Internet Appendix for:

Price and Liquidity Spillovers during Fire Sale Episodes

November 6, 2017

This internet appendix collects additional material accompanying the paper "Price and Liquidty Spillovers during Fire Sale Episodes." In Section A, we present a short noisy rational expectations equilibrium model and derive the empirical predictions tested in this paper. In Section B, we show results using a traditional event study approach. In Section C, we show results for a robustness check for different risk-adjusted returns.

Appendix A: A Multi-Asset NREE Model

In this appendix, we present the solution to a plain-vanilla NREE model with two risky stocks (Grossman, 1976; Hellwig, 1980; Admati, 1985). Our aim is to show how the empirical predictions regarding price and liquidity spillovers naturally arise in a standard model of cross-asset learning. The model is a simplified version of Admati (1985).

Setup: Trading takes place at $t = 0$ and payoffs are realized at $t = 1$. There is a riskless asset in infinitely elastic supply with a gross return normalized to one and there are two risky stocks that pay off

$$\begin{pmatrix}\theta_1\\ \theta_2\end{pmatrix} \sim N\left(\begin{pmatrix}\bar{\theta}\\ \bar{\theta}\end{pmatrix}, \begin{pmatrix}\sigma_\theta^2 & \rho\sigma_\theta^2\\ \rho\sigma_\theta^2 & \sigma_\theta^2\end{pmatrix}\right).$$

Here, $\bar{\theta}$ is the expected payoff of a given stock, σ_θ^2 is the variance of the payoff, and $\rho \in [-1,1]$ is the correlation between the payoffs of the two stocks.

There is a unit-mass of investors with CARA utility that maximize the expected utility of terminal wealth. Investors are assumed to have the same risk tolerance $\gamma > 0$. Each investor i receives a pair of signals about the two stocks:

$$\begin{pmatrix}s_{1i}\\ s_{2i}\end{pmatrix} = \begin{pmatrix}\theta_1\\ \theta_2\end{pmatrix} + \begin{pmatrix}\varepsilon_{1i}\\ \varepsilon_{2i}\end{pmatrix} \quad \text{where} \quad \begin{pmatrix}\varepsilon_{1i}\\ \varepsilon_{2i}\end{pmatrix} \sim N\left(\begin{pmatrix}0\\ 0\end{pmatrix}, \begin{pmatrix}\sigma_\varepsilon^2 & 0\\ 0 & \sigma_\varepsilon^2\end{pmatrix}\right)$$

Signal errors are assumed to be independent across investors. Thus, investors have dispersed information and try to learn about other investors' signals from the equilibrium prices. To prevent prices from being fully revealing, the asset supply of the two stocks is assumed to be random:

$$\begin{pmatrix}z_1\\ z_2\end{pmatrix} \sim N\left(\begin{pmatrix}\bar{z}\\ \bar{z}\end{pmatrix}, \begin{pmatrix}\sigma_{z1}^2 & 0\\ 0 & \sigma_{z2}^2\end{pmatrix}\right)$$

An equilibrium is obtained when (1) investors choose optimal demands given their beliefs conditional on their respective information sets $\{s_{1i}, s_{2i}, p_1, p_2\}$ and (2) markets clear given these optimal demands.

Matrix notation: For notational convenience, the model solution is given in matrix notation. Let $\boldsymbol{\theta}$ denote the vector of payoff realizations, $\bar{\boldsymbol{\theta}}$ be the vector of expected payoffs, $\boldsymbol{\varepsilon_i}$ be the vector of investor i's signal errors, $\boldsymbol{z}$ be the vector of realized stock supplies, and $\bar{\boldsymbol{z}}$ be the vector of average (expected) stock supplies. Let the variance-covariance matrixes of $\boldsymbol{\theta}$, $\boldsymbol{\varepsilon_i}$, and $\boldsymbol{z}$ be given by $\boldsymbol{V}$, $\boldsymbol{S}$, and $\boldsymbol{U}$, respectively. Let $\boldsymbol{p} = (p_1 \quad p_2)'$ be the vector of equilibrium prices. Finally, it is useful to define the matrix $\boldsymbol{Q} \equiv \gamma \boldsymbol{S}^{-1}$.

Theorem (Admati, 1985): There exists a unique linear rational expectations equilibrium price of the form $\boldsymbol{p} = \boldsymbol{A} + \boldsymbol{B\theta} - \boldsymbol{Cz}$ where

$$\boldsymbol{A} = \gamma(\gamma\boldsymbol{V}^{-1} + \gamma\boldsymbol{QU}^{-1}\boldsymbol{Q} + \boldsymbol{Q})^{-1}(\boldsymbol{V}^{-1}\bar{\boldsymbol{\theta}} + \boldsymbol{QU}^{-1}\bar{\boldsymbol{z}}),$$

$$\boldsymbol{B} = (\gamma\boldsymbol{V}^{-1} + \gamma\boldsymbol{QU}^{-1}\boldsymbol{Q} + \boldsymbol{Q})^{-1}(\boldsymbol{Q} + \gamma\boldsymbol{QU}^{-1}\boldsymbol{Q}),$$

$$\boldsymbol{C} = (\gamma\boldsymbol{V}^{-1} + \gamma\boldsymbol{QU}^{-1}\boldsymbol{Q} + \boldsymbol{Q})^{-1}(\boldsymbol{I} + \gamma\boldsymbol{QU}^{-1}).$$

Proof: See Admati (1985).

Matrix $\boldsymbol{C}$ plays an important role for the arguments to follow as it governs how the equilibrium prices respond to changes in asset supplies—like from a fire sale—and thus captures price impact—i.e., the sensitivity of the price to a (hypothetical) trade of one share. Given the structure imposed on $\boldsymbol{V}$, $\boldsymbol{U}$ and $\boldsymbol{Q}$, we can apply simple matrix algebra to derive

$$\boldsymbol{C} = \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix},$$

$$c_{11} = \frac{1}{\bar{c}}\left(1 + \frac{\gamma^2}{\sigma_{z1}^2\sigma_\varepsilon^2}\right)\left(\frac{\gamma^2}{\sigma_{z2}^2\sigma_\varepsilon^4} + \frac{1}{\sigma_\varepsilon^2} + \frac{1}{\sigma_\theta^2(1-\rho^2)}\right),$$

$$c_{12} = \frac{\rho}{\bar{c}\sigma_\theta^2(1-\rho^2)}\left(1 + \frac{\gamma^2}{\sigma_{z2}^2\sigma_\varepsilon^2}\right),$$

$$c_{21} = \frac{\rho}{\bar{c}\sigma_\theta^2(1-\rho^2)}\left(1 + \frac{\gamma^2}{\sigma_{z1}^2\sigma_\varepsilon^2}\right),$$

$$c_{22} = \frac{1}{\bar{c}}\left(1 + \frac{\gamma^2}{\sigma_{z2}^2\sigma_\varepsilon^2}\right)\left(\frac{\gamma^2}{\sigma_{z1}^2\sigma_\varepsilon^4} + \frac{1}{\sigma_\varepsilon^2} + \frac{1}{\sigma_\theta^2(1-\rho^2)}\right),$$

with $\bar{c} = \gamma\left(\frac{\gamma^2}{\sigma_{z1}^2\sigma_\varepsilon^4} + \frac{1}{\sigma_\varepsilon^2} + \frac{1}{\sigma_\theta^2(1-\rho^2)}\right)\left(\frac{\gamma^2}{\sigma_{z2}^2\sigma_\varepsilon^4} + \frac{1}{\sigma_\varepsilon^2} + \frac{1}{\sigma_\theta^2(1-\rho^2)}\right) - \frac{\rho^2\gamma}{\sigma_\theta^4(1-\rho^2)^2}$.

The following corollary follows immediately:

Corollary: Given the structure imposed on $\boldsymbol{V}$, $\boldsymbol{U}$ and $\boldsymbol{Q}$, all elements of matrix $\mathbf{C}$ are strictly positive and c_{jj} is increasing in $\sigma_{z\neg j}^2$ for $j \in \{1,2\}$.

Note that this corollary depends on the assumptions that asset supplies and signal errors are assumed to be independent across stocks. Admati (1985) shows that, when these assumptions and especially the one about independent supplies do not hold, counterintuitive results are possible. We feel, however, that these assumptions are intuitively justified as a large body of empirical evidence shows that uninformed (noise) trading is associated with idiosyncratic volatility (e.g., Brandt et al., 2010; Foucault et al., 2011)—suggesting that asset supply shocks are not much correlated. We also emphasize that these assumptions are shared with a large bulk of the theoretical literature (e.g., Veldkamp, 2006; Cespa and Foucault, 2014).

Fire sales: A fire sale can be thought of as having two distinct effects in our model. First and foremost, a fire sale can be interpreted as a sudden increase in the asset supply realization of one stock. Second, a fire sale may also *indirectly* affect equilibrium by increasing the perceived uncertainty about asset supply shocks.

Intuitively, an increase in σ_{zj}^2, the variance of supply shocks, reduces the signal-to-noise ratio of stock j's price signal, and thereby reduces the price informativeness of the fire sale stock. To see this in our model, note that the variance of the price signal depends on the variance of the term $(c_{jj}/b_{jj})z_j$, which can be shown to be increasing in σ_{zj}^2. In the context of our model, the increase in σ_{zj}^2 can be rationalized by noting that fire sales can be understood as a sequence of serially correlated noise shocks. An extreme noise realization in one period will then cause market makers to update their expectations about noise trader risk in future periods. There are at least two other channels—outside of our model—for why price informativeness may decrease during a fire sale. First, when market makers are uncertain whether informed traders are present, a large unexpected trade (as from a fire sale) may cause them to update this probability, leading them to demand a higher price impact (e.g., Easley and O'Hara, 1992; Avery and Zemsky, 1998; Banerjee and Green, 2015), which reduces price informativeness. Second, fire sale shocks may hurt informed arbitrageurs, causing them to trade less aggressively in the fire sale stock and thereby rendering it less informationally-efficient (Dow and Han, 2016).

For illustrational purposes, we now assume that stock 2 has the fire sale (z_2 and σ_{z2}^2 go up) and that stock 1 is a close economic peer of stock 2 (i.e., $\rho > 0$). We establish two distinct empirical predictions that follow from these assumptions.

Price spillover effect: The price spillover effect follows from the increase z_2. Formally, such an increase in stock 2's asset supply causes a price drop in both the fire sale stock and its economic peer:

$$\underbrace{\frac{\partial p_2}{\partial z_2} = -c_{22} < 0}_{\text{"fire sale price effect"}} \quad \text{and} \quad \underbrace{\frac{\partial p_1}{\partial z_2} = -c_{12} < 0}_{\text{"price spillover effect"}}$$

Intuitively, the most direct consequence of the increase in z_2 is a drop in stock 2's price, which occurs for two reasons. First, since investors are risk-averse, stock 2 must offer them a bigger discount in order for them to hold more of it. Second, since a given investor is unable to disentangle the supply shock from low demand by the other investors, which he would attribute to them having received low signal realizations, he downgrades his expectations about θ_2 and thus demands less itself. The price of stock 2 must then fall further for the market to clear.

The drop in stock 2's price caused by the fire sale should then spill over to stock 1. This is due to a simple *learning* effect: since the two stock payoffs are positively correlated, investors view the drop in stock 2's price as bad news about stock 1, leading them to curb back their demand in response. Thus, for the market to clear, stock 1's price has to fall as well.

Liquidity spillover: The liquidity spillover effect comes from the increase in σ_{z2}^2 and says that the peer of a fire sale stock suffers from lower liquidity as a result of the fire sale:

$$\underbrace{\frac{\partial}{\partial \sigma_{z2}^2}\left(-\frac{\partial p_1}{\partial z_1}\right) = \frac{\partial c_{11}}{\partial \sigma_{z2}^2} > 0}_{\text{"liquidity spillover effect"}}$$

The (negative of the) partial derivative of the equilibrium price with respect to its own asset supply measures how much the price changes in response to selling (buying) one additional share. In the model, this derivative equals $-c_{jj}$ for $j \in \{1,2\}$ and thus c_{jj} can be interpreted as a measure of stock j's liquidity (akin to Kyle's lambda).

The expression derived above for c_{jj} does not depend on z_j and so there is no direct effect of the change in stock 2's asset supply on its own liquidity or the liquidity of its peer. However, under the assumption that there is also an increase in σ_{z2}^2, we expect the liquidity of stock 1 to decrease.[1] The intuition for this is as follows: by increasing the uncertainty about stock 2's supply, the fire sales reduces the informativeness of stock 2's price (see above). Since this price serves as a signal for stock

[1] Whether or not the liquidity of the fire sale stock 2 should also deteriorate is unclear and depends on the model assumptions. In Admati (1985), an increase in σ_{z2}^2 actually increases liquidity, as it makes each investor less concerned about trading with other better-informed investors (much like in Kyle, 1985). In Cespa and Foucault (2014), this adverse-selection channel is shut down by assuming that each stock has its own specialized market makers who all know the same. An increase in the variance of supply shocks then decreases liquidity, as risk-averse investors become more reluctant to take on additional inventory.

1, investors become less certain about θ_1 and thus more reluctant to accommodate supply shocks in stock 1. In other words, stock 1 becomes less liquid.

Cross-asset hedging: One alternative explanation for a price spillover effect comes from the *hedging* activity of liquidity-providing arbitrageurs. In a stock market with price pressure, the fire sale causes a temporary price drop in stock 2 which attracts liquidity-providing arbitrageurs. These arbitrageurs want to hedge their increased exposure in stock 2 by selling stock 1, which causes stock 1's price to fall as well. Hence, even in the absence of asymmetric information, a simple story based on cross-asset hedging by liquidity providers can explain a price spillover from stock 2 to stock 1.

This can be seen in the model: when investors' private signals become completely uninformative ($\sigma_\varepsilon^2 \to \infty$), c_{12} converges to $\rho\sigma_\theta^2/\gamma$, which is positive. Thus, an increase in z_2 still causes a drop in p_1. However, the model also shows that a story based on cross-asset hedging cannot explain the existence of a liquidity spillover effect. Indeed, when $\sigma_\varepsilon^2 \to \infty$, c_{11} converges to σ_θ^2/γ, which is independent of σ_{z2}^2. Hence, without information asymmetry, a larger uncertainty about stock 2's supply should not affect stock 1's liquidity.

Appendix B: Event study results

B.1 For Fire Sales

The main result of our paper is that fire sales spill over to the returns of peer firms. In the paper, we show this in a panel regression setting, which we argue is best suited to isolate the return evolution for a given event in the presence of event clustering (i.e., the fact that sometimes fire sale events follow right after another). Here, we show that our spillover results are robust to using a standard event study approach—only that the evolution of returns is "smoothed out" due to not accounting for event clustering.

As in the paper, our fire sale events comprise all permno-quarter observations in which *mfflow* (the Edmans et al., 2012, measure of mutual funds' selling pressure) is in the bottom decile. For each event, we obtain the (value-weighted) portfolio of the ten closest peer stocks (in terms of the TNIC similarity score). We calculate abnormal returns using the market-model. Specifically, for each event, we estimate the intercept and β-coefficient from regressing returns of the fire sale stock and the corresponding peer portfolio on the CRSP value-weighted market index over a five-year period ending one year before the event-quarter (e.g., for quarters t=-24 to t=-5 where t=0 marks the event). We work with monthly return data to increase the precision of this estimation:

$$ret_{i\tau} = \alpha_i + \beta_i \times CRSPmktret_\tau \qquad \text{for} \qquad \tau = [-92, -13]$$

where τ indicates the distance in number of months from the event quarter.

In the event period, we then calculate abnormal returns (ARs) as the difference of realized returns minus the expected return based on the market-model:

$$AR_{it} = ret_{it} - (\widehat{\alpha_i} + \widehat{\beta_i} \times CRSPmktret_t) \qquad \text{for} \qquad t = [-4, +12]$$

For each event, we then cumulate abnormal returns (CARs) during the event period. Figure B.1 shows the evolution of average CARs in event-time—in Panel A for fire sale firms and in Panel B for the corresponding peer portfolio. 95%-confidence intervals are based on standard errors clustered by event-quarter.

B.2 For S&P 500 Index Additions

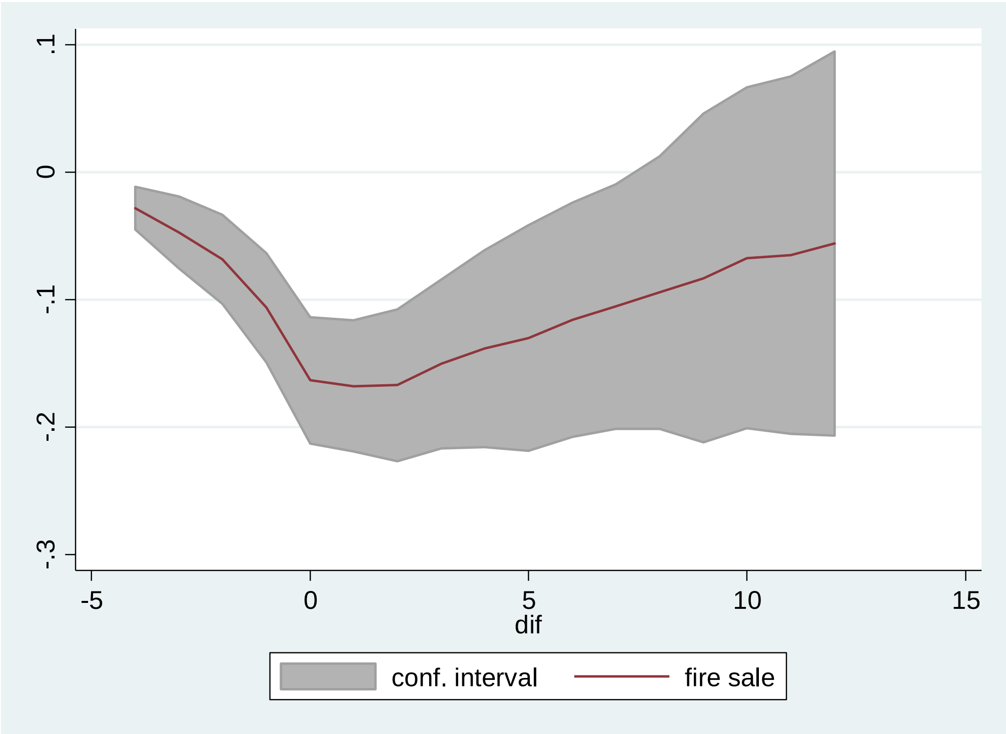
We also show event study results for S&P 500 index additions and their peers. Since this analysis is at the daily frequency, we estimate the market-model using daily return data over the period [-300, -50] relative to the effective date of the index addition. For each addition event, we again focus on the (value-weighted) portfolio of the top ten peers of the added stock.

Figure B.2 depicts the results. While added stocks experience a strong run-up in returns over the days preceding the effective inclusion (Panel A), there is no significant spillover to peer firms (Panel B).

Figure B.1: Event study results for Fire Sale and Peer Firms

This figure shows cumulative abnormal returns based on the market-model for fire sale firms (Panel A) and the (value-weighted) portfolio of the top ten peer firms (Panel B) in event-time (where 0 is the quarter of the fire sale). The grey band around the cumulated returns represents the 95%-confidence interval based on standard errors clustered at the event-quarter level.

Panel A: Fire Sale Firms



Panel B: Peer Firms

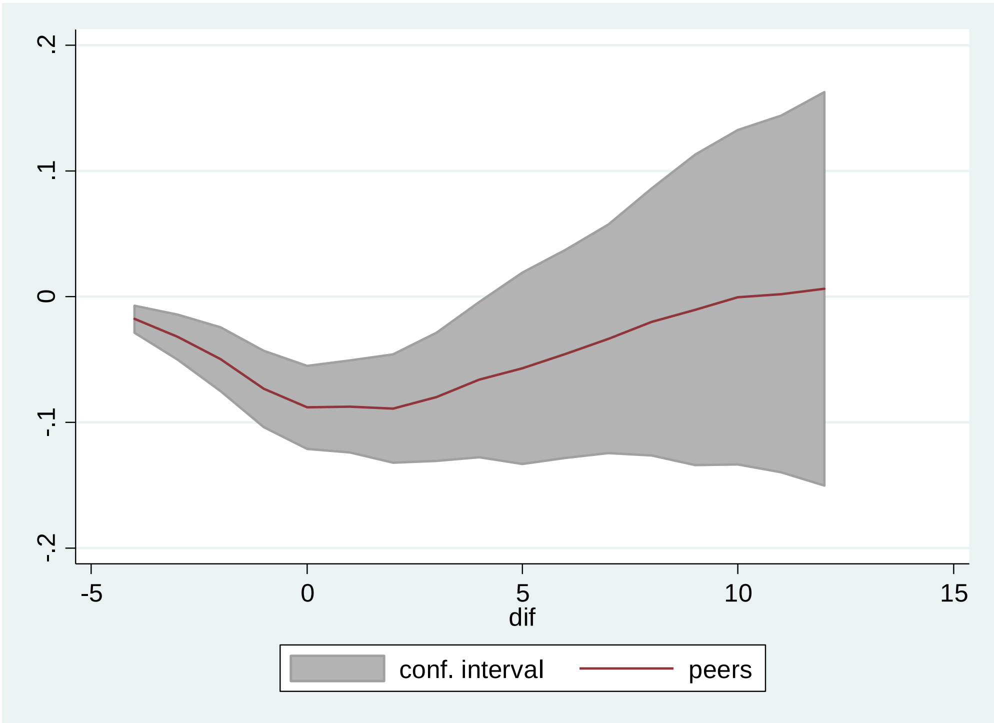
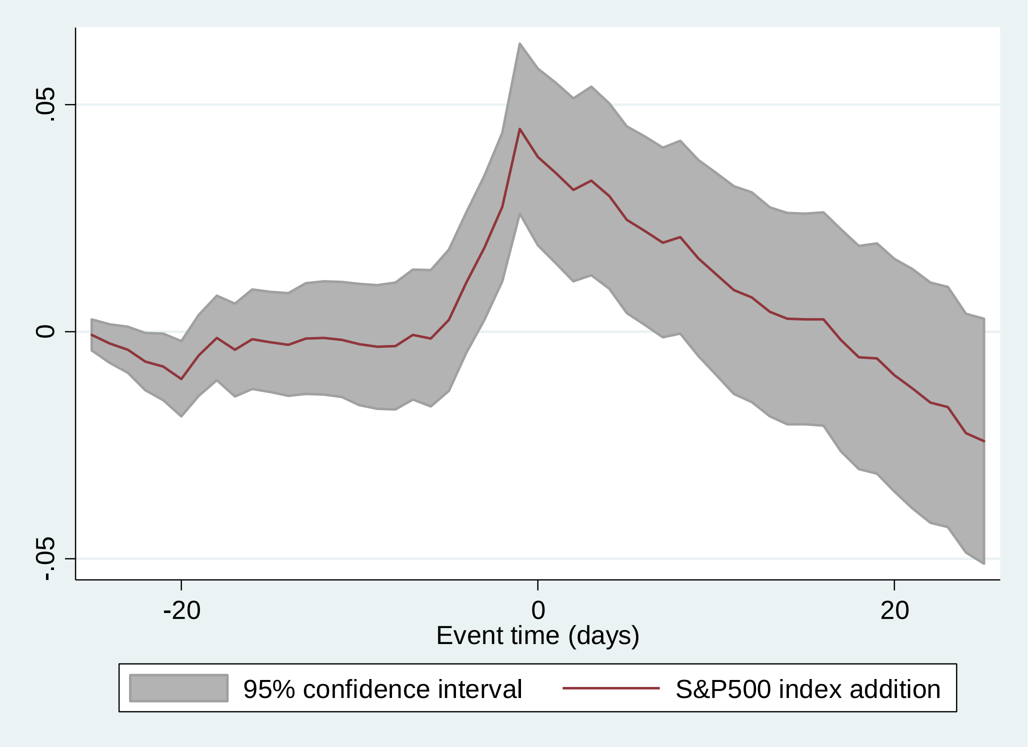


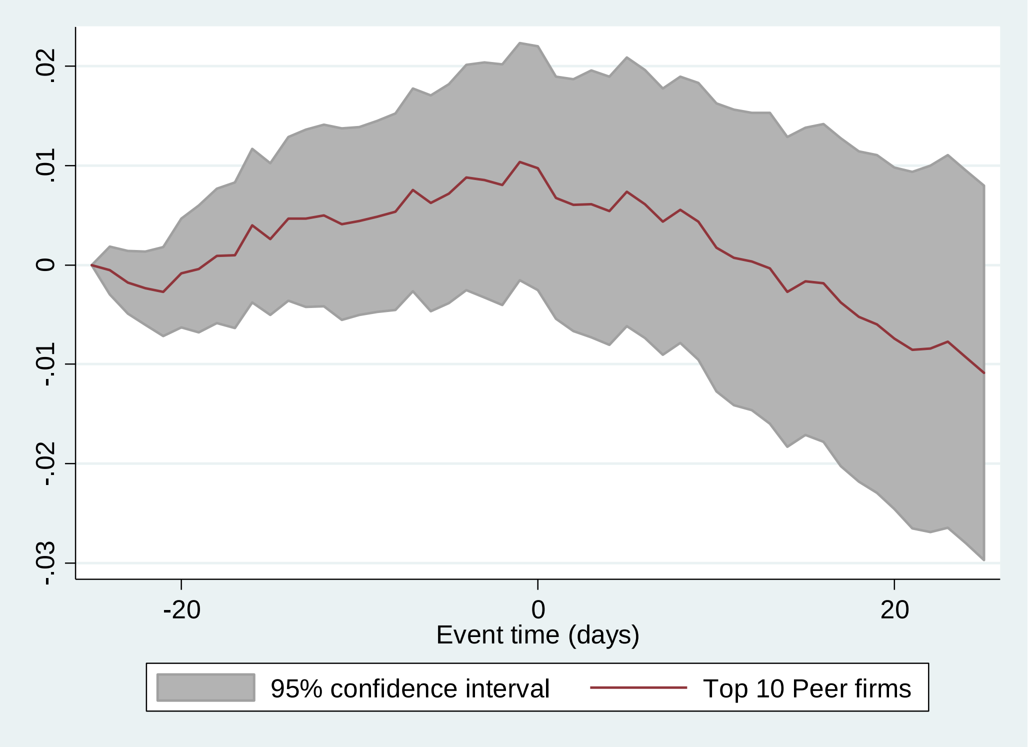
Figure B.2: Event study results for S&P 500 Index Additions and Peer Firms

This figure shows cumulative abnormal returns based on the market-model for firms added to the S&P 500 index (Panel A) and the (value-weighted) portfolio of the top ten peer firms (Panel B) in event-time (where 0 is the day when the addition becomes effective). The grey band around the cumulated returns represents the 95%-confidence interval based on standard errors clustered at the event-quarter level.

Panel A: Added Firms



Panel B: Peer Firms



Appendix C: Robustness Check for different Risk-adjusted Returns

In this subsection, we re-run our baseline specification (1) for various measures of risk-adjusted returns. In specification 1, we use benchmark-adjusted returns as recommended by Daniel et al. (1997). Specifically, we sort stocks into one of twenty-five portfolios based on market capitalization and book-to-market quintiles and subtract from each stock return the value-weighted average return of its corresponding benchmark portfolio. In specification 2, we use CAPM-alphas. In specification 3, we use Fama and French (1993) 3-factor alphas. In specification 4, we use Carhart (1997) 4-factor alphas. In specification 5, we use Fama and French (2014) 5-factor alphas. All alphas are estimated in a two-step approach. In the first step, we run the corresponding factor-model regressions using daily return data in a rolling window covering the previous four quarters. Daily factor returns come from Kenneth French's website and the AQR data library (for the Carhart momentum factor). Following Levi and Welch (2017), we shrink the resulting factor loadings towards their cross-sectional averages. We then compound daily stock and factor returns at the quarterly frequency and calculate alphas as

$$\alpha_{it}^{M} = ret_{it} - \widehat{\boldsymbol{\beta}}_{it}^{M'} \boldsymbol{X}_{t}^{M} \ ,$$

where superscript $M \in \{CAPM, FF3, Carhart, FF5\}$ denotes the factor model and $\widehat{\boldsymbol{\beta}}_{it}^{M}$ and $\boldsymbol{X}_{t}^{M}$ capture the corresponding vectors of estimated factor loadings and factor returns, respectively.

Table C shows the results. We see that, regardless of the risk-adjustment being used, we always obtain a highly significant fire sale effect of about -6% to -7% that partially reverts over the subsequent quarters. We also consistently observe a significant return spillover effect onto peer firms that is between one-quarter and one-sixth of that magnitude. Although the cumulated return reversal coefficients for these return spillovers are not always statistically significant, they are economically sizable and indicate an almost complete reversal of returns. Indeed, when we test whether the cumulated peer dummy coefficients in the window [0, +8] are significantly different from zero, we are always far from rejecting the hypothesis that there was a complete return reversal over this window (i.e., t-statistics for these tests never exceed 1; results available upon request).

In conclusion, both fire sale and spillover effects are robust to using different variants of risk-adjusted returns.

Table C: Robustness Check for different Risk-adjusted Returns

This table reports results from estimating equation (1) at the stock-quarter level. In specification 1, the dependent variable is the benchmark-adjusted return (Daniel et al., 1997). In specification 2, the dependent variable is the CAPM-alpha. In specification 3, the dependent variable is the Fama and French (1993) 3-factor alpha. In specification 4, the dependent variable is the Carhart (1997) 4-factor alpha. In specification 5, the dependent variable is the Fama and French (2014) 5-factor alpha. The main independent variables are FS and PEER dummies that flag fire sale events and peers for fire sale events, respectively. For example, the FS(t=4) dummy equals one when the given firm experienced a fire sale 4 quarters ago and the PEER(t=4) dummy equals one for all peer firms of a firm that experienced a fire sale 4 quarters ago (and that did not themselves experience a fire sale in the previous or subsequent 8 quarters). All regressions include dummies from t=-16 to t=16; for brevity we only show the coefficients for t=-2 to t=8. Firm-level controls (logarithm of total assets, logarithm of leverage, investment grade dummy, speculative grade dummy, market-to-book ratio, return on assets, logarithm of number of analysts), ownership controls (mutual fund ownership, institutional ownership), mutual fund flow controls (separately for fire sale funds and others) and firm and quarter fixed effects are included in all specifications. All variables are defined in Appendix A. Standard errors are double-clustered at the firm and quarter level. *t*-statistics are reported below coefficient estimates in parentheses. At the bottom of the table, we report the sum of the FS and PEER dummy coefficients for windows [1, 4] and [1, 8], respectively, together with the corresponding *t*-statistic for the cumulated return reversal. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels.

Dep. variable:	Benchmark-adj. return		CAPM-alpha		FF3-alpha		Carhart-alpha		FF5-alpha	
	(1)		(2)		(3)		(4)		(5)	
Event-time	FS	PEER	FS	PEER	FS	PEER	FS	PEER	FS	PEER
t = -2	-0.001	-0.002	-0.002	-0.001	-0.000	-0.002	-0.001	-0.001	-0.001	-0.002
	(-0.13)	(-0.60)	(-0.44)	(-0.51)	(-0.02)	(-0.65)	(-0.24)	(-0.45)	(-0.16)	(-0.60)
t = -1	-0.009**	-0.004	-0.014**	-0.004	-0.011**	-0.004	-0.012***	-0.005	-0.009*	-0.004
	(-2.07)	(-1.21)	(-2.46)	(-1.02)	(-2.48)	(-1.30)	(-2.74)	(-1.42)	(-1.95)	(-1.27)
t = 0	-0.057***	-0.015***	-0.067***	-0.012***	-0.064***	-0.011***	-0.062***	-0.010***	-0.063***	-0.011***
	(-10.24)	(-3.90)	(-9.32)	(-3.42)	(-9.79)	(-3.52)	(-10.24)	(-3.25)	(-9.88)	(-3.34)
t = 1	0.002	0.006**	0.004	0.004	0.003	0.004*	0.002	0.004	0.002	0.003
	(0.56)	(2.26)	(0.83)	(1.66)	(0.63)	(1.70)	(0.51)	(1.50)	(0.56)	(1.42)
t = 2	0.005	0.001	0.010*	0.002	0.009*	0.001	0.009*	0.000	0.009*	0.000
	(1.34)	(0.46)	(1.86)	(0.54)	(1.90)	(0.25)	(1.81)	(0.06)	(1.90)	(0.00)
t = 3	0.006	0.003	0.013*	0.001	0.009	0.002	0.010	0.001	0.009*	0.002
	(1.14)	(0.75)	(1.76)	(0.32)	(1.49)	(0.58)	(1.63)	(0.17)	(1.70)	(0.59)
t = 4	0.007	0.006*	0.002	0.006*	0.003	0.005*	0.004	0.005*	0.002	0.003
	(1.64)	(1.68)	(0.46)	(1.92)	(0.71)	(1.78)	(0.95)	(1.99)	(0.48)	(1.37)
t = 5	-0.004	-0.002	-0.004	-0.002	-0.001	-0.003	0.000	-0.003	-0.001	-0.003
	(-1.40)	(-0.49)	(-0.90)	(-0.73)	(-0.36)	(-0.86)	(0.09)	(-1.00)	(-0.17)	(-0.92)
t = 6	0.002	-0.000	0.002	-0.001	0.000	-0.001	0.001	-0.001	-0.000	-0.001
	(0.40)	(-0.04)	(0.63)	(-0.34)	(0.18)	(-0.30)	(0.50)	(-0.28)	(-0.04)	(-0.33)
t = 7	0.006	-0.001	0.006	0.002	0.004	0.002	0.004	0.002	0.002	0.003
	(1.13)	(-0.32)	(1.07)	(0.77)	(0.98)	(0.86)	(0.92)	(0.83)	(0.49)	(1.23)
t = 8	-0.004	0.000	-0.002	0.001	-0.001	0.001	-0.000	-0.001	-0.002	0.000
	(-0.88)	(0.12)	(-0.40)	(0.22)	(-0.25)	(0.31)	(-0.01)	(-0.50)	(-0.50)	(0.11)
N	298,921		302,082		302,082		302,082		302,082	
adj. R^2	0.033		0.081		0.046		0.037		0.045	
Firm & quart. f.e.	Yes		Yes		Yes		Yes		Yes	
Firm controls	Yes		Yes		Yes		Yes		Yes	
Ownership controls	Yes		Yes		Yes		Yes		Yes	
Flow controls	Yes		Yes		Yes		Yes		Yes	
Reversal [1, 4]	0.020**	0.016**	0.029**	0.013*	0.024**	0.011*	0.025**	0.009	0.022**	0.009
	(2.12)	(2.61)	(2.42)	(1.92)	(2.23)	(1.89)	(2.38)	(1.62)	(2.28)	(1.45)
Reversal [1, 8]	0.019	0.013*	0.031**	0.012	0.027**	0.010	0.031**	0.006	0.021*	0.008
	(1.54)	(1.75)	(2.07)	(1.48)	(2.03)	(1.54)	(2.45)	(0.98)	(1.75)	(1.23)