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# Fire sale risk and expected stock returns

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ABSTRACT

We measure a stock's exposure to fire sale risk through its ownership links to mutual funds that anticipate significant outflows during periods of systematic outflows from the fund industry. We find that stocks with higher exposure to this risk earn higher average returns: a portfolio that buys (shorts) stocks with the highest (lowest) exposure outperforms by 3-7% annually. Our findings cannot be explained by several known determinants of average returns and support the ex-ante pricing of the risk of fire sales. We conclude that stocks' exposures to risks inherited from the constraints of shareholders have important implications for stock prices.



## 1. Introduction

Prior studies show that investor outflows from equity mutual funds can force fund managers to sell their stock holdings at prices below fundamental values, and that these price effects are largest when many fund managers enter distress at the same time (Coval and Stafford, 2007). An interesting question is whether stocks earn a risk premium, ex-ante, from being more exposed to the risk of such mutual fund "fire sales." A possible channel is through a stock's ownership links to mutual funds that are expected to experience outflows when outflows are systematic to the industry. Such stocks become targets of distressed sales by mutual fund owners precisely when distressed selling is widespread and, hence, there are relatively few potential mutual fund buyers to absorb the price pressure of distressed sellers. Stock market investors could therefore demand higher expected returns in anticipation of realizing negative returns from fire sales during periods of systematic outflows. In this article, we examine the relation between stock returns and fire sale risk using a novel measure of a stock's exposure to fire sales. We focus on a stock's ownership by equity mutual funds with a high "flow beta" —i.e., the sensitivity of fund investor flows to systematic flows. In this way, our measure identifies stocks as having greater fire sale risk when they are held by mutual funds that experience outflows precisely when outflows are systematic within the industry.

To motivate our empirical work, we first introduce a variation of the Acharya and Pedersen (2005) model of asset pricing with liquidity risk that highlights how a stock's exposure to mutual fund fire sales can impact its expected returns. In our model, we link a stock's illiquidity costs to the flow shocks of its mutual fund owners. Mutual funds' flow shocks have both systematic and non-systematic (fund-specific) components, and some mutual funds are more exposed to systematic flow shocks than others as indicated by a higher flow beta. The model predicts that a

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stock's expected return is increasing in its exposure to the systematic flow risk as measured by the average flow beta of its mutual fund owners. Furthermore, a stock's exposure to systematic flow risk is the only component of flow risk that matters for ex ante pricing because non-systematic flows are a diversifiable risk that "averages out" by holding a well-diversified portfolio of stocks.

In our empirical analysis, we extract common factors from quarterly U.S. equity mutual fund flows. We use the method of Ferson and Kim (2012) and define systematic flows as the first common factor extracted from the principal component analysis of Connor and Korajczyk (1986). We find that the quarterly time series of the flow factor serves as a significant explanatory variable for the aggregate stock market illiquidity costs. This evidence suggests that the flow factor is correlated with fundamental liquidity shocks to the aggregate market, leading to a large price impact. The flow factor is also significantly correlated with macroeconomic variables and financial market conditions, indicating that our measure of systematic flows captures a risk that matters for investors and could factor into asset pricing. For example, the flow factor is highly correlated with the net purchases of assets by equity, corporate bond, municipal bond, and hybrid funds, which suggests that systematic flows capture a broad component of capital market flows and is an effective measure of the aggregate net trading by mutual funds that occurs in response to flows.

Next we estimate a mutual fund's exposure to systematic flows (i.e., its flow beta) by regressing its quarterly fund flows on the flow factor. As found empirically by Ferson and Kim (2012), a fund's flow beta depends on whether systematic flows are positive or negative. Therefore, we partition the flow factor into negative (i.e., systematic outflows) and positive (i.e., systematic inflows) values, and estimate a fund's negative and positive flow betas, respectively. We use a recursive procedure to re-estimate the flow factor and flow betas each quarter so that only backward-looking information is used to construct our key exposure variables. We then calculate a stock's fire sale exposure (*FSE*) as the ownership-weighted average of the negative flow betas of its mutual fund owners. Intuitively, *FSE* captures a stock's ownership by mutual funds that are expected to experience significant outflows during periods of systematic outflows. Similarly, we measure a stock's fire purchase exposure (*FPE*) using the positive flow betas of its mutual fund owners.

We find a positive relation between fire sale risk and average returns over 1989-2017. A value-weighted portfolio of stocks with *FSE* in the top quintile subsequently earns abnormal returns of 1.9% per year, while a portfolio of stocks with *FSE* in the bottom quintile earns −2.3%. The difference, 4.2% per year, is significant ($t$-statistic = 4.14). In contrast, we do not find a significant relation between average returns and a stock's *FPE*. These results are consistent with the asymmetric nature of funding constraints faced by mutual fund managers. Funds are not forced to buy stocks in response to inflows, but may temporarily hold additional cash while implementing an orderly reallocation of new capital to the equity market; in contrast, mutual funds are generally required to satisfy redemptions in cash on a daily basis and, therefore, may be forced to liquidate the fund's equity positions.[1] Accordingly, Falato et al. (2021) find less significant price impacts resulting from funds' inflow-induced purchases than outflow-induced sales. Consequently, unlike with fire sale exposure, investors are less concerned about price pressure resulting from funds' flow-related purchases and, hence, do not require a higher risk premium from fire purchase exposure.

We further show that the high-minus-low *FSE* return spread experiences its lowest returns during periods when forced sales by mutual funds are likely to coincide with periods of market stress, such as those following the Asian Financial Crisis (November 1997, -3.8%), the unraveling of the tech bubble (June 2000, -4.7%), and the S&P downgrade of the United States credit rating (August 2011, -3.5%). However, the *FSE* return spread is not simply mimicking known measures of liquidity risk since it earns a positive 2.8% return over 2008Q1 when Bear Stearns received a Fed bailout and the Pástor and Stambaugh (2003) tradeable liquidity portfolio returned -2.1%. It is also distinct from the returns associated with several known stock return benchmarks, including the size, value, and market portfolios of Fama and French (1992), stock return momentum (Jegadeesh and Titman, 1993; Carhart, 1997), market liquidity risk (Pástor and Stambaugh, 2003), betting-against-beta risk (Frazzini and Pedersen, 2014), leverage constraint tightness (Boguth and Simutin, 2018), co-skewness risk (Harvey and Siddique, 2000), and downside risk (Ang et al., 2006).

Our results also withstand further scrutiny from quarter-by-quarter, stock-level return regressions to control for several stock characteristics that may be correlated with *FSE*, including the level of mutual fund ownership and the illiquidity measures of Amihud (2002) and Sadka (2006). We also reach similar conclusions using panel regressions with stock fixed effects to control for time-invariant stock characteristics. Finally, we find a positive interaction between *FSE* and mutual funds' total share of shares outstanding, indicating that the exposure of stocks to mutual fund fire sales matters more when more of the stock's holders are mutual funds. Taken together, our evidence shows that stock prices reflect a risk premium from exposure to the risk of fire sales.

A potential concern is that *FSE* captures the ownership of relatively skilled mutual fund managers. Under this alternative, fund managers with higher negative flow betas are more skilled at selecting stocks and, hence, stocks with greater ownership by such managers (i.e., high *FSE* stocks) realize abnormal returns because they are undervalued, not because they are riskier. However, in contrast to this alternative story, we do not find a significant relation between a mutual fund's negative flow beta and mea-

[1] For example, Lou (2012) finds that, while mutual fund managers liquidate their holdings dollar-for-dollar in response to outflows, managers only invest 62 cents out of each dollar of inflow in their existing holdings (his Table 2) and use more of their new capital to initiate new positions; Pollet and Wilson (2008) find that mutual funds diversify their position in response to asset growth, adding new stock positions following inflows; and Chen (2022) finds that mutual funds sell shares in existing positions that performed well recently due to risk management motives.

sures of manager skill, such as fund size. In addition, a mutual fund's negative flow beta does not predict higher portfolio alpha, beyond that which can be attributed to a greater portfolio-level *FSE*. Therefore, it is unlikely that the positive relation between fire sale exposure and stock returns is driven by informed stock trading by mutual fund managers.

We conduct two further tests to corroborate our interpretation of the evidence. First, we use stock inclusion into the S&P 500 Index as a plausibly exogenous shock to the *FSE* of newly-included stocks. Bartram et al. (2015) find that Index inclusion impacts the composition of mutual fund ownership of newly-added stocks. Hence, such events could also impact a stock's fire sale exposure because *FSE* depends on the flow beta characteristics of its mutual fund owners. We would expect stocks with larger increases in *FSE* near the inclusion event to realize lower contemporaneous stock returns, as a higher risk premium is factored into its price. We conduct an event study of Index inclusions and find that, consistent with our prediction, stocks with a larger increase in *FSE* realize lower returns (i.e., smaller positive returns) near the inclusion event. Farther away and subsequent to the event, such stocks earn higher average returns, similar to our main result for the full sample.

Second, if *FSE* correctly identifies stocks that are exposed to the risk of fire sales by mutual funds, then stocks with higher *FSE* should indeed experience greater selling by mutual funds during periods of systematic outflows, as compared to stocks with less exposure to fire sale risk. This is exactly what we find in the data. During periods of systematic outflows, stocks in the top quintile of *FSE* experience higher net selling by mutual funds as compared to stocks in the bottom quintile. Moreover, this pattern is asymmetric across the fund industry conditions. During periods of systematic inflows, the spread in mutual fund selling across top and bottom *FSE* quintiles is significantly narrower. This evidence supports the mechanism by which investors require a risk premium for bearing fire sale risk, as such risk cannot be diversified owing to the systematic outflow risk faced by mutual funds that hold the stock.

Our findings contribute to existing evidence that the distressed selling by institutional investors can negatively impact asset prices.[2] In the case of mutual funds, the underlying mechanism is the open-end fund structure which constrains managers to meet the daily redemption needs of fund investors. Since fund investors may freely redeem their shares for cash on a daily basis, fund managers may be forced to liquidate portfolio assets at fire sale prices.[3] However, much less is known about whether investors' anticipation of fire sales affects risk premiums in asset prices, which is the subject of our analysis. One exception, Nanda, Wu and Zhou (2019), use ownership by insurance companies as a proxy for fire sale risk in corporate bonds, and find that fire sale risk is related to higher bond yields. Our paper builds on this recent work by constructing an ownership-based measure of fire sale risk in equity markets and finding evidence of a fire sale risk premium.

Massa, Schumacher and Wang (2021) use the merger of BlackRock and Barclays Global Investors as an exogenous shock to ownership concentration in individual stocks. They find that stocks experiencing an increase in ownership concentration via the merger experience negative stock returns around the event. The authors attribute this finding to selling pressure from investors who anticipate future fire sales in those stocks, and are now trading strategically away from these stocks to avoid this risk. Greenwood and Thesmar (2011) find that a stock's fragility—the concentration of ownership among funds with correlated liquidity shocks—predicts greater stock return volatility. Our paper builds on this work by examining whether the risk of future fire sales has an impact on required stock returns.

Our paper is also related to but fundamentally different from Kim (2020) and Dou, Kogan and Wu (2022) who argue that fund managers have an incentive to hedge their flow risk by underweighting stocks with returns that covary highly with aggregate fund flows, resulting in a premium for these stocks. In contrast, we argue that stocks held primarily by mutual funds whose flows are highly correlated with systematic outflows are more likely to be sold in fire sales, leading to greater illiquidity during periods of systematic outflows and hence, higher expected returns. As a result, we can measure a stock's exposure to fire sale risk based on its mutual fund owners' sensitivities to systematic outflows.

Finally, our paper is related to recent research on how commonality in the holdings of institutional investors can impact asset prices. Several papers find that commonality in mutual fund ownership increases co-movement in equity prices and market liquidity.[4] Our paper provides evidence that commonality in ownership by mutual funds with high systematic flows is associated with greater stocks returns, because these stocks are exposed to greater fire sale risk.

## 2. Conceptual framework and methodology

In this section, we develop the hypotheses underpinning our empirical analysis on the pricing of fire sale risk in stock markets. We also discuss our methodology for estimating the systematic factor in mutual fund flows, the

[2] Evidence of institutional price pressure is found in U.S. equity markets (Coval and Stafford, 2007; Aragon and Strahan, 2012; Tang, 2014; Kang et al., 2014; and Hau and Lai, 2017), bond markets (Manconi et al., 2012; Falato et al., 2021), and international equity markets (Jotikasthira et al., 2012). Diamond and Dybvig (1983), Brunnermeier and Pedersen (2009), and Shleifer and Vishny (1992) develop theoretical predictions on the effects of financial distress on asset values. Chen, Goldstein and Jiang (2010) and Goldstein, Jiang and Ng (2017) find evidence that the investor flow patterns differ across mutual funds based on their exposure to illiquid assets.

[3] Mutual fund managers can take actions, such as cash buffers, inter-fund lending, and redemption-in-kind, to help reduce the risk of fire sales. See, e.g., Chen, Goldstein and Jiang (2010), Liu and Mello (2011), Simutin (2014), Chernenko and Sunderam (2016), Zeng (2017), Agarwal and Zhao (2019), and Agarwal et al. (2023).

[4] See, e.g., Chordia, Roll and Subrahmanyam (2000), Kamara, Lou and Sadka (2008), Jotikasthira, Lundblad and Ramadorai (2012), Anton and Polk (2014), Hau and Lai (2017), Bartram et al. (2015), and Koch, Ruenzi and Starks (2016).

flow betas of mutual funds, and stocks' exposures to fire sale risk. Finally, we describe the main databases used in our analysis and explain and summarize the sample constructed.

### 2.1. Conceptual framework

To fix ideas, we solve a simple theoretical model of asset pricing with mutual fund flows. A full exposition of our model and implications can be found in Appendix A. Our model is a variation of Acharya and Pedersen (2005) where we express the illiquidity costs of selling a stock in their model as increasing with the outflow shocks of its mutual fund owners. This assumption is consistent with our empirical evidence in Appendix A.3 that illiquidity costs are related to mutual fund flows at both the stock- and aggregate market-level, as well as existing evidence that outflow-motivated trading can create price pressure that increases the transaction costs (Coval and Stafford, 2007; Falato et al., 2021). We further assume that mutual fund flows have a factor structure where flows have both systematic and non-systematic (fund-specific) components. This is motivated by empirical evidence that common factors in mutual fund flows explain significant fractions of flows to individual funds (Ferson and Kim, 2012). In the factor structure, mutual fund flows are correlated with systematic outflow shocks, and the correlation indicates the sensitivity of fund flows to the negative part of the flow factor ("negative flow betas").

The main prediction of the model (see Corollary 1 of Appendix A) is that the expected return of security $i$ can be expressed as follows:

$$E_t\left(r_{i,t+1}\right) = r_{f,t} + E_t\left(c_{i,t+1}\right) + \beta_{i,t}\lambda_t + \beta_{i,t}^{f-}\lambda_t^f, \qquad (1)$$

where $r_{i,t+1}$ is the time $t+1$ return on stock $i$, $r_{f,t}$ is the risk-free rate, $E_t(c_{i,t+1})$ is the expected illiquidity cost of stock $i$, $\beta_{i,t}$ is the market beta defined as the sensitivity of the security $i$'s return to the market return net of the illiquidity cost, $\lambda_t$ is the market risk premium, $\beta_{i,t}^{f-}$ is the sensitivity of security $i$'s illiquidity costs to the negative flow factor and is equal to a weighted average of the negative flow betas of its mutual fund owners, and $\lambda_{f,t}$ is the fire sale risk premium.

Eq. (1) directly motivates our key empirical measure of a stock's fire sale exposure (*FSE*) which is also a weighted average of the negative flow betas of its mutual fund owners. It also delivers our main empirical prediction that stocks with a greater exposure to systematic flow risk (measured by *FSE*) earn higher expected returns, and that systematic flow risk is the only component of flow risk that matters for ex ante pricing. The basic intuition is that, by holding a diversified portfolio of stocks, investors can diversify away the idiosyncratic component of flow risk that drives stocks' illiquidity costs; in contrast, investors demand a risk premium for bearing systematic flow risk which is not diversifiable. Finally, besides the exposure to systematic flow risk, the only characteristics that matter for cross-sectional expected returns are a stock's expected illiquidity and its market return beta, which we control for in the empirical analysis.

### 2.2. The flow factor

We construct the flow factor using the method of Ferson and Kim (2012). Specifically, we apply the asymptotic principal components estimator of Connor and Korajczyk (1986) to extract common factors from the quarterly net flows of U.S. equity mutual funds. Principal components analysis (PCA) is designed to statistically extract the factor that maximizes the variance of the systematic flow component while minimizing the variance of the idiosyncratic flow, and PCA estimates converge to a transformation of the true unobservable factors as the number of sample observations increases (Connor and Korajczyk, 1986). In Appendix B.1, we use simulations to show that the first principal component (PC) of fund flows closely tracks the true flow factor, consistent with Connor and Korajczyk's 1988 evidence that the PCA provides accurate estimates of the pervasive factors in equity returns.

Using the first PC as the flow factor also has the advantage of effectively capturing commonality in fund flows, which is crucial since liquidity risks are driven by commonality in liquidity needs. Coval and Stafford (2007) note that a fire sale price is more likely when there are many sellers relative to potential buyers, as opposed to only a single large fund selling when others are willing and able to provide liquidity. In Appendix B.2 and Table A-2, we demonstrate that the first PC is superior to asset-weighted average flows (value-weighted aggregate flows) in measuring commonality in flows and explaining variations in the illiquidity costs for the aggregate market. This suggests that the first PC more closely tracks fire sale events that are correlated with fundamental shocks, which leads to a larger price impact. Finally, the first PC can accurately measure the effect of mutual fund flows on their aggregate net trading of the average stock. As we discuss in Appendix B.3, if all funds hold the same portfolios, then the aggregate net trading of a stock by mutual funds is equal to value-weighted aggregate flows. However, heterogeneity in fund holdings breaks the connection between the aggregate net trading and value-weighted aggregate flows, and the first PC is the accurate measure of mutual funds' net trading of a stock that occurs in response to money flows.

Net flows are calculated in the usual way as the percentage change in the fund's total net assets (TNA) minus its net-of-fees returns. The data are from Morningstar and cover the period 1980Q2 to 2016Q4. Starting in 1989Q1, we use a recursive method in which we extract the time-series of flow factor realizations at the end of each quarter. We use an expanding window so that, for example, the first realization is obtained in 1989Q1 based on the 36 quarterly observations of fund flows from 1980Q2 through 1989Q1, while the 1989Q2 realization is based on the 37 observations from 1980Q2 through 1989Q2, and so on. In our main analysis, we focus on the first flow factor (hereafter, the flow factor), which explains the largest share of the variation in fund flows. We scale the flow factor such that a 1% increase of the flow factor is associated with an average increase of 1% of value-weighted aggregate flows.[5]

Panel A of Table 1 reports summary statistics of the flow factor for the 147 quarters in our sample. Both the flow factor and aggregate flows have a positive sample mean. The sample correlation between the flow factor and aggregate flows is about 82%, suggesting that approximately 68% ($= 0.82^2$) of the variation in aggregate flows is systematic and explainable by the flow factor; any residual variation in aggregate flows is non-systematic and diversifiable. The flow factor is also positively related to U.S. economic conditions as determined by consumer opinion (changes in the University of Michigan Consumer Sentiment Index) and stock market returns, and negatively related to stock market return volatility. This evidence confirms (over an expanded sample period) the finding of Ferson and Kim (2012) that the flow factor is significantly related to financial market conditions. The flow factor is also positively related to net purchases of stocks and bonds by mutual funds as provided in the Financial Accounts of United States by the Board of Governors of the Federal Reserve System.[6] This relation holds in aggregate across all mutual fund types as well as by mutual fund sector, including equity funds, hybrid funds, and municipal bond funds. Together, the systematic flow factor is related to variation in financial market conditions and trading activity both within and outside the equity fund industry and, hence, could reflect a risk that matters for investors and asset pricing.

### 2.3. Mutual fund flow betas

We estimate the flow betas of individual mutual funds as loadings of fund flows on the flow factor. Ferson and Kim (2012) document that mutual funds have different exposures to positive and negative systematic flows. Therefore, to isolate the sensitivity of fund flows to systematic outflows versus inflows, we decompose the flow factor into its negative and positive parts. Specifically, for each fund $k$, we run the following time series regression:

$$f_{k,q} = \alpha_k + \beta_k^- F_q^- + \beta_k^+ F_q^+ + e_{k,q},$$
$$E(e_{k,q}) = E(e_{k,q}F_q^-) = E(e_{k,q}F_q^+) = 0, \tag{2}$$

where $f_{k,q}$ is fund $k$'s net flow in quarter $q$, $F_q^- \equiv \min\{F_q, 0\}$, $F_q^+ \equiv \max\{F_q, 0\}$, and $F_q$ is the flow factor in quarter $q$. The loading $\beta_k^-$ represents a fund's negative flow beta. It captures a fund's flow exposure to systematic outflows and is a key ingredient in our stock-level measure of fire sale risk.

We estimate mutual fund flow betas for all equity mutual funds in a matched sample of mutual fund holdings and returns. Specifically, we start with the Thomson-Reuters Mutual Fund Holdings database and only include equity funds—i.e., those with objective codes representing aggressive growth, growth, or growth and income. Each fund is then matched to the Center for Research in Security Prices (CRSP) Survivor-Bias-Free US Mutual Funds Database after aggregating across different share classes of the same fund. We then estimate Eq. (2) using a fund's historical net flows computed from its available history of TNA and returns. Similar to our estimation of the flow factor realizations, we re-estimate $\beta_k^-$ and $\beta_k^+$ each quarter using a recursive method that only uses backward-looking fund flow data. For example, the earliest estimate of flow betas uses quarterly data through 1989Q1. Subsequent estimates are based on an expanding window including all prior data. We require at least 30 quarterly observations to compute a fund's flow betas.

Panel B of Table 1 summarizes mutual fund flow betas and other characteristics. The average negative flow beta ($\beta^-$) is 5.21, which means that a mutual fund's expected outflow is about 5 times as much as systematic outflows.[7] To put this into perspective, for a mutual fund with a negative flow beta of 5.21, a one standard deviation decline in the flow factor would correspond to 8.86% ($= 5.21 \times 1.7\%$) lower quarterly flows. We also see that $\beta^-$ tends to be larger among younger funds, which tend to have “hot-money” and a greater sensitivity of flows to fund performance (Spiegel and Zhang, 2013). However the magnitude of the correlation between $\beta^-$ and fund age is small. Ferson and Kim (2012), their Table 7) also find that $\beta^-$ tends to be larger among past losers than past winners and among large funds than small funds. Negative flow beta is negatively related to positive flow beta (correlation coefficient = -0.14)—in other words, funds that tend to experience high net outflows during periods of systematic outflows do not tend to experience high net inflows when systematic flows are positive. Finally, in untabulated results, we find no clear relation between a fund's negative flow beta and its portfolio weights in small, large, value, growth, past winner, and past loser stocks. This is consistent with our evidence later in Sections 3 and 4 that stock characteristics, such as the market capitalization, book-to-market ratio, and past return, do not subsume the predictability of FSE for future stock returns.

### 2.4. Fire sale exposure

We measure a stock's fire sale exposure (*FSE*) as an ownership-weighted average of the negative flow betas of its mutual fund owners. Specifically, the *FSE* of stock $i$ at

[5] Specifically, we scale the flow factor by $\frac{\text{Cov(aggregate flows, x)}}{\text{Var(x)}}$, where $x$ is the raw, unscaled flow factor. This ensures a beta coefficient of one when aggregate flows are regressed on the flow factor. Ferson and Kim (2012) employ the same procedure using a 48-quarter rolling window and provide further details on estimating the flow factor.

[6] These data are available beginning in the first quarter of 1991. Edelen, Marcus and Tehranian (2010) also use the Financial Accounts to measure the difference in portfolio allocations to risky assets between retail and institutional investors.

[7] The flow beta of the aggregate flow is equal to one by the scaling in footnote 5. However, the negative and positive flow beta averages in Panel B of Table 1 are not equal to one because 1) they are equally-weighted (not asset-weighted) and 2) they are estimated using the multivariate regression in Eq. (2) rather than a simple regression of $f_{it}$ on $F_t$.

**Table 1**
Summary statistics.
The table summarizes the quarterly time series of aggregate flow variables (Panel A), pooled fund-quarterly observations of mutual fund variables (Panel B), and pooled stock-quarter observations of stock characteristics (Panel C). The p-values of correlation coefficients are reported in parentheses. The number of observations varies depending on the number of periods required to construct the variable. All variables are defined in Appendix C. The sample is from January 1980 to December 2016.

Panel A: Aggregate flow variables (quarter)

| | N | mean | SD | P25 | median | P75 |
|---|---|---|---|---|---|---|
| Flow factor (%) | 147 | 0.69 | 1.70 | -0.37 | 0.12 | 1.12 |
| aggregate flow (%) | 147 | 0.76 | 2.07 | -0.75 | 0.27 | 2.15 |

Correlation coefficients

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) Flow factor | 1.00 | | | | | | | | | | | |
| (2) aggregate flow | 0.82 | 1.00 | | | | | | | | | | |
| | (0.00) | | | | | | | | | | | |
| (3) Δ Michigan index | 0.10 | 0.09 | 1.00 | | | | | | | | | |
| | (0.22) | (0.28) | | | | | | | | | | |
| (4) D/P ratio - Treasury | -0.25 | -0.33 | -0.03 | 1.00 | | | | | | | | |
| | (0.00) | (0.00) | (0.71) | | | | | | | | | |
| (5) Stock market volatility | -0.31 | -0.37 | -0.06 | 0.17 | 1.00 | | | | | | | |
| | (0.00) | (0.00) | (0.49) | (0.04) | | | | | | | | |
| (6) Stock return - TBill | 0.23 | 0.36 | 0.41 | -0.07 | -0.48 | 1.00 | | | | | | |
| | (0.01) | (0.00) | (0.00) | (0.41) | (0.00) | | | | | | | |
| (7) BAA - AAA rate | -0.22 | -0.23 | 0.07 | -0.21 | 0.49 | -0.21 | 1.00 | | | | | |
| | (0.01) | (0.00) | (0.39) | (0.01) | (0.00) | (0.01) | | | | | | |
| (8) AAA - TBill | 0.23 | 0.26 | 0.01 | -0.96 | -0.08 | 0.00 | 0.39 | 1.00 | | | | |
| | (0.01) | (0.00) | (0.86) | (0.00) | (0.36) | (0.97) | (0.00) | | | | | |
| (9) All funds' net purchases | 0.79 | 0.85 | 0.03 | -0.54 | -0.32 | 0.27 | -0.33 | 0.61 | 1.00 | | | |
| | (0.00) | (0.00) | (0.75) | (0.00) | (0.00) | (0.01) | (0.00) | (0.00) | | | | |
| (10) Municipal bond funds | 0.59 | 0.51 | -0.03 | -0.15 | -0.13 | 0.02 | -0.01 | 0.29 | 0.81 | 1.00 | | |
| | (0.00) | (0.00) | (0.74) | (0.14) | (0.20) | (0.87) | (0.96) | (0.00) | (0.00) | | | |
| (11) Bond funds | 0.21 | 0.17 | -0.07 | 0.06 | 0.01 | 0.11 | 0.12 | 0.06 | 0.60 | 0.74 | 1.00 | |
| | (0.03) | (0.08) | (0.51) | (0.54) | (0.92) | (0.29) | (0.23) | (0.56) | (0.00) | (0.00) | | |
| (12) Hybrid funds | 0.75 | 0.66 | 0.08 | -0.22 | -0.50 | 0.21 | -0.34 | 0.28 | 0.71 | 0.61 | 0.34 | 1.00 |
| | (0.00) | (0.00) | (0.40) | (0.02) | (0.00) | (0.03) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | |
| (13) Equity funds | 0.74 | 0.91 | 0.08 | -0.79 | -0.35 | 0.31 | -0.52 | 0.77 | 0.78 | 0.34 | 0.01 | 0.46 |
| | (0.00) | (0.00) | (0.41) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.92) | (0.00) |

Panel B: Mutual fund variables (fund-quarter)

| | N | mean | SD | P25 | median | P75 |
|---|---|---|---|---|---|---|
| Negative fund flow beta ($\beta^-$) | 105,685 | 5.21 | 25.89 | -1.46 | 5.00 | 14.36 |
| Positive fund flow beta ($\beta^+$) | 105,685 | 13.92 | 51.17 | -0.09 | 1.85 | 10.72 |
| Net flow (%) | 179,826 | 0.93 | 17.91 | -4.07 | -1.12 | 2.83 |
| Net return (%) | 179,826 | 2.29 | 9.43 | -1.97 | 2.85 | 7.58 |
| Total net assets ($ billions) | 179,826 | 1.62 | 7.46 | 0.07 | 0.25 | 0.95 |
| Family size ($ billions) | 179,826 | 28.44 | 90.65 | 0.46 | 3.20 | 16.45 |
| Age (years) | 179,826 | 14.91 | 12.34 | 6.75 | 11.33 | 18.42 |
| expense ratio (%) | 164,553 | 2.19 | 8.38 | 1.01 | 1.37 | 1.70 |

Correlation coefficients

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| (1) Negative fund flow beta ($\beta^-$) | 1.00 | | | | | | |
| (2) Positive fund flow beta ($\beta^+$) | -0.14 | 1.00 | | | | | |
| | (0.00) | | | | | | |
| (3) Net flow | -0.04 | -0.01 | 1.00 | | | | |
| | (0.00) | (0.00) | | | | | |

(*continued on the next page*)

**Table 1**
(*continued*).

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| (4) Net return | 0.00 | 0.01 | 0.08 | 1.00 | | | |
| | (0.20) | (0.00) | (0.00) | | | | |
| (5) Total net assets ($ billions) | 0.01 | -0.02 | 0.00 | 0.00 | 1.00 | | |
| | (0.00) | (0.00) | (0.29) | (0.06) | | | |
| (6) Family size ($ billions) | 0.03 | 0.12 | 0.01 | 0.01 | 0.34 | 1.00 | |
| | (0.00) | (0.00) | (0.02) | (0.00) | (0.00) | | |
| (7) Age (years) | -0.02 | -0.15 | -0.07 | 0.00 | 0.18 | 0.09 | 1.00 |
| | (0.00) | (0.00) | (0.00) | (0.77) | (0.00) | (0.00) | |
| (8) expense ratio | 0.00 | -0.01 | -0.01 | 0.01 | -0.02 | -0.02 | -0.04 |
| | (0.63) | (0.00) | (0.00) | (0.01) | (0.00) | (0.00) | (0.00) |

Panel C: Stock characteristics (stock-quarter)

| | N | mean | SD | P25 | median | P75 |
|---|---|---|---|---|---|---|
| Fire sale exposure (*FSE*) | 321,463 | 4.92 | 17.98 | 0.07 | 4.84 | 8.87 |
| Fire purchase exposure (*FPE*) | 321,463 | 3.56 | 8.89 | 0.00 | 1.06 | 4.67 |
| Market capitalization ($ billions) | 321,463 | 3.46 | 16.48 | 0.11 | 0.38 | 1.53 |
| Book-to-market ratio (B/M) | 321,463 | 0.67 | 0.87 | 0.32 | 0.54 | 0.82 |
| Past one-year return (%) | 321,463 | 24.46 | 83.24 | -10.58 | 12.03 | 39.17 |
| Ownership (%) | 321,463 | 12.00 | 11.52 | 2.52 | 8.46 | 18.88 |
| Change in breadth of ownership (%) | 291,051 | 0.02 | 0.40 | -0.08 | 0.00 | 0.12 |
| Amihud illiquidity | 311,310 | 0.60 | 1.79 | 0.00 | 0.02 | 0.23 |
| Market beta | 281,244 | 0.97 | 0.67 | 0.54 | 0.91 | 1.32 |
| Liquidity beta (PS) | 281,244 | 0.00 | 0.38 | -0.18 | 0.00 | 0.18 |
| Liquidity beta (PS-tradable) | 281,244 | 0.00 | 0.60 | -0.30 | -0.01 | 0.29 |
| Liquidity beta (Sadka-fixed transitory) | 261,205 | 3.06 | 34.26 | -5.76 | 0.26 | 7.75 |
| Liquidity beta (Sadka-variable permanent) | 261,205 | -0.21 | 4.50 | -2.09 | -0.11 | 1.82 |

Correlation coefficients

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) FSE | 1.00 | | | | | | | | | | | |
| (2) *FPE* | -0.03 | 1.00 | | | | | | | | | | |
| | (0.00) | | | | | | | | | | | |
| (3) Market capitalization | 0.00 | 0.03 | 1.00 | | | | | | | | | |
| | (0.98) | (0.00) | | | | | | | | | | |
| (4) Book-to-market ratio (B/M) | 0.02 | 0.03 | -0.06 | 1.00 | | | | | | | | |
| | (0.00) | (0.00) | (0.00) | | | | | | | | | |
| (5) Past one-year return | -0.01 | -0.01 | -0.01 | -0.13 | 1.00 | | | | | | | |
| | (0.00) | (0.00) | (0.00) | (0.00) | | | | | | | | |
| (6) Ownership | 0.08 | 0.27 | 0.09 | -0.10 | -0.04 | 1.00 | | | | | | |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | | | | | | | |
| (7) Change in breadth | 0.01 | 0.00 | 0.02 | -0.04 | 0.16 | 0.06 | 1.00 | | | | | |
| | (0.00) | (0.12) | (0.00) | (0.00) | (0.00) | (0.00) | | | | | | |
| (8) Amihud illiquidity | 0.02 | -0.07 | -0.10 | 0.19 | -0.05 | -0.26 | -0.02 | 1.00 | | | | |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | | | | | |
| (9) Market beta | 0.00 | 0.02 | 0.01 | -0.04 | 0.07 | 0.16 | 0.00 | -0.17 | 1.00 | | | |
| | (0.76) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.03) | (0.00) | (0.00) | | | |
| (10) Liquidity beta (PS) | 0.00 | 0.00 | -0.01 | 0.00 | 0.02 | -0.01 | 0.00 | 0.01 | -0.04 | 1.00 | | |
| | (0.29) | (0.49) | (0.00) | (0.40) | (0.00) | (0.00) | (0.07) | (0.00) | (0.00) | (0.00) | | |
| (11) Liquidity beta (PS-tradable) | 0.00 | 0.01 | 0.00 | 0.00 | 0.03 | 0.01 | 0.00 | 0.01 | -0.08 | 0.15 | 1.00 | |
| | (0.20) | (0.00) | (0.48) | (0.52) | (0.00) | (0.00) | (0.24) | (0.00) | (0.00) | (0.00) | (0.00) | |
| (12) Sadka beta (fixed transitory) | 0.02 | 0.05 | -0.01 | 0.02 | 0.05 | 0.03 | 0.01 | 0.03 | 0.08 | 0.07 | 0.21 | 1.00 |
| | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |
| (13) Sadka beta (variable permanent) | 0.00 | -0.02 | -0.01 | 0.02 | 0.00 | -0.04 | 0.00 | 0.05 | -0.08 | 0.19 | -0.07 | 0.08 |
| | (0.53) | (0.00) | (0.01) | (0.00) | (0.64) | (0.00) | (0.89) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) |

the end of quarter $q$ is given by

$$FSE_{i,q} = \sum_{k=1}^{K} \beta^{-}_{k,q} \frac{shr_{i,k,q}}{\sum_{k=1}^{K} shr_{i,k,q}}, \tag{3}$$

where $shr_{i,k,q}$ is the number of shares of stock $i$ that a fund $k$ owns at the end of quarter $q$ and $K$ is the total number of mutual funds that hold shares of stock $i$, as reported in the Thomson-Reuters Mutual Fund Holdings data. We also calculate a stock's fire purchase exposure (*FPE*) in a similar way after replacing funds' negative flow betas with their positive flow betas (i.e., $\beta^{+}_{k,q}$ instead of $\beta^{-}_{k,q}$). Scaling by stock $i$'s shares outstanding instead of $\sum_{k=1}^{K} shr_{i,k,q}$ in Eq. (3) is equivalent to $FSE_{i,q}$ times the total mutual ownership of stock $i$ at the end of quarter $q$ (*Ownership*). Since we include *Ownership* as a separate control in our stock return regressions, we use the specification in Eq. (3) to avoid multicollinearity issues.[8] Nevertheless, to check robustness, we repeated our stock return tests using an alternative definition of *FSE* in which we scale by a stock's shares outstanding rather than its total mutual fund ownership. The results (shown in Appendix D) are similar to those tabulated here, indicating that the denominator in Eq. (3) is not driving our results.[9]

We obtain stock returns and other stock-level information (e.g., market value, number of shares outstanding, etc.) from the CRSP stock files. Our sample includes all common stocks that are listed on NYSE/NASDAQ/AMEX. To avoid microstructure issues, we exclude stocks with monthly stock prices less than $5 at the beginning of trading. We do not adjust CRSP stock returns using delisting returns. However, our main results are qualitatively unchanged when we include low-priced stocks or CRSP delisting returns (see Appendix D).

We summarize our stock sample in Panel C of Table 1. The median values of *FSE* and *FPE* are 4.84 and 1.06, respectively, and of similar magnitude to the median negative and positive flow betas. This makes sense because *FSE* and *FPE* are weighted averages of negative and positive flow betas, respectively. Mutual fund stock ownership has a sample mean of 12%, which is in line with Koch, Ruenzi and Starks' 2016 estimate that average mutual fund ownership is 11% over 1980-2010. Stocks in our sample also have a mean market capitalization of $3.46 billion and a recent one-year return of 24.46%. For comparison, Bessembinder (2018) reports that annual stock returns have a sample mean of 15% over 1925-2016. Our estimate of average annual stock returns is higher because we exclude low-priced stocks (less than $5) which tend to have below-average performance. When we add back such penny stocks to our sample, the mean annual return is 16% and about the same as that reported by Bessembinder (2018).

Panel C of Table 1 also reports pairwise correlations between *FSE* and other stock characteristics. Stocks with higher *FSE* tend to have higher book-to-market ratio, higher mutual fund ownership, higher changes in breadth of ownership, higher values of Amihud's 2002 illiquidity measure, and lower past returns.[10] However, the magnitudes of the pairwise correlations between *FSE* and stock characteristics range from just 2% to 8%. This suggests that *FSE* lacks a strong connection to known predictors of stock returns and, hence, is a novel risk measure. Even so, we control for several stock characteristics in our subsequent analysis on the relation between *FSE* and average returns.

## 3. Analysis and results

In this section, we present our main findings on the relation between fire sale exposure and the cross-section of stock returns.

### 3.1. Fire Sale Risk Sorted Portfolios

We first investigate the pricing of fire sale risk using portfolios of individual stocks. Specifically, we form five portfolios of stocks using *FSE* values as of the current quarter. Stocks are kept in the portfolio for three months. As previously described, we avoid forward-looking information and calculate *FSE* values based on the updated series of flow factor realizations, the estimated fund flow betas, and most recent mutual fund ownership. In practice, however, mutual funds have 60 days to publicly disclose their quarter-end holdings, so ownership data is not immediately known to investors at the end of the quarter. Therefore, we form portfolios two months after each quarter-end to allow a "real-time" investor time to observe ownership information and form portfolios. For example, *FSE*-based portfolio returns in March, April, and May 2001 are based on *FSE* values using ownership data as of December 2000 (but might not have been publicly known until the following February), while portfolio returns in June, July, and August 2001 are based on stocks' *FSE* values prevailing at the end of March 2001, and so on. This "skip-two-months" strategy helps ensure that investors have available the required information to estimate *FSE* and, therefore, that portfolios are investable in "real-time" and only use backward-looking information. Nevertheless, our main results are similar when we do not use a "skip-two-months" strategy and instead assume investors can form portfolios exactly at each quarter-end (see Appendix D and Section 4.7).

Panel A of Table 2 describes the portfolios. The average *FSE* ranges from -10.32 for bottom quintile stocks to 20.36 for stocks in the top quintile. Furthermore, we do not find a monotonic relation between *FSE* and any of the stock characteristics, including stock market capitalization,

[8] The pairwise correlation between *Ownership* and the alternative measure of FSE where fund betas are weighted by funds' shares of total shares outstanding is 57%, much higher that of FSE and *Ownership* (8%, see Panel C of Table 1).

[9] An interesting variation of our definition of FSE would be to incorporate funds' exposures to extreme negative outflows instead of all negative flows. However, we cannot reliably estimate such "negative tail flow betas" because we only have 147 quarterly observations of the flow factor; longer and higher-frequency data sets are needed to accurately estimate tail risk (Bollerslev and Todorov, 2011).

[10] Breadth of ownership is the ratio of the number of mutual funds that own the stock to the total number of mutual funds. We calculate change in breadth following Chen, Hong and Stein (2002). See Appendix C for the definition.

**Table 2**
FSE Sorted.
Portfolios Stocks are sorted into 5 portfolios according to *FSE* values at the end of each quarter. A stock's *FSE* is the average negative flow beta ($\beta^-$) of mutual funds that own the stock with weights proportional to the number of shares that each mutual fund owns. Panel A summarizes stock characteristics for each *FSE* portfolio; the numbers are pooled sample means across stock-quarter observations. Panel B reports the time-series average of portfolio returns for each *FSE* portfolio. Stocks are sorted based on *FSE* at each quarter-end and portfolios are formed two months later. Portfolio weights are either value-weighted according to stock market capitalization (VW) or equally-weighted (EW). Only stocks with a closing price of at least $5 on the date of portfolio formation are included in the portfolio. The position is held for three months and rebalanced every three months. High-Low represents returns on a trading strategy that is long stocks in the top quintile portfolio and short stocks in the bottom quintile portfolio. Returns represent annualized average monthly returns. DGTW returns are equal to returns minus benchmark returns, which are returns on the stocks in the same quintiles of B/M, size, and past 1-year return (Daniel et al., 1997). Panel C is the same as Panel B, except the portfolios are formed by sorting stocks into 5 portfolios according to historical *FPE*. A stock's *FPE* is the average positive flow beta ($\beta^+$) of mutual funds that own the stock with weights proportional to the number of shares that each mutual fund owns. Standard errors are Newey-West standard errors with 4 lags. All variables are defined in Appendix C. The flow exposures are estimated from 1989Q1–2016Q4, and the return period is from June 1989 to May 2017.

Panel A: Characteristics of stocks sorted on *FSE*

| *FSE* quintiles | *FSE* | *FPE* | Size | B/M | Past 1-yr return | Market beta | Ownership | Change in breadth | Illiquidity |
|---|---|---|---|---|---|---|---|---|---|
| 1 | -10.324 | 4.787 | 2.084 | 0.750 | 0.248 | 0.871 | 0.079 | -0.013 | 0.908 |
| 2 | 1.708 | 3.431 | 4.830 | 0.684 | 0.228 | 0.945 | 0.113 | 0.015 | 0.687 |
| 3 | 4.403 | 3.396 | 5.302 | 0.617 | 0.250 | 1.028 | 0.136 | 0.029 | 0.387 |
| 4 | 8.051 | 3.408 | 3.604 | 0.600 | 0.252 | 1.058 | 0.151 | 0.039 | 0.292 |
| 5 | 20.363 | 2.830 | 1.391 | 0.712 | 0.245 | 0.949 | 0.119 | 0.017 | 0.755 |

| Panel B: Returns on the *FSE* portfolios | | | | | Panel C: Returns on the *FPE* portfolios | | | | |
|---|---|---|---|---|---|---|---|---|---|
| *FSE* quintiles | VW | EW | DGTW VW | DGTW EW | *FPE* quintiles | VW | EW | DGTW VW | DGTW EW |
| 1 | 0.084 | 0.112 | -0.023 | -0.012 | 1 | 0.108 | 0.122 | -0.006 | -0.003 |
| 2 | 0.094 | 0.112 | -0.005 | -0.005 | 2 | 0.103 | 0.118 | 0.002 | -0.003 |
| 3 | 0.100 | 0.114 | 0.002 | 0.001 | 3 | 0.105 | 0.121 | -0.003 | 0.002 |
| 4 | 0.126 | 0.125 | 0.008 | 0.002 | 4 | 0.117 | 0.129 | 0.007 | 0.004 |
| 5 | 0.149 | 0.144 | 0.019 | 0.014 | 5 | 0.120 | 0.123 | 0.008 | -0.002 |
| High-Low | 0.065 | 0.032 | 0.042 | 0.026 | High-Low | 0.012 | 0.001 | 0.014 | 0.001 |
| (t-statistics) | (4.175) | (3.489) | (4.141) | (3.964) | (t-statistics) | (0.507) | (0.082) | (0.320) | (0.875) |

book-to-market ratio, or Amihud illiquidity. This is consistent with our earlier observation that *FSE* is not strongly correlated with most stock characteristics (Table 1, Panel C).

Panel B of Table 2 reports average portfolio returns and *t*-statistics computed using Newey and West's (1987) adjusted standard errors.[11] We see that average returns increase monotonically with fire sale exposure. Value-weighted portfolios (i.e., weighting a stock's returns based on its market capitalization as of the rebalancing date) of stocks in the highest *FSE* quintile earn 14.9% per year, while stocks in the lowest *FSE* quintile earn just 8.4%. A spread portfolio that is long stocks in the top quintile and short stocks in the bottom quintile earns 6.5% per year ($t$-statistic $=$ 4.18). The average return spread from equally-weighted portfolios is smaller, but still significant at 3.2% per year ($t$-statistic $=$ 3.49). For robustness, we follow Fama and French (1993) and compute a value-weighted portfolio return spread between stocks with top 30% and bottom 30% *FSE* (rather than top and bottom quintiles). The mean return is 5.3% per year and significant ($t$-statistic $=$ 3.98). Thus, it is unlikely that the higher returns on high-*FSE* stocks are driven by the portfolio sorting method. Overall, our evidence shows that *FSE*-based portfolio strategies are significantly profitable.[12]

To gauge whether the magnitudes of our empirical estimates of the fire sale risk premium are reasonable, we can compute the model-implied risk premium—i.e., the $\lambda_t^f$ in Eq. (1) and Corollary 1 of Appendix A. We assume i) $cov(F^-, r_M - c_M) = 0.0012$ which is the product of the pairwise correlation between the two variables ($= 0.23$, Panel A of Table 1), the standard deviation of the flow factor ($= 0.017 \times \sqrt{4}$), and the standard deviation of the market excess return ($= 0.154$, not tabulated); ii) $var(r_M - c_M) = 0.024$ which is the annualized sample variance of monthly excess market return (not tabulated); and iii) $\lambda_t = E(r_M - c_M - r_f) = 0.074$ which is the annualized sample mean of the monthly excess market return (not tabulated). This gives a model implied premium of $\lambda_t^f = (0.0012/0.024) \times 0.074 = 0.37\%$ per year. As a result, a one standard deviation increase in *FSE* ($= 17.98$ as reported in Panel C of Table 1) leads to an increase in the model-implied fire sale premium of $6.76\%(17.98 \times 0.0037)$, which is on the higher end of our empirical estimate of 3-7% per year;

[11] We select 4 lags as the bandwidth for Newey West because we find a marginally significant autocorrelation of monthly portfolio returns at lag 4, and no significant autocorrelation at shorter or longer lags. The results are similar using bandwidths of either 0, 5, or 8 lags.

[12] The predictive power of FSE for stocks returns is insignificant (not tabulated) when using value-weighted aggregate flows to estimate mutual funds' negative flow betas and stocks' FSE values, instead of using the principal component of flows. This is not surprising given that aggregate flows do not track either the true flow factor or flow commonality as closely as the first principal component (see Appendix B) and often misclassifies stocks (relative to PCA) as having top or bottom fire sale risk (not tabulated).

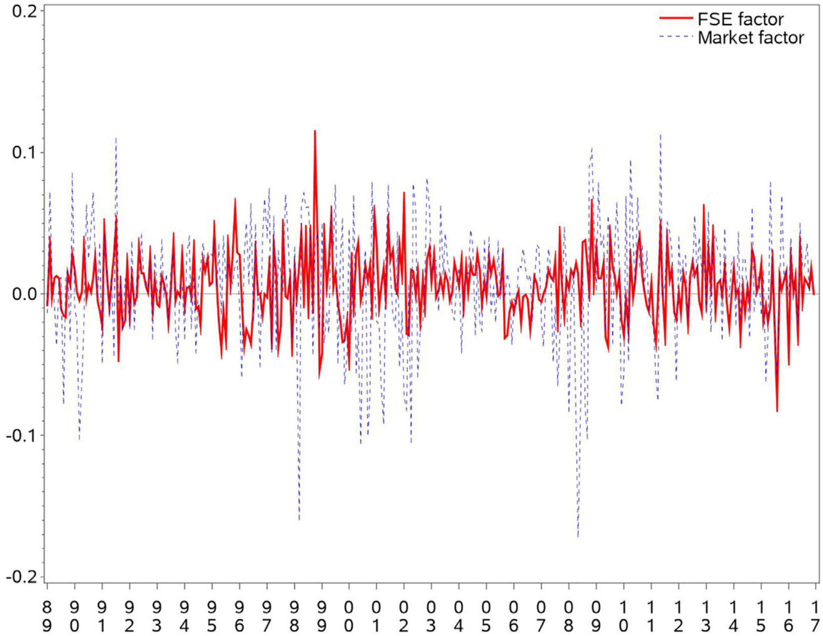



**Fig. 1.** Time-series of monthly high-minus-low *FSE* returns.
The figure plots the monthly returns on the high-minus-low *FSE* spread portfolio (solid line) and the market factor (dashed line) from June 1989 to May 2017. The high-minus-low *FSE* spread portfolio is long a portfolio of stocks in the top *FSE* quintile and short a portfolio of stocks in the bottom *FSE* quintile. Each portfolio is formed two months after each quarter and the weights are proportional to market value of equity. Only stocks with the closing price of at least $5 are included in the portfolio. The position is held for three months and is rebalanced every three months. A stock's *FSE* is the average negative flow beta ($\beta^-$) of mutual funds that own the stock with weights proportional to the number of shares that each mutual fund owns. A mutual fund's negative flow beta ($\beta^-$) is estimated from time-series regressions of fund flows on the negative and positive parts of the flow factor. The market factor is from Kenneth French's website and is the value-weighted return on all NYSE, AMEX, and NASDAQ stocks (from CRSP) minus the one-month Treasury bill rate. See Appendix C for additional details.

or using the interquartile range of *FSE* of 8.8 (Panel C of Table 1), the model-implied premium is 3.31% per year ($= 8.8 \times 0.0037$). Together, our model-implied estimates are within range of our empirical estimate of 3-7% per year.

If a stock's fire sale risk, measured by *FSE*, indeed measures its exposure to distressed selling during periods of distress, then the fire sale-risk strategy should earn negative returns during such periods. This is borne out in the data. Fig. 1 plots the time series of monthly returns on the spread portfolio. The return has a significant pairwise correlation of 0.20 ($p$ -value $= 0.00$) with the market factor (dashed line). Furthermore, cumulative monthly returns on the spread portfolio are $-4.0\%$ during 2002Q3 when the Dow Jones Industrial Average reached a four-year low following the tech bubble unraveling, $-5.7\%$ during 2011Q3 when Standard and Poor's rating agency downgraded U.S. sovereign debt, and $-1.5\%$ and $-6.3\%$ when Chinese stock markets experienced turbulence in 2015Q4 and 2016Q1. These quarters also coincide with negative realizations of the flow factor.

The portfolio analysis provides a simple way of estimating the economic magnitude of the impact of fire sale risk on the cross-section of stock returns. As we show, an *FSE*-based strategy earns significant returns of 3-7% per year. This would be altered in only a minor way by incorporating transaction costs associated with these portfolios. The quarterly turnover in the high and low *FSE* portfolios is about 33%. A round-trip trading cost of 1%—an estimate that includes explicit and implicit (e.g., price impact) costs—would then reduce the outperformance to a still significant 2.67-6.67%.[13] This strategy also does not use forward-looking information and, therefore, is implementable by a real-time investor.

Panel C of Table 2 reports average returns of portfolios sorted on fire purchase exposure (*FPE*), instead of fire sale exposure. In contrast to *FSE*, we find no evidence that *FPE* predicts higher stock returns. The average high-minus-low return spread is miniscule for equally-weighted portfolios (0.10% per year; $t$-statistic $= 0.082$). This evidence is consistent with investors being concerned about the risk of fire sales, but not fire purchases. This makes sense given that mutual funds are not required to purchase stocks when they receive new capital from fund investors and, thus, are less likely to engage in forced purchases of stocks. Furthermore, previous empirical studies suggest that liquidity premiums in the equity market are primarily due to concerns among investors about the impact of seller-initiated trades on prices, rather than buyer-initiated trades. For example, Brennan et al. (2012) estimate "Kyle's Lambda" for NYSE stocks and demonstrate that the illiquidity risks priced in cross-sectional expected returns result from sell orders, not buy orders. Similarly, Brennan, Huh and Subrahmanyam (2013) find that the

[13] Specifically, Keim and Madhavan (1997) report that total one-way trading costs for institutions, including price impact, are about 0.50%. Transaction costs are even lower over our sample period as indicated by the findings of Frazzini, Israel and Moskowitz (2018).

most significant risk premium for Amihud's illiquidity is earned on stocks where the order flows tend to cluster on the sell side on negative return days.[14]

The analysis so far focuses on average returns, without controlling for other sources of risk. To address this, we report equally and value-weighted adjusted portfolio returns in the final two columns of Panel B of Table 2. Adjusted returns are computed as the difference between the stock's monthly return and the return on its size, book-to-market, and momentum benchmark as defined by Daniel et al. (1997). As expected, the adjusted returns are lower than raw returns for each quintile. Importantly, consistent with our raw return results, adjusted returns increase monotonically with fire sale exposure. Value-weighted portfolios of stocks in the highest *FSE* quintile outperform their size, value, and momentum benchmarks by 1.9% per year, while stocks in the lowest *FSE* underperform with adjusted returns of -2.3%. Together, the long-short spread portfolio outperforms its benchmark by 4.2% per year on a value-weighted basis ($t$ -statistic = 4.14); for equally-weighted portfolios, the return spread is 2.6% and also significant ($t$-statistic = 3.96). Also, as shown in the final two columns of Panel C, the adjusted returns on *FPE* portfolios are indistinguishable from zero. This confirms our earlier findings for raw returns that fire sale risk matters, but fire purchase risk does not.

We further control for the predictive power of other stock characteristics using a two-way sorting procedure. Specifically, we group stocks into 25 independently double-sorted portfolios based on their *FSE* and one of the following characteristics: market capitalization, book-to-market ratio, past one-year return, and mutual fund ownership. We choose these characteristics to align with the size, value, and momentum benchmarks of Daniel et al. (1997), and because *FSE* is correlated with ownership (Panel C of Table 1). Table 3 shows the annualized average return on the long-short *FSE* portfolio for each characteristic quintile. The positive and significant *FSE* return spread shown in Table 2 is generally robust across quintiles for each characteristic. For example, in Panel A, the mean return has a positive sign in every subportfolio and a $t$-statistic larger than two in 12 of the 25 subportfolios. The results in Panel B for equally portfolios are similar; however, as in the univariate sorts, the magnitudes are smaller. In sum, our findings from DGTW-adjusted returns and the two-way sorting analysis indicate that the predictive power of *FSE* is not subsumed by stock characteristics.

Finally, we adjust for risk using time series regressions of monthly returns on the high-minus-low *FSE* portfolio against a host of stock market benchmarks, including Carhart's 1997 four factors, the tradable liquidity factor of Pástor and Stambaugh (2003, denoted LIQ), the betting-against-beta factor of Frazzini and Pedersen (2014, denoted BAB), the mutual fund market beta factor of Boguth and Simutin (2018, denoted MFB), and coskewness (Harvey and Siddique, 2000) and downside risk (Ang et al., 2006) factors. Details for the construction of these factors are provided in Appendix C. We choose these factors to address concerns that our fire sale risk measure is picking up other risk measures known to predict average returns.

Table 4 reports the factor loadings and annualized alphas (i.e., 12 times the regression intercept) from regressions of the monthly returns on the *FSE* spread portfolio. Panel A shows that many benchmarks have explanatory power for value-weighted spread returns. Column (1) shows that the *FSE* spread portfolio loads positively on the equity market benchmark (coef. = 0.106; $t$-statistic = 3.24) and that this specification has an adjusted R-squared of 3.8%. The spread portfolio also shows a tilt towards small market capitalization stocks (SMB), stocks with market liquidity risk (LIQ), stocks with funding liquidity risk (MFB), and stocks with greater downside risk (DOWNSIDE). Column (11) shows that only downside risk is significant in a "kitchen-sink" specification that includes most of the other benchmarks. Importantly, the alphas on the *FSE* spread

**Table 3**
Two-way sorts: *FSE* versus other characteristics.
Stocks are double-sorted (independently) according to historical *FSE* and one other stock characteristic at the end of the quarter, and portfolios are formed two months later. The other stock characteristic is either B/M (book-to-market ratio), size (market capitalization), past one-year return, and mutual fund ownership. The table shows returns on the trading strategy of buying stocks in the top *FSE* quintile and short-selling stocks in the bottom *FSE* quintile, for each quintile of the other characteristic. The numbers in parentheses are $t$-statistics based on Newey-West standard errors with 4 lags. Only stocks with a closing price of at least $5 are included in the portfolio. The two-way quintile portfolios are either value-weighted according to stock market capitalization (Panel A) or equally-weighted (Panel B). The position is held for three months and rebalanced every three months. All variables are defined in Appendix C. The return period is from June 1989 to May 2017.

| | Stock characteristics quintile portfolios | | | |
|---|---|---|---|---|
| | B/M | Size | Past 1-yr return | ownership |
| Panel A: Value-weighted returns | | | | |
| Low | 0.083 | 0.037 | 0.066 | 0.081 |
| | (3.076) | (2.944) | (2.297) | (3.229) |
| 2 | 0.053 | 0.037 | 0.022 | 0.029 |
| | (2.559) | (2.325) | (0.939) | (1.101) |
| 3 | 0.021 | 0.016 | 0.061 | 0.023 |
| | (1.205) | (1.038) | (2.753) | (0.951) |
| 4 | 0.061 | 0.042 | 0.040 | 0.048 |
| | (3.106) | (1.841) | (2.055) | (2.192) |
| High | 0.008 | 0.053 | 0.095 | 0.086 |
| | (0.349) | (1.271) | (3.808) | (2.735) |
| Panel B: Equally-weighted returns | | | | |
| Low | 0.049 | 0.028 | 0.031 | 0.054 |
| | (2.674) | (2.667) | (1.843) | (2.323) |
| 2 | 0.064 | 0.028 | 0.032 | 0.019 |
| | (3.982) | (1.858) | (2.629) | (1.505) |
| 3 | 0.038 | 0.021 | 0.012 | 0.025 |
| | (2.521) | (1.271) | (1.028) | (1.748) |
| 4 | 0.019 | 0.042 | 0.011 | 0.034 |
| | (1.592) | (1.941) | (0.858) | (2.379) |
| High | 0.013 | 0.022 | 0.069 | 0.025 |
| | (1.034) | (0.597) | (4.065) | (1.466) |

[14] We also find no evidence of predictability when sorting stocks based on the ownership-weighted average flow betas of mutual funds when flow betas are computed from a single beta with respect to the value-weighted aggregate flows, rather than negative flow betas with respect to the principal component (not tabulated). This is not surprising given that a stock's exposure to fire purchase risk (FPE) is not a significant predictor of its returns (Panel C of Table 2) and a fund's single flow beta does not differentiate between negative and positive flow betas.

**Table 4**
High-minus-low *FSE* returns: Time series regressions.
The table shows coefficient estimates and t-statistics (in parentheses) of time-series regressions of monthly high-minus-low returns on factors. Alphas are regression intercepts and are annualized (i.e., monthly estimates multiplied by 12). High-minus-low returns are returns on the trading strategy of buying stocks in the top *FSE* quintile and short selling the stocks in the bottom *FSE* quintile. See Appendix C for additional details. The portfolio is either value-weighted (Panel A) or equal-weighted (Panel B). The factors include Fama and French's (1992) three factors (MKT, SMB, and HML), Carhart's (1997) momentum factor (MOM), Pástor and Stambaugh's (2003) tradable liquidity factor (LIQ), the betting-against-beta factor (BAB), mutual funds' market beta (MFB), coskewness (COSKEW), and downside risk (DOWNSIDE). BAB is suggested by Frazzini and Pedersen (2014) and available on Andrea Frazzini's website. MFB is the change in the value-weighted average of CAPM beta of all equity mutual funds as suggested by Boguth and Simutin (2018). COSKEW is the return on a trading strategy that buys the top 30% and short sells the bottom 30% of stocks in terms of coskewness. DOWNSIDE is the return on a trading strategy that buys the top 30% and short sells the bottom 30% of stocks in terms of the loading on the negative part of the value-weighted return on all NYSE, AMEX, and NASDAQ stocks (from CRSP). See Harvey and Siddique (2000) and Ang, Chen and Xing (2006) for details about coskewness and downside risk, respectively. Standard errors are Newey-West standard errors with 4 lags. The sample period is from June 1989 to May 2017.

Panel A: Monthly value-weighted High-Low *FSE* quintile returns

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| alpha | 0.057 | 0.056 | 0.057 | 0.054 | 0.053 | 0.052 | 0.054 | 0.054 | 0.054 | 0.054 | 0.049 |
| | (3.457) | (3.424) | (3.390) | (3.214) | (2.912) | (2.979) | (2.810) | (3.117) | (2.842) | (3.288) | (2.532) |
| MKT | 0.106 | 0.090 | 0.088 | 0.082 | 0.084 | 0.096 | 0.093 | 0.087 | 0.088 | -0.003 | -0.007 |
| | (3.244) | (2.590) | (2.314) | (2.160) | (2.240) | (2.411) | (2.388) | (2.097) | (2.151) | (-0.085) | (-0.187) |
| HML | | 0.020 | 0.018 | 0.022 | 0.012 | -0.025 | -0.017 | 0.003 | -0.001 | 0.028 | -0.007 |
| | | (0.379) | (0.331) | (0.421) | (0.238) | (-0.440) | (-0.325) | (0.050) | (-0.014) | (0.470) | (-0.137) |
| SMB | | 0.112 | 0.112 | 0.113 | 0.114 | 0.127 | 0.127 | 0.118 | 0.118 | 0.086 | 0.088 |
| | | (1.834) | (1.848) | (1.897) | (1.894) | (2.027) | (1.989) | (1.885) | (1.865) | (1.368) | (1.422) |
| MOM | | | -0.006 | -0.009 | -0.013 | -0.022 | -0.017 | -0.008 | -0.010 | 0.015 | 0.004 |
| | | | (-0.180) | (-0.282) | (-0.357) | (-0.693) | (-0.464) | (-0.237) | (-0.267) | (0.423) | (0.102) |
| LIQ | | | | 0.062 | 0.061 | 0.065 | 0.067 | 0.057 | 0.056 | 0.038 | 0.028 |
| | | | | (1.812) | (1.812) | (1.847) | (1.968) | (1.738) | (1.745) | (1.018) | (0.764) |
| BAB | | | | | 0.016 | | -0.027 | | 0.009 | | 0.062 |
| | | | | | (0.321) | | (-0.452) | | (0.168) | | (1.024) |
| MFB | | | | | | 0.092 | 0.107 | | | | |
| | | | | | | (1.693) | (1.694) | | | | |
| COSKEW | | | | | | | | 0.059 | 0.056 | | |
| | | | | | | | | (0.760) | (0.684) | | |
| DOWNSIDE | | | | | | | | | | 0.130 | 0.150 |
| | | | | | | | | | | (3.354) | (3.245) |
| $R^2$ | 0.041 | 0.064 | 0.064 | 0.074 | 0.075 | 0.093 | 0.094 | 0.077 | 0.077 | 0.107 | 0.114 |
| Adjusted $R^2$ | 0.038 | 0.055 | 0.053 | 0.060 | 0.058 | 0.076 | 0.074 | 0.060 | 0.057 | 0.090 | 0.095 |

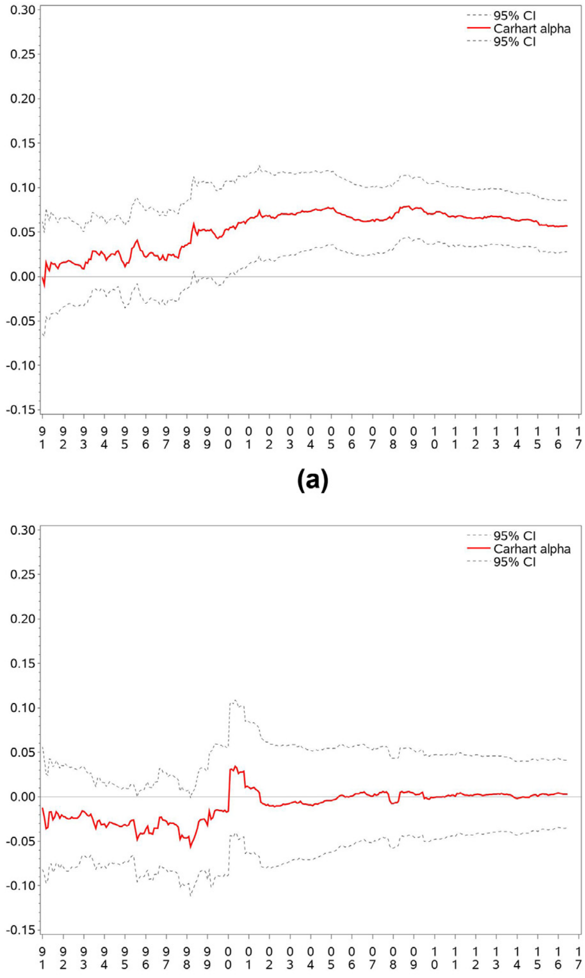
Panel B: Monthly equal-weighted High-Low *FSE* quintile returns

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| alpha | 0.029 | 0.028 | 0.027 | 0.027 | 0.021 | 0.026 | 0.024 | 0.027 | 0.022 | 0.027 | 0.021 |
| | (3.177) | (3.063) | (2.727) | (2.626) | (1.973) | (2.705) | (2.268) | (2.666) | (2.051) | (2.630) | (1.879) |
| MKT | 0.034 | 0.040 | 0.041 | 0.040 | 0.050 | 0.054 | 0.056 | 0.046 | 0.053 | 0.042 | 0.037 |
| | (1.195) | (1.427) | (1.336) | (1.282) | (1.609) | (1.581) | (1.649) | (1.278) | (1.506) | (1.087) | (0.978) |
| HML | | 0.056 | 0.057 | 0.058 | 0.018 | -0.005 | -0.012 | 0.034 | 0.006 | 0.058 | 0.015 |
| | | (1.364) | (1.486) | (1.515) | (0.562) | (-0.129) | (-0.352) | (0.816) | (0.172) | (1.348) | (0.430) |
| SMB | | 0.010 | 0.010 | 0.010 | 0.016 | 0.021 | 0.022 | 0.016 | 0.020 | 0.010 | 0.012 |
| | | (0.235) | (0.227) | (0.228) | (0.392) | (0.516) | (0.539) | (0.383) | (0.483) | (0.233) | (0.293) |
| MOM | | | 0.004 | 0.004 | -0.013 | -0.006 | -0.011 | 0.005 | -0.011 | 0.003 | -0.011 |
| | | | (0.165) | (0.144) | (-0.463) | (-0.226) | (-0.396) | (0.191) | (-0.376) | (0.113) | (-0.370) |
| LIQ | | | | 0.011 | 0.004 | 0.002 | 0.001 | 0.004 | 0.000 | 0.012 | 0.000 |
| | | | | (0.437) | (0.165) | (0.105) | (0.033) | (0.162) | (0.006) | (0.449) | (-0.012) |
| BAB | | | | | 0.069 | | 0.025 | | 0.062 | | 0.075 |
| | | | | | (2.252) | | (0.747) | | (2.121) | | (2.317) |
| MFB | | | | | | 0.123 | 0.108 | | | | |
| | | | | | | (3.430) | (2.472) | | | | |
| COSKEW | | | | | | | | 0.075 | 0.050 | | |
| | | | | | | | | (1.716) | (1.241) | | |
| DOWNSIDE | | | | | | | | | | -0.003 | 0.021 |
| | | | | | | | | | | (-0.119) | (0.899) |
| $R^2$ | 0.011 | 0.024 | 0.025 | 0.025 | 0.050 | 0.079 | 0.082 | 0.035 | 0.054 | 0.025 | 0.052 |
| Adjusted $R^2$ | 0.008 | 0.015 | 0.013 | 0.011 | 0.033 | 0.062 | 0.062 | 0.018 | 0.034 | 0.008 | 0.032 |

portfolios are positive and significant across all models; the magnitudes range from 4.9% to 5.7% per year and the *t*-statistics range from 2.53 to 3.46.

Panel B of Table 4 shows the results for equally-weighted *FSE* spread portfolio. Compared to value-weighted portfolios, the benchmark factors explain less of the variation in *FSE* spread returns. In addition, the equally-weighted alphas are smaller in magnitude, but are nonetheless positive and significant across models and range from 2.1% to 2.9% per year. Overall, the evidence further shows that the positive return premium associated with fire sale exposure is robust to the choice of benchmark model; *FSE* captures a novel component of the cross-sectional variation in stock returns.

The results in Table 4 show alphas of *FSE*-sorted portfolios over the entire sample period. However, we would expect fire sale risk to matter more during the latter part of our sample period when the mutual fund industry is




(a)

(b)

**Fig. 2.** Expanding window estimates of high-minus-low alphas.
Panel A plots the alpha (annualized) and the 95% confidence interval of a trading strategy that is long a portfolio of stocks in the top quintile of *FSE* and is short a portfolio of stocks in the bottom quintile of *FSE*. Panel B plots the alpha for the same trading strategy based on the top and bottom quintile of *FPE*. See Appendix C for additional details. Given a time-series of returns on the trading strategy, alpha is defined as the estimated intercept from regressions of monthly high-minus-low portfolio returns on the Carhart (1997) four factors. The alpha is estimated in each month from December 1991 to May 2017 using the time-series of the returns up to that month (recursive estimation).

much larger and has a larger footprint in equity markets. Panel A of Figure 2 plots the recursively-estimated alpha of the *FSE* spread portfolio for each month in our sample. For example, the first observation in the plot is the estimated alpha from using the 31 monthly portfolio return observations from June 1989 up to December 1991, while the second observation uses the 32 monthly observations from June 1989 up to January 1992, and so on. The final observation in the plot uses the entire sample period and, therefore, is the same as the Carhart (1997) alpha of 5.7% reported in Column (3) of Table 4 Panel A. Fig. 2 shows that the *FSE* alpha is larger and more significant in 1998 and afterwards; before 1998, we do not find a significant return spread related to fire sale exposure. This suggests that investors care more about fire sale risk (and, hence, require a higher risk premium) in the latter part of the sample, when mutual funds have a large impact on financial markets. Finally, consistent with our Table 2 evidence, we find no evidence of a significant return premium associated with *FPE* (Panel B of Fig. 2). We now see that this result holds throughout our sample period.

## 4. Additional tests

In this section, we provide additional analysis and discussion to highlight the significance of our main result on the impact of fire sale exposure on the cross-section of stock returns.

### 4.1. Fama and MacBeth (1973) regressions

To further assess the significance of our main results from the portfolio-level analysis, we examine how individual stock returns are related to fire sale exposure. We follow Fama and MacBeth (1973) and run the following cross-sectional regression of quarterly stock returns for each quarter $q$ of our sample:

$$R_{i,q} = \alpha_q + \beta_q FSE_{i,q-1} + \theta_q' \mathbf{X}_{i,q-1} + \epsilon_{i,q} \tag{4}$$

where $X_{i,q-1}$ is a vector of stock characteristics at the end of quarter $q$-1, $FSE_{i,q-1}$ is the fire sale exposure of stock $i$ at the end of quarter $q$-1, and $R_{i,q}$ is the cumulative return of stock $i$ over the three months following $q$-1 in excess of the cumulative return of the CRSP value-weighted stock index. To be consistent with our portfolio-level results in Section 3, we skip two months following each quarter-end before computing cumulative returns. For example, we estimate whether stock $i$'s *FSE* and other characteristics at the end of December in 2000 can predict stock $i$'s cumulative return over March, April, and May in 2001. From parameter $\beta$ of this regression we can infer the return relation between fire sale exposure and future stock returns.

Table 5 reports the averages and $t$-statistics of the 112 sets of coefficients obtained by estimating Eq. (4) every quarter in our sample from 1989Q1 to 2016Q4. Standard errors are adjusted by the Newey-West method. Consistent with our portfolio-level results, we find a positive and significant relation between *FSE* and future stock returns. For example, the specification in Column (4) shows that a one standard deviation higher measure of *FSE* predicts higher stock returns of 0.32% over the following quarter ($= 0.018\% \times 17.98$). Past one-year stock return and the liquidity beta using Sadka's 2006 fixed-temporary liquidity measure are also positive and significant in some specifications; however, *FSE* is the only variable that is significant across all specifications.

### 4.2. Panel regressions with stock fixed effects

Our fire sale risk measure depends on a stock's ownership linkages to mutual funds and their negative flow betas as shown in Eq. (3). Since a mutual fund's flow beta and its stock portfolio can both change over time, so can a

**Table 5**
Stock-level regressions: Fama-MacBeth approach.
The table shows results from stock-level, cross-sectional regressions of quarterly excess stock returns on lagged independent variables. The cross-sectional regression is run every quarter. The dependent variable is a stock's cumulative return over the three months following each quarter-end, in excess of the cumulative return of the CRSP value-weighted stock index. Consistent with our analysis of portfolio returns, we skip two months following each quarter-end before computing cumulative returns. The table reports the averages of the coefficients obtained by estimating the regression every quarter in our sample. *t*-statistics are reported in parentheses. Standard errors are Newey-West standard errors with 4 lags. The sample period is from June 1989 to May 2017. All variables are defined in Appendix C.

| | Future market-adjusted returns over 3 months (%) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| FSE | | 0.021 | 0.019 | 0.018 | 0.010 | 0.009 |
| | | (2.362) | (2.211) | (2.082) | (0.940) | (0.831) |
| FSE × High ownership | | | | | 0.042 | 0.043 |
| | | | | | (2.932) | (2.958) |
| Book-to-market ratio | 0.023 | 0.029 | 0.035 | 0.020 | 0.035 | 0.020 |
| | (0.074) | (0.092) | (0.114) | (0.065) | (0.113) | (0.067) |
| Past one-year return (%) | 0.006 | 0.006 | 0.009 | 0.009 | 0.009 | 0.009 |
| | (1.101) | (1.304) | (2.292) | (2.484) | (2.037) | (2.501) |
| Log market cap | -0.113 | -0.104 | -0.105 | -0.106 | -0.103 | -0.104 |
| | (-0.888) | (-0.709) | (-0.791) | (-0.800) | (-0.919) | (-0.794) |
| Change in breadth | 0.242 | 0.268 | 0.292 | 0.274 | 0.289 | 0.271 |
| | (0.945) | (0.952) | (1.222) | (1.126) | (1.618) | (1.114) |
| Ownership (%) | 0.000 | -0.002 | -0.005 | -0.002 | -0.016 | -0.014 |
| | (-0.014) | (-0.120) | (-0.301) | (-0.142) | (-1.103) | (-0.863) |
| Return two-month (%) | 0.012 | 0.010 | 0.009 | 0.010 | 0.009 | 0.010 |
| | (1.045) | (0.874) | (0.828) | (0.893) | (0.854) | (0.892) |
| Stock market beta | | 0.134 | 0.220 | 0.212 | 0.214 | 0.205 |
| | | (0.385) | (0.547) | (0.548) | (0.582) | (0.531) |
| Amihud illiquidity | | 0.062 | | | | |
| | | (0.726) | | | | |
| Liq beta (PS-tradable) | | | -0.121 | | -0.120 | |
| | | | (-0.373) | | (-0.381) | |
| Liq beta (Sadka-FT) | | | | 0.017 | | 0.017 |
| | | | | (1.705) | | (1.696) |
| Liq beta (Sadka-VP) | | | | -0.008 | | -0.008 |
| | | | | (-0.237) | | (-0.238) |
| Average adjusted $R^2$ | 0.037 | 0.047 | 0.052 | 0.049 | 0.053 | 0.050 |

stock's *FSE*. We exploit this time variation in *FSE* using the following panel regression with stock fixed effects:

$$R_{i,q} = \alpha_i + \beta FSE_{i,q-1} + \theta' \mathbf{X}_{i,q-1} + \epsilon_{i,q} \quad (5)$$

where $R_{i,q}$ is the cumulative return of stock $i$ over the three months following $q$-1 in excess of the cumulative return of the CRSP value-weighted stock index, $FSE_{i,q-1}$ is the fire sale exposure of stock $i$ at the end of quarter $q$-1, $X_{i,q-1}$ is a vector of observable stock characteristics at the end of quarter $q$-1, and $\alpha_i$ are stock fixed effects. As previously mentioned, we continue to follow a "skip-two-months" strategy and compute $R_{i,q}$ as the cumulative three-month return starting at the end of the second month following quarter $q$.

The results from estimating Eq. (5) are shown in Table 6. Standard errors account for heteroskedasticity and are clustered at the calendar quarter level. Consistent with our earlier results, *FSE* is a positive and significant predictor of stock returns. The coefficient on *FSE* is about 0.04; hence, a one standard deviation increase in *FSE* predicts higher stock returns of 0.72% per quarter (= 0.04% × 17.98). This result goes above and beyond the returns on stocks with similar observable characteristics, and any time-invariant, unobservable characteristics due to the presence of stock fixed effects.

Table 6 also shows that many control variables are significant in a way that is consistent with prior work: stock returns are higher among stocks with higher book-to-market values, stocks with smaller market capitalization, and stocks with greater institutional ownership.[15] In addition, our evidence is consistent with Frazzini and Pedersen's (2014) finding of a negative relation between market beta and stock returns, and Sadka's (2006) finding that loadings on the variable-permanent factor have a positive relationship with returns. Importantly, the predictive power of *FSE* is not subsumed by these other variables.[16]

### 4.3. Fire sale risk and mutual fund ownership

As discussed above, we compute a stock's fire sale exposure (*FSE*) by weighting the fund flow betas of its mu-

[15] See, e.g., Gompers and Metrick (2001), Nagel (2005), Sias, Starks and Titman (2006), Boehmer and Kelley (2009), and Koch, Ruenzi and Starks (2016) for evidence linking institutional ownership and stock returns.

[16] In Tables 5 and 6, we also follow Ang, Chen and Xing (2006) and include stocks' upside and downside betas with respect to the market and liquidity risk factors (asymmetric loadings on the market and liquidity risk factors). The results (not tabulated) show that FSE remains a positive and significant predictor of stock returns even after allowing for asymmetric loadings on these risk factors.

**Table 6**
Panel regressions with stock fixed effects.
The table shows coefficient estimates and $t$-statistics (in parentheses) of panel regressions of quarterly excess stock returns (returns in excess of the market returns) on lagged independent variables as listed in the first column. The dependent variable is the cumulative return of a stock over the three months following each quarter-end, in excess of the cumulative return of the CRSP value-weighted stock index. Consistent with our analysis of portfolio returns, we skip two months following each quarter-end before computing cumulative returns. All regressions include stock fixed effects. Standard errors are clustered by time. All variables are defined in Appendix C. The sample period is from June 1989 to May 2017.

| | Future market-adjusted returns over 3 months (%) | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| FSE | | 0.041 | 0.043 | 0.043 | 0.036 | 0.037 |
| | | (3.670) | (3.762) | (3.808) | (3.025) | (3.043) |
| FSE × High ownership | | | | | 0.035 | 0.034 |
| | | | | | (2.258) | (2.213) |
| Book-to-market ratio | 0.593 | 0.656 | 0.567 | 0.624 | 0.558 | 0.657 |
| | (2.064) | (2.040) | (2.002) | (2.016) | (1.973) | (2.176) |
| Past one-year return (%) | 0.003 | 0.004 | 0.003 | 0.004 | 0.003 | 0.004 |
| | (0.594) | (0.692) | (0.586) | (0.688) | (0.593) | (0.688) |
| Log market cap | -3.955 | -3.877 | -3.918 | -4.033 | -3.921 | -4.127 |
| | (-12.629) | (-11.999) | (-12.620) | (-12.301) | (-12.629) | (-12.260) |
| Change in breadth | 0.138 | 0.062 | 0.127 | 0.151 | 0.123 | 0.118 |
| | (0.475) | (0.197) | (0.435) | (0.481) | (0.424) | (0.379) |
| Ownership (%) | 0.061 | 0.052 | 0.054 | 0.047 | 0.047 | 0.042 |
| | (2.419) | (2.008) | (2.122) | (1.765) | (1.836) | (1.555) |
| Return two-month (%) | 0.005 | -0.004 | 0.004 | 0.009 | 0.004 | 0.005 |
| | (0.234) | (-0.182) | (0.188) | (0.366) | (0.181) | (0.223) |
| Stock market beta | -0.457 | -0.398 | -0.413 | -0.471 | -0.418 | -0.456 |
| | (-1.242) | (-1.070) | (-1.136) | (-1.224) | (-1.151) | (-1.118) |
| Amihud illiquidity | | -0.007 | | | | |
| | | (-0.084) | | | | |
| Liq beta (PS-tradable) | | | 0.301 | | 0.308 | |
| | | | (1.090) | | (1.115) | |
| Liq beta (Sadka-FT) | | | | 0.003 | | 0.003 |
| | | | | (0.619) | | (0.564) |
| Liq beta (Sadka-VP) | | | | 0.025 | | 0.034 |
| | | | | (1.054) | | (0.714) |
| Adjusted $R^2$ | 0.016 | 0.017 | 0.017 | 0.018 | 0.017 | 0.018 |

tual fund owners by the fund's share of total mutual fund holdings. A natural question is whether there is a positive interaction between *FSE* and mutual funds' total share of shares outstanding. In other words, does the exposure of the stock to mutual fund fire sales matter more when more of the stock's holders are mutual funds? To test, we run the following cross-sectional regression of quarterly stock returns for each quarter $q$ of our sample:

$$R_{i,q} = \alpha_q + \beta_q FSE_{i,q-1} + \gamma_q FSE_{i,q-1} \times High\ ownership_{i,q-1} + \theta_q' \mathbf{X}_{i,q-1} + \epsilon_{i,q}$$

where High ownership is a dummy variable that equals one if the mutual fund ownership of stock $i$ (ownership) is above the sample median. We can infer the *FSE*–return relation for stocks with low mutual fund ownership from parameter $\beta$. From $\gamma$, we can infer the incremental effect that high mutual fund ownership has on this relation. The remaining variables are the same as those in Eq. (4).

Columns (5) and (6) of Table 5 show that $\gamma$ is positive and significant, indicating that the predictive power of *FSE* for stock returns is significantly greater among stocks with greater mutual fund ownership. This shows that the exposure of a stock to the fire sales of its mutual fund owners matters more when mutual funds own more of the stock. Strikingly, *FSE* is not significant after including the interaction variable, indicating that only stocks with high mutual fund ownership earn a fire sale risk premium ex ante. Also, Columns (5) and (6) of Table 6 show the results after incorporating the interaction variable into our panel regression framework with stock fixed effects. Once again, the coefficient on the interaction variable is positive and significant, indicating that a stock's exposure to fire sale risk matters more when mutual funds represent a larger share of its owners. In the panel regression, *FSE* is still significant after including the interaction variable.

Our evidence on the interaction between *FSE* and mutual fund ownership can also be related to Greenwood and Thesmar's 2011 stock price fragility measure. Assuming a factor structure for fund flows as in Eq. (2) and that a fund's negative flow beta equals its positive flow beta (i.e., $\beta_k^- = \beta_k^+$), we can show that:

$$G_{i,t} = \underbrace{\left(FSE_{i,t} \times Ownership_{i,t}\right)^2 \times Var_t(F_{t+1})}_{\text{systematic flow volatility}} + \underbrace{\sum_{k=1}^{K_{i,t}} \left(\frac{shr_{i,k,t}}{SharesOutstanding_{i,t}}\right)^2 \times Var_t(e_{k,t+1})}_{\text{non-systematic flow volatility}}$$

where $G_{i,t}$ is the Greenwood and Thesmar (2011) fragility measure of stock $i$ in time $t$ (their Eq. (8)), $Ownership_i$ is the fraction of $SharesOutstanding_i$ held by all mutual funds,

$shr_{i,k}$ is the number of shares of stock $i$ held by mutual fund $k$, $K_i$ is the number of mutual fund owners of stock $i$, and $Var(F)$ and $Var(e_k)$ are the volatilities of the flow factor and fund-specific flows (assumed to be independently and identically distributed across funds), respectively. The first term relates to systematic flow volatility and shows that fragility is greater among high *FSE* stocks, especially those with greater mutual fund ownership. Our evidence therefore shows that the component of fragility related to systematic flow volatility positively predicts stock returns.[17]

### 4.4. Alternative story: Fire sale risk or managerial skill?

A potential alternative explanation is that managers of funds with larger negative fund flow beta (i.e., $\beta^-$) have greater stock selection skill. Hence, stocks with a lot of ownership by such managers (i.e., high *FSE* stocks) subsequently earn higher returns because they are undervalued, not because they earn a risk premium from their exposure to fire sale risk. Under this scenario, we should observe a positive relationship between mutual funds' $\beta^-$ and measures of manager skill.

We address this hypothesis in two ways. First, Panel B of Table 1 shows that the correlation between negative flow beta and fund size, while statistically significant, is nearly zero. In contrast, the alternative "skill" hypothesis would have predicted a meaningful positive correlation between negative flow beta and size to the extent that fund size is a sufficient metric of manager skill (e.g., Berk and Van Binsbergen, 2015). Second, we estimate the following panel regression of quarterly fund performance:

$$Perf_{k,q} = \alpha + \theta_1 \beta^-_{k,q-1} + \theta_2 TopFSE_{k,q-1} + \gamma' \mathbf{X}_{k,q-1} + \varphi' \mathbf{Z}_q + \epsilon_{k,q-1} \tag{6}$$

where $Perf_{k,q}$ is a measure of fund $k$'s portfolio performance during quarter $q$, $\beta^-_{k,q-1}$ is the quarter $q$-1 estimate of fund $k$ 's negative flow beta, $TopFSE_{k,q-1}$ is fund $k$'s portfolio weight in top quintile *FSE* stocks at the end of $q$-1, $X$ is a vector of control variables, and $Z$ is a vector of aggregate variables, such as the Carhart's (1997) four factors and Pástor and Stambaugh's (2003) tradeable liquidity factor. Standard errors account for heteroskedasticity and are clustered at the quarter level.

All control variables in $X$ in Eq. (6) are measured at the end of quarter $q$-1 and include fund $k$'s positive flow beta, portfolio size, age, expense ratio, net flow, family TNA, and portfolio exposures to the Carhart (1997) benchmarks. Controlling for *TopFSE* is important because *FSE* predicts higher stock returns (Tables 2–6) and is directly related to the negative flow betas of a stock's mutual fund owners (Eq. (3)). Our performance measure is either a fund's raw return in excess of the one-month Treasury bill yield, or the fund's Carhart (1997) alpha. A finding $\theta_1 > 0$ would imply that fund managers with higher negative flow betas tend to outperform, over and above their greater exposure to high-*FSE* stocks, and lend support to the alternative hypothesis.

The results are presented in Table 7 and are contrary to the alternative hypothesis. We find no evidence that negative flow betas can predict better future fund performance.[18] The coefficient on $\beta^-$ is positive, but not significant with $t$-statistics ranging from 0.81 to 1.44. This "non-result" holds whether we use excess returns or alpha to measure fund performance, and whether fund fixed effects are included or not. The results for other control variables presented in Table 7 are in line with prior work. For example, fund performance is significantly lower among larger funds (Chen et al., 2004) and, consistent with our earlier findings for stock returns, a fund's exposure to *FSE* stocks is predictive of higher fund returns. The negative relationship between past fund returns and negative flow betas (Ferson and Kim, 2012) also suggests that high FSE stocks are unlikely to be those held by past winner funds that attract investor flows and subsequently boost prices via flow-induced stock purchases (Lou, 2012).

In summary, our analysis indicates that a fund's negative flow beta does not significantly predict its portfolio performance beyond its exposure to top-*FSE* stocks. This finding suggests that the predictive power of *FSE* for stock returns is unlikely to be influenced by ownership patterns of fund managers with stock selection skills. This finding also contradicts the alternative "skill" hypothesis that funds with high negative flow beta are more skilled than other funds, and that high FSE stocks earn higher returns because they are undervalued, rather than due to a fire sale risk premium. These results support our interpretation that high FSE stocks earn a risk premium because of their greater exposure to fire sales.

### 4.5. FSE shocks around S&P 500 inclusion events

Our evidence on the positive cross-sectional relation between stock returns and *FSE* supports our proposition that, over time, expected fire sale risk positively affects expected stock returns. By the same token, an unexpected increase in a stock's fire sale exposure should be accompanied with lower contemporaneous stock prices. This is because an increase in fire sale exposure raises expected stock returns and lowers stock prices (assuming no relation between cash flows and fire sale risk). We now study the contemporaneous relation between stock returns and shocks to fire sale risk by investigating a specific channel that could result in unexpected changes in a stock's fire sale exposure: S&P 500 Index inclusion.

Inclusion of a stock into the S&P 500 Index is typically associated with significant announcement date capital gains for firm shareholders. This upward price pressure has been attributed to a subsequent shift in demand for

[17] To derive the decomposition, start with the fragility measure, $G_{i,t} = (\frac{1}{\theta_{i,t}})^2 W'_{i,t} \Omega_{t+1} W_{i,t}$ where $\theta_i$ is the market capitalization of stock i, $W_i$ is the vector of weight $w_{i,k}$ of stock $i$ in mutual fund $k$'s portfolio, and $\Omega$ is the variance-covariance matrix of mutual funds' dollar flows. A typical element of $\Omega$ is $cov(\omega_k, \omega_l)$ where $\omega_k = a_k f_k$ and $a_k$ is fund $k$'s total assets under management, and $f_k = \frac{\omega_k}{a_k}$ follows a factor structure, $f_{k,t+1} = \alpha_k + \beta_k F_{t+1} + e_{k,t+1}$. Finally, use the equality $\frac{w_{i,k} a_k}{\theta_i} = \frac{shr_{i,k}}{\sum_{k=1}^{K_i} shr_{i,k}} \times Ownership_i$ and Eq. (3).

[18] The high R-squared values in Columns (1) and (2) are attributable to the market factor (MKT).

**Table 7**
Fund performance and the alternative skill hypothesis.
The table shows the coefficient estimates and *t*-statistics (in parentheses) from panel regressions of quarterly fund performance on lagged fund characteristics. The unit of observation is fund-quarter. Fund performance is either a fund's quarterly raw return in excess of the one-month Treasury bill yield (Panel A), or the fund's quarterly Carhart (1997) four-factor alpha (Panel B). Carhart (1997) alpha is estimated as the difference between the fund's quarterly excess return and the loadings on the four factors multiplied by the corresponding quarterly factor returns. The factor loadings are estimated over the prior 36 months. The key independent variable is the fund's negative flow beta. Control variables include the sum of weights of the stocks that are in the top quintile of *FSE* (Top *FSE* weight), the fund's positive flow beta, portfolio size, fund age, expense ratio, net flow, family size, the fund's loadings on the Carhart (1997) four factors, and contemporaneous aggregate variables, such as the Carhart's four factors and Pástor and Stambaugh's (2003) tradable liquidity factor. All variables are defined in Appendix C. Regressions (2) and (4) include fund fixed effects. Standard errors are clustered by time. The sample period covers 1989Q1–2017Q1.

| | Panel A | | Panel B | |
|---|---|---|---|---|
| | Excess returns (%) | | Carhart alpha (%) | |
| | (1) | (2) | (3) | (4) |
| Negative fund flow beta | 0.001 | 0.006 | 0.001 | 0.002 |
| | (0.855) | (1.439) | (0.969) | (0.811) |
| Positive fund flow beta | 0.002 | 0.009 | 0.001 | 0.003 |
| | (1.698) | (1.087) | (1.206) | (0.473) |
| Top *FSE* weight | 3.058 | 4.261 | 0.544 | 1.396 |
| | (2.576) | (2.411) | (1.173) | (1.919) |
| Portfolio size | -0.048 | -0.480 | 0.008 | -0.374 |
| | (-1.704) | (-5.533) | (0.378) | (-7.203) |
| Fund age | 0.001 | 0.005 | 0.000 | -0.004 |
| | (0.456) | (0.238) | (-0.016) | (-0.354) |
| Expense ratio | -0.133 | 0.910 | -2.026 | -0.693 |
| | (-0.192) | (0.810) | (-3.047) | (-0.672) |
| Net flow | 0.008 | -0.186 | -0.034 | -0.282 |
| | (0.028) | (-0.667) | (-0.204) | (-1.543) |
| Family size | 0.024 | 0.035 | 0.008 | -0.001 |
| | (1.385) | (0.882) | (0.438) | (-0.025) |
| Market beta | -0.895 | -1.311 | | |
| | (-1.247) | (-1.353) | | |
| Value beta | 0.603 | 0.412 | | |
| | (0.939) | (0.631) | | |
| Size beta | -0.067 | -0.058 | | |
| | (-0.131) | (-0.131) | | |
| Momentum beta | -0.864 | -1.273 | | |
| | (-0.587) | (-0.767) | | |
| MKT | 1.037 | 1.034 | 0.010 | 0.009 |
| | (41.679) | (41.494) | (0.899) | (0.762) |
| HML | 0.171 | 0.168 | -0.006 | -0.009 |
| | (5.626) | (5.501) | (-0.350) | (-0.494) |
| SMB | 0.023 | 0.025 | -0.002 | 0.000 |
| | (0.722) | (0.793) | (-0.128) | (-0.015) |
| MOM | 0.053 | 0.056 | 0.000 | 0.003 |
| | (2.076) | (2.323) | (-0.028) | (0.248) |
| LIQ | 0.024 | 0.026 | -0.005 | -0.005 |
| | (1.205) | (1.347) | (-0.437) | (-0.440) |
| Fixed effects | none | fund | none | fund |
| $R^2$ | 0.814 | 0.814 | 0.012 | 0.068 |

the firm's shares by index funds attempting to mimic the Index (Shleifer, 1986; Bartram et al., 2015). However, since inclusion in the Index can dramatically change the stock ownership patterns of mutual funds, a stock's fire sale exposure could also change during these periods. For example, stocks included in the Index may also attract mutual funds that are more exposed to systematic outflows, given that Index constituents tend be highly liquid. Therefore, fund with high negative flow betas may desire to hold index constituents for liquidity management purposes. Under this scenario, we would expect 1) a tendency for newly-added index constituents to experience an increase in fire sale exposure around inclusion events, and 2) contemporaneously lower stock returns (i.e., smaller capital gain) for newly-added stocks with increased fire sale exposure around inclusion events.

We test these predictions using an event study around S&P 500 Index inclusion events. The estimation window covers the four quarters prior to and including the quarter of the inclusion event (i.e., event quarter 0), and the twelve quarters following event quarter 0. Fig. 3 plots the average *FSE* of treatment stocks for each quarter in the event window (solid line). *FSE* is relatively flat during the four quarters before index inclusion, increases sharply during the event quarter, and remains elevated over the twenty quarters following the event. This suggests that *FSE* shocks emanating from S&P 500 Index inclusion materialize soon after the inclusion event and do not reverse in subsequent

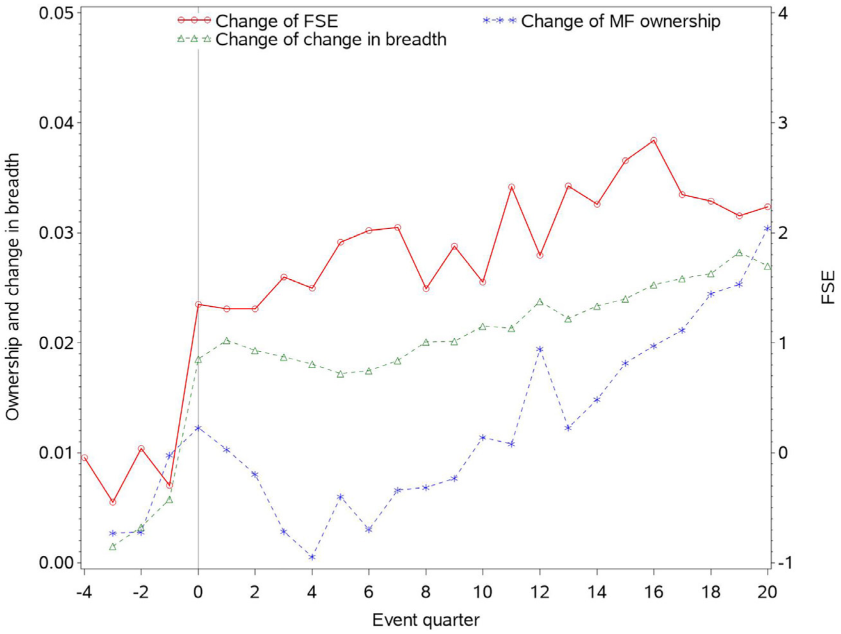



**Fig. 3.** *FSE* shocks around S&P 500 Index inclusion events.
The figure plots the average change of *FSE* (circles), ownership (stars), and change in breadth (asterisks) of stocks that are included in the S&P500 Index. See Appendix C for variable definitions. The change in a variable is measured relative to its level of 4 quarters prior to the inclusion (i.e., event time -4). The right y-axis represents the *FSE* and the left y-axis represents the ownership and change in breadth. The x-axis represents the event time from 4 quarters prior to the inclusion and 20 quarters after the inclusion, [-4, +20]. The vertical line at 0 indicates the quarter in which the stock was added to the Index. The data period is from 1989Q1-2017Q1.

quarters. The magnitude of the shock is also significant: the average *FSE* increases from around 4.2 to 5.7, or, about 36%, amid the inclusion event.

As noted above, we would expect any positive announcement effect associated with index inclusion to be attenuated among stocks that experience a concurrent increase in *FSE*. To test this prediction, we run the following regression of quarterly stock returns over the event window:

$$R_{i,q} = \alpha + \beta_1 Event_{i,q} + \beta_2\left(FSE_{i,q} - FSE_{i,-4}\right) + \beta_3 Event_{i,q} \times \left(FSE_{i,q} - FSE_{i,-4}\right) + \gamma' \mathbf{X}_{i,q} + \epsilon_{i,q} \quad (7)$$

where $R_{i,q}$ is stock *i*'s abnormal return during event quarter $q$ (in %), $Event_{i,q}$ is an indicator variable that equals one if event quarter $q$ is within four quarters before or four quarters after the stock was added to the Index (i.e., event quarter 0), $\left(FSE_{i,q} - FSE_{i,-4}\right)$ measures how much stock *i*'s *FSE* value has changed from event quarter -4 to event quarter $q$. Control variables include stock *i*'s market capitalization (log) and book-to-market ratio at the end of quarter $q$, the change in stock *i*'s mutual fund ownership and change in breadth from event quarter -4 to $q$, and their interactions with $Event_{i,q}$. Abnormal returns in quarter $q$ are calculated as the stock's excess return minus expected excess return, which is the stock's intercept plus CAPM beta times the excess return on the market in quarter $q$. The intercept and CAPM beta are estimated over the prior 36 months up to the end of quarter $q-1$. Only stocks that are newly-added to the Index are included in Eq. (7).

From parameter $\beta_1$ we can infer how the returns on S&P Index constituents near their inclusion dates differ from those far from their inclusion dates. A finding $\beta_1 > 0$ would be consistent with evidence of a positive announcement effect from Index inclusion as shown in prior studies.[19] From parameter $\beta_3$ we can infer how changes in a stock's *FSE*, attributed to the inclusion event, impact this announcement effect. A finding $\beta_3 < 0$ would support our prediction that shocks to *FSE* cause an increase in the risk premium required for bearing greater fire sale risk. Finally, from $\beta_2$ we can infer how increases in a stock's *FSE* are related to its stock returns far away from and subsequent to the inclusion date. A finding $\beta_2 > 0$ would support our story and findings that high-*FSE* stocks are riskier and, hence, earn higher average returns.

The results from estimating Eq. (7) are shown in Table 8. The estimated coefficient on the interaction variable ($\beta_3$) is negative and significant, indicating that an increase in *FSE* is associated with lower stock returns during the event period. This is consistent with our prediction that an unexpected increase in a stock's fire sale exposure is accompanied with lower contemporaneous stock prices, due to an increase in its risk premium. In addition, $\beta_2$ is positive and significant, consistent with our earlier results for the broader universe of CRSP stocks and the proposition that, over time, expected fire sale

[19] Granted, our use of quarterly returns does not allow us to directly compare our findings with prior event studies of Index inclusion which use a daily frequency to pinpoint the exact announcement day of a stock's inclusion in the Index (see, e.g., Shleifer, 1986).

**Table 8**
Stock returns around S&P 500 Index inclusion events.
The table shows the coefficient estimates and $t$-statistics (in parentheses) from panel regressions of abnormal stock returns around S&P 500 Index inclusion events. The unit of observation is stock-quarter. The dependent variable is a stock's quarterly abnormal return (%). Abnormal returns in event quarter $q$ are calculated as the stock's excess return minus expected excess return, which is the stock's intercept plus CAPM beta times the excess return on the market in event quarter $q$. The intercept and CAPM beta are estimated over the prior 36 months up to the end of event quarter $q-1$. $Event_q$ is an indicator variable that equals one if event quarter $q$ is within four quarters before or four quarters after the stock was added to the Index (i.e., event quarter 0), $(FSE_q - FSE_{-4})$ is the difference between the stock's $FSE$ value in event quarter $q$ and its value in event quarter $-4$. Control variables include the stock's market capitalization (log) and book-to-market ratio at the end of quarter $q$, the change in the stock's mutual fund ownership and change in breadth from event quarter $-4$ to $q$, and their interactions with $Event_q$. Ownership and change in breadth are in percentage (%). All variables are defined in Appendix C. Standard errors are clustered by stock. The sample only includes stocks that are newly-added to the Index, from four quarters before and until 20 quarters after the stock was added to the Index. The sample period covers 1989Q1–2017Q1.

| | Quarterly abnormal returns (%) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $FSE_q - FSE_{-4}$ | 0.129 | 0.191 | 0.217 | 0.218 |
| | (2.538) | (3.849) | (4.357) | (4.390) |
| $(FSE_q - FSE_{-4}) \times Event_q$ | -0.186 | -0.237 | -0.233 | -0.230 |
| | (-2.448) | (-3.164) | (-3.148) | (-3.146) |
| $\text{Ownership}_q$-$\text{Ownership}_{-4}$ | | -0.006 | | 0.185 |
| | | (-0.102) | | (2.872) |
| $(\text{Ownership}_q$-$\text{Ownership}_{-4}) \times Event_q$ | | 0.256 | | 0.101 |
| | | (2.375) | | (0.909) |
| Change in $\text{breadth}_q$-Change in $\text{breadth}_{-4}$ | | | -1.165 | -1.446 |
| | | | (-6.932) | (-7.549) |
| (Change in $\text{breadth}_q$-Change in $\text{breadth}_{-4}) \times Event_q$ | | | 0.784 | 0.664 |
| | | | (2.859) | (2.242) |
| Intercept | -11.905 | -9.622 | -25.098 | -29.522 |
| | (-2.267) | (-1.863) | (-5.258) | (-6.062) |
| $Event_q$ | 2.976 | 0.129 | -1.636 | -2.017 |
| | (4.470) | (0.129) | (-1.264) | (-1.534) |
| $R^2$ | 0.035 | 0.041 | 0.056 | 0.061 |

risk positively affects expected stock returns. The evidence here shows that this result also holds among Index constituents for which fire sale risk rises due to the inclusion event.

The remaining columns in Table 8 show that our main results on the effects of *FSE* changes around the S&P 500 inclusion still hold after controlling for the effects of stock ownership and breadth of ownership. We include these variables as controls because, in addition to *FSE*, inclusion events also coincide with changes in mutual fund ownership and the breadth of ownership (see Fig. 3), and these variables are known predictors of stock returns. Column (4) shows that these control interaction variables are also significant: inclusion-related increases in the level and breadth of ownership are associated with higher returns around S&P 500 inclusion events. This is consistent with existing evidence of temporary price pressure induced by mutual fund purchases of stocks newly-added to the Index (e.g., Shleifer, 1986 and Harris and Gurel, 1986), and evidence that increases in ownership breadth predict higher returns (Chen et al., 2002).

### 4.6. Mutual funds' stock selling and market conditions

An important premise to our risk-based story is that stocks with higher *FSE* are sold more by mutual funds during periods of fund industry-wide distress. To test this hypothesis, we compare the average change in mutual fund ownership of stocks in the top and bottom quintiles of *FSE*, depending on whether the flow factor is negative or positive. The quarterly change in mutual fund ownership for a stock is the difference of the ownership (the number of shares owned by mutual funds divided by the number of shares outstanding) between the current and prior quarters. We use split-adjusted share positions of mutual funds to control for non-trading reasons for changes in the number of shares held. We only consider mutual funds that hold the stock at the end of the prior quarter and, thus, focus on the trading activity of existing owners.

Panel A1 of Table 9 shows that mutual funds reduce their ownership of stocks in the top quintile of *FSE* by 0.89%, on average, during periods of systematic outflows. The ownership of stocks in the bottom quintile of *FSE* also falls, but by a smaller magnitude of 0.66%. The difference, -0.23%, is significant ($t$-statistic $= -3.10$). The next column compares the average ownership changes during periods of systematic inflows. As expected, during periods of inflows, the magnitude of stock selling by mutual funds is lower for both quintiles of stocks. Importantly, the spread between the quintiles narrows significantly in case of systematic inflows as compared to systematic outflows (-0.09% vs. -0.23%); the difference-in-differences is -0.14% and significant ($t$-statistic $= -3.70$). The results are similar in Panel A2 when we split the sample periods based on the sign of aggregate value-weighted flows rather than the flow factor.

**Table 9**
Mutual funds' stock selling and market conditions.
The table reports the average quarterly change in mutual funds' existing ownership and corresponding $t$-statistics (in parentheses) of stocks in the top and bottom *FSE* quintiles. The unit of observation is stock-quarter. Stocks are sorted based on *FSE* at the end of quarter $q-1$. Change in existing ownership scaled by shares outstanding (%) in Panels A1 and A2 is the difference of the ownership (the number of shares owned by mutual funds divided by the number of shares outstanding) between the quarters $q$ and $q-1$. Change in existing ownership scaled by monthly volume (%) in Panels B1 and B2 is the difference of the numbers of shares owned by mutual funds between the quarters $q$ and $q-1$ divided by the average monthly volume in the quarter $q-1$. Only mutual funds with an existing position in the stock at the end of quarter $q-1$ are included in the calculation. Standard errors are clustered by stock and time. In Panels A1 and B1, changes in ownership are reported separately depending on whether the flow factor is negative (outflow) or positive (inflow), respectively. In Panels A2 and B2, outflow and inflow periods are based on whether the value-weighted aggregate flow is negative or positive, respectively. The sample period is from 1989Q1–2017Q1.

Panel A: Change in mutual funds' existing ownership scaled by shares outstanding (%)

| | Panel A1: flow factor | | | Panel A2: aggregate flow | | |
|---|---|---|---|---|---|---|
| | outflow | inflow | outflow-inflow | outflow | inflow | outflow-inflow |
| Top *FSE* | -0.886 | -0.449 | -0.437 | -0.878 | -0.500 | -0.378 |
| | (-11.517) | (-10.152) | (-4.973) | (-10.664) | (-10.462) | (-4.014) |
| Bottom *FSE* | -0.657 | -0.359 | -0.298 | -0.644 | -0.409 | -0.235 |
| | (-7.910) | (-9.082) | (-3.270) | (-6.734) | (-11.017) | (-2.315) |
| Top-bottom | -0.229 | -0.090 | -0.139 | -0.234 | -0.092 | -0.143 |
| | (-3.102) | (-2.017) | (-3.696) | (-2.808) | (-2.227) | (-3.593) |

Panel B: Change in mutual funds' existing ownership scaled by monthly volume (%)

| | Panel B1: flow factor | | | Panel B2: aggregate flow | | |
|---|---|---|---|---|---|---|
| | outflow | inflow | outflow-inflow | outflow | inflow | outflow-inflow |
| Top *FSE* | -4.516 | -3.217 | -1.299 | -4.423 | -3.427 | -0.996 |
| | (-12.803) | (-9.075) | (-2.631) | (-11.797) | (-9.945) | (-1.982) |
| Bottom *FSE* | -2.823 | -2.386 | -0.437 | -2.580 | -2.651 | 0.071 |
| | (-7.836) | (-9.110) | (-0.995) | (-6.594) | (-9.929) | (0.151) |
| Top-bottom | -1.693 | -0.831 | -0.862 | -1.843 | -0.777 | -1.066 |
| | (-4.380) | (-2.334) | (-3.118) | (-4.355) | (-2.363) | (-3.873) |

We also divide the change in shares held by mutual funds during the quarter by the stock's average monthly trading volume, rather than shares outstanding. Panel B1 of Table 9 shows that, during quarters of systematic outflows, mutual funds reduce their holdings of top *FSE* stocks by -4.52% whereas holdings of bottom *FSE* stocks are reduced by just 2.82%; the difference, -1.69%, is statistically significant ($t$-statistic $= -4.38$). To put this number into perspective, note that Coval and Stafford (2007) find that stocks targeted for fire sales by distressed mutual funds significantly underperform during the fire sale period by about 8%, and that the change in mutual fund holdings associated with this fire sale activity is 2% of abnormal monthly trading volume in the stock (their Table 4).[20] This suggests that the observed magnitudes of mutual funds' selling of top *FSE* stocks (versus bottom *FSE* stocks) during periods of systematic outflows are of similar magnitudes to those associated with significant price effects from mutual fund fire sales (the $-8\%$ return documented in Coval and Stafford (2007)). In Panel B2, we report similar results based on value-weighted aggregate flows.

Overall, the evidence here helps to validate the mechanism behind the pricing of fire sale risk: high *FSE* stocks are targeted for selling by mutual funds when distressed selling is systematic and widespread in the industry.

[20] They note that, "Over the two quarters...with severe distressed selling of the same stock, the average abnormal stock return is -7.9% with a t-statistic of -3.45. Over the quarter in which fire sales are occurring, the net forced selling pressure accounts for roughly 2% of average volume." (p.495)

### 4.7. Falsification test using ownership data not yet disclosed

An interesting question is how stock market investors know what stocks have high fire sale risk. One possibility is that stock market participants use (as we do) publicly available data on mutual fund flows and stock holdings to develop ownership-based measures of a stock's exposure to mutual fund fire sales. If so, changes in fire sale exposure should not be priced before such changes are publicly observable to investors.

We test this idea by running a "falsification" exercise that exploits the reporting lag in ownership data. Specifically, we repeat our analysis of *FSE*-based portfolios in Table 2 for the subset of stocks that have recently moved by more than one quintile group of the *FSE* return distribution (e.g., from quintile 3 to quintile 5). We then track the performance of these stocks over a two-month "interim" period where it would be difficult for investors to detect that these stocks' fire sale exposures have substantially changed. For example, we focus on stocks that are in quintile 5 given their holdings on September 2010 but were in quintile 3 (or lower) based on their holdings on June 2010. We then track the performance of these "new addition" stocks over October and November 2010. The idea is that, since the ownership data are reported with a 60 day lag, investors may not know the "true" composition of *FSE* quintiles until the end of November 2010. We would therefore expect these newly added Q5 stocks to behave "as if" they were Q3 (or lower) stocks over these two months. We do the same in classifying new addition stocks to the remaining quintiles.

**Table 10**
*FSE* Sorted Portfolios of New and Existing Stocks
Stocks are sorted into 5 portfolios according to *FSE* values at the end of each quarter and further divided into new and existing stocks. New stocks in each quintile are the stocks of which the quintile is different from the prior *FSE* quintile by two or more. Existing stocks in each quintile are the stocks of which the quintile is the same as the prior quintile or different by one quintile. Panel A reports the time-series average of portfolio returns for each *FSE* portfolio of new stocks. Panel B is the same as Panel A, except the portfolios consist of existing *FSE* stocks. Stocks are sorted based on *FSE* at each quarter-end and portfolios are formed at the end of the quarter. Portfolio weights are either value-weighted according to stock market capitalization (VW) or equally-weighted (EW). Only stocks with a closing price of at least $5 on the date of portfolio formation are included in the portfolio. The position is held for two months (e.g., April and May for the first quarter), and rebalanced every three months. Interim returns are the two monthly returns following each quarter-end over which the portfolios are held. High-Low represents returns on a trading strategy that is long stocks in the top quintile portfolio and short stocks in the bottom quintile portfolio. Returns represent annualized average monthly returns. DGTW returns are equal to returns minus benchmark returns, which are returns on the stocks in the same quintiles of B/M, size, and past 1-year return (Daniel et al., 1997). Standard errors are Newey-West standard errors with 4 lags. All variables are defined in Appendix C. The flow exposures are estimated from 1989Q1–2016Q4 and the return period is from June 1989 to May 2017.

| Panel A: Interim returns on the new *FSE* portfolios | | | | |
|---|---|---|---|---|
| *FSE* quintiles | VW | EW | DGTW VW | DGTW EW |
| 1 | 0.126 | 0.159 | -0.011 | 0.003 |
| 2 | 0.092 | 0.166 | -0.016 | -0.004 |
| 3 | 0.129 | 0.160 | 0.010 | -0.003 |
| 4 | 0.146 | 0.166 | 0.001 | -0.001 |
| 5 | 0.172 | 0.180 | 0.008 | 0.004 |
| High-Low | 0.046 | 0.021 | 0.020 | 0.001 |
| (t-statistics) | (1.165) | (0.854) | (1.008) | (0.078) |
| Panel B: Interim returns on the existing *FSE* portfolios | | | | |
| *FSE* quintiles | VW | EW | DGTW VW | DGTW EW |
| 1 | 0.076 | 0.130 | -0.023 | 0.026 |
| 2 | 0.105 | 0.149 | 0.004 | 0.033 |
| 3 | 0.124 | 0.147 | 0.008 | 0.035 |
| 4 | 0.128 | 0.164 | 0.007 | 0.042 |
| 5 | 0.138 | 0.178 | 0.011 | 0.059 |
| High-Low | 0.063 | 0.048 | 0.033 | 0.033 |
| (t-statistics) | (3.167) | (4.060) | (2.088) | (3.810) |

The results are reported in Panel A of Table 10. The excess returns on the High-Low portfolio consisting of newly added stocks are small in magnitude and not significant. Panel B shows the results for stocks that did not change by more than one quintile over the prior quarter (“existing stocks”) and, therefore, are correctly classified based on the publicly available information over the two-month interim period. In contrast to newly added stocks, *FSE* portfolios of existing stocks have a significant positive return spread between the high and low *FSE* quintiles, in line with our baseline results in Table 2. This evidence suggests that a stock’s exposure to fire sale risk is priced only when information about its exposure to fire sale risk is publicly available, and sheds light on how investors know which stocks have more fire sale risk.

## 5. Conclusions

We construct a measure of a stock’s exposure to fire sale risk (*FSE*) through its ownership links to mutual funds with high fund flow betas, i.e., the sensitivity of fund flows to systematic outflows from the fund industry. Stocks with higher levels of *FSE* subsequently earn higher average returns. A long-short portfolio that buys (sells) stocks with largest (smallest) *FSE* earns about 3-7% per year. We interpret this as evidence that investors demand a return premium for bearing the risk of future fire sales during periods of systematic outflows. Systematic outflows are also related to macroeconomic variables and financial market conditions, including the net selling activity of the broader equity, bond, and hybrid mutual fund universe. This helps corroborate our conclusions that systematic outflows appear to be a state variable that matters in the pricing of stocks. Furthermore, we find evidence that a stock’s exposure to fire sale risk matters more when mutual funds represent a larger share of its owners.

The return premium associated with *FSE* cannot be fully explained by several other known contributors to expected stock returns, including market or funding liquidity risk, downside or co-skewness risk, or the level of institutional ownership. In addition, we find no empirical support for an alternative explanation in which the higher returns on more exposed stocks reflect stock ownership by skilled fund managers with a greater capacity for informed trading. We also exploit unexpected changes in the *FSE* of stocks that stem from their inclusion in the S&P 500 Index. Consistent with an unexpected increase in *FSE* resulting in a higher risk premium, we find that stocks with greater inclusion-related increases in *FSE* experience contemporaneously lower stocks returns (i.e., smaller capital gains) around the inclusion event. Finally, our measure of a stock’s exposure to fire sale risk indeed helps predict which stocks are sold most by mutual funds during periods of systematic outflows from the industry.

Overall, by showing that investors demand a risk premium in anticipation of future fire sales, our findings build on existing research documenting significant negative stock returns upon the realization of fire sales. Our evidence also shows that the risk exposures of stocks can be inherited from the risk exposures of its shareholders in a way that significantly impacts stock prices.


## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.


## Data availability

Fire Sale Risk and Expected Stock Returns (Aragon and Kim) https://data.mendeley.com/datasets/jmm8smf4sc.

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## Appendix A. Flow-driven liquidity-adjusted capital asset pricing model

In this section, we introduce a flow-driven liquidity-adjusted capital asset pricing model (CAPM). Acharya and Pedersen (2005, hereafter AP) derive a liquidity-adjusted version of the CAPM with illiquidity costs of selling securities, which can be interpreted in many ways. Our model applies AP's model to an economy with mutual funds where the illiquidity cost increases in the aggregate order flow from individual investors and mutual funds who own the stock. We derive a pricing relation for returns and the illiquidity cost and discuss how the liquidity risks discussed in AP result in the construction of our main empirical variable that measures a stock's exposure to flow-driven liquidity risk.

### *A1. Assumptions*

All assumptions in AP are carried over to our model. Both models have the same overlapping generations economy in which a new generation of agents is born at any time ($t$) and live for two periods ($t$ and $t+1$). Generation $t$ consists of $N$ agents, who receive endowments at time $t$ and derive utility from consumption $x_{t+1}$ at time $t+1$. Agents, indexed by $n$, have constant absolute risk aversion $A^n$ with utility functions given by $-\exp(-A^n x_{t+1})$.

Agents have no sources of income other than an endowment and can lend or borrow at the risk free rate $r^f$ and invest in $I$ securities, indexed by $i$, at time $t$. In addition to investing directly in the stock market, agents can also invest in the market portfolio by purchasing shares of any of $K$ mutual funds. The mutual funds are formed at the beginning of each period $t$ and are closed at the end of the period $t+1$ when agents of generation $t$ redeem their mutual fund shares for consumption. In this economy, a mutual fund is not a decision-making agent but rather another type of security in which agents can invest. Mutual funds invest all money received from agents in the market portfolio at time $t$ and sell their holdings of the securities when agents redeem their fund shares in time $t+1$. The mutual funds in the model are similar to market index funds in the real world, with the exception that they do not charge fees and do not aim to maximize their assets under management.[21]

As in AP, trading involves an illiquidity cost $C_{it}$ that is modeled as the per-share cost of selling security $i$ at time $t$. Hence, mutual funds and agents can buy at $P_{it}$ but must sell at $P_{it} - C_{it}$. The new element of our model is that we explicitly model the per-share cost of selling a security in terms of 1) the aggregate order flow of the stock's mutual fund owners and 2) the aggregate order flow of the agents who directly hold the stock. Specifically, the illiquidity cost is given by

$$C_{i,t+1} = \sum_{k=1}^{K} P_{i,t}\delta_{i,k,t} l_{k,t+1} + \sum_{n=1}^{N} P_{i,t}\delta_{i,n,t}\varepsilon_{n,t+1} \quad \text{(A.1)}$$

$$c_{i,t+1} = \sum_{k=1}^{K} \delta_{i,k,t} l_{k,t+1} + \sum_{n=1}^{N} \delta_{i,n,t}\varepsilon_{n,t+1}, \quad \text{(A.2)}$$

where the first and second terms on the right side of Eq. (A.1) capture order flows of mutual funds and individual investors, respectively. We assume that aggregate order flows of investors increase with their ownership of the security and their liquidity needs. The ownership is measured by the price $P_{i,t}$ of the security $i$ at time $t$ multiplied by scaling factors $\delta_{i,k,t}$ and $\delta_{i,n,t}$ that increase with the number of shares of the security held by fund $k$ and agent $n$, respectively. Investors' liquidity needs are denoted by $l_{k,t+1}$ and $\varepsilon_{n,t+1}$ for mutual funds and individual investors, respectively. Agents of generation $t$ need to sell direct holdings of the stock for consumption at time $t+1$. In addition, agents redeem their shares of mutual funds for consumption, which in turn causes liquidity needs to mutual funds. Therefore, we model mutual funds' liquidity needs as investors' money flows out of mutual funds. In the real world, the flow-motivated trading of mutual funds is supported by existing evidence that mutual funds trade the underlying securities in their portfolios in response to investor outflows, and such flow-motivated trading creates downward price pressure (Coval and Stafford, 2007). In Eq. (A.2), we define the relative illiquidity cost $c_{i,t+1} = C_{i,t+1}/P_{i,t}$ by dividing (A.1) by the price $P_{i,t}$ as in AP.

A fund's liquidity needs arise when agents who invested in the fund at time $t$ redeem their shares for consumption in their final period $t+1$. We assume that the liquidity needs of an individual fund are directly proportional to the fund's money outflows, which represent the absolute value of negative net flows. Based on prior studies that have shown mutual fund flows to have commonality or a factor structure (e.g., Ferson and Kim, 2012) as in Eq. (2), we also assume that a fund's outflows in $t+1$

[21] We abstract from potential agency conflicts between fund managers and investors to highlight our key mechanism—the diversification of idiosyncratic flow shocks—for why a stock's exposure to systematic fire sales should earn a premium ex ante. Nevertheless, how fire sale considerations interact with agency issues related to performance benchmarking and the fund managers' incentive system (e.g., Ma et al., 2019; Kim and Zapatero, 2023) is an interesting avenue for future research.

consist of a systematic part, which is based on systematic outflows (represented by the absolute value of the negative flow factor), and an idiosyncratic flow part that is fund-specific. Therefore, an individual fund's liquidity needs can be calculated as follows,

$$l_{k,t+1} = a + \beta_k^{f-} f_{t+1} + \varepsilon_{k,t+1}, \tag{A.3}$$

where $l_{k,t+1}$ is the liquidity needs of mutual fund $k$ in $t+1$, and $f_{t+1} \equiv |F_t^-|$ is the systematic outflow, which is the absolute value of the negative part of the flow factor $F_t$, i.e., $F_t^- \equiv \min(F_t, 0)$.[22] The coefficient $\beta_k^{f-}$ is the flow loading of fund $k$ on the systematic outflow as in fund $k$'s "flow beta (-)," $\beta_k^-$ in Eq. (2), and $\varepsilon_{k,t+1}$ is the mean-zero, fund-specific component of flows. Both $\varepsilon_{k,t+1}$ (fund-specific money flow) and $\varepsilon_{n,t+1}$ (the agent $n$'s order flow) are uncorrelated with the flow factor,

$$E_t[\varepsilon_{k,t+1}|f_{t+1}] = E_t[\varepsilon_{n,t+1}|f_{t+1}] = 0. \tag{A.4}$$

### A2. Flow-driven liquidity-adjusted CAPM

We combine (A.2) and (A.3) and write the relative illiquidity cost,

$$\begin{aligned} c_{i,t+1} &= \sum_{k=1}^{K} \delta_{i,k,t}(a + \beta_k^{f-} f_{t+1} + \varepsilon_{k,t+1}) + \sum_{n=1}^{N} \delta_{i,n,t}\varepsilon_{n,t+1} \\ &= a + \left(\sum_{k=1}^{K} \delta_{i,k,t}\beta_k^{f-}\right) f_{t+1} + \sum_{k=1}^{K} \delta_{i,k,t}\varepsilon_{k,t+1} + \sum_{n=1}^{N} \delta_{i,n,t}\varepsilon_{n,t+1} \\ &= a + \beta_{i,t}^{f-} f_{t+1} + \varepsilon_{i,t+1}, \end{aligned} \tag{A.5}$$

where the scaling factor sums to a constant, which is assumed to be one without loss of generality, $\sum_{k=1}^{K} \delta_{i,k,t} = 1$. In the second term of (A.5), $\beta_{i,t}^{f-} \equiv \sum_{k=1}^{K} \delta_{i,k,t}\beta_k^{f-}$ denotes the aggregate sensitivity of the illiquidity cost of the security $i$ to the flow factor $f_{t+1}$. The last term $\varepsilon_{i,t+1}$ is the illiquidity cost of security $i$ that is uncorrelated with the flow factor, $\varepsilon_{i,t+1} \equiv \sum_{k=-1}^{K} \delta_{i,k,t}\varepsilon_{k,t+1} + \sum_{n=1}^{N} \delta_{i,n,t}\varepsilon_{n,t+1}$, by Eq. (A.4). As a result, the illiquidity cost $c_{i,t+1}$ of the security has commonality due to the commonality in flows of mutual funds that own the security.

By Eq. (A.5), the market illiquidity cost, $c_{M,t+1} \equiv \sum_{i=1}^{I} w_{i,t}c_{i,t+1}$, at time $t+1$ is given by

$$\begin{aligned} c_{M,t+1} &= \sum_{i=1}^{I} w_{i,t}(a + \beta_{i,t}^{f-} f_{t+1} + \varepsilon_{i,t+1}) \\ &= a + \left(\sum_{i=1}^{I} w_{i,t}\beta_{i,t}^{f-}\right) f_{t+1} + \sum_{i=1}^{I} w_{i,t}\varepsilon_{i,t+1} \\ &= a + \beta_{M,t}^{f-} f_{t+1}, \end{aligned} \tag{A.6}$$

where $w_{i,t}$ is the weight of the security $i$ in the market portfolio with the market return equal to $r_{M,t+1} = \sum_{i=1}^{I} w_{i,t}r_{i,t+1}$. The sensitivity $\beta_{M,t}^{f-}$ of the market illiquidity cost to the flow factor is given by $\beta_{M,t}^{f-} \equiv \sum_{i=1}^{I} w_{i,t}\beta_{i,t}^{f-}$. The component uncorrelated with the flow factor is equal to zero for a well-diversified portfolio of a large number $I$ of securities, $\sum_{i=1}^{I} w_{i,t}\varepsilon_{i,t+1} = 0$.

We first quote Proposition 1 of AP to derive a flow-driven liquidity-adjusted CAPM.

*Proposition 1. In the unique linear equilibrium, the conditional expected net return of the security i is*

$$E_t(r_{i,t+1} - c_{i,t+1}) = r_{f,t} + \lambda_t \frac{cov_t(r_{i,t+1} - c_{i,t+1}, r_{M,t+1} - c_{M,t+1})}{var_t(r_{M,t+1} - c_{M,t+1})}, \tag{A.7}$$

*where $\lambda_t \equiv E_t(r_{M,t+1} - c_{M,t+1} - r_f)$ is the risk premium. Equivalently, the conditional expected return is*

$$\begin{aligned} E_t(r_{i,t+1}) = r_{f,t} + E_t(c_{i,t+1}) + \lambda_t \frac{cov_t(r_{i,t+1}, r_{M,t+1} - c_{M,t+1})}{var_t(r_{M,t+1} - c_{M,t+1})} \\ + \lambda_t \frac{cov_t(c_{i,t+1}, c_{M,t+1})}{var_t(r_{M,t+1} - c_{M,t+1})} - \lambda_t \frac{cov_t(c_{i,t+1}, r_{M,t+1})}{var_t(r_{M,t+1} - c_{M,t+1})}. \end{aligned} \tag{A.8}$$

*Proof.* See Appendix of AP for the proof. □

In Proposition 1, we expand the covariance of the security's illiquidity cost $c_{i,t+1}$ in Eq. (A.7) to derive (A.8). Our model interprets the illiquidity cost $c_{i,t+1}$ as arising from the selling pressure by order flows, in particular, driven by investors' money flows out of mutual funds. We replace $c_{i,t+1}$ and $c_{M,t+1}$ by (A.5) and (A.6), respectively, and focus on two liquidity risks related to the security's illiquidity cost $c_{i,t+1}$ in (A.8), i.e., $cov_t(c_{i,t+1}, c_{M,t+1})$ and $cov_t(c_{i,t+1}, r_{M,t+1})$.

The first liquidity risk related to $c_{i,t+1}$ is the covariance between the security's liquidity and the market liquidity costs:

$$\begin{aligned} cov_t(c_{i,t+1}, c_{M,t+1}) &= cov(\beta_{i,t}^{f-} f_{t+1} + \varepsilon_{i,t+1}, \beta_{M,t}^{f-} f_{t+1}) \\ &= \beta_{i,t}^{f-}\beta_{M,t}^{f-} var(f_{t+1}), \end{aligned} \tag{A.9}$$

where $\beta_M^{f-} var(f_{t+1})$ is common to all securities. This liquidity risk is high in times when the flow factor is more volatile and the market portfolio is more sensitive to the flow factor. On the other hand, the cross-section of the liquidity risk depends on the stock's exposure $\beta_i^{f-}$ to the flow factor. Investors demand high expected returns for holding stocks that are more sensitive to systematic outflows, i.e., become more illiquid when the market experiences high flows out of mutual funds. AP also discuss a time-varying common factor in liquidity for pricing implications of this liquidity risk. We model the common factor in liquidity as a flow factor and pin down the sensitivity of the security's illiquidity cost to the flow factor as the main driver for the cross section of expected returns by liquidity risk.

The second liquidity risk related to $c_{i,t+1}$ is its covariance with the market return:

$$\begin{aligned} cov_t(c_{i,t+1}, r_{M,t+1}) &= cov_t(\beta_{i,t}^{f-} f_{t+1} + \varepsilon_{i,t+1}, r_{M,t+1}) \\ &= \beta_{i,t}^{f-} cov_t(f_{t+1}, r_{M,t+1}), \end{aligned} \tag{A.10}$$

which is a product of the stock's flow exposure $\beta_i^{f-}$ and the covariance between the flow factor and market return.

[22] Given the definition of the positive and negative parts of the flow factor in Eq. (2), net flows for an individual fund load on only the negative part when the factor is negative: $f_{k,t} = \alpha_k + \beta_k^- F_t^- + e_{k,t}$ because the positive part is zero ($F_t^+ \equiv \max(F_t, 0) = 0$) when $F_t < 0$.

As AP discuss, this liquidity risk decreases the expected return of the security as shown in (A.8). This is because investors are willing to accept lower expected returns if the stock becomes more illiquid when the market pays more or conversely, becomes more liquid (less illiquid) when the market pays less. The covariance between the flow factor and market return lowers expected returns as it is beneficial to be liquid in a down market.

We use (A.9) and (A.10) for the conditional expected return in Proposition 1 of AP and derive a flow-driven liquidity-adjusted CAPM in Corollary 1.

*Corollary 1. In the unique linear equilibrium, the conditional expected gross return of the security i is*

$$E_t(r_{i,t+1}) = r_{f,t} + E_t(c_{i,t+1}) + \beta_{i,t}\lambda_t + \beta^{f-}_{i,t}\lambda^f_t,$$

*where* $\beta_{i,t} \equiv \frac{cov_t(r_{i,t+1}, r_{M,t+1}-c_{M,t+1})}{var_t(r_{M,t+1}-c_{M,t+1})}$ *is the sensitivity of the return on the security i to the market's return net of the market liquidity cost and* $\lambda_t$ *is the risk premium,* $\lambda_t \equiv E_t(r_{M,t+1} - c_{M,t+1} - r_f)$. *The last term is a product of the sensitivity of the security's illiquidity cost to the flow factor* ($\beta^{f-}_{i,t} \equiv \sum_k^K \delta_{i,k,t}\beta^{f-}_k$) *and the flow risk premium given by* $\lambda^f_t \equiv \frac{\beta^{f-}_M var_t(f_{t+1}) - cov_t(f_{t+1}, r_{M,t+1})}{var_t(r_{M,t+1}-c_{M,t+1})}\lambda_t$ *or equivalently* $\lambda^f_t \equiv \frac{cov_t(f_{t+1}, \beta^{f-}_M f_{t+1}) - cov_t(f_{t+1}, r_{M,t+1})}{var_t(r_{M,t+1}-c_{M,t+1})}\lambda_t = \frac{cov_t(-f_{t+1}, r_{M,t+1}-c_{M,t+1})}{var_t(r_{M,t+1}-c_{M,t+1})}\lambda_t$ *because* $c_{M,t+1} = \beta^{f-}_M f_{t+1}$. *Note that* $-f_{t+1} = F^-_{t+1}$ *in Eq. (2) because* $f_{t+1} = |F^-_{t+1}|$ *is the absolute value of the negative part of the systematic flow and* $cov_t(-f_{t+1}, r_{M,t+1} - c_{M,t+1}) > 0$.

*Proof.* It is straightforward to show by Proposition 1 and the illiquidity costs in (A.5) and (A.6). □

Corollary 1 ties our conceptual framework to our main empirical predictions and variable construction in Section 2. The main takeaway of the model is that only stocks' exposures to the systematic components of mutual fund flows generate the liquidity risks that are priced. It shows that the expected return on security $i$ increases with the weighted-average flow betas of its mutual fund owners ($\beta^{f-}_{i,t}$), which captures the sensitivity of its illiquidity costs to the flow factor. In other words, it shows that cross-sectional expected returns depend on the stock's exposure to systematic flows (via mutual fund owners' flow betas, not the total flow volatility). In contrast, stocks held by mutual funds with high idiosyncratic volatility do not earn a premium ex ante as the risk can be diversified away. This insight helps justify our empirical measure of a stock's exposures to the flow risk of mutual funds holding the stock. Besides a stock's exposures to the systematic components of mutual fund flows, the only other characteristics that matter for cross-sectional expected returns are a stock's expected illiquidity cost, $E_t(c_{i,t+1})$ and its market return beta ($\beta_{i,t}$), which we control for in the empirical analysis.

We can map $\beta^{f-}_{i,t}$ to our key empirical measure $FSE_{i,t}$ as follows. First, we take the weights $\delta_{i,k}$ as fund $k$'s holding of a stock $i$ divided by the aggregate shares of stock $i$ held by all mutual funds.[23] This is consistent with our model's assumption that the $\delta_{i,k}$ increase with the number of shares owned by the mutual funds indexed by $k$, and that the weights sum to a constant (equals to one without loss of generality) as shown in (A.5).[24] Second, we focus on mutual funds' "negative flow betas" which are estimated with respect to negative realizations (i.e., systematic outflows) of the flow factor, rather than positive realizations, as in Eq. (2). Similarly, $FPE_{i,t}$ is also estimated based on mutual funds' "positive flow betas" as in Eq. (2).

Finally, it is worth discussing why the model does not consider liquidity needs generated by money inflows that may force mutual funds to buy securities. In an overlapping generation economy like the one in Acharya and Pedersen (2005), agents purchase assets today and sell them for consumption in the future. As a result, the illiquidity costs of buying are known today and do not affect the liquidity risks. Therefore, incorporating money inflows into mutual funds would not change the main implication of the model, which is that a stock's exposures to its mutual fund owners' systematic flow risk—rather than their total flow risk—affect the expected returns on the stock.

### *A3. Further support for the model's assumptions*

In this section, we further justify the novel elements of our model that link a stock's illiquidity costs to mutual fund flows. The last assumption in Eq. (A.3) that mutual fund flows have commonality or a factor structure is justified by the empirical evidence in Ferson and Kim (2012). The assumption in Eqs. (A.1) and (A.2) that a stock's illiquidity cost is linear in the aggregate order flows of its current shareholders follows from the theoretical model of Kyle (1985) whereby the price impact of a stock is linear in aggregate order flows. Furthermore, the assumption that a mutual fund's order flows increase with their ownership and outflows is justified by empirical evidence that mutual funds' sell orders increase with their current ownership in the stock and money outflows (Coval and Stafford, 2007; Lou, 2012).

We also present direct empirical evidence to justify the relationship between a stock's transaction costs and the flows of mutual funds holding that stock. Specifically, we run the following regression of a stock's transaction costs on net flows of its mutual fund owners:

$$c_{i,q} = \alpha_i + \beta \text{Flow}_{i,q} + \text{Controls}_{i,q} + \epsilon_{i,q}, \tag{A.11}$$

This is a panel regression with stock-fixed effects $\alpha_i$ where the unit of observation is stock-quarter. Standard errors account for heteroskedasticity and are clustered at the quarter level. The dependent variable $c_{i,q}$ is the transaction

[23] Our empirical results are robust to an alternative scaling factor in which we divide fund $k$'s holding of a stock $i$ by stock $i$'s shares outstanding and find similar results (see Panel A of Appendix D).

[24] While our model assumes that all mutual funds hold the market portfolio for simplicity, we acknowledge that in reality, not all mutual funds are passive index funds, and actively-managed funds may have different ownership weights across stocks. Nonetheless, the main conclusion of our model that non-systematic flow risk diversifies away and only the systematic component of flow risk earns a premium remains valid.

**Table A-1**
Do a stock's transaction costs load on the flows of its mutual fund owners?
Panel regressions of a stock's transaction costs on the flows of mutual funds holding the stock. The unit of observation is stock-quarter. The dependent variable is the average daily Amihud (2002) illiquidity variable during quarter $q$, which measures transaction costs. The key independent variable is $\text{Flow}_{\text{i,q}}$, a weighted-average of the flows of mutual funds holding the stock: $\text{Flow}_{\text{i,q}} = \sum_{k=1}^{K} w_{k,q-1} f_{k,q}$ for all $K$ mutual funds that hold shares of stock $i$, where $f_{k,q}$ is the net flow of mutual fund $k$ during quarter $q$, and $w_{k,q-1}$ is the weight of mutual fund $k$ in the portfolio of stock $i$. The weight is calculated using the formula $shr_{i,k,q-1} / \sum_{k=1}^{K} shr_{i,k,q-1}$, where $shr_{i,k,q-1}$ represents the number of shares of stock $i$ that fund $k$ owns at the end of quarter $q-1$, as is done to calculate a stock's fire sale exposure in Eq. (3). Control variables are measured in the same quarter as the dependent variable except for size, which is measured at the beginning of the quarter, and lag return, which is measured over the previous quarter. Standard errors are clustered according to time (quarterly). $t$-statistics are in parentheses.

| Dependent variable: Stock-level $\text{illiquidity}_{\text{iq}}$ | | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| $\text{Flows}_{\text{iq}}$ | -5.189 | -2.432 | -1.240 | -0.885 | -0.697 |
| | (-14.583) | (-8.836) | (-6.654) | (-5.515) | (-4.884) |
| $\text{Size}_{\text{i,q-1}}$ | | -0.283 | -0.263 | -0.221 | -0.257 |
| | | (-20.640) | (-21.882) | (-15.604) | (-17.301) |
| $\text{Book-to-market}_{\text{iq}}$ | | 0.579 | 0.438 | 0.353 | 0.290 |
| | | (13.399) | (10.301) | (9.025) | (7.443) |
| $\text{Return}_{\text{iq}}$ | | -0.148 | -0.202 | -0.050 | -0.087 |
| | | (-3.108) | (-3.481) | (-1.642) | (-2.245) |
| Lag $\text{return}_{\text{i,q-1}}$ | | 0.147 | 0.014 | 0.066 | 0.052 |
| | | (3.303) | (0.257) | (2.578) | (1.434) |
| $\text{Ownership}_{\text{iq}}$ | | -0.492 | -3.364 | 0.226 | -0.731 |
| | | (-7.162) | (-13.425) | (4.150) | (-6.060) |
| Change in $\text{breadth}_{\text{iq}}$ | | 0.036 | 0.073 | 0.011 | 0.025 |
| | | (2.072) | (4.746) | (1.358) | (3.712) |
| Stock market $\text{beta}_{\text{iq}}$ | | -0.139 | -0.248 | -0.058 | -0.060 |
| | | (-10.910) | (-13.546) | (-5.811) | (-6.227) |
| Liq beta $\text{(PS-tradable)}_{\text{iq}}$ | | 0.009 | 0.003 | 0.018 | 0.022 |
| | | (0.718) | (0.234) | (1.768) | (2.203) |
| Quarter fixed effects | No | No | Yes | No | Yes |
| Stock fixed effects | No | No | No | Yes | Yes |
| R-squared | 0.017 | 0.123 | 0.146 | 0.391 | 0.395 |
| Observations | 308,168 | 232,359 | 232,359 | 231,928 | 231,928 |

costs of stock $i$ in quarter $q$. We follow Acharya and Pedersen (2005) and use the Amihud (2002) illiquidity variable to measure a stock's transaction costs. The key independent variable is $\text{Flow}_{\text{i,q}}$, a weighted-average of the flows of mutual funds holding the stock: $\text{Flow}_{\text{i,q}} = \sum_{k=1}^{K} w_{k,q-1} f_{k,q}$ for all $K$ mutual funds that hold shares of stock $i$, where $f_{k,q}$ is the net flow of mutual fund $k$ during quarter $q$, and $w_{k,q-1}$ is the weight of mutual fund $k$ in the portfolio of stock $i$. The weight is calculated using the formula $shr_{i,k,q-1} / \sum_{k=1}^{K} shr_{i,k,q-1}$, where $shr_{i,k,q-1}$ represents the number of shares of stock $i$ that fund $k$ owns at the end of quarter $q-1$, as is done to calculate a stock's fire sale exposure in Eq. (3). A finding $\beta < 0$ would indicate that a stock's transactions costs are higher when its mutual fund owners have lower net flows (i.e., greater outflows).

The results are reported in Table A-1. Transaction costs of a stock load significantly on the flows of mutual funds holding that stock. Column (1) shows that a one standard deviation (0.043) decrease in Flow is associated with an increase in Amihud illiquidity by 0.22 ($= -5.189 \times -0.043$). This is over one third of its sample mean of Amihud illiquidity (0.6). This finding is not subsumed by observable stock characteristics (Column (2)), unobservable stock characteristics captured by stock fixed effects (Column (4)), or general market conditions captured by quarter fixed effects (Column (5)). This evidence is consistent with the view that outflows of mutual funds have positive effects on the illiquidity costs of the stocks they hold.

As further justification for our model, we empirically validate the aggregate-level relation between transaction costs and flows in Eq. (A.6). In the equation, transaction costs for the aggregate market load on value-weighted aggregate flows. We test this prediction using the following regression:

$$c_{M,q} = \alpha + \beta \text{IndustryFlow}_q + \gamma_1 c_{M,q-1} + \gamma_2 c_{M,q-2} + \epsilon_q, \tag{A.12}$$

This is a time series regression where the unit of observation is a quarter. The dependent variable $c_{M,q}$ measures the transaction costs of the aggregate market during quarter $q$. It is defined as the market-capitalization weighted average of individual stocks' Amihud (2002) illiquidity. As in Acharya and Pedersen (2005), $c_{M,q}$ is persistent in our sample and has a significant autocorrelation structure with two quarterly lags. Therefore, we include its two lagged values, $c_{M,q-1}$ and $c_{M,q-2}$, as control variables. $\text{IndustryFlow}_q$ represents the asset-weighted flows of all mutual funds. As noted earlier, transaction costs should load negatively on flows. Therefore, a finding $\beta < 0$ would indicate that transaction costs for the aggregate market are greater during periods of lower aggregate flows.

**Table A-2**

Do transaction costs for the aggregate market load on systematic flows?

Time series regressions of transaction costs for the aggregate market on value-weighted flows (industry flow) and the first principal component (PC) of individual mutual fund flows, following Eqs. (A.12) to (A.16). The unit of observation is quarter, and the dependent variable in columns (1)-(5) is the market capitalization-weighted (VW) average of individual stocks' transaction costs during quarter $q$. In column (6), the dependent variable is the equally-weighted (EW) average of individual stocks' transaction costs during quarter $q$. An individual stock's transaction costs is represented by the average daily Amihud (2002) illiquidity variable during quarter $q$. IndustryFlow$_q$ represents the asset-weighted flows of all mutual funds during quarter $q$ and has two components: IndustryFlowSys$_q$ and IndustryFlowIdio$_q$. IndustryFlowSys$_q$ is the part of IndustryFlow$_q$ that is correlated with the first PC ($F_q$) of individual mutual fund flows during quarter $q$. Since the first PC is scaled to make the loading of the industry flow on the first PC equal to one, IndustryFlowSys$_q$ is equal to $F_q$, and IndustryFlowIdio$_q$ is the part that is uncorrelated with $F_q$. Standard errors are adjusted for heteroskedasticity, and t-statistics are presented in parentheses.

| Dependent variable: Market illiquidity$_q$ | | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| IndustryFlow$_q$ | -0.072 | | | | | |
| | (-2.304) | | | | | |
| IndustryFlowSys$_q$ (=$F_q$) | | -0.093 | -0.094 | | | |
| | | (-2.328) | (-2.343) | | | |
| IndustryFlowIdio$_q$ | | -0.038 | | 0.006 | | |
| | | (-0.725) | | (0.103) | | |
| min(IndustryFlowSys$_q$,0) | | | | -0.612 | -0.573 | -11.765 |
| | | | | (-2.022) | (-1.874) | (-2.391) |
| max(IndustryFlowSys$_q$,0) | | | | -0.064 | -0.066 | -0.509 |
| | | | | (-1.473) | (-1.524) | (-0.675) |
| min(IndustryFlowIdio$_q$,0) | | | | | -0.081 | -3.676 |
| | | | | | (-0.725) | (-1.903) |
| max(IndustryFlowIdio$_q$,0) | | | | | 0.093 | 2.227 |
| | | | | | (0.834) | (1.200) |
| Market illiquidity$_{q-1}$ | 0.708 | 0.710 | 0.713 | 0.707 | 0.722 | 0.699 |
| | (9.114) | (9.130) | (9.189) | (9.148) | (9.133) | (8.732) |
| Market illiquidity$_{q-2}$ | 0.274 | 0.279 | 0.278 | 0.303 | 0.275 | 0.205 |
| | (3.510) | (3.563) | (3.549) | (3.837) | (3.221) | (2.334) |
| Market illiquidity weights | VW | VW | VW | VW | VW | EW |
| R-squared | 0.957 | 0.957 | 0.957 | 0.958 | 0.958 | 0.966 |
| Observations | 145 | 145 | 145 | 145 | 145 | 145 |

To show that transaction costs for the aggregate market load on the systematic component of aggregate flows but not on the idiosyncratic component of aggregate flows (i.e., $\sum_{i=1}^{I} w_{i,t}\varepsilon_{i,t+1} = 0$ in Eq. (A.6)), we decompose IndustryFlow into: 1) the component that is correlated with the first PC of fund flows (IndustryFlowSys) and 2) the component that is uncorrelated with the first PC (IndustryFlowIdio). The first component is just the first PC—i.e., the first PC rescaled so that the loading of IndustryFlow on the first PC equals one. As a result, IndustryFlow$_q$ is the sum of the first PC and IndustryFlowIdio:

$$\begin{aligned}\text{IndustryFlow}_q &= \text{IndustryFlowSys}_q + \text{IndustryFlowIdio}_q \\ &= \text{F}_q + \text{IndustryFlowIdio}_q,\end{aligned} \tag{A.13}$$

where $F_q$ stands for the first PC of individual mutual fund flows during quarter $q$. It is worth noting that the first PC explains 68% of the total variance of aggregate flows, and the two variables have a pairwise correlation of 0.82 (see Table 1). We run two additional regressions that correspond to the second and third equalities of (A.6), respectively, as follows:

$$\begin{aligned}c_{M,q} &= \alpha + \beta_1 \text{IndustryFlowSys}_q + \beta_2\ \text{IndustryFlowIdio}_q \\ &\quad + \gamma_1 c_{M,q-1} + \gamma_2 c_{M,q-2} + \epsilon_q\end{aligned} \tag{A.14}$$

$$\begin{aligned}c_{M,q} &= \alpha + \beta \text{IndustryFlowSys}_q + \gamma_1 c_{M,q-1} \\ &\quad + \gamma_2 c_{M,q-2} + \epsilon_q.\end{aligned} \tag{A.15}$$

A finding $\beta_1 < 0$ and $\beta_2 = 0$ supports Eq. (A.6) as it indicates that a significant relation between $c_{M,q}$ and IndustryFlow$_q$ is driven by the first PC, not the idiosyncratic component of the aggregate flows.

The results are presented in Table A-2. Column (1) for regression Eq. (A.12) shows that transaction costs of the aggregate market are negatively related to industry flows (coef.= −0.072; $t$-statistic= −2.304). This is consistent with our panel regression results in Table A-1 showing a negative and significant relation between Amihud illiquidity and mutual fund flows at the stock level.

The results for regression (A.14) are presented in Column (2). Consistent with (A.6), $c_{M,q}$ loads significantly on the systematic component of value-weighted aggregate flows (coef.= −0.093; $t$ -statistic= −2.328), but not value-weighted idiosyncratic flows (coef.= −0.038; $t$-statistic= −0.725).[25] Column (3) shows the results for regression (A.15). Using the systematic part alone, which is equal to the first PC, leads to a coefficient that is negative, significant, and slightly larger in magnitude (coef.= −0.094; $t$-statistic= −2.343) as compared to IndustryFlow. We conclude that transaction costs for the aggregate market load

[25] By the Frisch-Waugh-Lowell theorem, the coefficient on IndustryFlowIdio in Column (2) for regression (A.14) is the same as the coefficient on IndustryFlow in a multivariate regression with IndustryFlow and IndustryFlowSys (the first PC) together as right-hand side variables. However, running this alternative regression results in insignificant coefficients on both IndustryFlow (coef. = -0.038; t-statistic = -0.725) and IndustryFlowSys (coef. = -0.055; t-statistic = -0.837). We attribute this to the multicollinearity due to the high correlation between IndustryFlow and IndustryFlowSys (0.82) as in Eq. (A.13).

more strongly on the flow factor than the idiosyncratic component of value-weighted fund flows.

A further partitioning of IndustryFlowSys, or equivalently the first PC, reveals more insights. Specifically, we regress $c_{M,q}$ on the negative part of IndustryFlowSys, $F_q^- \equiv \min(\text{IndustryFlowSys}_q, 0) = \min(F_q, 0)$, and the positive part of IndustryFlowSys, $F_q^+ \equiv \max(\text{IndustryFlowSys}_q, 0) = \max(F_q, 0)$:

$$c_{M,q} = \alpha + \beta_1 F_q^- + \beta_2 F_q^+ + \beta_3 \text{ IndustryFlowIdio}_q + \gamma_1 c_{M,q-1} + \gamma_2 c_{M,q-2} + \epsilon_q, \tag{A.16}$$

A finding $\beta_1 < 0$ would indicate that the transaction costs of the aggregate market are greater when the systematic outflows are greater; a finding $\beta_2 > 0$ would indicate that the transaction costs of the aggregate market are greater when the systematic inflows are greater.

Column (4) of Table A-2 shows that the coefficient on the negative part of the flow factor is -0.612 ($t$-statistic= $-2.022$); in contrast, the coefficient on the positive part of the flow factor is smaller in magnitude and not significant (coef. $= -0.064$; $t$-statistic$= -1.473$).

Additionally, Column (5) shows that neither the positive nor negative part of IndustryFlowIdio is significant while the loading on $F_q^-$ remains significant. A similar set of findings is reported in Column (6) when we define $c_{M,q}$ as the equal-weighted average Amihud (2002) illiquidity across stocks rather than the market capitalization-weighted average. Overall, the evidence helps to justify using systematic outflows as drivers of stock market illiquidity costs and is consistent with our empirical findings that a stocks' exposures to systematic outflow risk (i.e., FSE)—rather than systematic inflow risk (i.e., FPE)—affects its expected returns.

## Appendix B. Comparing the first principal component of fund flows with value-weighted aggregate flows

In this section, we compare the first principal component (PC) of fund flows with value-weighted aggregate flows (aggregate flows). First, we use simulations to compare the correlation coefficients of aggregate flows and the first PC of fund flows with the true unobservable flow factor. The first PC represents the common variation among fund flows and is used to estimate the flow factor. Second, we use simulations to compare the correlation coefficients of aggregate flows and the first PC of fund flows with commonality in fund flows. Commonality in fund flows is measured by the percentage of funds that experience net positive flows in a given period. Finally, we use a numerical example to compare the first PC and aggregate flows in measuring aggregate net trading of mutual funds.

### *B1. Correlations with the true factor: PCA vs. aggregate flows*

**Table B-1**
Correlations with the true flow factor: PCA vs. aggregate flows
Simulation comparison of the asymptotic principal components (PCA) factor estimates to value-weighted flows. The flow factor, flow betas relative to the flow factor, and idiosyncratic flow volatility in a single-factor model are based on sample characteristics. To generate simulated flows, a zero-mean idiosyncratic flow is added to the product of the flow factor and the flow beta for each fund and 147 quarterly periods. Panel A and B report the correlation coefficients ($\rho$) between the true flow factor ($F^{True}$) and the first PC ($F^{PCA}$) of fund flows, and between the true factor ($F^{True}$) and value-weighted aggregate flows ($F^{Industry}$), respectively. The average correlation is the mean value of $\rho$ across 100 iterations, and the maximum and minimum $\rho$ are also reported. For a detailed discussion of the simulation, please refer to Appendix B.1.

| Panel A: $\rho(F^{PCA}, F^{True})$ | | | |
|---|---|---|---|
| Number of funds | Average $\rho$ | Maximum $\rho$ | Minimum $\rho$ |
| 50 | 0.987 | 0.992 | 0.979 |
| 100 | 0.993 | 0.996 | 0.991 |
| 1000 | 0.999 | 1.000 | 0.999 |
| 2000 | 1.000 | 1.000 | 0.999 |
| 3000 | 1.000 | 1.000 | 1.000 |
| 10000 | 1.000 | 1.000 | 1.000 |
| Panel B: $\rho(F^{Industry}, F^{True})$ | | | |
| Number of funds | Average $\rho$ | Maximum $\rho$ | Minimum $\rho$ |
| 50 | 0.787 | 0.957 | 0.301 |
| 100 | 0.832 | 0.973 | 0.387 |
| 1000 | 0.907 | 0.990 | 0.600 |
| 2000 | 0.915 | 0.992 | 0.602 |
| 3000 | 0.920 | 0.993 | 0.626 |
| 10000 | 0.930 | 0.995 | 0.715 |

Table B-1 shows the results from a simulation comparison of the asymptotic principal components (PCA) factor estimates versus value-weighted aggregate flows for a single-factor model (100 iterations). First, we draw 147 quarterly observations for the true flow factor ($F^{True}$) from a normal distribution with mean zero and standard deviation of 1.7%. This matches the length of our sample period which is 147 quarterly observations and the sample standard deviation of the scaled flow factor (Panel A of Table 1). Second, we draw 147 quarterly observations of idiosyncratic flows for $N$ funds. Idiosyncratic flows are assumed to be independently and identically distributed across funds and quarters, and drawn from a multivariate normal distribution with a mean of zero and standard deviation of 15.8%. This matches the standard deviation of the idiosyncratic flow for a typical fund in our sample and is based on the difference between the sample variance of fund flows ($17.91\%^2$) and the sample systematic variance of fund flows for the median fund $(5 \times\ 1.70\%)^2$ (Panel B of Table 1). Third, we assign a single flow beta to each fund along equally spaced increments between -1.46 to 14.36. This matches the interquartile range of the negative flow betas in our sample (Panel B of Table 1). Fourth, we compute a fund's total flows as the sum of its systematic flow (i.e., its mutual fund flow beta times the flow factor realization) and its idiosyncratic flow. Fifth, we generate a time series of assets under management for each fund based on a starting value of 100 and its simulated flow series. Sixth, given the simulated flow and AUM data, we estimate the flow factor as the first principal component using PCA ($F^{PCA}$) and compute aggregate flows as the value (AUM)-weighted average of individual fund flows ($F^{Industry}$). Finally, we estimate correlation coefficients ($\rho$) between $F^{PCA}$ and $F^{True}$ (Panel A), and between $F^{Industry}$ and $F^{True}$ (Panel B). A $\rho$ value of 1.0 implies zero error in factor estimate. Average correlation is the mean value of $\rho$ across the 100 iterations (similarly for maximum and minimum $\rho$).

Panel A of Table B-1 shows the results from comparing $F^{PCA}$ and $F^{True}$. The average $\rho$ values are large and nearly 1.0 for all values of $N$, including $N = 2000$ which is about the average number of funds per quarter in our sample. This is consistent with the simulation evidence in Connor and Korajczyk (1988) that the PCA provides accurate estimates of the pervasive factors in equity returns; we now know that it also provides accurate estimates of the pervasive factors in mutual fund flows. Panel B shows the results from comparing $F^{Industry}$ and $F^{True}$. In comparison to the PCA results, the $\rho$ values for aggregate flows have a lower average and a wider range. For example, when $N = 2000$, aggregate flows have an average $\rho$ of 0.915 and ranges from 0.602 to 0.992. Overall, the simulation evidence shows that PCA is relatively more accurate in capturing the variation in systematic flows as compared to value-weighted aggregate flows. This helps support our preferred method of using the first principal component of flows to estimate the true flow factor, flow betas, and, hence, stocks' exposures to systematic fire sale risk ($FSE$).

### B2. Correlations with flow commonality: PCA vs. aggregate flows

Next, we run a simulation exercise to show that the flow factor is a better measure of flow commonality as measured by the percentage of funds with positive net flows. The simulated data are the same as those in Appendix B.1 but with the following additional elements:

1. Given the simulated flow and AUM data, compute the percentage of funds with positive net flows to measure commonality in fund flows.
2. Finally, estimate correlation coefficients ($\rho$) between the commonality and the first PC of fund flows, and between the commonality and value-weighted aggregate flows.

Table B-2 presents the average, maximum, and minimum $\rho$ values across 100 iterations of the simulation. Panel A shows that the average correlations between the commonality in fund flows and the first PC are large and range from 0.949 to 0.981 for all values of $N$, including $N = 2000$ which is about the average number of funds per quarter in our sample. Panel B shows the results for value-weighted aggregate flows. In comparison to the PCA results, the correlation values for aggregate flows have a lower average and a wider range. For example, when $N =$ 2000, the value-weighted aggregate flows have an average correlation of 0.897, and the correlations range from 0.566 to 0.979. Overall, the simulation evidence shows that the first PC is more accurate in capturing the variation in mutual fund flow commonality.

### B3. Numerical example of aggregate net trading by mutual funds

In this section, we present a numerical example of aggregate net trading by mutual funds that occurs in response to flows. We show that the aggregate net trading is equal to value-weighted aggregate fund flows when all funds hold the same portfolios, but not necessarily when holdings differ across funds.

**Table B-2**
Correlations with flow commonality: PCA vs. aggregate flows
Simulation comparison of the asymptotic principal components (PCA) factor estimates to value-weighted flows. The flow factor, flow betas relative to the flow factor, and idiosyncratic flow volatility in a single-factor model are based on sample characteristics. To generate simulated flows, a zero-mean idiosyncratic flow is added to the product of the flow factor and the flow beta for each fund and 147 quarterly periods. The commonality of fund flows is measured by the percentage of funds with positive net flows (inflows). Panel A and B report the correlation coefficients ($\rho$) between the flow commonality and the first PC ($F^{PCA}$) of fund flows, and between the commonality and value-weighted aggregate flows ($F^{Industry}$), respectively. The average correlation is the mean value of $\rho$ across 100 iterations, and the maximum and minimum $\rho$ are also reported. For a detailed discussion of the simulation, please refer to Appendix B.1 and B.2.

| Panel A: $\rho(F^{PCA},\ flow\ commonality)$ | | | |
|---|---|---|---|
| Number of funds | Average $\rho$ | Maximum $\rho$ | Minimum $\rho$ |
| 50 | 0.949 | 0.962 | 0.929 |
| 100 | 0.964 | 0.978 | 0.946 |
| 1000 | 0.979 | 0.989 | 0.965 |
| 2000 | 0.980 | 0.989 | 0.966 |
| 3000 | 0.980 | 0.989 | 0.966 |
| 10000 | 0.981 | 0.989 | 0.967 |
| Panel B: $\rho(F^{Industry}, flow\ commonality)$ | | | |
| Number of funds | Average $\rho$ | Maximum $\rho$ | Minimum $\rho$ |
| 50 | 0.790 | 0.933 | 0.331 |
| 100 | 0.824 | 0.949 | 0.379 |
| 1000 | 0.889 | 0.979 | 0.565 |
| 2000 | 0.897 | 0.979 | 0.566 |
| 3000 | 0.901 | 0.980 | 0.589 |
| 10000 | 0.910 | 0.982 | 0.670 |

The numerical example features 10 mutual funds, one large fund with \$65 in asset under management (AUM), and nine small funds with collectively \$35 in AUM (=\$35/9 per fund). Suppose the large fund has a net flow of -50% whereas the other 9 funds all have net flows of 25%. Due to the large fund's negative net flows, the value-weighted flows are -23.75%. In contrast, the equal-weighted flows are 17.5%, capturing the widespread inflows. The table below decomposes each flow of the 10 funds into the components of a single factor model for flows. The example shows that 9 out of 10 funds have inflows, and the flow factor (12%) and equal-weighted flows (17.5%) represent this commonality in fund flows better than value-weighted flows (-23.75%), which captures the one large fund's idiosyncratic flows of -56%.

| | AUM | Weight | Flow | Flow beta | Flow factor | Flow components systematic | fund-specific |
|---|---|---|---|---|---|---|---|
| Fund 1 | \$65 | 0.65 | -50% | 0.5 | 12% | 6% | -56% |
| Funds 2-10 | \$35 | 0.35 | 25% | 1.93 | 12% | 23% | 2% |

Suppose all funds hold 10% of their portfolio in a stock and scale their position dollar-for-dollar according to flows. In this case, the large fund sells \$3.25 dollars of the stock ($= \$65 \times -50\% \times 10\%$), and the nine small funds collectively buy \$0.875 dollars of the stock ($= \$35 \times 25\% \times 10\%$). As a result, the aggregate net trade is selling, -23.75% ($= \frac{-3.25+0.875}{10}$) of funds' total dollar holdings in that stock. This is exactly the same as value-weighted flows.

Now we will show that heterogeneity in fund holdings breaks the connection between aggregate trading and value-weighted flows. Suppose the large fund has a much smaller weight in the stock as compared to the smaller funds: 5% vs 19.29% as in the table below. The large fund's trade of the stock is -$1.625 (selling) whereas the other nine funds' collective trading is $1.688. As a result, the aggregate net trading is buying of 0.63% ($= \frac{-1.625+1.688}{10}$), in contrast to the negative value-weighted aggregate flows but consistent with the positive flow factor and equal-weighted flows. Therefore, the flow factor is the appropriate measure to captures the commonality in the flow-driven trading of mutual funds, as opposed to the value-weighted aggregate flows.

| | AUM | Weight | Flow | Holding weight | Holding in dollar | Trading |
|---|---|---|---|---|---|---|
| Fund 1 | $65 | 0.65 | -50% | 5.00% | $3.25 | -$1.625 |
| Funds 2-10 | $35 | 0.35 | 25% | 19.29% | $6.75 | $1.688 |
| Aggregate | | | | | $10.00 | $0.063 |

| | |
|---|---|
| Panel A: Aggregate flow and mutual fund variables | |
| Net flow | Growth of total net assets (TNA) net of returns. |
| Aggregate flow | TNA-weighted net flows of equity mutual funds. |
| Flow factor | The first principal component of equity mutual funds' net flows, estimated recursively (minimum 30 quarters) using the method of Ferson and Kim (2012) that applies the asymptotic principal components estimators in Connor and Korajczyk (1986). |
| Flow factor (-) | Min(flow factor, 0). |
| Flow factor (+) | Max(flow factor, 0). |
| Fund flow beta | Loadings of individual fund net flows on the flow factor estimated recursively (at least 30 quarters). |
| Negative flow beta ($\beta^-$) | Loadings of individual fund net flows on the flow factor (-). |
| Positive flow beta ($\beta^+$) | Loadings of individual fund net flows on the flow factor (+). |
| Net return | Quarterly returns, net of expenses and trading costs. |
| Family size | Sum of TNA of funds belonging to the fund family. |
| Age in years | The number of months since the inception date of the fund divided by 12. |
| Expense ratio | Expense ratio reported in the most recent annual reports. |
| Market/value/size/ momentum beta | Loadings on the Carhart's four factors (the market, value, size, and momentum factors), estimated over the prior 36 (minimum 30) months. |
| Carhart alpha | Returns in excess of the risk-free rate minus loadings on the Carhart's four factors multiplied by the corresponding factor returns. |
| Portfolio size | The sum of equity holdings. |
| Top *FSE* weight | Top-*FSE*-stock holdings divided by the sum of equity holdings. |
| Panel B: Stock variables | |
| Fire sale exposure (*FSE*) | Weighted-average of $\beta^-$ of mutual funds that own the stock. The weights are the ratio of the number of shares held by the fund to the number of shares held by all mutual funds. |
| Fire purchase exposure (*FPE*) | Weighted-average of $\beta^+$ of mutual funds that own the stock. |
| Flow exposure | Weighted-average of $\beta$ of mutual funds that own the stock. |
| Panel B: Stock variables (Continued) | |
| Market cap (size) | Closing price times the number of shares outstanding ($ billions). |
| Book-to-market ratio (B/M) | Book value (common stock minus treasury stock) divided by the market value of equity. |
| Past one-year return | Stock return over the last one year. |
| Market beta | Coefficient estimate on the excess return on CRSP VW. The beta estimate uses monthly excess returns over 60 (minimum 36) months ending in the prior quarter for each stock. |
| Ownership | Total number of shares owned by mutual funds divided by the total number of shares outstanding at the end of the quarter. |
| High ownership | A dummy variable that equals one if the ownership is above the median. |
| Change in breadth (of ownership) | Number of mutual funds that newly own the stock minus the number of mutual funds that sell out their existing position over the quarter, divided by the total number of mutual funds at the end of the previous quarter (see Chen et al., 2002). |
| Liq beta (PS) | Coefficient estimate on Pástor and Stambaugh's (2003) liquidity factor, estimated similar to market beta. The regression also includes Fama and French's 1992 three factors. |
| Liq beta (PS-tradable) | Coefficient estimate on Pástor and Stambaugh's (2003) tradable liquidity factor, estimated similar to Liquidity beta (PS). |
| Liq beta (Sadka-fixed transitory) | Coefficient estimate on Sadka's (2006) fixed transitory liquidity factor, estimated similar to Liquidity beta (PS). |
| Liq beta (Sadka-variable permanent) | Coefficient estimate on Sadka's (2006) variable permanent liquidity factor, estimated similar to Liquidity beta (PS). |
| Amihud illiquidity | Amihud's (2002) illiquidity measure over the past one year. |
| Return two-month | Return over the waiting period (2 months) before trading. |
| Event | A dummy variable that equals one if the event quarter is within four quarters before or four quarters after the stock was added to the S&P 500 Index. |
| Panel C: Aggregate and macroeconomic variables | |
| MKT/SMB/HML/MOM | Fama and French's three factors and Carhart's (1997) momentum factor, available on Kenneth French's website. |
| LIQ | Pástor and Stambaugh's (2003) tradable liquidity factor, available on Lubos Pastor's website. |
| BAB | Frazzini and Pedersen's (2014) betting against beta factor, available on Andrea Frazzini's website. |
| MFB | Boguth and Simutin's (2018) aggregate mutual fund beta as the weighted sum of individual stocks' market betas. |
| COSKEW | Returns on a trading strategy that buys the top 30% and short sells the bottom 30% of stocks in terms of coskewness. See Harvey and Siddique's (2000) Eq. (11). |

(*continued on next page*)

(*continued*)

| | |
|---|---|
| DOWNSIDE | Return on a trading strategy that buys the top 30% and short sells the bottom 30% of stocks in terms of the downside beta (loading on the negative part of the excess return on CRSP VW), estimated using daily stock returns over the past one year. See Ang, Chen and Xing (2006). |
| Δ CPI | Change in natural logarithm of the Consumer Price Index. |
| Exchange rate | Change in natural logarithm of the U.S. major foreign exchange index. |
| Δ Michigan index | Change in natural logarithm of the Michigan index. |
| Δ CPI | Change in natural logarithm of the Consumer Price Index. |
| Exchange rate | Change in natural logarithm of the U.S. major foreign exchange index. |
| Income growth | Change in natural logarithm of disposable personal income. |
| Production growth | Change in natural logarithm of the industry production index. |
| D/P ratio | The dividend-to-price ratio of the value- weighted CRSP index. |
| TBill | The yield on the 3-month Treasury Bill. |
| Treasury | The yield on the 10-year Treasury bond. |
| Stock market volatility | Annualized standard deviation of the return on the S&P 500 daily index. |
| Stock return | Annualized mean of the return on the S&P 500 daily index. |
| BAA (AAA) rate | Moody's Seasoned Baa (Aaa) corporate bond yield and Aaa bond yield. |
| Funds' net purchases | Funds' purchases minus sales as provided in the Financial Accounts of the U.S. by the Board of Governors of the Federal Reserve System. |

## Appendix C. Variable definition

## Appendix D. Robustness analysis of high-minus-low *FSE* portfolios

This table reports the results from variations of the portfolio analysis in Panel B of Table 2. Panel A shows the results using an alternative measure of fire sale exposure in which *FSE* is calculated as in Eq. (3), except stock *i*'s total mutual fund ownership at the end of quarter $q$ (i.e., $\Sigma_{k=1}^{K} shr_{i,k,q}$) is replaced by stock $i$ 's shares outstanding at the end of quarter $q$. Panels B-D use *FSE* as in Eq. (3), but either portfolio formation begins immediately at the end of the quarter without a "skip-two-months" strategy (Panel B), includes in the sample stocks with a price less than \$5 (Panel C), or includes any CRSP delisting returns in the calculation of stock returns (Panel D). Results are reported for value-weighted portfolios with weights proportional to stock market capi-

| *FSE* quintiles | VW | EW | DGTW VW | DGTW EW | *FSE* quintiles | VW | EW | DGTW VW | DGTW EW |
|---|---|---|---|---|---|---|---|---|---|
| Panel A: Using an alternative *FSE* measure | | | | | Panel B: Without waiting for two months | | | | |
| 1 | 0.084 | 0.108 | -0.022 | -0.015 | 1 | 0.075 | 0.101 | -0.026 | -0.016 |
| 2 | 0.109 | 0.117 | 0.004 | -0.004 | 2 | 0.089 | 0.121 | -0.007 | -0.001 |
| 3 | 0.089 | 0.115 | -0.002 | 0.001 | 3 | 0.102 | 0.121 | 0.000 | 0.002 |
| 4 | 0.113 | 0.127 | -0.001 | 0.007 | 4 | 0.127 | 0.128 | 0.016 | 0.008 |
| 5 | 0.142 | 0.141 | 0.019 | 0.012 | 5 | 0.142 | 0.134 | 0.009 | 0.009 |
| High-Low | 0.058 | 0.033 | 0.042 | 0.027 | High-Low | 0.066 | 0.033 | 0.035 | 0.026 |
| (t-statistics) | (3.930) | (2.475) | (3.896) | (2.957) | (t-statistics) | (4.518) | (3.724) | (3.525) | (3.879) |
| Panel C: Including penny stocks | | | | | Panel D: Including delisting returns | | | | |
| 1 | 0.086 | 0.126 | -0.027 | -0.019 | 1 | 0.084 | 0.113 | -0.023 | -0.012 |
| 2 | 0.098 | 0.160 | -0.005 | 0.011 | 2 | 0.094 | 0.112 | -0.005 | -0.005 |
| 3 | 0.071 | 0.129 | -0.016 | -0.004 | 3 | 0.100 | 0.114 | 0.002 | 0.001 |
| 4 | 0.110 | 0.138 | 0.004 | -0.001 | 4 | 0.126 | 0.125 | 0.008 | 0.002 |
| 5 | 0.142 | 0.151 | 0.018 | 0.003 | 5 | 0.149 | 0.145 | 0.019 | 0.014 |
| High-Low | 0.056 | 0.025 | 0.045 | 0.022 | High-Low | 0.065 | 0.032 | 0.041 | 0.026 |
| (t-statistics) | (3.806) | (1.633) | (4.051) | (2.133) | (t-statistics) | (4.161) | (3.483) | (4.130) | (3.955) |

talization (VW) and equally-weighted portfolios (EW). Returns are annualized average monthly returns. DGTW returns are equal to raw returns minus benchmark returns, which are returns on the stocks in the same quintiles of B/M, size, and past 1-year return (Daniel et al., 1997). Standard errors are Newey-West standard errors with 4 lags. The sample period is from June 1989 to May 2017.

## References


Acharya, V.V., Pedersen, L.H., 2005. Asset pricing with liquidity risk. J. Financ. Econ. 77 (2), 375–410.
Agarwal, V., Ren, H., Shen, K., Zhao, H., 2023. Redemption in kind and mutual fund liquidity management. Rev. Financ. Stud. 36 (6), 2274–2318.
Agarwal, V., Zhao, H., 2019. Interfund lending in mutual fund families: role in liquidity management. Rev. Financ. Stud. 32 (10), 4079–4115.
Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. J. Financ. Market. 5 (1), 31–56.
Ang, A., Chen, J., Xing, Y., 2006. Downside risk. Rev. Financ. Stud. 19 (4), 1191–1239.
Anton, M., Polk, C., 2014. Connected stocks. J. Finance 69 (3), 1099–1127.
Aragon, G.O., Strahan, P.E., 2012. Hedge funds as liquidity providers: evidence from the lehman bankruptcy. J. Financ. Econ. 103 (3), 570–587.
Bartram, S.M., Griffin, J.M., Lim, T., Ng, D.T., 2015. How important are foreign ownership linkages for international stock returns? Rev. Financ. Stud. 28 (11), 3036–3072.
Berk, J.B., Van Binsbergen, J.H., 2015. Measuring skill in the mutual fund industry. J. Financ. Econ. 118 (1), 1–20.
Bessembinder, H., 2018. Do stocks outperform treasury bills? J. Financ. Econ. 129 (3), 440–457.
Boehmer, E., Kelley, E.K., 2009. Institutional investors and the informational efficiency of prices. Rev. Financ. Stud. 22 (9), 3563–3594.
Boguth, O., Simutin, M., 2018. Leverage constraints and asset prices: insights from mutual fund risk taking. J. Financ. Econ. 127 (2), 325–341.
Bollerslev, T., Todorov, V., 2011. Estimation of jump tails. Econometrica 79 (6), 1727–1783.
Brennan, M., Huh, S., Subrahmanyam, A., 2013. An analysis of the amihud illiquidity premium. Rev. Asset Pric. Stud. 3 (1), 133–176.
Brennan, M.J., Chordia, T., Subrahmanyam, A., Tong, Q., 2012. Sell-order liquidity and the cross-section of expected stock returns. J. Financ. Econ. 105 (3), 523–541.
Brunnermeier, M.K., Pedersen, L.H., 2009. Market liquidity and funding liquidity. Rev. Financ. Stud. 22 (6), 2201–2238.
Carhart, M.M., 1997. On persistence in mutual fund performance. J. Finance 52 (1), 57–82.
Chen, H., 2022. The Demand for Large Stocks. Unpublished working paper. University of Notre Dame..
Chen, J., Hong, H., Huang, M., Kubik, J.D., 2004. Does fund size erode mutual fund performance? the role of liquidity and organization. Am. Econ. Rev. 94 (5), 1276–1302.
Chen, J., Hong, H., Stein, J.C., 2002. Breadth of ownership and stock returns. J. Financ. Econ. 66 (2-3), 171–205.
Chen, Q., Goldstein, I., Jiang, W., 2010. Payoff complementarities and financial fragility: Evidence from mutual fund outflows. J. Financ. Econ. 97 (2), 239–262.
Chernenko, S., Sunderam, A., 2016. Liquidity transformation in asset management: evidence from the cash holdings of mutual funds. Unpublished working paper. National Bureau of Economic Research.
Chordia, T., Roll, R., Subrahmanyam, A., 2000. Commonality in liquidity. J. Financ. Econ. 56 (1), 3–28.
Connor, G., Korajczyk, R.A., 1986. Performance measurement with the arbitrage pricing theory: a new framework for analysis. J. Financ. Econ. 15 (3), 373–394.
Connor, G., Korajczyk, R.A., 1988. Risk and return in an equilibrium APT: application of a new test methodology. J. Financ. Econ. 21 (2), 255–289.
Coval, J., Stafford, E., 2007. Asset fire sales (and purchases) in equity markets. J. Financ. Econ. 86 (2), 479–512.
Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. J. Finance 52 (3), 1035–1058.
Diamond, D.W., Dybvig, P.H., 1983. Bank runs, deposit insurance, and liquidity. J. Polit. Econ. 91 (3), 401–419.
Dou, W.W., Kogan, L., Wu, W., 2022. Common fund flows: Flow hedging and factor pricing. Forthcoming. Journal of Finance.
Edelen, R.M., Marcus, A.J., Tehranian, H., 2010. Relative sentiment and stock returns. Financ. Anal. J. 66 (4), 20–32.
Falato, A., Hortacsu, A., Li, D., Shin, C., 2021. Fire-sale spillovers in debt markets. J. Finance 76 (6), 3055–3102.
Fama, E.F., French, K.R., 1992. The cross-section of expected stock returns. J. Finance 47 (2), 427–465.
Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. J. Financ. Econ. 33 (1), 3–56.
Fama, E.F., MacBeth, J.D., 1973. Risk, return, and equilibrium: empirical tests. J. Polit. Econ. 81 (3), 607–636.
Ferson, W.E., Kim, M.S., 2012. The factor structure of mutual fund flows. Int. J. Portfolio Anal. Manag. 1 (2), 112–143.
Frazzini, A., Israel, R., Moskowitz, T.J., 2018. Trading Costs. Unpublished working paper. Available at SSRN 3229719.
Frazzini, A., Pedersen, L.H., 2014. Betting against beta. J. Financ. Econ. 111 (1), 1–25.
Goldstein, I., Jiang, H., Ng, D.T., 2017. Investor flows and fragility in corporate bond funds. J. Financ. Econ. 126 (3), 592–613.
Gompers, P.A., Metrick, A., 2001. Institutional investors and equity prices. Q. J. Econ. 116 (1), 229–259.
Greenwood, R., Thesmar, D., 2011. Stock price fragility. J. Financ. Econ. 102 (3), 471–490.
Harris, L., Gurel, E., 1986. Price and volume effects associated with changes in the s&p 500 list: new evidence for the existence of price pressures. J. Finance 41 (4), 815–829.
Harvey, C.R., Siddique, A., 2000. Conditional skewness in asset pricing tests. J. Finance 55 (3), 1263–1295.
Hau, H., Lai, S., 2017. The role of equity funds in the financial crisis propagation. Rev. Finance 21 (1), 77–108.
Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. J. Finance 48 (1), 65–91.
Jotikasthira, C., Lundblad, C., Ramadorai, T., 2012. Asset fire sales and purchases and the international transmission of funding shocks. J. Finance 67 (6), 2015–2050.
Kamara, A., Lou, X., Sadka, R., 2008. The divergence of liquidity commonality in the cross-section of stocks. J. Financ. Econ. 89 (3), 444–466.
Kang, N., Kondor, P., Sadka, R., 2014. Do hedge funds reduce idiosyncratic risk? J. Financ. Q. Anal. 49 (4), 843–877.
Keim, D.B., Madhavan, A., 1997. Transactions costs and investment style: an inter-exchange analysis of institutional equity trades. J. Financ. Econ. 46 (3), 265–292.
Kim, M., 2020. Cross-sectional asset pricing with fund flow and liquidity risk. Unpublished working paper. University of Melbourne.
Kim, M.S., Zapatero, F., 2023. Uncertainty and dispersion of opinions. Unpublished working paper. Boston University.
Koch, A., Ruenzi, S., Starks, L., 2016. Commonality in liquidity: a demand–side explanation. Rev. Financ. Stud. 29 (8), 1943–1974.
Kyle, A.S., 1985. Continuous auctions and insider trading. Econometrica 53 (6), 1315–1336.
Liu, X., Mello, A.S., 2011. The fragile capital structure of hedge funds and the limits to arbitrage. J. Financ. Econ. 102 (3), 491–506.
Lou, D., 2012. A flow-based explanation for return predictability. Rev. Financ. Stud. 25 (12), 3457–3489.
Ma, L., Tang, Y., Gomez, J., 2019. Portfolio manager compensation in the US mutual fund industry. J. Finance 74 (2), 587–638.
Manconi, A., Massa, M., Yasuda, A., 2012. The role of institutional investors in propagating the crisis of 2007–2008. J. Financ. Econ. 104 (3), 491–518.
Massa, M., Schumacher, D., Wang, Y., 2021. Who is afraid of blackrock? Rev. Financ. Stud. 34 (4), 1987–2044.
Nagel, S., 2005. Short sales, institutional investors and the cross-section of stock returns. J. Financ. Econ. 78 (2), 277–309.
Nanda, V., Wu, W., Zhou, X.A., 2019. Investment commonality across insurance companies: fire sale risk and corporate yield spreads. J. Financ. Q. Anal. 54 (6), 2543–2574.
Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55 (3), 703–708.
Pástor, L., Stambaugh, R.F., 2003. Liquidity risk and expected stock returns. J. Polit. Econ. 111 (3), 642–685.
Pollet, J.M., Wilson, M., 2008. How does size affect mutual fund behavior? J. Finance 63 (6), 2941–2969.
Sadka, R., 2006. Momentum and post-earnings-announcement drift anomalies: the role of liquidity risk. J. Financ. Econ. 80 (2), 309–349.
Shleifer, A., 1986. Do demand curves for stocks slope down? J. Finance 41 (3), 579–590.
Shleifer, A., Vishny, R.W., 1992. Liquidation values and debt capacity: a market equilibrium approach. J. Finance 47 (4), 1343–1366.

Sias, R.W., Starks, L.T., Titman, S., 2006. Changes in institutional ownership and stock returns: assessment and methodology. J. Bus. 79 (6), 2869–2910.
Simutin, M., 2014. Cash holdings and mutual fund performance. Rev. Finance 18 (4), 1425–1464.
Spiegel, M., Zhang, H., 2013. Mutual fund risk and market share-adjusted fund flows. J. Financ. Econ. 108 (2), 506–528.
Tang, Y., 2014. Leverage and Liquidity: evidence from the Closed-End Fund Industry. Unpublished working paper. University of Florida.
Zeng, Y., 2017. A dynamic theory of mutual fund runs and liquidity management. Unpublished working paper. University of Pennsylvania.