Price and Liquidity Spillovers during Fire Sale Episodes

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ABSTRACT

We document price and liquidity spillovers in U.S. stock markets. We exploit fire-sale episodes by mutual funds that experience large outflows which have been found to trigger impact-reversal patterns that extend over several quarters (e.g., Coval and Stafford, 2007). We show that impact-reversal patterns spill over to the economic peers of affected stocks, with a magnitude that is around one fifth of the original effect. These spillovers extend to liquidity and do not seem to be driven by common funding shocks or the activity by liquidity-providing arbitrageurs. We conclude that they represent information spillovers due to cross-asset learning, in line with recent theory (Cespa and Foucault, 2014).

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Hayek (1945) suggested that, in a market economy, the price system serves a vital role by aggregating dispersed information. This notion has been formalized in the noisy rational expectations equilibrium (NREE) literature (Grossman, 1976; Hellwig, 1980; Grossman and Stiglitz, 1980). Ever since, learning from prices is a recurrent ingredient in models of trading under asymmetric information. Yet, the extent to which investors actually do learn from prices is difficult to ascertain. On the one hand, it is certainly the case that investors update their expectations about the value of a given stock—say stock A—when its price suddenly halves—even if they didn't receive any other news about the company. On the other hand, it is less clear whether investors will be able to correctly assess the value implications of A's stock price decline for all the other stocks in the market. Indeed, given that other stock price movements may potentially also contain value-relevant information about stock A, modern stock markets pose a tremendous filtering problem that is likely to overwhelm even the most sophisticated investors. Thus, despite being a theoretically appealing ideal, cross-asset learning from prices will hardly be perfect.

In this paper, we attempt to study the extent—and limitations—of cross-asset learning in U.S. stock markets. This task is challenging because the econometrician does not observe all the information (other than prices) that was circulating among investors, for example stemming from newswires, analyst reports, industry experts, internet chat rooms or even word-of-mouth. Hence, if another stock B drops at the same time as stock A, the econometrician cannot be sure whether this happened because (a) investors learnt about stock B from stock A's price (or vice versa) or (b) because investors in stocks A and B responded to the same piece of information (unobserved by him). We overcome this problem by isolating stock price movements in stock A where it becomes clear *ex post* that these price movements did not have a fundamental reason. Specifically, we consider price movements that turn out to be price pressure effects triggered by mutual fund fire sales and, consequently, they revert over the subsequent quarters—proving that the long-run fundamentals of affected firms are unchanged on average. We then ask whether these price pressure effects spill over to the product-market peers of affected stocks (identified from the text-based network industry classification developed by Hoberg and Phillips 2010a; 2015). Indeed, when investors learn from the price of peer stocks and when they are not able to see through the non-fundamental reason for stock A's price drop, they should downgrade their expectations about peer firm B.[1] As A's stock price recovers, investors become gradually aware that there was in fact no fundamental reason to downgrade stock B and it reverts as well. Thus, cross-asset learning predicts that firm B should have the same price pressure-reversal pattern that we find for stock A, even after controlling for the selling-pressure by funds owning firm B. Put differently, we test the simple intuition that learning from the stock prices of peer firms entails that investors should occasionally respond to noise. And because fire sale shocks are noise, there is no potentially unobserved fundamental news that could drive B's price reaction.

Figure 2 illustrates the main finding of our paper: fire sales do spill over to peer firms (that do not experience fire sales themselves). In the quarter where a mutual fund fire sale hits a firm (Panel A), its economic peers experience a stock price drop that is approximately one fifth of the fire sale effect (Panel B). Both the fire sale and the peer effect reverse over subsequent quarters, confirming the non-fundamental nature of the fire sale shocks. In addition to the evidence on stock returns, we document that fire sale firms see a strong dry-

[1] We expect a downgrade if negative news for one firm also constitutes negative news for the other firm. This is likely to be the case for firms competing in the same product market where they will be affected by the same demand shocks.

up in liquidity, which also spills over to peer firms. Taken together, these findings are most consistent with the "learning channel" posited by multi-asset rational expectation models. In particular, as we argue in more detail below, the return spillover is unlikely to be caused by common funding shocks, reverse causality or cross-asset liquidity provision. To the best of our knowledge, we are the first to test and confirm the importance of the "learning channel"—the bedrock of the rational expectations literature—in driving commonality in returns and liquidity.

We test and confirm several auxiliary predictions of a cross-asset learning channel. First, we study how the return spillover effect varies in the cross-section of stocks. Cross-asset learning should be more important for peer stocks with less informative prices. Consistent with this intuition, we find that the return spillover effect is stronger for small firms, firms without an investment grade rating, and firms with low analyst coverage or high analyst forecast errors. Second, we find that the same peer characteristics also affect the severity of the original fire sale effect: when their peers are more informative, firms suffer less from mutual funds' selling pressure. This provides indirect evidence for the existence of a feedback effect as hypothesized by cross-asset learning models (e.g., Cespa and Foucault, 2014). Third, we conduct a placebo experiment by testing for spillover effects of another well-known price pattern attributed to a sudden shift in institutional investors' demand—S&P 500 index additions (Harris and Gurel, 1986; Shleifer, 1986; Beneish and Whaley, 1996; Lynch and Mendenhall, 1997). Though the literature doesn't quite agree on whether the run-up in prices of newly added stocks reflects pure price pressure or something else (e.g., Wurgler and Zhuravskaya, 2002; Denis et al., 2003; Chen et al., 2004), the fact that additions are *publicly announced* means investors should not expect any value implications for peer stocks. We indeed find that the economic peers of added stocks have insignificant returns throughout the inclusion event, even though index addition and fire sales cause price effects with comparable (absolute) magnitudes. This suggests that, consistent with a cross-asset learning mechanism, the lack of public information surrounding fire sales is key to understanding the return spillover effect that we document.

Our identification rests on the assumption that mutual fund fire sales are exogenous to affected stocks. While we are by far not the only paper making this assumption (see below), the endogeneity of fire sales is of particular concern in the context of identifying spillover effects. To be precise, there are two layers of endogeneity. First, Huang et al. (2016) find evidence that funds facing large outflows *choose* to sell stocks about which they have negative information. To the extent that this information also pertains to industry peers, we may thus expect fire sale stocks and their peers to fall in value at the same time. Second, we may face a reverse causality in that industry distress triggers outflows from funds heavily invested in that industry. To immunize us against the first concern, we follow Edmans et al. (2015) and identify fire sales based on "hypothetical" sales imputed from a proportional downscaling of a fund's previous portfolio holdings (instead of using their actual sales). To deal with the second concern, we verify in numerous robustness checks that our results are not driven by broad industry trends or funds whose outflows are likely to be explained by industry distress. As we discuss in detail below, the existence of the return reversal within one or two years is further evidence against the reverse causality argument as industry cycles take longer to unfold (Hoberg and Phillips, 2010b).

Our paper contributes to several strands of research. First, we speak to the literature on comovement and spillovers in asset markets. There is strong evidence for commonalities in returns and liquidity (Pindyck and Rotemberg, 1993; Chordia et al., 2000; Hasbrouck and Seppi, 2001, Korajczyk and Sadka, 2008). Since especially the former appears to be too large relative to the comovement in fundamentals, subsequent research has explored both behavioral-based explanations (Lee et al., 1991; Bodurtha et al, 1995; Barberis and Shleifer, 2003; Barberis et al., 2005) as well as financial friction-based explanations (Greenwood and Thesmar, 2011; Anton and Polk, 2014) for this phenomenon. We contribute to this literature by identifying a purely learning-based channel for stock price spillovers, as predicted by theory (Cespa and Foucault, 2014).

Second, we add to the vast literature on learning in financial markets. While there is a large body of theory on information asymmetry and learning from prices (e.g., Hellwig, 1980; Grossman and Stiglitz, 1980; Admati, 1985; Wang, 1993), clean empirical tests of primitive predictions from these models are still rare, most certainly because investors' information sets are inherently difficult to observe and highly endogenous. One notable exception is Kelly and Ljungqvist (2012) who exploit exogenous variation in analyst coverage to study how shocks to information asymmetry affect firm valuations. We contribute by testing another primitive prediction from this literature—namely that investors learn from peer prices. We do so in the context of mutual fund fire sales, as this setting allows us to isolate spillover effects due to cross-asset learning from comovements triggered by unobserved news common to multiple stocks.

Third, we contribute to the literature on mutual fund trading pressure. Coval and Stafford (2007) were the first to show that the trading behavior of mutual funds with extreme outflows lead to price pressure effects for affected stocks. Since mutual fund flows can be treated as largely exogenous from the perspective of affected stocks,[2] mutual fund trading

[2] This identifying assumption is supported by the fact that the price pressure effect reverses over subsequent quarters, proving that the fundamentals of affected stocks are unchanged on average. See the robustness section for more discussion on this point.

pressure is increasingly used to shed light on the real effects of stock price changes on corporate outcomes: the depressed share price due to a fire sale predicts an increase in takeover activity (Edmans et al., 2012) and leads affected firms to cut investment and employment (Hau and Lai, 2013). Managers seem to be aware that their stock is temporarily mispriced as there is evidence for opportunistic option grant timing, insider purchases (Ahiq et al., 2011) and seasoned equity offerings (Khan et al., 2012). The paper most closely related to ours is Dessaint et al. (2015), who show that peer firms of fire sale stocks curb their investment, consistent with these managers learning from stock prices but failing to filter out the noise induced by fund selling pressure. Instead of looking at corporate outcomes (such as investment), we take a step back and study *price* and *liquidity spillovers* between fire sale stocks and their economic peers. In our view, documenting these spillovers is important because it sheds light on the drivers of commonality in returns and liquidity.

Finally, we contribute to an old literature that aims to understand the variation in stock returns. Starting with Roll (1988) and Cutler et al. (1989), researchers have concluded time and again that firm-specific or market-wide news explain a surprisingly low fraction of the variation in stock return.[3] Our results suggest a new way for understanding this apparent puzzle. Specifically, we show that stock prices co-move due to cross-asset learning among close economic peers, and that this co-movement may be triggered by noise. As such, future investigations on the drivers of the stock return variation may want to consider the rich network structure and implied cross-asset learning effects that naturally arise when investors cannot perfectly tell apart fundamentals from noise.

[3] See, e.g., Boudoukh et al. (2015) for a recent analysis of the relation between the stock return variation and news arrivals. The low explanatory power of fundamental news for stock returns is further echoed by a large literature trying to understand the causes for the excessive volatility of stock returns and attributing it mostly to discount rate shocks (Shiller, 1981; Campbell and Shiller, 1988a, 1988b).

The remainder of this paper is organized as follows. Section I lays out the hypotheses tested in this paper. Section II describes the data and methodology. Section III presents the main results on return spillovers, including a cross-sectional analysis and numerous robustness checks. Section IV provides additional evidence in favor of the cross-asset learning channel. Section V concludes.

I. Hypotheses

According to multi-asset models with learning from prices, mutual fund fire sales should be associated with two kinds of *informational* spillover effects. First, to the degree that other market participants do not know of the fire sale, they may mistake the price decline in a fire sale stock to be due to informed trading on negative private signals, leading them to downgrade their expectations about the fundamentals of economically-related *peer* firms (e.g., Admati, 1985; Caballé and Krishnan, 1994; Veldkamp 2006). Second, if the fire sale also impairs the price informativeness of the affected stock,[4] there is an additional *liquidity spillover*, which further amplifies the stock price reduction for peer firms (Cespa and Foucault, 2014).[5] This is because the fire sale stock was an important source of information about its peers. Thus, market makers in peer stocks face higher uncertainty and begin

[4] In Cespa and Foucault (2014), it is a priori unclear why a large negative realization in uninformed noise trades (the theoretical equivalent of the fire sale) should lead to a deterioration in its liquidity. Indeed, illiquidity—defined as the price impact of order flow as in Kyle (1985)—is a function of the variance of uninformed noise trades, but not its realization. Hence, the model predicts liquidity feedback effects for shocks to the noise trader variance. In the data, we find that fire sale stocks do experience a drop in liquidity (see subsection IV.A below). In a model with risk-averse market makers (and without adverse selection, as in Cespa and Foucault, 2014), this 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, to which they respond by decreasing liquidity. In models with adverse selection, there are at least two other channels as to why fire sales may cause illiquidity. 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). 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).

[5] See also Asriyan et al. (2015).

withdrawing their liquidity in response. This makes peer stocks less informative, which, in addition to depressing their stock prices, feeds back into the fire sale stock, thereby rendering its stock price even more illiquid/uninformative and so forth—a classic feedback loop. To sum up, we expect cross-asset learning to lead to price and liquidity spillovers between fire-sale stocks and their economic peers. We call this the *information spillover hypothesis*.

In their updating decisions, rational learners naturally place larger weights on signals with higher signal precision (signal-to-noise ratio). Hence, the information spillover hypothesis does not only predict the existence of a return spillover effect but also offers an important cross-sectional prediction: information spillovers should be stronger for stocks about which the available public information (including its own stock price) is relatively uninformative because then investors should put a larger weight on the stock price signals of economic peers. In our empirical analysis, we test this prediction using a variety of proxies for the strength of a stock's information environment. Cross-asset learning further predicts that there should be a feedback loop between fire sale stocks and their peers: when spillovers are severe, investors worry more about the possibility that mutual funds' selling pressure reflects bad news and thus discount fire sale stocks more heavily. We test whether peer characteristics indeed affect the magnitude of the price drop in fire sale firms.

Clearly, there are several alternative explanations for the existence of spillover effects. For instance, spillover effects between two assets can be triggered by financially-constrained arbitrageurs that are actively trading in both (Kyle and Xiong, 2001; Gromb and Vayanos, 2002). As these traders suffer losses in one asset, they may be forced (e.g., because of margin calls) to exit their positions in the other asset. Such a contagion effect fits well with anecdotal evidence from prominent fire sale crises such as the collapse of the hedge fund LTCM in 1998;

it is also consistent with empirical evidence that stocks with common owners (Anton and Polk, 2014) or different owners with common shocks (Greenwood and Thesmar, 2011) exhibit comovement over and above what can be explained by fundamentals. The *funding shock channel* could presumably also explain a joint liquidity dry-up, although it has a harder time to rationalize why stocks in a weaker information environment would systematically be more affected than those with stronger public information. To address the possibility that return spillovers are explained by common funding shocks, we control for a rich set of proxies intended to capture common ownership and common flow shocks.[6]

Another explanation for a return pattern that resembles a spillover effect concerns the activity of liquidity-providing arbitrageurs. Indeed, arbitrageurs that buy shares from distressed sellers at a discount may want to hedge their positions by selling peer stocks.[7] If they do so in droves and demand curves are downward-sloping, peer stocks could themselves see a price pressure effect (albeit on a smaller scale than for the fire sale stocks). We attempt to control for this *liquidity provision channel* in our empirical tests. We also note that this explanation is inconsistent with a liquidity spillover effect (see Cespa and Foucault, 2014) and predicts that there should be no cross-sectional differences in return spillover effects across peers (assuming they are equally good for hedging).

Empirically, one key challenge is to distinguish spillover effects—where movements in one stock *cause* movements in another—from comovements driven by other unobserved factors like common economic trends. We argue that we can overcome this challenge by studying

[6] These controls also help to counter the empirical concern that the peer effect could be driven by small-scale fire sales in disguise.

[7] Another possibility is front-running: when some arbitrageurs anticipate the fire sale, they can short-sell the fire sale stock and cover their shorts by buying from distressed funds (indirect evidence for front-running by hedge funds is documented in Chen et al., 2008). When arbitrageurs engaging in front-running want to hedge their positions, they may similarly sell peer stocks at the time of the fire sale.

spillovers triggered by idiosyncratic fire sale shocks. One important concern, however, is *reverse causality*: it may be that fire sales, rather than causing spillover effects, are themselves caused by industry distress and the simultaneous stock price decline among industry stocks. While we defer a detailed discussion of this potential concern to the robustness section, we note here that the reverse causality story does not predict a return reversal as industry distress should arguably persist over several quarters if not years (e.g., Hoberg and Phillips, 2010b). Empirically, we attempt to mitigate reverse causality concerns by controlling for industry×time fixed effects.

Finally, we note that one key ingredient for the information spillover story is the presence of uncertainty: when a stock falls, investors are unsure whether this reflects uninformed selling pressure (i.e., a fire sale) or negative information and the possibility of the latter causes them to discount peer stocks. This logic leads us to conduct a placebo experiment by looking at another instance of price pressure—S&P 500 index addition events—where there is arguably no uncertainty about the value implications for peer firms. We therefore do not expect a return spillover under the information spillover hypothesis, whereas the alternative explanations put forth above should still apply in this context.

II. Data and Methodology

Stock market data is obtained from CRSP; mutual fund returns and monthly total net asset (TNA) values come from the CRSP mutual fund database; and quarterly mutual fund holdings are gathered from the Thomson Reuters S12 holdings data. We start from the sample of all common stocks (share codes 10 or 11) with an end-of-quarter price above one dollar and at least 10 non-missing daily returns in a quarter. For each stock, we calculate a measure of hypothetical selling pressure by "fire sale funds" as in Edmans et al. (2012). A detailed description of the construction of their measure is provided in Appendix B. Here, we only provide its intuition. Following their example, we exclude sector funds (third letter of CRSP objective code equal to "S")—as they could suffer from reverse causality—and drop all international, municipal, bond and metal funds (investment objective codes 1, 5, 6, 8). For each fire sale fund, defined as a mutual fund with quarterly outflows exceeding 5% of TNA, we calculate the imputed dollar selling volume for each portfolio stock if the fund had just downscaled his pre-existing portfolio. Then, we aggregate the imputed selling pressure of fire sale funds at the stock level and call this variable *mfflow*. Importantly, by using imputed rather than actual sales, we shut down endogeneity concerns coming from the choice of which stocks are being sold. Following Edmans et al. (2012), we say that a fire sale event (defined at the stock-quarter level) occurs when *mfflow* is in the lowest decile.

We identify the economic peers of fire sale stocks using the Text-based Network Industry Classification (TNIC) developed by Hoberg and Phillips (2010a; 2015). This data covers the period from 1996 to 2013 and is based on a textual analysis of the product description section contained in annual 10-K reports that must be filed with the SEC. For each year, Hoberg and Philips (2015) compute firm-by-firm pairwise similarity scores based on the number of words that two firms share in their product market descriptions. They then define two firms to be economic peers if their similarity score exceeds a pre-specified minimum threshold (chosen such that TNIC has the same level of coarseness as the 3-digit SIC industry classification).

In our main analysis, we do not consider a peer when it has been involved in a fire sale in the preceding or succeeding 8 quarters. We do this to ensure that any spillover effect we document is not confounded by another preceding or succeeding fire sale event. In addition, we focus on the 10 closest economic peers (based on the product similarity score) for each fire sale event as we expect cross-asset learning and thus potential spillovers to be the strongest for those firms.[8]

Fire sale events have the tendency to cluster. For example, conditional on having a fire sale, a firm has a 61% (69%) probability of experiencing another fire sale over the subsequent four (eight) quarters, while unconditionally the probability of having a fire sale over a four (eight) quarter period is only 21% (30%). To deal with this clustering of fire sale events, we conduct a multivariate panel analysis that allows to isolate the return effect of a particular point in event-time.[9] Specifically, we run regressions of the following type:

$$y_{it} = \alpha_i + \alpha_t + \sum_{\tau=-16}^{16} \beta_\tau \times FS_{it-\tau} + \sum_{\tau=-16}^{16} \delta_\tau \times PEER_{it-\tau} + \gamma' X_{it-1} + \varepsilon_{it} \qquad (1)$$

where y_{it} is a dependent variable of interest, α_i and α_t are firm and quarter fixed effects, $FS_{it-\tau}$ and $PEER_{it-\tau}$ are a set of dummy variables that flag fire sale firms and their peers in event time, and X_{it-1} is a vector of pre-specified control variables. To see how this works, consider the case where firm A has a fire sale in the first quarter of 2008, implying that $FS_{A2008Q1} = 1$. If firm B is a peer to fire sale stock A (and does not have a fire sale itself), then $PEER_{B2008Q1} = 1$. The specification further includes 32 dummies that flag the 16 preceding and succeeding quarters for the two event firms. For example, the dummies $FS_{A2008Q1-1}$ and $PEER_{B2008Q1-1}$ take the value one in the fourth quarter of 2007 for firm A and B, respectively.

[8] Our main results do not depend on these filters. Indeed, we still find a strongly significant spillover effect for returns when we include all peers (instead of only the top 10) or when we do not impose the restriction of there being no potentially confounding fire sale effect, but the results are a bit weaker (as expected) and we find that the return reversal is less pronounced.

[9] In the Online Appendix, we also report results from a classic event study approach. These results also exhibit an impact-reversal pattern for peer firms, but due to event clustering there is pre-event drift and the reversal is more protracted.

Importantly, if firm A had another fire sale in, say, the first quarter of 2007, then $FS_{A2008Q1}$ and $FS_{A2008Q1+4}$ would be one at the same time, ensuring that any reversal from the preceding fire sale does not confound the estimation of the second fire sale effect. In this way, our panel specification allows us to isolate the evolution in y_{it} for fire sale and peer events in event-time. Standard errors are double-clustered at the firm and quarter level.

For our multivariate analyses, we gather a host of firm-specific control variables from a variety of sources: accounting data comes from Compustat; the number of analysts following a stock is taken from I/B/E/S; institutional holdings data are from CDS Spectrum (S34); and quarterly measures of the probability of informed trading (PIN; Easley et al., 1996) are downloaded from Professor Stephen Brown's website.[10] Table I reports descriptive statistics and Appendix A provides detailed variable descriptions for the control variables used in this study. Our final dataset spans the period from 1996 to 2013 and includes 31,403 fire sale events as well as 66,696 associated peer events. Figure 1 shows how these events spread out over time. While the number of events fluctuates quite a bit, there is no apparent trend or an indication that events are concentrated in one particular period.

III. Return Spillover

A. Baseline Results

In this section, we study the effect of fire sales on the stock returns of their peers. Specifically, Table II shows the results from estimating equation (1) for the cumulated quarterly return as the dependent variable. For each specification, we show fire sale and peer event-time

[10] Available at: http://scholar.rhsmith.umd.edu/sbrown/pin-data. These PIN measures are estimated using the Venter and de Jongh (2004) model.

dummies next to each other to facilitate the comparison.[11] First, we note that the fire sale dummies display the typical impact-reversal pattern. In the fire sale quarter, affected stocks shed 7-8% of their value, which they partly recover over the subsequent 8 quarters. The magnitude of this effect is close to what has been found in the literature (Coval and Stafford, 2007; Edmans et al., 2012; Dessaint et al., 2015). It is also remarkably consistent across different specifications, showing that the results obtain after controlling for a host of accounting variables (column 2), ownership measures (column 3), fund flow proxies (column 4), or all of these combined (column 6). The key result of this table is that the dummy for peer firms in the event quarter (t = 0) indicates a drop in returns of about 1.5%. This amounts to approximately one fifth of the original fire sale effect (e.g., in column 1, ~1.5%/7.5%), which is a reasonable magnitude for a spillover effect.[12] Like the fire sale effect, this drop in peer returns remains stable and highly statistically significant across specifications. We further find that this return spillover completely reverses within four quarters.[13] For example, in column 1, the cumulated reversal over four quarters equals 1.6% and is significant at the 5%-level. The existence of the reversal confirms that the stock price drop for peer firms is not caused by fundamental news. Rather, it suggests that investors become aware of the non-fundamental reason for the price drop in the fire sale stock and reevaluate their initial negative assessment for peer firms.

[11] For brevity, we only report results for event-time dummies $-2 \leq \tau \leq 8$. The other event-time dummies are mostly insignificant.

[12] When observing a drop in the stock price of a peer firm, investors will not be sure whether this negative price drop reflects fundamentals or noise. For mixed prior beliefs about the unconditional probabilities of fundamental and non-fundamental shocks, it is natural to expect an update which is a fraction of the original price shock.

[13] Interestingly, the reversal for peer firms seems to occur somewhat faster than the reversal for fire sale stocks themselves, as the latter have not fully reversed after even 8 quarters. Recent research explains this slow reversal for fire sale firms by adverse selection risk (Dow and Han, 2016; Ringgenberg et al., 2016). In the model of Dow and Han (2016), decreased price informativeness of the fire sale stock aggravates the adverse selection risk for potential buyers and thus causes a higher fire sale discount. Since the drop in returns (and liquidity; see below) for fire sale firms is multiple times larger than the one for peers, the adverse selection problem would seem to be more acute for fire sale stocks, potentially explaining why their impact-reversal pattern is more protracted.

We emphasize that the return spillover effect obtains after controlling for an array of potentially confounding factors. The inclusion of firm and quarter fixed effects, for instance, ensures that our results are not driven by unobserved (fixed) firm characteristics or market-wide trends. Nor is the effect explained by standard accounting controls, analyst coverage or institutional ownership. Given our identifying assumption that fire sales occur for reasons outside of affected firms, it is actually reassuring to observe that the return spillover effect is unaffected by the inclusion of these controls. Finally, we note that both the spillover and reversal are robust to controlling for the mutual fund selling pressure in peer firms (columns 4-6). This suggests that the return spillover we document is not driven by peer firms experiencing distressed selling themselves, a point which we belabor further in the robustness section.

One slightly worrying aspect of Table II is that returns of fire sale stocks already show a small but significant reduction one quarter prior to the fire sale event. This could be indicative of reverse causality: some stocks experience distress and this makes investors to pull out of funds heavily invested in these stocks. While we tackle this concern in the robustness section, we acknowledge that it is difficult to rule this out completely. We note, however, that reverse causality cannot explain the entirety of our findings. In particular, it is hard to explain the return reversal without resorting to price pressures triggered by fire-selling mutual funds. Thus, even if some fire sales have been caused by negative fundamentals, the fire sales events themselves cause an impact-reversal pattern, which we show to be spilling over to peer firms (that do not experience a fire sale themselves). Potential endogeneity concerns notwithstanding, the fact that we do observe an impact-reversal pattern for peer firms constitutes strong evidence in favor of a learning-based spillover mechanism as predicted by theory.

B. Cross-sectional Tests

The information spillover hypothesis predicts that the return spillover effects should be stronger for peer firms with less informative stock prices. In this section we test this prediction by conducting sample splits based on several proxies of a stock's information quality. For brevity, we drop fire sale firms—i.e., firms that have had a fire sale within the previous or succeeding eight quarters—from the analysis because our focus is on how peer characteristics mediate the spillover effect (rather than on how firm characteristics mediate the fire sale effect).[14]

In our first test, reported in columns 1 and 2 of Table III, we split peer firms by their size (measured as total assets). The literature routinely finds that small stocks are less efficient and more often mispriced (Lee et al., 1991; Hong et al., 2000; Hou and Moskowitz, 2005). In addition, big stocks are known to lead small stocks in terms of price discovery (e.g., Lo and MacKinlay, 1990; and Hou, 2007). Thus, when conditioning on publicly available prices, investors of small firms should put a lower weight on their own stock and a higher weight on other stocks. As such, small stocks should respond more strongly to a fire sale hitting one of its peers. The results confirm this intuition: with 2.4%, the spillover effect for small peers is almost twice as large as the one for large peers (1.3%).

Next, we investigate the effect of having an investment grade credit rating. Rating agencies have been found to provide valuable information for stock market investors (Holthausen and Leftwich, 1986) and firms with an investment grade rating should thus be deemed as safer than those with a speculative grade rating or even no rating at all. We therefore expect a

[14] When we do not drop fire sale firms, we find that some characteristics—in particular the absence of an investment grade credit rating—are associated with a stronger fire sale effect. Our sample split results for peer firms are unaffected by including fire sale stocks.

lower return spillover effect for investment grade firms. Columns 3 and 4 of Table III indeed show that the spillover effect for non-investment grade firms (i.e., unrated or speculative grade firms) is more than three times larger than the one for investment grade ones. In columns 5 and 6, we split peer firms by S&P 500 index membership. Index members are widely recognized and receive more attention by the public media (Chang et al., 2014), which should make their prices more efficient. Consistent with this intuition, we find that the return spillover for S&P 500 members is only half as large as for non-members.

Finally, we turn to financial analyst data to measure a stock's information environment more directly. We start by splitting the sample based on the number of analysts following a firm. The literature finds that analysts provide valuable information to investors and reduce information asymmetry in the market (Brennan and Subrahmanyam, 1995; Womack, 1996; Barber et al., 2001; Gleason and Lee, 2003; Loh and Stulz, 2011; Kelly and Ljungqvist, 2012). Consistently, we find that the return spillover effect is more than twice as large for peer stocks with below-median analyst following (column 7) compared to those with above-median analyst following (column 8). For our last test, we compute stocks' average (absolute) forecast error (AFE) based on one year ahead EPS forecasts over the previous five years. The idea is that stocks with a low AFE have more precise public information and investors should thus place a lower weight on stock prices of their peers (Dessaint et al., 2015). The results shown in columns 9 and 10 confirm this intuition: whereas the spillover effect for stocks with low AFE is 1.2%, it climbs to 2.4% for stocks with above-median AFE.

Overall, the results in this section show that return spillovers are stronger for stocks whose own prices are less efficient, consistent with the notion that investors rely more heavily on cross-asset learning for these stocks. We find little evidence that less efficient stocks also display a stronger reversal effect, but this largely seems to stem from a loss in statistical power. While being insignificant, reversals are of the same economic magnitude than those found in Table II and we cannot reject the hypothesis of there being a full reversal within four quarters (unreported).

C. Robustness

In this section we check the robustness of the return spillover effect. The first concern we consider is reverse causality: it could be that negative fundamentals about an industry trigger outflows for mutual funds heavily invested in that industry, which forces them to liquidate part of their assets at fire sale prices. The worry is that the drop in returns for peer firms just reflects the negative fundamentals instead of being caused by an information spillover channel like we claim. As noted above, the quick reversal of the peer effect is clearly inconsistent with this concern. We now strengthen this conclusion by showing that the return spillover effect is robust to controlling for industry trends through the inclusion of industry-quarter fixed effects.[15] The results in the first column of Table IV confirm that the impact-reversal pattern for both the fire-sale stocks as well as for their close economic peers is hardly affected by this change. We conclude that the return spillover result cannot be explained by industry distress.

The second alternative explanation we consider is liquidity provision. Even in a world without asymmetric information, price pressure effects can arise when market makers are averse to deviating from their target inventory (e.g., Ho and Stoll, 1981; Grossman and Miller, 1988). When there is a drop in stock prices due to a fire sale, arbitrageurs have the incentive to provide liquidity to the fire-selling funds and they may want to hedge their positions by selling peer stocks. If enough arbitrageurs hedge their purchase of fire sale stocks in this way,

[15] We use the Fama-French 48 industry classification.

this may explain why peer stocks also see a small price pressure effect themselves. Our first argument against this alternative story draws on the model of cross-asset learning by Cespa and Foucault (2014). In an extension to their model, the authors consider the presence of arbitrageurs that are trading across markets and show that it cannot explain and should rather dampen the liquidity spillover effect that is predicted by the learning channel. Indeed, since the cross-market arbitrageurs absorb part of the selling pressure by distressed funds, the initial shock to the price informativeness of the fire sale stock is less severe, implying that the liquidity spillover should be weaker.[16] Thus, evidence for liquidity spillovers to peer stocks (see section IV.A below) mitigates the liquidity provision concern.

To get another handle on this explanation, we construct a proxy for the activity of liquidity-providing arbitrageurs. We start from the idea that the current owners of peer stocks are natural candidates for acting as liquidity providers to fire-selling funds. They can buy from these funds at fire sale prices and hedge their purchases by selling peer stocks without needing to sell short—a trade that promises to return the fire sale discount in expectation. Our proxy is designed to measure the extent by which current peer stock owners enter this trade. Specifically, for each stock, we calculate the minimum of the dollar selling volume by its current owners and their corresponding buy volume in fire sale stocks, and scale this by the stock's market capitalization.[17] A high value for this *liquidity provision* proxy thus indicates that a large fraction of a given stock is sold by investors entering the arbitrage trade. The results in the second column of Table IV show that price spillover result is not subsumed

[16] In the extreme case of there being only cross-market arbitrageurs and no cross-market learning, the liquidity is independent across stocks and there is no liquidity spillover effect.

[17] Because it is not clear how we should define the liquidity provision proxy for fire sale stocks, we exclude all stock-quarter observations in which the stock experienced a fire sale within eight quarters (before or after) and drop the fire sale dummies from the specification. Leaving these observations in and setting the liquidity provision proxy arbitrarily to zero for fire sale stocks gives similar results.

by the inclusion of this control. Hence, the drop in the stock price observed for peer firms is not explained by the arbitrage activity of their current owners.[18]

Next, we discuss the possibility that peer firms themselves experience mutual fund selling pressure which causes the impact-reversal pattern we observe for their stock returns. Note that this selling pressure could not have been too large, however, as in order to be a peer for some fire sale event we require the firm not to have had a fire sale itself within eight quarters of that event (i.e., *mfflow* not in the bottom decile). Nevertheless, since the impact-reversal pattern for peer firms is only one fifth of the fire sale effect, it is conceivable that it was triggered by a small-scale fire sale. In our main specification from Table 2, we deal with this concern by including *mfflow* as a control variable. The *mfflow* measure turns out to be non-normal and highly skewed, however (see Table 1). As a robustness check, we therefore replace it by a set of dummy variables that flag different *mfflow* deciles. In different tests, we also try to control for the fraction of the stock owned by fire sale funds (labeled *fire sale fund share*) and for the portfolio fraction of fire sale stocks held by the mutual funds owning the stock (labeled *fire sale stock share*). Columns 3 to 5 of Table IV report that the price spillover effect is not affected by any of these changes.[19] We conclude that it is unlikely that the impact-reversal pattern for peer firms is due to forced selling by distressed mutual funds.

Finally, we verify that the return spillover results is robust to measuring returns in different ways. Note first that, although we use raw returns for our main spillover tests in Table II, the inclusion of time fixed effects means that we are always neutralizing general market trends.

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[18] This leaves open the possibility that the return spillover could be explained by the arbitrage activity of investors that are short-selling the stock. We would then expect the return spillover to be stronger for stocks that are easy to short. In fact, we find that the return spillover effect is weaker for large stocks and stocks that are member of the S&P 500, which should be stocks that are easier to short (e.g., Saffi and Sigurdson, 2011).

[19] Because *mfflow* decile dummies and fire sale controls only make sense for non-fire sale stocks, we exclude all stock-quarter observations in which the stock experienced a fire sale within eight quarters (before or after) and drop the fire sale dummies from these specifications.

In other words, it is as if we were effectively using market-adjusted returns. In column one of Table IV, we further show that the spillover effect survives the inclusion of industry-time fixed effects. This implies that the spillover effect is robust to using industry-adjusted returns. In our last robustness test, we check that we get similar results when 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. As shown in column 6 of Table IV, the impact-reversal pattern for peer firms remains robust and significant when we use these benchmark-adjusted returns as our dependent variable.

IV. Additional Evidence

A. Liquidity Spillovers

To the extent that fire sales lead to a dry-up in liquidity in fire sale stocks, theory predicts that this heightened illiquidity should also spill over to peer stocks (Cespa and Foucault, 2014). Fire sale stocks may exhibit a dry-up in liquidity for many reasons. First, the selling pressure by fire sale funds may lead to the perception of higher noise trader risk, for which risk-averse market makers would demand higher compensation (e.g., Ho and Stoll, 1981; Grossman and Miller, 1988). Second, when there is uncertainty about whether informed traders are present, a large unexpected fire sale may lead to an update of this probability, causing market makers to demand a higher price impact to protect themselves against the perceived increase in adverse selection (e.g., Easley and O'Hara, 1992). Third, it is possible that the price drop hurts informed arbitrageurs, which in response trade less aggressively, thereby rendering the stock price less efficient (Dow and Han, 2016). Whatever the cause, once liquidity dries up, a feedback spiral is set in motion: because prices of fire sale stocks become less informative, liquidity providers in peer stocks face higher uncertainty and curb their own liquidity provision.

In this subsection we test whether mutual fund selling pressure hurts the liquidity of fire sale stocks and, if so, whether peer stocks are also affected. To this end, we estimate equation (1) for four different liquidity proxies: bid-ask spreads, the logarithm of the Amihud illiquidity ratio (Amihud, 2002), the probability of informed trading (PIN, Easley et al., 1996), and share turnover. Table V, Panels A to D, show the results. The first thing to notice is that there is strong evidence for a dry-up in liquidity for fire sale firms with all four liquidity measures. For instance, bid-ask spreads go up by roughly 20 basis points (Panel A), representing an increase of 10% relative to the unconditional mean, and remain elevated for about four quarters after the fire sale. For PIN, the increase is smaller with about 4-5% (Panel C) but still statistically significant. For the logarithm of Amihud (Panel B) and share turnover (Panel D), the decrease in liquidity is orders of magnitude larger, but we acknowledge that these results have a mechanical touch to them, as fire sale events are defined as events where funds' selling pressure is large relative to the stock's trading volume. Overall, the evidence for a deterioration is nonetheless overwhelming.

Table V also shows that the dry-up in liquidity spills over to the economic peers of fire sale firms: with the exception of bid-ask spreads in specification 2 and PIN in specification 6, the event-time dummy for peer firms is at least marginally significant for all four measures of liquidity in the quarter of the fire sale (and for at most one additional quarter thereafter). In terms of magnitude, the liquidity spillover represents between one tenth (for turnover) to one third (for bid-ask spreads) of the original fire sale effect. These results are consistent with the model of Cespa and Foucault (2014), which predicts that market makers react to the decreased price informativeness of the fire sale stock by curbing back their liquidity provision in peer firms. Since theirs is a model of cross-asset learning, the results reinforce our "learning channel" interpretation of the return spillover effect.

B. Feedback

We found above that the return spillover effect is stronger for peer firms with low information quality. A strong spillover effect, in turn, will increase concerns that the selling pressure for fire sale stocks is due to bad information rather than noise. In other words, cross-asset learning predicts that the spillover effect *feeds back* to fire sale firms. While the joint determinacy makes such feedback effects difficult to identify directly, this subsection tests for their existence indirectly by looking at whether peer characteristics affect how much fire sale stocks drop in response to mutual funds' selling pressure. Specifically, we focus on the sample of fire sale events and run regressions of the type:

$$y_{it} = \alpha_t + \beta \times \overline{PEER\ Characteristics}_{it} + \gamma' X_{it-1} + \varepsilon_{it} \qquad (2)$$

where y_{it} is the return of fire sale stock *i* in quarter *t*, $\overline{PEER\ Characteristics}_{it}$ is a measure of peer characteristics averaged over the ten closest peers of firm *i*, and X_{it-1} is the same vector of control variables already used for specification (1) above. We include quarter fixed effects but not firm fixed effects as the latter would throw away all the meaningful variation in (persistent) peer characteristics across event firms. Standard errors are again double clustered at the firm and quarter level.

As peer characteristics, we consider the same five dummy variables that we used for sample splits reported in section III.B—above-median firm size, investment grade rating, S&P 500 membership, above-median analyst coverage, and above-median average forecast error. In addition, we consider a composite "information index" that is defined as the mean of these five dummy variables for a given peer stock. Since the characteristics of closer economic peers should matter more, we calculate weighted averages of peer characteristics across the ten closest peers based on the TNIC similarity scores.[20] For each characteristic, we run two regressions—one in which we control for the continuous *mfflow* measure and one in which we replace it by decile dummies to allow for a non-linear relationship between returns and mutual funds' selling pressure.

Since there should be less feedback from peers with more informative prices, we expect fire sales of such peers to exhibit a smaller (i.e., less negative) drop in price, implying a positive β coefficient. The results in Table VI confirm this prediction: β is positive across all specifications. It is also at least marginally significant for three out of the five information quality proxies (the exceptions are analyst coverage and average forecast error, for which the t-statistics are between 1 and 1.4). The coefficient estimate in column 1, for example, implies that the price drop for fire sale firms is lower by 1.2% when all peers have above-median size. For the information quality index, the effect rises to a strongly significant 1.8%, suggesting that the index summarizes the different information proxies in a meaningful way. Compared to the unconditional price drop of roughly 7.2% (see Table II, column 6), the fire sale effect is thus about 25% lower for firms with informative peers. These results are consistent with a feedback effect as hypothesized by cross-asset learning models (e.g., Cespa and Foucault, 2014).

C. Placebo

The "learning channel" explanation for the return spillover of fire sales relies on the presence of uncertainty: investors cannot be sure that the price decline in a fire sale stock is not due

[20] Using equal weights gives similar albeit slightly weaker results.

to fundamentals and therefore discount its peer firms. In other words, if we were to identify price pressure effects whose causes are well understood by the market, there should be no learning and thus no spillover to economic peers. We argue that S&P 500 index additions are ideally suited for this type of placebo experiment. Indeed, the literature finds that stocks that are announced to become a member of the S&P 500 index experience a strong run-up in returns (Harris and Gurel, 1986; Shleifer, 1986; Beneish and Whaley, 1996; Lynch and Mendenhall, 1997; Chen et al., 2004), commonly attributed to the forced buying by passive index funds tracking the S&P 500.[21] While there is no agreement in the literature as to whether this run-up completely or only partially reverses after the addition becomes effective,[22] the crucial feature for us is that the public announcement of the addition should remove any uncertainty regarding the run-up's value implications for peer firms. As such, we don't expect a return spillover for S&P 500 index addition events, even though the run-up in returns is almost as large in (absolute) magnitude as the fire sale effect.

To identify the inclusion effect as well as any potential spillover, we run panel regressions similar to specification (1) but at daily frequency and where the fire sale dummies are replaced by "addition (AD) dummies" that flag the days surrounding an index addition event, defined as the day when a stock's addition to the S&P 500 index becomes effective according to the Compustat index constituents database. Our sample includes 247 index addition events and 2,502 corresponding peer events over the sample period 1996 to 2013.[23] The

[21] Consistent with this interpretation, the run-up in returns has been increasing concomitant to the growth of passive investment.

[22] It is thus not clear whether the run-up constitutes a pure price pressure effect or also something else. For instance, Denis et al. (2003) show that newly added stocks see a rise in analysts' earnings forecasts as well as realized earnings and Chen et al. (2004) document evidence of increasing investor awareness in line with the Merton (1987) model. The literature agrees, however, that price pressure is part of the explanation (see, for instance, Lynch and Mendenhall, 1997; Chen et al., 2004, and Chang et al., 2014).

[23] We again focus on the top ten peers excluding all firms that become S&P 500 index members themselves within one year of the respective addition event.

peer dummies now flag the economic peers of newly added stocks in event-time and we employ the same battery of controls from before. All regressions include firm and day fixed effects and standard errors are double-clustered at the firm and day level.[24]

The results are reported in Table VII and visualized in Figure 3. For the added stocks, we find a statistically significant and economically sizable run-up in returns setting in about five days prior to the effective index addition. This is consistent with previous literature (Beneish and Whaley, 1996; Lynch and Mendenhall, 1997; Chen et al., 2004) and reflects the fact that S&P typically announces the index change roughly five days before it becomes effective (Beneish and Whaley, 1996). Column 1 shows, for instance, that added stocks rise by 5.4% over the eight trading days before the effective date of the addition (t=0) and see their returns partly reversed thereafter (see also Figure 3, Panel A). In contrast, we find little to no abnormal returns for peer stocks in the pre-addition window. For instance, in the specification without controls (column 1), peer stocks have a marginally significant cumulated abnormal return of only 0.5% over the eight days before the addition (see also Figure 3, Panel B).[25] When all controls are added (column 6), this figure becomes even smaller and insignificant. To the extent that it exists at all, the spillover to peers is less than 10% when compared to the size of the addition effect. This contrasts with a spillover of about 20% that we found for fire sales (see Section III.A).

The absence of a significant return spillover for S&P 500 index additions provides indirect support for the information spillover hypothesis. Indeed, information spillovers should only

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[24] In the Online Appendix, we report similar results using an event study methodology.

[25] If anything, Figure 3, Panel B, shows slowly increasing returns for peer stocks *after* the addition event. This may reflect the existence of a common upward trend underlying all stocks in that industry. After all, stocks that are added to the S&P 500 have been growing in the past and this may be also true for their peers.

occur when investors do not understand the reasons for an underlying price movement. Since index additions are publicly announced, the uncertainty about the cause of the price movement is removed, thus explaining why there are no spillover effects.

V. Conclusion

In this paper we test and confirm a basic tenet of the large literature on the informativeness of stock prices—the assumption that investors can and do learn from prices. We test this conjecture in the context of mutual fund fire sales, which have been found to trigger substantial price pressure effects (Coval and Stafford, 2007). We argue that, in the quarter of the fire sale, investors are unsure whether the price decline is caused by forced selling or negative news about fundamentals. Thus, if investors learn from prices, they should update their expectations of close economic peers. Over time, the non-fundamental nature of the price decline becomes apparent and investors return to their initial expectations. The learning channel therefore predicts that the impact-reversal pattern for fire sale stocks spills over to economic peers and this is exactly what we find. It is precisely the non-fundamental nature of the fire sale shock that helps our identification, as it ensures that our findings for peer firms cannot be explained by investors reacting to new information common to many stocks.

Additional results corroborate the learning channel interpretation. First, the return spillover effect is stronger for peer stocks in a weaker information environment (i.e., smaller stocks, unrated stocks, stocks with fewer analysts, and stocks with larger forecast errors), consistent with the intuition that investors updating about these stocks rationally place a larger weight on the prices of other stocks. Second, we find evidence of a liquidity spillover to peer firms and, third, the effect of peer characteristics feeds back into fire sale stocks. These findings support recent theory showing how cross-asset learning leads to an interdependence of the informational efficiency across stocks (Cespa and Foucault, 2014). Finally, we show that another type of price pressure—the S&P 500 index addition effect—does not affect peer firms, confirming that information spillovers do not occur when the ultimate cause of the price pressure is widely understood by market participants.

Apart from confirming a long-held but hitherto untested assumption regarding learning from prices, our results have broader implications for our understanding of return and liquidity comovements in the stock market. They show that, as investors try to solve the massive filtering problem posed by a stock market in which every price is a potential signal about every other stock, they occasionally make mistakes and update on noise. Thus, the very fact that investors engage in cross-asset learning causes spillover effects that contribute to the documented comovement in returns and liquidity (e.g., Pindyck and Rotemberg, 1993; Chordia et al., 2000). Future research on the sources of commonalities in returns and liquidity should take this cross-asset learning channel into account.

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Figure 1: Number of Fire Sale and Peer Events over time

This figure shows the number of fire sale and peer events over our sample period from 1996 to 2013. Fire sale events are defined as in Edmans et al. (2012) [and explained in the Appendix B]. For each fire sale event, we define as peer events the ten closest economic peers (according to the TNIC similarity score developed by Hoberg and Philips, 2010a, 2015) that are not undergoing a fire sale themselves in the preceding or succeeding eight quarters.

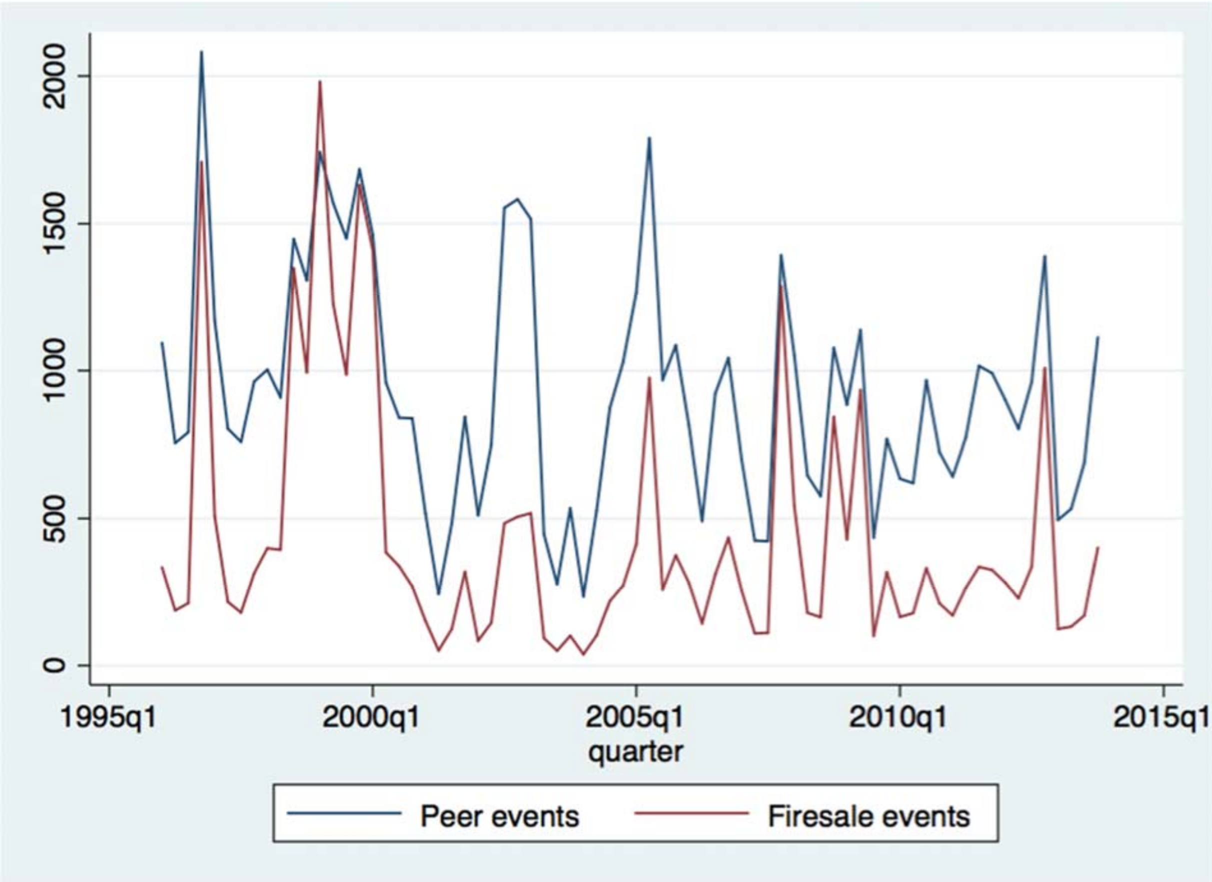
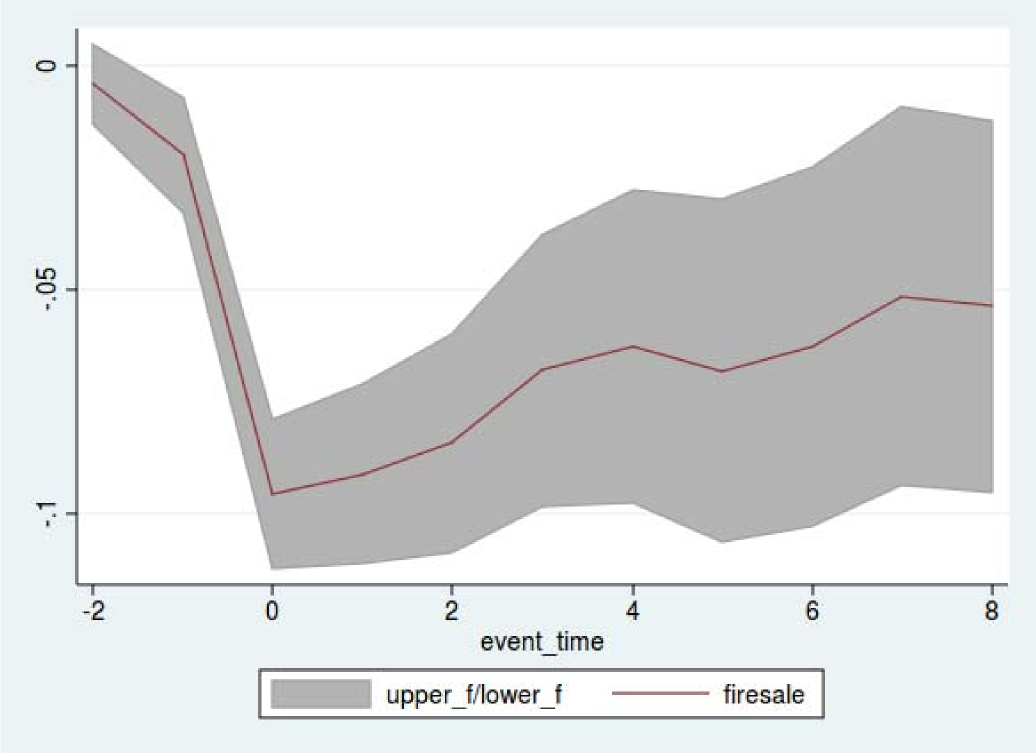


Figure 2: Event-time Returns for Fire Sale and Peer Firms

This figure shows returns for fire sale firms (Panel A) and peer firms (Panel B) in event-time (where 0 is the quarter of the fire sale). These graphs are based on the cumulated coefficient estimates of the fire sale and peer dummies shown in Table II, column 1. The grey band around the cumulated returns represents the 95%-confidence interval.

Panel A: Fire Sale Firms



Panel B: Peer Firms

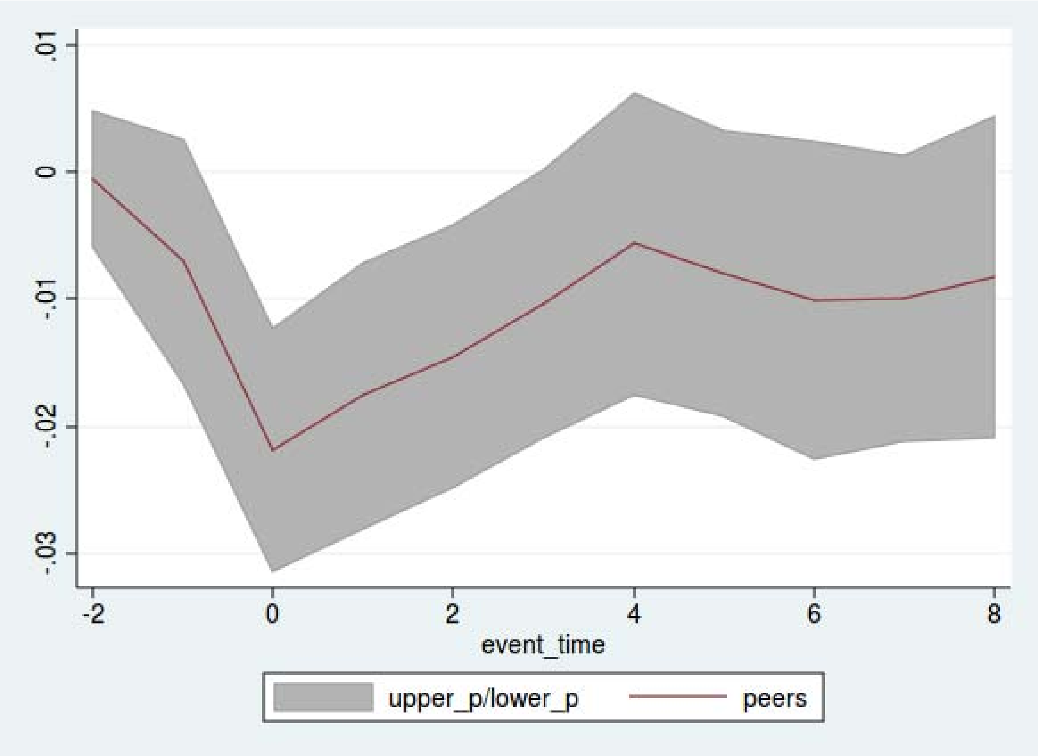
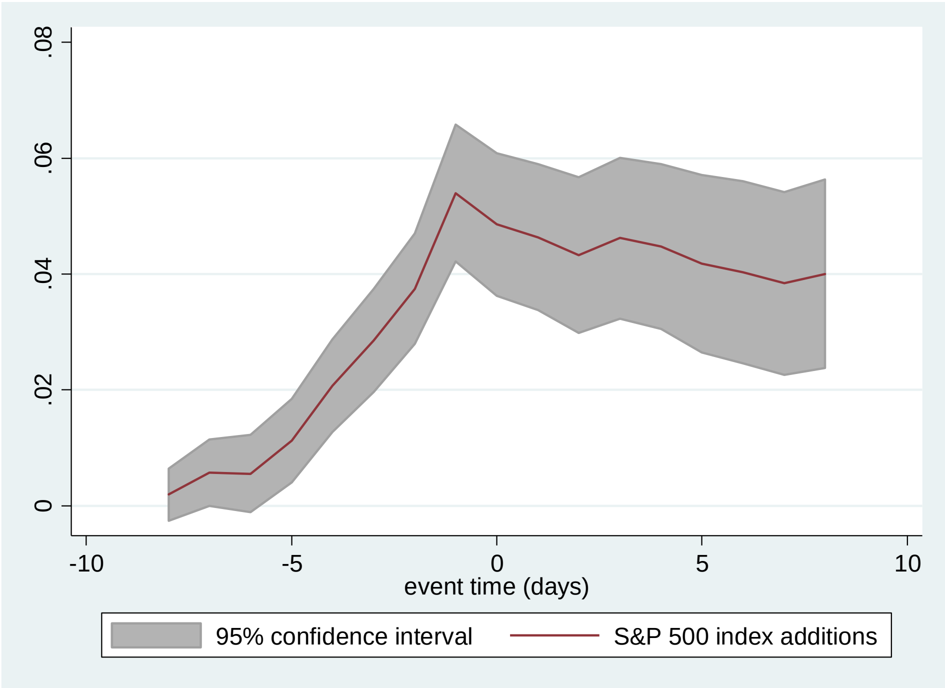


Figure 3: Event-time Returns for S&P 500 Index Additions and Peer Firms

This figure shows returns for firms added to the S&P 500 index (Panel A) and their peers (Panel B) in event-time (where 0 is the day when the index addition becomes effective). These graphs are based on the cumulated coefficient estimates of the addition and peer dummies shown in Table VII, column 1. The grey band around the cumulated returns represents the 95%-confidence interval.

Panel A: Added Firms



Panel B: Peer Firms

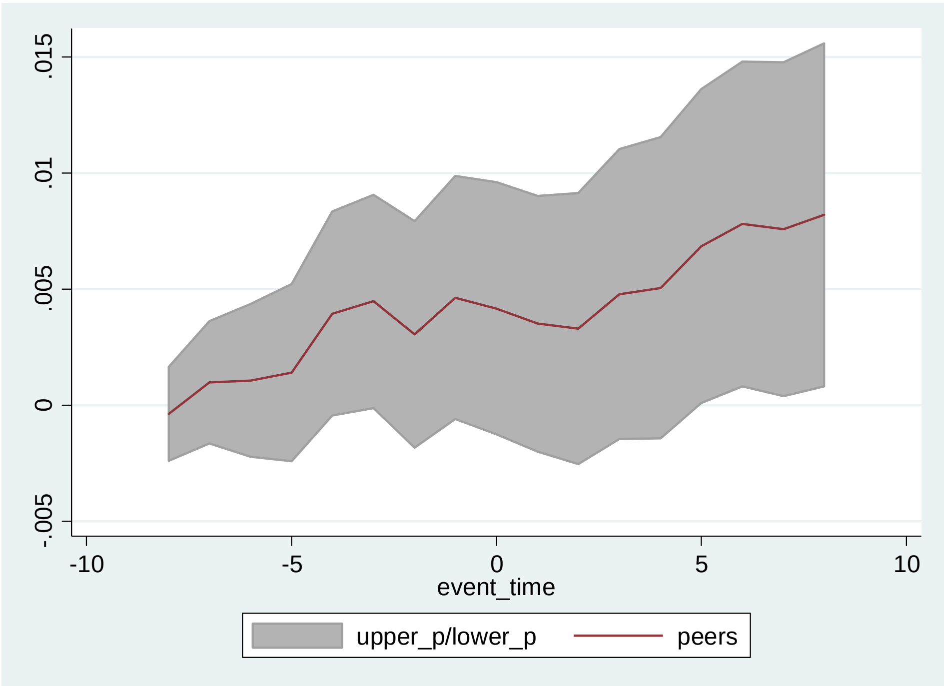


Table I: Descriptive Statistics

This table shows descriptive statistics for the main dependent and control variables used in this study. *N* indicates the number of non-missing observations at the stock-quarter level over our sample period (after dropping non-common shares [i.e., retaining only CRSP share codes 10 and 11], stocks with an end-of-quarter price below $1, and stocks with less than 10 daily non-missing return observations in a quarter). Return is the compounded quarterly return. Bid-ask spread is defined as the average daily relative bid-ask spread (multiplied by 100). Log Amihud is defined as the natural logarithm of the average ratio of absolute returns over dollar volume scaled by one million. PIN is the probability of informed trading (Easley et al., 1996) estimated at quarterly frequency. Turnover is defined as the total dollar volume in the quarter divided by the market capitalization at the end of the previous quarter. Total assets and return on assets are those reported for the end of the previous fiscal year. Leverage is the ratio of long-term debt and current liabilities over stockholders' equity (at the end of the previous fiscal year). Market-to-book is the ratio of the stock's market value at the end of the previous quarter over the stockholders' equity. Investment (speculative) grade is a dummy variable that indicates whether a firm's long-term debt has an investment grade (speculative grade) rating given by S&P. The remaining fraction of stock-quarter observation does not have a long-term bond rating. Num. analysts is the number of analysts following a stock at the end of the previous quarter. Mutual fund ownership is the fraction of shares outstanding owned by open-ended mutual funds at the end of the previous quarter. Institutional ownership is the fraction of shares outstanding owned by institutional investors at the end of the previous quarter. Mfflow is the selling pressure by mutual funds experiencing a fire sale as defined in Edmans et al. (2012). Mfflow complement is the difference between mutual fund trading pressure by all mutual funds and the selling pressure by fire-selling mutual funds. All variables are winsorized at the 0.5% level on both sides.

					Quantiles			
	N	Mean	S.D.	Min	0.25	Median	0.75	Max
Dependent variables:								
Return	353,146	0.04	0.29	-0.71	-0.12	0.02	0.15	1.7
Bid-ask spread	352,528	2.18	3.19	0.01	0.23	1.06	2.83	33.33
Log Amihud	353,138	-3.23	3.38	-11.43	-5.83	-3.34	-0.63	4.94
PIN	271,492	0.21	0.12	0	0.12	0.18	0.28	0.93
Turnover	342,933	0.43	0.55	0	0.11	0.25	0.54	4.53
Control variables:								
Total assets	340,919	3762.2	16159.73	0.28	76.86	326.38	1363.87	1.80E+05
Leverage	338,024	1.08	2.85	0	0.04	0.39	1.07	35.2
Investment grade	353,146	0.13	0.33	0	0	0	0	1
Speculative grade	353,146	0.11	0.32	0	0	0	0	1
Market-to-book	340,921	3975.91	8635.7	166.25	1161.45	1940.01	3540.11	90303.82
Return on assets	292,008	-0.03	0.25	-2.69	-0.03	0.03	0.07	0.58
Num. analysts	353,146	5.04	6.33	0	0	3	7	56
Mutual fund ownership	353,146	0.16	0.14	0	0.03	0.13	0.26	1
Inst. ownership	353,146	0.43	0.31	0	0.15	0.4	0.7	1
Mfflow	326,122	-0.01	0.06	-13.73	-0.01	0	0	0
Mfflow complement	326,122	0.09	5.53	-5.58	0	0.01	0.02	3010.7

Table II: Return Spillover Effect

This table reports results from estimating equation (1) at the stock-quarter level. The dependent variable is the quarterly return. The main independent variables are FS and PEER dummies that flag fire sale events and peers for fire sale events, respectively. All regressions include dummies from t=-16 to t=16; for brevity we only show the coefficients for t=-2 to t=8. Firm and quarter fixed effects are included in all specifications. In specification 2, additional firm-level controls are included (total assets, leverage, investment grade dummy, speculative grade dummy, market-to-book ratio, return on assets, number of analysts). In specification 3, ownership controls are included (mutual fund ownership, institutional ownership). In specification 4, mutual fund flow controls are included (separately for fire sale funds and others). In specification 5, ownership and flow controls are included. In specification, firm-level, ownership and flow controls are included. 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.

	(1)		(2)		(3)		(4)		(5)		(6)	
Event-time	FS	PEER	FS	PEER	FS	PEER	FS	PEER	FS	PEER	FS	PEER
t = -2	-0.004	-0.001	-0.005	0.000	-0.001	-0.001	-0.004	-0.001	-0.001	-0.001	-0.004	-0.001
	(-0.77)	(-0.15)	(-0.89)	(0.02)	(-0.14)	(-0.16)	(-0.82)	(-0.39)	(-0.16)	(-0.39)	(-0.74)	(-0.25)
t = -1	-0.016**	-0.007	-0.017**	-0.006	-0.012*	-0.007	-0.016**	-0.006	-0.012	-0.006	-0.016**	-0.006
	(-2.27)	(-1.56)	(-2.26)	(-1.43)	(-1.75)	(-1.61)	(-2.15)	(-1.35)	(-1.64)	(-1.40)	(-2.06)	(-1.44)
t = 0	-0.076***	-0.015***	-0.078***	-0.014***	-0.071***	-0.016***	-0.071***	-0.013***	-0.067***	-0.014***	-0.072***	-0.014***
	(-8.58)	(-3.52)	(-8.03)	(-3.29)	(-8.14)	(-3.68)	(-9.08)	(-3.18)	(-8.66)	(-3.45)	(-8.49)	(-3.01)
t = 1	0.004	0.004	0.003	0.005*	0.008	0.004	0.005	0.006*	0.008	0.006*	0.005	0.007**
	(0.71)	(1.38)	(0.38)	(1.68)	(1.21)	(1.39)	(0.82)	(1.87)	(1.31)	(1.88)	(0.64)	(2.13)
t = 2	0.007	0.003	0.006	0.004	0.009	0.004	0.007	0.003	0.009	0.003	0.007	0.003
	(1.10)	(0.93)	(0.93)	(1.10)	(1.50)	(1.06)	(1.12)	(0.87)	(1.50)	(0.99)	(1.05)	(0.94)
t = 3	0.016*	0.004	0.015	0.005	0.018*	0.005	0.015	0.004	0.017*	0.004	0.014	0.005
	(1.69)	(1.00)	(1.43)	(1.24)	(1.89)	(1.12)	(1.53)	(0.86)	(1.71)	(0.96)	(1.38)	(1.06)
t = 4	0.006	0.005	0.004	0.006	0.007	0.005	0.008	0.006	0.010	0.006	0.007	0.006
	(0.83)	(1.22)	(0.53)	(1.44)	(1.09)	(1.36)	(1.24)	(1.46)	(1.51)	(1.62)	(0.88)	(1.50)
t = 5	-0.006	-0.002	-0.007	-0.000	-0.004	-0.002	-0.006	-0.003	-0.005	-0.002	-0.006	-0.001
	(-0.85)	(-0.57)	(-0.90)	(-0.09)	(-0.65)	(-0.42)	(-0.90)	(-0.64)	(-0.70)	(-0.48)	(-0.87)	(-0.13)
t = 6	0.005	-0.002	0.004	-0.001	0.007	-0.002	0.006	-0.002	0.007	-0.002	0.006	-0.002
	(1.09)	(-0.50)	(0.75)	(-0.29)	(1.40)	(-0.38)	(1.21)	(-0.55)	(1.49)	(-0.44)	(0.97)	(-0.36)
t = 7	0.011	0.000	0.014	0.002	0.013*	0.001	0.011	0.000	0.013*	0.001	0.014	0.002
	(1.49)	(0.05)	(1.56)	(0.46)	(1.69)	(0.28)	(1.49)	(0.10)	(1.68)	(0.36)	(1.61)	(0.45)
t = 8	-0.002	0.002	-0.002	0.002	-0.001	0.002	-0.003	0.001	-0.002	0.002	-0.001	0.003
	(-0.36)	(0.53)	(-0.23)	(0.70)	(-0.16)	(0.81)	(-0.39)	(0.45)	(-0.21)	(0.76)	(-0.14)	(0.90)
N	352,870		290,454		352,870		325,817		325,817		272,376	
adj. R^2	0.153		0.180		0.160		0.163		0.172		0.191	
Firm & quart. f.e.	Yes		Yes		Yes		Yes		Yes		Yes	
Firm controls	No		Yes		No		No		No		Yes	
Ownership contrls	No		No		Yes		No		Yes		Yes	
Flow controls	No		No		No		Yes		Yes		Yes	
Reversal [1, 4]	0.033**	0.016**	0.028	0.020***	0.042**	0.018**	0.035**	0.018**	0.044***	0.019**	0.032*	0.021**
	(2.01)	(2.26)	(1.54)	(2.73)	(2.56)	(2.45)	(2.17)	(2.37)	(2.72)	(2.55)	(1.87)	(2.63)
Reversal [1, 8]	0.042*	0.014*	0.037	0.022**	0.057**	0.018**	0.044**	0.015*	0.058**	0.019**	0.044*	0.023**
	(1.89)	(1.69)	(1.48)	(2.52)	(2.53)	(2.21)	(1.99)	(1.75)	(2.61)	(2.24)	(1.82)	(2.42)

Table III: Cross-sectional tests for Return Spillover Effect

This table reports results from estimating regressions of quarterly returns on PEER dummies that flag peers for fire sale events. All regressions include dummies from t=-16 to t=16; for brevity we only show the coefficients for t=-2 to t=8. Firm and quarter fixed effects are included in all specifications. To focus on how the return spillover effect varies across different firm characteristics, stock-quarter observations with fire sales in the preceding or succeeding eight quarters are excluded. In columns 1 and 2, stocks are split along the median of firms' total assets. In columns 3 and 4, stocks are split into firms with an investment grade rating and others. In columns 5 and 6, stocks are split for whether they are a constituent of the S&P 500 index or not. In columns 7 and 8, stocks are split along the median of analyst coverage. In columns 9 and 10, stocks are split along the median of analysts' average forecast error. 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 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.

	Firm size		Rating		S&P 500 member		Analyst coverage		Average forecast error	
	Small	Large	Other	IG	No	Yes	Low	High	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Event-time	PEER	PEER	PEER	PEER	PEER	PEER	PEER	PEER	PEER	PEER
t = -2	-0.000	-0.000	-0.000	0.000	-0.000	0.001	0.000	-0.002	0.004	-0.005
	(-0.02)	(-0.02)	(-0.01)	(0.15)	(-0.00)	(0.15)	(0.09)	(-0.57)	(0.89)	(-1.20)
t = -1	-0.010	-0.004	-0.009	-0.004	-0.009	-0.005	-0.009	-0.009**	-0.007	-0.012**
	(-1.33)	(-1.33)	(-1.54)	(-1.44)	(-1.51)	(-1.48)	(-1.30)	(-2.23)	(-1.22)	(-2.39)
t = 0	-0.024***	-0.013***	-0.021***	-0.006**	-0.020***	-0.009***	-0.025***	-0.015***	-0.024***	-0.012***
	(-3.81)	(-3.84)	(-4.25)	(-2.06)	(-4.24)	(-2.74)	(-4.36)	(-3.96)	(-4.20)	(-2.95)
t = 1	-0.002	0.000	0.000	-0.001	-0.000	0.002	0.002	-0.001	0.002	0.000
	(-0.40)	(0.12)	(0.01)	(-0.42)	(-0.08)	(0.53)	(0.48)	(-0.23)	(0.53)	(0.11)
t = 2	0.000	0.002	0.002	0.002	0.002	0.001	-0.003	0.003	-0.001	0.005
	(0.07)	(0.58)	(0.48)	(0.61)	(0.46)	(0.39)	(-0.62)	(0.99)	(-0.21)	(1.20)
t = 3	0.002	0.002	0.004	-0.000	0.004	0.001	0.007	0.001	0.002	-0.002
	(0.32)	(0.57)	(0.84)	(-0.13)	(0.78)	(0.25)	(1.27)	(0.36)	(0.48)	(-0.38)
t = 4	0.005	0.006	0.006	0.002	0.006	0.006	0.007	0.006*	0.007	0.008*
	(0.72)	(1.53)	(1.36)	(0.66)	(1.26)	(1.31)	(1.41)	(1.87)	(1.32)	(1.97)
t = 5	0.003	-0.004	-0.002	-0.003	-0.002	-0.004	0.001	-0.007*	-0.003	-0.010**
	(0.45)	(-1.08)	(-0.42)	(-0.89)	(-0.41)	(-1.18)	(0.28)	(-1.96)	(-0.70)	(-2.40)
t = 6	-0.000	0.003	-0.000	0.001	0.001	0.002	-0.000	0.001	-0.003	0.005
	(-0.03)	(0.77)	(-0.00)	(0.42)	(0.14)	(0.61)	(-0.02)	(0.21)	(-0.69)	(1.03)
t = 7	0.005	0.000	0.002	-0.002	0.003	-0.001	0.001	0.003	-0.002	0.004
	(0.91)	(0.07)	(0.51)	(-0.55)	(0.71)	(-0.33)	(0.12)	(0.99)	(-0.37)	(1.02)
t = 8	-0.001	0.003	0.001	0.002	0.001	0.004	-0.002	0.003	0.006	0.001
	(-0.14)	(0.98)	(0.27)	(0.57)	(0.19)	(1.17)	(-0.62)	(0.97)	(1.32)	(0.15)
N	89,957	90,175	163,461	25,260	164,587	24,166	103,736	84,014	57,393	57,255
adj. R^2	0.144	0.199	0.144	0.279	0.141	0.278	0.125	0.232	0.169	0.191
Firm & quart. f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	No	No	No	No	No	No	No	No	No	No
Ownership controls	No	No	No	No	No	No	No	No	No	No
Flow controls	No	No	No	No	No	No	No	No	No	No
Reversal [1, 4]	0.005	0.010	0.012	0.002	0.011	0.010	0.014	0.010	0.010	0.011
	(0.44)	(1.39)	(1.30)	(0.38)	(1.19)	(1.34)	(1.41)	(1.28)	(1.10)	(1.26)
Reversal [1, 8]	0.011	0.012	0.013	0.000	0.013	0.011	0.014	0.010	0.008	0.011
	(0.86)	(1.43)	(1.19)	(0.06)	(1.22)	(1.31)	(1.46)	(0.96)	(0.64)	(0.89)

Table IV: Robustness of Return Spillover Effect

This table reports results from estimating equation (1) at the stock-quarter level. In specifications 1 to 5, the dependent variable is the quarterly return. In specification 6, it is a benchmark-adjusted return where stocks are benchmarked to one out of twenty-five benchmark portfolios based on a market capitalization and book-to-market quintiles. In specifications 1 and 6, the main independent variables are FS and PEER dummies that flag fire sale events and peers for fire sale events, respectively. In specifications 2 to 5, stock-quarter observations with a fire sale in the preceding or succeeding eight quarters are excluded and the main independent variables are PEER dummies that flag peers for fire sale events. All regressions include dummies from t=-16 to t=16; for brevity we only show the coefficients for t=-2 to t=8. All regressions include firm-level controls (total assets, leverage, investment grade dummy, speculative grade dummy, market-to-book ratio, return on assets, 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. In specification 2, a liquidity provision proxy is added as an additional control variable. In specification 3, dummies for different mutual fund flow deciles (separately for fire sale funds and others) are used instead of the continuous fund flow variables. In specification 4, the fire sale fund share is added as an additional control variable. In column 5, the fire sale stock share is added as an additional control variable. 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.

	(1)		(2)		(3)		(4)		(5)		(6)	
Event-time	FS	PEER	FS	PEER	FS	PEER	FS	PEER	FS	PEER	FS	PEER
t = -2	-0.003	0.000	N/A	-0.000	N/A	0.000	N/A	-0.000	N/A	0.000	-0.002	-0.001
	(-0.65)	(0.06)		(-0.02)		(0.03)		(-0.07)		(0.03)	(-0.46)	(-0.36)
t = -1	-0.008*	-0.004	N/A	-0.008*	N/A	-0.008	N/A	-0.008*	N/A	-0.008	-0.012**	-0.005
	(-1.94)	(-1.26)		(-1.68)		(-1.61)		(-1.68)		(-1.61)	(-2.23)	(-1.38)
t = 0	-0.062***	-0.010***	N/A	-0.014***	N/A	-0.015***	N/A	-0.015***	N/A	-0.015***	-0.060***	-0.014***
	(-9.71)	(-3.23)		(-3.71)		(-3.77)		(-3.81)		(-3.76)	(-9.50)	(-3.63)
t = 1	0.006	0.003	N/A	0.001	N/A	0.001	N/A	0.001	N/A	0.001	0.001	0.007**
	(1.05)	(1.32)		(0.45)		(0.27)		(0.23)		(0.27)	(0.24)	(2.47)
t = 2	0.008	0.000	N/A	0.002	N/A	0.001	N/A	0.001	N/A	0.001	0.004	0.001
	(1.50)	(0.04)		(0.63)		(0.31)		(0.31)		(0.32)	(1.06)	(0.35)
t = 3	0.013*	0.002	N/A	0.004	N/A	0.003	N/A	0.003	N/A	0.003	0.006	0.003
	(1.89)	(0.66)		(0.97)		(0.69)		(0.67)		(0.69)	(0.94)	(0.78)
t = 4	0.006	0.006*	N/A	0.008**	N/A	0.007*	N/A	0.007*	N/A	0.007*	0.006	0.006
	(1.03)	(1.79)		(2.10)		(1.89)		(1.85)		(1.89)	(1.21)	(1.59)
t = 5	-0.002	0.000	N/A	-0.001	N/A	-0.001	N/A	-0.001	N/A	-0.001	-0.005	-0.001
	(-0.41)	(0.10)		(-0.14)		(-0.31)		(-0.35)		(-0.31)	(-1.42)	(-0.34)
t = 6	0.006	-0.001	N/A	0.002	N/A	0.001	N/A	0.001	N/A	0.001	0.001	-0.001
	(1.43)	(-0.52)		(0.49)		(0.23)		(0.35)		(0.23)	(0.13)	(-0.23)
t = 7	0.012**	0.002	N/A	0.005	N/A	0.004	N/A	0.004	N/A	0.004	0.007	-0.001
	(2.28)	(0.99)		(1.57)		(1.31)		(1.36)		(1.31)	(1.23)	(-0.22)
t = 8	-0.003	0.002	N/A	0.001	N/A	0.001	N/A	0.001	N/A	0.001	-0.003	0.001
	(-0.58)	(0.81)		(0.33)		(0.44)		(0.33)		(0.44)	(-0.57)	(0.33)
N	272,367		134,563		134,563		134,563		134,563		257,882	
adj. R^2	0.243		0.228		0.211		0.214		0.211		0.037	
Firm & quart. f.e.	Yes		Yes		Yes		Yes		Yes		Yes	
Firm controls	Yes		Yes		Yes		Yes		Yes		Yes	
Ownership contrls	Yes		Yes		Yes		Yes		Yes		Yes	
Flow controls	Yes		Yes*		Yes		Yes		Yes		Yes	
Reversal [1, 4]	0.032**	0.010**	N/A	0.015*	N/A	0.012	N/A	0.011	N/A	0.012	N/A	0.017**
	(2.58)	(2.09)		(1.86)		(1.41)		(1.38)		(1.42)		(2.63)
Reversal [1, 8]	0.045***	0.014**	N/A	0.022*	N/A	0.017	N/A	0.017	N/A	0.017	N/A	0.015*
	(2.83)	(2.09)		(1.97)		(1.47)		(1.45)		(1.47)		(1.87)

Table V: Liquidity Spillover Effect

This table reports results from estimating equation (1) at the stock-quarter level. In Panel A, the dependent variable is the average bid-ask spread (multiplied by 100). In Panel B, the dependent variable is the natural logarithm of the average Amihud ratio (scaled by 1,000,000). In Panel C, the dependent variable is the Probability of Informed Trading (PIN) estimated at quarterly frequency. In Panel D, the dependent variable is the natural logarithm of share turnover. The main independent variables are FS and PEER dummies that flag fire sale events and peers for fire sale events, respectively. All regressions include dummies from t=-16 to t=16; for brevity we only show the coefficients for t=-2 to t=8. Firm and quarter fixed effects are included in all specifications. In specification 2, additional firm-level controls are included (total assets, leverage, investment grade dummy, speculative grade dummy, market-to-book ratio, return on assets, number of analysts). In specification 3, ownership controls are included (mutual fund ownership, institutional ownership). In specification 4, mutual fund flow controls are included (separately for fire sale funds and others). In specification 5, ownership and flow controls are included. In specification, firm-level, ownership and flow controls are included. 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. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels.

Panel A: Bid-ask spreads

	(1)		(2)		(3)		(4)		(5)		(6)	
Event-time	FS	PEER	FS	PEER	FS	PEER	FS	PEER	FS	PEER	FS	PEER
t = -2	-0.074**	-0.040	-0.061*	-0.035	-0.057	-0.040	-0.038	-0.017	-0.020	-0.017	-0.031	-0.011
	(-2.08)	(-1.66)	(-1.91)	(-1.62)	(-1.66)	(-1.66)	(-1.23)	(-0.98)	(-0.66)	(-0.99)	(-1.04)	(-0.66)
t = -1	-0.024	-0.029	-0.014	-0.026	-0.005	-0.029	0.010	-0.005	0.030	-0.006	0.014	-0.001
	(-0.65)	(-1.40)	(-0.40)	(-1.37)	(-0.14)	(-1.44)	(0.25)	(-0.32)	(0.75)	(-0.39)	(0.34)	(-0.07)
t = 0	0.154***	0.043*	0.169***	0.028	0.173***	0.038*	0.156***	0.081***	0.176***	0.074***	0.156***	0.062***
	(3.63)	(1.93)	(4.05)	(1.36)	(4.02)	(1.73)	(3.00)	(5.31)	(3.37)	(4.95)	(2.97)	(4.16)
t = 1	0.128***	0.022	0.133***	0.010	0.141***	0.021	0.149***	0.032**	0.163***	0.031**	0.147***	0.021
	(3.29)	(1.01)	(3.64)	(0.50)	(3.62)	(0.99)	(3.56)	(2.17)	(3.90)	(2.13)	(3.60)	(1.40)
t = 2	0.074**	-0.011	0.067**	-0.015	0.086**	-0.009	0.097**	-0.005	0.109***	-0.002	0.084**	-0.008
	(2.23)	(-0.43)	(2.06)	(-0.59)	(2.61)	(-0.33)	(2.35)	(-0.25)	(2.66)	(-0.12)	(2.04)	(-0.42)
t = 3	0.085**	-0.011	0.069**	-0.014	0.095**	-0.008	0.101**	-0.009	0.111***	-0.007	0.081**	-0.012
	(2.31)	(-0.44)	(2.01)	(-0.55)	(2.57)	(-0.31)	(2.46)	(-0.51)	(2.67)	(-0.37)	(2.01)	(-0.60)
t = 4	0.084**	-0.005	0.068*	-0.002	0.095**	-0.002	0.094**	-0.010	0.105***	-0.007	0.074*	-0.008
	(2.08)	(-0.20)	(1.75)	(-0.07)	(2.34)	(-0.08)	(2.48)	(-0.56)	(2.76)	(-0.40)	(1.94)	(-0.41)
t = 5	0.055	-0.001	0.044	0.005	0.063*	0.003	0.064**	-0.004	0.072**	0.000	0.053*	0.004
	(1.57)	(-0.02)	(1.46)	(0.18)	(1.81)	(0.14)	(2.06)	(-0.18)	(2.30)	(0.02)	(1.86)	(0.21)
t = 6	0.034	0.016	0.021	0.018	0.043	0.020	0.041	0.014	0.049	0.017	0.025	0.014
	(0.92)	(0.61)	(0.59)	(0.69)	(1.14)	(0.74)	(1.20)	(0.63)	(1.43)	(0.78)	(0.74)	(0.65)
t = 7	0.030	0.016	0.015	0.018	0.037	0.021	0.043	0.016	0.050	0.021	0.025	0.018
	(0.69)	(0.61)	(0.37)	(0.73)	(0.90)	(0.80)	(0.95)	(0.76)	(1.14)	(1.01)	(0.58)	(0.87)
t = 8	0.063	0.003	0.055	0.003	0.070	0.009	0.065	-0.002	0.072	0.003	0.057	-0.003
	(1.29)	(0.14)	(1.08)	(0.11)	(1.46)	(0.34)	(1.24)	(-0.11)	(1.39)	(0.14)	(1.06)	(-0.12)
N	352,250		289,949		352,250		325,224		325,224		271,892	
adj. R^2	0.677		0.698		0.679		0.663		0.666		0.684	
Firm & quart. f.e.	Yes		Yes		Yes		Yes		Yes		Yes	
Firm controls	No		Yes		No		No		No		Yes	
Ownership contrls	No		No		Yes		No		Yes		Yes	
Flow controls	No		No		No		Yes		Yes		Yes	

Panel B: Log Amihud

	(1)		(2)		(3)		(4)		(5)		(6)	
Event-time	FS	PEER	FS	PEER	FS	PEER	FS	PEER	FS	PEER	FS	PEER
t = -2	0.036	-0.027*	0.075***	-0.018	0.105***	-0.028*	0.048*	-0.021	0.116***	-0.021	0.111***	-0.013
	(1.46)	(-1.74)	(3.22)	(-1.36)	(4.68)	(-1.91)	(1.98)	(-1.42)	(5.18)	(-1.53)	(4.94)	(-1.04)
t = -1	0.100***	0.007	0.130***	0.009	0.181***	0.004	0.110***	0.014	0.188***	0.011	0.168***	0.014
	(3.17)	(0.45)	(4.70)	(0.74)	(6.28)	(0.32)	(3.54)	(0.91)	(6.57)	(0.80)	(6.33)	(1.24)
t = 0	0.311***	0.085***	0.341***	0.066***	0.407***	0.070***	0.305***	0.096***	0.391***	0.077***	0.363***	0.062***
	(8.45)	(5.28)	(10.44)	(5.19)	(11.89)	(4.69)	(8.47)	(5.86)	(11.56)	(4.98)	(11.44)	(4.82)
t = 1	0.234***	0.031**	0.244***	0.024**	0.298***	0.031**	0.244***	0.036**	0.305***	0.036**	0.273***	0.020*
	(6.37)	(2.08)	(8.60)	(2.06)	(9.42)	(2.21)	(6.76)	(2.44)	(9.63)	(2.54)	(10.09)	(1.75)
t = 2	0.164***	0.004	0.169***	0.008	0.215***	0.011	0.176***	0.007	0.225***	0.014	0.195***	0.007
	(5.19)	(0.23)	(7.57)	(0.71)	(7.69)	(0.80)	(5.63)	(0.48)	(7.87)	(1.01)	(8.47)	(0.65)
t = 3	0.142***	-0.019	0.139***	-0.012	0.181***	-0.010	0.156***	-0.017	0.191***	-0.009	0.160***	-0.012
	(5.08)	(-1.30)	(7.69)	(-1.19)	(7.68)	(-0.83)	(5.67)	(-1.18)	(7.98)	(-0.75)	(9.28)	(-1.27)
t = 4	0.116***	-0.029**	0.114***	-0.013	0.153***	-0.022*	0.125***	-0.031**	0.162***	-0.024**	0.134***	-0.017*
	(3.91)	(-2.23)	(4.47)	(-1.34)	(6.34)	(-1.87)	(4.32)	(-2.47)	(6.71)	(-2.02)	(5.83)	(-1.72)
t = 5	0.093***	-0.027**	0.089***	-0.005	0.119***	-0.016	0.105***	-0.026**	0.130***	-0.014	0.111***	-0.002
	(3.66)	(-2.14)	(5.85)	(-0.50)	(5.92)	(-1.47)	(4.21)	(-2.11)	(6.54)	(-1.37)	(8.04)	(-0.24)
t = 6	0.082***	-0.024	0.077***	-0.009	0.107***	-0.014	0.093***	-0.020	0.116***	-0.011	0.097***	-0.005
	(3.23)	(-1.63)	(4.35)	(-0.77)	(5.49)	(-1.08)	(3.76)	(-1.40)	(5.90)	(-0.82)	(6.19)	(-0.39)
t = 7	0.069***	-0.013	0.053***	-0.000	0.095***	0.003	0.080***	-0.012	0.104***	0.004	0.072***	0.007
	(2.84)	(-0.83)	(3.32)	(-0.02)	(4.94)	(0.22)	(3.39)	(-0.79)	(5.40)	(0.31)	(4.80)	(0.64)
t = 8	0.062***	-0.030**	0.061***	-0.013	0.087***	-0.014	0.071***	-0.030**	0.094***	-0.015	0.081***	-0.006
	(2.93)	(-2.04)	(4.27)	(-1.14)	(5.23)	(-1.10)	(3.41)	(-2.12)	(5.58)	(-1.15)	(6.12)	(-0.54)
N	352,863		290,450		352,863		325,817		325,817		272,376	
adj. R^2	0.863		0.906		0.884		0.858		0.881		0.908	
Firm & quart. f.e.	Yes		Yes		Yes		Yes		Yes		Yes	
Firm controls	No		Yes		No		No		No		Yes	
Ownership contrls	No		No		Yes		No		Yes		Yes	
Flow controls	No		No		No		Yes		Yes		Yes	

Panel C: PIN

	(1)		(2)		(3)		(4)		(5)		(6)	
Event-time	FS	PEER	FS	PEER	FS	PEER	FS	PEER	FS	PEER	FS	PEER
t = -2	0.001	-0.001	0.002	-0.001	0.003**	-0.000	0.001	-0.000	0.004**	-0.000	0.004**	-0.001
	(0.64)	(-0.67)	(1.63)	(-1.38)	(2.11)	(-0.58)	(0.80)	(-0.40)	(2.31)	(-0.26)	(2.48)	(-1.05)
t = -1	0.002	-0.000	0.002*	-0.000	0.004***	-0.000	0.002	-0.000	0.005***	0.000	0.004***	-0.000
	(0.98)	(-0.42)	(1.67)	(-0.38)	(3.02)	(-0.35)	(1.20)	(-0.05)	(3.20)	(0.00)	(2.80)	(-0.10)
t = 0	0.009***	0.002**	0.011***	0.002**	0.013***	0.002**	0.008***	0.002**	0.011***	0.002*	0.010***	0.001
	(5.00)	(2.24)	(6.02)	(2.40)	(7.40)	(2.05)	(4.26)	(2.26)	(6.48)	(1.94)	(6.45)	(1.60)
t = 1	0.006***	0.001	0.007***	0.001	0.008***	0.001	0.005***	0.001	0.008***	0.001	0.008***	0.001
	(2.73)	(0.74)	(3.42)	(1.22)	(4.16)	(0.83)	(2.73)	(0.74)	(4.10)	(0.81)	(4.12)	(0.85)
t = 2	0.004**	0.000	0.005***	0.001	0.006***	0.001	0.004**	0.000	0.006***	0.001	0.005***	0.001
	(2.42)	(0.46)	(2.99)	(0.75)	(3.58)	(0.93)	(2.53)	(0.52)	(3.62)	(0.98)	(3.51)	(0.69)
t = 3	0.003**	0.000	0.003***	0.001	0.004***	0.001	0.004**	0.001	0.005***	0.001	0.004***	0.001
	(2.37)	(0.35)	(2.83)	(0.83)	(3.60)	(0.71)	(2.63)	(0.60)	(3.80)	(0.93)	(3.55)	(0.88)
t = 4	0.005***	0.000	0.005***	0.001	0.006***	0.001	0.005***	0.000	0.006***	0.001	0.006***	0.001
	(2.97)	(0.42)	(3.26)	(1.13)	(4.28)	(0.85)	(3.36)	(0.55)	(4.68)	(0.99)	(4.34)	(1.15)
t = 5	0.005***	0.000	0.005***	0.001	0.006***	0.001	0.005***	0.000	0.006***	0.001	0.006***	0.001
	(3.61)	(0.53)	(3.89)	(1.17)	(4.73)	(1.11)	(3.87)	(0.51)	(4.87)	(1.11)	(4.64)	(1.38)
t = 6	0.002	-0.001	0.003*	0.000	0.003*	-0.000	0.003	-0.000	0.003**	0.000	0.004**	0.001
	(1.27)	(-0.63)	(1.69)	(0.39)	(1.98)	(-0.17)	(1.59)	(-0.34)	(2.28)	(0.11)	(2.32)	(0.59)
t = 7	0.003*	-0.002**	0.004*	-0.001**	0.004**	-0.001	0.004**	-0.001*	0.005**	-0.001	0.005**	-0.001
	(1.81)	(-2.13)	(1.99)	(-2.01)	(2.28)	(-1.50)	(2.11)	(-1.76)	(2.54)	(-1.10)	(2.50)	(-1.19)
t = 8	0.003	-0.001	0.004**	-0.000	0.004**	-0.001	0.003*	-0.001	0.004**	-0.001	0.005**	-0.000
	(1.64)	(-1.50)	(2.00)	(-0.58)	(2.16)	(-0.84)	(1.81)	(-1.36)	(2.27)	(-0.76)	(2.47)	(-0.13)
N	271,148		229,130		271,148		256,029		256,029		217,479	
adj. R^2	0.574		0.575		0.588		0.576		0.592		0.587	
Firm & quart. f.e.	Yes		Yes		Yes		Yes		Yes		Yes	
Firm controls	No		Yes		No		No		No		Yes	
Ownership contrls	No		No		Yes		No		Yes		Yes	
Flow controls	No		No		No		Yes		Yes		Yes	

Panel D: Log turnover

	(1)		(2)		(3)		(4)		(5)		(6)	
Event-time	FS	PEER	FS	PEER	FS	PEER	FS	PEER	FS	PEER	FS	PEER
t = -2	-0.057***	0.014*	-0.068***	0.014*	-0.080***	0.015*	-0.059***	0.012	-0.081***	0.012	-0.084***	0.013
	(-3.19)	(1.76)	(-3.77)	(1.71)	(-4.57)	(1.86)	(-3.26)	(1.55)	(-4.65)	(1.62)	(-4.75)	(1.63)
t = -1	-0.117***	0.002	-0.127***	0.002	-0.146***	0.002	-0.116***	-0.001	-0.143***	-0.000	-0.144***	-0.001
	(-6.19)	(0.19)	(-6.72)	(0.18)	(-7.94)	(0.28)	(-6.10)	(-0.11)	(-7.84)	(-0.02)	(-7.76)	(-0.09)
t = 0	-0.318***	-0.032***	-0.327***	-0.033***	-0.351***	-0.027***	-0.286***	-0.034***	-0.316***	-0.028***	-0.318***	-0.029***
	(-19.31)	(-3.91)	(-19.28)	(-3.83)	(-22.59)	(-3.40)	(-17.50)	(-4.20)	(-20.59)	(-3.55)	(-20.41)	(-3.44)
t = 1	-0.099***	0.004	-0.104***	0.005	-0.122***	0.004	-0.096***	0.005	-0.118***	0.004	-0.115***	0.009
	(-5.59)	(0.49)	(-6.35)	(0.56)	(-7.24)	(0.47)	(-5.34)	(0.56)	(-6.92)	(0.55)	(-7.01)	(1.03)
t = 2	-0.070***	0.013*	-0.074***	0.010	-0.088***	0.011	-0.072***	0.012	-0.090***	0.010	-0.087***	0.011
	(-5.32)	(1.68)	(-6.27)	(1.14)	(-6.72)	(1.38)	(-5.32)	(1.56)	(-6.57)	(1.28)	(-6.76)	(1.24)
t = 3	-0.066***	0.006	-0.071***	0.000	-0.077***	0.004	-0.068***	0.004	-0.079***	0.003	-0.080***	0.000
	(-4.78)	(0.75)	(-5.35)	(0.05)	(-5.74)	(0.50)	(-4.97)	(0.62)	(-5.95)	(0.38)	(-6.23)	(0.06)
t = 4	-0.060***	0.007	-0.060***	0.003	-0.073***	0.005	-0.061***	0.011	-0.073***	0.009	-0.070***	0.007
	(-4.76)	(1.08)	(-4.92)	(0.37)	(-5.99)	(0.78)	(-4.79)	(1.60)	(-6.06)	(1.26)	(-5.71)	(0.92)
t = 5	-0.052***	0.006	-0.057***	0.004	-0.060***	0.003	-0.055***	0.006	-0.064***	0.003	-0.066***	0.004
	(-4.62)	(0.75)	(-5.44)	(0.47)	(-5.49)	(0.37)	(-4.96)	(0.73)	(-5.73)	(0.34)	(-5.95)	(0.44)
t = 6	-0.039***	0.003	-0.043***	-0.002	-0.047***	-0.000	-0.044***	0.002	-0.051***	-0.001	-0.053***	-0.004
	(-3.56)	(0.33)	(-4.21)	(-0.24)	(-4.22)	(-0.04)	(-4.15)	(0.26)	(-4.71)	(-0.10)	(-5.01)	(-0.48)
t = 7	-0.041***	0.014*	-0.040***	0.017**	-0.050***	0.009	-0.048***	0.014*	-0.056***	0.009	-0.052***	0.013*
	(-3.82)	(1.87)	(-3.37)	(2.20)	(-4.40)	(1.21)	(-4.48)	(1.84)	(-5.00)	(1.13)	(-4.33)	(1.69)
t = 8	-0.048***	0.011	-0.052***	0.005	-0.056***	0.006	-0.054***	0.010	-0.061***	0.005	-0.063***	0.003
	(-4.34)	(1.29)	(-4.67)	(0.65)	(-5.20)	(0.71)	(-4.76)	(1.23)	(-5.48)	(0.65)	(-5.78)	(0.46)
N	342,642		282,014		342,642		316,221		316,221		264,389	
adj. R^2	0.671		0.666		0.686		0.673		0.690		0.682	
Firm & quart. f.e.	Yes		Yes		Yes		Yes		Yes		Yes	
Firm controls	No		Yes		No		No		No		Yes	
Ownership contrls	No		No		Yes		No		Yes		Yes	
Flow controls	No		No		No		Yes		Yes		Yes	

Table VI: Feedback Effect

This table reports results from estimating equation (2) at the stock-quarter level for the sample of fire sale events. The dependent variable is the quarterly return. The main independent variables are TNIC similarity score-weighted averages of peer characteristics as indicated by the table rows. In row 1), the average across peers is formed over a dummy variable for whether the peer is above median in terms of size. In row 2), the average across peers is formed over a dummy variable for whether the peer has an investment-grade rating. In row 3), the average across peers is formed over a dummy variable for whether the peer is a S&P 500 index member. In row 4), the average across peers is formed over a dummy variable for whether the peer is above median in terms of analyst coverage. In row 5), the average across peers is formed over a dummy variable for whether the peer is above median in terms of average forecast error. In row 6), the average across peers is formed over a dummy variable for whether the peer is above median in terms of the "information index", which is defined as the mean across the five dummy variables analyzed in rows 1)-5). Firm-level controls (total assets, leverage, investment grade dummy, speculative grade dummy, market-to-book ratio, return on assets, number of analysts), ownership controls (mutual fund ownership, institutional ownership) and quarter fixed effects are included in all specifications. In the odd specifications (1, 3, 5, 7, 9, 11), the fund flow by fire-selling funds (*mfflow*) is included as a control. In the even specifications (2, 4, 6, 8, 10, 12), dummies for different mutual fund flow deciles are used instead of the continuous *mfflow* variable. 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. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Peer characteristics:												
1) Above-median size	0.0118**	0.0127**										
	(2.46)	(2.56)										
2) Investment-grade rating			0.0099*	0.0109*								
			(1.81)	(1.97)								
3) S&P 500 membership					0.0115*	0.0122*						
					(1.93)	(1.99)						
4) Above-median analyst coverage							0.0054	0.0047				
							(1.10)	(0.95)				
5) Above-median average forecast error									0.0064	0.0063		
									(1.37)	(1.32)		
6) Above-median information index											0.0176***	0.0181***
											(2.79)	(2.76)
N	24,291	24,291	24,368	24,368	24,368	24,368	24,368	24,368	23,047	23,047	24,368	24,368
adj. R^2	0.256	0.259	0.256	0.259	0.256	0.259	0.256	0.259	0.254	0.257	0.256	0.259
Quarter f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ownership contrls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Flow controls	Yes	Yes*	Yes	Yes*	Yes	Yes*	Yes	Yes*	Yes	Yes*	Yes	Yes*

Table VII: Placebo Test of S&P 500 Index Additions

This table reports results from estimating regressions in the spirit of equation (1) at the stock-day level. The dependent variable is the daily return. The main independent variables are AD and PEER dummies that flag S&P 500 index addition events and peers for these addition events, respectively. All regressions include dummies from t=-25 to t=25; for brevity we only show the coefficients for t=-8 to t=8. Firm and day fixed effects are included in all specifications. In specification 2, additional firm-level controls are included (total assets, leverage, investment grade dummy, speculative grade dummy, market-to-book ratio, return on assets, number of analysts). In specification 3, ownership controls are included (mutual fund ownership, institutional ownership). In specification 4, mutual fund flow controls are included (separately for fire sale funds and others). In specification 5, ownership and flow controls are included. In specification, firm-level, ownership and flow controls are included. All variables are defined in Appendix A. Standard errors are double-clustered at the firm and day level. *t*-statistics are reported below coefficient estimates in parentheses. At the bottom of the table, we report the sum of the AD and PEER dummy coefficients for windows [-4, -1] and [-8, -1] respectively together with the corresponding *t*-statistic for the cumulated price pressure effect. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels.

	(1)		(2)		(3)		(4)		(5)		(6)	
Event-time	AD	PEER	AD	PEER	AD	PEER	AD	PEER	AD	PEER	AD	PEER
t = -8	0.002	-0.000	0.004	0.001	0.002	-0.000	0.002	-0.000	0.002	-0.000	0.004	0.001
	(0.83)	(-0.37)	(1.27)	(0.41)	(0.87)	(-0.35)	(0.83)	(-0.22)	(0.87)	(-0.20)	(1.30)	(0.41)
t = -7	0.004**	0.001	0.003	0.000	0.004**	0.001	0.004**	0.001	0.004**	0.001	0.003	0.000
	(2.12)	(1.52)	(1.19)	(0.44)	(2.16)	(1.55)	(2.00)	(1.45)	(2.04)	(1.48)	(1.20)	(0.18)
t = -6	-0.000	0.000	0.002	-0.000	-0.000	0.000	-0.000	0.000	-0.000	0.000	0.002	0.000
	(-0.08)	(0.08)	(0.97)	(-0.13)	(-0.05)	(0.10)	(-0.10)	(0.20)	(-0.07)	(0.23)	(0.93)	(0.15)
t = -5	0.006***	0.000	0.006**	0.001	0.006***	0.000	0.005***	0.000	0.005***	0.000	0.005**	0.001
	(3.00)	(0.34)	(2.18)	(0.83)	(3.04)	(0.36)	(2.86)	(0.18)	(2.89)	(0.21)	(2.02)	(0.47)
t = -4	0.010***	0.003**	0.010***	0.002	0.010***	0.003**	0.010***	0.002**	0.010***	0.002**	0.011***	0.001
	(4.52)	(2.23)	(3.90)	(1.28)	(4.55)	(2.25)	(4.60)	(2.05)	(4.63)	(2.08)	(3.95)	(1.18)
t = -3	0.008***	0.001	0.007**	-0.000	0.008***	0.001	0.008***	0.001	0.008***	0.001	0.007**	0.000
	(3.78)	(0.55)	(2.31)	(-0.10)	(3.82)	(0.58)	(3.74)	(0.67)	(3.77)	(0.70)	(2.28)	(0.04)
t = -2	0.009***	-0.001	0.006**	-0.001	0.009***	-0.001	0.009***	-0.002*	0.009***	-0.002*	0.006**	-0.001
	(4.06)	(-1.52)	(2.34)	(-0.62)	(4.09)	(-1.49)	(3.98)	(-1.74)	(4.01)	(-1.70)	(2.25)	(-0.72)
t = -1	0.016***	0.002	0.013***	0.002	0.017***	0.002	0.016***	0.001	0.016***	0.001	0.012***	0.002
	(5.37)	(1.51)	(3.43)	(1.62)	(5.39)	(1.53)	(5.22)	(1.38)	(5.24)	(1.41)	(3.25)	(1.49)

(continued on next page)

	(1)		(2)		(3)		(4)		(5)		(6)	
Event-time	AD	PEER	AD	PEER	AD	PEER	AD	PEER	AD	PEER	AD	PEER
(continued from previous page)												
t = 0	-0.005***	-0.000	-0.003	-0.001	-0.005***	-0.000	-0.006***	-0.001	-0.006***	-0.001	-0.003	-0.001
	(-2.69)	(-0.46)	(-1.08)	(-0.78)	(-2.68)	(-0.43)	(-2.77)	(-0.63)	(-2.76)	(-0.60)	(-0.98)	(-0.71)
t = 1	-0.002	-0.001	-0.005*	-0.002*	-0.002	-0.001	-0.002	-0.001	-0.002	-0.001	-0.004*	-0.002**
	(-1.25)	(-0.84)	(-1.95)	(-1.68)	(-1.24)	(-0.81)	(-1.23)	(-1.05)	(-1.23)	(-1.01)	(-1.91)	(-1.98)
t = 2	-0.003*	-0.000	-0.002	-0.000	-0.003*	-0.000	-0.003*	-0.000	-0.003*	-0.000	-0.002	0.000
	(-1.77)	(-0.23)	(-0.95)	(-0.01)	(-1.76)	(-0.20)	(-1.67)	(-0.13)	(-1.67)	(-0.09)	(-0.92)	(0.03)
t = 3	0.003*	0.002	0.002	0.001	0.003*	0.002	0.003*	0.001	0.003*	0.001	0.003	0.001
	(1.70)	(1.45)	(1.14)	(1.05)	(1.70)	(1.48)	(1.76)	(1.27)	(1.76)	(1.30)	(1.13)	(1.06)
t = 4	-0.001	0.000	-0.002	0.000	-0.001	0.000	-0.002	0.000	-0.001	0.000	-0.002	0.000
	(-0.93)	(0.29)	(-1.14)	(0.32)	(-0.92)	(0.32)	(-0.94)	(0.23)	(-0.93)	(0.27)	(-1.12)	(0.03)
t = 5	-0.003*	0.002*	-0.004	0.002	-0.003*	0.002*	-0.003**	0.002*	-0.003*	0.002*	-0.004	0.002
	(-1.66)	(1.78)	(-1.45)	(1.41)	(-1.65)	(1.82)	(-1.96)	(1.81)	(-1.96)	(1.85)	(-1.45)	(1.32)
t = 6	-0.001	0.001	-0.000	0.002*	-0.001	0.001	-0.002	0.001	-0.002	0.001	-0.001	0.002**
	(-0.92)	(1.04)	(-0.21)	(1.90)	(-0.91)	(1.08)	(-0.94)	(1.00)	(-0.93)	(1.04)	(-0.24)	(2.00)
t = 7	-0.002	-0.000	-0.002	-0.000	-0.002	-0.000	-0.002	-0.000	-0.002	-0.000	-0.002	0.000
	(-0.91)	(-0.21)	(-0.52)	(-0.08)	(-0.90)	(-0.18)	(-0.96)	(-0.05)	(-0.95)	(-0.01)	(-0.57)	(0.04)
t = 8	0.002	0.001	0.003	-0.000	0.002	0.001	0.002	0.001	0.002	0.001	0.003	0.000
	(0.89)	(0.64)	(1.34)	(-0.07)	(0.90)	(0.67)	(0.93)	(0.90)	(0.93)	(0.94)	(1.32)	(0.11)
N	17,739,694		10,688,859		17,739,694		15,953,631		15,953,631		9,784,911	
adj. R^2	0.077		0.079		0.077		0.093		0.094		0.093	
Firm & day f.e.	Yes		Yes		Yes		Yes		Yes		Yes	
Firm controls	No		Yes		No		No		No		Yes	
Own. contrls	No		No		Yes		No		Yes		Yes	
Flow controls	No		No		No		Yes		Yes		Yes	
Run-up [-4, -1]	0.043***	0.003	0.036***	0.003	0.043***	0.003*	0.043***	0.003	0.043***	0.003	0.035***	0.003
	(8.71)	(1.64)	(5.70)	(1.16)	(8.77)	(1.69)	(8.57)	(1.46)	(8.62)	(1.52)	(5.56)	(1.07)
Run-up [-8, -1]	0.054***	0.005*	0.051***	0.005	0.055***	0.005*	0.053***	0.004	0.054***	0.005*	0.050***	0.004
	(8.97)	(1.73)	(6.46)	(1.40)	(9.07)	(1.81)	(8.76)	(1.61)	(8.86)	(1.70)	(6.30)	(1.24)

Appendix A: Definition of Variables

Variable name	Source	Definition
Return	CRSP	Quarterly compounded return.
Bid-ask spread	CRSP	Difference between closing bid and ask prices, divided by the mid-price. Daily observations averaged quarterly.
Log Amihud	CRSP	Natural logarithm of the average ratio of absolute returns over dollar volume multiplied by one million.
PIN	Stephen Brown	Probability of informed trading (Easley et al., 1996) estimated at quarterly frequency. Data available at: http://scholar.rhsmith.umd.edu/sbrown/pin-data
Turnover	CRSP	Turnover is the total dollar volume in the quarter divided by the market capitalization at the end of the previous quarter.
S&P 500 member	CRSP	Dummy equal to one if the stock is a current constituent of the S&P 500 index.
Total assets	Compustat	Logarithm of total assets from the previous fiscal year.
Leverage	Compustat	Ratio of long-term debt and current liabilities over stockholders' equity at the end of the previous fiscal year.
Investment grade Speculative grade	Compustat	Investment (speculative) grade is a dummy variable that indicates whether a firms long-term debt has an investment grade (speculative grade) rating given by Standard&Poors.
Market-to-book	Compustat	Market-to-book is the ratio of the stock's market capitalization at the end of the previous quarter over the stockholders' equity.
Return on assets	Compustat	Return on assets as reported for the previous fiscal year.
Num. analysts	I/B/E/S	Num. analysts is the number of analysts following a stock and/or issuing recommendations at the end of the previous quarter.
Average absolute forecast error	I/B/E/S	Absolute forecast error for analysts' one year ahead EPS forecasts averaged over the previous five fiscal years.
Mutual fund ownership	Thomson Reuters S12	Mutual fund ownership is the fraction of shares outstanding owned by open-ended mutual funds at the end of the previous quarter.
Inst. ownership	Thomson Reuters S34	Institutional ownership is the fraction of shares outstanding owned by institutional investors at the end of the previous quarter.
Mfflow	S12 / CRSP MF database	*Mfflow* is the selling pressure by mutual funds experiencing a fire sale as defined in Edmans et al. (2012). See Appendix B for details.
Mfflow complement	S12 / CRSP MF database	*Mfflow complement* is the difference between mutual fund trading pressure by all mutual funds and the selling pressure by fire-selling mutual funds. See Appendix B for details.
Liquidity provision proxy	S12 / CRSP MF database	For each stock, we calculate the aggregated dollar selling volume in that stock by its current fund owners and their simultaneous aggregate dollar buy volume in peer stocks experiencing a fire sale. We then take the minimum of those two numbers to measure liquidity provision by current owners to fire sale funds. The measure is not defined for fire sale stocks.
Fire sale fund share	S12 / CRSP MF database	Fraction of holdings by current owners invested in fire sale stocks. The measure is not defined for fire sale stocks.
Fire sale stock share		Fraction of shares outstanding owned by fire sale funds (i.e., funds with flow < -5%). The measure is not defined for fire sale stocks.

Appendix B: Construction of the Edmans et al. (2012) Mfflow measure

We compute the mutual fund selling pressure proxy for each stock as in Edmans et al. (2012). The same approach is also used in Dessaint et al. (2015). For every fund, we find monthly total net assets (*TNA*) and returns (*ret*) from the CRSP Mutual Fund Database. We then compute

$$flow_{j,t} = \frac{(TNA_{j,t} - \left(1 + ret_{t,j}\right) * TNA_{j,t-1})}{TNA_{j,t-1}}$$

at quarterly frequency and construct the *mfflow* measure as

$$mfflow_{i,t} = \sum_{j=1}^{M} flow_{j,t} * \frac{shares_{i,j,t-1} * prc_{i,t-1}}{vol_{i,t}}$$

using only the funds *j* which have *flow<-5%* (called "fire sale funds"). $shares_{i,j,t-1}$ is the number of shares of company *i* owned by fund *j* in quarter *t-1*. ($shares_{i,j,t-1} * prc_{i,t-1}$) gives the total value of investment held in company *i* by fund *j* in quarter *t-1*. $flow_{j,t} * (shares_{i,j,t-1} * prc_{i,t-1})$ gives the "hypothetical" selling volume (in dollars) by fire sale fund *j*. We then sum this hypothetical selling volume over all fire sale funds and scale by trading volume (in dollars) to obtain the *mfflow* measure. Finally, we designate stock-quarter observations in the bottom decile of *mfflow* as "fire sale" events.

Using "hypothetical" rather than actual sales immunizes our approach against selection concerns stemming from funds' endogenous decisions to sell particular portfolio stocks as opposed to others (Ringgenberg et al., 2016). Scaling by dollar volume singles out fire sale events where mutual funds' selling pressure makes up a large fraction of the overall trading volume, ensuring a large price impact.

Finally, as a control variable, we also construct $mfflow\ complement_{i,t}$ as the sum of hypothetical fund sales (and/or purchases) over mutual funds with *flow>-5%* (non-fire sale funds).

Online Appendix for:

Price and Liquidity Spillovers during Fire Sale Episodes

Pekka HONKANEN and Daniel SCHMIDT

November 17, 2016

A. Event study results

A.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 A.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.

A.2 For S&P 500 Index Additions

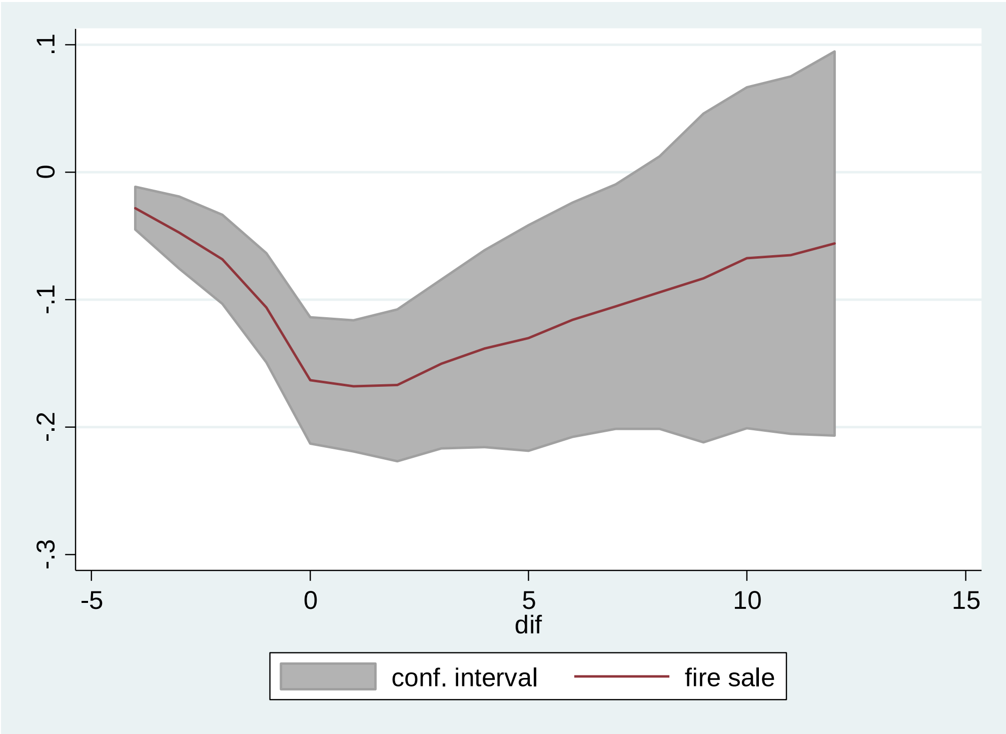
We also show event study results for S&P 500 index additions and their peers. Since this analysis is at the daily frequency, we estimate the market-model using daily return data over the period [-300, -50] relative to the effective date of the index addition. For each addition event, we again focus on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

Figure A.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 A.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

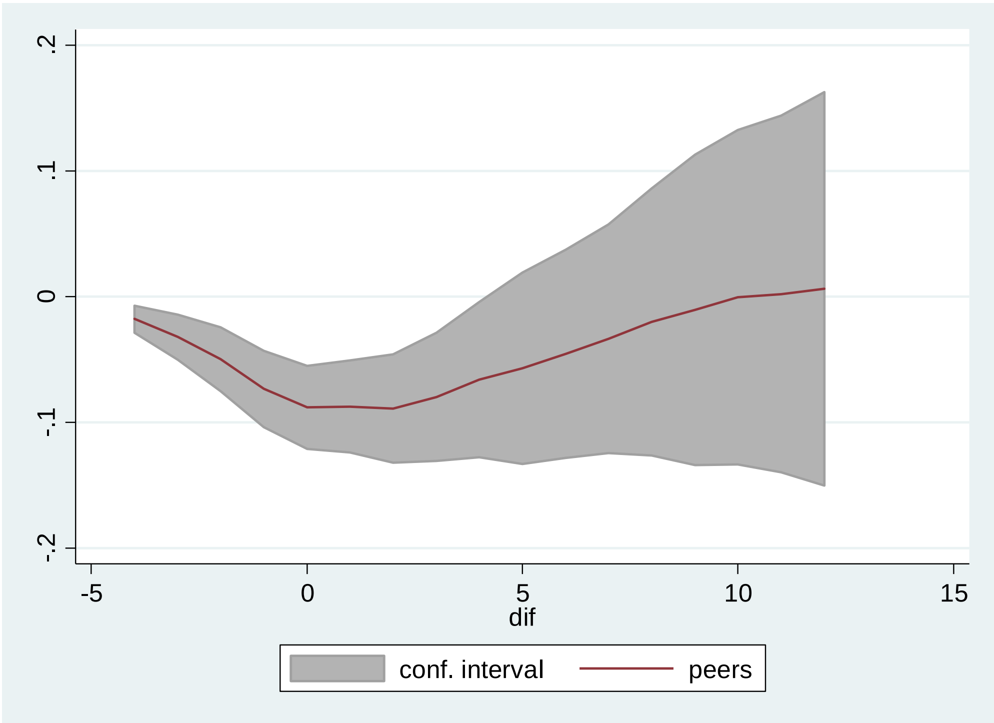
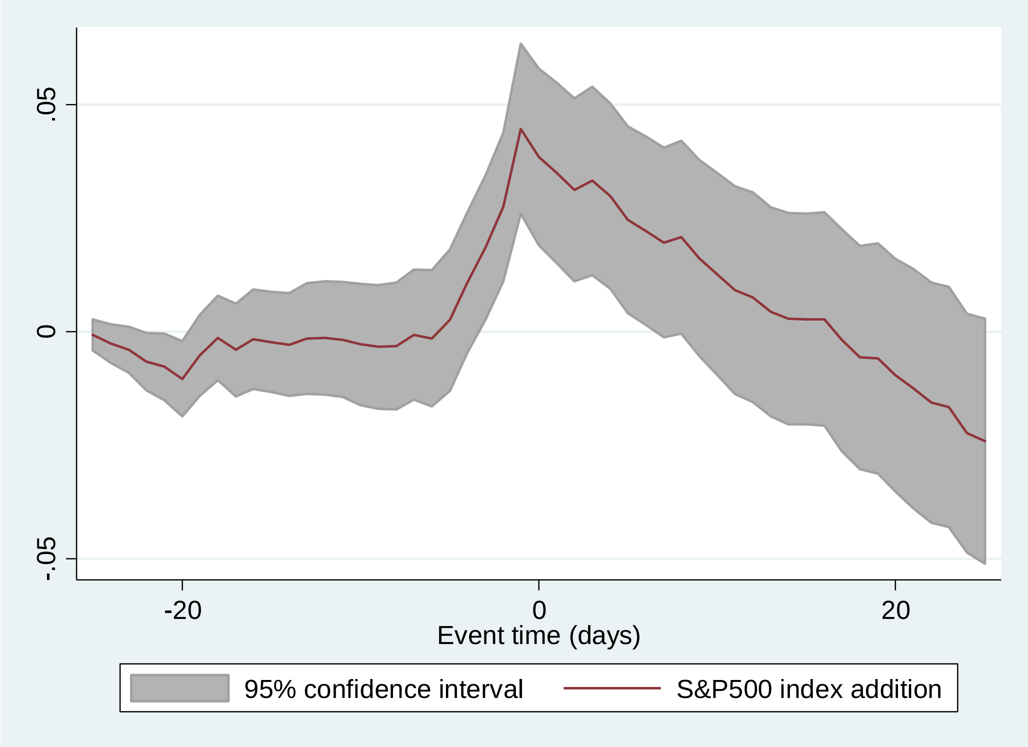


Figure A.2: Event study results for S&P 500 Index Additions and Peer Firms

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