Financial Contagion in the Mutual Fund Industry

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Abstract

We show that a liquidity shock to closed-end funds can lead to liquidity withdrawals from open-end funds, thus causing a cascade of fire-sales. The failure of the market for auction rate securities in 2008 triggered asset sales at some highly levered closed-end funds. These asset sales led to temporary price declines of up to -10%. Open-end funds that held significant numbers of these fire-sale stocks experienced outflows, forcing them to sell assets. These forced sales induced additional price pressure. Our results show that financial contagion can originate in a relatively small sector of the mutual fund industry and spread to a much larger one.

Keywords: Mutual funds, closed-end funds, financial contagion, fire-sales, flow-performance relationship, auction rate securities

JEL-Classification: G01, G11, G14, G23, G28

"The first sale can set off a cascade of fire-sales that inflicts losses on many institutions [...] reducing the financial system's capacity to bear risk."

-- French, Baily, and Campbell (2010), Princeton University Press

1 Introduction

Due to the strong interdependencies of our financial system, liquidity shocks can become contagious by spreading from one market to another. While much analysis has focused on explaining and understanding financial contagion in the banking industry, less attention has been paid to the question whether and how shocks can transmit across non-bank financial institutions, such as mutual funds. In this paper, we address this question empirically by examining whether 'fire-sale cascades' can explain the spillover of a liquidity shock from the closed-end to the open-end fund industry.

Fire-sales are forced asset sales triggered by liquidity needs, which can cause temporary asset price declines (Scholes, 1972; Shleifer and Vishny, 1997). Given that fire-sale assets are not only held by the selling institutions, they simultaneously cause temporary losses to the portfolios of others. If fund investors react to these losses by withdrawing liquidity, as predicted by the well-known flow-performance relationship (Sirri and Tufano, 1998; Chevalier and Ellison, 1997), they can spur a cascade of additional forced fire-sales at those funds.[1] For that reason, a liquidity shock at some funds can transmit through fire-sales to other, initially unaffected, institutions.[2]

To study fire-sale cascades as a channel of financial contagion, we proceed along the following line of inquiry. First, we use an exogenous liquidity shock in the closed-end fund industry to overcome the primary challenge of distinguishing between unforced and forced sales. This shock only affected some levered closed-end funds and, hence, allows for a clear identification of initial fire-sales. In the second step, we examine whether these fire-sales result in outflows at open-end funds that were not directly affected by the initial shock. Such outflows can emerge if investors of open-end funds do not differentiate between a performance deterioration caused by fire-sales and performance losses that are caused by

[1] Coval and Stafford (2007) document that outflows can force mutual funds to sell at fire-sale prices.

[2] This argument has been made by Shleifer and Vishny (2011), but is not empirically examined by them.

other factors, such as poor managerial investment decisions. The examination of the flow-performance relationship and whether this relationship is affected by the reason for poor performance is, therefore, a critical part of this paper. Finally, we test whether open-end funds that were exposed to initial fire-sales sell assets at fire-sale prices themselves.

To identify initial fire-sales, we exploit the failure of the auction rate security (ARS) market in February 2008, which resulted in a sudden increase in borrowing costs for some levered closed-end funds. As the shock only affected levered funds, it is an ideal setting to examine spillover effects to open-end funds, which typically do not rely on leveraged investment strategies. ARS are preferred equity instruments, which accounted for almost 70% of total fund leverage by the end of 2007. The coupon rate of ARS is determined weekly, bi-weekly, or monthly through an auction mechanism. In February 2008, the auction mechanism for ARS stopped working due to reasons that were exogenous to the closed-end fund industry. As a result, ARS dividend rates were set to pre-specified maximum rates, which on average were twice the rates determined through the regular auction mechanism. In response to this sudden increase in borrowing costs, closed-end funds redeemed 90% of their ARS leverage over the following two years. These leverage redemptions were financed by asset sales as closed-end funds replaced their ARS only partially by other debt instruments.[3] We use these sales to construct a variable on the stock level, called ‘selling pressure'. This measure captures the aggregate sales of all funds that redeem ARS in a given period and proxies for the extent of price pressure that a stock experiences due to fire-sales in the selling quarter.

Using the asset sales of 53 ARS-levered closed-end funds, we find that stocks in the two highest selling pressure quintiles experience 4-factor abnormal stock returns of -9.1% to -10.4% in the selling quarter.[4] This price drop is followed by strong price reversals over the next 12 months that almost completely offset the initial price depreciation. Such a reversal is

[3] Anecdotal evidence suggests that some funds were unable to replace their ARS by other debt instruments. For example, the Denali and Calmos Strategic Total Return Fund writes: 'At this time, the Fund has not found an adequate alternative to replace the ARPs [a form of ARS]' (The Denali Fund, N-CSRS, March 2008); 'Our ability to refinance all preferred shares with debt was constrained by regulations that require total assets in closed-end funds to be at least three times the amount of debt leverage' (Calamos Strategic Total Return Fund, N-CSRS, June 2008).

[4] Our results are obtained using the event-study methodology by Kolari and Pynnönen (2010), which accounts for cross-sectional correlations of returns and inflated volatiles in the event window.

consistent with a temporary price drop caused by fire-sales, but inconsistent with a permanent price drop due to new information.

Some open-end funds that are not directly affected by the failure of the ARS market are significantly exposed to these fire-sales. We measure this exposure using a variable called ‘fire-sale exposure'. Funds with the highest exposure to fire-sales (i.e. funds in the top fire-sale exposure quintile) hold, on average, 16% of their portfolio in stocks that belong to the highest two selling pressure quintiles. These investments are costly. On average, the 3-month fund performance deteriorates by 1.1% per one standard deviation increase in fire-sale exposure. More importantly, these performance losses lead to significant fund outflows as most investors appear to be insensitive to the reason for poor performance. We, however, observe differences between investor classes. When open-end funds are exposed to fire-sales, we show that the flow-performance relationship is weaker for institutional than for retail investors. This difference is not observable in other non-exposure periods and suggests that retail investors pay less attention to the cause of the performance deterioration.

Finally, we examine whether sales of open-end funds that are exposed to fire-sales show also return patterns that are consistent with fire-sales. For that purpose, we define, analog to the selling pressure variable for closed-end funds, a pressure variable for sales by open-end funds, which we call ‘cascade pressure'. The cascade pressure variable measures the fraction of shares sold in aggregate by all open-end funds weighted by each fund's ‘fire-sale exposure' during the previous quarter. Weighting by the fire-sale exposure means that we put more weight on sales of open-end funds that were strongly exposed to closed-end fund fire-sales. Consistent with fire-sale cascades, we find that stocks in the top cascade pressure quintile have on average negative abnormal returns of -6.4% (as measured by 4-factor alphas) in the selling quarter, even after we eliminate all stocks held by ARS-levered funds. This return pattern reverses in the quarter that follows. Our results suggest that fire-sales can spread from one market segment (stocks held by closed-end funds) to an initially unaffected market segment (stocks held by open-end funds), posing a potential threat to financial stability.

One concern that needs to be addressed is the possibility that the observed stock return patterns are driven by unobserved variables or events such as the financial crisis. We try to mitigate this concern by running placebo tests using two control groups. To construct the first group, we use the sales of the same ARS-levered funds, but consider only periods in which they do not redeem their ARS leverage. Hence, we can compare sales of redeeming funds with non-redeeming funds in the same period. The second control group is based on sales by funds that were not levered by ARS leverage. Thus, these funds should not be impacted by the failure of the ARS market. We use the same method as before to calculate two placebo measures of selling pressure based on the sales by both control groups. We do not find evidence for fire-sales for any of the two measures.

The strong price reaction of stocks sold by ARS-levered funds raises the question whether the observed price drop is only a result of fire-sales by the closed-end fund sector, which is relatively small compared to the total mutual fund industry. While we believe that closed-end fund sales exerted significant price pressure, the price effect might have been amplified by front-running speculators such as hedge funds, as described by Brunnermeier and Pedersen (2005). Consistent with this argument, we observe a strong increase in short sales for stocks in the top selling quintile during the selling quarter, while we do not find any increase in short sales for the placebo groups.

Our paper relates to different strands of the existing literature. First, our study adds to the growing literature on fire-sales, which is pioneered by Shleifer and Vishny (1992), who describe how forced sales can drive market prices temporarily away from their fundamental values. The empirical literature has shown that fire-sales can occur in both financial and product markets. For example, Campbell, Giglio, and Pathak (2011) show that forced sales can occur in the housing market. Pulvino (1998) and Benmelech and Bergman (2011) document that airline companies near or in bankruptcy sell aircrafts below value. Coval and Stafford (2007) and Jotikasthira, Lundblad, and Ramadorai (2012) document temporary price declines in stocks that are sold by open-end funds experiencing severe outflows. Mitchell, Pedersen, and Pulvino (2007) and Aragon and Strahan (2012) find that forced sales by hedge funds affect asset prices and liquidity. The work closest to our project is the study by Tang (2014), who documents price declines of stocks held by levered closed-end funds that experience an unexpected increase in borrowing costs. We go beyond Tang's findings by providing evidence that these initial fire-sales can cause a cascade of additional fire-sales by open-end funds. We also differ from Tang in our identification strategy. In contrast to Tang, we do not only compare stocks of ARS-levered funds with stocks of non-ARS-levered funds in the year following the shock, but compare quarterly sales by ARS-levered funds during redemption periods with sales by ARS-levered funds during non-redemption periods.

Second, our paper is directly linked to the literature focusing on fire-sale cascades. Most related to our work are the models by Vayanos and Woolley (2013) and He and Krishnamurthy (2012, 2013). Vayanos and Woolley (2013) argue that initial price declines can be amplified by flow-induced fire-sales. He and Krishnamurthy (2012, 2013) develop two more general models, which explain how equity withdrawals from financial intermediaries can be reinforcing in a general equilibrium framework. Lou (2012) argues that fire-sale cascades can explain mutual fund performance persistence, stock momentum, and the smart-money-effect. In a summary paper, Shleifer and Vishny (2011) present anecdotal evidence for such cascades. Other papers focus on fire-sales cascades that emerge due to de-leveraging cycles. Such de-leveraging cycles can arise if falling prices cause (i) margin requirements to rise or funding supplies to decline (Brunnermeier and Pedersen, 2009; Brunnermeier and Sannikov, 2014; Dudley and Nimalendran, 2011), (ii) the value of debt collateral to decline (Gromb and Vayanos, 2002), or (iii) leverage levels to rise above self-imposed or regulatory limits (Kiyotaki and Moore, 1997; Stein, 2009). We add to this literature by showing that initial fire-sales in one market can trigger fire-sales in other, initially unaffected markets.

Third, studying fire-sales also contributes to the stream of literature that investigates the role of non-banks in financial contagion, excess co-movement of asset prices, and abnormal asset volatility. Barberis and Shleifer (2003) show that excess stock co-movement and volatility can be caused by funds with similar investment styles. Bartram, Griffin, Lim, and Ng (2015) find empirical evidence that stock co-movement is related to common mutual fund ownership. Barberis, Shleifer, and Wurgler (2005) and Greenwood (2005, 2008) argue that the sentiment and preferences of fund managers affect stock return correlations. Anton and Polk (2014) show that two unrelated stocks can experience similar negative returns if they are held by the same funds with strong outflows. Greenwood and Thesmar (2011) show that non-fundamental stock volatility can be explained by correlated liquidity withdrawals from mutual funds. Boyson, Stahel, and Stulz (2010) find that hedge fund returns correlate more strongly as fundamentals would suggest because of common shocks to funds' funding situations. While these studies provide evidence that stock returns are strongly linked and affected by mutual fund behavior and ownership in general market conditions, Manconi, Massa, and Yasuda (2012), Hau and Lai (2013) and Adams, Füss, and Gropp (2014) emphasize the importance of funds in transmitting liquidity shocks. Manconi, Massa, and Yasuda (2012) argue that funds that were invested in both secured bonds and corporate bonds were largely responsible for spreading the crisis from the secured bond market to the corporate bond market. Hau and Lai (2013) find that the shock to bank stocks in the recent financial crisis spilled-over to non-bank stocks because of outflows at funds that were invested in both assets. Adams, Füss, and Gropp (2014) quantify risk spillovers from hedge funds to banks and insurance companies. Our research will be the first to show that a shock to closed-end funds can spread to open-end funds and the assets they hold.

Finally, our paper is connected to studies that inquire the flow-performance relationship that was first documented by Sirri and Tufano (1998) and Chevalier and Ellison (1997). Del Guercio and Tkac (2002) show that investors of pension funds react more strongly to risk-adjusted performance measures, while mutual fund flows react more strongly to raw returns. James and Karceski (2006) provide evidence that flows respond less strongly to past performance when the fund is an institutional opposed to a retail fund. Wei, and Yan (2007), Ivkovic and Weisbenner (2009), and Chen, Goldstein, and Jiang (2010) find that the flow-performance relationship is affected by the level of participation costs, expenses, and the funds' asset compensation, respectively. We add to this literature by examining whether the flow-performance relationship is sensitive to the reason for poor performance.

The remainder of this paper is structured as follows. In Section 2, we describe the experimental design and our main variables, Section 3 covers the data and data sources. Section 4 reports our empirical results. In Section 5, we present robustness and additional tests. Section 6 concludes.

2 Experimental design and variables

2.1 Fire-sales by ARS-levered funds

In the first part of our analysis, we study fire-sales by levered closed-end funds. We identify these fire-sales by exploiting an unexpected shock to the borrowing costs of some levered funds, which resulted in de-leveraging and portfolio liquidations. Relying on an exogenous shock for the identification of fire-sales is advantageous as it allows us to refrain from fund flows, which are potentially endogenous.

2.1.1 The failure of the auction rate security market

In early 2008, some levered closed-end funds were exposed to a funding shock, when the auction rate security (ARS) market collapsed. ARS are preferred equity securities, which were used by 21% of our sample funds and accounted for 70% of total fund leverage by the end of 2007. The feature that distinguishes ARS from other sources of leverage is that the dividend yield is reset weekly, bi-weekly, or in rare cases monthly through an auction mechanism. In such an auction, all existing bids are ranked and the lowest rate at which all ARS can be (re-) allocated at par value establishes the clearing rate, which is valid up to the next auction date. Should the auction mechanism fail, the fund must pay a pre-specified maximum dividend rate on its outstanding ARS. An auction failure is usually caused by a demand-supply imbalance, which prevents the market from clearing.

Before 2008, auction failures of ARS were extremely rare. A special report of Moody's (2008), for example, recorded only 44 failures in over 100,000 auctions. Starting in mid-February 2008, however, the market for ARS securities suddenly collapsed and almost all auctions began to fail. The auctions in our sample showed similar failures.[5] The main reason for the ARS market collapse was an unexpected liquidity withdrawal by brokers-dealers (Han and Li, 2009; Tang, 2014). Brokers-dealers regularly supported auctions by buying ARS on their own accounts and acting as a market maker. When they withdrew collectively from the market, there was no buffer for demand and supply imbalances, which caused the liquidity in the ARS market to quickly dry up. Consequently, auction failure became a permanent symptom of the ARS market.

When the ARS market collapsed, the dividend rate of ARS jumped to their pre-specified maximum rates. Figure 1 captures the development of these rates around the failure of the ARS market in February 2008. Since our data set does not contain dividend rates of the sample funds before the ARS market failure, we complement our data with the SIFMA Auction Rate Preferred 7-Day Index. This index contains self-reported data from actual ARS issues (including issues by other institutions than closed-end funds). As shown, the average dividend rate of the SIFMA index was relatively stable and fluctuated at about 0.75 of the 1-week US LIBOR rate before the ARS market failure. Beginning in February, however, the

[5] One ARS issue was not subject to auction failure because the whole issue was bought by an affiliated investor.

index suddenly increased to a maximum of about 1.4 of LIBOR.[6] This corresponds well to the average maximum dividend yield observed among our sample funds, which amounts to about 1.5 of LIBOR in the periods subsequent to the ARS market failure. This suggests that our sample funds experienced on average almost a doubling of their borrowing costs. Since the failure of the ARS market was predominantly driven by liquidity needs of brokers-dealers and since other non-funds institutions were similarly affected, this increase in funding costs was plausibly exogenous to the mutual fund industry.

*** Insert Figure 1 about here ***

In response to the sudden increase in borrowing costs, many funds redeemed their outstanding ARS, as illustrated in Figure 2.[7]Between February 2008 and February 2010, the total volume of outstanding ARS (solid blue line) declined by about 12 billion, which represents a reduction of almost 90%. The number of funds that used ARS as a source of leverage (green dashed line) shrunk in a similar manner. The dotted-dashed red line, which shows the volume of non-ARS liabilities, indicates that funds partially replaced their ARS by other liability types. In fact, about 12% of our sample funds replaced their ARS completely by other debt instruments. In contrast, 14% did not raise any (non-ARS) debt. Most funds substituted only partially. One reason for this incomplete substitution is that the SEC imposes lower restrictions on ARS-leverage (100% of TNA) when compared to debt-leverage (50% of TNA).[8] Incomplete substitutions, however, may also have resulted from capital supply frictions.[9] Since closed-end funds did not completely substitute their ARS-leverage, they had

[6] Note that the fluctuation in the ARS index after the failure of the ARS market are caused by a weekly changing composition of issues. Hence, the index strongly depends on the fraction of failed auctions used to calculate the index at a given date.

[7] Most ARS issues are perpetual, but redeemable at the fund's option.

[8] In unreported tests we, however, do not find evidence that sales by funds with more than 50% leverage result in larger price effects.

[9] Since the failure of the ARS market was triggered by broker-dealers that were impacted by tightening credit markets themselves, it is not surprising that closed-end funds could not easily replace their ARS by bank leverage. We also found anecdotal evidence for credit supply frictions in fund reports. For example: 'At this time, the Fund has not found an adequate alternative to replace the ARPs [A form of ARS]' (The Denali Fund, N-CSRS, March 2008); 'Our ability to refinance all preferred shares with debt was constrained by regulations that require total assets in closed-end funds to be at least three times the amount of debt leverage' (Calamos Strategic Total Return Fund, N-CSRS, June 2008).

to sell assets to finance their ARS redemptions.[10] We will use these sales to identify stocks that were fire-sold.

*** Insert Figure 2 about here ***

2.1.2 Treatment and control groups

One advantage of our setting is that we observe sales of ARS-levered funds during periods in which they reduced their ARS and during periods in which they did not alter their ARS positions. While funds needed to sell assets to finance ARS reductions in redemption periods, they faced no selling pressure in non-redemption periods. We use this information to differentiate between sales by ARS-levered funds in redemption (treatment group) and non-redemption periods (control group I). Moreover, as an additional control group, we also examine the sales by closed-end funds that did not rely on ARS-leverage and, hence, faced no direct increase in borrowing costs. Thus, we can examine the sales of three different groups:

(i.) Treatment: Sales of *ARS-levered* funds in *ARS redemption periods*
(ii.) Control I: Sales of *ARS-levered* funds in *non-ARS redemption periods*
(iii.) Control II: Sales of *non-ARS-levered* funds

We expect fire-sales only to be present when studying stock sales of ARS-levered funds in ARS redemption periods (treatment group), while we should not find similar evidence in both control groups. Since funds redeemed their ARS redemptions in different time periods, we can examine the return patterns of (forced) asset sales throughout the sample period from 2008 to 2010. This mitigates concerns that price movements of stocks in the treatment group are driven by reasons unrelated to fire-sales.

2.1.3 Identification of fire-sales

We identify fire-sale stocks by constructing a time-varying pressure measure for each stock j, similar to the pressure measure used by Coval and Stafford (2007). This measure is based on the selling behavior of ARS-levered closed-end funds during redemption periods (treatment group).

[10] The average cash position of our ARS-levered funds is less than 1% of total assets and, hence, plays no significant role in the financing of ARS redemptions.

$$Selling\ pressure\ (TG)_{j,t} = \sum_{i}^{i \in ARS} \left(\frac{\max(-\Delta Shares_{i,j,t}, 0)}{NOSH_{j,t}} \middle| Redemption_{i,t} = 1 \right) \quad (1)$$

$\Delta\ Shares_{i,j,t}$ is fund i's sales of stock j between quarter t-1 and quarter t. $NOSH_{j,t}$ is stock j's total shares outstanding at quarter t. $Redemption_{i,t}$ is a dummy variable that equals one if fund i reduces its outstanding ARS between quarter t-1 and quarter t. Intuitively, the selling pressure measure captures the aggregate sales of stock j by all ARS-levered funds, which redeemed ARS in a given quarter (treatment group). If the selling pressure measure is high, the stock is a potential fire-sale stock in the respective quarter. As noted earlier, closed-end funds redeemed their ARS in different time periods. Hence, the selling pressure measure has substantial cross-sectional and time-series variation.

We use an analogous procedure to calculate two placebo selling pressure measures using the stock sales of ARS-levered funds during non-redemption periods (control group I) and using the sales of non-ARS levered funds during the entire sample period (control group II). As those sales were not triggered by the need to finance ARS redemptions, there should be no evidence for fire-sales for these transactions.

$$Selling\ pressure(CGI)_{j,t} = \sum_{i}^{i \in ARS} \left(\frac{max(-\Delta Shares_{i,j,t}, 0)}{NOSH_{j,t}} \middle| Redemption_{i,t} = 0 \right) \quad (2)$$

$$Selling\ pressure(CGII)_{j,t} = \sum_{i}^{i \in non-ARS} \left(\frac{max(-\Delta Shares_{i,j,t}, 0)}{NOSH_{j,t}} \right) \quad (3)$$

2.1.4 Analyzing fire-sale return patterns in event studies

We follow Coval and Stafford (2007) and analyze stock return patterns in event studies to examine whether our selling pressure measure truly identifies fire-sale stocks. Fire-sold stocks should experience negative return in the selling quarter followed by subsequent reversals. Such a reversal is consistent with a temporary price drop caused by fire-sales, but inconsistent with a permanent price drop due to a change in investors' expectations. To analyze stock returns, we split our stocks into five quintiles according to each stock's selling pressure. The probability of detecting fire-sale patterns should increase as we move along these quintiles.

We define for each stock an event quarter, which is the quarter in which the stock's selling pressure is the highest during the sample period.

*** Insert Figure 3 about here ***

Figure 3 shows the distribution of these event quarters for the top selling pressure quintiles of treatment and control groups. While the event quarters of control group II (non-ARS levered funds) are quite equally distributed throughout the sample period, most event quarters of the treatment and control group I are found between the second quarter of 2008 and the first quarter of 2009. Due to this event clustering, abnormal returns are likely correlated in the cross-section. Moreover, test statistics might be misspecified due to event-induced volatility. To account for both, cross-correlation and variance inflation, we use a recent event study methodology proposed by Kolari and Pynnönen (2010), which we detail in Appendix A.II.[11]

For each group and quintile, we conduct separate event studies, in which we test for abnormal returns in the event quarter and the following 12 months. Abnormal returns are measured by 4-factor alphas, which account for the stocks' risk exposure to the following four factors: (i) the market, (ii) the size, (iii) the value-to-book, and (iv) the momentum factor. The betas used to calculate these alphas are estimated using daily returns over the year preceding the ARS market failure. The test-statistics are computed using the methodology of Kolari and Pynnönen (2010) and are based on the average cumulative abnormal return of all stocks in the respective group, quintile, and event period.

2.2 The impact of fire-sales on open-end funds

To investigate whether fires-sales by ARS-levered closed-end funds can lead to financial contagion, we study the impact of fire-sales on open-end funds that were not directly affected by the ARS market failure. If fire-sales negatively affect asset prices, portfolios of open-end funds with large investments in these stocks should lose in value. We, therefore, start by investigating whether open-end funds with high exposure to fire-sale stocks show abnormal performance losses. Such a performance deterioration can lead to fund outflows if investors ignore the reason for poor performance and withdraw liquidity from the fund, as predicted by the well-known flow-performance relationship (e.g. Chevalier and Ellison, 1997; and Sirri

[11] We do not use non-parametric event study tests or a portfolio approach as the test statistic of Kolari and Pynnönen (2010) is more powerful in long-horizon event studies.

and Tufano, 1998). Thus, the main objective of this section is to examine whether the flow-performance relationship is affected by the reason for poor performance.

To examine the impact of fire-sales on the performance and flows of open-end funds, we construct a variable that measures the extent to which an open-end fund is exposed to fire-sale stocks, which we call ‘fire-sale exposure'.

$$Monthly\ selling\ pressure\ (TG)_{j,t} = \sum\nolimits_{m=1}^{2} \frac{1}{3} * Selling\ pressure_{j,t+m} \tag{4}$$

$$FS\ exposure_{i,t} = \sum_{m=0}^{2} \sum_{j} Monthly\ selling\ pressure\ (TG)_{j,t-m} * w_{i,j,t-3} \tag{5}$$

Note that the variable selling pressure (TG) at period t measures stock j's price pressure during the last *three* months. To compute a monthly selling pressure variable, we take the average of all selling pressure measures that affect a stock in a given month, i.e. the selling pressure of t, t+1, and t+2.[12]

Fund i's fire-sale (FS) exposure equals the sum of each stock j's monthly selling pressure (TG) in quarter t weighted by fund i's relative investment in the stock at the beginning of the quarter ($w_{i,j,t-3}$). Intuitively, an open-end fund with high fire-sale exposure holds a large proportion of fire-sale stocks. We hypothesize that the fire-sale exposure measure is negatively related to fund performance. This relation is not mechanically because open-end funds could avoid a performance loss by selling a stock before the fire-sales takes place or make other profitable investments. We then test in our main analysis whether the flow-performance relationship holds even if the performance deterioration appears to be driven by price movements due to fire-sales.

[12] We need to compute the monthly selling pressure variable since funds report to their shareholders in different calendar months.

2.3 Fire-sale cascades

Coval and Stafford (2007) show that outflows at open-end funds can result in fire-sales. Fire-sold stocks depreciate in the selling quarter and show significant reversals in the subsequent months. If fire-sales by closed-end funds cause outflows at open-end funds, as predicted in the previous section, assets sold by open-end funds with high fire-sale exposure should show similar fire-sale patterns during the outflow quarter. To test this hypothesis, we construct a pressure measure using our sample of open-end funds, which we call ‘cascade pressure'.

$$Cascade\ pressure_{j,t} = \sum_{i}^{i \in Open} \frac{max(-\Delta Shares_{i,j,t}, 0) * \ FS\ exposure_{i,t-3}}{NOSH_{j,t}} \tag{6}$$

Intuitively, the cascade pressure measure captures the proportion of shares sold in aggregate by all open-end funds weighted by each fund's fire-sale (FS) exposure during the previous quarter. We weight by the funds' fire-sale exposure to give more weight to sales by open-end funds that hold a larger proportion of ARS fire-sales stocks in their portfolios. Large sales of stocks by open-end funds that were heavily invested in ARS fire-sale stocks are likely fire-sale candidates. To isolate the cascade pressure effect from a potential price impact due to sales of closed-end funds, we will analyze stock returns only for stocks that were not held by ARS-levered closed-end funds in the previous quarter. Using the same event study methodology as described in Section 2.1.4, we will examine whether stocks in the highest cascade pressure quintile have abnormal stock returns in the selling quarter and show subsequent reversals.

3 Data

Our sample period spans from February 2008 to February 2010 to cover the period in which the majority of ARS leverage is redeemed in response to the ARS market failure in February 2008.[13] Our data set consists of two sub-samples: Closed-end and open-end funds.

We use web-crawling techniques to extract information on closed-end funds from N-SAR forms, which have to be filed by all U.S. investment companies in a semi-annual frequency.

[13] In some descriptive statistics, we also present data of before February 2008 to describe the evolution of leverage over time.

N-SAR forms contain a large number of fund characteristics and detailed balance sheet data.[14] Closed-end funds are identified through question 27 (Q27) on the N-SAR form. We drop all entries for which the date of filling or the fund name is not extractable as well as records for which total assets or net assets are zero, negative, or not available. We only keep funds that primarily invest in equity securities (N-SAR Q66) since our analyses require detailed holding data that are more extensive for equity funds.[15] Using Q69 on the N-SAR form and the inspection of fund names, we exclude index and real estate funds. To eliminate funds that only show up in our sample due to misreporting, we only keep funds for which we have at least five consecutive observations.

To obtain access to quarterly fund holdings, we carefully merge this data with the Morningstar Direct and the Thomson Reuters S12 Ownership Database using fund names and tickers. We follow Coval and Stafford (2007) and require funds to report a minimum of 20 holdings at least once during the sample period.[16]

Since data on ARS leverage is not available in any standard database, we hand-collect quarterly ARS positions as well as quarterly total net assets for all closed-end funds in our sample from SEC N-CSR(S) and N-Q fillings. We use the latest available information on ARS leverage before February 2008, the failure of the ARS market, to differentiate between ARS-levered funds that were exposed to the funding shock and non-ARS-levered funds. Our closed-end equity fund sample consists of 53 ARS-levered and 155 non-ARS-levered funds.

To construct our open-end fund data set, we collect all open-end funds available in the CRSP Survivor-Bias-Free US Mutual Fund Database. Using MFLINKS we match this data to quarterly holdings available in the Thomson Reuters S12 Ownership Database. We eliminate all index funds (as defined by CRSP) and non-equity funds, which we identify by Thomson's investment objective code. We address the incubation bias in the CRSP database identified by Elton, Gruber, and Blake (2001) and Evans (2004) by removing observations of funds with less than 5 million assets under management in the previous month. Similar as with the

[14] To ensure the quality of our data, we manually inspect a random sample of 100 N-SAR fillings, which show no identifiable extraction error.

[15] Although focusing on relative liquid equity markets, makes it harder to identify mis-pricing, several studies (e.g. Coval and Stafford 2007, Jotikasthira et al. 2012) document that stocks sometimes sell at fire-sale prices.

[16] Coval and Stafford (2007) argue that the holdings of funds with less than 20 holdings are less reliable.

closed-end fund data, we remove funds that never report more than 20 holdings throughout the sample period. We are left with 1,469 open-end equity funds.

We match all open-end and closed-end fund holdings to the CRSP Stock Database using 8-digit CUSIPs to obtain stock prices, returns, and other stock characteristics. Our sample includes 8,746 different stocks, which represent 70.7% of all common stocks (share code 10 or 11) contained in the CRSP Stock Database.

The paper also relies on several other data sources. Dividend yields of ARS issues are obtained from the Securities Industry and Financial Markets Association (SIFMA). 1-week US LIBOR as well as 1-month Treasury Bill rate are provided by St. Louis Fed. To calculate abnormal returns, we use the market, size, value-to-book, and momentum factors from the Fama/French website. The liquidity factor of Pastor and Stambaugh (2003), which is used to estimate liquidity betas, is downloaded from Lubo Pastor's research website. Short sale data on stocks are obtained from the Bats Exchange website.[17]

The data is used to construct a number of variables that are described and defined in Appendix A.I. All continuous variables are winsorized at the 1% levels to alleviate the effect of outliers.

4 Results

4.1 Descriptives

Table 1 shows descriptive statistics for ARS-levered and non-ARS-levered as well as open-end funds in the last quarter before the failure of the ARS market in February 2008. As observed in Panel A, the ARS-levered and non-ARS levered funds in our sample are considerably large despite their closed-end structure. While total assets of ARS-levered funds amount to $1,000 million on average, non-ARS-levered funds manage on average assets worth of $558 million. This difference is partially attributable to different levels of TNA ($679 million compared to $509 million), but is predominantly a result of distinct leverage policies. ARS-levered funds use considerably more leverage averaging at 51% of TNA, compared to non-ARS-levered funds (9%). Among the ARS-levered funds, ARS-leverage

[17] Unreported analyses reveal that the short sale data of the Bats Exchange website has 90% correlation with the short sale data from NASDAQ.

accounts for the majority of leverage amounting to almost 45% of TNA on average. This is important for our identification strategy as it shows that ARS-levered funds were strongly exposed to the failure of the ARS market. In contrast, the amount of other leverage accounts only for 6% of TNA and is comparable to the average amount of other leverage used by non-ARS-levered funds (9%).

The TNA of open-end funds are on average significantly higher compared to both closed-end fund groups (1,135 million). However, since open-end funds usually do not use leverage, the amount of total assets is comparable to the assets managed by ARS-levered funds.

We observe strong differences in the turnover ratios across all three groups. The turnover ratio of ARS-levered funds (22%) is on average about half the turnover ratio of non-ARS-levered funds (42%) and about a quarter of the turnover ratio of open-end funds (85%). The comparably lower turnover ratio of closed-end funds is consistent with the findings of Deli and Varma (2002).

Panel B compares the holding characteristics of the sample funds. Both closed-end fund groups as well as the open-end funds in our sample invest in stocks that have similar market capitalization and trading volumes. Stocks held by open-end funds tend to have slightly lower bid-ask spreads than both closed-end fund groups. Examining the market beta, we observe that open-end funds and non-ARS levered funds tend to have a market beta close to one. In contrast, ARS-levered funds appear to invest in stocks with slightly lower market betas (0.8). This is consistent with the idea that ARS-levered funds buy low beta stocks and use leverage to increase their market exposure (Frazzini and Pedersen, 2014).

*** Insert Table 1 about here ***

The differences observed in leverage, turnover, and the holdings indicate that ARS-levered and non-ARS-levered funds follow different investment strategies and, hence, are only imperfect candidates for control and treatment group. For this reason, we use a different identification strategy as Tang (2014), who compares returns of stocks held by ARS-levered with the stocks held by non-ARS-levered funds. Instead, we compare stock *sales* by ARS-levered funds during redemption periods (treatment group) with stock sales during non-redemption periods (control group I) and complement this analysis by studying stock sales by non-ARS-levered funds (control group II). Using this strategy, we search for fire-sales in periods in which ARS-levered funds sold assets to finance their ARS redemptions.

Consistent with this argument, Panel A of Table 2 shows that the reduction of total investments is unusually strong for ARS-levered funds during redemption periods. On average, total investments shrink by 13.7% in ARS redemption periods, while total investments fall only by 3.88% if ARS-levered funds do not redeem. The stronger decrease in total investments stems at least partly from large reductions in ARS-leverage of about 16.5% on average. ARS-levered funds in redemption periods seem to be unable to substitute their ARS-leverage by other debt financing. Therefore, total leverage decreases by 6.3%. For comparison, the leverage ratio decreases only by 1.1% on average in non-redemption periods. During the same period, the assets of non-ARS-levered funds only decline by about 5% and leverage remains fairly stable. This evidence suggests that ARS-levered funds sold assets to finance their redemptions. Note that our results also indicate that assets are not sold before the redemption quarter to strategically avoid fire-sale costs.

*** Insert Table 2 about here ***

For our identification strategy, it is important that our treatment and control groups sell the same type of stocks. Panel B shows characteristics for stocks that are sold and not sold by all three groups. Overall, the sales of ARS-levered funds in ARS redemption periods are comparable to the sales in non-redemption periods. The stocks are of similar size, experienced in the past small negative returns of between -1.7% and -2.2%, and differ not substantially in terms of volatility, dividend yield, and market beta. Sales in ARS redemption periods tend to have a slightly lower trading volume and a smaller relative bid ask spread. In contrast, sales of non-ARS levered funds differ more strongly from the two other groups. Non-ARS-levered funds tend to sell bigger stocks, stocks with more turnover, higher past stock volatility, and higher dividend yield. These differences are consistent with our previous observations that non-ARS-levered funds and ARS-levered funds follow different investment strategies and justify our approach to compare ARS-levered funds during redemption with ARS-levered funds during non-redemption periods.

4.2 Fire-sales by ARS-levered funds

4.2.1 Selling pressure and stock returns

In this section, we study whether the failure of the ARS market resulted in fire-sales. As described in Section 2.1, we identify fire-sales by studying the sales of ARS-levered funds in periods in which they had to finance their ARS redemptions and, hence, were likely forced to liquidate assets.

In Panel A of Table 3, stocks are split into five quintiles according to the selling pressure measure, which captures the extent to which a stock is sold by ARS-levered funds during their ARS redemption periods. The highest quintile contains stocks that experience the highest selling pressure during the sample period and, hence, are the most likely fire-sale candidates. The lowest quintile, in contrary, contains stocks with the lowest selling pressure.[18] We define the 'event quarter' of a stock as the quarter in which its selling pressure was the highest during the sample period and document (cumulative) 4-factor adjusted stock returns for the event quarter and the following 12 months.[19] For statistical inference, we rely on the event study methodology of Kolari and Pynnönen (2010), which accounts for cross-sectional return correlations across stocks and inflated return volatility in the event period.

*** Insert Figure 4 about here ***

Consistent with fire-sales, we find that stocks with high selling pressure show negative and statistically significant abnormal returns in the event quarter, i.e. the quarter, in which they are sold by ARS-redeeming funds. These abnormal returns are economically large. Stocks that are sorted into the fourth and fifth quintile experience on average abnormal stock returns of -9.1% and 10.4%, respectively (see Figure 4 for a graphical representation of the fifth quintile). Importantly, the price decline observed in the upper two quintiles is followed by substantial price reversals. In the 3 to 12 months that follow the fire-sale quarter, stock returns reverse by an average abnormal stock return of 14.3% for the fifth and an average abnormal

[18] Stocks that were not sold by ARS-levered funds during ARS redemption periods are not included.

[19] Results are robust if we study 1-factor or 5-factor abnormal returns.

stock return of 19.1% for the fourth quintile.[20] Such a reversal is consistent with a temporary price drop caused by fire-sales, but inconsistent with a permanent price drop due to a change in investors' expectations.

Note that in the fifth quintile both, the price decreases as well as the price reversal, are only significant at the 10% level despite their high economic significance. This comparably low level of significance is caused by the choice of our event study methodology, which accounts for potential correlations across returns. Given that event dates in the fifth quintile are more clustered when compared to the other quintiles, t-statistics in this quintile need to be adjusted more strongly for potential cross-correlations.[21] We believe this conservative approach is important to make sure that t-statistics are not biased upwards.

We find similar downward patterns for the third quintile (-9.3%), but no subsequent reversals. Hence, the price drop in this quintile is not explainable by price pressure.[22] Among the stocks with low selling pressure (lowest two quintiles), we do not observe any statistically significant price change. Hence, stock prices appear to be only affected if they are heavily sold during redemption periods.

Overall, our results indicate that the sudden need to repay leverage can result in significant downward price pressure on individual stocks that is not explainable by information based theories.

*** Insert Table 3 about here ***

A valid concern is that the observed price patterns are spurious or driven by other contaminating events such as the financial crisis. One feature of our identification strategy

[20] Note that stock prices in the fifth quintile continue to fall in the subsequent three months after the fire-sale quarter. Two possible reasons for this price decline include fire-sale cascades, which we examine in Section 4.4, and predatory trading, for which we present evidence in Section 4.2.2.

[21] For example, the estimated cross-correlation in the fifth quintile is 0.02, while it is below 0.004 for the other quintiles. If we do not adjust for this correlation across returns, the price effect documented in the fifth quintile is significant to the 1% level.

[22] Coval and Stafford (2007) report similar price effects resulting from voluntary trades. They believe this effect to be driven by funds bringing information into prices or by unloading poor performing stocks.

that mitigates this concern is the fact that our sample funds redeem their ARS in different time periods. Hence, the individual event quarters differ across stocks.

We further address this issue by conducting two placebo tests. For that purpose, we repeat the analysis of Panel A, but construct quintiles according to two placebo selling pressures (defined in Section 2.1). These placebo measures are based on the sales of ARS-levered funds during non-redemption periods (control group I) and the sales of non-ARS-levered funds (control group II). As both groups had no need to finance ARS redemptions during the event quarter, we can interpret the stocks in the highest quintiles as those stocks that were heavily, but voluntarily sold within the sample period. Panel B and C reveal that there is no evidence for fire-sales in both placebo tests. For control group I, we find no price effect in the event quarter for all quintiles except the third (Panel B). For control group II, we observe a weak but significant price drop in the event quarter for the top quintile (Panel C). However, reversals do not follow on any of these price decreases. This suggests that the price drop is not caused by fire-sales, but rather the result of funds selling due to information or in an attempt to eliminate underperforming stocks. Therefore, in contrast to our treatment stocks, sales of our control groups show no price movements consistent with fire-sales.

4.3 Predatory trading and characteristics of fire-sale stocks

Although about $190 billion of assets were managed by U.S. closed-end funds by 2008 alone, the industry is relatively small compared to the open-end fund industry with total net assets of about $9,600 billion.[23] This difference might raise the question whether closed-end funds can create sufficient price pressure to cause the observed price drop.

We present two arguments to address this question. First, we want to draw attention to the magnitude of sales by ARS-levered funds during redemption periods. During ARS-redemptions total investments by ARS-levered funds shrink by about 13.7% or $155 million on average (see Table 2). When multiple funds need to liquidate such a significant proportion of their assets during adverse market conditions and low market liquidity, which predominated during the sample period, it seems reasonable that stock prices are not immune to these transactions.

[23] Investment Company Fact Book, 2009.

Second, and even more importantly, we believe that the price pressure effect created by ARS-levered funds was amplified by front-running speculators, such as hedge funds. Brunnermeier and Pedersen (2005) show that front-running or - as they label it - predatory trading can lead to additional price overshooting and reduced market liquidity.

*** Insert Figure 5 about here ***

The first graph of Figure 5 provides descriptive evidence for front-running by displaying the short sale volume around the event quarter for stocks in the highest selling pressure quintile, i.e. for those stocks that showed strong price declines. The red dashed line indicates that the short-sale volume amounts to about 0.05% of shares outstanding six months before the event quarter. About three months before the event quarter short sales start to increase continuously and the volume reaches a level of about 0.4% one month after the fire-sale quarter. In the months thereafter, short sales decrease again to a volume similar to the level before the event quarter. The increase before the event quarter is consistent with predatory speculators trying to exploit the funds' selling needs in advance of the transaction.

To ensure that the increase of short sales is not only a byproduct of the financial crisis or some other phenomena in the sample period, Figure 5 also contains the short sale volume for the top quintile of our two placebo selling pressures, which we calculate using sales of ARS-levered funds during non-redemption periods (control group I) and using sales of non-ARS-levered funds (control group II). For control group I, the fluctuations of the short sale volume seem to be unrelated to the stocks' selling pressure. For example, there is virtually no increase in short sales during the event quarter. The short sale volume of control group II is stable throughout the considered time period. Hence, there is no evident link between short-sales and selling pressure in the two control groups.

While this evidence is indicative for front-running, it is only feasible if speculators had access to two pieces of information: (i) The period in which the fund was forced to sell and (ii) the position that was sold by the pressurized fund. The first piece of information is publicly known as funds announced their planned ARS-redemptions in advance. We argue that the speculator could infer the second piece of information from the funds' past holdings, which are known to be sticky.

*** Insert Table 4 about here ***

Table 4 presents evidence that supports our argument. Stocks that were held in large proportions by ARS-levered funds one quarter before the ARS market failure turn out to experience higher selling pressure and end up in the top selling pressure quintile with higher probability. Hence, a speculator could easily profit from the funds' selling needs by short-selling stocks in which ARS-levered funds had the highest ownership. While the ownership by ARS-levered funds is by far the most predictive variable, fire-sale stocks also tend to have a smaller market capitalization, higher dividend yields, higher trading volumes, and a lower sensitivity to the aggregated market liquidity. The latter two findings support the idea that funds tried to mitigate fire-sale costs by selling more liquid assets.

4.4 The impact of fire-sales on open-end funds

4.4.1 Univariate results

Although open-end funds are not directly affected by the collapse of the ARS market, open-end funds are indirectly affected by the shock if they are invested in stocks that experience price pressure due to fire-sales by ARS-levered funds. We measure the exposure to fire-sales using a variable called 'fire-sale exposure', as defined in Section 2.2. Our main objective in this section is to examine whether this exposure leads to fund outflows at open-end funds. These outflows may emerge if fund investors withdraw liquidity from funds whose performance suffered from investments in fire-sale stocks. The empirical fact that fund investors respond to fund performance has been well documented by several studies in the literature (see e.g. Chevalier and Ellison, 1997; and Sirri and Tufano, 1998). The main question, therefore, is whether investors react to poor performance even if the performance deterioration results from an exposure to fire-sale stocks. This question is important as outflows can trigger additional fire-sales (Coval and Stafford, 2007).

*** Insert Table 5 about here ***

We start by analyzing this question descriptively. For that purpose, we sort the open-end funds in our sample into five quintiles according to each fund's level of fire-sale (FS) exposure. We then document (i) the average fire-sale exposure, (ii) the average proportion of the portfolio invested in stocks that were fire-sold by closed-end funds, (iii) the average 3-

month abnormal fund performance, and (iv) the average netflows in the subsequent quarter. 3-month abnormal fund returns are calculated by adjusting fund returns by the weighted return of all sample funds.[24] All other variables are defined in Appendix A.I.

As shown in in Table 5 and confirming the validity of our measure, open-end funds with the lowest fire-sale exposure (quintile 1) have less than 1% of their assets invested in stocks whose selling pressure is in the top three quintiles. Hence, their portfolios are essentially not affected by any price pressure induced by closed-end fund fire-sales. In contrast, open-end funds with the highest fire-sale exposure (5. quintile) have about 8% of their holdings invested in stocks belonging to the fifth selling pressure quintile and about 9% of the assets invested in stocks belonging to the fourth quintile. Since these stocks experience significant price declines of up to 10%, these investments should be costly. Consistent with this argument, funds with the highest fire-sale exposure have abnormal 3-month fund returns that are on average 1% lower than funds in the lowest exposure quintile. Funds in the fifth exposure quintile also have on average 1.6% lower netflows than funds in the first exposure quintile. This suggests that fund investors reacted to the poor performance by withdrawing liquidity.

4.4.2 Multivariate results

To test whether our descriptive results hold in a multivariate framework, we estimate the relationship between fire-sale exposure, fund performance, and fund flows in several regressions. In all of these regressions, we control for common time trends by including time fixed effects and for unobserved heterogeneity across styles using style fixed effects. Similar to Coval and Stafford (2007), we also control for lagged performance and flow variables to ensure that our results are not driven by delayed investor reactions. We cluster standard errors at the fund level to account for non-independent observations within funds (Petersen, 2009) and report all regression results in Table 6.

*** Insert Table 6 about here ***

We first examine the link between fund performance and fire-sale exposure by regressing 3-month abnormal fund returns on the fire-sale (FS) exposure variable. As evident in column

[24] We do not measure performance using factor models as the existing literature shows that investors react predominantly on raw returns relative to the market.

(1), there exists a negative relationship between exposure and fund performance. A one standard derivation increase in fire-sale exposure is associated with a decrease in fund performance of about 1.1% (in absolute terms).

In column (2), we examine how fund flows respond to fund performance in general by regressing the funds' quarterly performance on their netflows in the next quarter. Consistent with the literature, we find that future netflows tend to be low when fund performance is poor.

In columns (3) to (5), we investigate whether this flow-performance relationship still holds if the performance drop is a result of holding fire-sale stocks. Column (3) shows that fire-sale pressure is negatively correlated with future fund flows if we do not adequately control for fund performance in the current quarter. An increase in fire-sale exposure by one standard deviation, is associated with 0.6% higher outflows in the next quarter.

In column (4), we run the same regression, but control for fund performance in the fire-sale quarter. If the correlation between fire-sale exposure and flows is, as argued, driven by the flow-performance relationship and investors do not differentiate between the reasons for poor performance, the exposure coefficient should now become insignificant. As expected, we do not find any significant relationship between flows and the exposure variable once we adequately control for fund performance.

In column (5) we additionally interact fund performance with our fire-sale exposure variable. The interaction term turns out to be insignificant, while the flow-performance relationship continues to hold. Our results indicate that investors withdraw liquidity even if the poor performance results from price pressure induced by fire-sales.

4.4.3 Institutional vs. retail investors

Our finding that investors do not differentiate between the reasons for poor performance is perhaps somewhat surprising as the performance of funds with high fire-sale exposure should revert once fire-sale stocks start to recover. Hence, some sophisticated investors, such as institutional investors, might conclude to refrain from withdrawing liquidity. We analyze, therefore, whether retail and institutional investors react differently to performance losses that are linked to closed-end fund fire-sales. For that purpose, we calculate for each fund the aggregate flows to all of its institutional and, separately, all of its retail share classes. Hence, we end up with two share class observations for each fund. We then analyze whether institutional and retail fund flows of the same fund differ, when funds are exposed to fire-sales. To conduct this analysis, we estimate the following regression framework:

$$\begin{aligned} SC\ Flows_{c,i,q+1} &= \beta_1 \cdot FS\ Exposure_{i,q} \cdot Retail_{c,q} \cdot Performance_{i,q} + \beta_2 \cdot Retail_{c,q} \\ &\cdot Performance_{i,q} + \beta_3 \cdot FS\ Exposure_{i,q} \cdot Retail_{c,q} + \beta_4 \cdot Retail_{c,q} \\ &+ \gamma \cdot X_{c.q} + \alpha_{i,q} + \epsilon_{c,i,q} \end{aligned} \tag{7}$$

The variable $SC\ Flows_{c,i,q+1}$ denotes the flows to share class c of fund i at quarter q+1. $FS\ Exposure_{i,q}$ measures each fund's exposure to closed-end fund fire-sales. $Performance_{i,q}$ captures the 3-month abnormal performance of each fund. $Retail_{c,q}$ is a dummy variable that equals one if the share class is a retail class and zero if the share class is catered to institutional investors. Similar to the regressions above, we control for lagged netflows of each share class to account for potential long-term trends ($X_{c,q}$). We include 'fund x time' fixed effects to only consider the variation between institutional and retail investors of the same fund at the same time. Note that all variables that do not vary at the share class level are absorbed by these fixed effects (e.g. $FS\ Exposure_{i,q} \cdot Performance_{i,q}$). We expect the β_1 coefficient to be positive, which would indicate that institutional investors withdraw less liquidity from a fund with poor performance and high exposure to fire-sales. If institutional investors, however, react differently to performance regardless of the level of exposure, we should only observe a significant β_2 coefficient.

*** Insert Table 7 about here ***

As evident in Table 7, we do not find evidence that institutional investors respond differently than retail investors to fund performance in general. The \beta_2 coefficient is insignificant in both columns regardless whether the triple interaction term is included or not. However, we find evidence that institutional investors react less strongly to past performance if the fire-sale exposure is high, supporting our hypothesis.

4.5 Fire-sale cascades

As shown in the previous section, open-end funds that are strongly invested in fire-sold stocks suffer from subsequent performance losses. This performance drop results in fund outflows. Coval and Stafford (2007) document that outflows can cause fire-sales. Therefore, we examine in this section whether the exposure to fire-sales results in sufficiently high outflows to induce a cascade of additional fire-sales by open-end funds.

We examine this question following a similar procedure as in Section 4.2.1, in which we studied the fire-sales of ARS-levered funds. Instead of using the selling pressure measure based on ARS-levered funds, however, we sort all stocks in five quintiles according to our cascade pressure measure, which we defined in Section 4.4. Cascade pressure measures the extent to which a stock is sold by all open-end funds, weighting the sale of each fund by its exposure to fire-sale stocks in the previous quarter. We exclude all stocks that are held by ARS-levered funds at the beginning of each quarter to isolate the price pressure induced by open-end funds from the price pressure created by ARS-levered funds.[25] Similar as before, we define each stock's event quarter as the quarter in which the cascade pressure is highest within the sample period and use the event study methodology of Kolari and Pynnönen (2010) to analyze abnormal stock returns.

*** Insert Figure 6 about here ***

Table 8 and Figure 6 show that stocks in the highest quintile have on average strong 4-factor abnormal returns of -6.4% in the event quarter. These stock returns are not only economically large, but also significant at the 1% level. Moreover, they are followed by a strong reversal over the following four months, which amounts to 7.4%.[26] This reversal is consistent with a temporary price drop due to fire-sales and rebuts other explanations such as a change in investors' expectations, which would require permanent price changes. Note that the event quarter in this table is not the quarter in which stocks by ARS-levered funds are fire-sold, but the quarter thereafter. This timing difference mitigates the concern that the observed price patterns are related to macro effects, general co-movements of portfolios, or general market trends. Overall, our findings suggest that a shock in the closed-end fund sector can transmit to

[25] Our results are stronger if stocks held by ARS-levered funds are included.

[26] Note that we changed the table labels in comparison to the previous section slightly to document this effect.

stocks in the open-end fund industry. This highlights that markets are strongly interconnected and emphasizes the risk of financial contagion.

*** Insert Table 8 about here ***

While we do not find evidence for fire-sales in the lower quintiles consistent with our story, it should be noted that stocks in the second quintile experience on average a weaker but statistically significant price decrease. This price decrease is followed by significant reversals. We do not have an explanation at hand to explain these findings.

5 Robustness and further tests

5.1 Pseudo cascade pressure

To verify that the channel of contagion is linked to investor flows, we conduct a placebo test based on all *non-ARS levered* closed-end funds. For that propose, we construct a placebo cascade pressure for these funds. This measure is constructed similarly to the cascade pressure in the previous section, but relies on the aggregate sales by non-ARS levered funds.

$$FS\ exposure_{i,t}^{non-ARS} = \sum_{m=0}^{2} \sum_{j} Monthly\ selling\ pressure\ (TG)_{j,t-m} \cdot w_{i,j,t-3} \quad (8)$$

$$Cascade\ pressure_{j,t}^{non-ARS} = \sum_{i}^{non-ARS} \frac{max(-\Delta Shares_{i,j,t}, 0) \cdot FS\ exposure_{i,t-3}^{non-ARS}}{NOSH_{j,t}} \quad (9)$$

Due to their closed structure, closed-end funds are not subject to inflows or outflows. Consequently, non-ARS levered closed-end funds should not feel any pressure to fire-sale assets due to being exposed to initial fire-sales by ARS-levered funds. We, therefore, expect no price fluctuation in response to their asset sales.

As in the previous section, we use event studies to test whether stocks with high pseudo cascade pressure show abnormal fund returns. We exclude all stocks that were held by ARS-levered funds at the beginning of the quarter. We also exclude all stocks whose (true) cascade pressure belongs to the top quintile. This way we make sure that we do not pick up any price effect that arises due to fire-sales by other institutions.

As evident in Table 9, we do not find evidence for fire-sales using our pseudo cascade pressure measure. The abnormal returns of the considered stocks are statistically not differentiable from zero except for stocks whose pseudo cascade pressure belongs to the fourth quarter. Within this fourth quintile, however, the average abnormal return is positive. Thus, the sales by non-ARS levered funds, which are not subject to the flow-performance relationship, do not appear to have caused price pressure.

5.2 Robustness tests

We examine the robustness of our results by making several changes to our experimental design.[27] First, we follow Coval and Stafford (2007) and repeat our analysis using the following alternative measure for selling pressure:

$$Selling\ pressure(TG)^{alt}_{j,t} = \sum_{i}^{i \in ARS} \left(\frac{max(-\Delta Shares_{i,j,t}, 0)}{Avg.trading\ vol_{j,t-6;\,t-12}} \middle| Redemption\_\{i,t\} = 1 \right) \quad (10)$$

We use this alternative measure to make sure that our results are not driven by the denominator (i.e. shares outstanding). Our results remain very similar with negative stock returns of about -8.2% in the selling quarter for the top selling pressure quintile, followed by significant reversals.

Second, we use alternative event study methodologies. While magnitudes are not affected by this robustness test, the statistical significance increases to the 1% level if we use the methodology proposed by MacKinlay (1997) or by Boehmer, Masumeci, and Poulsen (1991), which do not account for correlations across returns.

Third, instead of using 4-factor abnormal returns we analyze stock returns that are adjusted for only one (market factor) or five factors (Fama and French, momentum and the liquidity factor of Pastor and Stambaugh, 2003).[28] The fire-sale patterns are visible in all specifications, while magnitudes vary from -8.5% to -14% for the top selling pressure quintile.

[27] All results are available upon request.

[28] We do not use the 5-factor model as our base specification since the liquidity factor is only available in a monthly frequency. Hence, we would need to estimate betas over a five-year window.

Finally, as control group II differs in several dimensions from the treatment group, we use propensity score matching techniques to select those non-ARS levered funds that compare best to the ARS-levered funds in our sample based on observables such as leverage and size. We do not find any evidence for fire-sales in this redefined control group II.

6 Conclusion

In this study, we use the failure of the auction rate security (ARS) market in February 2008 as a natural experiment to provide evidence for fire-sale cascades. We find that funds exposed to the shock sell assets to finance ARS redemptions. These sales are associated with negative 4-factor stock returns of up to -10%. Consistent with fire-sales and inconsistent with permanent price declines due to changes in the stocks' fundamentals, this price drop is followed by reversals in the following 12 months. We show that the price pressure effect induced by ARS-levered funds transmits to initially unaffected open-end funds that are invested in fire-sale stocks. When open-end fund investors observe the performance deterioration resulting from this investment in fire-sale stocks, they withdraw liquidity. This investor behavior is well known in the literature and it is also observable if poor performance results from price pressure induced by fire-sales. In response to these fund outflows, open-end funds are forced to liquidate assets themselves. We find that those sales show similar, but weaker fire-sale patterns. In the selling quarter stocks sold by pressurized open-end funds fall by up to -6.4%, even if we exclude all stocks held by ARS-levered funds at the beginning of the quarter. This price decline is only from temporary nature and reverses in the subsequent months. Our findings suggest that initial fire-sales can create sufficient price pressure to set off a cascade of additional fire-sale cascades posing a threat to financial stability.

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Figures

Figure 1: Dividend yields around the failure of the ARS market

This figure shows the SIFMA Auction Rate 7-Day index, the 1-month treasury rate and the average (maximum) dividend yield of ARS issues in our sample around the ARS market failure in February 2008. The SIFMA Auction Rate 7-day index is based on self-reported (weekly changing) data from actual ARS issues provided by broker dealers and auction agents. The average maximum dividend yield is based on 38 ARS issues in our sample, for which data is available. All rates are scaled by the 1-week US LIBOR interest yield.

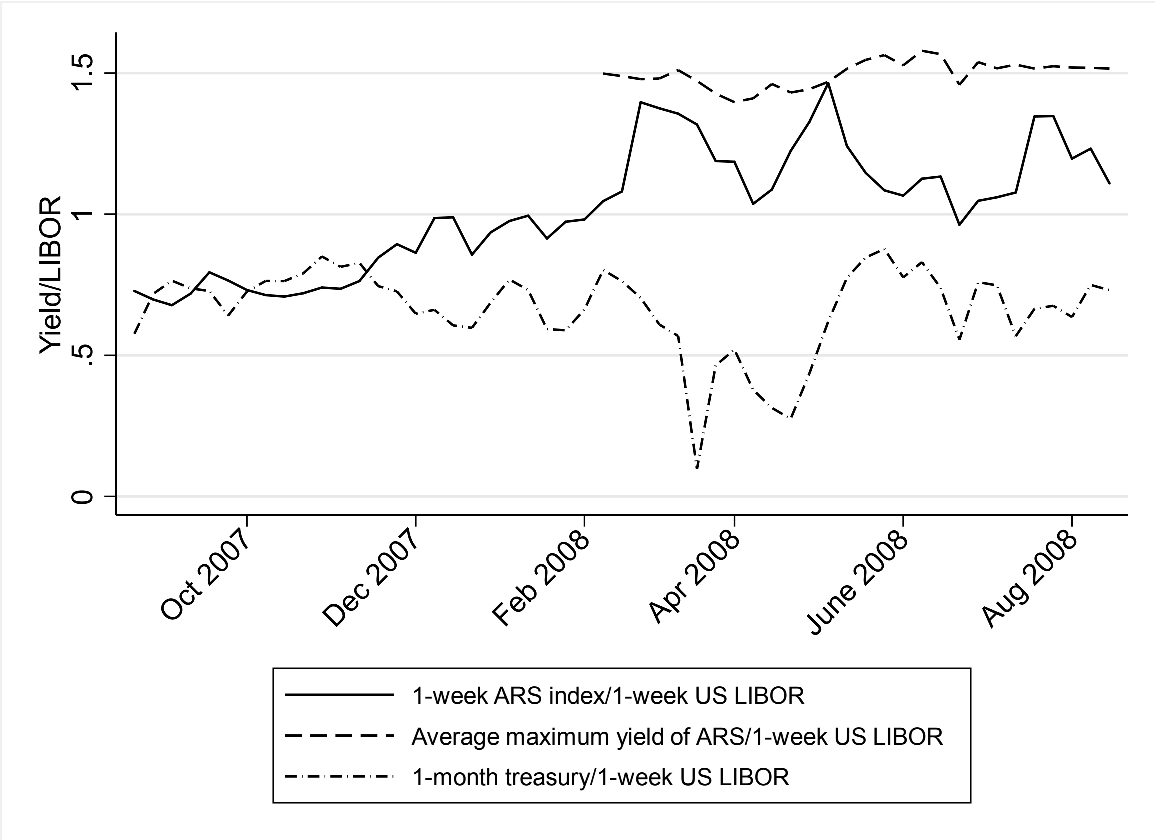


Figure 2: The volume of ARS and other liabilities

This figure shows the number of auction rate security (ARS) users as well as the total volume of outstanding ARS and other liabilities around the ARS market failure in February 2008. A fund is defined to be an ARS user if the fund reports ARS on its balance sheet in a given period. The figure is based on 53 funds that use ARS as part of their leverage strategy.

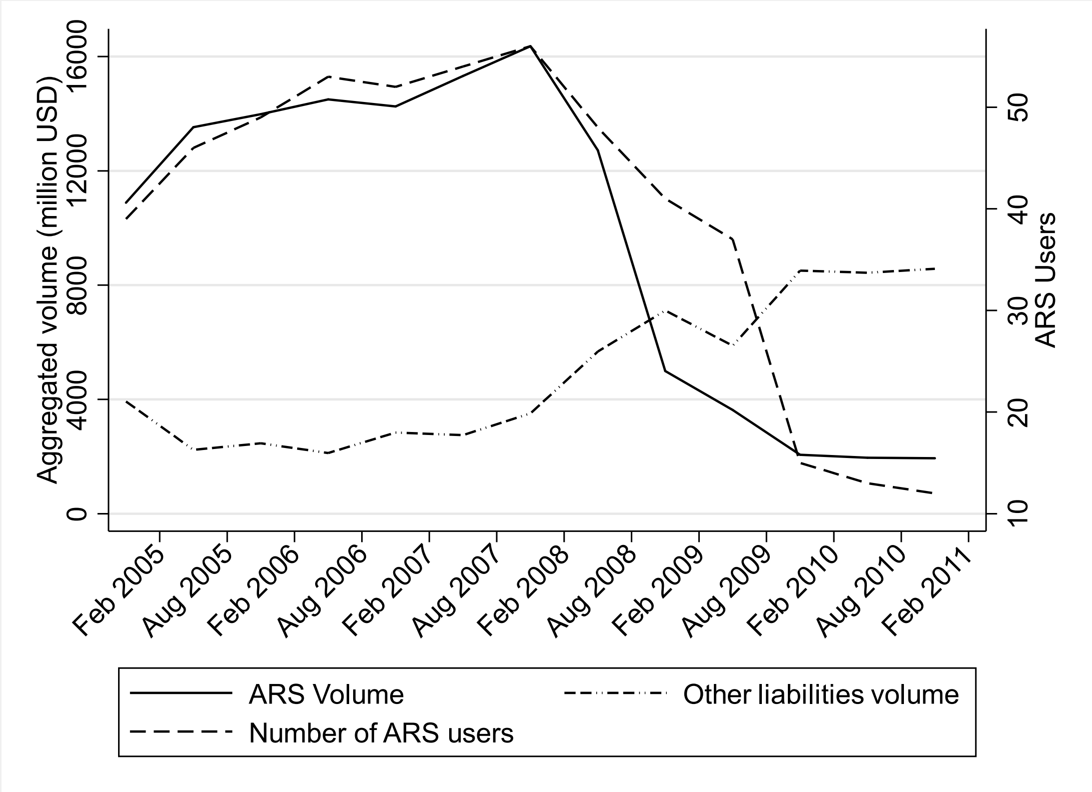


Figure 3: The distribution of fire-sales

This figure shows the distribution of stocks in the top selling pressure quintile of the treatment group (TG), control group I (CGI) and control group II (CGII). The TG (CGI) is based on sales by ARS-levered funds in (non-) redemption periods. CGII is based on sales by non-ARS levered funds. Selling pressure (TG), (CGI) and (CGII) measures the extent to which a stock is sold by the respective group. Each stock is counted at most once by only considering the quarter in which the stock has its highest selling pressure within the sample period from 2008 to 2010. The figure is based 169, 253 and 630 stocks in the top selling pressure quintile of the treatment, control group I and control group II, respectively.

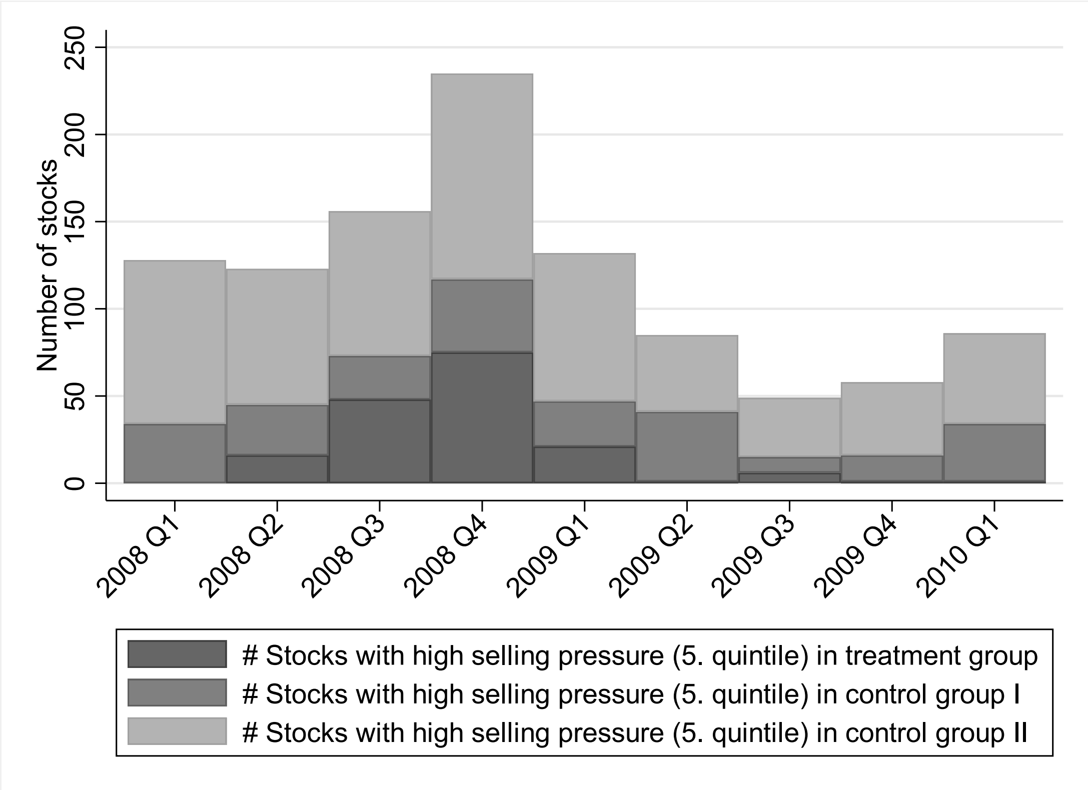


Figure 4: Selling pressure & stock returns

These figures show 4-factor cumulative abnormal returns for stocks in the top selling pressure quintile of the treatment group (TG), control group I (CGI) and control group II (CGII). The TG (CGI) is based on sales by ARS-levered funds in (non-) redemption periods. CG II is based on sales by non-ARS levered funds. Selling pressure (TG), (CGI) and (CGII) measures the extent to which a stock is sold by the respective group. The event quarter of a stock (E1, E2, E3) is the quarter in which its selling pressure is the highest within the sample period from 2008 to 2010. The cumulative returns are based on monthly returns around this quarter. All variables are defined in Appendix A.I.

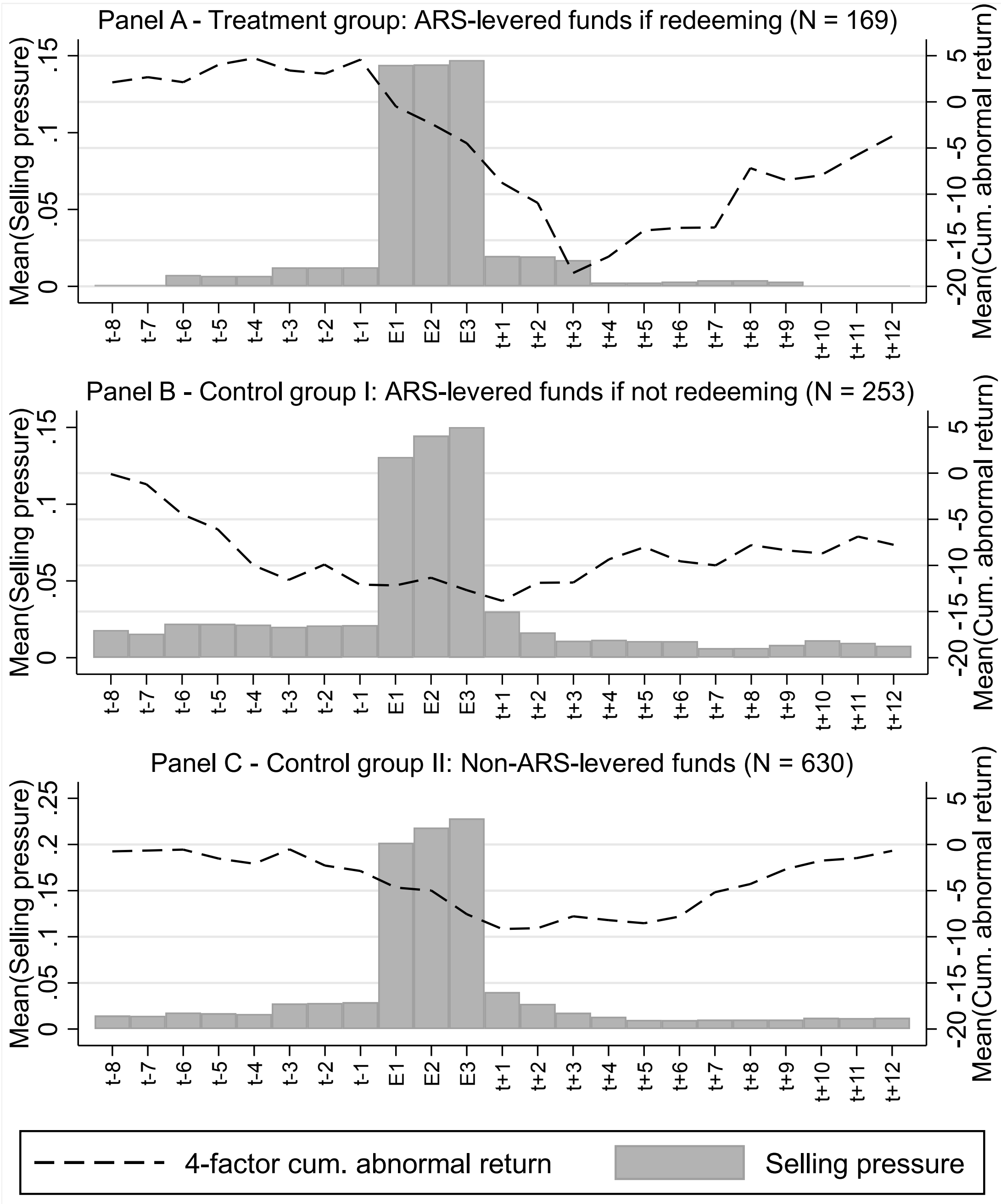


Figure 5: Selling pressure & short sales

These figures show 4-factor cumulative abnormal returns and the short sale volume for stocks in the top selling pressure quintile of the treatment group (TG), control group I (CGI) and control group II (CGII). The TG (CGI) is based on sales by ARS-levered funds in (non-) redemption periods. CGII is based on sales by non-ARS levered funds. Selling pressure (TG), (CGI) and (CGII) measures the extent to which a stock is sold by the respective group. The event quarter of a stock (E1, E2, E3) is the quarter in which its selling pressure is the highest within the sample period from 2008 to 2010. The cumulative returns are based on monthly returns around this quarter. All variables are defined in Appendix A.I.

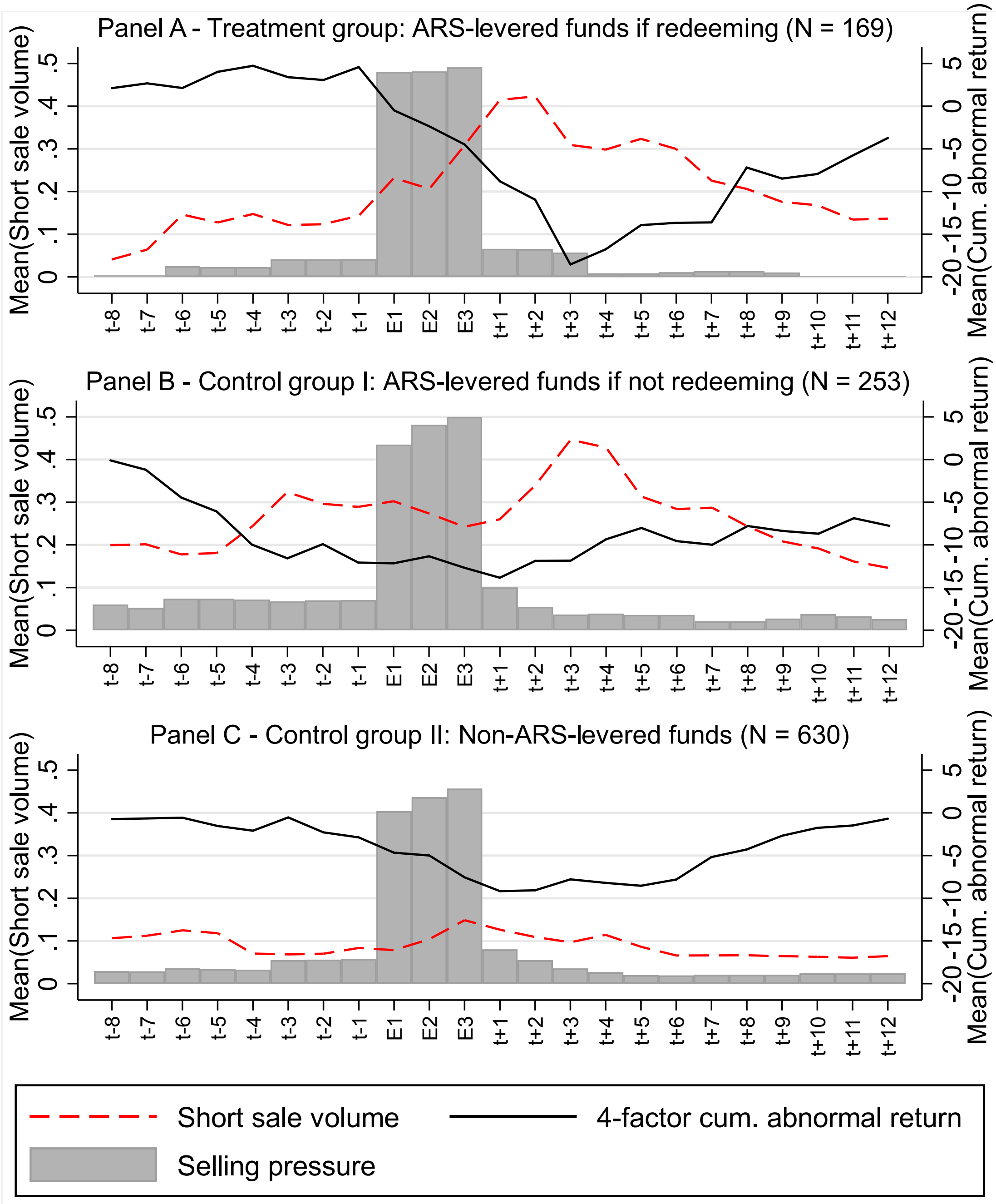
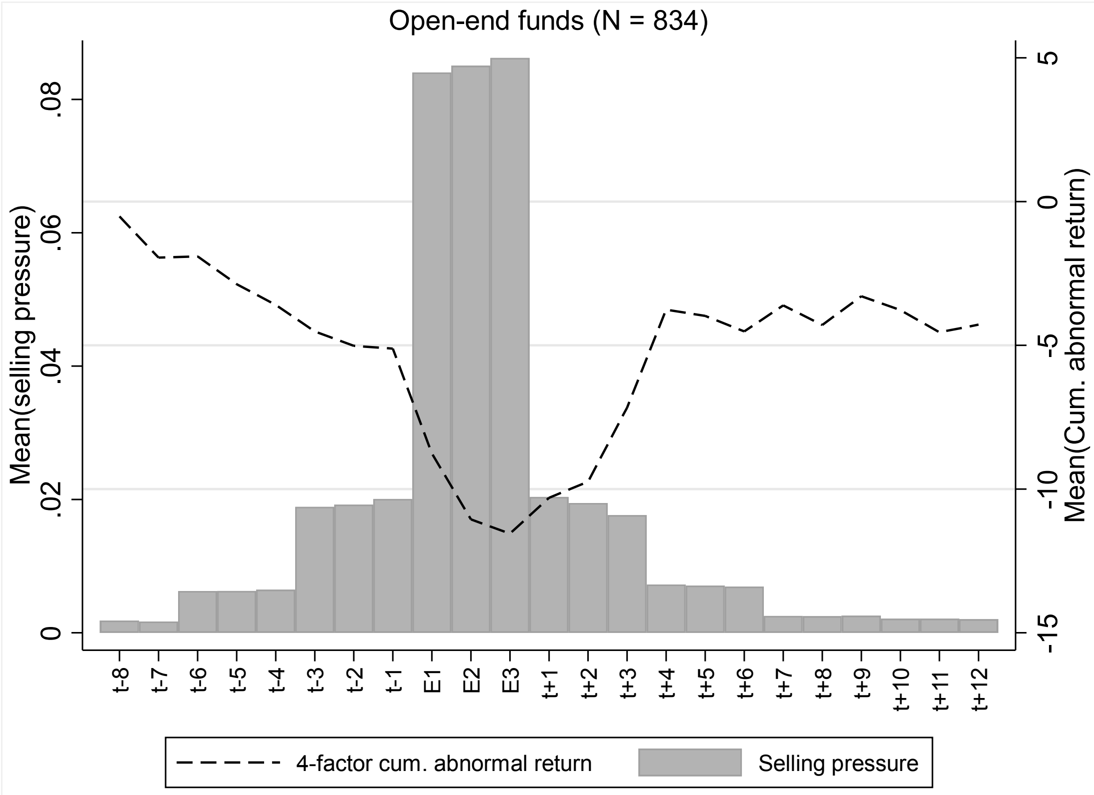


Figure 6: Cascade pressure & stock returns

This figure shows 4-factor cumulative abnormal returns for stocks in the top cascade pressure quintile. Cascade pressure is defined in Section 4.4 and captures the extent to which a stock is sold by all open-end funds weighted by each fund's exposure to fire-sales by ARS-levered funds in the previous quarter. The event quarter of a stock (E1, E2, E3) is the quarter in which its cascade pressure is the highest within the sample period from 2008 to 2010. The cumulative returns are based on monthly returns around this quarter. All variables are defined in Appendix A.I.



Tables

Table 1: Descriptive Statistics - ARS-levered, non-ARS levered and open-end funds

This table reports descriptive statistics for fund and holding characteristics of ARS-levered and non-ARS levered funds as well as open-end funds for December 2007. (Non-) ARS-levered funds are closed-end funds that (do not) have ARS on their balance sheets at the end of 2007. Panel A contains summary statistics on the fund level, while descriptives for fund stock holdings are reported in Panel B. Variables that are scaled by total net assets (TNA) are marked accordingly. All variables are defined in Appendix A.I.

	TG and CG I		**CG II**			
	ARS-levered (N = 53)		**Non-ARS-levered (N = 155)**		**Open-end (N = 1,469)**	
	Mean	p50	Mean	p50	Mean	p50
Panel A: Fund characteristics, December 2007						
Total assets (mio USD)	1,000	720	558	312	1,135	258
TNA (mio USD)	679	485	509	278	1,135	258
Turnover ratio (%)	21.85	17.6	42.13	27.03	84.53	62
Total leverage (% TNA)	50.96	53.8	9.12	2.24		
ARS leverage (% TNA)	44.87	46.51	0	0		
Other leverage (% TNA)	6.36	0.21	9.12	2.24		
Panel B: Stock holding characteristics, December 2007						
Avg. Market cap (bill USD)	28.407	19.321	26.44	18.376	26.762	23.309
Avg. Trading volume (bill USD)	216.281	168.069	221.92	194.013	237.824	210.549
Avg. Relative bid-ask (%)	0.169	0.158	0.202	0.131	0.139	0.121
Avg. Market beta	0.814	0.93	1.116	1.065	1.089	1.084

Table 2: Treatment and Control Groups

This table reports descriptive statistics from February 2008 to February 2010 for three groups: (i) ARS-levered funds in periods in which they redeem auction rate securities (ARS), (ii) ARS-levered funds in periods in which they do not redeem ARS and (iii) non-ARS levered funds over the entire sample period. (Non-) ARS-levered funds are closed-end funds that (do not) have ARS on their balance sheets at the end of 2007. Panel A displays the average change in total investments, total leverage and ARS leverage as a percentage of total investments of the previous quarter. Panel B shows average stock characteristics based on stocks that are sold or not sold by each of the above groups. All variables are defined in Appendix A.I.

Panel A: Total investments and leverage (means)

	Treatment group	Control group I	Control group II
	ARS-levered funds if redeeming	ARS-levered funds if not redeeming	Non-ARS-levered funds
Δ Total investments (% TI_{t-1})	-13.70	-3.88	-5.35
Δ Total leverage (% TI_{t-1})	-6.32	-1.10	-0.55
Δ ARS (% TI_{t-1})	-16.46	.	.

Panel B: Portfolio characteristics (means)

	Treatment group		Control group I		Control group II	
	ARS-levered funds if redeeming		ARS-levered funds if not redeeming		Non-ARS-levered funds	
	Stocks sold	Stocks not sold	Stocks sold	Stocks not sold	Stocks sold	Stocks not sold
Market cap (bill USD)	18.692	19.043	18.760	20.560	22.139	19.417
Trading volume (bill USD)	218.056	218.565	245.106	238.186	265.112	222.292
Past monthly return (%)	-2.243	-0.903	-1.652	-0.741	-0.847	-1.105
Past stock volatility (%)	3.120	3.231	3.629	3.494	3.665	3.535
Past dividend yield (%)	3.134	2.609	2.825	3.087	2.169	2.090
Market beta	1.048	1.091	1.107	1.107	1.100	1.064
Relative bid-ask (%)	0.197	0.203	0.221	0.224	0.224	0.230

Table 3: Selling pressure and stock returns

This table shows 4-factor abnormal returns for stocks in the treatment group (TG), control group I (CGI) and control group II (CGII). The TG (CGI) is based on sales by ARS-levered funds in (non-) redemption periods. CGII is based on sales by non-ARS levered funds. Stocks are sorted into five quintiles according to each stock's highest selling pressure during the sample period. Selling pressure (TG), (CG I) and (CG II) measures the extent to which a stock is sold by the respective group. The event quarter of a stock is the quarter in which its selling pressure is the highest within the sample period from 2008 to 2010. All variables are defined in Appendix A.I. T-Values are reported in parentheses and are based on the event study methodology of Kolari and Pynnoenen (2010). *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

Panel A - Treatment group: ARS-levered funds if redeeming (169 observations per quintile)

		4-factor abnormal returns					
	Selling pressure	Event	t;t+3	t+3;t+6	t+6;t+9	t+9;t+12	t+3;t+12
Quintile 1 (lowest)	0.001**	-1.785	-1.142	-1.572	0.618	-0.631	-1.577
		(-0.55)	(-0.73)	(-0.84)	(0.02)	(-0.40)	(-0.70)
Quintile 2	0.003**	-1.742	-4.324	0.369	2.927	0.711	3.94
		(-0.70)	(-1.58)	(0.24)	(0.63)	(0.16)	(0.38)
Quintile 3	0.008**	-9.321***	-2.679	-0.588	2.353	-0.189	1.552
		(-3.74)	(-1.20)	(-0.01)	(1.23)	(-0.02)	(0.64)
Quintile 4	0.025**	-10.410***	-5.307	4.085	8.457***	6.880***	19.097***
		(-3.19)	(-1.60)	(1.18)	(2.71)	(2.83)	(3.53)
Quintile 5 (highest)	0.147**	-9.062*	-13.670***	4.614	4.883	5.027	14.344*
		(-1.77)	(-2.95)	(0.87)	(1.35)	(1.55)	(1.78)

Panel B - Control group I: ARS-levered funds if not redeeming (253 observations per quintile)

Quintile 1 (lowest)	0.001	-1.802	-0.739	-0.557	1.450*	0.435	1.278
		(-1.00)	(-0.92)	(-0.29)	(1.73)	(0.07)	(0.82)
Quintile 2	0.004	-1.609	-2.299	2.839*	1.411	-1.433	2.848
		(-1.53)	(-1.36)	(1.72)	(0.60)	(-1.30)	(0.58)
Quintile 3	0.011	-5.819***	-2.649	-2.059*	0.633	-0.04	-1.49
		(-3.40)	(-1.15)	(-1.83)	(0.10)	(-0.17)	(-1.16)
Quintile 4	0.029	-1.429	0.144	1.736	2.325	-1.708	2.381
		(-0.15)	(0.46)	(0.75)	(1.47)	(-0.65)	(0.94)
Quintile 5 (highest)	0.150	-0.611	0.294	3.098	0.972	-0.497	3.569
		(-0.44)	(0.53)	(1.62)	(0.81)	(-0.06)	(1.45)

continued on next page

Table 3: continued from previous page

Panel C: Non-ARS-levered funds (630 observations per quintile)

		4-factor abnormal returns					
	Selling pressure	Event	t;t+3	t+3;t+6	t+6;t+9	t+9;t+12	t+3;t+12
Quintile 1 (lowest)	0.003	-3.227**	1.741	0.439	-0.155	-2.965***	-2.533
		(-2.51)	(0.62)	(0.06)	(-0.21)	(-2.85)	(-1.24)
Quintile 2	0.013	-1.288	0.168	0.226	-0.242	-1.254	-1.232
		(-1.27)	(0.31)	(0.71)	(-0.20)	(-0.88)	(-0.21)
Quintile 3	0.031	-0.963	-1.761	-1.607	-1.157	0.559	-2.204
		(-0.95)	(-1.41)	(-1.12)	(-0.48)	(1.27)	(-0.21)
Quintile 4	0.068	-0.44	1.977	3.025**	1.126	2.826**	6.797**
		(-0.01)	(1.03)	(2.14)	(0.30)	(2.02)	(2.28)
Quintile 5 (highest)	0.228	-4.683***	-0.64	-0.814	2.264	2.452	3.608
		(-2.66)	(-0.37)	(-0.12)	(1.42)	(1.45)	(1.58)

Table 4: Predictability and stock characteristics of fire-sale stocks

This table report OLS and logit regressions to evaluate which factors determine high selling pressure. Selling pressure is defined in Section 2.1.3 and measures the extent to which a stock is sold by ARS-levered funds during redemption periods. The dependent variable is each stock's highest value of selling pressure during the sample period from 2008 to 2010, and expressed either as a continuous variable or as a dummy variable. The dummy variable equals one if a stock's maximum selling pressure belongs to the top quintile. The variable 'Total shares held by ARS-levered funds is defined for each stock as the aggregated sum of shares held by ARS-levered funds at the end of 2007, scaled by shares outstanding. All other variables are defined in Appendix A.I. Marginal effects are shown for regression (2) and are computed at mean values. Standard errors are heteroskedasticity robust. T-Values are reported in parentheses. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	Dependent variable	
	Selling pressure (TG)	
	Selling pressure (%)	5. Quintile (highest)
	(1)	(2)
Predictability		
Shares held by ARS-levered funds$_{2007}$ (%)	0.024***	0.695***
	(6.50)	(5.61)
Stock characteristics		
Log(Market cap)	-0.018***	-0.857***
	(-4.68)	(-4.72)
Market beta	-0.01	-0.229
	(-1.56)	(-0.93)
Liquidity beta	-0.036***	-1.376***
	(-3.13)	(-2.61)
Log(Trading Volume)	0.012***	0.595***
	(3.11)	(3.65)
Dividend yield (%)	0.004***	0.152***
	(4.21)	(4.05)
N	530	530
R^2	0.387	
Pseudo R^2		0.274
Marginal Effects	No	Yes
Positive predictive value (%)	-	68.63
Negative predictive value (%)	-	84.97
Correctly classified (%)	-	83.4

Table 5: Open-end fund exposure to fire-sales by ARS-levered funds

This table shows mean values of (i) the fire-sale (FS) exposure variable, (ii) the proportion of assets invested in stocks with different levels of selling pressure, (iii) the abnormal fund performance and (iv) the netflows in the subsequent quarter. The mean values are based on 1,469 open-end funds that are sorted into five quintiles according to their level of fire-sale exposure within the sample period from 2008 to 2010. Fire-sale exposure is defined in Section 2.2 and captures the extent to which an open-end fund is exposed to fire-sales by ARS-levered funds. Selling pressure is defined in Section 2.1.3 and measures the extent to which a stock is sold by ARS-levered funds during redemption periods. All other variables are defined in Appendix A. I.

		% invested in stocks with selling pressure...				
	FS exposure	in quintile 3	in quintile 4	in quintile 5	3m abn. return$_q$ (%)	3m fund net flows$_{q+1}$
Quintile 1 (lowest)	0.0000	0.2411	0.0549	0.0027	-0.0008	1.0174
Quintile 2	0.0005	3.3475	0.9396	0.1285	-0.0030	0.1059
Quintile 3	0.0012	6.9155	2.8159	0.3870	-0.0056	0.3053
Quintile 4	0.0027	8.7719	6.2923	1.4392	0.0033	-0.4105
Quintile 5 (highest)	0.0099	6.1623	9.0567	8.2273	-0.0099	-0.6967

Table 6: Fire-sale exposure, fund performance and fund flows

In Column (1) we report a OLS regression relating the fire-sale exposure of open-end funds to 3-month abnormal fund returns. Columns (2) to (5) show regression estimations relating the fire-sale exposure to the funds' 3-month netflows experienced in the next quarter. Fire-sale (FS) exposure is defined in Section 2.2 and measures the extend to which an open-end fund is exposed to fire-sales by ARS-levered funds. The 3m abnormal return is the 3-month fund return in excess of the value weighted return of all open-end sample funds. All other variables are defined in Appendix A.I. The regressions are based on all open-end funds during the sample period from February 2008 to February 2010. T-Values are reported in parentheses. Standard errors are heteroskedasticity robust and clustered at the fund level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	3m abn ret$_q$	3m fund net flows$_{q+1}$			
	(1)	(2)	(3)	(4)	(5)
Main Variables					
FS exposure (%)	-1.91***		-0.87***	-0.38	-0.62
	(-14.28)		(-2.68)	(-1.14)	(-1.16)
3m abn ret$_1$		0.35***		0.25***	0.27***
		(10.01)		(4.68)	(4.62)
FS exposure * 3m abn ret$_q$					-3.89
					(-0.53)
Lagged Variables					
3m abn ret$_{q-1}$		0.13***	0.15***	0.15***	0.15***
		(4.13)	(3.28)	(3.38)	(3.39)
3m abn ret$_{q-2}$		0.15***	0.18***	0.20***	0.20***
		(3.48)	(2.96)	(3.22)	(3.16)
3m abn ret$_{q-3}$		0.08***	0.12**	0.12**	0.12**
		(2.61)	(2.42)	(2.56)	(2.56)
3m abn ret$_{q-4}$		-0.03	-0.04	-0.01	-0.02
		(-0.90)	(-0.72)	(-0.27)	(-0.30)
3m abn ret$_{q-5}$		0.04	0.04	0.06	0.05
		(1.14)	(0.78)	(1.20)	(1.19)
3m abn ret$_{q-6}$		0.01	-0.03	-0.03	-0.03
		(0.42)	(-0.49)	(-0.49)	(-0.47)
3m fund flows$_q$		0.13***	0.09**	0.08**	0.08**
		(5.24)	(2.37)	(2.18)	(2.18)
3m fund flows$_{q-1}$		0.10***	0.16***	0.16***	0.16***
		(5.40)	(4.19)	(4.19)	(4.18)
3m fund flows$_{q-2}$		0.05***	0.02	0.02	0.02
		(4.51)	(1.02)	(0.97)	(0.98)
3m fund flows$_{q-3}$		0.05***	0.06*	0.06*	0.06*
		(3.84)	(1.93)	(1.91)	(1.91)
3m fund flows$_{q-4}$		0.02	-0.01	-0.01	-0.01
		(1.61)	(-0.20)	(-0.23)	(-0.24)
3m fund flows$_{q-5}$		0.03*	0.02	0.02	0.02
		(1.93)	(0.76)	(0.77)	(0.78)
3m fund flows$_{q-6}$		0.03**	0.04	0.04	0.04
		(2.06)	(1.59)	(1.63)	(1.63)
N	7,106	19,301	6,285	6,285	6,285
Adjusted R^2	0.0798	0.1	0.076	0.0811	0.081
Style fixed effects	Yes	Yes	Yes	Yes	Yes

Quarter-time fixed effects	Yes	Yes	Yes	Yes	Yes

Table 7: Retail vs. Institutional fund flows

This table reports OLS regression results examining the relationship between fund performance, fire-sale exposure and netflows to institutional and retail share classes of open-end funds. For each fund, the 3-month netflows to all institutional and retail share classes are separately aggregated, such that for each fund only two share class observations remain. 3-month netflows for share class c (retail or institutional) and fund i are the sum of monthly net flows which are calculated using the following formula: Monthly net $flows_{c,t} = TNA_{c,t} - TNA_{c,t-1} \times (1 + R_{c,t})$. Fire-sale exposure is defined in Section 2.2 and measures the extent to which an open-end fund is exposed to fire-sales by ARS-levered funds. Retail is a dummy variable that equals one if the share class caters to retail investors, and zero otherwise. The 3m abnormal return is the 3-month fund return in excess of the value weighted return of all open-end sample funds. All other variables are defined in Appendix A.I. The regressions are based on share classes of all open-end funds during the sample period from February 2008 to February 2010. T-Values are reported in parentheses. Standard errors are heteroskedasticity robust and clustered at the share class level. *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

	3m fund net $flows_{q+1}$	
	(1)	(2)
FS exposure * 3m abn fund ret_q * Retail		13.04**
		(2.03)
3m abn fund ret_q * Retail	-0.1	-0.16
	(-1.11)	(-1.37)
Retail (Y/N)	-0.03***	-0.04***
	(-6.71)	(-6.92)
FS exposure * Retail		1.52*
		(1.86)
N	6,648	6,648
Adjusted R^2	0.223	0.223
Fund x quarter time fixed effects	Yes	Yes
Lagged flows	No	No

Table 8: Cascade pressure and stock returns

This table shows 4-factor abnormal returns for stocks split into five quintiles according to the stocks' cascade pressure. Cascade pressure is defined in Section 4.4 and captures the extent to which a stock is sold by all open-end funds weighted by each fund's exposure to fire-sales by ARS-levered funds in the previous quarter. The event quarter of a stock is the quarter in which its cascade pressure is highest during the sample period from February 2008 and February 2010. All variables are defined in Appendix A.I. T-Values are reported in parentheses and are based on the event study methodology of Kolari and Pynnoenen (2010). *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

Open-end funds: 834 observations per quintile

		4-factor abnormal returns						
	Cascade pressure	Event	t;t+1	t+1;t+2	t+2;t+3	t+3;t+4	t;t+4	t+4;t+12
Quintile 1 (lowest)	0.000	2.093	-0.025	0.476	-2.449***	0.121	-1.748	10.040***
		(1.09)	(-0.01)	(0.50)	(-2.70)	(0.60)	(-0.86)	(3.69)
Quintile 2	0.002	-3.648**	1.539	-0.866	1.650	3.200**	5.297*	7.721**
		(-2.16)	(0.81)	(-0.61)	(1.52)	(2.47)	(1.85)	(1.96)
Quintile 3	0.009	-2.002	2.100	-0.094	1.395	2.423*	5.681	2.138
		(-1.09)	(1.22)	(-0.42)	(0.95)	(1.82)	(1.48)	(0.38)
Quintile 4	0.028	-0.525	1.821	0.312	1.097	2.503	5.638	-1.793*
		(-0.17)	(1.02)	(0.23)	(0.48)	(1.39)	(1.39)	(-1.73)
Quintile 5 (highest)	0.086	-6.435***	1.306	0.757	2.244	3.238*	7.416*	-2.969
		(-2.75)	(0.77)	(0.62)	(1.31)	(1.84)	(1.92)	(-1.06)

Table 9: Placebo: Pseudo cascade pressure and stock returns

This table shows 4-factor abnormal returns for stocks split into five quintiles according to each stock's pseudo cascade pressure. Pseudo cascade pressure is defined in Section 5.1 and captures the extent to which a stock is sold by all non-ARS funds weighted by each fund's exposure to fire-sales by ARS-levered funds in the previous quarter. The event quarter of a stock is the quarter in which its pseudo cascade pressure is highest during the sample period from February 2008 and February 2010. All variables are defined in Appendix A.I. T-Values are reported in parentheses and are based on the event study methodology of Kolari and Pynnoenen (2010). *,**,*** indicate significance at the 10%, 5% and 1% levels respectively.

Non-ARS-levered funds: 218 observations per quintile

		4-factor abnormal returns						
	Cascade pressure	Event	t;t+1	t+1;t+2	t+2;t+3	t+3;t+4	t;t+4	t+4;t+12
Quintile 1 (lowest)	0.000	-1.725	1.764	-1.464	-0.034	0.961	1.212	-7.529***
		(-1.00)	(1.18)	(-1.26)	(-0.27)	(0.41)	(0.10)	(-3.16)
Quintile 2	0.000	1.309	1.365	0.506	3.068**	2.497**	7.320***	5.939
		(1.04)	(0.88)	(0.30)	(2.34)	(2.02)	(2.65)	(1.51)
Quintile 3	0.000	-1.737	0.449	1.327	1.810*	0.875	4.419	3.876
		(-0.31)	(0.10)	(0.57)	(1.75)	(0.26)	(0.98)	(1.35)
Quintile 4	0.000	5.284**	2.572*	2.615	3.576***	2.640**	11.355***	8.362**
		(2.03)	(1.72)	(1.38)	(3.76)	(2.16)	(4.02)	(2.48)
Quintile 5 (highest)	0.005	-4.426	0.027	-0.064	1.751	2.153	3.746	5.362**
		(-1.49)	(0.33)	(-0.11)	(1.38)	(1.45)	(1.21)	(2.09)

Appendix

Table A.I: Definitions

Variable Name	Definition	Source
Leverage characteristics:		
ARS leverage	Liquidation value of all auction rate securities on the fund's balance sheet, scaled by TNA.	N-SAR, N-CSR, N-Q
Other leverage	The sum of all liabilities on the fund's balance sheet less the liquidation value of all auction rate securities, scaled by TNA.	N-SAR, N-CSR, N-Q
Total leverage	The sum of other and ARS leverage.	N-SAR, N-CSR, N-Q
Redemption	A dummy variable which equals one if the fund reports a decrease in its outstanding ARS by more than 1% in comparison to the previous quarter.	N-SAR, N-CSR, N-Q
Types of funds:		
ARS-levered fund	A closed-end fund that reports ARS leverage on its last available balance sheet before February 2008.	N-SAR, N-CSR, N-Q
Non-ARS-levered fund	A closed-end fund that reports no ARS leverage on its last available balance sheet before February 2008.	N-SAR, N-CSR, N-Q
Pressure measures:		
Selling pressure$(TG)_{j,t}$	$\sum_{i}^{i\in ARS}\left(\frac{\max(-\Delta Shares_{i,j,t},0)}{NOSH_{j,t}}\middle\vert Redemption_{i,t}=1\right)$	
Selling pressure$(CGI)_{j,t}$	$\sum_{i}^{i\in ARS}\left(\frac{max(-\Delta Shares_{i,j,t},0)}{NOSH_{j,t}}\middle\vert Redemption_{i,t}=0\right)$	
Selling pressure$(CGII)_{j,t}$	$\sum_{i}^{i\in non-ARS}\left(\frac{max(-\Delta Shares_{i,j,t},0)}{NOSH_{j,t}}\right)$	
M. selling pressure$(TG)_{j,t}$	$\sum_{m=1}^{2}\frac{1}{3} * Selling\ pressure_{j,t+m}$	
FS exposure$_{i,t}$	$\sum_{m=0}^{2}\sum_{j} Monthly\ selling\ pressure\ \ (TG)_{j,t-m} * w_{i,j,t-3}$	
Cascade pressure$_{j,t}$	$\sum_{i}^{i\in Open}\frac{max(-\Delta Shares_{i,j,t},0) * FS\ exposure_{i,t-3}}{NOSH_{j,t}}$	

continued on next page

Table A.I: continued from previous page

Variable Name	Definition	Source
Fund characteristics:		
Turnover ratio	Min(purchases, sales)/average value of portfolio	N-SAR, CRSP
Monthly fund flows$_{i,t}$	$TNA_{i,t} - TNA_{i,t-1} \cdot (1 + \text{Fund return}_{i,t})$	CRSP
3-month abn. return	3-month fund return over the weighted return by all open-end funds in the sample.	CRSP
Stock characteristics:		
4−factor abnormal return$_{j,t}$	$Stock\ return_{j,t} - \sum_{k=1}^{4} factor\ return_{k,t} * \beta_{j,k,t}$, where the factor returns are the (i) market, (ii) size, (iii) value-to-book, and (iv) momentum factors. The betas are estimated by regressing the stocks' excess daily returns on the factor returns over 250 trading days.	CRSP, Fama/French, Pastor
Liquidity beta	The regression coefficient of the Pastor liquidity factor when regressing the fund's monthly excess returns over the previous six years on the (i) excess market return, (ii) the Pastor liquidity factor, (iii) the size factor, (iv) the value-to-book factor, and (v) the momentum factor.	CRSP, Fama/French, Pastor

A.II Event study methodology

The event study methodology used in this paper is adopted from a recent study by Kolari and Pynnönen (2010). Their design accounts for potential return autocorrelations and cross-correlations across stock returns as well as event-induced increases in stock return volatility. The test statistics reported in all event-study tables are obtained in the following way:

1. For each stock j, we estimate betas by running the following time-series regression:
$$Stock\ return_{j,t} = \alpha_j + \sum_{k=1}^{4} Factor\ return_{k,t} * \beta_{j,k,t} + \epsilon_{j,t}$$
The regressions are based on daily returns in the estimation window $[t_0, t_1]$ that spans from February 2007 to January 2008. Factor loadings are only estimated if more than 40 stock observations are available during the estimation period. The factor returns are (i) the excess market return, (ii) the size factor, (iii) the value-to-book factor, and the (iv) momentum factor.

2. We use the factor loadings to calculate abnormal returns:
$$Abnormal\ return_{j,t} = Stock\ return_{j,t} - \hat{\alpha}_j - \sum_{k=1}^{4} Factor\ return_{k,t} * \hat{\beta}_{j,k,t}$$

3. We obtain cumulative abnormal returns for event window [t_2, t_3] by taking the sum of stock j's abnormal return in this window:
$$CAR[t_2, t_3]_j = \sum_{z=t_2}^{t_3} Abnormal\ return_{j,z}$$

4. We calculate standardized cumulative abnormal returns using the following formulas:
$$SCAR_j = \frac{CAR[t_2, t_3]_j}{s_j^{CAR}},$$

$$s_j^{CAR} = \sqrt{s_j^2 \cdot \frac{T_{Event}^2}{T_{Estimation}} + \sum_{k=1}^{4} \frac{\sum_{y=t_2}^{t_3}\left(Factor\ return_{k,y} - \overline{Factor\ return_k}\right)^2}{\sum_{z=t_0}^{t_1}\left(Factor\ return_{k,z} - Factor\ return_k\right)^2}},$$

$$s_j = \frac{1}{T_{Estimation} - 1} \sum_{z=t_0}^{t_1}\left(Abnormal\ return_{j,z} - \overline{Abnormal\ return_j}\right)^2,$$

where T_{Event} and $T_{Estimation}$ denotes the number of observations in the event $[t_2, t_3]$ and estimation window $[t_0, t_1]$, respectively. $\overline{Factor\ return_k}$ and $\overline{Abnormal\ return_j}$ is the average (abnormal) return of factor k and stock j in the estimation period.

5. Using the $SCAR_j$ of all N event stocks, we construct the average standardized cumulative abnormal return in the event window:

$$ASCAR = \frac{1}{N}\sum_{N} SCAR_j$$

6. We calculate the Boehmer, Musumeci,and Poulsen(1991) t-test by dividing the $ASCAR$ by its cross-sectional standard deviation:

$$T_{BMP} = \sqrt{N}\frac{ASCAR}{s^{CAR}}$$

$$s^{CAR} = \sqrt{\frac{1}{N-1}} \cdot \sum_N \left(SCAR_j - ASCAR\right)^2$$

7. To account for cross-sectional correlation of abnormal returns, we finally adjust this test-statistic using the average cross-correlation of abnormal returns ($\bar{r}$) across all event stocks in the estimation period:

$$T_{KP} = T_{BMP}\sqrt{\frac{1-\bar{r}}{1+(N-1)\,\bar{r}}},$$

$$\bar{r} = \frac{1}{N(N-1)}\sum_{k=1}^{q} N_k\,(N_k - 1)\overline{r_k}$$

where N_k event stocks with the same event date are assigned to group k and $\overline{r_k}$ denotes the cross-correlation of abnormal returns of these stocks in the estimation period.