course, if price impact is non-linear in the quantity of shares traded, it is possible that *discretionary* trades could have a larger impact than *expected* trades if *discretionary* trades were significantly larger in size. However, as shown in Table I, *discretionary trading* and *expected trading* have a similar range and standard deviation.

In light of these findings, we next examine whether negative fundamental information can explain the persistence of fire sale discounts. Existing evidence suggests that asset prices remain depressed for two years (or more) following fire sales. Accordingly, we run panel regressions of the form:

$$Correction_{i,t} = \beta_1 ExpectedTrading + \beta_2 DiscretionaryTrading + FE_i + FE_t + \epsilon_{i,t}, \quad (8)$$

where $Correction_{i,t}$ is the number of quarters following a fire sale that it takes the stock's cumulative return to reach zero. We define the number of quarters to correction as a number between 1 and 12 if the return reverts to zero within 12 quarters, and we set the value to 13 if the reversion does not occur during the time period.[28] We again examine the impact of $DiscretionaryTrading$ and $ExpectedTrading$. If $DiscretionaryTrading$ is driven by negative information, we would expect that those stocks that were sold as discretionary trades are less likely to experience a price correction.

The results are shown in Table VI with t-statistics calculated using standard errors clustered by firm and date shown below the estimates in italics. We include firm fixed effects, date fixed effects, and/or industry×date fixed effects, as indicated at the bottom of the table. As before, models (1) through (3) display the baseline relation between the duration of the price correction and fire sales, as measured by $Pressure$, while models (4) through (6) examine the relation between the duration of price corrections and $DiscretionaryTrading$ and $ExpectedTrading$. In column (1), the negative and statistically significant coefficient on $Pressure$ indicates that stocks with more selling pressure are likely to take significantly longer to achieve a price correction. Specifically, a one standard deviation increase in $Pressure$ is associated with a 4% increase in the time to correction. In columns (4) through (6), we see that once again, this result holds primarily in *discretionary* trades.

The results in this section provide clear evidence that the *discretionary* trades of mutual

[28]Note that most observations revert within 13 quarters, so this does not result in a significant censoring problem. Our results are robust to alternate cutoff points that extend beyond 12 quarters.

fund managers are associated with significant price drops that persist for prolonged periods of time. These results are consistent with extant theoretical models of adverse selection. In the next section, we test specific predictions of these models.

C. Impact of Adverse Selection

So far, our evidence suggests that when faced with a flow shock, fund managers strategically choose which stocks to sell and these choices contain valuable information about future prices. Moreover, our findings suggest that fund managers will choose to sell low-quality assets, but because flow shocks can be large in magnitude, they will also sell some high-quality assets. The resulting mix of low-quality and high-quality asset sales leads to an adverse selection problem similar to the classic lemons problem (Akerlof (1970)). In this section, we test the predictions of theoretical models on adverse selection in fire sales regarding the impacts of market conditions and funds' cash holdings, respectively.

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 test the predictions of this model by examining whether market stress exacerbates information asymmetries, leading to larger price drops for both $ExpectedTrading$ and $DiscretionaryTrading$. To do this, we download a time-series of 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 private 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 fire 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:

$$AbnRet_{i,t} = \beta_1 ExpectedTrading_{i,t} + \beta_2 DiscretionaryTrading_{i,t} + \beta_3 S_{i,t} + \Gamma X_{i,t} + FE_i + \epsilon_{i,t}, \tag{9}$$

where $AbnRet_{i,t}$ is the abnormal return in quarter t=0, where t=0 is the quarter of the fire sale for stock i, $ExpectedTrading_{i,t}$ is the portion of $Pressure$ that equals fund flows 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 $ExpectedTrading \times S_{i,t}$ and $DiscretionaryTrading \times S_{i,t}$. The Malherbe (2014) model predicts that $DiscretionaryTrading$ will have a larger impact when funds have higher cash holdings, while the Dow and Han (2018) model predicts that $ExpectedTrading$ and $DiscretionaryTrading$ will have a larger impact when VIX is high.

The results are shown in Table VII. Models (1), (2), and (5) display the benchmark cases, without conditioning on whether the trades were *discretionary* or *expected*. In models (1) and (2) we find limited evidence that cash holdings are associated with a worse adverse selection problem. In both models, the coefficient on $Pressure \times Cash$ is positive but not statistically significant at the usual levels with a p-value of approximately 0.12. However, in model (5) when we interact $Pressure \times Stress$, we do find a positive and statistically significant coefficient. The result suggests that market stress hinders the ability of specialized arbitrageurs to buy assets, and as a result, fire sale assets are sold at larger discounts.[29]

In models (3), (4), and (6), we examine the results for *discretionary* and *expected* trading. In models (3) and (4), the coefficient on $Discretionary \times Cash$ is positive and statistically significant, however the coefficient on $Expected \times Cash$ 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 $Discretionary \times Stress$ and $Expected \times Stress$ are both positive and statistically significant.[30] 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

[29] 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.

[30] 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.

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.

D. The Value of Fire Sale Information

Finally, we explore the *value* of the information in fund manager's selling decisions around fire sales. To do this, we examine risk-adjusted portfolio returns to strategies that condition on whether mutual fund fire sales are *discretionary*. As a benchmark, we first note that the Sharpe ratio from unconditionally buying all fire sale stocks and holding them from quarter 5 to quarter 8 after the fire sale event quarter is only 0.02. Specifically, even though Figure 1 shows that fire sales stock prices are likely to rise from quarter 5 to quarter 8, these returns exhibit huge variation: the standard deviation of returns is 63%, relative to a mean raw return of 3.13%.[31] The Sharpe ratio results highlight that buying all fire sale stocks is a risky proposition, thereby explaining the reluctance of arbitrageurs to correct this apparent mispricing. We next show that the large standard deviation of fire sale stock returns can be explained by the *discretionary* trading decisions of fund managers.

We start by forming two portfolios: the first portfolio consists of fire sale stocks with low *discretionary* selling; in other words, this portfolio is composed of stocks that were sold less than expected. The second portfolio consists of fire sale stocks with high *discretionary* selling; in other words, this portfolio is composed of stocks that were sold more than expected. As before, on each date we form terciles based on *discretionary* trading, stocks in the lowest tercile have more selling pressure than expected (*Sold More*) while stocks in the highest tercile have less selling pressure than expected (*Sold Less*). We then calculate calendar time returns to these portfolios over various horizons, using equal-weighted portfolio returns. We also calculate calendar time returns to a long-short strategy that buys stocks that were sold less than expected, and short sells stocks that were sold more than expected. Finally, we

[31] Note that, to be consistent with Coval and Stafford (2007), Figure 1 shows abnormal returns, which exhibit larger return movements from quarter 5 to quarter 8 than the raw returns although raw returns are also statistically significantly and positive over this period.

regress the monthly excess returns of our portfolios on the Fama and French (2015) five factors.[32]

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 VIII, 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 VIII, 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 VIII 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%.[33] 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 private 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

[32]The monthly Fama and French (2015) factors are from Kenneth French's website.

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

important implications for macro-economic policies. For example, Lorenzoni (2008) argues that inefficient credit booms can occur in an economy where investors do not internalize 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 flows 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 fire 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 findings, investors were unaware of the signal value in these variables within the fire sale context. Several paper shows that return predictability diminishes after the publication of academic studies (e.g., Schwert (2003) and McLean and Pontiff (2015)). As a result, it is possible that price pressure from fire sales will diminish going forward as investors learn to separate low-quality fire sale assets from high-quality fire sale assets. Future research should continue to explore these issues.

IV. Conclusion

Asset fire sales can have an important impact on firms and the economy (Shleifer and Vishny (2011), Lorenzoni (2008), Kurlat (2018)). It is well documented that asset prices remain low for prolonged periods of time when managers are forced to sell assets to meet creditor demands (e.g., Coval and Stafford (2007), Ellul et al. (2011), Pulvino (1998), Campbell et al. (2011), etc.). Yet, the precise reason for these large and persistent mispricings remains unclear. We use mutual funds as a setting to understand whether asymmetric information affects asset prices during fire sales.

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. 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.

References

Akerlof, G. A. (1970). The market for "lemons": Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, *84*, 488-500.

Alexander, G., Cici, G., & Gibson, S. (2007). Trade performance? an analysis of mutual funds. *Review of Financial Studies*, *20*, 125-150.

Arif, S., Ben-Rephael, A., & Lee, C. M. (2016). Short-sellers and mutual funds: Why does short-sale volume predict stock returns? *Working Paper*.

Barbon, A., Maggio, M. D., Franzoni, F., & Landier, A. (2019). Brokers and order flow leakage: Evidence from fire sales. *Journal of Finance*, *Forthcoming*.

Berger, E. A. (2018). Does stock mispricing drive firm policies: Mutual fund fire sales and selection bias. *Cornell University Working Paper*.

Berk, J., & Green, R. (2004). Mutual fund flows and performance in rational markets. *Journal of Political Economy*, *112*, 1269-1295.

Boehmer, E., Jones, C., & Zhang, X. (2008). Which shorts are informed? *Journal of Finance*, *63*, 491-527.

Campbell, J. Y., Giglio, S., & Pathak, P. (2011). Forced sales and house prices. *American Economic Review*, *101*(5), 2108-31.

Chen, Jegadeesh, N., & Wermers, R. (2000). The value of active mutual fund management: An examination of the stockholdings and trades of fund managers. *Journal of Financial and Quantitative Analysis*, *35*, 343-368.

Chen, J., Hong, H., Huang, M., & Kubik, J. D. (2004). Does fund size erode mutual fund performance? the role of liquidity and organization. *American Economic Review*, *94*, 1276-1302.

Coval, J., & Stafford, E. (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics*, *86*, 479-512.

Daniel, K., Grinblatt, M., Titman, S., & Wermers, R. (1997). Measuring mutual fund performance with characteristic-based benchmarks. *Journal of Finance*, *52*, 1035-1058.

Diamond, D. W., & Rajan, R. G. (2011). Fear of fire sales, illiquidity seeking, and credit freezes. *Quarterly Journal of Economics*, *2*, 557–591.

Dow, J., & Han, J. (2018). The paradox of financial fire sales: The role of arbitrage capital in determining liquidity. *Journal of Finance*, *73*, 229-274.

Dyakov, T., & Verbeek, M. (2013). Front-running of mutual fund fire-sales. *Journal of Banking and Finance*, *37*, 4931-42.

Edmans, A., Goldstein, I., & Jiang, W. (2012). The real effects of financial markets: the impact of prices on takeovers. *Journal of Finance*, *67*, 933–971.

Ellul, A., Jotikasthira, C., & Lundblad, C. (2011). Regulatory pressure and fire sales in the corporate bond market. *Journal of Financial Economics*, *101*, 596–620.

Engelberg, J., Reed, A. V., & Ringgenberg, M. C. (2012). How are shorts informed? Short sellers, news, and information processing. *Journal of Financial Economics*, *105*, 260-278.

Fama, E., & French, K. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 1-22.

Gromb, D., & Vayanos, D. (2002). Equilibrium and welfare in markets with financially constrained arbitrageurs. *Journal of Financial Economics*, *66*, 361-407.

Jiang, H., Verbeek, M., & Wang, Y. (2014). Information content when mutual funds deviate from benchmarks. *Management Science*, *60*, 238-253.

Jotikasthira, C., Lundblad, C., & Ramadorai, T. (2012). Asset fire sales and purchases and the international transmission of funding shocks. *Journal of Finance*, *67*, 2015-2050.

Karpoff, J., & Lou, X. (2010). Short sellers and financial misconduct. *Journal of Finance*, *65*, 1879-1913.

Khan, M., Kogan, L., & Serafeim, G. (2012). Mutual fund trading pressure: Firm-level stock price impact and timing of SEOs. *Journal of Finance*, *67*, 1371-1395.

Kurlat, P. (2018). How I Learned to Stop Worrying and Love Fire Sales. *Stanford University Working Paper*.

Livnat, J., & Mendenhall, R. R. (2006). Comparing the post–earnings announcement drift for surprises calculated from analyst and time series forecasts. *Journal of Accounting Research*, *44*, 177-205.

Lorenzoni, G. (2008). Inefficient credit booms. *Review of Economic Studies*, *75*, 809-833.

Malherbe, F. (2014). Self-fulfilling liquidity dry-ups. *Journal of Finance*, *69*, 947-970.

McLean, R. D., & Pontiff, J. (2015). Does academic research destroy stock return predictability? *Journal of Finance*, *forthcoming*.

Merrill, C. B., Nadauld, T., Stulz, R. M., & Sherlund, S. M. (2014). Were there fire sales in the RMBS market? *Working Paper*.

Novy-Marx, R., & Velikov, M. (2016). A taxonomy of anomalies and their trading costs. *Review of Financial Studies*, *29*, 104-147.

Pulvino, T. C. (1998). Do asset fire sales exist? an empirical investigation of commercial aircraft transactions. *Journal of Finance*, *53*, 939-978.

Rapach, D., Ringgenberg, M. C., & Zhou, G. (2016). Aggregate short interest and return predictability. *Journal of Financial Economics*, *121*, 46-65.

Schwert, G. (2003). Anomalies and market efficiency. In G. Constantinides, M. Harris, & R. Stultz (Eds.), *Handbook of the economics of finance* (p. 939-974). Elsevier.

Senchack, A. J., & Starks, L. T. (1993). Short-sale restrictions and market reaction to short-interest announcements. *Journal of Financial and Quantitative Analysis*, *28*, 177-194.

Shive, S., & Yun, H. (2012). Are mutual fund sitting ducks? *Journal of Financial Economics*, *107*, 220-237.

Shleifer, A., & Vishny, R. (2011). Fire sales in finance and macroeconomics. *Journal of Economic Perspectives*, *25*(1), 29-48.

Shleifer, A., & Vishny, R. W. (1992). Liquidation values and debt capacity: A market equilibrium approach. *Journal of Finance*, *47*(4), 1343-1366.

Shleifer, A., & Vishny, R. W. (1997). The limits of arbitrage. *Journal of Finance*, *52*, 35-55.

Simutin, M. (2013). Cash holdings and mutual fund performance. *Review of Finance*, *18*, 1425-1464.

Strahan, P. E., & Tanyeri, B. (2014). Once burned, twice shy: Money market fund responses to a systemic liquidity shock. *Journal of Financial and Quantitative Analysis*.

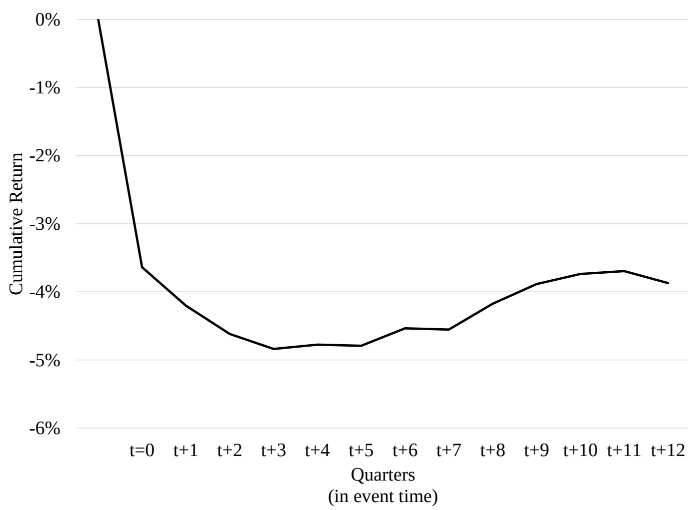
Wardlaw, M. (2018). Measuring Mutual Fund Flow Pressure as Shock to Stock Returns. *Working Paper*.

Williamson, O. (1988). Corporate finance and corporate governance. *Journal of Finance*, *43*(3), 567-91.

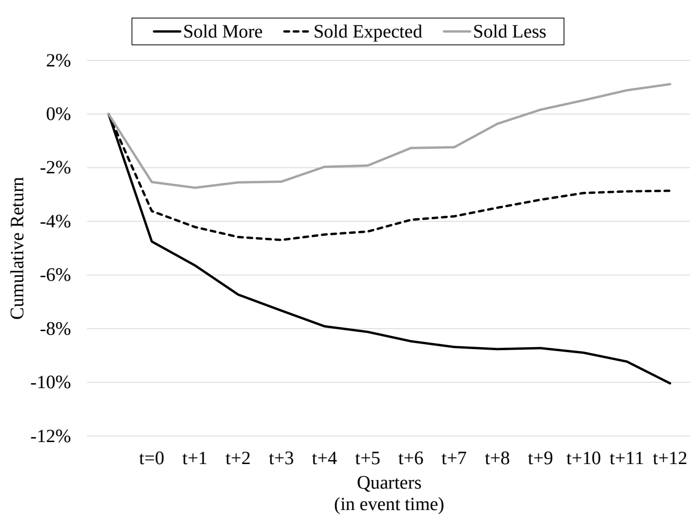
Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT Press.

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

The figure 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 fire sale stocks, while Panel B examines this same sample broken into terciles based on whether fund managers: (i) sold more shares than expected, (ii) sold the expected amount, or (iii) sold less shares than expected, given the asset's weight and the size of the flow shock. Stocks that were sold in greater than expected proportion are assigned to the *Sold More* portfolio (solid black line), stocks that are sold as expected are assigned to the *Sold Expected* portfolio (dashed black line), and stocks that are sold less than expected are assigned to the *Sold Less* portfolio (solid gray line). As in Coval and Stafford (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 definitions are provided in Section II.C of the text.



Panel A: All Fire Sales



Panel B: Discretionary vs. Expected Sales

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.

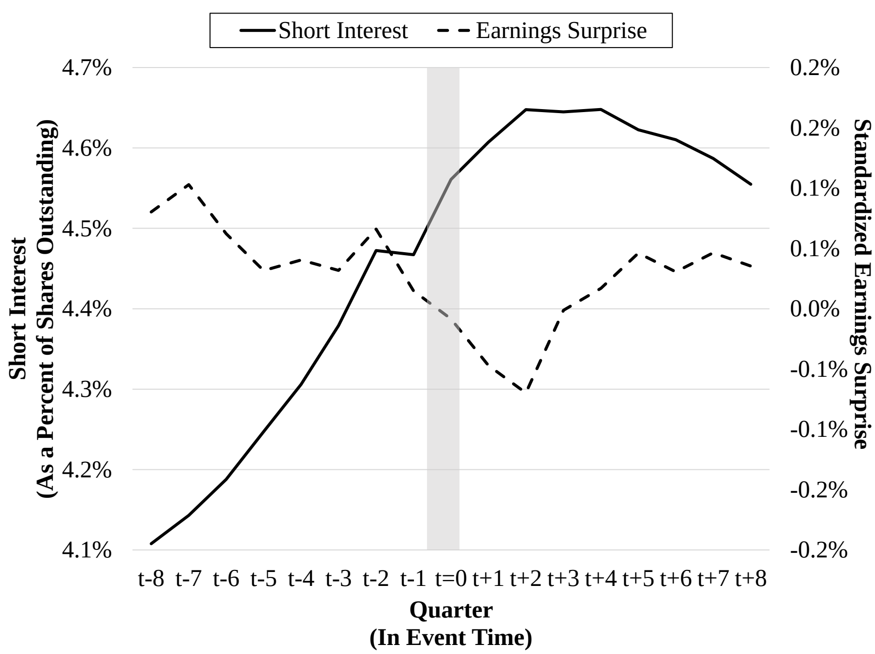


Table I

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 defined in equation (2) and based on Coval and Stafford (2007) and Kahn, Kogan, and Serafeim (2012). $ExpectedTrading_{i,t}$ is the portion of *Pressure* that equals fund flows 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 fire 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.

	(1)	(2)	(3)	(4)	(5)
Variable	Mean	Median	1st %	99th %	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 fire 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 fire sale quarter. Panel B examines a linear probability model of the form:

$$\mathbb{1}_{[Sell]i,t} = \beta_1 StockCharacteristics + FE_i + FE_t + \epsilon_{i,t}, \tag{10}$$

where $\mathbb{1}_{[Sell]i,t}$ is an indicator variable that takes the value one if asset i was sold by a distressed fund in quarter t, and zero otherwise, and $StockCharacteristics$ is one of two proxy variables for information about the fundamental value of the firm, either: (i) $LN(ShortInterest)_{i,t-1}$ or (ii) future earnings surprises ($EarnSurprise_{i,t+1}$). Distressed funds are funds in the top 10% of outflows each quarter. In addition, we include two measures of firm liquidity: (i) the bid-ask spread and (ii) market capitalization. Firm fixed effects are included in all models and we include either date (year-quarter) or date × industry fixed effects, as indicated at the bottom of the table. t-statistics calculated using standard errors clustered by firm and date are shown below the estimates in italics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Trading Behavior of Fire Sale Funds

	Decreased (1)	Increased (2)	Held Constant (3)
Percent of Positions	43.2%	19.6%	37.2%

Panel B: Linear Probability Model

Explanatory Variable	Dependent Variable: Sell Indicator (1)	(2)	(3)	(4)
LN(Short Interest %)	0.0223***	0.0217***		
	(9.95)	(9.85)		
SUE			-0.2314***	-0.2041***
			(-7.27)	(-6.58)
LN(Bid-Ask %)	-0.0159***	-0.0169***	-0.0076***	-0.0103***
	(-5.96)	(-6.58)	(-2.87)	(-4.22)
LN(Market Cap.)	0.0996***	0.1070***	0.0942***	0.0995***
	(20.11)	(21.64)	(16.39)	(17.77)
Firm FE	*Yes*	*Yes*	*Yes*	*Yes*
Date FE	*Yes*	*No*	*Yes*	*No*
Industry × Date FE	*No*	*Yes*	*No*	*Yes*
Observations	205,150	204,649	162,715	161,929
R-squared	55.0%	57.2%	47.0%	50.7%

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:

$$\Delta Holdings_{i,t} = \beta_1 StockCharacteristics + Controls + FE_i + FE_t + \epsilon_{i,t},$$

where $\Delta Holdings_{i,t}$ is either $DiscretionaryTrading$ in models (1) and (2) or $ExpectedTrading_{i,t}$ in models (3) and (4). $ExpectedTrading_{i,t}$ is the portion of $Pressure$ that equals fund flows prorated to the stock-level using each stock's weight in the portfolio, and $DiscretionaryTrading$ is the portion of $Pressure$ this is not from $ExpectedTrading$. $StockCharacteristics$ is one of two proxy variables for information about the fundamental value of the firm, either: (i) $LN(ShortInterest)_{i,t-1}$ or (ii) future earnings surprises ($EarnSurprise_{i,t+1}$). In addition, we include two measures of firm liquidity: (i) the bid-ask spread and (ii) market capitalization. Firm fixed effects and industry × date (year-quarter) fixed effects are included in all models. t-statistics calculated using standard errors clustered by firm and date are shown below the estimates in italics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable:			
Explanatory	Discretionary Trading		Expected Trading	
Variable	(1)	(2)	(3)	(4)
LN(Short Interest %)$_{i,t-1}$	-0.0417**		0.0035	
	(-2.16)		(0.13)	
SUE$_{i,t+1}$		1.1935*		0.2532
		(1.70)		(0.54)
LN(Bid-Ask %)$_{i,t-1}$	0.0479	0.0358	-0.0576	-0.1025***
	(1.63)	(1.13)	(-1.48)	(-2.89)
LN(Market Cap.)$_{i,t-1}$	-0.2151***	-0.2600***	0.1027	0.0571
	(-3.49)	(-4.16)	(1.56)	(0.82)
Firm FE	Yes	Yes	Yes	Yes
Industry × Date FE	Yes	Yes	Yes	Yes
Observations	204,649	161,929	204,649	161,929
R-squared	10.4%	10.3%	22.8%	22.8%

Table IV
Abnormal Returns in Event Time around Fire Sales

The table displays monthly abnormal returns and cumulative abnormal returns (CAAR) in event time around fire sales, where the event quarter (t=0) is the quarter in which a stock had intensive selling pressure. $ExpectedTrading_{i,t}$ is the portion of $Pressure$ that equals fund flows prorated to the stock-level using each stock's weight in the portfolio and $DiscretionaryTrading$ is the portion of $Pressure$ this is not from $ExpectedTrading$. Each quarter, all fire sale stocks are sorted into terciles based on $DiscretionaryTrading$. Stocks in the lowest tercile had more selling pressure than expected (*Sold More*), stocks in the middle tercile had selling pressure approximately equal to the expected selling pressure (*Sold Expected*), and stocks in the highest tercile had less selling pressure than expected (*Sold Less*). We form portfolio based on these terciles and examine returns in event time. As in Coval and Stafford (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. The table reports the mean abnormal return in columns (1) through (3) and the cumulative average abnormal return (CAAR) in columns (4) through (6).

	Monthly Average Abnormal Return			Cumulative Average Abnormal Return		
Event Time	Sold Less (1)	Sold Expected (2)	Sold More (3)	Sold Less (4)	Sold Expected (5)	Sold More (6)
t=0	-2.5%	-3.6%	-4.8%	-2.54%	-3.62%	-4.75%
t+1	-0.2%	-0.6%	-0.9%	-2.75%	-4.21%	-5.64%
t+2	0.2%	-0.4%	-1.1%	-2.55%	-4.59%	-6.73%
t+3	0.0%	-0.1%	-0.6%	-2.52%	-4.69%	-7.32%
t+4	0.6%	0.2%	-0.6%	-1.97%	-4.49%	-7.91%
t+5	0.0%	0.1%	-0.2%	-1.92%	-4.38%	-8.12%
t+6	0.7%	0.4%	-0.3%	-1.26%	-3.94%	-8.47%
t+7	0.0%	0.1%	-0.2%	-1.24%	-3.81%	-8.68%
t+8	0.9%	0.3%	-0.1%	-0.36%	-3.49%	-8.76%
t+9	0.5%	0.3%	0.0%	0.16%	-3.19%	-8.73%
t+10	0.4%	0.2%	-0.2%	0.51%	-2.95%	-8.90%
t+11	0.4%	0.1%	-0.3%	0.89%	-2.88%	-9.22%
t+12	0.2%	0.0%	-0.8%	1.11%	-2.86%	-10.04%

Table V
Relation between Fire Sales and Returns

We estimate OLS panel regressions of the form:

$$AbnRet_{i,t:t+h} = \beta_1 ExpectedTrading_{i,t} + \beta_2 DiscretionaryTrading_{i,t} + Controls + FE_i + FE_t + \epsilon_{i,t:t+h},$$

where $AbnRet_{i,t:t+h}$ is the abnormal return from quarter t to quarter $t+h$ for stock i, where t=0 in models (1) to (3) and t=+5 to +12 in models (4) through (6), $ExpectedTrading_{i,t}$ is the portion of $Pressure$ that equals fund flows prorated to the stock-level using each stock's weight in the portfolio, and $DiscretionaryTrading$ is the portion of $Pressure$ this is not from $ExpectedTrading$. As in Coval and Stafford (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) and (4) display the baseline relation between returns and fire-sales, as measured by $Pressure$, while models (2), (3), (5), and (6) examine the relation between returns and $ExpectedTrading$ and $DiscretionaryTrading$. We include firm fixed effects in all models, and either date (year-quarter) or industry × date fixed effects, as indicated at the bottom of the panel. t-statistics calculated using standard errors clustered by firm 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 significance at the 10%, 5%, and 1% levels, respectively.

Explanatory	Dependent Variable: $AbnRet_{i,t=0}$			Dependent Variable: $AbnRet_{i,t+5:t+12}$		
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Pressure	0.0040***			-0.0058*		
	(3.01)			(-1.87)		
Expected Trading		0.0014	0.0007		-0.0087**	-0.0078*
		(0.80)	(0.35)		(-2.17)	(-1.92)
Discretionary Trading		0.0046***	0.0049***		-0.0050	-0.0053
		(3.33)	(3.39)		(-1.33)	(-1.46)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	No	Yes	No	No	Yes	No
Industry × Time FE	Yes	No	Yes	Yes	No	Yes
Observations	50,633	52,354	50,633	39,016	40,767	39,016
R-squared	34.6%	18.5%	34.6%	54.7%	39.4%	54.7%

Table VI
Duration of Price Pressure Following Fire Sales

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

$$Correction_{i,t} = \beta_1 ExpectedTrading + \beta_2 DiscretionaryTrading + FE_i + FE_t + \epsilon_{i,t},$$

where $Correction_{i,t}$ is the number of quarters following a fire sale that it takes the stock's cumulative abnormal return to reach zero. The number of quarters to correction varies between 1 and 12 if the abnormal return reverts to zero within 12 quarters, and we set the value to 13 if the reversion does not occur during the time period. $ExpectedTrading_{i,t}$ is the portion of $Pressure$ that equals fund flows 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 firm fixed effects in all models, and either date (year-quarter) or industry × date fixed effects, as indicated at the bottom of the panel. t-statistics calculated using standard errors clustered by firm 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 significance at the 10%, 5%, and 1% levels, respectively.

Explanatory	Dependent Variable: Number of Quarters to Price Correction					
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Pressure	-0.1383***	-0.0496*	-0.0450			
	(-4.84)	(-1.88)	(-1.60)			
Expected Trading				-0.0636**	-0.0059	0.0053
				(-2.02)	(-0.20)	(0.18)
Discretionary Trading				-0.1392***	-0.0557**	-0.0537*
				(-4.92)	(-2.06)	(-1.84)
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	1.9%	22.2%	37.1%	1.9%	22.2%	37.1%

Table VII

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:

$$AbnRet_{i,t} = \beta_1 ExpectedTrading_{i,t} + \beta_2 DiscretionaryTrading_{i,t} + \beta_3 S_{i,t} + \Gamma X_{i,t} + FE_i + \epsilon_{i,t},$$

where $AbnRet_{i,t}$ is the abnormal return in quarter t=0, where t=0 is the quarter of the fire sale for stock i, $ExpectedTrading_{i,t}$ is the portion of $Pressure$ that equals fund flows 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 $ExpectedTrading \times S_{i,t}$ and $DiscretionaryTrading \times S_{i,t}$. As in Coval and Stafford (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 fire-sales, as measured by $Pressure$, while models (3), (4), and (6) examine the relation between future returns and $ExpectedTrading$ and $DiscretionaryTrading$. We include firm fixed effects in all models, and date (year-quarter) or industry × date fixed effects, as indicated at the bottom of the panel. t-statistics calculated using standard errors clustered by firm 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 significance at the 10%, 5%, and 1% levels, respectively.

Explanatory	Dependent Variable: Abnormal Announcement Quarter Return					
Variables	(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**		
			(1.81)	(2.00)		
Stress Indicator					0.0121*	0.0121*
					(1.89)	(1.89)
Pressure × Stress					1.1546**	
					(2.21)	
Expected × Stress						1.7662**
						(2.37)
Discretionary × Stress						1.0211*
						(1.92)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	No	Yes	No	No	No
Industry × Date FE	No	Yes	No	Yes	No	No
Observations	52,354	50,633	52,354	50,633	52,354	52,354
R-squared	18.5%	34.6%	18.5%	34.6%	16.5%	16.5%

Table VIII

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

The table examines five-factor (Fama and French (2015)) alphas from portfolios formed by conditioning on the discretionary selling decisions of stocks that are experiencing fire sales. We calculate $ExpectedTrading$ as the portion of $Pressure$ that equals fund flows 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 fire sale stocks into terciles based on $DiscretionaryTrading$. Column (2) shows the alpha (intercept) and factor loads associated with a portfolio that is formed by buying fire sale stocks in tercile 1 of $DiscretionaryTrading$, which consists of stocks with greater than expected selling pressure. Column (4) shows the alpha (intercept) and factor loads associated with a portfolio that is formed by buying fire sale stocks in tercile 3 of $DiscretionaryTrading$, which consists of stocks with lower than expected selling pressure. Finally, column (6) shows the alpha to a long-short portfolio that buys stocks with lower than expected selling pressure and short sells stocks with higher than expected selling pressure. t-statistics, calculated using standard errors clustered by firm, are shown next to the coefficient estimates in italics. In Panel A, we examine abnormal returns to a portfolio that begins 5 quarters after the event date and holds stocks until quarter t+8. In Panel B, we examine annualized abnormal returns to a portfolio that begins 5 quarters after the event date and holds stocks until quarter t+12.

Panel A: Holding period = quarter t+5 through quarter t+8

	(1)	(2)	(3)	(4)	(5)	(6)
Explanatory	Sold More		Sold Less		Long-Short	
Variable	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Intercept (α)	-1.1256**	*(-2.10)*	0.8190*	*(1.66)*	**1.9446*** **	***(2.90)***
Mkt	0.1475	*(1.17)*	0.2452**	*(2.13)*		
SMB	-0.7590***	*(-3.88)*	-0.6131***	*(-3.42)*		
HML	-0.6131***	*(-2.77)*	-0.4245**	*(-2.02)*		
RMW	-0.4615**	*(-2.39)*	-0.4433***	*(-2.59)*		
CMA	1.7338***	*(5.77)*	1.3646***	*(4.79)*		

Panel B: Holding period = quarter t+5 through quarter t+12

Explanatory	Sold More		Sold Less		Long-Short	
Variable	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Intercept (α)	-0.0718	*(-0.16)*	2.0915***	*(5.08)*	**2.1633*** **	***(3.97)***
Mkt	-0.1548*	*(-1.73)*	0.0030	*(0.04)*		
SMB	0.4608***	*(3.32)*	0.1744	*(1.40)*		
HML	0.2873	*(1.57)*	-0.1226	*(-0.78)*		
RMW	0.1087	*(0.56)*	0.4881***	*(2.90)*		
CMA	-0.6001**	*(-2.27)*	-0.1483	*(-0.62)*		

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:

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

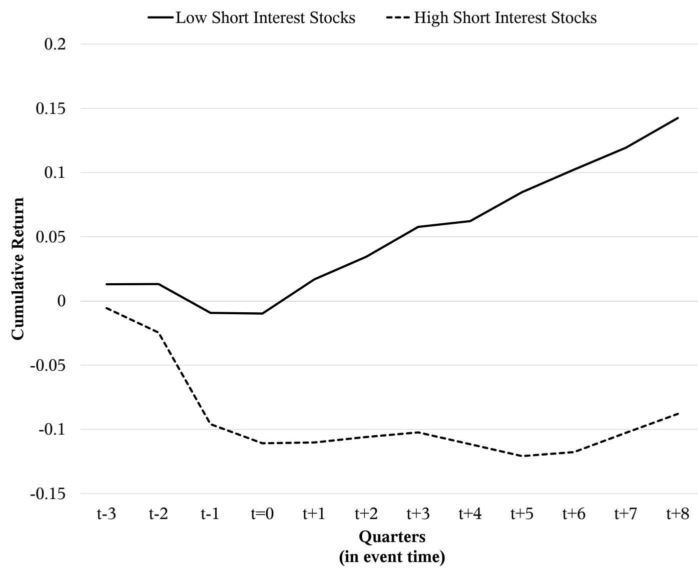
  where $ActualTrades_{i,t}$ is the actual change in holdings by mutual funds between period $t-1$ and t for stock i. The results in Table A2 shows that fund managers are more likely to have *discretionary* sales in stocks with high short interest in all periods regardless of flow shocks (model (1)). Moreover, consistent with the placebo test in the main text, we find 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 fire-sales.

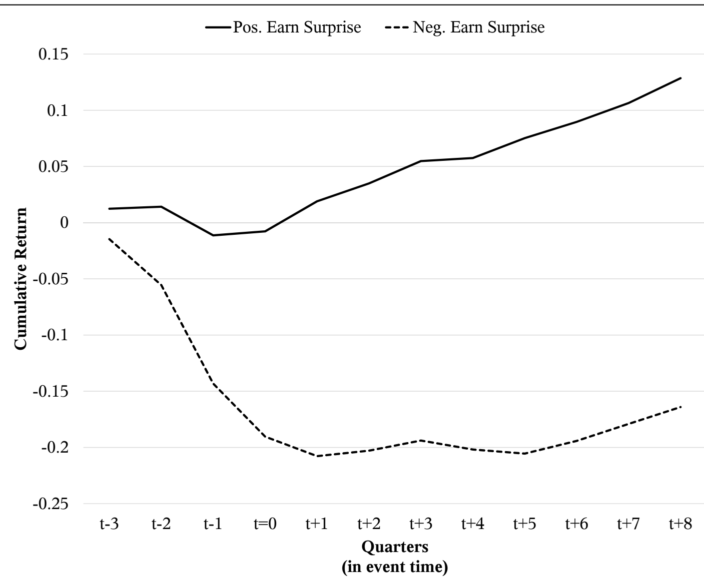
- In Section V.A, we provide a detailed discussion of the requirements for a valid proxy variable.

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

The figure plots cumulative average returns (CAARs) in quarterly event time for sub-samples of stocks formed using two different 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 Stafford (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 definitions are in Section II.C of the text.



Panel A: Short Interest



Panel B: Future Earnings Surprises

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 defined in equation (2) and based on Coval and Stafford (2007) and Kahn, Kogan, and Serafeim (2012). $ExpectedTrading_{i,t}$ is the portion of *Pressure* that equals fund flows 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 fire 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
Discretionary and Expected Trading Decisions of Fund Managers without Conditioning on the occurrence of Fire Sales

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

$$\Delta Holdings_{i,t} = \beta_1 StockCharacteristics + Controls + FE_i + FE_t + \epsilon_{i,t},$$

where $\Delta Holdings_{i,t}$ is $DiscretionaryTrading$ in model (1) and $ExpectedTrading_{i,t}$ in model (2). The specifications are similar to Table III of the main text, which shows the determinants of trading decisions by fund managers experiencing large flow shocks, except they look at *all* trades, not just trades that occurred following large flow shocks. $ExpectedTrading_{i,t}$ is the portion of $Pressure$ that equals fund flows prorated to the stock-level using each stock's weight in the portfolio, and $DiscretionaryTrading$ is the portion of $Pressure$ this is not from $ExpectedTrading$. $StockCharacteristics$ is one of two proxy variables for information about the fundamental value of the firm, either: (i) $LN(ShortInterest)_{i,t-1}$ or (ii) future earnings surprises ($EarnSurprise_{i,t+1}$). In addition, we include two measures of firm liquidity: (i) the bid-ask spread and (ii) market capitalization. Firm fixed effects and industry × date (year-quarter) fixed effects are included in all models. Standard errors clustered by firm and date are shown below the estimates in italics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable:	
Explanatory	Discretionary Trading	Expected Trading
Variables	(1)	(2)
LN(Short Interest %)$_{i,t-1}$	-0.0009***	0.0000
	(-2.93)	(1.35)
SUE$_{i,t+1}$	0.0020	0.0001
	(0.30)	(1.04)
LN(Bid-Ask %)$_{i,t-1}$	-0.0003	0.0000
	(-1.41)	(1.01)
LN(Market Cap.)$_{i,t-1}$	0.0018***	0.0000
	(3.25)	(0.61)
Firm FE	Yes	Yes
Industry × Date FE	Yes	Yes
Observations	125,524	125,524
R-squared	27.0%	36.1%

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 fire-sales. Specifically, we examine the determinants of price corrections following fire sales. To do this, we examine linear probability panel models of the form:

$$\mathbb{1}_{Correction_{i,t}} = \beta_1 ExpectedTrading + \beta_2 DiscretionaryTrading + FE_i + FE_t + \epsilon_{i,t},$$

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 fire sale, and zero otherwise. $ExpectedTrading_{i,t}$ is the portion of $Pressure$ that equals fund flows 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 fixed effects in all models, as indicated at the bottom of the panel. t-statistics calculated using standard errors clustered by firm and year-quarter are shown below the estimates. *, **, *** indicate statistical significance 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 $\mathrm{E}[\cdot]$ is the expectations operator and $\mathrm{L}[\cdot]$ is a linear projection operator. The first condition says that the proxy variable z is not related to y after accounting for q. In our case, this condition seems uncontroversial and implies that short interest or earnings surprises would not be related to fire sales if we could control for the actual quantity of negative information about a stock. The second condition is more complicated, and is similar to an exclusion restriction in a standard instrumental variables model. It requires the correlation between the latent variable q and each covariate x to be zero after we include the proxy variable z. Of course, since q is unobservable, this restriction is inherently untestable. However, Wooldridge (2010) notes that even if z is an imperfect proxy such that the second condition does not hold, it is likely that the Ordinary Least Squares ("OLS") estimator will be better than if no proxy variable is included. Accordingly, we proceed by defining $ShortInterest_{i,t-1}$ and $EarnSurprise_{i,t+1}$ as our proxy variables for unobservable negative information about stock i in quarter t.