Money in the right hands*

Aleksandra Rzeźnik[‡] **Rüdiger Weber**[§]

September 5, 2022

Abstract

We study stock liquidity from a demand-based perspective in the context of mutual fund fire sales. We construct a stock-level measure of what we call *specialized demand*, the available investment capacity of investors likely to have a high valuation for that stock and find that it is a key determinant of fire sale price discounts. Only when specialized demand is scarce, we observe the marked price pressure effects recorded previously in the literature. Our findings are robust to using the exogenous variation in fire sale pressure due to the 2003 late trading scandal. Importantly, specialized demand is not a proxy for informed trading, i.e., asset quality and adverse selection do not explain our results. Rather, inefficient allocations induced by forced sales lead to transiently higher discount rates and price pressure. This implies that fire-sale pressure in the absence of active specialized demand can be interpreted as a non-fundamental shock to prices. We find similar results when studying index reconstitutions as another instance of non-fundamental price pressure.

Keywords: Demand-based asset pricing, Mutual funds, Fire sales, Liquidity

JEL codes: G11, G12, G14, G23

*We thank Felix Fattinger, Michael Halling, Alexander Hillert, Marie Hoerova, Paul Hübner, Sven Klingler, Matthias Molnar, Matthieu Picault, Matthew Ringgenberg, Simon Rottke, Ben Sand, Malcolm Wardlaw, Florian Weigert and Josef Zechner, seminar participants at the University of Vienna, WU, Schulich School of Business and conference participants at TBEAR, AFFI, CEA for helpful comments and suggestions.

‡Schulich School of Business; York University; 4700 Keele St.; M3J 1P3 Toronto, ON; Canada; Email: `arz@yorku.ca`

§WU Vienna University of Economics and Business and VGSF; Welthandelsplatz 1; 1020 Vienna; Austria; Email: `ruweber@wu.ac.at`

1 Introduction

In the end, it all comes down to supply and demand. That rare baseball card you want to sell may be worth \$300 if you sell it to a true aficionado. But if you would like to quickly sell ten of those and there are only five such specialists with \$300 to spare, you may have to sell for less. Asset liquidity dries up and prices come under pressure when there is only little specialized demand.

In this paper, we study the effects of specialized demand on stock liquidity. More specifically, we study how the presence or absence of specialized demand affects the price pressure exerted by mutual fund fire sales. Mutual fund fire sales had long been considered a prime example of exogenous price pressure but have been recently questioned, both in terms of magnitude and with respect to whether they reflect non-fundamental selling pressure. Inspired by the recent literature in asset pricing (Koijen and Yogo, 2019; Haddad, Huebner, and Loualiche, 2021), we take a closer look at the demand side and find a marked price pressure due to non-fundamental reasons. In particular, we find that, for a given level of supply of shares due to fire sales, the price pressure depends not on demand *per se* but on "money in the right hands" – the funding liquidity available to active, potential *high-valuation buyers* (in the sense of Shleifer and Vishny, 1992) who are familiar with a specific asset or have a specific predilection for it. We refer to such high-valuation investors as *specialized* and to their demand accordingly as *specialized demand*. We show that a one standard deviation drop in specialized demand leads to a 4pp fire sale discount in the fire sale quarter. This result is similar in magnitude to the findings of Coval and Stafford (2007) or Edmans, Goldstein, and Wei (2012) but is not subject to the critique of their methodology (Wardlaw, 2020; Berger, 2021).

We illustrate our main finding in Figure 1, where we relate the cumulative average abnormal returns (CAARs) of fire-sale stocks to one of our measures of specialized demand. Specifically, at a given time, we sort stocks exposed to extreme outflow-induced sales by the total amount of net flows received by other active funds that also hold the stock but do not experience sizable outflows. Holding a specific stock is one way in which we proxy for the potential that a fund has a high valuation of that stock. That is, in the sense of revealed preferences, we argue that active funds which hold a specific stock are generally more optimistic, or less averse towards its risks, or simply 'like' it more than funds which decided against holding it. Because investor inflows determine how much a mutual fund can invest, we then interpret inflows into specialized funds as a natural measure of the effective investment capacity of high-valuation investors, i.e. specialized demand. We plot the CAARs of stocks in the top and bottom net flow quintiles. Stocks that are also held by active non-fire sale funds with high inflows (light grey) are unaffected by the fire sales. Stocks held by low-inflow/outflow funds (dark grey) suffer a severe fire sale price discount before they eventually revert to their pre-fire sale prices.

In essence, the intuition behind this result is similar to the argument in Shleifer and Vishny (1992, 1997). When active, high-valuation investors in fire-sale stocks have inflows, they can pick up firms under sale pressure, preserve the efficient allocation of stocks across investors and thereby keep prices stable. If specialized demand is scarce though, less specialized investors will step in, requiring higher expected returns, resulting in lower prices and a less efficient allocation. This intuition is seen easily in a simple one-period model (see Appendix A for a detailed derivation). Two investors i and j maximize time-one CRRA utility over wealth. They differ in their beliefs about an asset's expected payoff, μ_x, its volatility, σ_x, or have different risk aversion, γ. It is readily visible that these differences lead to different portfolio shares q as a function of price $q_i(p) \approx \frac{\ln \mu_{x,i} + 0.5\sigma_{x,i}^2}{\gamma_i \sigma_{x,i}^2} - \frac{\ln p}{\gamma_i \sigma_{x,i}^2}$. Investor i has a higher valuation because of higher $\mu_{x,i}$, or lower $\sigma_{x,i}$, or lower γ_i relative to investor j and hence holds more of the asset.

In equilibrium, overall demand for the asset must equal its supply: $p \cdot \bar{S} = \sum q_i W_i$, where W_i denotes the available funds of investor i and $\bar{S}$ is the fixed supply of assets. Obviously, relatively more wealth in the hands of high-valuation (i.e., more optimistic, less risk-averse) investors with high μ, low σ, low γ and thus high q will lead to higher prices.

When there is a fire sale event where the investors with high valuation of the asset lose funds W (assets under management, AUM) relative to the less enthusiastic and more risk averse ones, prices drop. The size of this drop depends on the difference in the average valuations of the stock by the two groups of investors. When there are sufficient flows (i.e., positive changes in W) to investors with similar beliefs and preferences, the effect is small or non-existent. Empirically, we remain agnostic about why some investors have a higher valuation for an asset. To the extent that higher valuations are due to informational advantages, we would like to point out that our empirical analysis does not support informed trading, adverse selection and the revelation of poor stock quality during fire sales as an explanation for our findings. Rather, our findings are consistent with transient, non-fundamental shocks driven by a disruption in the allocation of capital across investors. These discount-rate shocks may be driven by investors' disagreement, corresponding to differing values of $\mu_{x,k}$ or lower $\sigma_{x,k}$ across investors $k \in \{i, j\}$ in the model.

Specialized demand plays a focal role in our analysis, however, it is not directly observable. Therefore, we introduce a set of proxies for specialized demand for a stock along three separate dimensions. First, a fund's available liquidity is an obvious determinant of demand. Irrespective of whether a fund has a high valuation of a stock, it cannot soak up the additional, outflow-induced supply of shares if it lacks funding liquidity. Since mutual funds are typically long-only investors, we measure the availability of funding liquidity by the net-flows a fund receives.[1]

Second, specialized investors are investors that have a higher valuation for a given stock as compared to others, e.g. because they are well-informed or because of their preferences for certain securities. Such preferences may be due to a variety of reasons, including specific investment objectives such as investment horizons, ESG objectives, clients' hedging needs, fund managers' benchmarking concerns, behavioral biases, or taste in the sense of Fama and French (2007). We begin with considering funds as 'specialized' if they already invest in a specific stock, as in Figure 1. The intuition is straight-forward. Holding a stock reveals a preference for the stock in the sense that investors who hold it are on average more optimistic about it, are less concerned about its risk or simply 'like' it for any other reason than investors who chose not to hold it. So rather than basing our measure of specialization on our preconceptions of who should have a high valuation for a given stock, we go with the simplest manifestation of heightened valuation. That said, we also study more 'structural' measures of specialization because funds may be familiar with or simply be positive about a stock without currently holding it. That is why we introduce two additional proxies of specialized demand for a specific stock. In particular, we measure the investor flows to funds that invest in firms in the same industry as well the net-flows to funds that are located in the proximity of the firm's headquarters.

Third, it matters for specialized demand to be price-elastic. This means, that potential investors need to be in the position to increase demand in response to a non-information driven price change. In line with the recent literature on demand-based asset pricing such as Haddad et al. (2021), we argue that active mandates are crucial for demand to be price-elastic. Hence, we introduce the average active share of funds that hold the stock (i.e., the degree to which

[1] Fund liquidity is also affected by cash holdings and access to inter-fund lending. We control for both variables in our later analysis, see Section 3.3.

their portfolios deviate from their benchmark) as a key determinant of its demand elasticity.

Our results suggest that all three determinants of money in the right hands – specialization, net-flows, and activeness – are important in stabilizing prices in times of sizable liquidity shocks to the shareholders. By comparing stocks within a given fire sale episode, we show that price pressure is not just determined by the overall available liquidity in the market but specifically by the *distribution* of liquidity across investors with different degrees of specialization. If there is a shortage of liquidity in the hands of high-valuation investors, we observe the pronounced fire sale-induced price pressure effects that have been documented earlier in the literature (see, e.g. Coval and Stafford, 2007; Edmans et al., 2012).

Our analysis indicates that this is not due to fundamental information about the stock being revealed in the fire sale. First, we use measures of supply (fund outflows scaled by normalized stock holdings) and demand (inflows to specialized funds) that can be understood as instruments for actual supply and demand. Hence, we avoid the endogenous relationship between prices, supply, and demand. We use both, Edmans et al.'s (2012) mutual fund flow price pressure measure as well as Wardlaw's (2020) two alternative fire sale pressure measures and find that stocks experience a significant price discount due to fire sales when the liquidity of specialized investors is low. By using Wardlaw's (2020) measures, we rule out the possibility of a mechanical relationship between fire sale pressure measure and stock returns. We also do not condition on stocks being actually sold as in Coval and Stafford (2007), which helps us to alleviate concerns about adverse selection in fire sales as potential driver of our results. Second, our results also hold within a sample of stocks under fire sale pressure by passive mutual funds whose sales are unlikely to reflect any private information. Hence, it is rather implausible that our results on fire sale discounts are driven by fire-sale funds' decision to sell specific stocks that they expect to underperform. Similarly, our measure of specialized demand does not condition on a stock's being bought by specialized funds, which could indicate superior quality. Third, we observe that stock prices revert to their pre-fire sale levels which provides further support that our results indeed capture a transient lack of specialized demand rather than asset quality or asymmetric information. Finally, we find similar results using index reconstitutions as another instance of non-fundamental price pressure.

In the first part of our analysis, we investigate the effect of specialized demand on stock prices using four proxies for specialized demand that capture different dimensions of specialized demand. First, we use a measure of specialized flows, Spec Flow, which reflects the flows into active funds that hold a specific stock that is under selling pressure (defined by Wardlaw's (2020) measures, flow-to-volume and flow-to-stock, as well as Edmans et al.'s (2012) mutual fund flow price pressure). We find that when Spec Flow is one standard deviation below its mean, fire sale discounts are reduced by up to 30 percent relative to the mean, depending on the employed fire-sale pressure measure. If it is high, i.e., if specialized investors in the stock have available liquidity, there is no negative price impact. This result is robust to controlling for a wide set of time-varying stock characteristics as well as stock and (industry×) time fixed effects. By controlling for industry×time fixed effects, we can ensure that it is not the availability of cash *per se* but the liquidity available to active, high-valuation investors that drives the result.

Next, we investigate the role of active investment mandates. We expect that inflows to *passive* 'co-investors' (funds investing in the same stock as a fire sale fund) only modestly reduce price pressure. This is because passive funds are likely to increase all their positions proportionally, rather than take full advantage of flow-induced underpricing by picking up a specific fire-sale stock. Both, regression analysis and a visual inspection, using a version of our measure for the availability of specialized liquidity that only considers passive funds, confirms this conjecture. There is only a mild reduction in fire sale discounts when specialized passive investors have inflows. This points to the importance of active mandates for asset liquidity and ultimately market price efficiency.

Flows to active investors holding the same stock may prove to be a bit narrow as a measure of active, high-valuation demand. So, we extend our analysis to include definitions of flows to specialized investors based on geographical proximity, Geo Flow, familiarity with a stock's industry, Ind Flow, as well as a measure of the average degree of investors' activeness according to Cremers and Petajisto (2009), Active Share. We find a markedly lower price impact of fire sales during the event quarter (1) when funds, which hold stocks in the same industry, have inflows (13% to 28% lower relative to the mean for a one standard deviation higher industry flow measure), (2) when funds located near the firm have inflows (38% lower relative to the mean), and (3) when funds, which hold fire sale stocks, are more active (40% lower relative to the mean for one standard deviation increase in active share). Moreover, the effect of the specialization index on price pressure is larger than that of each of the individual specialization and activeness measures.

After experiencing quick price reversals which indicates resiliency (the ability of liquid markets to quickly push prices back to fundamental values), stocks whose fire sale pressure is met by high specialized demand have relatively lower average returns *after* the fire sale episode. Conversely, stocks with low specialized demand tend to have higher average returns in the months following the fire-sale episode. Consequently, we find that 30 months after the begin of the fire-sale episode, the fire sale discounts of stocks with low specialized demand have evaporated entirely. Both, the transient nature of price pressure and higher subsequent stock returns in the absence of specialized demand are consistent with an interpretation of our effect as a (transiently) positive discount-rate shock due to the disruption of the ex-ante efficient allocation. In line with this hypothesis, we find that this positive discount rate shock is accompanied by more non-specialized investors buying the fire sale stock.

The recent empirical literature suggests that fire sale price discounts are determined by fundamental asset characteristics. Funds are more likely to sell 'bad' stocks during fire sale episodes, presumably due to asymmetric information (Huang, Ringgenberg, and Zhang, 2020). Though we do not rule out asset quality as a potential driver of fire sale discounts, we find that it does not explain *our* result, i.e. the role specialized demand plays in mitigating a negative fire-sale price pressure. We find no systematic differences across Spec Index-sorted stocks in terms of future negative earnings surprises, short interest, and Llorente, Michaely, Saar, and Wang's (2002) asymmetric information measure. Moreover, the analysis of truly uninformed sales pressure by passive funds, which experience extreme outflows, yields overall similar results. Even though informed trading or adverse selection do not explain our result, "informational differences" in form of disagreement, a gap in optimism and pessimism between high- and low-valuation investors may have an impact on fire-sale discounts.[2] However, this is a transient effect on discount rates rather than the permanent effect of a revelation of poor stock fundamentals during a fire-sale event in an instant of adverse selection which, as shown by Huang et al. (2020), would result in permanently lower prices, rather than in the reversals we observe.

A general concern with studying fire sales is that there may be a reverse causality relation between future fire sales and price pressure. When investors expect the fund's assets to be

[2]E.g., different information sets may lead some investors to have higher valuations such that they stabilize the price if they have available liquidity. This would correspond to a higher μ and σ in the model presented above.

exposed to price pressure or to underperform, they may try to sell shares in the fund or stocks exposed to fire sale funds, leading to outflows. We therefore exploit the unexpected fire sales brought about by the 2003 late trading scandal. We find that in the case of these (truly) unexpected fire sales, stocks with a high specialization index experienced smaller price discounts than those with lower specialization values. This is a crucial piece of evidence because it also suggests that our results hold among stocks that were similarly exposed to outflows prior to the fire sale quarter.

To address any remaining concerns that the inclusion of trading volume in the fire-sale pressure measure might potentially contaminate the measure with fundamental information about a stock, we extend our analysis to another instance of non-fundamental price pressure. Specifically, we investigate the simultaneous inclusion of stocks in the Russell 1000 and exclusion from the Russell 2000 Index. Because the index weight changes dramatically, moving from the Russell 2000 to the Russell 1000 is associated with negative price pressure (Chang, Hong, and Liskovich, 2015). We find that when there is specialized demand as measured by Spec Index, the negative price pressure is significantly dampened. This suggests that our results hold also without using any fire-sale pressure measure to identify sales pressure. We document that, high-valuation demand helps in stabilizing prices not just in the case of fire sales but more generally.

Overall, we show that stocks can have significant fire-sale discounts in the absence of specialized demand. Our results point to non-fundamental discount rate shocks due to inefficient allocations rather than adverse selection as an explanation. This highlights the role of allocational efficiency for price efficiency and suggests that fire sale discounts are truly non-fundamental price shocks if there is no specialized demand.

Relation to literature. This paper relates to the literature on mutual funds' fire sales and the underlying drivers of fire sale discounts. In the seminal work by Coval and Stafford (2007), the authors study the CAARs of stocks that were sold by funds with extreme outflows in order to gauge fire sale-induced price pressure. Because funds make conscious decisions on what to sell, this measure is potentially subject to selection bias. Edmans et al.'s (2012) measure overcomes this potential issue by using an instrument, i.e., mutual fund flows scaled by funds' holdings in time $t-1$ dollars and normalized by the time t dollar trading volume. However, Wardlaw (2020) points out that the use of this measure induces a mechanical relation between said measure and raw returns and proposes two measures that are not subject to such a relation. He finds no marked impact of mutual fund flows measured this way on stock prices. In our paper, we use both Wardlaw's (2020) and Edmans et al.'s (2012) measures and show that whether mutual fund fire sales induce price pressure, or not, depends on the degree of specialized demand. When there is only little specialized demand, we find the pronounced price pressure reported earlier in the literature. We thereby shed light on a potential underlying driver of fire sale discounts – i.e., the mismatch between specialized supply and demand that leads to less efficient asset allocations across investors and price discounts that are unlikely due to fundamental information.

Our paper is closely related to the theoretical work of Dow and Han (2018) who argue that when specialized traders are liquidity-constrained, they cannot bid up prices of good assets (that only they can detect due to specialization). Hence, adverse selection occurs and only bad assets are sold. Our results are broadly consistent with the main idea of Dow and Han (2018) in that we emphasize the importance of specialized demand. However, the evidence in our paper does not suggest that adverse selection can explain the relation between fire sale price pressure and the availability of specialized demand. Our proxies for specialized supply and demand do not convey (private) information about fundamentals, and our results hold when using uninformed fire sales by passive funds. Moreover, stocks exposed to different degrees of inflows to specialized funds do not differ with respect to measures of quality and we find that fire sale stocks eventually revert to their pre-fire sale prices.

Similar in spirit to Dow and Han (2018), Huang et al. (2020) study fire sale discounts (defined as in Coval and Stafford (2007)) and relate them to asymmetric information. They find that for stocks that they deem to be sold deliberately, there is no subsequent price reversal, suggesting that fire sale funds sell low quality stocks. Our paper may be viewed as complementary since we study non-information driven sales and find fire-sale price-pressure in form of heightened discount rates as opposed to fundamental information being revealed. Methodologically, while controlling for the supply of fire sale stocks, we primarily focus on the demand side. We find that supply-matching specialized demand can ameliorate the price pressure and shorten the reversal period. Only in case of a mismatch between supply and specialized demand, we observe pronounced price effects.

Our findings can also be understood in the context of studies on asset liquidity. The proposed explanation for our results echoes Shleifer and Vishny's (1992) seminal paper. The authors argue that the liquidity of 'special assets' depends on the state-contingent valuation by industry peers. Our notion of 'specialized demand' is related to this idea and may be viewed as an empirical application in the broadest sense. With respect to the link between funding and market liquidity, Brunnermeier and Pedersen (2009) show in their theoretical work how feedback spirals between market and funding liquidity can arise in the presence of funding frictions such as margin requirements. While it is reasonable to assume a feedback relation between fund inflows and funds' portfolios that is reminiscent of the Brunnermeier and Pedersen (2009) setup, our empirical evidence points less to funding frictions *per se* as source of market illiquidity. Rather, funds' constraints with respect to investment mandates and specialization seem to drive their inability to pick up assets under price pressure.

This paper is furthermore related to the emerging literature on demand-based asset pricing which identifies demand (in)elasticity as a core determinant for the variation in asset prices, both over time on aggregate (see, e.g. Koijen and Yogo, 2019; Gabaix and Koijen, 2021; Pavlova and Sikorskaya, 2022) and in particular in the cross-section (see Haddad et al., 2021). We contribute to this literature by exploring the effects of heterogeneity in demand elasticity due to active investment mandates and specialization on the variation in stock prices. Specifically, we show that liquidity needs to be in the hands of funds with highly elastic demand (high-valuation investors with an active mandate) in order to mitigate sales-induced price pressure. The variation in stocks' discount rates that is generated by inefficient allocations due to heterogeneous specialization across investors is suggested as a reason for why stocks with high institutional ownership have time-varying expected returns documented by Weber (2021). Our work also complements the recent paper by Pavlova and Sikorskaya (2022) investigating price fragility due to benchmarking intensity – a measure of inelastic demand that a stock attracts. In contrast to Pavlova and Sikorskaya (2022), we focus on the elastic part of the demand and document that the lack of specialized demand leads to considerable price discounts during fire sale episodes. Several papers investigate the effect of passive investment on market efficiency and typically find deteriorating effects (see, e.g., Stambaugh, 2014; Israeli, Lee, and Sridharan, 2017; Ben-David, Franzoni, and Moussawi, 2018; Sammon, 2021). Consistent with this literature, we show that the presence of active and specialized investors leads to more efficient prices in the sense that non-fundamental supply shocks exert only negligible price pressure. We highlight that the reason for "price inefficiency" in the absence of active investors is due to the underlying inefficient allocation of assets that can push prices below the 'fundamental value'.

Finally, our paper relates to the literature that uses mutual funds fire sales as a source of non-fundamental variation in stock prices such as, e.g., Edmans et al. (2012); Phillips and Zhdanov (2013); Lou and Wang (2018). By finding price effects of fire sales in the absence of active and specialized demand which are unrelated to firm fundamentals, we corroborate the validity of using fire sale discounts in the absence of specialized demand as an exogenous negative shock to firms' stock market value.

2 Data and Variable Construction

In this section, we introduce our data source and processing procedures. We also explain the construction of the variables used for our analysis and discuss descriptive statistics.

2.1 Data

We collect data on mutual fund quarterly holdings from Thomson/CDA Spectrum. We use the Wharton Research Data Services (WRDS) MFLinks file to merge holdings database with the Center for Research in Security Prices (CRSP) Survivorship Bias Free Mutual Fund database. Following recent literature (Coval and Stafford, 2007; Edmans et al., 2012; Wardlaw, 2020), our sample consists of domestic equity mutual funds but not sector mutual funds that only invest in a specific industry. We determine whether a fund is an active or a passive fund by identifying index and target-date mutual funds by their names in the CRSP Mutual Funds database and by using the CRSP index fund flag (Kacperczyk, Sialm, and Zheng, 2008). Thomson's WFICN unique fund identifier allows us to link monthly total net assets (TNA), net returns, net flows, and holdings to Cremers and Petajisto's (2009) active share measure available at the University of Notre Dame's website. The full sample spans the period from 1990 to 2016 and contains 114,737 fund-quarter observations for 3,497 distinct mutual funds. In Table 1, we report the annual summary statistics as of December of each year for our sample of mutual funds. In column (2), we report the number of equity mutual funds by year. Columns (3) and (4) show that both the average total net assets (TNAs) and the average value of equity holdings increased by over ten times over the sample period. The last column documents an increase in mutual fund ownership in U.S. equities from 2.74% in 1990 to 15.41% in 2016.

We obtain the stock data (returns, prices, trading volumes, and shares outstanding) for common shares (share code 10 and 11) from the CRSP. We use Compustat to assemble data on headquarters' addresses, reported earnings, and earning announcement dates. We make use of Hoberg and Phillips's (2016) text-based network industry classifications data to assign a company to a group of peers. Our final sample consists of a subset of stocks held by mutual funds that were potentially subject to fire sales according to one of three measures defined in the next subsection between January 1990 and December 2016.

2.2 Variable Construction

2.2.1 Measures of supply pressure

We use three different ways to identify stocks exposed to fire sales. In line with the recent literature, we define a fire sale event as quarter in which a mutual fund experiences 'extreme' outflows reaching 5% or more of TNA in a given quarter (e.g., Coval and Stafford, 2007; Edmans et al., 2012; Wardlaw, 2020). We compute fund's percentage net flows in the standard way:

$$\textsc{Flow}_{f,q} = \frac{\text{TNA}_{f,q} - \text{TNA}_{f,q-1} \cdot (1 + r_{f,q})}{\text{TNA}_{f,q-1}}, \tag{1}$$

where $\text{TNA}_{f,q}$ is TNA of fund f in quarter q and $r_{f,q}$ is fund f's return over quarter q. Next, to determine which stocks are potentially subject to fire sales in a given quarter, we use three different definitions of extreme outflow-induced sales. First, we choose two measures recently proposed by Wardlaw (2020):

$$\textsc{Flow-To-Volume}_{i,q} = \sum_{f=1}^{M} \textsc{Flow}_{f,q} \cdot \frac{\textsc{Shares}_{i,f,q-1}}{\textsc{Volume}_{i,q}} \tag{2}$$

and

$$\textsc{Flow-To-Stock}_{i,q} = \sum_{f=1}^{M} \textsc{Flow}_{f,q} \cdot \frac{\textsc{Shares}_{i,f,q-1}}{\textsc{Shrout}_{i,q-1}}, \tag{3}$$

conditional on the outflow of fund f being greater than 5% of total net assets. $\textsc{Shares}_{i,f,q-1}$ is the number of shares of stock i held by fund f at the end of quarter $q-1$. Flow-To-Volume and Flow-To-Stock both measure flows to a fund holding a specific stock but differ by how flows are scaled. Flow-To-Volume scales flows to a fund with the shares it owns divided by $\textsc{Volume}_{i,q}$, the share trading volume of stock i over quarter q. Flow-To-Stock sets the number of shares held by fund f relative to $\textsc{Shrout}_{i,q-1}$, the number of shares outstanding of stock i at the end of quarter $q-1$. Alternatively, we use the MFFlow measure proposed by Edmans et al. (2012):

$$\text{MFF}\textsc{low}_{i,q} = \sum_{f=1}^{M} \textsc{Flow}_{f,q} \cdot \frac{\textsc{Shares}_{i,q-1} \cdot \textsc{Prc}_{i,q-1}}{\text{DV}\textsc{ol}_{i,q}}, \tag{4}$$

also conditional on the net-outflows of fund f being greater than 5% of total assets. $\textsc{Prc}_{i,q-1}$ is price of stock i at the end of quarter $q-1$ and $\text{DV}\textsc{ol}_{i,q}$ is stock i's dollar volume over quarter q. Berger (2021) and Wardlaw (2020) argue that due to the use of dollar values, MFFlow is confounded with stocks' inverse raw returns. The analysis of Flow-To-Stock is likely to yield a meaningful estimate of outflow-induced pressure only if a large share of shares outstanding is actively traded. Against this backdrop, Flow-To-Volume is arguably the most apt measure of fire-sale pressure when studying stock liquidity. We nevertheless report results using all three measures throughout the paper and find that our results are qualitatively similar.

Finally, we identify fire sale stocks as firms with the lowest values of Flow-To-Volume, Flow-To-Stock, or MFFlow – i.e., firms that belong to the bottom decile of quarterly values of Flow-To-Volume, Flow-To-Stock, or MFFlow over the full sample period. To examine the price pressure stemming from mutual fund fire sales, we compute CAR in excess of the CRSP equally-weighted index as in Edmans et al. (2012) during the event period, as well as 12 months preceding and 27 months following the fire sale event quarter. Other measures of cumulative abnormal returns are of course possible. Our results remain qualitatively unchanged (see Section 3.3 with Table C.4 and Figure C.2). Figure C.1 in the Appendix shows the distribution of fire sale episodes across time for each fire sale pressure measure.

2.2.2 Specialized demand

Next, we focus on variables capturing investors' specialization and their available liquidity. An active fund manager holding a given stock is likely to generally consider it a good investment. If the fund manager observes a considerable drop in the firm's share price unaccompanied by any news, she might be willing to provide liquidity and pick up the stock at a potential discount if she has cash available (Christoffersen, Keim, Musto, and Rzeźnik, 2022). Our first specialization measure – $\textsc{Spec Flow}_{i,q}$ – captures those two features: familiarity with the stock and available liquidity. We define $\textsc{Spec Flow}_{i,q}$ as follows:

$$\textsc{Spec Flow}_{i,q} = \frac{1}{F}\sum_{f=1}^{F}(\textsc{Flow}^{i}_{f,q} \mid \textsc{Flow}^{i}_{f,q} > -5\% \cap f \text{ is active}), \tag{5}$$

where $\textsc{Flow}^{i}_{f,q}$ is percentage net flow of fund f, which held stock i at the beginning of quarter q, over the fire sale event quarter q. We only include active *non-fire sale* mutual funds – i.e., with net flows above -5% of TNA over quarter q. F is the number of active funds that were holding stock i at the beginning of quarter q. We compute Spec Flow by equally weighting net-flows, thus we treat investor flows to each specialized fund in the same way. In contrast, using a value-weighted measure of Spec Flow would indicate that investor flows to a fund holding relatively few shares are less important than investor flows to a fund with a large number of shares of a fire sale stock, even though the latter fund might have already been overexposed to the stock. We also compute a *passive* specialization specialization measure, $\textsc{Passive Spec Flow}_{i,q}$, which is constructed in exactly the same way as $\textsc{Spec Flow}_{i,q}$ in Equation (5) but using only passive funds. $\textsc{Spec Flow}_{i,q}$ and $\textsc{Passive Spec Flow}_{i,q}$ allow us to investigate the role played by active and passive mandates in mitigating fire sale price pressure. Our measure of $\textsc{Spec Flow}_{i,q}$ is constructed in the same way as Bartik instrument (Bartik, 1991) by interacting a stock's exposure to high-valuation investors (i.e., whether a stock is held or not by a given fund) and *common* funding liquidity shocks (i.e., flows to those high-valuation investors).

So far our specialization variable defines a specialized investor as an active mutual fund holding a fire sale stock at the beginning of the fire sale event quarter. However, it is possible that there are stocks, which fund managers pay attention to, follow closely, or perceive as a potential investment but currently do not hold in their portfolios. While it is impossible to directly pinpoint which stocks fund managers are interested in, we propose two measures that are supposed to capture this unobservable investors' specialization. Specifically, we look at fund managers' specialization within an industry and/or geographical region.

Our industry specialization measure exploits the time-varying industry classifications proposed by Hoberg and Phillips (2016), which use the text-based analysis of firm product descriptions filed with the Securities and Exchange Commission (SEC). Specifically, for each fire sale stock in a given year, we determine the twenty closest peers/competitors based on firm-by-firm pairwise similarity scores.[3] Then we identify non-fire sale mutual funds holding the closest peers of stock i at the beginning of the fire sale quarter q. We compute the industry specialization measure as follows:

$$\text{Ind Flow}_{i,q} = \sum_{f=1}^{F} \sum_{j=1,\ j \in s_i}^{20} \eta_{i,j} (\text{Flow}^{j}_{f,q} \ \mid \ \text{Flow}^{j}_{f,q} > -5\% \cap f \text{ is active}), \tag{6}$$

where $\text{Flow}^{j}_{f,q}$ is a percentage net flow of fund f, which held stock j that belongs to the same industry s_i as stock i, at the beginning of the fire sale event quarter q. We weight fund flows with a pairwise similarity score between firms i and j, $\eta_{i,j}$. Thus, we assign a greater weight to net flows of a fund holding shares of a close peer. We only include active non-fire sales mutual funds. Overall, $\text{Ind Flow}_{i,q}$ captures the liquidity available to investors, who may not hold the stock *yet*, but hold shares of other closely related firms and thus, are specialized in this industry.

Our third measure of specialization reflects investors' geographical focus. Recent empirical studies document home bias – investors' preferences for local stocks – which arises due to either superior information concerning local stocks (Coval and Moskowitz, 2001; Ivkovic and Weisbenner, 2005) or familiarity bias (Grinblatt and Keloharju, 2001; Seasholes and Zhu, 2010; Pool, Stoffman, and Yonker, 2012). In our analysis, we remain agnostic about the mechanism driving local equity preferences. We evaluate net flows of funds located in close proximity l (within a 100km radius) to the headquarters of fire sale stocks in the following way[4]:

$$\text{Geo}_{i,q} = \frac{1}{F} \sum_{f=1}^{F} (\text{Flow}^{i \in l}_{f,q} \ \mid \ \text{Flow}^{i \in l}_{f,q} > -5\% \cap f \text{ is active}), \tag{7}$$

where $\text{Flow}^{i \in l}_{f,q}$ is a percentage net flow of fund f, which is located within 100km radius from headquarters of stock i, over the fire sale event quarter q. Similarly to previous specialization variables, we only include active non-fire sales mutual funds. Note that there is a significant number of firms whose administrative headquarters are located more than 100km away from mutual funds' main offices, which makes a continuous $\text{Geo}_{i,q}$ variable intractable. To circumvent this issue, we construct an indicator variable $\text{Geo Flow}_{i,q}$ that takes a value of one if stock i's $\text{Geo}_{i,q}$ belongs to the top quintile of the $\text{Geo}_{i,q}$ distribution in a given quarter, and otherwise zero. This implies that $\text{Geo}_{i,q}$ equals to zero for the stocks with headquarters located far off

[3] Our results are robust to using other thresholds defining stock's closest peers/competitors.

[4] Our results remain robust to using other thresholds defining 'close proximity.'

mutual funds' main offices.

We also explore differences in the degree of active management. Even within active mutual funds, there is a lot of variation in how actively fund managers manage their portfolios (see, e.g., Cremers and Petajisto, 2009; Amihud and Goyenko, 2013; Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2016). To investigate the relationship between fire sale price discounts and the degree of active management of funds holding them, we compute an active share measure for each fire sale stock i in the event quarter q in the following way:

$$\textsc{Active Share}_{i,q} = \frac{1}{F}\sum_{f=1}^{F}(\textsc{Active Share}^{i}_{f,q} \mid \textsc{Flow}^{i}_{f,q} > -5\% \cap f \text{ is active}), \tag{8}$$

where $\textsc{Active Share}^{i}_{f,q}$ is Cremers and Petajisto's (2009) active share measure of fund f, which held stock i at the beginning of quarter q. Similarly to $\textsc{Spec Flow}_{i,q}$, we only include active non-fire sale mutual funds – i.e., with net flows above -5% over quarter q.

Finally, we construct a specialization index, which allows us to combine all four different dimensions of specialization and investors' available cash. We use a similar approach to Asness, Frazzini, and Pedersen (2019) in their construction of the *quality* measure to construct the specialization index. As we have argued so far, an active specialization can be measured by specialized flows ($\textsc{Spec Flow}$), active share ($\textsc{Active Share}$), industry-specialized flows ($\textsc{Ind Flow}$), and geographically specialized flows ($\textsc{Geo Flow}_{i,q}$). To put each measure on equal footing and combine them, we standardize all variables x (except from the indicator variable $\textsc{Geo Flow}_{i,q}$) and obtain z-scores $z(x) = zx$.[5] Our specialization index is the sum of the individual z-scores:

$$\textsc{Spec Index}_{i,q} = z(z\textsc{Spec Flow}_{i,q} + z\textsc{Active Share}_{i,q} + z\textsc{Ind Flow}_{i,q} + \textsc{Geo Flow}_{i,q}). \tag{9}$$

To understand the role that active (and therefore price-elastic) portfolio allocation plays in determining a fire sale price discount, we also compute a passive specialization index – $\textsc{Passive Spec Index}_{i,q}$. The passive specialization index is constructed in an analogous way to $\textsc{Spec Index}_{i,q}$. To compute $\textsc{Passive Spec Index}_{i,q}$, we use the same four specialization proxies but computed using passive non-fire sale mutual funds ($\textsc{Passive Spec Flow}_{i,q}$, $\textsc{Passive Active Share}_{i,q}$, $\textsc{Passive Ind Flow}_{i,q}$, and $\textsc{Passive Geo Flow}_{i,q}$).

[5] Let x be the variable of interest. Then the z-score of x is given by $z(x) = zx = (x - \mu_x)/\sigma_x$, where μ_x and σ_x are mean and standard deviation of x.

Table 2 reports summary statistics for our specialization variables. We use three different measures to capture fire sale pressure: FLOW-TO-VOLUME in Panel A, FLOW-TO-STOCK in Panel B, and MFFLOW in Panel C. Depending of the specification, fire sales stocks experience on average a negative cumulative abnormal return (CAR) during the event quarter between -1.2% (FLOW-TO-STOCK) and -5.6% (MFFLOW).

3 Empirical analysis

Our empirical approach is to compare the differences in fire sale discounts during fire sale event quarters across stocks with different degrees of specialized capital flows. We expect stocks with an active and specialized (potential) ownership to have a higher propensity to be picked up in the event of fire sales, and thus experience a smaller price discount than stocks whose other or potential owners do not have available cash or are passive investors.

3.1 Specialized flows and fire sales discount

We begin our analysis by examining the effect of specialized investor flows on CAR during the fire sale event quarter. We estimate the following linear model:

$$\mathrm{CAR}_{i,q} = \alpha_0 + \alpha_1 \mathrm{SPEC\ FLOW}_{i,q} + \alpha_2 \mathrm{FS}_{i,q} + \Lambda' \mathrm{X}_{i,q-1} + \mathrm{D}_i + \mathrm{D}_q + \epsilon_{i,q}, \tag{10}$$

where $\mathrm{CAR}_{i,q}$ is a cumulative abnormal return of stock i during the fire sale event quarter q. $\mathrm{SPEC\ FLOW}_{i,q}$ is our measure of specialized investor flows defined in Section 2.2. $\mathrm{FS}_{i,q}$ is stock i's fire sales pressure measure, using three different definitions of fire sales: Wardlaw's (2020) FLOW-TO-STOCK and FLOW-TO-VOLUME as well as Edmans et al.'s (2012) MFFLOW. $\mathrm{X}_{i,q}$ is a vector of control variables.[6] We also include (industry×)quarter, D_q, and stock, D_i, fixed effects. Standard errors are two-way clustered at the quarter and stock level. The results are presented in Panel A of Table 3.

We use three definitions of fire sales to construct our sample: FLOW-TO-VOLUME in columns (1) – (4), FLOW-TO-STOCK in columns (5) – (8), and MFFLOW in columns (9) – (12). In each

[6]Control variables include Greenwood and Thesmar's (2011) stock fragility measure computed prior to the fire sale event quarter, $\mathrm{FRAGILITY}_{i,q-1}$, the one quarter lagged Amihud's (2002) liquidity measure, $\mathrm{LIQ}_{i,q-1}$, standard deviation of daily stock returns in the previous quarter, $\mathrm{SD(RET)}_{i,q-1}$, the average monthly return in the previous quarter, $\mathrm{RET}_{i,q-1}$, an indicator variable that takes a value of one if a firm discloses a negative earning surprise in the fire sale event quarter, otherwise zero, $\mathrm{NEGATIVE\ ES}_{i,q}$, the lagged natural logarithm of market capitalization, $\mathrm{LOG(MCAP)}_{i,q-1}$, and the percentage of shares outstanding held by 13F investors at the beginning of the fire sale event quarter, $\mathrm{INST\ OWN}_{i,q-1}$.

of the specifications, we control for the fire sale measure and year×quarter fixed effects. In columns (2) – (4), (6) – (8), and (10) – (12), we include time-varying stock-specific controls. In columns (3) – (4), (7) – (8), and (11) – (12), we add industry×quarter fixed effects. Finally in columns (4), (8), and (12), we include stock fixed effects, which among others control for average stock quality. This is our most conservative specification, which requires at least two fire sale episodes for each stock (thus a slightly lower number of observations). In this specification, we relate a price discount of the same stock over time to specialized investor flows while controlling for stock-specific time-varying characteristics. Thus, the variation that we use stems from shifts in SPEC FLOW$_{i,q}$ within a stock over time and between fire-sale stocks within a single industry at a given time.

Regardless of the specification, coefficient estimates on SPEC FLOW$_{i,q}$ are positive and statistically significant. The SPEC FLOW$_{i,q}$ coefficients are also very stable across specifications within each fire sale definition indicating that our results are unlikely to be driven by omitted variables bias. The positive coefficient on SPEC FLOW$_{i,q}$ suggests that fire sales stocks that are already held by active mutual funds with available liquidity are subject to less pronounced fire-sale price pressure. In the specifications with stock fixed effects, we observe that even the same stock can experience larger or smaller fire sale price pressure in two different time periods due to the differences in the degree of cash available to investors that hold the stock. In terms of economic significance, a one standard deviation increase in specialized investor flows reduces the fire sale discount by between 12% (flow-to-stock specifications) and 30% (flow-to-volume) relative to the mean.

Since the sample consists exclusively of stocks exposed to fire sales and we control for time fixed effects, we can rule out that the availability of funding liquidity *per se* (specialized or non-specialized) is the main driver behind our results. Moreover, we control for fire-sale pressure itself (variables FLOW-TO-VOLUME, FLOW-TO-STOCK and MFFLOW) to investigate the effect of specialized demand while keeping the supply of shares constant. This rules out a potential concern that our results are driven by a correlation between SPEC FLOW and fire-sale pressure or other fire-sale-related stock characteristics (Berger, 2021), which would result in omitted variable bias.[7] Wardlaw (2020) and Berger (2021) show that stocks under fire sale pressure tend to have

[7]Indeed, as shown in Table C.5 in the Appendix, fire sale pressure measures are not correlated with the availability of specialized demand.

lower market capitalization. Note that our sample consists exclusively of stocks under fire sale pressure such that this concern does not confound our results. Nevertheless, we also explicitly control for differences in market capitalization and stock fixed effects in specifications (2) – (4), (6) – (8), and (10) – (12). Moreover, as shown in Table C.2 in the appendix, our results remain robust *within* samples of small and large stocks. In line with the idea that co-owning institutional investors other than mutual funds may help to mitigate the effect of fire sales, the coefficient on Inst Own is significantly positive.

We also provide a visual presentation of our results. Following recent studies (Coval and Stafford, 2007; Edmans et al., 2012; Wardlaw, 2020; Berger, 2021), Figure 1 plots CAARs for firms classified as fire sale stocks based on Flow-To-Volume in Panel A, Flow-To-Stock in Panel B, and MFFlow in Panel C. The orange line with orange circles denotes an CAAR for fire sale firms. The magnitude and the pattern of the CAAR are very similar to those reported by Edmans et al. (2012) and Wardlaw (2020), among others. However, we find stark differences when conditioning on the amount of (potential) specialized demand. In every quarter, we sort fire sale stocks into quintiles based on Spec $\text{Flow}_{i,q}$. We use light-gray circles to depict the CAAR for the quintile with the highest specialized flows and dark-gray circles to plot the CAAR for the quintile with the lowest non-fire sales flows. Consistent with our results tabulated in Panel A of Table 3, stocks that are held by non-fire sale funds with high net inflows experience only a very mild price discount during the fire sale event quarter. On the other hand, the fire sale price pressure is especially pronounced for firms in the bottom Spec $\text{Flow}_{i,q}$ quintile – i.e., firms that are held not only by fire sale funds but where other co-holders experience low net flows. The figure also shows that CAAR paths for stocks in the top and bottom quintiles of Spec $\text{Flow}_{i,q}$ diverge before the fire sale event quarter. This is likely due to the fact that mutual fund flows are persistent (Frazzini and Lamont, 2008). Funds that experience extreme outflows in one quarter, were likely subject to investor withdrawals in the preceding quarters. Thus the presence of specialized liquidity seems to ameliorate not only fire sale discounts but also regular outflow-induced price pressure (Lou, 2012). On average, all stocks, including those with strong discounts (i.e., in the bottom quintile), eventually revert to old or even higher price levels, suggesting that their sale is not indicative of low asset quality. In Figure C.2 and Table C.4 in the Appendix, we show that results are qualitatively and quantitatively similar when using other definitions of cumulative abnormal returns. Figure C.4 shows the corresponding results for stocks that had exactly one fire sale episode during the observation window.

To further understand the relationship between the fire sales price pressure and investors' specialization we investigate whether the fire sale discount is differentially impacted by firms with different degrees of *passive* rather than active specialized flows. Specifically, we focus on flows to passive mutual funds holding a fire sale stock at the beginning of the fire sale event quarter. We construct an analogous measure to SPEC FLOW$_{i,q}$ – passive specialized flows, PASSIVE SPEC FLOW$_{i,q}$ – that captures an average investor flows to passive funds holding the fire sale stock at the beginning of the fire sale event quarter (see Appendix A for a formal definition). The incorporation of passive funds and their flows allows us to understand whether *any* cash inflow can reduce the fire sales price discount or rather the available liquidity should be in the hands of active, specialized investors. If information production and active portfolio allocation indeed matter, we should see either very small or no effect of passive specialized investor flows on CARs of fire sale stocks during the fire sale event quarter.

We re-estimate Equation (5), but use PASSIVE SPEC FLOW$_{i,q}$ in place of SPEC FLOW$_{i,q}$. We report our regression estimates in Panel B of Table 3. The coefficient estimates on PASSIVE SPEC FLOW$_{i,q}$ are much smaller than those of SPEC FLOW$_{i,q}$ and in most cases insignificant. This suggests that specialized investors with inflows need to have active mandates in order to pick up fire sale stocks and thus ameliorate fire-sale price pressure.

Figure 2 further confirms our regression-based results. Analogously to Figure 1, we plot CAARs for portfolios of firms sorted on PASSIVE SPEC FLOW$_{i,q}$ and classified as fire sale stocks. There are only very small differences in cumulative returns of stocks with different degrees of PASSIVE SPEC FLOW. Overall, our results suggest that investors' active specialization plays an important role in mitigating temporary price impact stemming from asset fire sales.

3.2 Other specialization proxies

We now build on our initial results and further investigate the importance of active specialization in reducing market inefficiencies due to fire sales. So far, when relating the CAR of fire sale stocks to specialized investor flows as measured by SPEC FLOW$_{i,q}$, we implicitly assumed that active mutual funds are equally active. However, there is a wide dispersion across active funds in terms of their degree of active management ranging from closet indexers to concentrated stock pickers. Funds with a high active share – that is with a portfolio composition distinct from a benchmark composition – can be expected to have price-elastic demand and compete for fire sale stocks by purchasing stocks from liquidity-constrained fund managers who experience extreme outflows. Moreover, they are likely to have better information about firm fundamentals than rather passive investors. Thus, fire sales stocks held by non-fire sale funds with a high degree of active management are less likely to be subject to sizeable fire sale price pressure.

To test our conjecture, we construct the variable $\text{Active Share}_{i,q}$ (see Section 2.2), which captures the average active share of non-fire sale funds that hold a fire sale stock at the beginning of the event quarter. Then, we link the CAR of fire sale stocks to their average active share by estimating the following specification:

$$\text{CAR}_{i,q} = \alpha_0 + \alpha_1 \text{Active Share}_{i,q} + \alpha_2 \text{FS}_{i,q} + \Lambda' \text{X}_{i,q-1} + \text{D}_i + \text{D}_q + \epsilon_{i,q}. \tag{11}$$

If our prediction is correct, we would expect the coefficient on $\text{Active Share}_{i,q}$ to be positive and statistically significant.

We report our results in Panel A of Table 4. We use the same set of specifications and fire sale definitions as in Table 3. To conserve space, we only report the coefficients on $\text{Active Share}_{i,q}$. All remaining regression estimates are available upon request. Our results suggest that stocks held by more active mutual funds experience smaller price discounts during fire sale episodes – the coefficient on $\text{Active Share}_{i,q}$ is positive and significant. A one standard deviation increase in the average active share of funds that hold a stock reduces the fire sale price discount by around 28% relative to the mean.[8] This implies that stocks with high exposure to more active specialized investors are more likely to be picked up in case of fire sales since those investors have the ability to react with elastic demand to the price pressure induced by fire sales. This in turn ameliorates the negative price pressure induced by extreme outflows.

Up to this point, we have determined the universe of active specialized investors based on mutual funds' ownership in a stock at the beginning of the fire sales event quarter. Now, we relax our definition of specialized (co-)investors and include mutual funds potentially interested in or informed about a firm without requiring them to hold any of its shares. Although it is impossible to identify the unobservable interests of fund managers, we proxy for them by investigating mutual funds' specialization within an industry and/or geographical region.

We first focus on industrial specialization. We construct $\text{Ind Flow}_{i,q}$, defined in Section 2.2,

[8] $-\frac{0.052 \cdot 0.141}{-0.026} = 0.282$.

that captures firm's average investor flows over the fire sale event quarter to and from mutual funds holding other stocks that are the closest peers/competitors of the fire sale stock. As in the case of active specialized investor flows, SPEC $\text{FLOW}_{i,q}$ in Section 3.1, we expect the fire sale price discounts to be moderated by the amount of liquidity available to funds investing in firms within a single industry. We examine the link between industrial specialization and fire sale price discounts by estimating the following specification:

$$\text{CAR}_{i,q} = \alpha_0 + \alpha_1 \text{IND FLOW}_{i,q} + \alpha_2 \text{FS}_{i,q} + \Lambda' \text{X}_{i,q-1} + \text{D}_i + \text{D}_q + \epsilon_{i,q}. \tag{12}$$

We report our results in Panel B of Table 4. The coefficient estimates on IND $\text{FLOW}_{i,q}$ are positive and statistically significant throughout all specifications, indicating that the fire sale price discount is ameliorated for stocks whose industry-specialized investors experience cash inflows. In economic terms, this translates to a reduction in fire sale discount of about 19% relative to the mean (flow-to-volume specification) for a one standard-deviation increase in IND $\text{FLOW}_{i,q}$.

Finally, we investigate the impact of geographical specialization on fire sale price pressure. We build on recent findings (Kacperczyk, Sialm, and Zheng, 2005; Ivkovic and Weisbenner, 2005; Coval and Moskowitz, 1999, 2001; Massa and Simonov, 2005, among others) and argue that a local fund manager is likely to have above average interest in a local firm due to her close proximity to the firm even if she does not currently invest in its stock. For instance, she may be more confident about firm fundamentals due to the proximity or have a preference (home bias) for geographically close firms. Similar to other specialization proxies, we expect stocks with higher inflows to geographically proximate mutual funds to experience less pronounced price pressure during fire sales episodes.

To capture geographical specialization, we construct GEO $\text{FLOW}_{i,q}$ (defined in Section 2.2), a dummy variable that takes a value of one if a stock's average local net flows belong to the top quintile of local flows distribution in a given quarter, otherwise zero. We estimate again a version of Equation (10), where we use GEO $\text{FLOW}_{i,q}$ in place of SPEC $\text{FLOW}_{i,q}$.

$$\text{CAR}_{i,q} = \alpha_0 + \alpha_1 \text{GEO FLOW}_{i,q} + \alpha_2 \text{FS}_{i,q} + \Lambda' \text{X}_{i,q-1} + \text{D}_i + \text{D}_q + \epsilon_{i,q}. \tag{13}$$

We report our results in Panel C of Table 4. Regardless of the specification, we observe a positive loading on GEO $\text{FLOW}_{i,q}$. The coefficient estimates remain significant, as long as we do not include stock fixed effects. This is because there is only little variation in $\text{Geo Flow}_{i,q}$ within a stock over time. That is, $\text{Geo Flow}_{i,q}$ always takes a value of zero for firms without any local mutual funds, while firms surrounded by several local funds are likely to belong to the top quintile in terms local net flows. Our results suggest that proximity to local mutual funds helps to mitigate the negative price pressure stemming from fire sales. The price discount is reduced by roughly 23% relative to the mean for stocks that belong to the top quintile of the local flows distribution.[9]

Overall, our analyses with different specialization proxies offer the same insight; the availability of specialized liquidity matters for market efficiency. So far, we examined the effect of each specialization proxy on price discount separately. However, a fire sale stock is exposed to all those specialization dimensions at the same time. In the next section, we therefore turn to the specialization index, which combines different aspects of specialization into a single measure, into our analysis.

3.3 Specialization index

Having established a link between a number of individual specialization proxies and fire sale price discount, we now focus on a combined measure of stock's active specialization – the specialization index (defined in Section 2.2). The index allows us to capture an overall measure of specialized demand. This is important because the different measures of active specialization represent different dimensions and are likely to interact in their effect on price discounts. For example, a fire sale stock can be currently held by closet indexers (low value of $\text{Active Share}_{i,q}$) and at the same time exposed to 'specialized' investor inflows (high value of $\text{Spec Flow}_{i,q}$). Using the two specialization proxies separately results in two very different potential outcomes. We would expect the fire sale stock to experience relatively mild fire sales price pressure based on specialized investor inflows, but large price discount given the current closet indexers ownership structure. The specialization index allows us to examine the joint effect of different specialization dimensions on a stock's fire sale price discount.

We evaluate the effect of the specialization index on fire sales discount by estimating the following specification:

$$\text{Car}_{i,q} = \alpha_0 + \alpha_1 \text{Spec Index}_{i,q} + \alpha_2 \text{FS}_{i,q} + \Lambda' \text{X}_{i,q-1} + \text{D}_i + \text{D}_q + \epsilon_{i,q}. \tag{14}$$

[9] $-\frac{0.006}{-0.026} = 0.23$.

We report our regression estimates in Panel A of Table 5. Consistent with our previous results, the coefficient on Spec Index$_{i,q}$ is positive and highly statistically significant.[10] The Spec Index$_{i,q}$ coefficient estimates are also very stable across specifications *within* the same definition of fire sale pressure suggesting that omitted variable bias is unlikely to be the driver of our results. The effect of Spec Index$_{i,q}$ on fire sales price pressure is also economically large. One standard deviation increase in specialization index translates into roughly 50% reduction in the discount relative to the mean.[11] In absolute terms, the fire sale discount for stocks with a one standard deviation lower specialization index during the fire sale quarter is about four percent, i.e. roughly the magnitude of discounts in Coval and Stafford's seminal (2007) paper.[12]

Figure 3 provides visual representation of our results. The light- (dark-)gray circles plot CAARs for fire sales stock with high (low) values of specialization index. The orange circles represent CAARs for all fire sales firms. Consistent with the regression-based results, prices of stocks with high values of the specialization index remain almost unaffected by fire sales. On the other hand, stocks with specialization index in the bottom quintile, are subject to a significant and sizable negative price pressure due to extreme-outflow-induced sales. The presence of reversals suggests that the results are not driven by differential asset quality.

Finally, it could be that the effect of Spec Index shown in Table 5 is only driven by a few outliers. Figure C.5 in the appendix reveals that this is not the case. It shows the coefficients of a regression of CAR on dummy variables indicating whether the respective stock is in the low, medium low, medium high, and high quintile of Spec Index, relative to the effect of being the medium quintile bucket. Figure C.5 shows a monotonic relation between Spec Index ranks and returns in the fire sale quarter across all three fire sale pressure measures.

It is natural to conjecture that a fund's cash holdings can mitigate sale pressure, which in turn affects the prices of the stocks it holds. A fund under pressure equipped with a large amount of cash may not have to sell as much of their less liquid equity holdings and thus exert less pressure on their prices. Similarly, fire sale funds' access to interfund lending could dampen the effect of large outflows on the prices of stocks they hold. However, it is just as obvious that access to interfund lending is endogenously related to portfolio decisions, as is the choice of how

[10] Corresponding results using other measures of cumulative abnormal average returns can be found in Table C.4 in the Appendix.

[11] $-\frac{\text{mean discount}+\text{coefficient in column 4}}{\text{mean discount}} = -\frac{-0.026+0.013\cdot 1}{-0.026} = 0.5.$

[12] $-0.026 - 1\cdot 0.013 = -0.039 \approx 4\%.$

much cash a fund holds (see, e.g. Yan (2006), Acharya and Pedersen (2005) and Agarwal and Zhao (2019) on cash holdings and interfund lending, respectively). Hence, the empirical relation between fire sale price discounts and cash holdings or access to interfund lending are unclear. Nevertheless, we estimate a version of Equation (14) in which we additionally control for i) the share of fire-sale funds holding a stock that have access to interfund lending (weighted by how much of the stock they hold) and ii) the cash holdings of fire-sale funds. The tabulated results in Panel B of Table 5 suggest that neither affects our results.

To demonstrate the role of *active* investors' specialization, we evaluate the effect of a specialization index constructed using only *passive* mutual funds, PASSIVE SPEC INDEX$_{i,q}$, on the fire sale price discount. Finding that our passive specialization index measure reduces the fire sale price pressure to the same extent as active specialization index would cast doubt on the interpretation of our previous results. Even though passive fund managers might 'specialize' in a given fire sale stock, because they hold it or other same-industry stocks in their portfolio or are located nearby its headquarters, their portfolio allocation decisions are bounded by their benchmark and tracking error. Hence when faced with investor inflows, passive funds proportionally scale up their portfolios to maintain the index composition rather than target specific stocks under fire sale pressure. Consequently, it is plausible that PASSIVE SPEC INDEX somewhat ameliorates the negative price pressure stemming from fire sales, but we expect it to reduce the discount less than SPEC INDEX.

We re-estimate Equation (14), where we replace SPEC INDEX$_{i,q}$ with the passive specialization index, PASSIVE SPEC INDEX$_{i,q}$. Panel C of Table 5 reports regression estimates. The coefficient estimates on PASSIVE SPEC INDEX$_{i,q}$ are much smaller than the coefficient estimates on SPEC INDEX$_{i,q}$ tabulated in Panel A of the same table and only significant in half of the specifications. Panel D of Table 5 shows the coefficient estimates with PASSIVE SPEC INDEX$_{i,q}$ as the independent variable while controlling for cash holdings and access to interfund lending, which yields similar results. Figure 5 provides a consistent visual piece of evidence of a very small or negligible relationship between passive specialization index and fire sale price discount.

When a market is illiquid, it lacks a feature called resiliency – i.e., the ability to *quickly* push back prices to their fundamental value after they have been moved by a large trade (Bessembinder, Carrion, Tuttle, and Venkataraman, 2016). If the availability of specialized demand really ameliorates liquidity, we would expect prices to revert back to pre-fire sale prices faster when there is more specialized demand. Figures 1 and 3 suggest that this is indeed the case. We investigate the relationship between the reversal, that is the length of the fire sale price pressure, and the active specialization index more formally in the regression framework. We use the number of months it takes for a stock to recover from the fire sale price discount, truncated at 28 months, $\textsc{Trunc Reversal}_{i,q}$ and regress it on $\textsc{Spec Index}_{i,q}$ in the following way:

$$\textsc{Trunc Reversal}_{i,q} = \alpha_0 + \alpha_1 \textsc{Spec Index}_{i,q} + \alpha_2 \text{FS}_{i,q} + \Lambda' \text{X}_{i,q-1} + \text{D}_i + \text{D}_q + \epsilon_{i,q}. \quad (15)$$

The results are presented in Panel A of Table 6. The coefficient on $\textsc{Spec Index}_{i,q}$ is negative and significant, indicating that stocks revert more quickly, i.e. markets are more resilient when there is more specialized active demand. A one standard deviation increase in $\textsc{Spec Index}_{i,q}$ decreases the truncated reversal by 5 – 7.75% relative to the mean.[13] Truncating the reversal at 28 months makes our estimates conservative since we do not fully take advantage of the variation between low active specialization levels and long reversal periods.

Alternatively, we use an additional reversal measure, $\textsc{Only Reversal}_{i,q}$, which captures the time it takes for stocks to revert to their pre-fire sale prices but excludes stocks that have not recovered within 27 months since the end of fire sale event quarter. Thus, our new, restricted sample is unlikely to comprise low quality stocks subject to adverse selection during fire sales. We re-estimate the reversal regression Equation (15) and use $\textsc{Only Reversal}_{i,q}$ as a LHS variable.

We present the regression estimates in Panel B of Table 6. Again, the coefficient on $\textsc{Spec Index}_{i,q}$ remains negative and significant. A one standard deviation increase in $\textsc{Spec Index}_{i,q}$ translates into 4.2 – 6.6% decrease in the reversal length.[14] Finally, we also evaluate the relationship between the passive specialization index and the price reversal in Panels C and D of Table 6. We re-estimate Equation (15), where we replace $\textsc{Spec Index}_{i,q}$ with $\textsc{Passive Spec Index}_{i,q}$. The coefficient estimates on $\textsc{Passive Spec Index}_{i,q}$ are generally insignificant. This again suggests that while passive specialization may affect fire sale discounts and reversals to some degree, active mandates are crucial to ensure resiliency in the market.

The fast *short-run* reversal of higher Spec Index stocks which indicates resiliency should

[13] $1 - \frac{8.5-0.48}{8.5} = 5.6\%$.
[14] $1 - \frac{3.1-0.19}{3.1} = 6.1\%$.

be followed by lower returns of those stocks in the *medium run*, i.e. in the months after the fire sale episode. This is because the prices of stocks with high specialized demand were depressed only briefly (if there was a price impact at all) so prices are already close to their fundamental values. Conversely, stocks with low specialized demand should have (transiently) higher discount rates if the outflow-induced sales led to a less efficient allocation. We would thus expect higher average returns for stocks with lower Spec Index values in the months following the fire-sale episode, until eventually, the difference in cumulative returns between fire-sale stocks with high and low specialized demand has evaporated completely. To see if this is the case, we estimate the following specification with the cumulative abnormal return over the 30 months following the start of the fire sale episode as the dependent variable.

$$\text{CAR}^{30m}_{i,q} = \delta_0 + \delta_1 \text{FS}_{i,q} + \delta_2 \text{Low} + \delta_3 \text{Medium Low} + \delta_4 \text{Medium High} + \delta_5 \text{High} + \text{D}_q + \varepsilon_{i,q}. \quad (16)$$

Here, Low, Medium Low, Medium High and High denote dummy variables equal to one if a stock belongs to the bottom, second, fourth or upper quintile of the Spec $\text{Index}_{i,q}$ distribution in a given quarter, respectively. This means that all effects are estimated relative to the medium quintile.

The results are presented in Figure 4. For the whole thirty-month period there is no significant difference between the CAR of stocks whose fire sale pressure was met with high or low specialized demand as measured by quintiles of Spec Index. This has two important implications: First, it indicates that reversals are complete and fire sale discounts are transient. Second, and perhaps more importantly, after the significantly more negative returns that stocks with low Spec Index experience during the fire sale episode, they do have higher returns on average subsequent to the fire sale event quarter.[15] Both, the transient nature of the phenomenon and the higher returns for stocks with low specialized demand following the fire sale episode point to positive discount rate shocks driving fire-sale discounts.

We argued above that a natural source of such positive discount rate shocks could be new, less efficient allocations where less specialized investors hold relatively more of a given stock, as illustrated by the model in Section A in the Appendix. To test whether there are indeed more non-specialized investors holding the stock when there is little specialized demand, we

[15] The effect is somewhat masked in the figures showing the cumulative average abnormal return but becomes clearer by considering the average cumulative abnormal return in the rightmost column of Figure C.2.

regress the number of non-specialized investors that have bought a fire-sale stock in the fire sale event quarter on SPEC INDEX.[16] As shown in Table 7, this number is about 12% larger when SPEC INDEX is one standard deviation below its mean in the most conservative flow-to-volume specification.[17] In line with our hypothesis, the positive discount rate shocks when there is little specialized demand are accompanied by more non-specialized investors buying the stock.

4 Robustness

Our results in the previous section showed that both the magnitude of mutual fund fire sale-induced price pressure as well as the time it takes for prices to revert to previous levels depends on 'money in the right hands' – the funding liquidity of specialized active investors. In this section, we investigate the relationship between information asymmetry and our active specialization index to ensure that the index is not just another proxy for asymmetric information. We also explore a shock to investor net flows – the 2003 late trading scandal. The quasi-natural experiment allows us to address potential endogeneity concerns between mutual fund flows and fire sale discounts. Finally, we investigate the role of active, specialized demand in the presence of another instance of non-fundamental price pressure. Specifically, we explore exogenous variation stemming from the Russell 1000 and 2000 Index reconstitutions. This final robustness analysis allows us to examine whether we can generalize our results to other market setting where the identification of stock under price pressure does not depend on any fire-sale price pressure measure.

4.1 Adverse selection

In a recent empirical study, Huang et al. (2020) suggest that fire sale discounts are mostly due to adverse selection. So far, our results suggest that the *differences* in price discounts across stocks exposed to different levels of specialized demand are not determined by asymmetric information. For example, we would not expect prices to revert to their pre-fire sale levels if price discounts reflected the revelation of low stock quality. This notwithstanding, the theoretical framework of Dow and Han (2018) would suggest that fire sale funds sell more low-quality assets during fire sale episodes which merits further robustness checks.

[16] See Appendix B for a formal definition of non-specialized investors.
[17] $\frac{0.012}{0.099} = 0.12$

To this end, we investigate the relationship between our specialization index and three measures related to asymmetric information. In particular, we study how SPEC INDEX is related to future negative earnings, short interest and Llorente et al.'s (2002) asymmetric information measure. The reasoning behind the first two measures is motivated by their use in Huang et al. (2020). If, among the stocks with little specialized demand, there was a larger share of stocks with negative earnings surprises, that would suggest that funds deliberately sell low quality stocks when there is little specialized demand. In that case, the price discounts may be attributed to those stocks being revealed to have low quality (in a 'market for lemons' type of way). Similarly, high short interest could be indicative of negative private information. Finally, we use Llorente et al.'s (2002) asymmetric information measure that captures a dynamic volume-return relation for each stock in a quarter.

We measure the strength of the relationship between our active specialization index and the three asymmetric information proxies by estimating the following specification:

$$\begin{aligned} \mathrm{AI}_{i,q+1} &= \delta_0 + \delta_1 \mathrm{FS}_{i,q} + \delta_2 \textsc{Low} + \delta_3 \textsc{Medium Low} + \delta_4 \textsc{Medium High} \\ &\quad + \delta_5 \textsc{High} + \mathrm{D}_q + \varepsilon_{i,q}, \end{aligned} \tag{17}$$

where $\mathrm{AI}_{i,q+1}$ denotes one of the asymmetric information proxies for stock i in the quarter following a fire sale event, $q+1$. LOW is a dummy variable that takes a value of one if a stock belongs to the bottom quintile of SPEC $\mathrm{INDEX}_{i,q}$ distribution in a given quarter, otherwise zero. MEDIUM LOW, MEDIUM HIGH and HIGH are defined analogously. This regression specification allows us to compute an average degree of asymmetric information in each SPEC $\mathrm{INDEX}_{i,q}$ quintile, while controlling for the fire sale exposure, $\mathrm{FS}_{i,q}$, industry-wide shocks that affect all stocks in a given quarter, D_q, as well as stock-specific time-invariant and time-varying characteristics. If the active specialization index captures the degree of informational asymmetry, we would expect to observe a consistent monotonic relationship between the degree of a stock's specialized demand and the asymmetric information proxies.

We plot the coefficients estimates on LOW, MEDIUM LOW, MEDIUM HIGH, and HIGH in Figure 6 together with 95% confidence intervals computed with standard errors clustered at the stock and year×quarter level. We report coefficient estimates from two regression models: a baseline and a full regression specifications. In the baseline model (light-gray circles with light-gray solid line), we use Equation (17) to estimate the coefficients. In the full regression specification (dark-gray circles with dark-gray solid line), we add time-varying stock-specific controls and stock fixed effects. In Panel A, the LHS variable is a dummy that takes a value of one if a firm discloses negative earnings surprise in a quarter following a fire sale event. In Panel B, we use Llorente et al.'s (2002) asymmetric information measure (C2 coefficient) in a quarter following a fire sale event. In Panel C, we use the average future short interest as the dependent variable.

Given our regression estimates in Panels A and B, we find no significant relationship between earnings surprises or the asymmetric information measure and our active specialization index. The coefficient estimates are generally insignificant and change their signs depending on the specification. In Panel C, we observe a U-shaped relation (high and low Spec Index stocks have low short interest, indicating little information asymmetry) in the baseline model. In the full specification, we observe either a slightly negative and rather insignificant relation. Overall, the picture is unclear but it seems that stocks in the top quintile of Spec $\text{Index}_{i,q}$ have lower short interest than stocks in the Medium quintile in the quarter following the fire sale episode. Short-sellers are generally perceived as informed investors, so they may want to refrain from shorting stocks exposed to liquid, active, and specialized investors, i.e. stocks for which there is elastic, high-valuation demand such that short-selling seems less likely to be profitable.

Finally, we look at a subset of stocks under fire-sale pressure induced by passive funds, to address a potential concern that information asymmetries drive our results. We do so since passive funds have no or just a very limited discretion over which stocks they sell. Given investor withdrawals, passive funds sell off shares of all portfolio firms in proportion to their portfolio weights (Berger, 2021). Passive funds' fire sales therefore do not convey any sort of private information. We present the results in Table C.3. Our results are quantitatively similar to the ones from the main sample. This indicates that our results are not driven by funds selling low-quality stocks when there is low specialized demand.

While asset quality and information asymmetry likely contribute to fire sale discounts, active specialized demand has its own independent effect on fire-sale induced price pressure. Our active specialization index remains highly significant after controlling for the average stock quality and time-varying stock characteristics (including a negative earnings surprise control) and it seems uncorrelated with informational asymmetry proxies.

4.2 Mutual fund late trading scandal

Recent empirical studies argue that fire sales price pressure is predictable at least to some extent (Coval and Stafford, 2007; Dyakov and Verbeek, 2013). Thus investors could react ahead of time (before fire sales take place) by selling stocks plausibly subject to fire sales discount, which could potentially result in the observed negative price pressure before the fire sale event in Figure 1. This in turn could further contribute to and induce fire sales. In order to address the potential issue of reverse causality, we build on previous empirical studies that explore exogenous variation in mutual fund flows due to the 2003 late trading scandal outbreak (see Antón and Polk, 2014; Falato, Hortaşçu, Li, and Shin, 2021; Rzeźnik, 2021). McCabe (2008) and Kisin (2011) document that scandal-implicated mutual funds experienced significant and long-lasting withdrawals once their involvement in the scandal became publicly known. We explore this negative shock to mutual fund flows and defined our sample of fire sale stocks only based on portfolio holdings of mutual funds involved in the 2003 late trading scandal and subject to extreme investor outflows ($\textsc{Flow} < -5\%$).

The mutual fund trading scandal erupted on September 3, 2003 when the then New York State Attorney General made public allegations regarding the involvement of several mutual funds families in illegal practices like late trading and market timing. The scandal news was unexpected and revealed over the following months that overall 25 fund families were allegedly involved in the scandal.

In our robustness analysis, we explore extreme investor outflows from scandal-implicated funds due to reputational damage, once a fund's involvement in the scandal was know to the public. As the scandal news was unexpected, it is very unlikely that non-implicated investors sell their holdings in the anticipation of the scandal-induced fire sales. Rzeźnik (2021) shows that even scandal-implicated mutual funds appeared to be caught off guard by the scandal news.[18] Our sample covers the two-year period since the initial news regarding the late trading scandal – from September 2003 to August 2005. We use the same three definitions of fire sales, but only include stocks that were held by scandal-implicated funds with extreme investor withdrawals. We use the same regression specification as in Section 3 to evaluate the effect of active specialization on scandal-induced fire sale price discount.

[18] They did not adjust the liquidity of their portfolios before September 2003 or in the first months of the scandal outbreak.

We report our regression estimates in Table 8. In Panel A, we focus on the effect of the active specialization index on fire sales price pressure. The coefficient estimates on Spec Index$_{i,q}$ are positive, very stable, and almost always significant. The effect of Spec Index$_{i,q}$ on the fire sales price discount is also of economic relevance. A one standard deviation increase in Spec Index seems to completely eliminate the fire sales price pressure.[19] Conversely, the coefficient estimates on Passive Spec Index$_{i,q}$ in Panel B are insignificant and prone to change a sign depending on the specification. Thus, we conclude that our results are not confounded by simultaneity bias and thus active, specialized demand plays an important role in mitigating a negative price pressure stemming from forced sales.

4.3 Russell 1000 and 2000 Index reconstitutions

Finally, we examine whether our results can be generalized to other market settings – i.e., whether the availability of specialized demand can help ameliorate nonfundamental price pressure in contexts other than fire sales. To do so, we build on the recent empirical study by Chang et al. (2015) that shows considerable price declines for stocks deleted from the Russell 2000 and at the same time included in the Russell 1000 Index. The documented negative price pressure comes from passive funds rebalancing their portfolios in response to the shift in the stock's value-weighted index weight. A stock that is deleted from the Russell 2000 and included in the Russell 1000, is one of the largest stocks in the Russell 2000, but one of the smallest in the Russell 1000 Index, leading to a negative demand shock from passive funds.

We focus on 317 stocks that were deleted from the Russell 2000 and included in the Russell 1000 Index over the period of 2003 – 2013.[20] Thus, similar to our fire sale analysis, we only focus on the subset of stocks that are subject to nonfundamental negative price pressure. We use the regression Equation (14) with stock i's abnormal return in June (Russell's index reconstitution month – see Chang et al. (2015) for more details) as a LHS variable to evaluate the effect of active specialization on the indexing-induced price discount.

We report our regression estimates in Table 9. We compute abnormal returns in excess of the CRSP equally-weighted index in columns (1) – (4), Fama and French (1993) three-factor expected return in columns (5) – (8), and Carhart (1997) four-factor expected return in columns

[19] $1 - \frac{0.009-0.01}{0.009} = 110\%$

[20] Our Russell index constituents data set currently covers only the period from January 2003 to December 2013.

(9) – (12). To construct Spec Index, we include all active mutual funds (including funds experiencing extreme outflows – i.e., larger than 5% of fund's AUM). We also add the same set of stock-specific time-varying control variables. Regardless of the specification, we observe a positive, stable, and statistically significant coefficient on Spec Index. This indicates that stocks under negative pressure due to index reconstitution experience less of a price discount, when there is more active and specialized, high-valuation demand. A one standard deviation increase in specialized demand increases the abnormal return by 0.19 standard deviation.[21] Overall, our results suggest that the available funding liquidity in the hands of high-valuation investors does not only help to ameliorate negative price pressure due to fire sales but likely due to any nonfundamental reason.

5 Conclusion

We study mutual fund fire sales and the price pressure they exert on the stocks held by fire sale funds from a demand-side perspective. In particular, we trace back the magnitude of fire sale discounts to the availability of *specialized* demand, determined by the funding liquidity of active, investors with a high valuation for the stock who are familiar with it.

We find that the price impact of fire sales on stock prices is negligible when fire sale pressure is met by 'money in the right hands,' that is specialized demand proxied by the inflows into active mutual funds that are familiar with that stock. Using four measures of active and specialized demand, we document that fire sale price pressure is lower when there are higher inflows to funds that (i) already hold the stock, (ii) hold other stocks in the same industry, or (iii) are located in the same geographical region. Similarly, stock prices are less affected by sale pressure when funds that invest in the stock are more active in the sense that their investment decisions deviate more strongly from their benchmark. When specialized demand is scarce, stock prices plunge considerably before they slowly revert to their pre-fire sale levels. We find that inflows to passive funds have little to no impact on fire sale discounts. This shows the importance of active mandates for restoring market price efficiency.

Neither our main measures of supply shocks nor our proxies for specialized demand condition on actual sales and buys, so it is unlikely that our results are driven by adverse selection. Stocks exposed to either little or a lot of specialized demand do not systematically differ in terms of

[21] $\frac{1 \cdot 0.021}{0.11} = 0.19$, where 0.11 is the untabulated standard deviation of equal-weighted abnormal returns in June.

their quality or informational asymmetry attached to them.

Rather, our findings point to inefficient allocations due to a lack of specialized demand as an explanation for fire sale-induced price pressure. Specifically, our results suggest that fire sales induce an inefficient allocation of stocks across funds, which results in a significant but transient price discount for misallocated stocks. This is, funds that are ex-ante not as well equipped to hold a specific stock as their previous holders need to step in to ensure market clearing. Fire sales and – by extension – the risk of fire sales can lead to variation in prices and capital costs that is unrelated to firm fundamentals, i.e. a purely exogenous discount rate shock. An interesting implication of our analysis is that exposure to fire sale pressure in the absence of active specialized demand may be used as an instrument, e.g., for takeover risk. In terms of policy implications, our results may be viewed as supportive of the argument that mutual funds should have access to (central-) bank lending in order to keep prices stable.

References

Acharya, V. V. and L. H. Pedersen (2005). Asset pricing with liquidity risk. *Journal of Financial Economics 77*(2), 375–410.

Agarwal, V. and H. Zhao (2019, 01). Interfund Lending in Mutual Fund Families: Role in Liquidity Management. *The Review of Financial Studies 32*(10), 4079–4115.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets 5*(1), 31–56.

Amihud, Y. and R. Goyenko (2013). Mutual Fund's R2 as predictor of performance. *Review of Financial Studies 26*(3), 667–694.

Antón, M. and C. Polk (2014). Connected stocks. *Journal of Finance 69*(3), 1099–1127.

Asness, C. S., A. Frazzini, and L. H. Pedersen (2019). Quality minus junk. *Review of Accounting Studies 24*, 34—112.

Bartik, T. J. (1991). *Who Benefits from State and Local Economic Policies?* MI: Upjohn Press.

Ben-David, I., F. Franzoni, and R. Moussawi (2018). Do etfs increase volatility? *The Journal of Finance 73*(6), 2471–2535.

Berger, E. (2021). Selection bias in mutual fund fire sales. *Journal of Financial and Quantitative Analysis*.

Bessembinder, H., A. Carrion, L. Tuttle, and K. Venkataraman (2016). Liquidity, resiliency and market quality around predictable trades: Theory and evidence. *Journal of Financial Economics 121*(1), 142–166.

Brunnermeier, M. K. and L. H. Pedersen (2009). Market liquidity and funding liquidity. *Review of Financial Studies 22*(6), 2201–2238.

Campbell, J. Y. and L. M. Viceira (2002). *Strategic asset allocation: portfolio choice for long-term investors.* Clarendon Lectures in Economic.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance 52*(1), 57–82.

Chang, Y.-C., H. Hong, and I. Liskovich (2015). Regression discontinuity and the price effects of stock market indexing. *Review of Financial Studies 28*(1), 212–246.

Christoffersen, S. K., D. B. Keim, D. K. Musto, and A. Rzeźnik (2022). Passive-Aggressive Trading: The Supply and Demand of Liquidity by Mutual Funds. *Review of Finance*, 1–36.

Coval, J. D. and T. J. Moskowitz (1999). Home Bias at Home: Local Equity Preference in Domestic Portfolios. *The Journal of Finance 54*(6), 2045–2073.

Coval, J. D. and T. J. Moskowitz (2001). The Geography of Investment: Informed Trading and Asset Prices. *Journal of Political Economy 109*(4), 811–841.

Coval, J. D. and E. Stafford (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics 86*(2), 479–512.

Cremers, K. J. M. and A. Petajisto (2009). How Active Is Your Fund Manager A New Measure That Predicts Performance. *Review of Financial Studies 22*(9), 3329–3365.

Dow, J. and J. Han (2018). The paradox of financial fire sales: The role of arbitrage capital in determining liquidity. *The Journal of Finance 73*(1), 229–274.

Dyakov, T. and M. Verbeek (2013). Front-running of mutual fund fire sales. *Journal of Banking and Finance 37*(12), 4931–4942.

Edmans, A., I. Goldstein, and J. Wei (2012). The Real Effects of Financial Markets: The Impact of Prices on Takeovers. *Journal of Finance 67*(3), 933–971.

Falato, A., A. Hortaşçu, D. Li, and C. Shin (2021). Fire-sale spillovers in debt markets. *Journal of Finance 76*(6), 1–58.

Fama, E. and K. French (1993). Common risk factors in stock and bond returns. *Journal of Financial Economics 33*(1), 3–56.

Fama, E. F. and K. R. French (1997). Industry cost of equity. *Journal of Financial Economics 43*, 153–193.

Fama, E. F. and K. R. French (2007). Disagreement, tastes, and asset prices. *Journal of Financial Economics 83*(3), 667–689.

Frazzini, A. and O. A. Lamont (2008). Dumb money: Mutual fund flows and the cross-section of stock returns. *Journal of Financial Economics 88*(2), 299–322.

Gabaix, X. and R. S. Koijen (2021). In search of the origins of financial fluctuations: The inelastic markets hypothesis. Technical report, National Bureau of Economic Research.

Greenwood, R. and D. Thesmar (2011). Stock price fragility. *Journal of Financial Economics 102*(3), 471–490.

Grinblatt, M. and M. Keloharju (2001). How distance, language, and culture influence stockholdings and trades. *Journal of Finance 56*(3), 1053–1073.

Haddad, V., P. Huebner, and E. Loualiche (2021). How competitive is the stock market? theory, evidence from portfolios, and implications for the rise of passive investing. *Available at SSRN*.

Hoberg, G. and G. Phillips (2016). Text-Based Network Industries and Endogenous Product Differentiation. *Journal of Political Economy 124*(5), 1423–1465.

Huang, S., M. C. Ringgenberg, and J. Zhang (2020). The information in asset fire sales.

Israeli, D., C. M. Lee, and S. A. Sridharan (2017). Is there a dark side to exchange traded funds? an information perspective. *Review of Accounting Studies 22*(3), 1048–1083.

Ivkovic, Z. and S. Weisbenner (2005). Local Does as Local Is: Information Content of the Geography of Individual Investors' Common Stock Investments. *The Journal of Finance 60*(1), 267–306.

Kacperczyk, M., C. Sialm, and L. Zheng (2005). On the industry concentration of actively managed equity mutual funds. *Journal of Finance 60*(4), 1983–2011.

Kacperczyk, M., C. Sialm, and L. Zheng (2008). Unobserved actions of mutual funds. *Review of Financial Studies 21*, 2379–2416.

Kacperczyk, M., S. Van Nieuwerburgh, and L. Veldkamp (2016). A rational theory of mutual funds' attention allocation. *Econometrica 84*(2), 571–626.

Kisin, R. (2011). The impact of mutual fund ownership on corporate investment: Evidence from a natural experiment. *Olin Business School Working Paper*, 1–40.

Koijen, R. S. J. and M. Yogo (2019). A demand system approach to asset pricing. *Journal of Political Economy 127*(4), 1475–1515.

Llorente, G., R. Michaely, G. Saar, and J. Wang (2002). Dynamic Volume-return Relation of Individual Stocks. *Review of Financial Studies 15*(4), 1005–1047.

Lou, D. (2012). A flow-based explanation for return predictability. *Review of Financial Studies 25*(12), 3457–3489.

Lou, X. and A. Y. Wang (2018). Flow-induced trading pressure and corporate investment. *Journal of Financial and Quantitative Analysis 53*(1), 171–201.

Massa, M. and A. Simonov (2005). Hedging, familiarity and portfolio choice. *Review of Financial Studies 19*(2), 633–685.

McCabe, P. (2008). The economics of the mutual fund trading scandal. *Federal Reserve Board Working Paper*, 1–74.

Pavlova, A. and T. Sikorskaya (2022). Benchmarking intensity. *Review of Financial Studies*.

Phillips, G. M. and A. Zhdanov (2013, 01). R&D and the Incentives from Merger and Acquisition Activity. *The Review of Financial Studies 26*(1), 34–78.

Pool, V. K., N. Stoffman, and S. E. Yonker (2012). No place like home: Familiarity in mutual fund manager portfolio choice. *Review of Financial Studies 25*(8), 2563–2599.

Rzeźnik, A. (2021). Skilled active liquidity management: Evidence from natural experiments.

Sammon, M. (2021). Passive ownership and price informativeness. *Available at SSRN*.

Seasholes, M. S. and N. Zhu (2010). Individual Investors and Local Bias. *Journal of Finance 65*(5), 1987–2010.

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

Shleifer, A. and R. W. Vishny (1997). The limits of arbitrage. *The Journal of Finance 52*(1), 35–55.

Stambaugh, R. F. (2014). Presidential address: Investment noise and trends. *The Journal of Finance 69*(4), 1415–1453.

Wardlaw, M. (2020). Measuring Mutual Fund Flow Pressure as Shock to Stock Returns. *Journal of Finance 75*(6), 3221–3243.

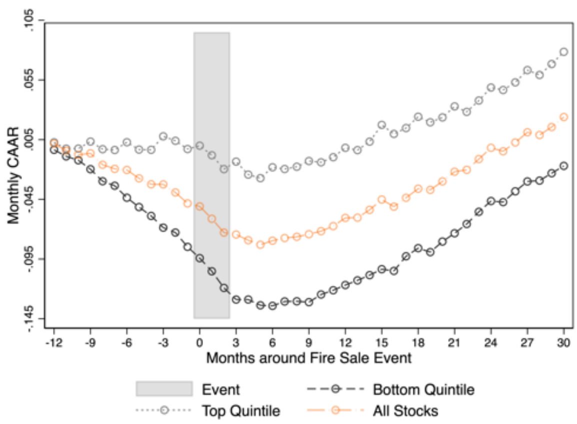
Weber, R. (2021). Institutional investors, households and the time-variation in expected stock returns. *Journal of Financial and Quantitative Analysis*, 1–71.

Yan, X. S. (2006). The determinants and implications of mutual fund cash holdings: Theory and evidence. *Financial Management 35*(2), 67–91.

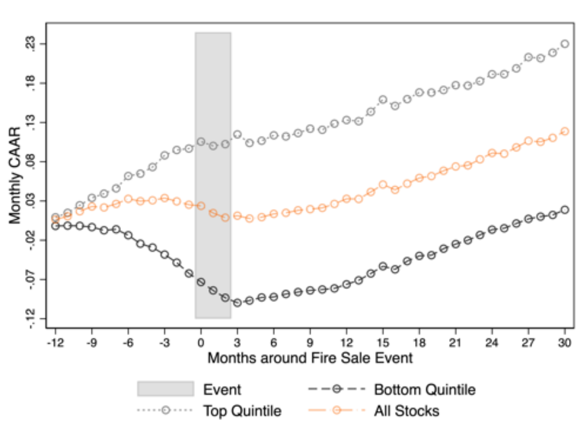
Figure 1: CAAR trajectories for fire sales stocks with different degrees of specialized flows

This figure shows CAAR trajectories for portfolios of stocks under fire sale pressure, sorted based on stocks' exposure to specialized investor flows. We use three different definitions of fire sale pressure: Flow-To-Volume – Panel A, Flow-To-Stock – Panel B, and MFFlow – Panel C. The grey shaded area indicates the fire sale event quarter. We plot the average CAARs for all fire sale stocks with orange circles. Every quarter, we identify active non-fire sale funds (with $\text{Flow}_{f,q} > -5\%$) that hold the stock at the beginning of the event quarter and calculate average fund flows for a given stock. Then we sort fire sale stocks based on their non-fire sale flows into quintiles. We use light-gray circles to plot the average CAAR of the quintile with the highest flows and dark-gray circles to indicate CAAR of the quintile with the lowest flows. The abnormal monthly return is calculated by subtracting the monthly equally-weighted market return.

(A) Flow-to-Volume



(B) Flow-to-Stock



(C) MFFlow

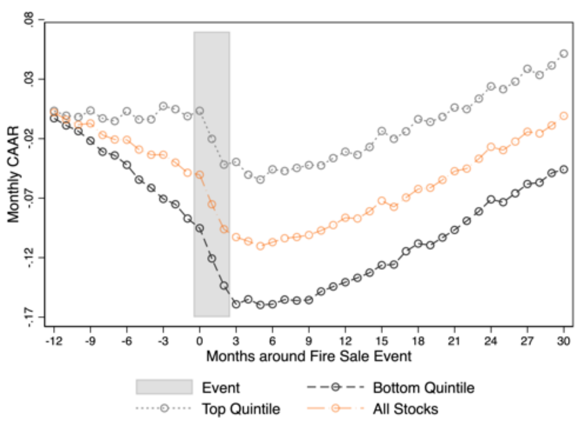
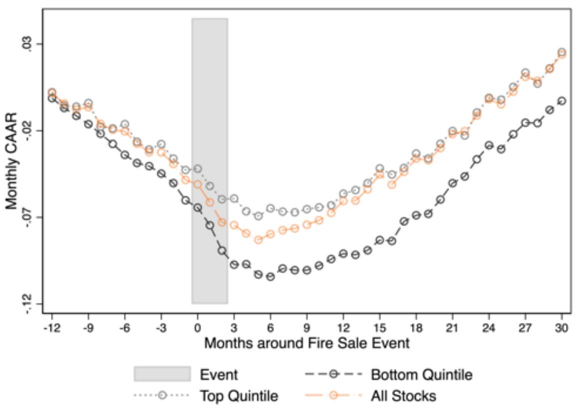


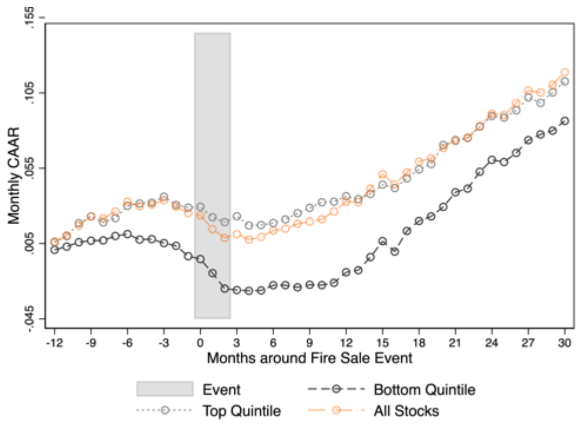
Figure 2: CAAR trajectories for fire sales stocks with different degrees of *passive* specialized flows

This figure shows CAAR trajectories for portfolios of stocks under fire sale pressure, sorted based on stocks' exposure to *passive* specialized investor flows. We use three different definitions of fire sale pressure: FLOW-TO-VOLUME – Panel A, FLOW-TO-STOCK – Panel B, and MFFLOW – Panel C. The grey shaded area indicates the fire sale event quarter. We plot the average CAARs for all fire sale stocks with orange circles. Every quarter, we identify passive non-fire sale funds (with $\text{FLOW}_{f,q} > -5\%$) that hold the stock at the beginning of the event quarter and calculate average fund flows for a given stock. Then we sort fire sale stocks based on their non-fire sale flows into quintiles. We use light-gray circles to plot the average CAAR of the quintile with the highest flows, and dark-gray circles to indicate CAAR of the quintile with the lowest flows. The abnormal monthly return is calculated by subtracting the monthly equally-weighted market return.

(A) Flow-to-Volume



(B) Flow-to-Stock



(C) MFFlow

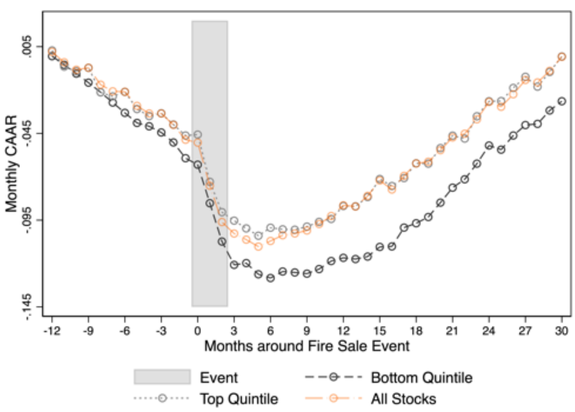
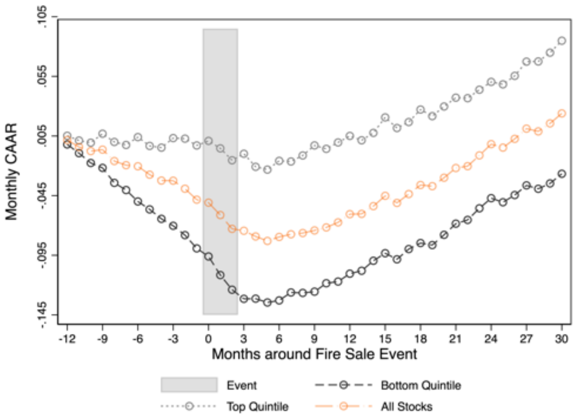


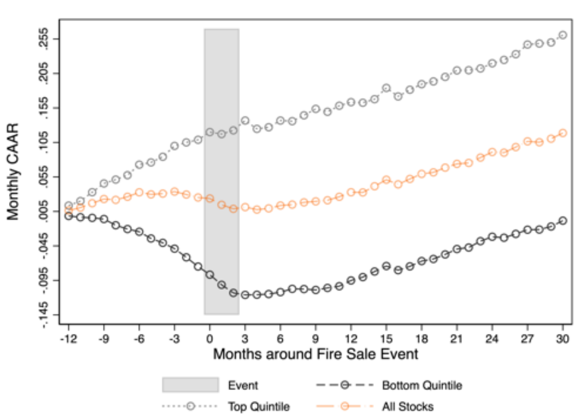
Figure 3: CAAR trajectories for fire sale stocks with different degrees of the *active* specialization index

This figure shows CAAR trajectories for portfolios of stocks under fire sale pressure, sorted based on their exposure to *active* specialization, as measured by SPEC INDEX. We use three different definitions of fire sale pressure: FLOW-TO-VOLUME – Panel A, FLOW-TO-STOCK – Panel B, and MFFLOW – Panel C. The grey shaded area indicates the fire sale event quarter. We plot the average CAAR for all fire sale stocks with orange circles. Every quarter, we sort fire sale stocks into quintiles based on SPEC INDEX$_{i,q}$. We use light-gray circles to plot the average CAAR of the quintile with the highest active specialization index, and dark-gray circles to indicate CAAR of the quintile with the lowest active specialization index. The abnormal monthly return is calculated by subtracting the monthly equally-weighted market return.

(A) Flow-to-Volume



(B) Flow-to-Stock



(C) MFFlow

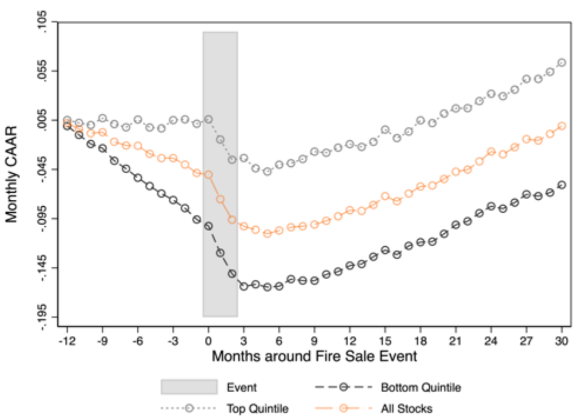


Figure 4: Active specialization and CAR over 30 months since fire sale event

This figure plots δ_2, δ_3, δ_4, and δ_5 coefficient estimates from a following regression:

$$\textsc{Car}^{30m}_{i,q} = \delta_0 + \delta_1 \text{FS}_{i,q} + \delta_2 \textsc{Low} + \delta_3 \textsc{Medium Low} + \delta_4 \textsc{Medium High} + \delta_5 \textsc{High} + \textsc{d}_q + \varepsilon_{i,q},$$

where $\text{FS}_{i,q}$ is $\textsc{Flow-To-Volume}_{i,q}$ in Panel A, $\textsc{Flow-To-Stock}_{i,q}$ in Panel B, and $\textsc{MFFlow}_{i,q}$ in Panel C. $\textsc{Car}^{30m}_{i,q}$ is cumulative abnormal return computed over 30 months since the first fire-sale-event month. Every quarter we sort all fire sale stocks into quintiles based on their active specialization measure $\textsc{Spec Index}_{i,q}$. Low is a dummy variable that takes a value of one if a stock belongs to the bottom quintile, otherwise zero. Medium Low is an indicator variable that takes a value of one if a stock belongs to the second lowest quintile, otherwise zero. Medium High is a dummy variable that takes a value of one if a stock belongs to the second highest quintile of active specialization, otherwise zero. High is an indicator variable that takes a value of one if a stock belongs to the top quintile, otherwise zero. We use the middle quintile as a reference group. $\textsc{d}_q$ denotes year×quarter fixed effects. We use three different definitions of fire sale pressure: Flow-To-Volume – Panel A, Flow-To-Stock – Panel B, and MFFlow – Panel C. The light-gray circles represent coefficient estimates from the base-line regression above. The dark-gray triangles denote coefficient estimates from the most strict specification, where we include a set of time-varying stock characteristics, stock, and industry×year-month fixed effects. The horizontal light- and dark-gray lines represent 95% confidence intervals. The standard errors are clustered at the stock and year×quarter level.

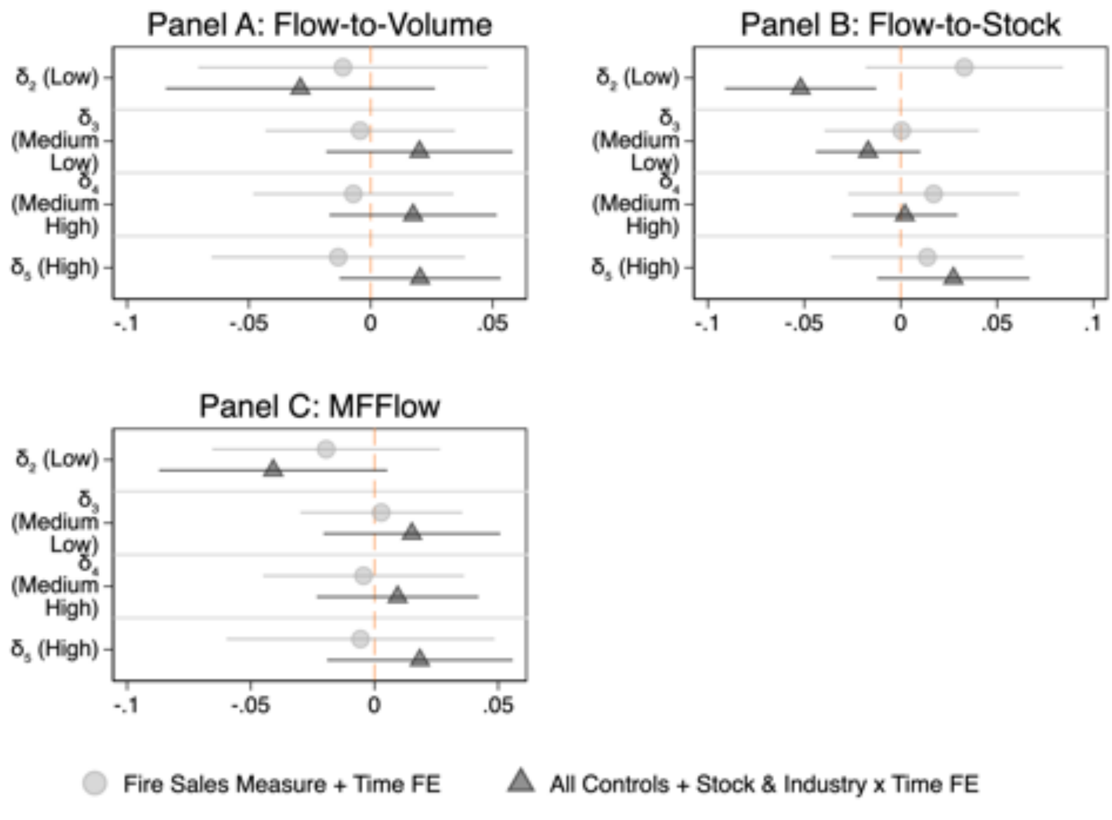
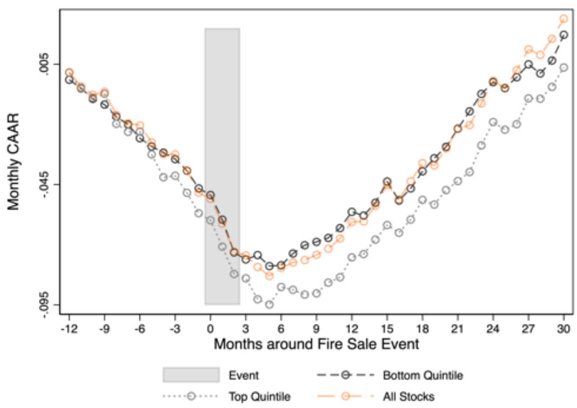


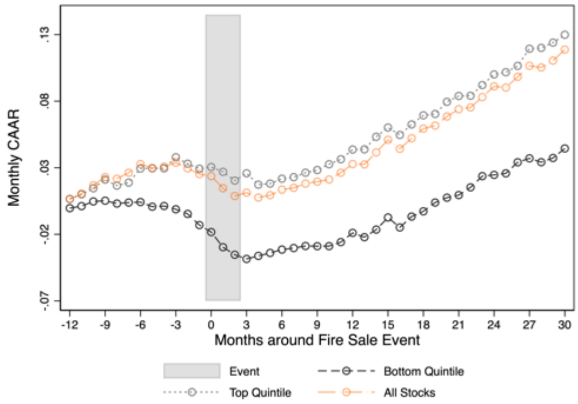
Figure 5: CAAR trajectories for fire sales stocks with different degrees of *passive* specialization index

This figure shows CAAR trajectories for portfolios of stocks under fire sale pressure, sorted based on their exposure to *passive* specialization, as measured by PASSIVE SPEC INDEX. We use three different definitions of fire sale pressure: FLOW-TO-VOLUME – Panel A, FLOW-TO-STOCK – Panel B, and MFFLOW – Panel C. The grey shaded area indicates the fire sale event quarter. We plot the average CAAR for all fire sale stocks with orange circles. Every quarter, we sort fire sale stocks into quintiles based on PASSIVE SPEC INDEX$_{i,q}$. We use light-gray circles to plot the average CAAR of the quintile with the highest passive specialization index, and dark-gray circles to indicate CAAR of the quintile with the lowest passive specialization index. The abnormal monthly return is calculated by subtracting the monthly equally-weighted market return.

(A) Flow-to-Volume



(B) Flow-to-Stock



(C) MFFlow

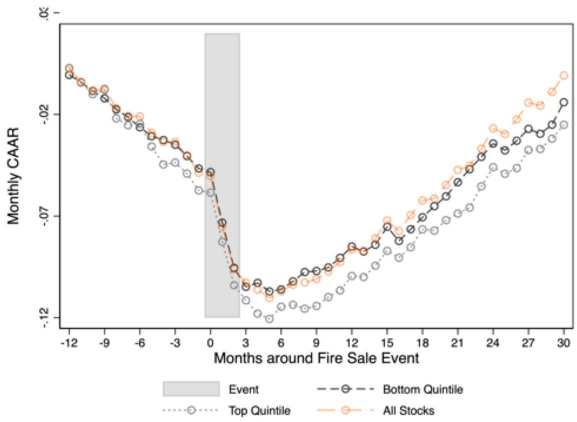


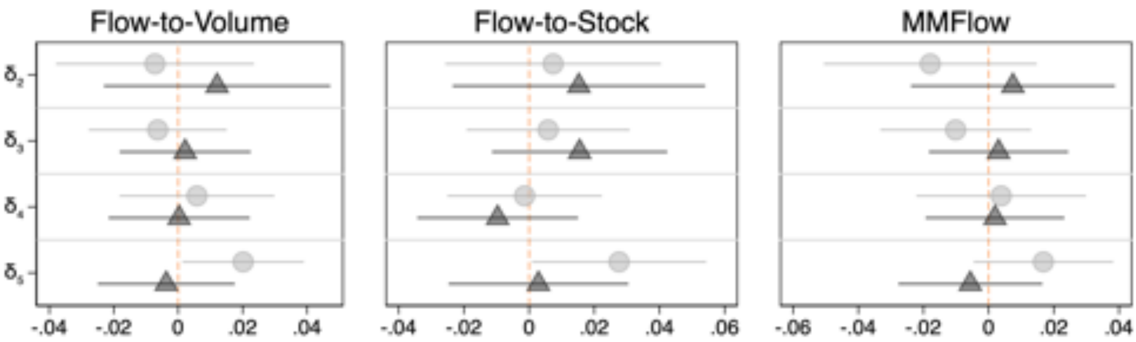
Figure 6: Active specialization index and information asymmetry

This figure plots δ_2, δ_3, δ_4, and δ_5 coefficient estimates from the following regression:

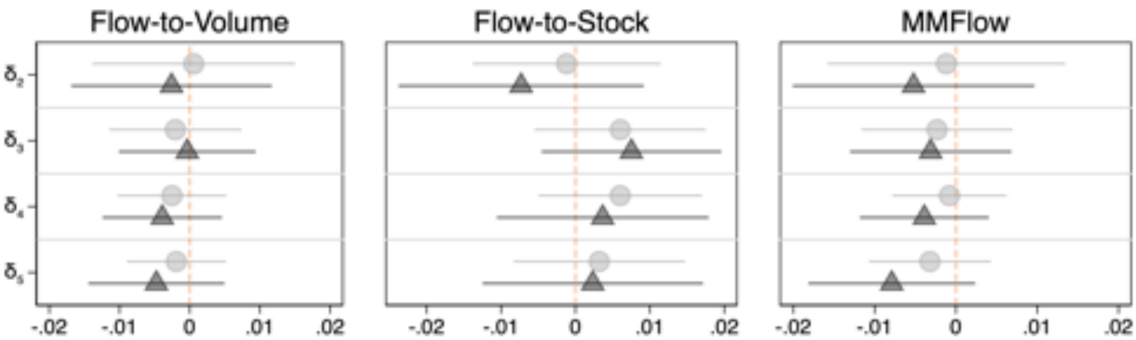
$$\mathrm{Y}_{i,q+1} = \delta_0 + \delta_1 \mathrm{FS}_{i,q} + \delta_2 \textsc{Low} + \delta_3 \textsc{Medium Low} + \delta_4 \textsc{Medium High} + \delta_5 \textsc{High} + \mathrm{D}_q + \varepsilon_{i,q},$$

where $\mathrm{Y}_{i,q+1}$ is an indicator variable that takes the value of one if a firm discloses a negative earnings surprise in a quarter following a fire sale event in Panel A, Llorente et al.'s (2002) information asymmetry measure calculated over a quarter following a fire sale episode in Panel B, and one quarter-ahead short interest of stock i in Panel C. We use three different definitions of fire sale pressure: FLOW-TO-VOLUME – the left column, FLOW-TO-STOCK – the middle columns, and MFFLOW – the right column. Every quarter we sort all fire sale stocks into quintiles based on their active specialization index, SPEC INDEX$_{i,q}$. LOW is a dummy variable that takes a value of one if a stock belongs to the bottom quintile, otherwise zero. MEDIUM LOW is an indicator variable that takes a value of one if a stock belongs to the second lowest quintile, otherwise zero. MEDIUM HIGH is a dummy variable that takes a value of one if a stock belongs to the second highest quintile of active specialization, otherwise zero. HIGH is an indicator variable that takes a value of one if a stock belongs to the top quintile, otherwise zero. We use the middle quintile as a reference group. D_q denotes year×quarter fixed effects. The light-gray circles represent coefficient estimates from the base-line regression above. The dark-gray triangles denote coefficient estimates from the most strict specification, where we include a set of time-varying stock characteristics and stock fixed effects. The horizontal light- and dark-gray lines represent 95% confidence intervals. The standard errors are clustered at the stock and year×quarter level.

(A) Negative earnings surprise in the quarter following a fire sale event



(B) Llorente et al.'s (2002) asymmetric information measure in the quarter following a fire sale event



(C) Average short interest in the quarter following a fire sale event

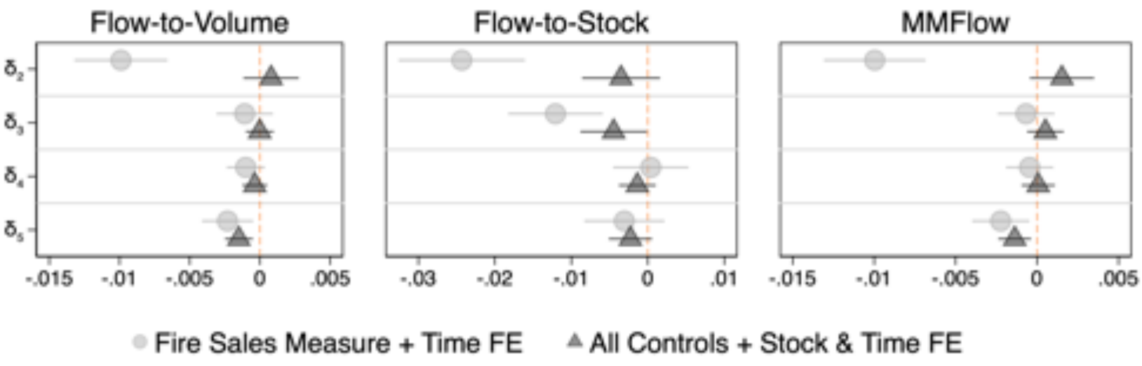


Table 1: Mutual Fund Descriptive Statistics

This table reports summary statistics of the domestic equity mutual funds in our sample from 1990 to 2016. We report the summary statistics as of December of each year. We obtain data on mutual fund size, monthly returns, and investor flows from the CRSP survivorship-bias-free mutual fund database. We use mutual fund holding data from Thompson Financial CDA/Spectrum. Number of Funds is the number of mutual funds in the sample at the end of each year; TNA is the total net assets for the average fund, reported in millions of dollars; Equity Holdings is the value of the equity holdings in each mutual fund using the stock price and holdings as of December reported in millions of U.S. dollars; % Market Held is the percentage of the total value of the U.S. equity market that is held by the mutual funds in the sample as of December each year.

Year	Number of funds	TNA (in $ Million)	Equity Holdings (in $ Million)	% Market Held
1990	277	372.38	295.22	2.74
1991	315	512.83	417.44	3.29
1992	344	690.42	528.30	4.13
1993	251	819.04	684.20	3.40
1994	206	816.72	686.89	2.83
1995	201	991.89	854.51	2.53
1996	289	809.62	746.86	2.60
1997	279	1524.87	1593.51	4.12
1998	619	1002.40	971.74	4.52
1999	974	1121.03	1007.95	5.77
2000	939	1049.69	1141.10	6.86
2001	995	697.96	660.86	4.75
2002	1163	752.67	776.11	8.18
2003	1216	950.84	892.09	7.44
2004	1759	1334.49	1179.30	12.61
2005	1556	1582.10	1362.69	12.20
2006	1668	1757.81	1597.87	13.58
2007	1755	1671.63	1443.51	12.53
2008	1836	930.19	798.17	12.07
2009	1696	1337.92	1162.35	12.46
2010	1414	1937.32	1682.61	12.85
2011	1717	1781.24	1406.75	13.50
2012	1599	2120.40	1728.10	13.56
2013	1479	3027.75	2481.95	13.95
2014	1457	3425.52	2822.51	14.19
2015	1354	3610.25	3075.67	15.05
2016	1336	4020.83	3479.56	15.41
Mean	1062.74	1505.55	1313.99	8.78

Table 2: Summary Statistics

This table reports summary statistics for our sample of fire sale stocks between 1990 and 2016. We use three different definitions of fire sale pressure: FLOW-TO-VOLUME in Panel A, FLOW-TO-STOCK in Panel B, and MFFLOW in Panel C. In Panel A, our sample consists of the bottom decile of FLOW-TO-VOLUME distribution. In Panel B, we only include stocks that belong to the bottom decile of FLOW-TO-STOCK distribution. In Panel C, our sample comprises stocks that belong to the bottom decile of MFFLOW distribution. We use Wardlaw's (2020) definition of FLOW-TO-VOLUME and FLOW-TO-STOCK. We follow Edmans et al. (2012) and compute $\text{MFFLOW}_{i,q}$ using hypothetical buy and sell orders projected from previously disclosed mutual fund portfolios. $\text{CAAR}_{i,q}$ is a cumulative abnormal return of stock i during fire sale quarter q. The abnormal monthly return is calculated by subtracting the monthly equally-weighted market return from the realized stock return. Every quarter for each fire sale stock, we identify active (passive) non-fire sale funds (i.e., $\text{FLOW}_{f,q} > -5\%$) that hold the stock at the beginning of the event quarter and calculate the average active (passive) specialized fund flows for stock i in quarter q, $\text{SPEC FLOW}_{i,q}$ ($\text{PASSIVE SPEC FLOW}_{i,q}$). $\text{ACTIVE SHARE}_{i,q}$ is the average active share of non-fire sale funds holding stock i at the beginning of quarter q. $\text{IND FLOW}_{i,q}$ is the average net flow of non-fire sale funds holding stocks, which belong to the same industry as stock i, at the beginning of the quarter q. We use the Hoberg and Phillips (2016) text-based measure to define industries. For each stock quarter, we calculate the average (geographical) flows of non-fire sale funds located within 100km from the headquarters of stock i. $\text{GEO FLOW}_{i,q}$ is a dummy variable that takes a value of one, if a stock belongs to the top quintile of geographical flows in a given quarter, and otherwise zero. $\text{SPEC INDEX}_{i,q}$ is the active specialization index. We construct it by adding z-scored $\text{SPEC FLOW}_{i,q}$, $\text{ACTIVE SHARE}_{i,q}$, $\text{IND FLOW}_{i,q}$, and the dummy variable $\text{GEO FLOW}_{i,q}$. $\text{NON-SPEC PARTICIPATION}_{i,q}$ is the non-specialized investor participation in a fire sale stock. We define non-specialized investors as non-fire sale mutual funds that do not hold a fire sale stock or any of the ten closest industry peers of a fire sale stock at the beginning of the fire sale event quarter and are located at least 100km away from the headquarters of fire sale stock. We compute the non-specialized investor participation in a fire sale stock by counting the number of non-specialized mutual funds that bought the shares of fire sale stock during the fire sale event quarter.

Panel A: Flow-to-Volume

	Mean	Median	SD	P1	P99	NOBS
Car$_{i,q}$	-0.026	-0.029	0.198	-0.490	0.533	24711
Flow-To-Volume$_{i,q}$	-4.526	-2.698	5.146	-33.515	-1.508	24711
Spec Flow$_{i,q}$	0.041	0.019	0.086	-0.040	0.379	24711
Passive Spec Flow$_{i,q}$	0.040	0.023	0.065	-0.015	0.289	24711
Active Share$_{i,q}$	0.748	0.763	0.141	0.366	0.978	24711
Ind Flow$_{i,q}$	0.044	0.034	0.050	-0.007	0.219	24711
Geo Flow$_{i,q}$	0.109	0.000	0.312	0.000	1.000	24711
Spec Index$_{i,q}$	0.000	-0.093	1.001	-1.775	3.218	24711
Non-Spec Participation$_{i,q}$	0.099	0.000	0.699	0.000	3.000	24711

Panel B: Flow-to-Stock

	Mean	Median	SD	P1	P99	NOBS
Car$_{i,q}$	-0.012	-0.019	0.249	-0.558	0.651	24685
Flow-To-Stock$_{i,q}$	-7.615	-6.461	3.463	-22.669	-4.472	24685
Spec Flow$_{i,q}$	0.041	0.025	0.073	-0.026	0.312	24685
Passive Spec Flow$_{i,q}$	0.050	0.035	0.058	-0.007	0.260	24685
Active Share$_{i,q}$	0.732	0.733	0.107	0.432	0.966	24685
Ind Flow$_{i,q}$	0.042	0.034	0.044	-0.002	0.200	24685
Geo Flow$_{i,q}$	0.128	0.000	0.334	0.000	1.000	24685
Spec Index$_{i,q}$	-0.002	-0.103	0.997	-1.781	3.292	24685
Non-Spec Participation$_{i,q}$	0.256	0.000	1.619	0.000	8.000	24685

Panel C: MFFlow

	Mean	Median	SD	P1	P99	NOBS
Car$_{i,q}$	-0.056	-0.049	0.191	-0.577	0.431	24712
MFFlow$_{i,q}$	-4.731	-2.811	5.458	-35.654	-1.547	24712
Spec Flow$_{i,q}$	0.040	0.018	0.085	-0.040	0.375	24712
Passive Spec Flow$_{i,q}$	0.041	0.022	0.066	-0.016	0.289	24712
Active Share$_{i,q}$	0.748	0.764	0.141	0.356	0.978	24712
Ind Flow$_{i,q}$	0.043	0.033	0.050	-0.007	0.217	24712
Geo Flow$_{i,q}$	0.107	0.000	0.309	0.000	1.000	24712
Spec Index$_{i,q}$	0.000	-0.092	1.000	-1.782	3.194	24712
Non-Spec Participation$_{i,q}$	0.093	0.000	0.668	0.000	3.000	24712

Table 3: Effect of Active and Passive Specialized Investor' Flows on Fire Sale Discount

This table reports OLS estimates of regressions of the cumulative abnormal return (CAR) of fire sale stocks on our measures of specialized investors' flows between 1990 and 2016. We use three different definitions of fire sale pressure: Flow-To-Volume in columns (1) – (4), Flow-To-Stock in columns (5) – (8), and MFFlow in columns (9) – (12). In columns (1) – (4), our sample consists of the bottom decile of the Flow-To-Volume distribution. In columns (5) – (8), we only include stocks that belong to the bottom decile of the Flow-To-Stock distribution. In columns (9) – (12), our sample comprises stocks that belong to the bottom decile of MFFlow distribution. We use Wardlaw's (2020) definition of Flow-To-Volume and Flow-To-Stock. We follow Edmans et al. (2012) and compute $\text{MFFlow}_{i,q}$ using hypothetical buy and sell orders projected from previously disclosed mutual fund portfolios. $\text{Car}_{i,q}$ is the cumulative abnormal return of stock i during fire sale quarter q. The abnormal monthly return is calculated by subtracting the monthly equally-weighted market return from the realized stock return. Every quarter for each fire sale stock, we identify active (passive) non-fire sale funds (i.e., $\text{Flow}_{f,q} > -5\%$) that hold the stock at the beginning of event quarter and calculate the average active (passive) specialized fund flows for stock i in quarter q, $\text{Spec Flow}_{i,q}$ ($\text{Passive Spec Flow}_{i,q}$). In Panel A, we investigate the effect of active specialized investor flows on the abnormal returns of fire sale stocks. In Panel B, we relate passive specialized flows to the fire sale discount. $\text{Fragility}_{i,q}$ is Greenwood and Thesmar's (2011) price fragility measured over one quarter prior to the fire sale event. $\text{Liq}_{i,q-1}$ is the lagged Amihud's (2002) liquidity measure. $\text{SD}(\text{Ret})_{i,q-1}$ is the standard deviation of daily returns estimated in the quarter prior to the fire sale event. $\text{Ret}_{i,q-1}$ is the lagged average monthly stock return. $\text{Negative ES}_{i,q}$ is an indicator variable that takes a value of one if a firm discloses a negative earnings surprise in the fire sale event quarter, otherwise zero. $\text{Log}(\text{Mcap})_{i,q-1}$ is the natural logarithm of stock i's market capitalization in the quarter prior to the fire sale event. $\text{Inst Own}_{i,q}$ is the percentage of shares outstanding of stock i held by institutional investors at the end of the fire sale event quarter q. $\text{Inst Own}_{i,q}$ is expressed in decimals. We include year×quarter fixed effects in columns (1), (2), (5), (6), (9), and (10). We add industry×year-quarter fixed effects in columns (3), (4), (7), (8), (11), and (12). We use Fama and French's (1997) 10 industry classification. Finally, in columns (4), (8), and (12) we control for time-invariant stock characteristics. We cluster the standard errors two-way: at the stock and year×quarter. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Specialized investor flows												
	Flow-to-volume				Flow-to-stock				Price Pressure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SPEC FLOW$_{i,q}$	0.090***	0.088***	0.086***	0.086***	0.205***	0.201***	0.184***	0.201***	0.076***	0.062***	0.064***	0.071***
	(3.66)	(3.50)	(3.36)	(2.66)	(4.01)	(3.73)	(3.36)	(3.36)	(4.33)	(4.16)	(4.28)	(4.31)
FLOW-TO-VOLUME$_{i,q}$	0.875***	0.578*	0.516	1.872***								
	(3.07)	(1.70)	(1.57)	(5.02)								
FLOW-TO-STOCK$_{i,q}$					0.331	0.975	0.614	1.085*				
					(0.48)	(1.47)	(1.00)	(1.68)				
MFFLOW$_{i,q}$									1.266***	2.260***	2.147***	3.984***
									(4.44)	(7.73)	(7.91)	(10.80)
FRAGILITY$_{i,q-1}$		-0.224	-0.060	-0.758		-2.296	-2.501	-3.452		2.571	2.248	0.116
		(-0.12)	(-0.04)	(-0.40)		(-1.08)	(-1.14)	(-1.13)		(1.13)	(1.27)	(0.05)
LIQ$_{i,q-1}$		-2.545	-3.373	-10.707***		3.978	6.007	1.875		16.316***	14.999***	-0.445
		(-0.86)	(-1.20)	(-3.05)		(0.72)	(1.21)	(0.29)		(6.32)	(6.39)	(-0.14)
SD(RET)$_{i,q-1}$		-0.208	-0.116	1.077***		0.484	0.572	1.307*		-1.813***	-1.638***	-0.018
		(-0.73)	(-0.42)	(2.95)		(0.82)	(0.96)	(1.92)		(-7.14)	(-6.83)	(-0.08)
RET$_{i,q-1}$		-4.675***	-5.044***	-7.857***		-0.345	-1.313	-3.503***		-0.853	-1.326	-5.174***
		(-4.37)	(-4.69)	(-7.57)		(-0.21)	(-0.85)	(-2.83)		(-0.94)	(-1.47)	(-5.74)
NEGATIVE ES$_{i,q}$		-0.046***	-0.047***	-0.054***		-0.040***	-0.041***	-0.051***		-0.041***	-0.043***	-0.052***
		(-13.93)	(-15.37)	(-15.38)		(-10.77)	(-11.65)	(-12.56)		(-14.01)	(-15.16)	(-16.72)
LOG(MCAP)$_{i,q-1}$		-4.582	-5.076	-69.301***		-2.708	1.875	-89.733***		11.670***	10.789***	-55.587***
		(-1.31)	(-1.52)	(-8.95)		(-0.39)	(0.30)	(-8.76)		(3.63)	(3.57)	(-7.85)
INST OWN$_{i,q}$		0.025**	0.022**	0.063***		0.066***	0.063***	0.140***		0.051***	0.050***	0.090***
		(2.55)	(2.54)	(3.37)		(3.36)	(3.41)	(7.01)		(5.56)	(5.93)	(4.74)
Observations	24711	24711	24711	23021	24782	24782	24685	23243	24712	24712	24712	22921
R^2	0.083	0.10	0.16	0.36	0.043	0.052	0.11	0.31	0.096	0.13	0.18	0.39
Controls:												
Stock FE				Yes				Yes				Yes
Year × Quarter FE	Yes	Yes			Yes	Yes			Yes	Yes		
Industry × Year-Quarter FE			Yes	Yes			Yes	Yes			Yes	Yes
Standard Errors Clustered at:												
Stock level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Quarter level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

Panel B: Passive specialized investor flows

	Flow-to-volume				Flow-to-stock				Price Pressure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Passive Spec Flow$_{i,q}$	0.021	0.008	0.007	0.025	0.015	0.036	0.052*	0.086**	0.011	-0.001	0.007	0.031
	(1.10)	(0.32)	(0.31)	(1.01)	(0.49)	(1.21)	(1.81)	(2.04)	(0.52)	(-0.04)	(0.29)	(1.30)
Flow-To-Volume$_{i,q}$	0.874***	0.574*	0.513	1.836***								
	(3.00)	(1.67)	(1.54)	(4.91)								
Flow-To-Stock$_{i,q}$					0.306	0.950	0.605	1.046				
					(0.43)	(1.38)	(0.95)	(1.58)				
MFFlow$_{i,q}$									1.270***	2.258***	2.144***	3.955***
									(4.42)	(7.60)	(7.77)	(10.63)
Fragility$_{i,q-1}$		-0.216	-0.076	-0.805		-2.079	-2.437	-3.214		2.580	2.239	0.074
		(-0.11)	(-0.05)	(-0.42)		(-0.95)	(-1.08)	(-1.01)		(1.12)	(1.25)	(0.03)
Liq$_{i,q-1}$		-2.730	-3.542	-11.052***		3.150	5.339	1.095		16.180***	14.882***	-0.693
		(-0.92)	(-1.25)	(-3.15)		(0.55)	(1.04)	(0.16)		(6.24)	(6.30)	(-0.21)
SD(Ret)$_{i,q-1}$		-0.229	-0.135	1.075***		0.454	0.543	1.314*		-1.828***	-1.652***	-0.020
		(-0.80)	(-0.49)	(2.94)		(0.77)	(0.91)	(1.91)		(-7.17)	(-6.87)	(-0.09)
Ret$_{i,q-1}$		-4.588***	-4.970***	-7.802***		-0.080	-1.085	-3.320***		-0.786	-1.264	-5.115***
		(-4.29)	(-4.62)	(-7.50)		(-0.05)	(-0.70)	(-2.68)		(-0.86)	(-1.40)	(-5.63)
Negative ES$_{i,q}$		-0.046***	-0.047***	-0.054***		-0.041***	-0.041***	-0.051***		-0.041***	-0.043***	-0.052***
		(-14.02)	(-15.51)	(-15.35)		(-10.78)	(-11.66)	(-12.44)		(-14.09)	(-15.27)	(-16.78)
Log(Mcap)$_{i,q-1}$		-4.850	-5.324	-69.526***		-4.156	0.560	-90.666***		11.526***	10.606***	-55.786***
		(-1.36)	(-1.56)	(-8.95)		(-0.58)	(0.09)	(-8.78)		(3.54)	(3.45)	(-7.82)
Inst Own$_{i,q}$		0.026**	0.023**	0.062***		0.066***	0.063***	0.138***		0.052***	0.051***	0.089***
		(2.60)	(2.60)	(3.30)		(3.38)	(3.42)	(6.97)		(5.58)	(5.95)	(4.69)
Observations	24711	24711	24711	23021	24782	24782	24685	23243	24712	24712	24712	22921
R^2	0.082	0.100	0.16	0.35	0.040	0.049	0.11	0.31	0.095	0.13	0.18	0.39
Controls:												
Stock FE				Yes				Yes				Yes
Year × Quarter FE	Yes	Yes			Yes	Yes			Yes	Yes		
Industry × Year-Quarter FE			Yes	Yes			Yes	Yes			Yes	Yes
Standard Errors Clustered at:												
Stock level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Quarter level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

Table 4: Effect of Specialization Proxies on Fire Sale Discount

This table reports OLS estimates of regressions of the CAR of fire sale stocks on our proxies for specialized demand between 1990 and 2016. We use three different definitions of fire sale pressure: Flow-To-Volume in columns (1) – (4), Flow-To-Stock in columns (5) – (8), and MFFlow in columns (9) – (12). In columns (1) – (4), our sample consists of the bottom decile of Flow-To-Volume distribution. In columns (5) – (8), we only include stocks that belong to the bottom decile of Flow-To-Stock distribution. In columns (9) – (12), our sample comprises stocks that belong to the bottom decile of MFFlow distribution. We use Wardlaw's (2020) definition of Flow-To-Volume and Flow-To-Stock. We follow Edmans et al. (2012) and compute MFFlow$_{i,q}$ using hypothetical buy and sell orders projected from previously disclosed mutual fund portfolios. Car$_{i,q}$ is the cumulative abnormal return of stock i during fire sales quarter q. The abnormal monthly return is calculated by subtracting the monthly equally-weighted market return from the realized stock return. In Panel A, we investigate the effect of mutual fund activeness on the abnormal returns of fire sale stocks. Active Share$_{i,q}$ is an average active share of non-fire sale funds holding a fire sale stock i at the beginning of the event quarter. In Panel B, we examine the effect of industry specialization on the fire sale discount. Ind Flow$_{i,q}$ is an average net flow of non-fire sale funds holding stocks, which belong to the same industry as fire sale stock i, at the beginning of quarter q. We use the Hoberg and Phillips (2016) text-based measure to define industries. In Panel C, we relate geographically specialized flows to the abnormal returns of fire sale stocks. Geo Flow$_{i,q}$ is a dummy variable that takes a value of one, if a stock belongs to the top quintile of geographical flows in a given quarter. In columns (2) – (4), (6) – (8), and (10) – (12), we add a vector of time-varying stock characteristics to the regression. Fragility$_{i,q}$ is Greenwood and Thesmar's (2011) price fragility measured one quarter prior to the fire sale event. Liq$_{i,q-1}$ is the lagged Amihud's (2002) liquidity measure. SD(Ret)$_{i,q-1}$ is the standard deviation of daily returns estimated in the quarter prior to the fire sale event. Ret$_{i,q-1}$ is the lagged average stock return. Negative ES$_{i,q}$ is an indicator variable that takes value of one if a firm discloses a negative earnings surprise in the fire sale event quarter, otherwise zero. Log(Mcap)$_{i,q-1}$ is the natural logarithm of stock i's market capitalization in the quarter prior to the fire sale event. Inst Own$_{i,q}$ is the percentage of shares outstanding of stock i held by institutional investors at the end of the fire sale event quarter. Inst Own$_{i,q}$ is expressed in decimals. We include year×quarter fixed effects in columns (1), (2), (5), (6), (9), and (10). We add industry×year-quarter fixed effects in columns (3), (4), (7), (8), (11), and (12). We use Fama and French's (1997) 10 industry classification. Finally, in columns (4), (8), and (12) we control for time-invariant stock characteristics. We cluster the standard errors two-way: at the stock and year×quarter. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Flow-to-volume				Flow-to-stock				MFFlow			
Panel A: Active share	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Active Share$_{i,q}$	0.048***	0.041**	0.039**	0.052**	0.097***	0.069***	0.061***	0.135***	0.047**	0.038**	0.039**	0.023
	(2.65)	(2.18)	(2.07)	(2.35)	(3.84)	(2.84)	(2.77)	(3.54)	(2.62)	(2.02)	(2.18)	(1.01)
Observations	24711	24711	24711	23021	24782	24782	24685	23243	24712	24712	24712	22921
R^2	0.082	0.10	0.16	0.36	0.041	0.049	0.11	0.31	0.095	0.13	0.18	0.39
Panel B: Industry Specialization	Flow-to-volume				Flow-to-stock				MFFlow			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Ind Flow$_{i,q}$	0.096*	0.094*	0.064	0.101**	0.406***	0.394***	0.325***	0.337***	0.094**	0.096**	0.079**	0.149***
	(1.86)	(1.78)	(1.38)	(2.47)	(3.39)	(3.47)	(3.11)	(3.08)	(2.40)	(2.41)	(2.13)	(4.15)
Observations	24711	24711	24711	23021	24782	24782	24685	23243	24712	24712	24712	22921
R^2	0.082	0.10	0.16	0.36	0.044	0.052	0.11	0.31	0.095	0.13	0.18	0.39
Panel C: Geographical Specialization	Flow-to-volume				Flow-to-stock				MFFlow			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Geo Flow$_{i,q}$	0.007*	0.011***	0.010***	0.006	0.010*	0.014**	0.011**	0.004	0.005	0.007*	0.007*	0.003
	(1.95)	(2.98)	(2.87)	(1.51)	(1.95)	(2.61)	(2.17)	(0.92)	(1.20)	(1.94)	(1.90)	(0.74)
Observations	24711	24711	24711	23021	24782	24782	24685	23243	24712	24712	24712	22921
R^2	0.082	0.10	0.16	0.35	0.041	0.049	0.11	0.31	0.095	0.13	0.18	0.39
Controls:												
Control Variables		Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes
Stock FE				Yes				Yes				Yes
Year × Quarter FE	Yes	Yes			Yes	Yes			Yes	Yes		
Industry × Year-Quarter FE			Yes	Yes			Yes	Yes			Yes	Yes
Standard Errors Clustered at:												
Stock level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Quarter level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

Table 5: Effect of Active and Passive Specialization Index on Fire Sale Discount

This table reports OLS estimates of regressions of the CAR of fire sale stock on our measures of active and passive specialized demand between 1990 and 2016. We use three different definitions of fire sale pressure: Flow-To-Volume in columns (1) – (4), Flow-To-Stock in columns (5) – (8), and MFFlow in columns (9) – (12). In columns (1) – (4), our sample consists of the bottom decile of Flow-To-Volume distribution. In columns (5) – (8), we only include stocks that belong to the bottom decile of Flow-To-Stock distribution. In columns (9) – (12), our sample comprises stocks that belong to the bottom decile of MFFlow distribution. We use Wardlaw's (2020) definition of Flow-To-Volume and Flow-To-Stock. We follow Edmans et al. (2012) and compute MFFlow$_{i,q}$ using hypothetical buy and sell orders projected from previously disclosed mutual fund portfolios. Car$_{i,q}$ is the cumulative abnormal return of stock i during fire sale quarter q. The abnormal monthly return is calculated by subtracting the monthly equally-weighted market return from the realized stock return. In Panel A, we investigate the effect of the active specialization index on the abnormal returns of fire sale stocks. Spec Index$_{i,q}$ denotes the active specialization index. We compute it by adding z-scored Spec Flow$_{i,q}$, Active Share$_{i,q}$, Ind Flow$_{i,q}$, and the dummy variable Geo Flow$_{i,q}$. To ease the interpretation of the impact of Spec Index$_{i,q}$ on abnormal returns, we also z-score Spec Index$_{i,q}$. In Panel B, we examine the effect of the active specialization index on the abnormal returns of fire sale stocks. Passive Spec Index$_{i,q}$ is the passive specialization index constructed in an analogous way but using only passive mutual funds. In columns (2) – (4), (6) – (8), and (10) – (12), we control for a stock's fire sale pressure measure and other control variables. Fragility$_{i,q}$ is Greenwood and Thesmar's (2011) price fragility measured one quarter prior to the fire sale event. Liq$_{i,q-1}$ is the lagged Amihud's (2002) liquidity measure. SD(Ret)$_{i,q-1}$ is the standard deviation of daily returns estimated in the quarter prior to the fire sale event. Ret$_{i,q-1}$ is the lagged average stock return. Negative ES$_{i,q}$ is an indicator variable that takes a value of one if a firm discloses a negative earnings surprise in the fire sale event quarter, otherwise zero. Log(Mcap)$_{i,q-1}$ is the natural logarithm of stock i's market capitalization in the quarter prior to the fire sale event. Inst Own$_{i,q}$ is the percentage of shares outstanding of stock i held by institutional investors at the end of the fire sale event quarter. Inst Own$_{i,q}$ is expressed in decimals. We include year×quarter fixed effects in columns (1), (2), (5), (6), (9), and (10). We add industry×year-quarter fixed effects in columns (3), (4), (7), (8), (11), and (12). We use Fama and French's (1997) 10 industry classification. Finally, in columns (4), (8), and (12) we control for time-invariant stock characteristics. We cluster the standard errors two-way: at the stock and year×quarter. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Flow-to-volume				Flow-to-stock				MFFlow			
Panel A: Active Specialization												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SPEC INDEX$_{i,q}$	0.013***	0.012***	0.011***	0.013***	0.028***	0.027***	0.024***	0.028***	0.011***	0.010***	0.010***	0.012***
	(4.63)	(4.46)	(4.31)	(4.22)	(6.72)	(6.14)	(5.45)	(5.00)	(5.52)	(5.18)	(5.28)	(5.37)
Observations	24711	24711	24711	23021	24782	24782	24685	23243	24712	24712	24712	22921
R^2	0.084	0.10	0.16	0.36	0.047	0.055	0.11	0.31	0.097	0.13	0.18	0.39
Panel B: Active Specialization with cash holdings and interfund lending controls												
	Flow-to-volume				Flow-to-stock				MFFlow			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SPEC INDEX$_{i,q}$	0.016***	0.015***	0.013***	0.015***	0.028***	0.027***	0.025***	0.025***	0.015***	0.014***	0.012***	0.012***
	(5.14)	(4.50)	(3.90)	(3.10)	(5.70)	(5.23)	(4.46)	(4.28)	(6.79)	(6.30)	(5.66)	(3.83)
Observations	17102	17102	17102	15821	17172	17172	17115	16037	17100	17100	17100	15759
R^2	0.087	0.10	0.16	0.36	0.042	0.051	0.11	0.34	0.10	0.13	0.18	0.39
Panel C: Passive Specialization												
	Flow-to-volume				Flow-to-stock				MFFlow			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PASSIVE SPEC INDEX$_{i,q}$	0.001	0.001	0.001	0.004	0.005**	0.005*	0.005**	0.009***	0.002	0.000	0.000	0.005*
	(0.35)	(0.58)	(0.32)	(1.57)	(2.26)	(1.83)	(2.19)	(3.37)	(0.99)	(0.03)	(0.10)	(1.95)
Observations	24679	24679	24679	22986	24716	24716	24627	23177	24681	24681	24681	22879
R^2	0.082	0.10	0.16	0.36	0.040	0.049	0.11	0.31	0.095	0.13	0.18	0.39
Panel D: Passive Specialization with cash holdings and interfund lending controls												
	Flow-to-volume				Flow-to-stock				MFFlow			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PASSIVE SPEC INDEX$_{i,q}$	-0.001	0.000	-0.001	0.001	0.004*	0.003	0.003	0.007**	-0.001	-0.001	-0.001	0.002
	(-0.51)	(0.14)	(-0.22)	(0.23)	(1.97)	(1.47)	(1.33)	(2.04)	(-0.35)	(-0.53)	(-0.46)	(0.51)
Observations	17099	17099	17099	15816	17170	17170	17115	16037	17098	17098	17098	15756
R^2	0.083	0.099	0.15	0.36	0.036	0.045	0.10	0.34	0.100	0.13	0.18	0.39
Controls:												
Control Variables		Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes
Stock FE				Yes				Yes				Yes
Year × Quarter FE	Yes	Yes			Yes	Yes			Yes	Yes		
Industry × Year-Quarter FE			Yes	Yes			Yes	Yes				Yes
Standard Errors Clustered at:												
Stock level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Quarter level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

Table 6: Effect of Active and Passive Specialization Index on Return Reversal

This table reports OLS regression estimates of the length of price reversal of fire sale stocks on active and passive specialization index between 1990 and 2016. We measure the length of the reversal period as the number of months it takes for a stock to recover from fire sale price discount since the last fire sale event quarter (i.e., when CAR is greater or equal to zero). We measure the CARs up to 27 months after the end of fire sale quarter. In Panels A and C, we assign a value of 28 months for stocks whose CAR remain negative for at least 27 months after the fire sale event quarter end. In Panels B and D, we limit our sample to stocks that experience reversal within 27 months. We use three different definitions of fire sale pressure: Flow-To-Volume in columns (1) – (4), Flow-To-Stock in columns (5) – (8), and MFFlow in columns (9) – (12). In columns (1) – (4), our sample consists of the bottom decile of Flow-To-Volume distribution. In columns (5) – (8), we only include stocks that belong to the bottom decile of Flow-To-Stock distribution. In columns (9) – (12), our sample comprises stocks that belong to the bottom decile of MFFlow distribution. We use Wardlaw's (2020) definition of Flow-To-Volume and Flow-To-Stock. We follow Edmans et al. (2012) and compute MFFlow$_{i,q}$ using hypothetical buy and sell orders projected from previously disclosed mutual fund portfolios. In Panels A and B, we investigate the effect of the active specialization index on the fire sale reversal. Spec Index$_{i,q}$ is a specialization index constructed using only active mutual funds. We compute it by adding z-scored Spec Flow$_{i,q}$, Active Share$_{i,q}$, Ind Flow$_{i,q}$, and the dummy variable Geo Flow$_{i,q}$. To ease the interpretation of the impact of Spec Index$_{i,q}$ on abnormal returns, we also z-score Spec Index$_{i,q}$. In Panels C and D, we examine the effect of the passive specialization index on the fire sale reversal. Passive Spec Index$_{i,q}$ is constructed in the same way as Spec Index but using only passive mutual funds. In columns (2) – (4), (6) – (8), and (10) – (12), we control for a stock's fire sale pressure measure and other control variables. Fragility$_{i,q}$ is Greenwood and Thesmar's (2011) price fragility measured one quarter prior to the fire sale event. Liq$_{i,q-1}$ is a lagged Amihud's (2002) liquidity measure. SD(Ret)$_{i,q-1}$ is a standard deviation of daily returns estimated in a quarter prior to the fire sale event. Ret$_{i,q-1}$ is a lagged average stock return. Negative ES$_{i,q}$ is an indicator variable that takes a value of one if a firm discloses a negative earning surprise in the fire sale event quarter, otherwise zero. Log(Mcap)$_{i,q-1}$ is a natural logarithm of stock i's market capitalization in a quarter prior to the fire sale event. Inst Own$_{i,q}$ is a percentage of shares outstanding of stock i held by institutional investors at the end of the fire sale event quarter. Inst Own$_{i,q}$ is expressed in decimals. We include year×quarter fixed effects in columns (1), (2), (5), (6), (9), and (10). We add industry×year-quarter fixed effects in columns (3), (4), (7), (8), (11), and (12). We use Fama and French's (1997) 10 industry classification. Finally, in columns (4), (8), and (12) we control for time-invariant stock characteristics. We cluster the standard errors two-way: at the stock and year×quarter. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Active Specialization & Truncated Reversal

	Flow-to-volume				Flow-to-stock				MFFlow			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SPEC INDEX$_{i,q}$	-0.504***	-0.481***	-0.478***	-0.446***	-0.624***	-0.634***	-0.552***	-0.461***	-0.443**	-0.420**	-0.436***	-0.410**
	(-3.18)	(-3.21)	(-3.43)	(-2.69)	(-3.11)	(-3.26)	(-3.30)	(-2.80)	(-2.56)	(-2.55)	(-2.75)	(-2.42)
Observations	24711	24711	24711	23021	24685	24685	24685	23243	24712	24712	24712	22921
R^2	0.073	0.083	0.14	0.39	0.043	0.049	0.11	0.36	0.072	0.083	0.14	0.40

Panel B: Active Specialization & Only Reversal Stocks

	Flow-to-volume				Flow-to-stock				MFFlow			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SPEC INDEX$_{i,q}$	-0.188*	-0.188*	-0.186**	-0.159**	-0.193*	-0.162*	-0.113	-0.126	-0.134	-0.147*	-0.153*	-0.131*
	(-1.98)	(-1.97)	(-2.18)	(-2.27)	(-1.91)	(-1.67)	(-1.31)	(-1.50)	(-1.63)	(-1.74)	(-1.96)	(-1.79)
Observations	19292	19292	19292	17623	19695	19695	19695	18259	18565	18565	18565	16873
R^2	0.059	0.064	0.12	0.31	0.034	0.038	0.087	0.27	0.059	0.064	0.12	0.32

Panel C: Passive Specialization & Truncated Reversal

	Flow-to-volume				Flow-to-stock				MFFlow			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PASSIVE SPEC INDEX$_{i,q}$	-0.068	-0.098	-0.050	-0.179	-0.021	-0.106	-0.087	-0.320**	-0.094	-0.069	-0.034	-0.180
	(-0.75)	(-1.11)	(-0.53)	(-1.59)	(-0.19)	(-0.91)	(-0.70)	(-2.58)	(-0.92)	(-0.70)	(-0.30)	(-1.52)
Observations	24679	24679	24679	22986	24627	24627	24627	23177	24681	24681	24681	22879
R^2	0.072	0.082	0.13	0.39	0.041	0.047	0.10	0.36	0.071	0.082	0.13	0.40

Panel D: Passive Specialization & Only Reversal Stocks

	Flow-to-volume				Flow-to-stock				MFFlow			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PASSIVE SPEC INDEX$_{i,q}$	0.021	0.007	0.057	-0.069	-0.011	-0.001	0.009	-0.075	-0.003	0.007	0.058	-0.086
	(0.47)	(0.16)	(1.20)	(-0.81)	(-0.23)	(-0.02)	(0.21)	(-0.93)	(-0.06)	(0.14)	(1.05)	(-1.06)
Observations	19265	19265	19265	17594	19652	19652	19652	18207	18538	18538	18538	16840
R^2	0.059	0.064	0.12	0.31	0.034	0.038	0.087	0.27	0.059	0.064	0.12	0.32
Controls:												
Control Variables		Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes
Stock FE				Yes				Yes				Yes
Year × Quarter FE	Yes	Yes			Yes	Yes			Yes	Yes		
Industry × Year-Quarter FE			Yes	Yes			Yes	Yes			Yes	Yes
Standard Errors Clustered at:												
Stock level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Quarter level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

Table 7: Effect of Active Specialization Index on Non-Specialized Investor Participation

This table reports OLS estimates of regressions of the non-specialized investor participation in a fire sale stock, Non-Spec Participation, on our measures of active specialized demand between 1990 and 2016. We define non-specialized investors as non-fire sale mutual funds that do not hold a fire sale stock or any of the ten closest industry peers of a fire sale stock at the beginning of the fire sale event quarter and are located at least 100km away from the headquarters of fire sale stock. We compute the non-specialized investor participation in a fire sale stock by counting the number of non-specialized mutual funds that bought the shares of fire sale stock during the fire sale event quarter. We use three different definitions of fire sale pressure: Flow-To-Volume in columns (1) – (4), Flow-To-Stock in columns (5) – (8), and MFFlow in columns (9) – (12). In columns (1) – (4), our sample consists of the bottom decile of Flow-To-Volume distribution. In columns (5) – (8), we only include stocks that belong to the bottom decile of Flow-To-Stock distribution. In columns (9) – (12), our sample comprises stocks that belong to the bottom decile of MFFlow distribution. We use Wardlaw's (2020) definition of Flow-To-Volume and Flow-To-Stock. We follow Edmans et al. (2012) and compute MFFlow$_{i,q}$ using hypothetical buy and sell orders projected from previously disclosed mutual fund portfolios. Spec Index$_{i,q}$ denotes the active specialization index. We compute it by adding z-scored Spec Flow$_{i,q}$, Active Share$_{i,q}$, Ind Flow$_{i,q}$, and the dummy variable Geo Flow$_{i,q}$. To ease the interpretation of the impact of Spec Index$_{i,q}$ on abnormal returns, we also z-score Spec Index$_{i,q}$. In columns (2) – (4), (6) – (8), and (10) – (12), we control for a stock's fire sale pressure measure and other control variables. Fragility$_{i,q}$ is Greenwood and Thesmar's (2011) price fragility measured one quarter prior to the fire sale event. Liq$_{i,q-1}$ is the lagged Amihud's (2002) liquidity measure. SD(Ret)$_{i,q-1}$ is the standard deviation of daily returns estimated in the quarter prior to the fire sale event. Ret$_{i,q-1}$ is the lagged average stock return. Negative ES$_{i,q}$ is an indicator variable that takes a value of one if a firm discloses a negative earnings surprise in the fire sale event quarter, otherwise zero. Log(Mcap)$_{i,q-1}$ is the natural logarithm of stock i's market capitalization in the quarter prior to the fire sale event. Inst Own$_{i,q}$ is the percentage of shares outstanding of stock i held by institutional investors at the end of the fire sale event quarter. Inst Own$_{i,q}$ is expressed in decimals. We include year×quarter fixed effects in columns (1), (2), (5), (6), (9), and (10). We add industry×year-quarter fixed effects in columns (3), (4), (7), (8), (11), and (12). We use Fama and French's (1997) 10 industry classification. Finally, in columns (4), (8), and (12) we control for time-invariant stock characteristics. We cluster the standard errors two-way: at the stock and year×quarter. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Flow-to-volume				Flow-to-stock				Price Pressure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SPEC INDEX$_{i,q}$	-0.016**	-0.020***	-0.022***	-0.012***	-0.099***	-0.103***	-0.111***	-0.091***	-0.019**	-0.022***	-0.024***	-0.018***
	(-2.00)	(-3.37)	(-3.23)	(-2.63)	(-3.36)	(-3.72)	(-3.79)	(-3.97)	(-2.18)	(-3.45)	(-3.36)	(-3.35)
FLOW-TO-VOLUME$_{i,q}$	4.727***	-0.017	-0.142	-0.619								
	(6.16)	(-0.03)	(-0.29)	(-1.23)								
FLOW-TO-STOCK$_{i,q}$					11.640***	5.818**	5.705**	0.763				
					(4.39)	(2.50)	(2.37)	(0.33)				
MFFLOW$_{i,q}$									4.320***	0.160	-0.024	-0.082
									(5.98)	(0.35)	(-0.06)	(-0.16)
Observations	24711	24711	24711	23021	24782	24782	24685	23243	24712	24712	24712	22921
R^2	0.014	0.025	0.061	0.40	0.0094	0.016	0.046	0.36	0.012	0.023	0.055	0.37
Controls:												
Control Variables		Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes
Stock FE				Yes				Yes				Yes
Year × Month FE	Yes	Yes			Yes	Yes			Yes	Yes		
Industry × Year-Month FE			Yes	Yes			Yes	Yes			Yes	Yes
Standard Errors Clustered at:												
Stock level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Month level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Effect of Active and Passive Specialization Index on Fire Sales Discount – the 2003 late trading scandal

This table reports OLS estimates of regressions of CAR of fire sale stocks on the active and passive specialization index for the two-year period following the news regarding mutual funds involvement in late trading activities – from September 2003 to August 2005. We only include stocks that were hold by scandal-implicated funds with outflows greater than -5%. We use three different definitions of fire sale pressure: Flow-To-Volume in columns (1) – (4), Flow-To-Stock in columns (5) – (8), and MFFlow in columns (9) – (12). In columns (1) – (4), our sample consists of the bottom decile of Flow-To-Volume distribution. In columns (5) – (8), we only include stocks that belong to the bottom decile of Flow-To-Stock distribution. In columns (9) – (12), our sample comprises stocks that belong to the bottom decile of MFFlow distribution. We use Wardlaw's (2020) definition of Flow-To-Volume and Flow-To-Stock. We follow Edmans et al. (2012) and compute MFFlow$_{i,q}$ using hypothetical buy and sell orders projected from previously disclosed mutual fund portfolios. Car$_{i,q}$ is the cumulative abnormal return of stock i during fire sale quarter q. The abnormal monthly return is calculated by subtracting the monthly equally-weighted market return from the realized stock return. In Panel A, we investigate the effect of the active specialization index, Spec Index$_{i,q}$, on the abnormal returns of fire sale stocks. Spec Index$_{i,q}$ is constructed using only active mutual funds. We compute it by adding z-scored Spec Flow$_{i,q}$, Active Share$_{i,q}$, Ind Flow$_{i,q}$, and the dummy variable Geo Flow$_{i,q}$. To ease the interpretation of the impact of Spec Index$_{i,q}$ on abnormal returns, we also z-score Spec Index$_{i,q}$. In Panel B, we examine the effect of the passive specialization index on the abnormal returns of fire sale stocks. Passive Spec Index$_{i,q}$ is constructed in the same way as Spec Index but using only passive mutual funds. In columns (2) – (4), (6) – (8), and (10) – (12), we control for a stock's fire sale pressure measure and other control variables. Fragility$_{i,q}$ is Greenwood and Thesmar's (2011) price fragility measured one quarter prior to a fire sale event. Liq$_{i,q-1}$ is the lagged Amihud's (2002) liquidity measure. SD(Ret)$_{i,q-1}$ is the standard deviation of daily returns estimated in the quarter prior to the fire sale event. Ret$_{i,q-1}$ is the lagged average stock return. Negative ES$_{i,q}$ is an indicator variable that takes a value of one if a firm discloses a negative earning surprise in the fire sale event quarter, otherwise zero. Log(Mcap)$_{i,q-1}$ is the natural logarithm of stock i's market capitalization in the quarter prior to the fire sale event. Inst Own$_{i,q}$ is the percentage of shares outstanding of stock i held by institutional investors at the end of the fire sale event quarter. Inst Own$_{i,q}$ is expressed in decimals. We include year×quarter fixed effects in columns (1), (2), (5), (6), (9), and (10). We add industry×year-quarter fixed effects in columns (3), (4), (7), (8), (11), and (12). We use Fama and French's (1997) 10 industry classification. Finally, in columns (4), (8), and (12) we control for time-invariant stock characteristics. We cluster the standard errors at the stock level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Flow-to-volume				Flow-to-stock				MFFlow			
Panel A: Active Specialization												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SPEC INDEX$_{i,q}$	0.010***	0.014***	0.012**	0.014**	0.016***	0.020***	0.014**	0.013*	0.011***	0.015***	0.011**	0.014**
	(2.69)	(3.01)	(2.56)	(2.12)	(3.10)	(3.36)	(2.22)	(1.84)	(2.88)	(3.24)	(2.49)	(2.36)
Observations	2135	2135	2135	1616	2136	2136	2134	1685	2135	2135	2133	1604
R^2	0.023	0.055	0.12	0.57	0.024	0.061	0.14	0.57	0.032	0.066	0.15	0.57
Panel B: Passive Specialization												
	Flow-to-volume				Flow-to-stock				MFFlow			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
PASSIVE SPEC INDEX$_{i,q}$	0.004	0.007	0.007	-0.005	0.002	0.005	0.006	-0.016*	0.002	0.006	0.005	-0.006
	(0.91)	(1.46)	(1.53)	(-0.60)	(0.43)	(0.92)	(0.91)	(-1.78)	(0.35)	(1.33)	(1.10)	(-0.84)
Observations	2135	2135	2135	1616	2136	2136	2134	1685	2135	2135	2133	1604
R^2	0.019	0.048	0.11	0.57	0.016	0.051	0.14	0.57	0.027	0.058	0.15	0.57
Controls:												
Control Variables		Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes
Stock FE				Yes				Yes				Yes
Year× Quarter FE	Yes	Yes			Yes	Yes			Yes	Yes		
Industry × Year-Quarter FE			Yes	Yes			Yes	Yes		Yes	Yes	Yes
Standard Errors Clustered at:												
Stock level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

Table 9: Russell 2000 Index Exclusions and Russell 1000 Index Inclusions

This table reports OLS estimates of regressions of abnormal returns of stocks excluded from Russell 2000 Index and Included in Russell 1000 Index on the active specialization index over 11-year period from 2003 to 2013. We measure stock's abnormal returns in June each year in three different ways: equal-weighted abnormal return, AbnRet$^{\text{EW}}$, in columns (1) – (4), Fama and French (1993) three-factor abnormal return, AbnRet$^{\text{3F}}$, in columns (5) – (8), and Carhart (1997) four-factor abnormal return, AbnRet$^{\text{4F}}$, in columns (9) – (12). Spec Index$_{i,q}$ is constructed using only active mutual funds with all types of flows (including funds with outflows greater than 5% of their TNAs). We compute Spec Index$_{i,q}$ by adding z-scored Spec Flow$_{i,q}$, Active Share$_{i,q}$, Ind Flow$_{i,q}$, and the dummy variable Geo Flow$_{i,q}$. To ease the interpretation of the impact of Spec Index$_{i,q}$ on abnormal returns, we also z-score Spec Index$_{i,q}$. In columns (2) – (4), (6) – (8), and (10) – (12), we control for a stock's fire sale pressure measure and other control variables. Fragility$_{i,q}$ is Greenwood and Thesmar's (2011) price fragility measured one quarter prior to a fire sale event. Liq$_{i,q-1}$ is the lagged Amihud's (2002) liquidity measure. SD(Ret)$_{i,q-1}$ is the standard deviation of daily returns estimated in the quarter prior to the fire sale event. Ret$_{i,q-1}$ is the lagged average stock return. Negative ES$_{i,q}$ is an indicator variable that takes a value of one if a firm discloses a negative earning surprise in the fire sale event quarter, otherwise zero. Log(Mcap)$_{i,q-1}$ is the natural logarithm of stock i's market capitalization in the quarter prior to the fire sale event. Inst Own$_{i,q}$ is the percentage of shares outstanding of stock i held by institutional investors at the end of the fire sale event quarter. Inst Own$_{i,q}$ is expressed in decimals. We include year×quarter fixed effects in columns (1), (2), (5), (6), (9), and (10). We add industry×year-quarter fixed effects in columns (3), (4), (7), (8), (11), and (12). We use Fama and French's (1997) 10 industry classification. We cluster the standard errors at the stock level in columns (1) – (3), (5) – (7), and (9) – (11) and at the stock and the industry×year-month level in columns (4), (8), and (12). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	$\textsc{AbnRet}^{\text{EW}}$				$\textsc{AbnRet}^{\text{3F}}$				$\textsc{AbnRet}^{\text{4F}}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\textsc{Spec Index}_{i,q}$	0.024***	0.025***	0.021**	0.021**	0.016*	0.017*	0.016*	0.016*	0.015*	0.016*	0.017*	0.017*
	(2.73)	(2.77)	(2.38)	(2.38)	(1.83)	(1.84)	(1.85)	(1.85)	(1.72)	(1.76)	(1.94)	(1.94)
Observations	317	317	317	317	317	317	317	317	317	317	317	317
R^2	0.23	0.23	0.49	0.49	0.16	0.16	0.44	0.44	0.090	0.097	0.35	0.35
Controls:												
Control Variables		Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes	Yes
Year × Month FE	Yes	Yes			Yes	Yes			Yes	Yes		
Industry × Year-Month FE			Yes	Yes			Yes	Yes			Yes	Yes
Standard Errors Clustered at:												
Stock level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year-Month level				Yes				Yes				Yes

A A comparative statics model of fire sale discounts

We consider a one-period economy with two funds i and j. Both funds maximize their expected CRRA utility over time 1 asset under management (AUM) W_1 by choosing a time 0 portfolio consisting of a claim to a risky payoff X and a risk-free asset. The risk-free asset pays one unit of the consumption good at 1. Its price is normalized to 1 and hence its return is normalized to 0. We use the Campbell and Viceira (2002) approximation of portfolio returns R_p under the assumption of log-normality to express the expected time 1 utility optimization problem $\max_q E_0[U(W_1)]$ as

$$\max_q (1-\gamma)E[\ln W_1] + 0.5(1-\gamma)^2 Var(\ln W_1) \tag{A.1}$$

$$\approx qE[\ln X/p] + 0.5q(1-q)\sigma_x^2 + 0.5(1-\gamma)q^2\sigma_x^2 \tag{A.2}$$

$$\approx q(\ln(\mu_x) - \ln(p)) + 0.5q(1-q)\sigma_x^2 + 0.5(1-\gamma)q^2\sigma_x^2 \tag{A.3}$$

where W is funds' asset under management, q is the share invested in the risky asset, μ_x is the asset's random mean payoff, p its time 0 market price, σ_x is its log volatility and γ is the risk aversion parameter. The first approximation is based on Campbell and Viceira's (2002) approximation, the second one follows from a first-order Taylor-approximation of $\ln X$ around $X = \mu_x$: $\ln X \approx \ln \mu_x + \frac{1}{\mu_x}(x - \mu_x)$.

The resulting optimal portfolio share invested in the risky asset is given (approximately) by:

$$q = \frac{\ln \mu_x - \ln p + 0.5\sigma_x^2}{\gamma\sigma_x^2} \tag{A.4}$$

Heterogeneity between investors is crucial in our paper. We thus allow for differences in beliefs about the distribution of asset payoffs that are specific to fund i or j with $\mu_{x,i}, \mu_{x,j}, \sigma_{x,i}$ and $\sigma_{x,j}$ as well as (risk) preferences γ_i and γ_j. Fund i's *specialization* with respect to the risky asset with payoff X may be reflected by $\mu_{x,i} > \mu_{x,j}$ (fund i is more optimistic about the asset's payoffs), $\sigma_{x,i} < \sigma_{x,j}$ (i is more certain in a Bayesian sense than j about the payoff X, or, alternatively simply thinks it is safer) or by $\gamma_i < \gamma_j$ (investor i is less risk averse than j with respect to the risk of X). Note that while we specify the differences in beliefs exogenously in our one-period model (i and j "agree to disagree"), this does not preclude agents' beliefs from having arisen through Bayesian updating based on different information sets. Alternatively, we may interpret payoffs X to differ between the agents if one agent gets a 'warm glow' effect from payoffs due to, e.g. a preference for environmentally responsible firms. Moreover, all results go through if we restrict beliefs to be identical and simply allow for differences in preferences γ_i, γ_j.

Markets must clear in equilibrium, i.e., the dollar value of the supply of the asset with payoff X in the market (given by the product of the number of shares $\bar{S}$ and its price p) must equal the dollar amount of the asset demanded by funds i and j:

$$p \cdot \bar{S} = q_i W_i + q_j W_j. \tag{A.5}$$

Plugging (A.4) into (A.5) yields:

$$p \cdot \bar{S} = \frac{M_{x,i}}{\gamma_i \sigma_{x,i}} W_i + \frac{M_{x,j}}{\gamma_j \sigma_{x,j}} W_j - \ln(p) \left(\frac{W_i}{\gamma_i \sigma_{x,i}} + \frac{W_j}{\gamma_j \sigma_{x,j}} \right), \tag{A.6}$$

with $M_{x,k} = \ln \mu_{x,k} + 0.5\sigma_{x,k}^2$. This expression allows us to study the impact of shifts in W_i and W_j in comparative statics. Equation (A.6) does not have a closed-form solution (see Figure A.1 for a graphical representation of the numerical solution) but it becomes obvious that any shift of assets under management from the specialized fund i to the less specialized fund j, $\Delta_{i \to j} W = \Delta W_i = -\Delta W_j < 0$ will negatively affect the price of the asset.

The fire sales of mutual funds studied in this paper represent examples of relative shifts in liquidity allocation across funds. To obtain an intuitive, closed-form expression for the equilibrium price p, we approximate $\ln p$ around the price of the risk-free asset, $\ln p \approx \ln 1 + \frac{1}{1}(p-1) = p - 1$:

$$p \cdot \bar{S} \approx M_{x,i} A_i + M_{x,j} A_j - (p-1)(A_i + A_j) \tag{A.7}$$

$$\Leftrightarrow p \approx \frac{(M_{x,i}+1)A_i + (M_{x,j}+1)A_j}{A_i + A_j + \bar{S}}, \tag{A.8}$$

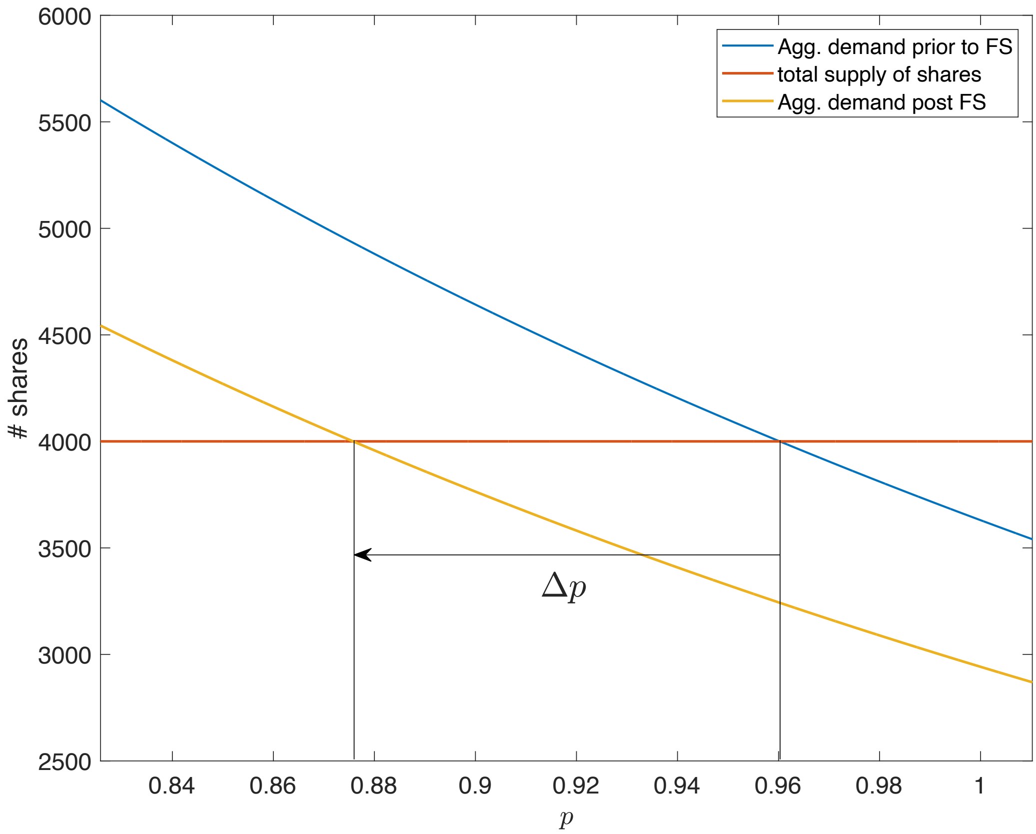
where $A_k = \frac{W_k}{\gamma_k \sigma_{x,k}}$. The effect of a disruption in AUM, $\Delta_{i \to j} W$ on the asset price is given by:

$$\frac{\partial p}{\partial \Delta_{i \to j} W} = \left(\frac{\partial A_i}{\partial W_i} - \frac{\partial A_j}{\partial W_j} \right) \left[\frac{M_{x,i}+1}{A_i + A_j + \bar{S}} - \frac{(M_{x,i}+1)A_i}{(A_i + A_j + \bar{S})^2} - \frac{(M_{x,j}+1)A_j}{(A_i + A_j + \bar{S})^2} \right] \tag{A.9}$$

which is always positive if i is more specialized with respect to the asset with payoff X than j. First, the square bracket term is positive. This can be seen from dividing the square bracket term by $M_{x,i} + 1$ (which exceeds $M_{x,j} + 1$), multiplying with $(A_i + A_j + \bar{S})^2$ and noting that $A_i + A_j + \bar{S} > 2 \cdot \max(A_i, A_j)$ for positive supply $\bar{S}$. Secondly, because $\frac{1}{\gamma_i \sigma_{x,i}} > \frac{1}{\gamma_j \sigma_{x,j}}$ if i is more specialized, the first term in brackets is positive as well. Hence, any shift in asset under management from i to j with $\Delta W_i = -\Delta W_j < 0$ will negatively affect the price p.

Thus, a shift of assets under management from i to j negatively affects the price of assets that i is specialized in. This holds for differences in specialization modeled by both, preferences γ and beliefs μ and σ. Figure A.1 illustrates this. The aggregate demand curve shifts left in case of a disruption of W across funds with differing specialization, leading to a decrease in prices marked by Δp.

Figure A.1: Numerical model solution
This figure shows the model solution for the comparative statics of a shift in AUM of 20% from specialized fund i to non-specialized fund j. Model parameters: $\ln mu_{x,i} = 0.7$, $\ln mu_{x,j} = 0.4$, $\sigma_{x,i} = 0.1, \sigma_{x,j} = 0.15 \gamma_i = 2, \gamma_j = 10, W_{i,0} = W_{0,j} = 100, \bar{S} = 4000$. The blue curve shows the aggregate demand for the asset as a function of the price before the fire sale event in which 20% of the AUM of fund i is reallocated to fund j, the yellow curve shows demand after the reallocation (the fire sale event). The red horizontal line indicates the (fixed) supply of the asset, $\bar{S}$. Δp denotes the price impact of of the disrupted allocation.



B List of Variable Names

Variable Name	Definition
ACTIVE SHARE$_{i,q}$	The measure of the degree of active management of funds holding a fire sale stock i in quarter q. We compute ACTIVE SHARE$_{i,q}$ in the following way: ACTIVE SHARE$_{i,q} = \frac{1}{F}\sum_{f=1}^{F}(\text{ACTIVE SHARE}^{i}_{f,q} \mid \text{FLOW}^{i}_{f,q} > -5\% \cap f \text{ is active})$, where ACTIVE SHARE$^{i}_{f,q}$ is Cremers and Petajisto's (2009) active share measure of fund f, which is holding stock i at the beginning of quarter q. We only include active non-fire sale mutual funds – i.e., with net flows above -5% over quarter q.
CAAR$_{i,q}$	Stock i's cumulative abnormal return over period q. We compute CAR in excess of the CRSP equally-weighted index as in Edmans et al. (2012).
C2$_{i,q}$	Llorente et al.'s (2002) information asymmetry measure computed in the following way: $r_{i,d+1} = \text{C0}_{i,q} + \text{C1}_{i,q} \cdot r_{i,d} + \text{C2}_{i,q} \cdot r_{i,d}\text{V}_{i,d} + \varepsilon_{i,d+1}$, where $r_{i,d}$ is the return of stock i on day d in quarter q. V$_{i,d}$ denotes the natural logarithm of detrended daily turnover.
FLOW$_{f,q}$	Fund f's percentage net flows over quarter q and defined as: $\text{FLOW}_{f,q} = \frac{\text{TNA}_{f,q} - \text{TNA}_{f,q-1}\cdot(1+r_{f,q})}{\text{TNA}_{f,q-1}}$, where TNA$_{f,q}$ is TNA of fund f in quarter q and $r_{f,q}$ is fund f's return over quarter q.

$\textsc{Flow-To-Stock}_{i,q}$	Wardlaw's (2020) fire sale pressure measure defined as: $\textsc{Flow-To-Stock}_{i,q} = \sum_{f=1}^{M} \left(\frac{\text{DF}\textsc{low}_{f,q}}{\text{TNA}_{f,q-1}} \cdot \frac{\textsc{Shares}_{f,i,q-1}}{\textsc{Shrout}_{i,q-1}} \right)$, conditional on the outflow of fund f being greater than 5% of total assets. $\text{DF}\textsc{low}_{f,q}$ is the net dollar flow to mutual fund f in quarter q. $\text{TNA}_{f,q-1}$ is fund's total net assets in quarter $q-1$. $\textsc{Shares}_{f,i,q-1}$ is the number of shares held by each fund at the end of the last quarter. $\textsc{Shrout}_{i,q-1}$ is the number of shares outstanding of stock i in quarter $q-1$. M is the number of funds experiencing extreme outflows in a given quarter.
$\textsc{Flow-To-Volume}_{i,q}$	Wardlaw's (2020) fire sale pressure measure defined as: $\textsc{Flow-To-Volume}_{i,q} = \sum_{f=1}^{M} \left(\frac{\text{DF}\textsc{low}_{f,q}}{\text{TNA}_{f,q-1}} \cdot \frac{\textsc{Shares}_{f,i,q-1}}{\textsc{Vol}_{i,q}} \right)$, conditional on the outflow of fund f being greater than 5% of total assets. $\text{DF}\textsc{low}_{f,q}$ is the net dollar flow to mutual fund f in quarter q. $\text{TNA}_{f,q-1}$ is fund's total net assets in quarter $q-1$. $\textsc{Shares}_{f,i,q-1}$ is the number of shares held by each fund at the end of the last quarter. $\textsc{Vol}_{i,q}$ is the share volume of stock i in quarter q. M is the number of funds experiencing extreme outflows in a given quarter.
$\textsc{Fragility}_{i,q}$	Greenwood and Thesmar's (2011) price fragility one quarter prior to the fire sale event and defined as: $\textsc{Fragility}_{i,q} = \left(\frac{1}{\theta}\right)^2 W'_{i,q-1}\Omega_{q-1}W_{i,q-1}$, where θ is stock i's market capitalization in quarter $q-1$, $W_{i,q-1}$ is the vector of weights of each mutual fund in stock i, Ω_{q-1} is the conditional variance-covariance matrix of dollar flows between $q-1$ and q.

$\textsc{Geo}_{i,q}$	The average net flows of funds located in close proximity l (within a 100km radius) to the headquarters of fire sale stocks and defined as: $\textsc{Geo}_{i,q} = \frac{1}{F}\sum_{f=1}^{F}(\textsc{Flow}_{f,q}^{i\in l} \mid \textsc{Flow}_{f,q}^{i\in l} > -5\% \cap f \text{ is active})$, where $\textsc{Flow}_{f,q}^{i\in l}$ is a percentage net flow of fund f, which is located within 100km radius from headquarters of stock i, over the fire sale event quarter q. We only include active non-fire sales mutual funds.
$\textsc{Geo Flow}_{i,q}$	The geographical specialization dummy variable that takes a value of one if stock i's $\textsc{Geo}_{i,q}$ belongs to the top 20th percentile of $\textsc{Geo}_{i,q}$ distribution in a given quarter, and otherwise zero.
$\textsc{High}$	High active specialization indicator variable that takes a value of one if a stock belongs to the top quintile of $\textsc{Spec Index}_{i,q}$ distribution, otherwise zero.
$\textsc{Ind Flow}_{i,q}$	The industry specialization measure defined as: $\textsc{Ind Flow}_{i,q} = \sum_{f=1}^{F}\sum_{j=1,\, j\in s_i}^{20}\eta_{i,j}(\textsc{Flow}_{f,q}^{j} \mid \textsc{Flow}_{f,q}^{j} > -5\% \cap f \text{ is active})$, where $\textsc{Flow}_{f,q}^{j}$ is a percentage net flow of fund f, which was holding stock j that belongs to the same industry s_i as stock i, over the fire sale event quarter q. We use the time-varying industry classifications proposed by Hoberg and Phillips (2016) to define the industry of stock i and its peers. We employ Hoberg and Phillips's (2016) pairwise similarity score between firms i and j, $\eta_{i,j}$, as weights for fund flows.
$\textsc{Inst Own}_{i,q}$	Percentage of shares outstanding of stock i held by institutional investors at the end of quarter q.

$\text{LIQ}_{i,q}$	Amihud's (2002) liquidity measure defined as: $\text{LIQ}_{i,q} = \frac{1}{Q}\sum_{d=1}^{Q}\frac{\lvert\text{RET}_{i,d}\rvert}{\text{DVOL}_{i,d}}$, where $\text{RET}_{i,d}$ is a return of stock i on day d and $\text{DVOL}_{i,q}$ is stock i's dollar volume on day d. Q denotes the number of days in quarter q.
$\text{LOG(MCAP)}_{i,q}$	Natural logarithm of stock i's market capitalization in quarter q.
LOW	Low active specialization dummy variable that takes a value of one if a stock belongs to the bottom quintile of $\text{SPEC INDEX}_{i,q}$ distribution, otherwise zero.
MEDIUM HIGH	Medium-high active specialization indicator variable that takes a value of one if a stock belongs to the second highest quintile $\text{SPEC INDEX}_{i,q}$ distribution, otherwise zero.
MEDIUM LOW	Medium-low active specialization indicator variable that takes a value of one if a stock belongs to the second lowest quintile $\text{SPEC INDEX}_{i,q}$ distribution, otherwise zero.
$\text{MFFLOW}_{i,q}$	Edmans et al.'s (2012) fire sale pressure measure defined as: $\text{MFFLOW}_{i,q} = \sum_{f=1}^{M}\left(\frac{\text{FLOW}_{f,q}\cdot \text{P}_{i,q-1}\cdot \text{SHARES}_{f,i,q-1}}{\text{DVOL}_{i,q}}\right)$, conditional on the outflow of fund f being greater than 5% of total assets. $\text{FLOW}_{f,q}$ is the percentage net flow to mutual fund f in quarter q. $\text{DVOL}_{i,q}$ is stock i's dollar volume over quarter q. $\text{P}_{i,q-1}$ is the stock price in quarter $q-1$. M is the number of funds experiencing extreme outflows in a given quarter.
$\text{NEGATIVE ES}_{i,q}$	Indicator variable that takes a value of one if a firm discloses a negative earning surprise in the fire sale event quarter, otherwise zero.

NON-SPEC PARTICIPATION$_{i,q}$ The number of non-specialized investors who purchased stock i during fire sale event quarter q. A non-specialized investor is a fund that (i) does not hold the fire sale stock at the beginning of fire sale event quarter, (ii) does not hold any of the (twenty) closest peers of stock i at the beginning of fire sale event quarter q, and (iii) its distance to stock i's headquarters is greater than 100km.

ONLY REVERSAL$_{i,q}$ Reversal length measured in the number of months since the end of the fire sale event quarter and computed only for stocks, whose prices recover within 27 months since the end of fire sale event quarter.

PASSIVE SPEC FLOW$_{i,q}$ Stock i's passive specialized flows over fire sale event quarter q defined as:

$\text{PASSIVE SPEC FLOW}_{i,q} = \frac{1}{F}\sum_{f=1}^{P}(\text{FLOW}^i_{f,q}|\text{FLOW}^i_{f,q} > -5\% \cap f \text{ is passive})$,

where $\text{FLOW}^i_{f,q}$ is percentage net flow of fund f, which held stock i at the beginning of quarter q, over the fire sale event quarter q. We only include passive non-fire sale mutual funds – i.e., with net flows above -5% over quarter q. F is the number of passive funds that were holding stock i at the beginning of quarter q.

$\textsc{Passive Spec Index}_{i,q}$	The passive specialization index defined as: $\textsc{Passive Spec Index}_{i,q} = z(z\textsc{Passive Spec Flow}_{i,q} + z\textsc{Passive Active Share}_{i,q} + z\textsc{Passive Ind Flow}_{i,q} + \textsc{Passive Geo Flow}_{i,q})$, where $\textsc{Passive Spec Flow}$ is passive specialized flows, $\textsc{Passive Active Share}$ is active share of passive funds, $\textsc{Passive Ind Flow}$ denotes industry-specialized passive flows, and $\textsc{Passive Geo Flow}_{i,q}$ represents geographically specialized passive flows. To put each measure on equal footing and combine them, we standardize all variables (except from the indicator variable $\textsc{Passive Geo Flow}_{i,q}$) and obtain z-scores.
$r_{f,q}$	Fund f's return over quarter q
$\textsc{Ret}_{i,q}$	Average stock return in quarter q.
$\textsc{Short Interest}_{i,q}$	Percentage of shares outstanding of stock i that has been sold short at the end of quarter q.
$\textsc{Spec Flow}_{i,q}$	Stock i's active specialized flows over fire sale event quarter q defined as: $\textsc{Spec Flow}_{i,q} = \frac{1}{F}\sum_{f=1}^{P}(\textsc{Flow}^{i}_{f,q} \mid \textsc{Flow}^{i}_{f,q} > -5\% \cap f \text{ is active})$, where $\textsc{Flow}^{i}_{f,q}$ is percentage net flow of fund f, which held stock i at the beginning of quarter q, over the fire sale event quarter q. We only include active non-fire sale mutual funds – i.e., with net flows above -5% over quarter q. F is the number of active funds that were holding stock i at the beginning of quarter q.

SPEC INDEX$_{i,q}$	Active specialization index defined as: $\text{SPEC INDEX}_{i,q} = z(z\text{SPEC FLOW}_{i,q} + z\text{ACTIVE SHARE}_{i,q} + z\text{IND FLOW}_{i,q} + \text{GEO FLOW}_{i,q})$, where SPEC FLOW is active specialized flows, ACTIVE SHARE is active share, IND FLOW denotes industry-specialized flows, and GEO FLOW$_{i,q}$ represents geographically specialized flows. To put each measure on equal footing and combine them, we standardize all variables (except from the indicator variable GEO FLOW$_{i,q}$) and obtain z-scores.
SD(RET)$_{i,q-1}$	Standard deviation of daily returns estimated in a quarter prior to the fire sale event.
TNA$_{f,q}$	Fund f's total net assets at the end of quarter q
TRUNC REVERSAL$_{i,q}$	Truncated reversal length measured in the number of months since the end of the fire sale event quarter. We assign a value of 28 months for stocks whose CAAR remain negative for at least 27 months after the fire sale quarter end.
$V_{i,d}$	Detrended natural logarithm of daily turnover defined as: $V_{i,d} = \text{logturnover}_{i,d} - \frac{1}{200}\sum_{t=-200}^{-1} \text{logturnover}_{i,d+t}$, where $\text{logturnover}_{i,d} = \log(\text{turnover}_{i,d} + 0.00000255)$ and $\text{turnover}_{i,d}$ is the total number of shares traded of stock i on a given day divided by the number of shares outstanding.

C Additional Tables and Figures

Table C.1: Summary Statistics – Control Variables

This table reports summary statistics of control variables for our sample of fire sale stocks between 1990 and 2016. We use three different definitions of fire sale pressure: FLOW-TO-VOLUME in Panel A, FLOW-TO-STOCK in Panel B, and MFFLOW in Panel C. In Panel A, our sample consists of the bottom decile of FLOW-TO-VOLUME distribution. In Panel B, we only include stocks that belong to the bottom decile of FLOW-TO-STOCK distribution. In Panel C, our sample comprises stocks that belong to the bottom decile of MFFLOW distribution. We use Wardlaw's (2020) definition of FLOW-TO-VOLUME and FLOW-TO-STOCK. We follow Edmans et al. (2012) and compute $\text{MFFLOW}_{i,q}$ using hypothetical buy and sell orders projected from previously disclosed mutual fund portfolios. $\text{FRAGILITY}_{i,q-1}$ is Greenwood and Thesmar's (2011) fragility measured one quarter prior to a fire sale event. $\text{LIQ}_{i,q-1}$ is the lagged Amihud's (2002) liquidity measure. $\text{SD(RET)}_{i,q-1}$ is the standard deviation of daily returns estimated in the quarter prior to the fire sale event. $\text{RET}_{i,q-1}$ is the lagged average monthly stock return. NEGATIVE $\text{ES}_{i,q}$ is an indicator variable that takes a value of one if a firm discloses a negative earnings surprise in the fire sale event quarter, otherwise zero. $\text{LOG(MCAP)}_{i,q-1}$ is the natural logarithm of stock i's market capitalization in the quarter prior to the fire sale event. INST $\text{OWN}_{i,q}$ is the percentage of shares outstanding of stock i held by institutional investors at the end of the fire sale event quarter q. INST $\text{OWN}_{i,q}$ is expressed in decimals.

Panel : Flow-to-Volume

	Mean	Median	SD	P1	P99	NOBS
$\text{FRAGILITY}_{i,q-1}$	1.780	0.037	11.473	0.000	55.599	24711
$\text{LIQ}_{i,q-1}$	-16.744	-16.786	2.823	-22.613	-10.296	24711
$\text{SD(RET)}_{i,q-1}$	0.029	0.024	0.019	0.008	0.104	24711
$\text{RET}_{i,q-1}$	0.000	0.000	0.004	-0.009	0.010	24711
$\text{NEGATIVE ES}_{i,q}$	0.322	0.000	0.467	0.000	1.000	24711
$\text{LOG(MCAP)}_{i,q-1}$	12.134	12.082	1.644	8.449	16.149	24711
$\text{INST OWN}_{i,q-1}$	0.514	0.500	0.283	0.032	1.065	24711

Panel B: Flow-to-Stock

	Mean	Median	SD	P1	P99	NOBS
$\text{FRAGILITY}_{i,q-1}$	1.042	0.055	8.917	0.001	24987	24685
$\text{LIQ}_{i,q-1}$	-19.367	-19.805	2.442	-23.639	-12.623	24685
$\text{SD(RET)}_{i,q-1}$	0.029	0.025	0.017	0.009	0.091	24685
$\text{RET}_{i,q-1}$	0.000	0.000	0.004	-0.011	0.011	24685
$\text{NEGATIVE ES}_{i,q}$	0.332	0.000	0.471	0.000	1.000	24685
$\text{LOG(MCAP)}_{i,q-1}$	13.307	13.419	1.493	9.515	16.654	24685
$\text{INST OWN}_{i,q-1}$	0.768	0.822	0.253	0.116	1.268	24685

Panel C: Price Pressure

	Mean	Median	SD	P1	P99	NOBS
$\text{FRAGILITY}_{i,q-1}$	1.839	0.037	11.691	0.000	59.638	24712
$\text{LIQ}_{i,q-1}$	-16.723	-16.771	2.803	-22.551	-10.300	24712
$\text{SD(RET)}_{i,q-1}$	0.029	0.024	0.019	0.008	0.107	24712
$\text{RET}_{i,q-1}$	0.000	0.000	0.004	-0.009	0.011	24712
$\text{NEGATIVE ES}_{i,q}$	0.328	0.000	0.469	0.000	1.000	24712
$\text{LOG(MCAP)}_{i,q-1}$	12.117	12.063	1.630	8.457	16.039	24712
$\text{INST OWN}_{i,q-1}$	0.510	0.496	0.282	0.032	1.063	24712

Table C.2: Effect of Active on Fire Sale Discount for Large and Small Capitalization Stocks

This table reports OLS estimates of regressions of CAR of fire sale stock on our measures of active specialized demand between 1990 and 2016. Firms are sorted into NYSE-based size deciles where size is defined as the market value of equity from the previous month. We define large (small) cap stocks as stocks in the top (bottom) five deciles. We use three different definitions of fire sale pressure: Flow-To-Volume in columns (1) – (4), Flow-To-Stock in columns (5) – (8), and MFFlow in columns (9) – (12). In columns (1) – (4), our sample consists of the bottom decile of Flow-To-Volume distribution. In columns (5) – (8), we only include stocks that belong to the bottom decile of Flow-To-Stock distribution. In columns (9) – (12), our sample comprises stocks that belong to the bottom decile of MFFlow distribution. We use Wardlaw's (2020) definition of Flow-To-Volume and Flow-To-Stock. We follow Edmans et al. (2012) and compute MFFlow$_{i,q}$ using hypothetical buy and sell orders projected from previously disclosed mutual fund portfolios. Car$_{i,q}$ is the cumulative abnormal return of stock i during fire sale quarter q. The abnormal monthly return is calculated by subtracting the monthly equally-weighted market return from the realized stock return. In Panel A, we investigate the effect of the active specialization index on the abnormal returns of small-cap (the bottom five deciles) fire-sale stocks. In Panel B, we investigate the effect of the active specialization index on the abnormal returns of large-cap (the top five deciles) fire-sale stocks. Spec Index$_{i,q}$ denotes the active specialization index. We compute it by adding z-scored Spec Flow$_{i,q}$, Active Share$_{i,q}$, Ind Flow$_{i,q}$, and the dummy variable Geo Flow$_{i,q}$. To ease the interpretation of the impact of Spec Index$_{i,q}$ on abnormal returns, we also z-score Spec Index$_{i,q}$. In columns (2) – (4), (6) – (8), and (10) – (12), we control for a stock's fire sale pressure measure and other control variables. Fragility$_{i,q}$ is Greenwood and Thesmar's (2011) price fragility measured one quarter prior to the fire sale event. Liq$_{i,q-1}$ is the lagged Amihud's (2002) liquidity measure. SD(Ret)$_{i,q-1}$ is the standard deviation of daily returns estimated in the quarter prior to the fire sale event. Ret$_{i,q-1}$ is the lagged average stock return. Negative ES$_{i,q}$ is an indicator variable that takes a value of one if a firm discloses a negative earnings surprise in the fire sale event quarter, otherwise zero. Log(Mcap)$_{i,q-1}$ is the natural logarithm of stock i's market capitalization in the quarter prior to the fire sale event. Inst Own$_{i,q}$ is the percentage of shares outstanding of stock i held by institutional investors at the end of the fire sale event quarter. Inst Own$_{i,q}$ is expressed in decimals. We include year×quarter fixed effects in columns (1), (2), (5), (6), (9), and (10). We add industry×year-quarter fixed effects in columns (3), (4), (7), (8), (11), and (12). We use Fama and French's (1997) 10 industry classification. Finally, in columns (4), (8), and (12) we control for time-invariant stock characteristics. We cluster the standard errors two-way: at the stock and year×quarter. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Flow-to-volume				Flow-to-stock				Price Pressure			
Panel A: Small Cap Stocks	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SPEC INDEX$_{i,q}$	0.014***	0.014***	0.013***	0.019***	0.027***	0.029***	0.026***	0.028***	0.013***	0.012***	0.011***	0.013***
	(4.37)	(4.24)	(4.21)	(4.12)	(4.90)	(4.84)	(4.32)	(4.07)	(5.10)	(4.84)	(4.80)	(4.51)
Observations	13104	13104	13104	11876	13213	13213	13100	11919	13101	13101	13101	11787
R^2	0.079	0.10	0.17	0.39	0.059	0.081	0.15	0.39	0.096	0.14	0.20	0.43
Panel B: Large Cap Stocks	Flow-to-volume				Flow-to-stock				Price Pressure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SPEC INDEX$_{i,q}$	0.013***	0.007*	0.007**	0.008**	0.034***	0.021**	0.016*	0.024**	0.009***	0.006*	0.005*	0.005
	(3.12)	(1.88)	(2.18)	(2.19)	(3.96)	(2.31)	(1.81)	(2.44)	(3.18)	(1.95)	(1.97)	(1.49)
Observations	11412	11412	11412	10719	11564	11564	11485	10833	11433	11433	11433	10706
R^2	0.23	0.25	0.34	0.51	0.060	0.080	0.16	0.43	0.24	0.25	0.33	0.51
Controls:												
Industry × Year-Month FE			Yes	Yes			Yes	Yes			Yes	Yes
Stock FE				Yes				Yes				Yes
Year × Month FE	Yes	Yes			Yes	Yes			Yes	Yes		
Standard Errors Clustered at:												
Stock level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Month level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

Table C.3: Effect of Active Specialization Index on Fire Sale Discount Due to Passive Fire Sales

This table reports OLS estimates of regressions of CAR of fire sale stock on our measures of active specialized demand between 1990 and 2016. We use three different definitions of fire sale pressure: Flow-To-Volume in columns (1) – (4), Flow-To-Stock in columns (5) – (8), and MFFlow in columns (9) – (12). We use only *passive* mutual fund holdings to identify stocks under fire sale pressure. In columns (1) – (4), our sample consists of the bottom decile of Flow-To-Volume distribution. In columns (5) – (8), we only include stocks that belong to the bottom decile of Flow-To-Stock distribution. In columns (9) – (12), our sample comprises stocks that belong to the bottom decile of MFFlow distribution. We use Wardlaw's (2020) definition of Flow-To-Volume and Flow-To-Stock. We follow Edmans et al. (2012) and compute MFFlow$_{i,q}$ using hypothetical buy and sell orders projected from previously disclosed mutual fund portfolios. Car$_{i,q}$ is the cumulative abnormal return of stock i during fire sale quarter q. The abnormal monthly return is calculated by subtracting the monthly equally-weighted market return from the realized stock return. We investigate the effect of the active specialization index on the abnormal returns of stocks under fire sale price pressure stemming from sales of passive mutual funds. Spec Index$_{i,q}$ denotes the active specialization index. We compute it by adding z-scored Spec Flow$_{i,q}$, Active Share$_{i,q}$, Ind Flow$_{i,q}$, and the dummy variable Geo Flow$_{i,q}$. To ease the interpretation of the impact of Spec Index$_{i,q}$ on abnormal returns, we also z-score Spec Index$_{i,q}$. In columns (2) – (4), (6) – (8), and (10) – (12), we control for a stock's fire sale pressure measure and other control variables. Fragility$_{i,q}$ is Greenwood and Thesmar's (2011) price fragility measured one quarter prior to the fire sale event. Liq$_{i,q-1}$ is the lagged Amihud's (2002) liquidity measure. SD(Ret)$_{i,q-1}$ is the standard deviation of daily returns estimated in the quarter prior to the fire sale event. Ret$_{i,q-1}$ is the lagged average stock return. Negative ES$_{i,q}$ is an indicator variable that takes a value of one if a firm discloses a negative earnings surprise in the fire sale event quarter, otherwise zero. Log(Mcap)$_{i,q-1}$ is the natural logarithm of stock i's market capitalization in the quarter prior to the fire sale event. Inst Own$_{i,q}$ is the percentage of shares outstanding of stock i held by institutional investors at the end of the fire sale event quarter. Inst Own$_{i,q}$ is expressed in decimals. We include year×quarter fixed effects in columns (1), (2), (5), (6), (9), and (10). We add industry×year-quarter fixed effects in columns (3), (4), (7), (8), (11), and (12). We use Fama and French's (1997) 10 industry classification. Finally, in columns (4), (8), and (12) we control for time-invariant stock characteristics. We cluster the standard errors two-way: at the stock and year×quarter. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Flow-to-volume				Flow-to-stock				Price Pressure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SPEC INDEX$_{i,q}$	0.016***	0.011***	0.010***	0.005*	0.019***	0.014**	0.013**	0.011**	0.017***	0.012***	0.011***	0.007**
	(4.18)	(2.97)	(3.18)	(1.75)	(3.42)	(2.39)	(2.57)	(2.44)	(5.53)	(3.40)	(3.68)	(2.35)
FLOW-TO-VOLUME$_{i,q}$	8.889**	9.291***	9.556***	11.333***								
	(2.17)	(3.35)	(2.88)	(3.07)								
FLOW-TO-STOCK$_{i,q}$					8.258**	9.805**	8.293**	1.561				
					(2.51)	(2.58)	(2.13)	(0.46)				
MFFLOW$_{i,q}$									16.418***	23.760***	23.723***	30.564***
									(4.17)	(6.48)	(6.22)	(6.16)
FRAGILITY$_{i,q-1}$		10.524	14.066**	-10.245		-47.664	-23.746	-69.643		0.737	5.657	-7.708
		(1.58)	(2.05)	(-1.13)		(-0.90)	(-0.47)	(-1.02)		(0.12)	(0.86)	(-0.97)
LIQ$_{i,q-1}$		0.205	-0.540	-9.873**		-2.437	-2.219	0.892		13.361***	12.156***	-2.718
		(0.06)	(-0.13)	(-2.45)		(-0.57)	(-0.46)	(0.14)		(3.47)	(3.23)	(-0.70)
SD(RET)$_{i,q-1}$		-1.437***	-1.354***	-0.678*		-0.607	-0.366	-0.835**		-2.449***	-2.303***	-1.026***
		(-3.47)	(-3.01)	(-1.68)		(-1.09)	(-0.64)	(-2.51)		(-5.42)	(-4.59)	(-2.69)
RET$_{i,q-1}$		-1.146	-1.314	-3.710*		-0.933	-1.353	-2.198		-0.339	-0.701	-3.569**
		(-0.63)	(-0.84)	(-1.99)		(-0.41)	(-0.85)	(-0.92)		(-0.19)	(-0.48)	(-2.19)
NEGATIVE ES$_{i,q}$		-0.038***	-0.038***	-0.048***		-0.038***	-0.039***	-0.049***		-0.036***	-0.037***	-0.046***
		(-10.66)	(-10.00)	(-12.16)		(-7.96)	(-7.95)	(-7.62)		(-11.20)	(-10.33)	(-12.16)
LOG(MCAP)$_{i,q-1}$		-0.489	-1.369	-81.923***		-4.761	-3.502	-94.331***		15.612***	13.930***	-68.019***
		(-0.17)	(-0.41)	(-7.01)		(-0.96)	(-0.57)	(-4.72)		(3.65)	(3.61)	(-5.88)
INST OWN$_{i,q}$		0.024	0.024	0.081**		0.050***	0.054***	0.177***		0.013	0.017	0.060***
		(1.35)	(1.50)	(2.46)		(3.29)	(4.45)	(4.24)		(0.69)	(1.02)	(2.80)
Observations	16479	16479	16479	14742	16494	16494	16494	14799	16480	16480	16480	14732
R^2	0.046	0.071	0.12	0.35	0.031	0.043	0.13	0.36	0.066	0.11	0.17	0.39
Controls:												
Stock FE				Yes				Yes				Yes
Year × Quarter FE	Yes	Yes			Yes	Yes		Yes	Yes	Yes		
Industry × Year-Quarter FE			Yes	Yes			Yes	Yes			Yes	Yes
Standard Errors Clustered at:												
Stock level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Quarter level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

Table C.4: Effect of Active Specialization Index on Fire Sale Discount Measured with Three- and Four-Factor Abnormal Returns

This table reports OLS estimates of regressions of CAR of fire sale stock on our measures of active specialized demand between 1990 and 2016. Firms are sorted into NYSE-based size deciles where size is defined as the market value of equity from the previous month. We define large (small) cap stocks as stocks in the top (bottom) five deciles. We use three different definitions of fire sale pressure: Flow-To-Volume in columns (1) – (4), Flow-To-Stock in columns (5) – (8), and MFFlow in columns (9) – (12). In columns (1) – (4), our sample consists of the bottom decile of Flow-To-Volume distribution. In columns (5) – (8), we only include stocks that belong to the bottom decile of Flow-To-Stock distribution. In columns (9) – (12), our sample comprises stocks that belong to the bottom decile of MFFlow distribution. We use Wardlaw's (2020) definition of Flow-To-Volume and Flow-To-Stock. We follow Edmans et al. (2012) and compute MFFlow$_{i,q}$ using hypothetical buy and sell orders projected from previously disclosed mutual fund portfolios. Car$_{i,q}$ is the cumulative abnormal return of stock i during fire sale quarter q. The abnormal monthly return is calculated by subtracting the monthly equally-weighted market return from the realized stock return. In Panel A, we investigate the effect of the active specialization index on the abnormal returns of fire sale stocks. We use Fama and French's (1993) three-factor model to construct abnormal returns. In Panel B, we use Carhart's (1997) four-factor model to estimate abnormal returns. Spec Index$_{i,q}$ denotes the active specialization index. We compute it by adding z-scored Spec Flow$_{i,q}$, Active Share$_{i,q}$, Ind Flow$_{i,q}$, and the dummy variable Geo Flow$_{i,q}$. To ease the interpretation of the impact of Spec Index$_{i,q}$ on abnormal returns, we also z-score Spec Index$_{i,q}$. In columns (2) – (4), (6) – (8), and (10) – (12), we control for a stock's fire sale pressure measure and other control variables. Fragility$_{i,q}$ is Greenwood and Thesmar's (2011) price fragility measured one quarter prior to the fire sale event. Liq$_{i,q-1}$ is the lagged Amihud's (2002) liquidity measure. SD(Ret)$_{i,q-1}$ is the standard deviation of daily returns estimated in the quarter prior to the fire sale event. Ret$_{i,q-1}$ is the lagged average stock return. Negative ES$_{i,q}$ is an indicator variable that takes a value of one if a firm discloses a negative earnings surprise in the fire sale event quarter, otherwise zero. Log(Mcap)$_{i,q-1}$ is the natural logarithm of stock i's market capitalization in the quarter prior to the fire sale event. Inst Own$_{i,q}$ is the percentage of shares outstanding of stock i held by institutional investors at the end of the fire sale event quarter. Inst Own$_{i,q}$ is expressed in decimals. We include year×quarter fixed effects in columns (1), (2), (5), (6), (9), and (10). We add industry×year-quarter fixed effects in columns (3), (4), (7), (8), (11), and (12). We use Fama and French's (1997) 10 industry classification. Finally, in columns (4), (8), and (12) we control for time-invariant stock characteristics. We cluster the standard errors two-way: at the stock and year×quarter. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Three-Factor Model CAAR												
	Flow-to-volume				Flow-to-stock				Price Pressure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SPEC INDEX$_{i,q}$	0.008***	0.009***	0.008***	0.010***	0.019***	0.018***	0.017***	0.022***	0.007***	0.006***	0.007***	0.008***
	(3.06)	(3.24)	(3.09)	(2.86)	(5.73)	(5.29)	(4.74)	(4.26)	(2.69)	(3.07)	(3.42)	(3.48)
Observations	23182	23182	23182	21674	23067	23067	22983	21712	23120	23120	23120	21533
R^2	0.038	0.058	0.11	0.32	0.025	0.033	0.092	0.29	0.049	0.080	0.13	0.34
Panel B: Four-Factor Model CAAR												
	Flow-to-volume				Flow-to-stock				Price Pressure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
SPEC INDEX$_{i,q}$	0.008***	0.008***	0.008***	0.010***	0.018***	0.018***	0.017***	0.023***	0.006**	0.005***	0.006***	0.007***
	(2.82)	(2.90)	(2.64)	(2.71)	(4.73)	(4.24)	(3.78)	(3.73)	(2.36)	(2.67)	(2.94)	(3.34)
Observations	23182	23182	23182	21674	23067	23067	22983	21712	23120	23120	23120	21533
R^2	0.024	0.045	0.095	0.31	0.014	0.024	0.079	0.28	0.036	0.064	0.11	0.34
Controls:												
Stock FE				Yes				Yes				Yes
Year × Quarter FE	Yes	Yes			Yes	Yes			Yes	Yes		
Industry × Year-Quarter FE			Yes	Yes			Yes	Yes			Yes	Yes
Standard Errors Clustered at:												
Stock level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Quarter level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

t statistics in parentheses

Table C.5: Relationship between Fire-Sale Price Pressure Measures and Active Specialization Index

This table reports the number of observations in each group formed based on a fire-sale price pressure measure and active specialization index. The rankings are performed independently such that each group contains stocks that are both in a given fire-sale price pressure category and a given active specialization index category. The sample consists of stocks in the lowest decile of Wardlaw's (2020) FLOW-TO-VOLUME in Panel A, FLOW-TO-STOCK in Panel B, and Edmans et al.'s (2012) MFFLOW in Panel C.

Panel A:		Deciles of SPEC INDEX$_{i,q}$									
		Low	2	3	4	5	6	7	8	9	High
Flow-to-volume	Low	277	122	200	237	252	236	243	295	311	306
	2	314	196	213	229	231	247	249	257	264	278
	3	295	255	223	212	235	237	229	280	258	254
	4	287	247	230	232	271	248	224	228	241	271
	5	270	270	264	241	245	217	234	255	246	236
	6	216	275	273	257	246	271	239	223	237	241
	7	246	273	265	247	230	242	251	236	267	222
	8	197	303	250	255	258	251	265	245	221	233
	9	184	276	271	280	267	281	280	233	200	206
	High	193	261	289	289	243	248	265	226	233	231

Panel B:		Deciles of SPEC INDEX$_{i,q}$									
		Low	2	3	4	5	6	7	8	9	High
Flow-to-stock	Low	347	263	246	211	198	227	217	214	243	313
	2	295	259	221	241	241	221	241	248	247	264
	3	239	245	239	224	259	255	263	250	244	260
	4	245	236	265	254	265	257	245	223	219	270
	5	222	252	246	243	248	258	259	238	275	237
	6	240	250	266	248	256	248	254	250	232	234
	7	231	263	237	269	273	238	243	242	247	236
	8	241	240	261	253	233	255	261	258	262	214
	9	215	237	260	270	243	255	235	278	255	230
	10	204	233	237	266	262	264	261	277	254	220

Panel C:		Deciles of SPEC INDEX$_{i,q}$									
		Low	2	3	4	5	6	7	8	9	High
MFFLow	Low	277	122	216	224	238	243	245	294	316	304
	2	310	203	207	235	239	229	251	273	252	279
	3	302	231	224	232	243	237	227	256	259	267
	4	298	237	230	237	257	241	239	248	240	252
	5	253	291	261	222	248	240	236	228	246	253
	6	262	276	250	266	236	240	245	235	233	235
	7	224	277	283	265	222	241	281	217	244	225
	8	185	285	282	267	249	262	252	235	238	223
	9	194	293	241	264	282	261	267	232	221	223
	10	174	263	284	267	264	284	236	260	229	217

Figure C.1: The distribution of fire sale episode across time.

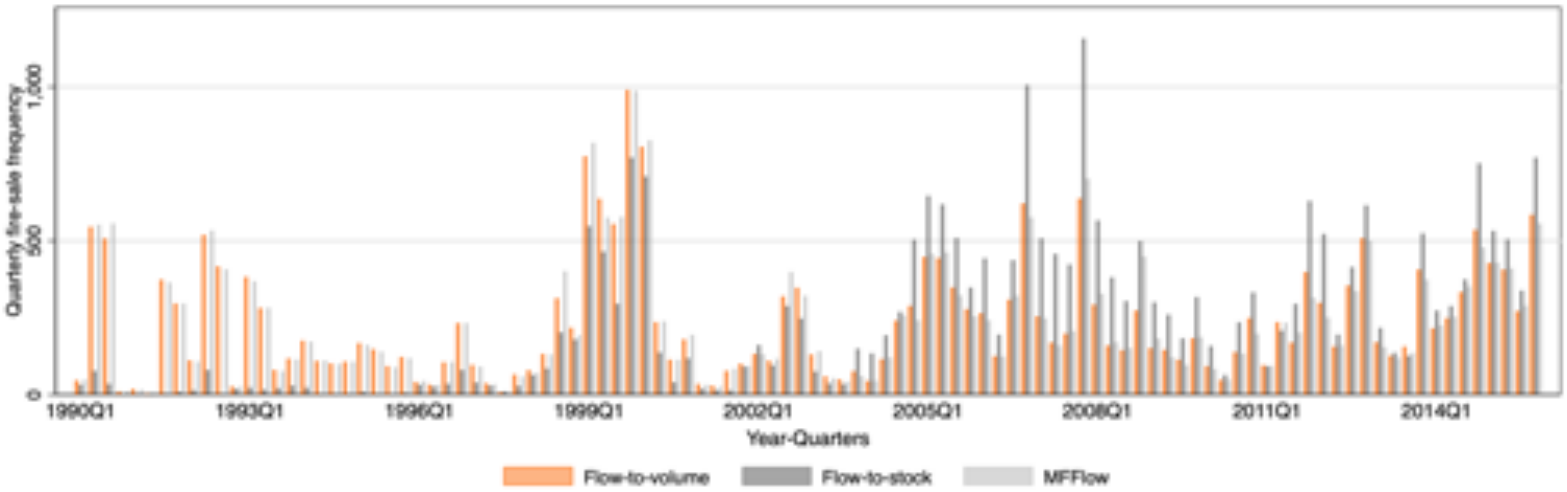
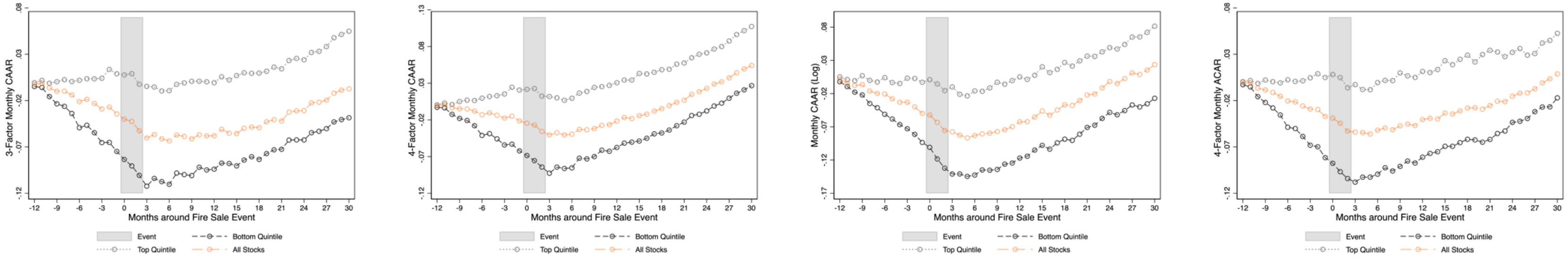
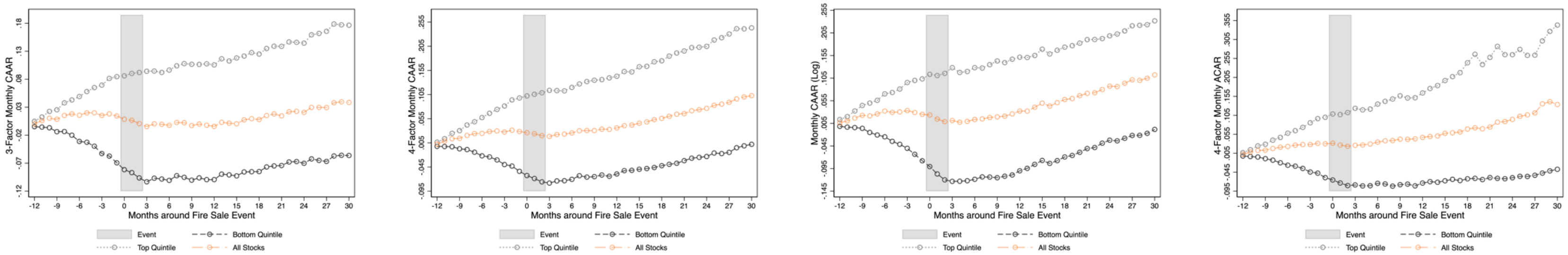


Figure C.2: Different CAR definitions and trajectories for fire sale stocks with different degrees of the *active* specialization index
This figure shows CAR trajectories for portfolios of stocks under fire sale pressure, sorted based on their exposure to *active* specialization, as measured by Spec Index. We use three different definitions of fire sale pressure: Flow-To-Volume – Panel A, Flow-To-Stock – Panel B, and MFFlow – Panel C. We compute CAR using Fama and French's (1993) three-factor model in the left column, Carhart's (1997) four-factor model in the middle column, and log returns in excess of the CRSP equally-weighted index in the right column. The grey shaded area indicates the fire sale event quarter. We plot the CAAR (columns (1) to (3)) and ACAR (column (4)) for all fire sale stocks with orange circles. Every quarter, we sort fire sale stocks into quintiles based on Spec Index$_{i,q}$. We use light-gray circles to plot the CAAR/ACAR of the quintile with the highest active specialization index, and dark-gray circles to indicate the CAAR/ACAR of the quintile with the lowest active specialization index.

(**A**) Flow-to-Volume



(**B**) Flow-to-Stock



(**C**) MFFlow

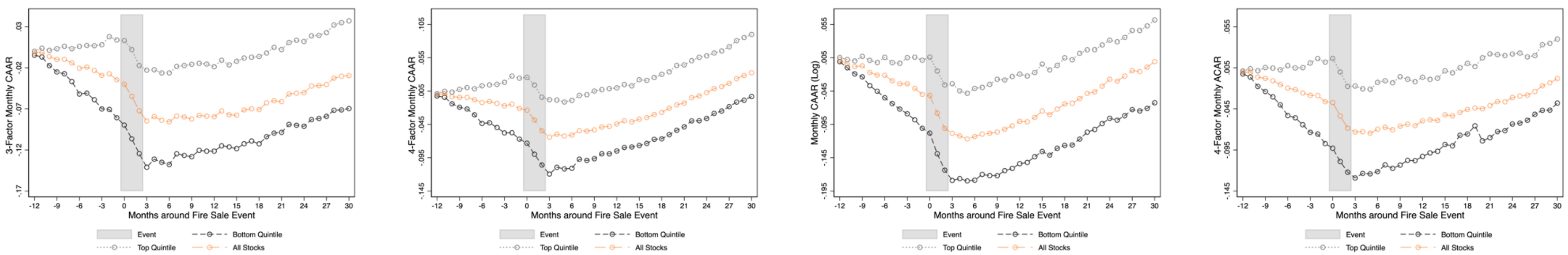
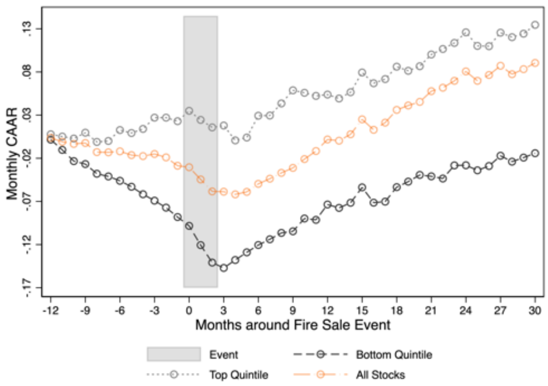


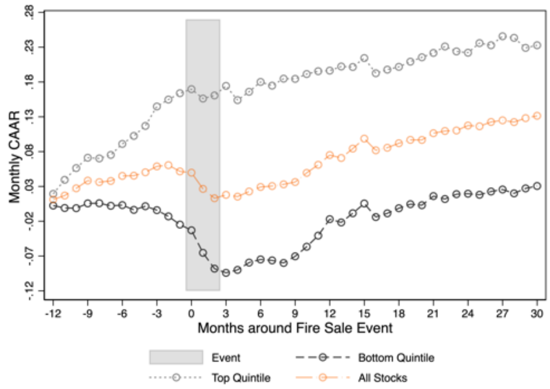
Figure C.4: CAAR trajectories for fire sale stocks with a single fire sale episode and different degrees of the *active* specialization index

This figure shows CAAR trajectories for portfolios of stocks under fire sale pressure, sorted based on their exposure to *active* specialization, as measured by SPEC INDEX. We use three different definitions of fire sale pressure: FLOW-TO-VOLUME – Panel A, FLOW-TO-STOCK – Panel B, and MFFLOW – Panel C. Our sample includes only a subset of fire-sale stocks, which are not under fire-sale pressure in the 12 months preceding and 30 months following a fire sale event. The grey shaded area indicates the fire sale event quarter. We plot the CAAR for all fire sale stocks with orange circles. Every quarter, we sort fire sale stocks into quintiles based on SPEC INDEX$_{i,q}$. We use light-gray circles to plot the CAAR of the quintile with the highest active specialization index, and dark-gray circles to indicate the CAAR of the quintile with the lowest active specialization index. The abnormal monthly return is calculated by subtracting the monthly equally-weighted market return.

(A) Flow-to-Volume



(B) Flow-to-Stock



(C) MFFlow

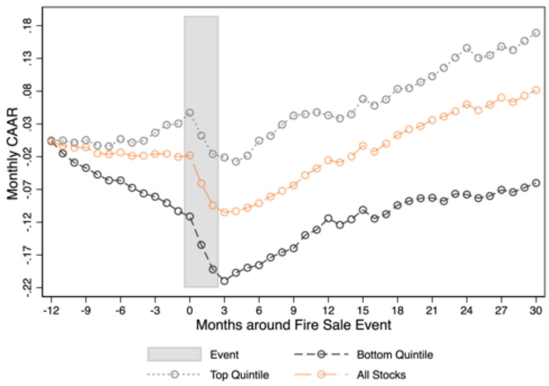


Figure C.5: The monotonic relationship between active specialization and CAR

This figure plots δ_2, δ_3, δ_4, and δ_5 coefficient estimates from a following regression:

$$\textsc{Car}_{i,q} = \delta_0 + \delta_1 \text{FS}_{i,q} + \delta_2 \textsc{Low} + \delta_3 \textsc{Medium Low} + \delta_4 \textsc{Medium High} + \delta_5 \textsc{High} + \textsc{d}_q + \varepsilon_{i,q},$$

where $\text{FS}_{i,q}$ is $\textsc{Flow-To-Volume}_{i,q}$ in Panel A, $\textsc{Flow-To-Stock}_{i,q}$ in Panel B, and $\text{MF}\textsc{Flow}_{i,q}$ in Panel C. Every quarter we sort all fire sale stocks into quintiles based on their active specialization measure $\textsc{Spec Index}_{i,q}$. Low is a dummy variable that takes a value of one if a stock belongs to the bottom quintile, otherwise zero. Medium Low is an indicator variable that takes a value of one if a stock belongs to the second lowest quintile, otherwise zero. Medium High is a dummy variable that takes a value of one if a stock belongs to the second highest quintile of active specialization, otherwise zero. High is an indicator variable that takes a value of one if a stock belongs to the top quintile, otherwise zero. We use the middle quintile as a reference group. $\textsc{d}_q$ denotes year×quarter fixed effects. We use three different definitions of fire sale pressure: Flow-To-Volume – Panel A, Flow-To-Stock – Panel B, and MFFlow – Panel C. The light-gray circles represent coefficient estimates from the base-line regression above. The dark-gray triangles denote coefficient estimates from the most strict specification, where we include a set of time-varying stock characteristics, stock, and industry×year-month fixed effects. The horizontal light- and dark-gray lines represent 95% confidence intervals. The standard errors are clustered at the stock and year×quarter level.