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The Information in Asset Fire Sales*

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Abstract

Asset prices remain depressed for years following mutual fund fire sales, but little is known about the causes of these price drops. We show that asymmetric information generates price pressure during fire sales. We separate trades into expected trades, which assume fund managers scale down their portfolio, and discretionary trades. We find that discretionary trades contain fundamental information, while expected trades do not. Moreover, other traders cannot distinguish between discretionary and expected trades. Our findings help explain the magnitude and persistence of fire sale discounts: fund managers *choose* which assets to sell and information asymmetries make it difficult for arbitrageurs to disentangle price pressure from fundamental information.

Keywords: asymmetric information, fire sales, price pressure, 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.

Given the importance of fire sales for the economy, it is important to understand why they occur. Standard models assume either that asset values depend on who owns the asset (e.g., Williamson (1988); Shleifer and Vishny (1992)) or there are market frictions that limit arbitrage (Shleifer and Vishny (1997), Gromb and Vayanos (2002)). In the former case, assets have a higher marginal product in the hands of certain owners, and if these owners need to sell the assets, the assets become less valuable in the hands of the next best owner. In the latter case, frictions like transaction costs prevent arbitrageurs from buying all fire sale assets. In both cases, the models generate downward sloping demand curves so that prices fall as more assets are sold. However, a number of papers have documented the existence and persistence of fire sale discounts even for highly liquid assets that do not have a specialized use, such as stocks and bonds. This begs the question: why do prices of such assets remain depressed for prolonged periods of time following fire sales? In this paper, we test another potential explanation – information asymmetries.

[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 fire sales in the aircraft market; Campbell, Giglio, and Pathak (2011) document evidence of fire sales in the real estate market.

Several recent models argue that information asymmetries can lead to fire sale discounts (Kurlat (2016), Dow and Han (2018)). The idea is straightforward: if fund managers know more about the fundamental value of their holdings than other investors, then potential buyers may be reluctant to purchase these assets even when the fund manager is forced to sell some of them. As a result, asset prices must fall for the market to clear. The result is similar to the classic "lemons" problem (Akerlof, 1970). Importantly, in a follow-up paper, Kurlat (2018) shows that the optimal policy response depends on whether information asymmetries can cause fire sale discounts.[2] Yet to date, there is little empirical evidence on the relation between information asymmetries and fire sale discounts.

We provide the first empirical tests on this important topic. To do this, we use mutual funds as a laboratory. In many ways, mutual funds are an ideal setting for examining whether information asymmetries matter for fire sales. First, our sample of U.S. equity mutual funds holds liquid assets that are not subject to significant limits to arbitrage.[3] Second, these assets do not have a specialized use; they represent claims on future cash flows.

Empirically, it is unclear if information asymmetries actually affect fire sale discounts. Even for mutual funds, the answer remains uncertain. On the one hand, it seems intuitive that fund managers would use all available information to help them liquidate assets. On the other hand, a number of papers argue that mutual fund mangers are not skilled (e.g., Carhart (1997), Fama and French (2010)). Moreover, mutual fund holdings are publicly released at regular intervals. And while 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)). Thus, even in financial assets, it is ultimately an empirical issue whether information asymmetries can generate fire sale discounts.

[2]In particular, he shows that optimal policies regarding aggregate investment depend on whether information asymmetries are a cause of fire sale price discounts.

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

In this paper, we show that information asymmetries can generate fire sale discounts. We start by examining how fund managers trade after a flow shock. If fire sale discounts are a result of information asymmetries, then we would expect fund managers to concentrate their selling in a particular subset of assets, rather than scaling down their entire portfolio. Following a large negative flow shock, we find that fund managers decrease their positions in 43.9% of their holdings, while 37.4% of their positions remain unchanged. More surprisingly, fire sale fund managers actually increase their holdings in 18.7% of securities.[4] In other words, fund managers continue to purchase securities even as their fund is shrinking in size. The results show that fund managers do not simply scale their fund down to meet redemptions, but *choose* which assets to sell.

Of course, even if fund managers choose to concentrate their selling in a subset of assets, it is possible that their choices are uninformed. In order to examine whether fund managers use fundamental information to make trading decisions, we next decompose the trades of fund managers into (i) *expected trading* and (ii) *discretionary trading*. *Expected trading* measures the portion of actual fund manager trades that would be expected if the fund manager simply prorated flow shocks across each asset in her portfolio. The intuition is simple: imagine a fund manager who has 40% of her portfolio allocated to stock A and the remaining 60% allocated to stock B. If the manager has no fundamental information about asset values, then following an outflow of \$5 we would expect her to sell $\$5 \times 40\% = \$2$ 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.

[4] Coval and Stafford (2007) document a similar finding and so they focus on a measure of forced selling (i.e., selling following a large outflow). Our finding is distinct from this: as we show later, even this forced selling measure contains a discretionary component that is related to fundamental information.

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. 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.

Our results suggest mutual fund managers attempt to use information to sell stocks after experiencing large outflows.[5] Following a large negative flow shock, a one-standard deviation increase in short selling is associated with discretionary sales that are 30% 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. Similarly, a one-standard deviation increase in positive future earnings surprises is associated with discretionary sales that are 2% 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

[5]While short interest data is publicly released, public information releases may generate disagreement, instead of resolving it, because of differences in information processing skills (e.g., Kandel and Pearson (1995), Kim and Verrecchia (1994), Rubinstein (1993)). The primary purpose of our study is to examine whether information asymmetries can generate fire sale discounts. Future research should continue to explore the precise source of these information asymmetries.

by mutual funds experiencing extreme outflows have significant price drops of over 4% and three years later, they still have negative cumulative returns. In contrast, in Panel B, it is clear 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 almost 6% 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 results from multivariate analyses (that account for time-series and cross-sectional heterogeneity in the performance of fire sale stocks) show 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. 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*. Overall, the results suggest that managers attempt to sell low-quality assets in their portfolio.

While fire sale managers try to selectively sell low-quality assets, because flow shocks can be large in magnitude, they may also have to sell some high-quality assets. We confirm that they do. We use return on equity (ROE) as a proxy for asset quality and find that fire sale fund managers sell a mix of stocks that have high and low ROE. The results suggest that price pressure from fire sales cannot be explained by pure selection (i.e., prices drop because the stocks are low quality); rather, arbitrageurs face a lemons problem. The fact that fire sales funds sell a mix of high- and low-quality assets makes it difficult for arbitrageurs to disentangle pure price pressure from negative information due to information asymmetries, leading to the lemons problem (Akerlof (1970)). Indeed, consistent with this, we find that high-quality stocks sold by fire sale funds experience a similar price pressure in the quarter of the fire sale as low-quality ones.

We also find that trades by fire sale funds can affect the trading decisions of other funds in the same stocks, which might also contribute to the magnitude and persistence of price pressure in those stocks. Specifically, when we examine *discretionary* trading by mutual funds that are *not* experiencing a fire sale, we find that these funds are more likely to sell stocks that were recently sold by funds experiencing a fire sale. Moreover, non-fire sale fund managers respond similarly to both *expected* and *discretionary* trading by fire sale funds. The results suggest that fire sales are likely to have a contagion effect, in part, because of information asymmetries so that other traders cannot separate price pressure from negative fundamental information. We confirm that stocks with a higher level of contagion-driven sales by non-distressed funds experience larger fire sale discounts, suggesting that this contagion can also generate price pressure.

Finally, we examine a simple trading strategy designed to measure the value of the information in asset fire sales. Specifically, 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 12 after the fire sale event quarter (i.e., over the two years following the sale), the annualized 5-factor alpha of the strategy for an equal-weighted portfolio (a gross-return-weighted portfolio) is 2.78% (2.76%). Put differently, understanding *why* fund managers sold a stock is crucial to understanding return movements following asset fire sales.

Our results are related to a growing theoretical literature on fire sales. We document a version of the "lemons" problem (Akerlof, 1970). In our setting, fund managers who own a particular stock may have some information advantage about the value of that asset. Following a flow shock, managers must sell some of their holdings and they use their information 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 are unable to distinguish between the two types. This causes all fire sale assets to experience price drops.[6] Consistent with the impact of information asymmetries, we show that the price drops are greater for more opaque stocks. We also provide novel evidence on the contagion effect of fire sales, which is consistent with the fire sale-triggered downward spirals and cascades in asset prices emphasized by the literature on fire sales (e.g., Shleifer and Vishny (1992)).

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 exacerbates information asymmetries, leading to larger price drops. We find that it does. Specifically, 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 make it harder for other investors to understand the motivation for the sale of an asset, leading to larger fire sale discounts.

[6] Our results show that *all* assets experience a significant initial price drop during a fire sale, however, after the initial period *discretionary* stock sales continue to fall in price, while other assets experience flat to increasing prices.

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 fundamental 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 (written after ours) argue that mutual fund fire sales do not satisfy the necessary conditions for a valid instrument. Berger (2019) argues that fire sales are not a valid instrument because they are correlated with firm fundamentals and Wardlaw (2020) shows that scaling by dollar volume induces a mechanical correlation with returns.[7] Our paper shows the economic mechanism that generates a correlation between fire sales and firm fundamentals.

Lastly, our finding also adds to the theoretical literature on discretionary liquidity trading (e.g., Admati and Pfleiderer (1988), Han, Tang, and Yang (2016)), which often interprets discretionary liquidity traders as funds suffering redemption and finds that discretionary traders concentrate their trades. In contrast, we show that such a concentration can also be driven by information advantages. We believe these two different views are complementary, which helps provide a complete picture of discretionary trades.

Overall, our primary contribution is that we provide the first evidence that information asymmetries are a significant determinant of the magnitude and persistence of price pressure from fire sales. Hendershott and Menkveld (2014) document systematic evidence of price pressure at the intraday level and show that price pressure has an adverse impact on market price efficiencies at multiple frequencies. More generally, 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. While our study examines fire sales in stocks, we note that stocks are arguably subject the least to information asymmetries (as a result of competitive market forces that make it

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

difficult for managers to predict stock returns). As such, our results can be generalized to other asset classes: anytime an owner is forced to liquidate assets for liquidity, it is possible that the owner will choose to sell their worst assets, but information asymmetries lead to large and long lasting price impact.

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 Thomson Financial, as discussed in detail below.

A. Sample Construction

Our sample consists of all U.S. firms in Compustat over the period 1980 to 2019. 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 and quarterly return on equity (ROE) from Compustat.[8] 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] In our analyses, we examine 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, daily

[8]Because ROE has several observations that are extreme outliers, we winsorize it at the 1st and 99th percentiles.

[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).

stock returns, 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 below in Section II.B. We then use the MFLINKS file to match the Thomson-Reuters data with the CRSP mutual fund data. We filter the mutual fund data to include only domestic equity funds using the filters in Khan, Kogan, and Serafeim (2012); we also exclude index funds from our sample.

To mitigate the impact of asset illiquidity, in each period we drop stocks with a price less than \$5. We also filter the mutual fund data to exclude funds with fewer than 10 holdings or assets less than \$5 million.

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

[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.

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

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

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:

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

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

[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 (2020) shows that scaling by dollar volume induces a mechanical correlation with returns; our calculation avoids this issue.

stock at the beginning of the quarter. The *expected trading* of the stock is then defined as the sum of the expected number of shares to be traded by all funds with extreme flow shocks.

Our measure of *expected trading* is designed to represent a counter-factual measure of fund trading absent a fire sale. Put differently, it answers the question, "What would we expect fund managers to do if a flow shock had not occurred?" While there is not necessarily one unique answer to this question, our measure has several desirable properties. First, our method is motivated by the idea that fund 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 (2020)).[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

[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.

Pressure into an expected component and a discretionary component.[13] The resulting variables allow us to measure (i) whether fund managers experiencing large outflows (inflows) react by scaling down (up) their portfolio and (ii) whether *discretionary trading* by these fund managers can explain the strong and long-lasting under-performance of fire sale assets.[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, both measured 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] While short interest data is publicly available, existing literature suggests investors may react differently to the signal in public information due to heterogeneity in information processing skills (e.g., Kandel and Pearson (1995), Rubinstein (1993)). To the extent that fund managers have selling skill, it is possible they are skilled at processing public information, like short interest, and/or they possess private information that is correlated with short interest. We

[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.

[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 fundamental information; thus, they focus on inflow-driven purchases. In contrast, we specifically focus on sales that are not driven by flows (i.e., *discretionary* sales).

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

discuss this issue further in Section III.E.

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). Specifically, we define earnings surprise as:

$$EarnSurprise_{i,t} = (X_{i,t} - X_{i,t-4})/P_{i,t}, \tag{5}$$

where $X_{i,t}$ is earnings per share excluding extraordinary items for firm i in quarter t and $P_{i,t}$ is the stock price per share for firm i in quarter t.[16] If the trading decisions of fund managers predict future earnings surprises, then it is evident that they have fundamental information.[17]

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 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.[18]

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

[16] This calculation assumes earnings follow a seasonal random walk model of the form $earnings_{i,t} = earnings_{i,t-4} + e_{i,t}$, where $e_{i,t}$ is white noise. Foster, Olsen, and Shevlin (1984) show the rolling seasonally adjusted random walk model performs as well or better than more complicated autoregressive moving average models. 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.

[17] In the Internet Appendix we examine an alternate measure of earnings surprise based on analyst forecasts, calculated as the difference between actual earnings and the median analyst forecast from IBES, scaled by quarterly stock price.

[18] 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).

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.[19]

D. Summary statistics

Table I provides summary statistics for the combined database (Panel A) as well as stocks that were sold by fire sale funds (Panel B). The mean (median) short interest ratio (*ShortInterest*) over our sample is 3.5% (1.6%). As previously mentioned, in our main specifications we use the natural log of short interest, since it is highly right-skewed (the 99th percentile is 24.7%). 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 and median of *discretionary trading* in Panel B are negative, indicating that on average, fire sale funds are more likely to make discretionary sales than discretionary buys.

[19] In the Internet Appendix, we discuss the formal requirements for a valid proxy variable.

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. We begin by examining the trading motivations of fund managers to determine which stocks they sell (and why) following fire sales. We then investigate the impact of their trading on other funds' trading. We also 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.[20] For example, if a manager had 40% of her portfolio allocated to stock A and 60% allocated to stock B and she experienced \$5 in redemptions, then we would expect her to sell \$2 of stock A and \$3 of stock B. On the other hand, if the manager has fundamental information that one of these stocks is likely to underperform going forward, we would expect the manager to concentrate her selling in that asset.

[20]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.

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 43.9% of assets and they maintain their position in 37.4% of assets. Moreover, they actually increase their holdings in 18.7% 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.

It seems intuitive that fund managers would use all available information in an attempt to help them liquidate assets. However, it is unclear if fund managers are good at doing this. Accordingly, we next examine whether these selling choices are motivated by fundamental information using linear probability panel regressions of the form:

$$\mathbb{1}_{[Sell]i,t} = \beta_1 StockCharacteristics + FE_i + FE_t + \epsilon_{i,t}, \tag{6}$$

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 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 Driscoll and Kraay (1998) standard errors shown below the estimates in italics.[21] We find that fund managers are significantly more likely to sell larger and more liquid stocks, consistent with existing evidence that managers under stress prefer to sell stocks that are easier to liquidate (e.g. Strahan and Tanyeri (2014)). More interestingly, 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 0.0522 on $Short\ Interest$ suggests that a one standard deviation increase in short interest is associated with a 17.0% increase in the probability of sale by a manager (relative to the unconditional mean). Similarly, the coefficient of -0.1907 on *EarnSurprise* suggests that a one standard deviation increase in future negative earnings surprises is associated with a 1% increase in the probability of sale by a manager. This result suggests that fund managers have fundamental information; their selling decisions are associated with future earnings *surprises*. [22]

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:

$$\Delta Holdings_{i,t} = \beta_1 StockCharacteristics + Controls + FE_i + FE_t + \epsilon_{i,t}, \tag{7}$$

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

[21] In all regressions, we set the lag length as $t^{1/4} = \approx 3$ as in Newey and West (1987).

[22] In Table A2 of the Internet Appendix, we show that our conclusions are unchanged when we use an alternate measure of earnings surprise that is calculated using analyst forecasts.

$DiscretionaryTrading$ 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 30% 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 2%, relative to the unconditional mean. 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.[23] Indeed, in columns (3) and (4) the coefficient estimates on *expected* trading are economically and statistically insignificant.[24]

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

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

[24]The results are similar when we use the alternate earnings surprise measure, calculated using analyst forecasts (see column (4) of Table A3 in the Internet Appendix).

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 43.9% 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.

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.

B.1. Univariate evidence

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 quintiles based on *discretionary* trading in quarter t. Stocks in the lowest quintile have more selling pressure than expected (*Sold More*), stocks in the middle quintiles have selling pressure approximately equal to the expected selling pressure (*Sold Expected*), and stocks in the highest quintile have less selling pressure than expected (*Sold Less*). 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.[25] 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 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 three separate lines 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. Four quarters after a fire sale, stocks that are sold in greater than expected quantities exhibit cumulative average abnormal returns below -5%. However, stocks that are sold as expected experience cumulative average abnormal returns of -4%. Moreover, stocks that are sold in lower than expected quantities exhibit cumulative average abnormal returns of only -3%.

Our results are generally consistent with models 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 sell for a discount.

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

B.2. Multivariate analysis

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:

$$\begin{aligned} AbnRet_{i,t:t+h} = \beta_1 ExpectedTrading_{i,t} + \beta_2 DiscretionaryTrading_{i,t} \\ + Controls + FE_i + FE_t + \epsilon_{i,t:t+h}, \end{aligned} \tag{8}$$

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 $Pressure_{i,t}$ that is not from $ExpectedTrading_{i,t}$.

The results are shown in Table IV with t-statistics calculated using Driscoll and Kraay (1998) standard errors 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 0.0039 on *Pressure* in model (1) indicates that a one standard deviation increase in selling pressure is associated with a 39 basis point decrease in abnormal returns during the event quarter.[26] In models (4) through (6), we test for evidence of return reversals. The coefficient of -0.0065 on *Pressure* in model (4), while marginally significant, indicates that a one standard deviation increase in selling pressure is associated with a 65 basis point increase in abnormal returns over the window t=+5 to +12, corresponding to a two-year return starting one year after the fire sale. Put differently, the results document evidence of fire sale price drops in the

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

event quarter (model (1)), which then reverse over a two year period starting the year after a fire sale (model (4)).

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 45 basis point increase in abnormal returns; this effect is over two times larger than the impact of *expected* trading. In models (5) and (6), we test for evidence of reversals over a two-year window starting one year after the file sale. In both models, the coefficient on *expected* trading is negative and significant indicating reversals. 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. In contrast, the estimates on *discretionary* trading are much smaller and not statistically significant at the 5% level (although the estimate in model (5) is marginally significant at the 10% level). The results suggest that *discretionary* sales are concentrated in low-quality assets; as such, these assets experience price declines that do not fully reverse.

In light of these findings, we also examine whether negative fundamental information can explain the persistence of fire-sale discounts. In Internet Appendix Table A5, we examine a Poisson model where the dependent variable is the number of quarters, following a fire sale, that it takes for a stock's cumulative abnormal return to reach zero or higher. In column (2), the negative and statistically significant coefficient on *discretionary* trading indicates that fire-sale stocks with more discretionary trading are less likely to see a price correction within 3 years of being sold.

Overall, the results suggest that asymmetric information can help explain both the magnitude and persistence of fire sale discounts.[27] Importantly, we note that our regression

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

results account for trade quantity. As such, 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*.[28]

The results in this section provide clear evidence that the *discretionary* trades of mutual fund managers are associated with significant price drops that persist for prolonged periods of time. These results are consistent with several theoretical models. In the next section, we test specific predictions of these models.

C. Tests of the Impact of Information Asymmetries

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. This results in a mix of low-quality and high-quality asset sales and other market participants are unable to distinguish between the two due to information asymmetries, leading to a lemons problem (Akerlof (1970)). In this section, we present further evidence on it and test predictions from several extant models.

C.1. Stock quality and price drop

We start by checking whether fire sale funds sell low-quality stocks, high-quality stocks, or a mix of both. We then test specific predictions of the lemons problem; namely, we examine whether both low- and high-quality stocks that are sold by fire sale funds experience a substantial price drop. We find that they do.

To measure asset quality, we use a well-known accounting measure: return on equity (ROE). On average, stocks with high ROE values are likely to be of higher quality than

[28] 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.

stocks with low ROE. In Panel A of Table V, we present the mean, median (p50), 1st percentile (p1), and 99th percentile (p99) of the distribution for stocks with discretionary sales by fire sale funds. In all cases, they are comparable to those of the distribution for all stocks held by all mutual funds shown in Panel A of Table I. The results show that discretionary sales by fire sale fund managers contain a mix of low- and high-quality stocks, and this mixture closely resembles the unconditional distribution of asset quality as held by all mutual funds. In other words, fire sale fund managers are not exclusively selling low-quality assets; they sell a mix of both low- and high-quality stocks.

We then examine whether both low- and high-quality stocks experience price pressure following fire sales. To do this, we augment the regression shown in equation (8) to include our measure of asset quality, ROE, and interact ROE with our price pressure measures according to the model:

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

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 $Pressure_{i,t}$ that equals fund flows prorated to the stock-level using each stock's weight in the portfolio, $DiscretionaryTrading_{i,t}$ is the portion of $Pressure_{i,t}$ that is not from $ExpectedTrading_{i,t}$, $ROE_{i,t}$ is return on equity in stock i on date t, and $X_{i,t}$ is a vector of interaction terms that contain $ExpectedTrading \times ROE_{i,t}$ and $DiscretionaryTrading \times ROE_{i,t}$.

The results are shown in Panel B of Table V, with t-statistics calculated using Driscoll and Kraay (1998) standard errors 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. Model (1) shows the baseline relation between returns and fire sales, as measured by $Pressure$. While the coefficient on $Pressure_{i,t}$ remains significantly positive, the coefficient on its interaction with $ROE_{i,t}$ is statistically insignificant. Models (2) and (3) show the results when we interact $ExpectedTrading_{i,t}$ and $DiscretionaryTrading_{i,t}$ with asset quality. In both models (2) and (3), we find similar results: the coefficient on $DiscretionaryTrading_{i,t}$ remains positive and statistically significant, indicating that there is significant price pressure from discretionary trades. However, the insignificant coefficients on $ExpectedTrading_{i,t} \times ROE$ and $DiscretionaryTrading_{i,t} \times ROE$ indicate that there is no incremental difference for stocks of low- and high-quality.[29] In other words, the results show that price pressure from fire sales is not a simple selection problem: if fire sale fund managers only sold low-quality assets and/or the price drop were concentrated in only low-quality assets, then fire sale discounts could be explained by a pure selection story (i.e., fire sale fund managers sell low-quality stocks, which perform poorly in the future and thus earn lower returns). In contrast, the results in Table V show that fire sale price drops are not driven purely by selection. The fact that fire sale fund managers sell both low- and high-quality assets, and both experience similar price pressure, suggests that information asymmetries lead to a lemons problem.

C.2. The impact of market stress, cash holdings, and other proxies for information asymmetry

We next examine theoretical predictions on the relation between information asymmetries and price pressure. Several models suggest that price pressure should be larger when information asymmetries are larger. For example, 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

[29] In Table A4 of the Internet Appendix, we show similar results when we measure asset quality using the percentage of analysts that recommend buying a stock.

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.

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

Second, Malherbe (2014) shows that selling decisions by fund managers are more likely to be a result of information if the fund holds a large amount of cash. The intuition 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 fire sales. To test this prediction, we construct an indicator variable for cash holdings ($Cash$) that takes the value of one if a stock is held by mutual funds that on average have more than 2% of net assets in cash, and zero otherwise.

Third, we conduct a direct test of whether the price drop is greater when a stock is more opaque. We use the natural log of the bid-ask spread as a measure of a stock's opaqueness ($LN(Bid - Ask\%)$). We then run OLS panel regressions of the form:

$$AbnRet_{i,t} = \beta_1 ExpectedTrading_{i,t} + \beta_2 DiscretionaryTrading_{i,t} + \beta_3 S_{i,t} + \Gamma X_{i,t} + FE_i + \epsilon_{i,t}, \tag{10}$$

where $AbnRet_{i,t:t}$ 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 $Pressure_{i,t}$ that equals fund flows prorated to the stock-level using each stock's weight in the portfolio, $DiscretionaryTrading_{i,t}$ is the portion of $Pressure_{i,t}$ that is not from $ExpectedTrading_{i,t}$, $S_{i,t}$ is either (i) $Cash$ or (ii) $Stress$, or (iii) $LN(Bid - Ask\%)$, 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. Finally, if a stock is more informationally opaque, as measured by a higher bid-ask spread, we would expect $DiscretionaryTrading$ to have a larger impact.

The results are shown in Table VI. Models (1), (2), (5), and (7) display the benchmark cases, without conditioning on whether the trades were *discretionary* or *expected*. In models (1) and (2) we find some evidence that cash holdings are associated with worse price drops. In both models, the coefficient on $Pressure \times Cash$ is positive, and it is statistically significant in model (1). Moreover, in model (5) when we interact $Pressure \times Stress$, we 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.[30] We also find some evidence that stock opaqueness is related with larger price drops. In model (7), the coefficient on $Pressure \times LN(Bid - Ask\%)$ is positive and marginally significant.

In models (3), (4), (6), and (8), we examine the results for *discretionary* and *expected* trading. In model (3), the coefficient on $Discretionary \times Cash$ is positive and statistically significant and it is positive (but not quite significant) in model (4), while the coefficient on $Expected \times Cash$ is insignificant in both models. This result broadly 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.

[30]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.

In model (6), we find that the coefficients on $Discretionary \times Stress$ and $Expected \times Stress$ are both positive and the estimate on $Discretionary \times Stress$ is highly significant.[31] It suggests that information asymmetries are exacerbated under market stress leading to larger price drops, especially for $DiscretionaryTrading$, consistent with the predictions in the Dow and Han (2018) model. When combined with our return results in Figure 1, which find 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 in normal time, such that not all of them sell for the same discount as discretionary trades. However, in time of market stress, these arbitrageurs are prevented from trading and as a result, all fire sale assets sell at a large discount.

Finally, we examine the impact of information asymmetries. In model (8), the coefficient on $Discretionary \times LN(Bid - Ask\%)$ is significantly positive, while the coefficient on $Expected \times LN(Bid - Ask\%)$ is negative and insignificant. As such, these results provide direct evidence that fire sale discounts are significantly larger for stocks with more severe information asymmetries. Overall, the results in Table VI support the theoretical predictions on price pressure and information asymmetries.

C.3. Contagion effect

We then examine implications of price pressure. Specifically, we examine how trades by non-fire sale funds may be related to the trades of fire sale funds. In other words, we test for a contagion effect from fire sales, which may also help explain the magnitude and persistence of price pressure. Specifically, due to information asymmetries, other market participants may not be able to distinguish between expected and discretionary trades, and they may incorrectly trade their own portfolio as a result. To test for this, we first examine the discre-

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

tionary trading of mutual fund managers who are *not* experiencing a fire sale, in response to trades by fire sale funds. Specifically, we conduct panel regressions of discretionary trading by non-fire sale funds as a function of recent trades by fire sale funds according to the model:

$$DiscretionTrade_{i,t}^{NoFire} = \beta_1 ExpectedTrade_{i,t-1}^{Fire} + \beta_2 DiscretionTrade_{i,t-1}^{Fire} + FE_i + FE_{j,t} + \epsilon_{i,t}, \tag{11}$$

where $DiscretionTrading^{NoFire}$ is discretionary trading by funds that are not experiencing fire sales.[32] $ExpectedTrading^{Fire}$ is expected trading by funds experiencing a fire sale and $DiscretionaryTrading^{Fire}$ is discretionary trading by funds experiencing a fire sale.

Then, we check whether the contagion-driven sales of non-distressed funds can move the market, that is, whether stocks with a higher level of contagion-driven trades are associated with larger fire sale discounts.[33] To do this, we first obtain the fitted value of discretionary trading by non-fire sale funds from the regression shown above in equation (11) (i.e., the portion of their trading that is attributable to trading by fire sale funds) and then conduct panel regressions of $AbnRet_{i,t}$ on it.

The results, presented in Table VII, show evidence of contagion that does lead to additional price pressure. Panel A shows that non-fire sale fund managers respond to trades by fire sales funds. Specifically, non-fire sale funds are more likely to sell stocks that were sold by funds experiencing a fire sale. More interestingly, they respond to both expected and discretionary trading, as shown in Columns (1) and (2). And this finding continues to hold even after controlling for firm fixed effects and the liquidity measures in Columns (3) and (4). The results again suggest that fire sales are likely to result in a contagion effect, in part, because of information asymmetries that make it difficult for other traders to separate price

[32] Formally, it is trading by funds that do *not* have flows in the top or bottom decile each period.

[33] Theoretically, the adverse selection mechanism should be stronger for sales than purchases. In our setting, more than 75% of expected and discretionary trading by fire sale funds represents selling behavior, so the contagion effect we document is necessarily driven by sales.

pressure from negative fundamental information.[34] Panel B shows that the coefficients on the fitted value of discretionary trading by non-fire sale funds are all significantly positive. The finding suggests that stocks which experience a higher level of contagion-driven trades exhibit even larger fire sale price drops.

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*.

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 (*Sold Less*). 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 (*Sold More*). 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 regress the monthly excess returns of our portfolios on the Fama and French (2015) five factors.[35]

The results are shown in Table VIII with t-statistics, calculated using Driscoll and Kraay (1998) standard errors, reported next to the coefficient estimates. The evidence in Figure 1 suggests that both *discretionary* and *expected* fire sale trades experience price drops, but *expected* fire sale trades begin to correct after approximately one year. Accordingly, in Panel A of Table VIII, we examine returns to an equal-weighted portfolio that begins trading five quarters after the event date (i.e., one year after the fire sale) and holds stocks until the twelfth quarter (corresponding to a two-year holding horizon). The annualized

[34] In results not tabulated for brevity, we also find similar results when we examine the contemporaneous relation between discretionary trading by non-fire sale funds and trading by fire sale funds.

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

5-factor alpha of the strategy is 2.78%. In Panel B of Table VIII, we examine returns to a weighted portfolio that begins trading five quarters after the event date and holds stocks until the twelfth quarter, where the weight is the prior period's gross return as in Asparouhova, Bessembinder, and Kalcheva (2010).[36] The annualized 5-factor alpha of the strategy is 2.76%. In sum, these findings further confirm that there is valuable information in asset fire sales.

E. Interpretation of Results

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

Meanwhile, two outstanding issues are noteworthy. First, any statement about the motivation of sales following flow shocks should explain both (i) the choice of assets which are

[36] Portfolio rebalancing can lead to biases in mean abnormal return due to the effects of slow systematic information diffusion (e.g., Boguth, Carlson, Fisher, and Simutin (2016)). Asparouhova et al. (2010) show that weighting by lagged gross returns can substantially eliminate this bias.

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, 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. Second, 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 learn of 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 to avoid further losses, although they may well have incurred losses from these holdings prior to the fire sales.

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? While it may seem natural that all investors should react to public information in the same way, a number of papers argue that public information releases may generate disagreement, instead of resolving it. Due to heterogeneity in information processing skills, investors may react differently to the signal in publicly observable short interest data (e.g., Kandel and Pearson (1995), Rubinstein (1993)). As noted in Rubinstein (1993), "In real life, differences in consumer behavior are often attributed to varying intelligence and ability to process information. Agents reading the same morning newspapers with the same stock price lists will interpret the information differently" (p. 473). Our results suggest mutual fund managers might use public information like short interest when choosing which assets to sell. As we note earlier, it is also possible that fund managers have the same private information as short sellers and they jointly react at the same time. Either way, our results show that fund managers use valuable information when selling assets during a fire sale.

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, but information asymmetries make it difficult for arbitrageurs to disentangle pure price pressure from negative information. Our finding is surprising in light of the large literature showing that mutual fund fire sales are predictable (e.g., Coval and Stafford (2007), Shive and Yun (2012), Dyakov and Verbeek (2013), Arif et al. (2016)). 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. 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.

Overall, our paper presents the first evidence that information asymmetries can generate price pressure during fire sales.

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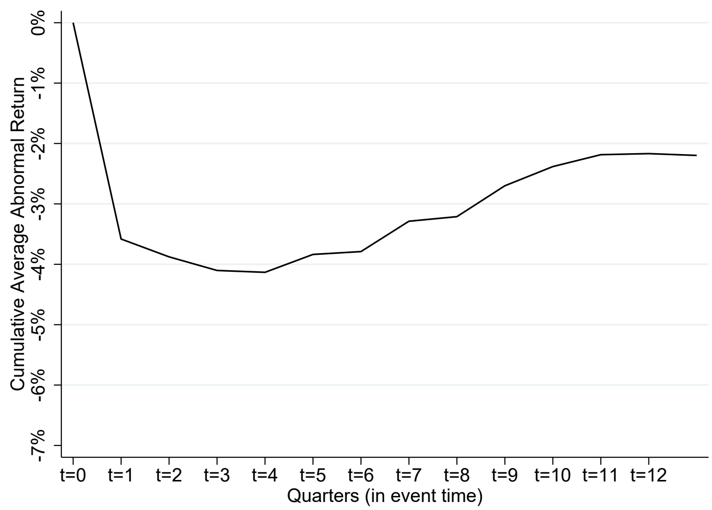
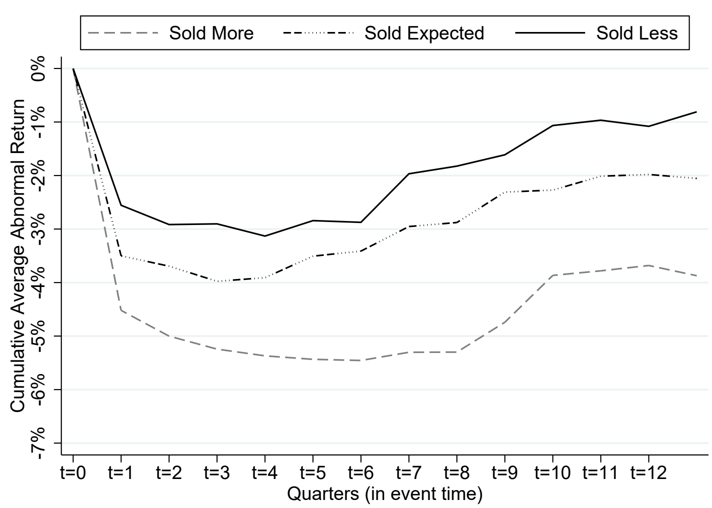
Figure 1. Cumulative Average Abnormal Returns in Event Time around Fire Sales

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 portfolios based on whether fund managers: (i) sold more shares than expected or (ii) 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 line) and stocks that are sold less than expected are assigned to the *Sold Less* portfolio (dashed 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*); the vertical gray bar at $t = 0$ indicates the fire sale quarter. Detailed variable definitions are provided in Section II.C of the text.

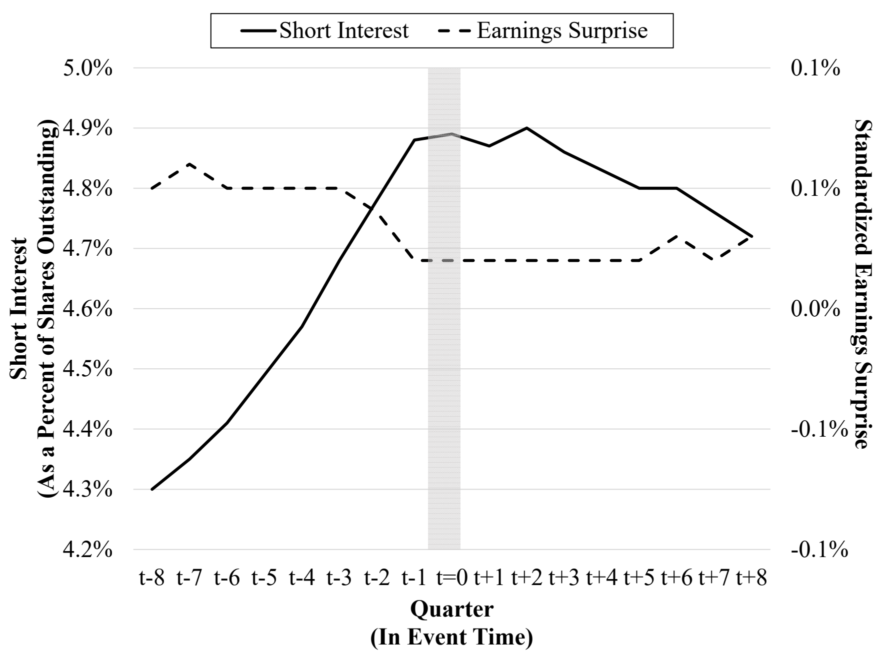


Table I
Summary Statistics

The sample includes all NYSE and NASDAQ common stocks (i.e., share codes 10 and 11) over the period January 1980 to December 2019. 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, *LN(Market Cap.)* is the natural log of market capitalization in millions of U.S. dollars, and *ROE* is return on equity. Panel A shows summary statistics for all stocks, while Panel B shows summary statistics for stocks held by a fire sale fund.

Variable	(1) Mean	(2) Median	(3) 1st %	(4) 99th %	(5) St. Dev.
Panel A: All Stocks					
Pressure	0.0005	0.0000	-0.0174	0.0214	0.0067
Expected Trading	0.0007	0.0000	-0.0094	0.0190	0.0050
Discrectionary Trading	-0.0003	0.0000	-0.0227	0.0202	0.0072
EarnSurprise	0.0001	0.0004	-0.0380	0.0240	0.0069
Short Interest (in %)	3.5163	1.6442	0.0008	24.7056	5.2140
LN(Short Interest %)	-4.5699	-4.0981	-10.8809	-1.3969	2.0663
LN(Bid-Ask %)	-5.2594	-4.8941	-9.0361	-2.2083	1.8060
LN(Market Cap.)	19.7804	19.6062	16.3674	24.7021	1.8562
ROE	0.0136	0.0243	-0.5978	0.5159	0.1011
Panel B: Stocks held by Fire Sale Funds					
Pressure	-0.0072	-0.0045	-0.0450	-0.0001	0.0093
Expected Trading	-0.0015	-0.0009	-0.0183	0.0128	0.0056
Discrectionary Trading	-0.0057	-0.0035	-0.0409	0.0085	0.0093
EarnSurprise	0.0002	0.0004	-0.0327	0.0208	0.0065
Short Interest (in %)	4.8880	2.8219	0.0067	28.9900	6.1122
LN(Short Interest %)	-3.8943	-3.5658	-9.4033	-1.2373	1.6943
LN(Bid-Ask %)	-5.7607	-5.7823	-9.0374	-2.6027	1.7456
LN(Market Cap.)	20.4268	20.3723	17.1798	24.1649	1.5317
ROE	0.0164	0.0247	-0.4560	0.5159	0.0968

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:

$$\mathbb{1}_{[Sell]i,t} = \beta_1 StockCharacteristics + FE_i + FE_t + \epsilon_{i,t}, \tag{12}$$

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 Driscoll and Kraay (1998) standard errors with 3 lags 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	43.9%	18.7%	37.4%

Panel B: Linear Probability Model

Explanatory Variable	Dependent Variable: Sell Indicator (1)	(2)	(3)	(4)
LN(Short Interest %)	0.0522***	0.0514***		
	(16.00)	(15.61)		
SUE			-0.1907***	-0.1703***
			(-7.87)	(-8.79)
LN(Bid-Ask %)	-0.0091***	-0.0099***	-0.0122***	-0.0151***
	(-3.46)	(-3.95)	(-3.15)	(-4.36)
LN(Market Cap.)	0.0807***	0.0833***	0.1131***	0.1153***
	(18.21)	(17.22)	(18.11)	(18.40)
Firm FE	Yes	Yes	Yes	Yes
Date FE	Yes	No	Yes	No
Industry × Date FE	No	Yes	No	Yes
Observations	247,499	246,976	259,871	258,980
R-squared	54.1%	56.3%	52.8%	55.4%

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 $Pressure$ that 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 Driscoll and Kraay (1998) standard errors with 3 lags 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 %)$_{i,t-1}$	-0.0562**		0.0183	
	(-1.99)		(0.52)	
SUE$_{i,t+1}$		0.7610*		0.3302
		(1.90)		(1.19)
LN(Bid-Ask %)$_{i,t-1}$	0.0386*	0.0042	-0.0262	-0.0497*
	(1.81)	(0.15)	(-1.01)	(-1.75)
LN(Market Cap.)$_{i,t-1}$	-0.0670	-0.1443***	0.0294	0.0993**
	(-1.08)	(-2.98)	(0.47)	(1.98)
Firm FE	Yes	Yes	Yes	Yes
Industry × Date FE	Yes	Yes	Yes	Yes
Observations	246,976	258,980	246,976	258,980
R-squared	10.9%	9.8%	23.1%	20.3%

Table IV
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 log 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 $Pressure$ that 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 $\times$ date fixed effects, as indicated at the bottom of the panel. t-statistics calculated using Driscoll and Kraay (1998) standard errors with 3 lags 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	0.0039***			-0.0065*		
	(2.67)			(-1.72)		
Expected Trading		0.0032	0.0020		-0.0128***	-0.0088*
		(1.59)	(0.93)		(-3.20)	(-1.98)
Discretionary Trading		0.0044***	0.0045***		-0.0070*	-0.0059
		(3.01)	(2.81)		(-1.69)	(-1.33)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	No	Yes	No	No	Yes	No
Industry $\times$ Date FE	Yes	No	Yes	Yes	No	Yes
Observations	56,958	58,891	56,958	41,674	43,657	41,674
R-squared	34.7%	19.1%	34.7%	46.4%	30.0%	46.4%

Table V

Test of Relation between Asset Quality and Price Pressure

The table examines the relation between trading, price pressure, and asset quality, where each stock's quality is proxied by its return on equity (ROE). Panel A displays summary statistics for ROE for stocks that experience a discretionary sale in the current quarter. Panel B examines 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 log 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 ROE, 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) displays the baseline relation between future returns and fire-sales, as measured by $Pressure$, while models (2) and (3) 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 Driscoll and Kraay (1998) standard errors with 3 lags 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.

Panel A: Summary Statistics for Stocks with Discretionary Sales

	Mean	p50	p1	p99
ROE	0.0153	0.0249	-0.5768	0.5159

Panel B: Regression Examining Price Pressure for High and Low Quality Stocks

Pressure	0.0061***		
	(3.45)		
Expected Trading		0.0036*	0.0028
		(1.67)	(1.08)
Discretionary Trading		0.0065***	0.0071***
		(3.80)	(3.65)
ROE	0.1868***	0.1850***	0.1906***
	(6.10)	(5.41)	(6.04)
Pressure × ROE	-0.0127		
	(-0.84)		
Expected × ROE		0.0041	0.0183
		(0.20)	(0.74)
Discretionary × ROE		-0.0215	-0.0261
		(-1.22)	(-1.41)
Firm FE	Yes	Yes	Yes
Date FE	No	Yes	No
Industry × Date FE	Yes	No	Yes
Observations	46,066	48,247	46,066
R-squared	36.5%	20.3%	36.5%

Table VI
Test of Relation between Information Asymmetries and Price Pressure

The table examines the relation between trading, price pressure, and variables that theoretically exacerbate information asymmetries 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 log 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 $Pressure$ that 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 the 95th percentile of all dates and zero otherwise ($Stress$) or (iii) the natural log of the bid-ask spread, and $X_{i,t}$ denotes interaction terms that contain $ExpectedTrading \times S_{i,t}$ and $DiscretionaryTrading \times S_{i,t}$. 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 Driscoll and Kraay (1998) standard errors with 3 lags 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							
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Pressure	-0.0007	0.0016			0.0038*		0.0132**	
	(-0.18)	(0.44)			(1.69)		(2.51)	
Expected Trading			0.0023	0.0043		0.0022		0.0020
			(0.73)	(1.21)		(0.78)		(0.32)
Discretionary Trading			-0.0019	0.0002		0.0039*		0.0152***
			(-0.44)	(0.04)		(1.75)		(3.03)
Cash Indicator	0.0041	0.0038	0.0040	0.0036				
	(1.06)	(1.10)	(1.03)	(1.06)				
Pressure × Cash	0.0072*	0.0043						
	(1.67)	(1.02)						
Expected × Cash			0.0014	-0.0021				
			(0.44)	(-0.57)				
Discretionary × Cash			0.0084*	0.0062				
			(1.73)	(1.34)				
Stress Indicator					0.0064	0.0064		
					(0.91)	(0.90)		
Pressure × Stress					0.0088**			
					(2.32)			
Expected × Stress						0.0045		
						(1.21)		
Discretionary × Stress						0.0091**		
						(2.45)		
LN(Bid-Ask %)							-0.0239***	-0.0239***
							(-5.66)	(-5.66)
Pressure × LN(Bid-Ask %)							0.0015*	
							(1.73)	
Expected × LN(Bid-Ask %)								-0.0001
								(-0.08)
Discretionary × LN(Bid-Ask %)								0.0019**
								(2.11)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	No	Yes	No	No	No	No	No
Industry × Date FE	No	Yes	No	Yes	No	No	Yes	Yes
Observations	58,891	56,958	58,891	56,958	58,891	58,891	49,015	49,015
R-squared	19.1%	34.7%	19.1%	34.7%	16.3%	16.3%	20.5%	20.6%

Table VII
Contagion Analysis: Discretionary Trading by Non-Fire Sale Funds

Models (1) through (4) examine trading decisions by non-distressed funds according to an OLS panel model of the form:

$$DiscretionTrade^{NoFire}_{i,t} = \beta_1 ExpectedTrade^{Fire}_{i,t-1} + \beta_2 DiscretionTrade^{Fire}_{i,t-1} + FE_i + FE_{j,t} + \epsilon_{i,t},$$

where $DiscretionTrading^{NoFire}$ is discretionary trading by funds that are not experiencing flows ranked in the top or bottom deciles each period. $ExpectedTrading^{Fire}$ is expected trading by funds experiencing a fire sale and $DiscretionaryTrading^{Fire}$ is discretionary trading by funds experiencing a fire sale. $Controls$ include the bid-ask spread ($LN(Bid-Ask\%_{i,t-1})$) and the natural log of market capitalization ($LN(MarketCap_{i,t-1})$). Panel B displays the second stage regression from an instrumental variables regressions that uses the regressions in Panel A as a first stage. The second stage examines price pressure from discretionary trading by funds that are not experiencing fire sales, using the fitted value from the first stage (i.e., the portion of their trading that is attributable to trading by fire-sale funds). Firm fixed effects are included in all models and industry × date (year-quarter) fixed effects are included in even numbered models. t-statistics calculated using Driscoll and Kraay (1998) standard errors with 3 lags are shown below the estimates in italics. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A (1st Stage): Dependent Variable = Discretionary trading by non-fire sale funds				
Explanatory Variable	(1)	(2)	(3)	(4)
Expected Trade Fire Funds$_{i,t-1}$	0.0244*	0.0267**	0.0267*	0.0257**
	(1.80)	(2.59)	(1.86)	(2.20)
Discretionary Trade Fire Funds$_{i,t-1}$	0.0554***	0.0540***	0.0563***	0.0562***
	(6.68)	(6.74)	(6.20)	(6.42)
LN(Bid-Ask %)$_{i,t-1}$			0.0001	-0.0000
			(1.36)	(-0.12)
LN(Market Cap.)$_{i,t-1}$			-0.0003	0.0000
			(-1.35)	(0.11)
Firm FE	Yes	Yes	Yes	Yes
Industry × Date FE	No	Yes	No	Yes
Observations	492,629	491,858	392,882	391,995
R-squared	4.2%	8.6%	4.4%	8.8%

Panel B (2nd Stage): Dependent Variable = AbnRet$_{i,t=0}$				
Explanatory Variable	(1)	(2)	(3)	(4)
Fitted Discret. Trade Non-Fire Funds$_{i,t}$	8.7644***	8.6097***	7.8832***	7.5405***
	(6.10)	(7.03)	(5.44)	(6.36)
Firm FE	Yes	Yes	Yes	Yes
Industry × Date FE	No	Yes	No	Yes
Observations	527,813	526,976	418,482	417,578

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 $Pressure$ that 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 Driscoll and Kraay (1998) standard errors with 3 lags, are shown next to the coefficient estimates in italics. In Panel A, we examine abnormal returns to an equal-weighted portfolio that begins 5 quarters after the event date and holds stocks until quarter t+12. In Panel B, we examine annualized abnormal returns to a weighted portfolio that begins 5 quarters after the event date and holds stocks until quarter t+12, where the weight is the prior period's gross return as in Asparouhova et al. (2010).

Panel A: Equal-Weighted Portfolio

	(1)	(2)	(3)	(4)	(5)	(6)
Explanatory	Sold More		Sold Less		Long-Short	
Variable	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Intercept	-0.0163	(-0.75)	0.0115	(0.50)	0.0278**	(2.30)
Mkt	0.4911***	(7.61)	0.4271***	(7.85)		
SMB	0.4786***	(5.87)	0.3836***	(5.99)		
HML	-0.0991	(-1.11)	-0.0388	(-0.43)		
RMW	-0.0126	(-0.13)	-0.0747	(-0.68)		
CMA	0.1809*	(1.68)	0.1957	(1.59)		

Panel B: Gross Return Weighted Portfolio

Explanatory	Sold More		Sold Less		Long-Short	
Variable	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Intercept	0.0035	(0.23)	0.0265	(1.58)	0.0276***	(2.71)
Mkt	0.4003***	(12.66)	0.3636***	(10.45)		
SMB	0.3144***	(5.49)	0.2825***	(6.18)		
HML	-0.0119	(-0.23)	0.0182	(0.30)		
RMW	-0.0980	(-1.39)	-0.1271	(-1.58)		
CMA	0.0777	(1.05)	0.1004	(1.13)		