Fire Sales and Liquidity Provision in the Corporate Bond Market

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Abstract

We investigate the role of corporate-bond mutual funds in providing liquidity to insurance companies that are forced to sell downgraded corporate bonds due to regulatory constraints (Ellul, Jotikasthira, and Lundblad, 2011). First, corporate-bond mutual funds purchase about 24% of fire sale bonds from insurance companies during the downgrading quarter. Second, while increasing the holding of fire sale bonds, corporate-bond mutual funds decrease the capital allocated to bonds with similar characteristics. This is consistent with the slow-moving capital theories (Duffie, 2010) based on the reallocation of limited capital capacity by financial intermediaries to trading opportunities. Third, corporate-bond mutual funds benefit from liquidity provision to insurance firms. Moreover, fund managers most actively and persistently engaging in liquidity provision demonstrate superior overall selection and timing skills in corporate bond investments.

1 Introduction

Asset fire sales occur when the original owners suffer collectively from a negative liquidity event and have to sell off due to financial and/or regulatory constraints. The supply shock immediately drives the asset price below the fundamental value. Over time, the price will recover and revert back to the fundamental value. The extent of immediate price impact and the time of reversal depend on the capital inflows from counterparties that take advantage of the mispricing. Duffie (2010) describes several theories that can cause the asset price dynamics consistent with what we observe in asset fire sales. These theories are based on the slow movement of investment capital to trading opportunities, which can be caused by searching costs, limited capacity of financial intermediaries to move investment capital, and trading delays due to limited attention that investors allocate to make their trading decisions.

The slow-moving capital theories highlight the crucial role of liquidity provision in stabilizing prices and easing capital constraints during asset fire sales. One impediment to capital formation arises from searching costs. For example, it is time consuming and costly for investors to locate suitable counterparties in over-the-counter (OTC) markets such as bonds, swaps, and securities lending due to decentralized market structure and information asymmetry.[1] Duffie, Gârleanu, and Pedersen (2007) develop a model for the OTC market in which the original natural owners of an asset suffer a preference shock that forces them to sell. The theories show that the immediate price impact and subsequent recovery time decrease in the arrival rate of new natural owners, which is a function of the searching costs in the OTC market.

Another impediment to liquidity provision is the limited capital capacity of financial intermediaries such as brokers, dealers, hedge funds, mutual funds, etc. The capital constraints for financial intermediaries could be due to significant trading losses and/or massive withdrawal of investor capital (Mitchell, Pedersen, and Pulvino, 2007). They can also arise from the inability of raising new capital in crisis period (Mitchell and Pulvino, 2012). Even in normal market conditions, significant adjustment costs can occur when reallocating capital from the current positions to new investment opportunities, especially in the OTC market. The process takes time and can incur significant transaction costs. Brunnermeier and Pedersen (2009) and Duffie and Strulovici (2012) , among others, model the asset price dynamics when financial intermediaries have limited capacity of moving capital to trading opportunities. They show that, relative to neoclassical settings, the limited capacity of intermediaries leads to distortions in risk premia.

[1] Empirical evidence of high transaction costs and large price dispersion can be found in Ashcraft and Duffie (2007), Green, Hollifield, and Schürhoff (2007a), Green, Hollifield, and Schürhoff (2007b), Goldstein, Hotchkiss, and Sirri (2007), Green, Li, and Schüfhoff (2010), and Schultz (2012).

The empirical literature on fire sales of financial assets has primarily focused on the causes and price patterns in various settings. Coval and Stafford (2007) examine the distressed selling of stocks commonly held by mutual funds experiencing large redemptions. Mitchell, Pedersen, and Pulvino (2007) study the downward price pressure on convertible bonds following the large withdrawal of capital from convertible-bond hedge funds in 2005 and the collapses of Long Term Capital Management in 1998. They also examine the forced selling of merger targets by merger arbitrage hedge funds during the 1987 market crash. Ellul, Jotikasthira, and Lundblad (2011) investigate fire sales of downgraded corporate bonds induced by regulatory constraints imposed on insurance companies. All studies show price patterns consistent with the slow-moving capital theory.

Despite our understanding about the sources of fire sales and the price impact, little is known about the trading behavior and profitability of the liquidity providers. Given that these liquidity providers play a crucial role in stabilizing prices and easing capital constraints, studying their trading behavior and skills is necessary for a complete understanding of the dynamics of asset fire sales. In this paper, we build upon Ellul, Jotikasthira, and Lundblad (2011) and focus on the liquidity provision to insurance companies, which are involved in fire sales of downgraded corporate bonds due to regulatory constraints. In particular, we investigate the extent to which corporate-bond mutual funds take advantage of the price dislocation in these fire sale events.

The insurance industry provides an ideal setting for studying fire sales in the OTC markets. Insurance companies mostly hold investment-grade bonds because regulations either prohibit or impose large capital requirements on the holdings of speculative-grade or junk bonds. Following a downgrading event, insurance companies holding the fallen angel may have the collective needs to sell the bond in the OTC market, incurring significant search and transaction costs. Ellul, Jotikasthira, and Lundblad (2011) show that the insurance companies, especially the regulatory-constrained ones, become net sellers of the fallen angel bonds during the weeks surrounding the downgrade. The forced selling on average leads to an abnormal price decline of 8.7% during the first five weeks after the downgrade. The prices then recover and revert back to the fundamental values by week +30.

Given the collective nature of forced selling by insurance companies facing similar regulatory constraints, the provision of liquidity most likely comes from outside the insurance industry. We focus on the role of mutual funds for several reasons. First, corporate-bond mutual funds have the capital capacity to absorb a significant portion of liquidity demand from the insurance industry during the downgrading events. As shown in Table 1, among the 2,115 downgraded bonds in our sample, insurance companies as a whole on average reduce the holdings by about 12% following the downgrading. Given the average offer size of \$445 million, this translates into a combined net sale of \$113 billion from 2002 to 2012. During the same period, the total net assets managed by corporate-bond mutual funds increase dramatically from \$289 billion to \$1.1 trillion. Second, unlike insurance companies, mutual funds in general are not constrained by regulation from holding speculative-grade bonds and thus have greater investment flexibility. Professional fund managers also possess the expertise to locate suitable counterparties in the OTC market. Moreover, a substantial portion of mutual funds actually specialize in speculative-grade bonds, and thus become the natural liquidity providers during the downgrading events. Even investment-grade bond funds can allocate a portion of their portfolios to junk bonds. Third, we acknowledge that mutual funds are unlikely the only liquidity provider for insurance companies during the downgrading events. Hedge funds and proprietary trading desks can also play an active role in trading fire sale bonds. An important reason why we choose to focus on mutual funds is the availability of holding data. Mutual funds are required to disclose their complete holdings on a quarterly basis for most part of our sample period. We can thus infer the bond transactions by mutual funds based on their holding disclosure, and match them with the transaction records for all insurance companies.

Our data sample consists of 2,115 corporate bonds that were downgraded from investment grade ratings to junk ratings between January 2001 and December 2012. Following the methodology in Ellul, Jotikasthira, and Lundblad (2011), we identify 969 fire sale bonds (FSBs) based on the proxies for regulatory-induced selling pressure. We use the remaining 1,146 downgraded bonds not involved in fire sales (non-FSBs) as the comparison group. To address the concern that these two types of downgraded bonds may have different fundamental characteristics, we construct another control group consisting of bonds matched to the FSBs by credit rating and duration. We then construct the trading volume measures for all FSBs and bonds in the control groups and examine the difference in trading patterns during a window surrounding the downgrading events.

Consistent with Ellul, Jotikasthira, and Lundblad (2011), we find that insurance companies are net sellers of FSBs. The bulk of net selling occurs during the downgrading quarter - accounting for more than 5% of the offer size on average. In contrast, mutual funds are the net buyers of FSBs during the downgrading quarter – accounting for about 1.20% of the offer size on average or about 24% of the net sale by insurance companies. This is consistent with the notion that mutual funds serve as an important liquidity provider for insurance companies involved in regulatory-induced fire sales. Moreover, they concentrate the liquidity provision during the downgrading quarters, when the immediate price impact of fire sales is likely to be the largest. We also conduct diff-in-diff tests using both non-FSBs and the matched bonds as the control groups. The results confirm that, while insurance companies sell significantly more FSBs relative to both non-FSBs and matched bonds during the downgrading quarter, mutual funds on the other hand purchase significantly more FSBs than the control groups. As another robustness check, we estimate a cross-sectional regression at the bond/industry level controlling for initial offer amount and time fixed effects. The results are similar.

Another interesting observation is the dynamics of mutual funds' net purchase of FSBs relative to the matched bonds during the event window. Before the downgrading quarter, mutual funds on average purchase significantly more matched bonds than the FSBs. During and immediately after the downgrading quarter, however, mutual funds' purchase of FSBs significantly outweighs that of the matched bonds. This dynamic change is driven by the increase (decrease) in net purchase of FSBs (matched bonds) during the event window. Note that the matched bonds have similar credit rating and duration to the FSBs. If the investment mandate of mutual funds allocates a fixed proportion of capital to bonds with certain characteristics, the above pattern reflects the process of portfolio rebalancing in which mutual funds overweigh the FSBs and underweigh other bonds with similar characteristics. This is consistent with theories based on the reallocation of limited capital capacity by financial intermediaries to trading opportunities.

We next investigate whether mutual funds, especially corporate-bond funds that actively engage in providing liquidity to the insurance industry, gain from such activity. We construct a FSB trade persistence measure ($TFSB$) which is defined as the net purchase of FSBs as a percentage of the fund's total dollar purchases over the quarter, averaged over the previous 12 quarters. At the beginning of each quarter, we sort all corporate-bond funds into quintile portfolios Based on the most recent $TFSB$. Several interesting results emerge. First, there is a large cross-sectional variation in the FSB trading intensities. The top quintile portfolio on average spends about 3.9% of quarterly purchases on FSBs, compared to only 0.24% for the bottom quintile portfolio. Second, we find a strong positive relationship between $TFSB$ and the subsequent fund performance. The top quintile portfolio with the highest $TFSB$ earns a significantly positive four-factor adjusted gross NAV return of 1.2% on an annual basis. When using holding-based abnormal returns, we find that funds in the top quintile portfolio exhibit both bond selection and timing ability. Third, the top quintile portfolio outperforms the bottom quintile portfolio by about 2% per year based on the four-factor adjusted gross NAV returns. Comparison in holding-based returns between the two groups reveals similar pattern.

Finally, we investigate the sources of outperformance by bond funds that actively engage in providing liquidity to insurance companies. Capturing the liquidity premium from fire sales contributes directly to the superior performance. Moreover, if the ability of capturing the liquidity premium reflects overall superior investment skills by fund managers, then we should observe outperformance from portfolio components other than the FSBs as well. We first decompose a fund's portfolio into speculative-grade bonds vs. investment-grade bonds and find that funds in the top $TFSB$ quintile portfolio significantly outperform funds in the bottom $TFSB$ quintile portfolio in both components. We then further decompose the speculative-grade bond holdings into the FSBs and other junk bonds. Regarding the profitability of trading FSBs, funds in the top $TFSB$ group outperform the bottom group by 3.8% per year based on the four-factor adjusted gross NAV returns. Performance comparison for other junk bond holdings suggests that the top $TFSB$ group again significantly outperforms the bottom group by 2.6% per year. Our results thus indicate that fund managers most actively engaging in liquidity provision demonstrate superior overall skills in corporate bond investments.

Our research is related to three strands of the literature. First, it contributes to the understanding of liquidity provision during asset fire sales. Mitchell, Pedersen, and Pulvino (2007) document that, during the 2005 fire sale of convertible bonds, multi-strategy hedge funds reacted slowly and waited a long time before increasing the convertible bond holdings. Moreover, the holding increase was largely driven by one out of 27 multi-strategy funds in their sample. In fact, more than half of the multi-strategy funds actually reduced their exposure following the fire sale event. They also consider 16 convertible-bond mutual funds and find no evidence of liquidity provision. One limitation of their analysis is the small sample size due to the availability of hedge fund holding data. The liquidity provision could also come from other types of fixed income hedge and mutual funds. Another related paper is Zhang (2009). This paper investigates whether some mutual funds benefit from providing liquidity to other distressed funds experiencing severe money outflows. The results show that more than half of the mutual funds engage in liquidity provision and about 15% of funds on average spend 5% of their total net assets on purchasing fire sale stocks.

Our paper investigates the provision of liquidity in fire sales induced by regulatory constraints. In this case, the source of liquidity must come from outside of the fire sale industry. We identify mutual funds as an important liquidity provider to insurance companies in the events of regulatory-induced fire sales. Our analysis is based on comprehensive holding data from both the insurance industry and the mutual fund industry. We believe that our paper is the first in the fire sale literature that provides direct evidence on the cross-industry liquidity provision at the aggregate level.

Second, our paper extends the studies on the liquidity provision activities by mutual funds. Gaspar, Massa, and Matos (2006) examine family favoritism and show that funds may provide liquidity to other funds within the same family through opposite trades. Da, Gao, and Jagannathan (2008) decompose the stock selection ability of a fund manager into information trading and liquidity provision. They show that some managers have strong informed trading skills, but find weak evidence on liquidity provision, which they attribute to the low frequency of liquidity events that last for more than a quarter. Zhang (2009) presents evidence that some mutual funds provide liquidity to other distressed funds experiencing redemption-induced fire sales. Bhattacharya, Lee, and Pool (2013) show that affiliated funds of mutual funds serve as an insurance tool that provides temporary liquidity to other funds in the same family. Our paper focuses on the liquidity provision activities by mutual funds when liquidity needs are from another industry, potentially more pronounced, and relatively long lasting. We present evidence that some fund managers have the skills to benefit from the price dislocation induced by forced selling.

Third, our paper is related to the large mutual fund literature on the investment skills of mutual fund managers. Studies based on the net returns document that mutual funds, on average, under-perform passive benchmarks (see Jensen (1968), Malkiel (1995), Gruber (1996), etc.). In contrast, studies based on the portfolio holdings (Grinblatt and Titman (1989), Grinblatt and Titman (1993), and Daniel et al. (1997)) find that managers who follow active investment strategies have stock-picking abilities. Moreover, recent studies have linked various fund characteristics to performance and provided evidence that at least some managers possess stock-selection skills. There have been few studies on the investment ability of bond fund managers and the evidence is mixed. Gutierrez, Maxwell, and Xu (2009) document strong performance persistence for corporate-bond mutual funds and attribute it to the bond-selection skill of the winning managers. Cici and Gibson (2012) examine the performance of corporate-bond mutual funds based on security-level holdings and conclude that bond fund managers in general do not possess superior bond selection and timing skills.

Our paper complements the performance literature by directly examining mutual fund trading activities, and provides evidence supporting the view that some corporate-bond fund managers have the ability to identify profitable trading opportunities. We show that some fund managers are able to consistently identify and trade the FSBs and benefit from the price dislocation induced by the forced selling from distressed insurance companies. Moreover, these managers exhibit overall investment skills beyond trading the FSBs, which lead to superior performance in the rest of their portfolios.

The remaining of the paper is organized as follows. Section 2 describes the data sample and summary statistics. In Section 3, we present evidence that corporate-bond mutual funds on aggregate provide significant liquidity to insurance companies during fire sale events. Section 4 investigates the profitability of liquidity provision by corporate-bond mutual funds and whether engaging in persistent liquidity provision indicates the possession of overall superior investment ability by fund managers. We conclude in Section 5.

2 Data Sample and Summary Statistics

2.1 Data Sources

The data sample used in our study comes from four main sources: (1) the National Association of Insurance Commissioners (NAIC) Database, (2) the Morningstar Mutual Fund Database, (3) the CRSP Survivor-Bias Free Mutual Fund Database, and (4) the Mergent Fixed Income Securities Database (FISD).

First, we obtain the transaction and year-end holding data for all insurance companies from the NAIC. The NAIC requires insurance companies to self-report all year-end bond positions and all bond transactions occurred during the year in Schedule D of their annual financial statements. Part 1 of Schedule D reports all bonds held as of December 31 of current year including the Committee on Uniform Securities Identification Procedures (CUSIP), date originally acquired, actual cost at time of acquisition, current fair value, par value, and other bond characteristics. Parts 3 to 5 report all bonds acquired, sold, or redeemed during current year. Each transaction record include the CUSIP, the date of transaction, the transaction price and quantity (par value), the counterparty involved (mostly dealers), etc. For our analysis, we infer quarter-end bond holdings based on year-end bond positions and transaction records.

Next, mutual fund holdings are from the Morningstar Mutual Fund Database. Most funds report holdings on a quarterly basis and some report monthly. For each fund on each report date, the reported items for each security held include the CUSIP identifier, the bond type, the par value, the fair value, the portfolio weight, etc. To be consistent with the insurance data, we infer the trading of each bond by a mutual fund based on the change of its reported holdings between two consecutive quarters. The database also reports for each fund the Morningstar investment category, statistics such as average credit quality and duration of the fund's holdings, and portfolio composition variables such as the percentage of total net assets (TNA) invested in government bonds, corporate bonds, bonds of a particular credit rating (e.g., AAA or BBB), etc. We also obtain from the CRSP Mutual Fund Database key fund characteristics such as investment style, fund age, monthly TNA, monthly returns, annual expense ratio, annual turnover ratio, etc. Since CRSP reports these statistics at the share class level, we aggregate them at the fund level. Fund age is defined as the age of the oldest share class. Fund TNA is the sum of TNAs across all share classes. Fund-level return, expense ratio, and turnover ratio are the TNA-weighted average of the corresponding share class statistics. We merge the Morningstar and the CRSP databases through tickers and fund names (if tickers are missing).

Finally, we obtain from the Mergent Fixed Income Securities Database (FISD) a list of key bond characteristics including offer amount, offer date, maturity date, credit rating, call schedule, redemption date, etc. We merge the FISD data with insurance and mutual fund holding data by CUSIP. For all fallen angels downgraded during the 2001-2012 period, our final transaction data sample covers the period from January 2002 to December 2012. We start the sample period at January 2002 because the CUSIP information for mutual fund holdings is missing in the Morningstar database for the pre-2002 period.

2.2 Identification of Fire Sale Bonds

From the Mergent FISD, we identify a total of 2,115 corporate bonds and medium term notes that were downgraded from investment-grade ratings to junk ratings during our sample period. We then follow the methodology in Ellul, Jotikasthira, and Lundblad (2011) to identify fire sales based on the proxies for regulatory-induced selling pressure. The intuition is that fire sales are most likely to occur when the downgraded bonds are mostly held by regulatory-constrained insurance companies. The NAIC prescribes guidelines adopted by most states to regulate insurance companies. One key element is the capital requirements for holding risky assets. The required capital is much higher for holding junk bonds than for holding investment-grade bonds. Moreover, the NAIC specifies a cap for the maximum holding of junk bonds in the overall portfolio of an insurance company. This suggests that regulatory constraints may force insurance companies with low risk-based capital (RBC) ratios to sell downgraded bonds in large scale. Such forced selling from regulatory-constrained insurers is likely to generate significant downward price pressure, especially when other insurers are unable to provide sufficient liquidity.

Following Ellul, Jotikasthira, and Lundblad (2011), we first model the probability of an insurance company to sell a downgraded bond within 5 weeks following the downgrading event as a probit function of the insurer's financial health (the logarithm of RBC ratio) and other firm and bond level characteristics. Since life insurers and property insurers face quite different liability structure and regulation constraints, we estimate the probit regression separately for each type of insurers. For each insurer holding the downgraded bond at the quarter-end preceding the downgrading event, we infer the probability of selling based on the estimation of the probit model. We then average across all insurers to get the mean selling probability. Finally, we define the downgraded bonds with above median selling probability as FSBs and those bonds with equal or below median selling probability as non-FSBs.

Panel A of Table 1 report the summary statistics for the 2,115 fallen angel bonds: 969 FSBs and 1,196 non-FSBs. The average initial offer size is $444.86 million. At the quarter-end preceding the downgrade, the average bond is 4.89 years old with 9.24 years left until maturity. Comparing the FSBs against the non-FSBs, we find that FSBs on average have larger offer size ($564.91 million vs. $343.35 million), younger age (3.39 years vs. 6.15 years), and shorter time to maturity (7.97 years vs. 10.32 years). Panel B shows that the median insurance holdings of all fallen angels are 30.71% during the two quarters before the downgrade and decline to 22.16% during the two quarters after the downgrade. The decline in FSB holdings is 9.64%, compared to only 4.59% for non-FSB holdings. In contrast, the median mutual fund holdings of FSBs increase by 1.52%, compared to only 0.71% increase in non-FSB holdings.

2.3 Corporate-Bond Fund Sample

We construct the corporate-bond fund sample based on the survivorship-bias free Morningstar Mutual Fund Database. First, we obtain holdings from January 1990 to December 2012 for 2,841 bond funds identified based on the Morningstar investment category. Next, we restrict our analysis to the post-2001 period when Morningstar provides reliable CUSIP identifiers for most of the fund holdings. Before 2002, the majority of CUSIPs are missing. This leaves us with 1,837 unique bond funds. Finally, for each fund quarter, we identify corporate-bond holdings as defined by the Mergent FISD and compute the total market value of corporate-bond holdings as a percentage of fund TNA. A fund is classified as a corporate-bond fund if its average corporate-bond holdings over our sample period account for at least 50% of its TNA. We end up with 765 unique corporate-bond funds in our sample from January 2002 to December 2012.

We report the summary statistics for corporate-bond funds in Table 2. Our sample consists of about 500 corporate-bond funds each year and 5,495 fund/year observations. The average TNA is $1.31 billion. The average expense ratio is 0.91% and the average turnover ratio is 123.4%. The average corporate-bond holdings account for 57.23% of TNA. The allocations to investment-grade and speculative-grade bonds are 55.45% and 44.55%, respectively.

3 Fire Sales by Insurance Companies and Liquidity Provision by Mutual Funds

In this section, we examine whether insurance companies indeed sell a disproportionally large number of FSBs following the downgrading. If so, do corporate-bond mutual funds step in and provide liquidity by purchasing the FSBs from insurance companies? As discussed earlier, corporate-bond mutual funds do not face capital requirement for holding speculative-grade bonds and have the financial capacity and expertise to trade these bonds in the OTC market.

3.1 Trading Pattern of FSBs

For each FSB, we compute on a quarterly basis the net trading volume by each insurance company as the total buy minus the total sell. For mutual funds, we compute the quarterly net trading volume as the reported holding changes between two consecutive quarters. To address the issue that bonds with larger issue size tend to have larger dollar trading volume, we normalize the dollar volume by the initial offer amount. Finally, we sum across all insurance companies (mutual funds) each quarter to obtain the aggregate net trading volume for the insurance (mutual fund) industry.

To detect the trading pattern for FSBs surrounding the downgrading events, we focus on a time window starting from two quarters before to two quarters after the downgrade. For each quarter, we compare the aggregate net trading volume for FSBs to two control groups. The first control group consists of all non-FSBs as identified in the previous section. They serve as a natural control group because they are fallen angel bonds as well. If downgrading from investment-grade to speculative-grade itself can trigger certain trading activities by mutual funds, using these fallen angel bonds without experiencing fire sales as controls can capture this impact. Therefore, any abnormal trading activities (relative to non-FSBs) should represent the effect of fire sales on mutual funds' trading decision toward FSBs.

However, compared to FSBs, non-FSBs may have different fundamental characteristics that lead to different trading patterns. To address this issue, we identify a second control group consisting of bonds matched by two important fundamental characteristics: credit rating and duration. Specifically, the matched bonds for each FSB must not have experienced any downgrading during the event window and must have the same credit rating and duration as the FSB during the month immediately following the downgrading. Following Cici and Gibson (2012), every month we assign each bond to 1 of 7 credit-quality categories: AAA; AA; A; BBB; BB; B; and below B (i.e., all CCC, CC, C, and D rated bonds). Every month each bond is also assigned to 1 of 5 duration categories, formed by ranking and sorting bonds into quintiles based on their modified duration, calculated as the Macaulay duration divided by 1 plus the yield to maturity. The credit-quality and duration sorts are conducted independently, resulting in 35 benchmark portfolios categorized by the 7 credit-quality categories and 5 duration categories. Due to missing duration data, we are able to identify the matched bonds for 625 FSBs.

Figure 1 shows the trading pattern for FSBs on a quarterly basis. The average net trading volume for the insurance industry is negative for all quarters surrounding the downgrading event, suggesting that insurance companies reduce FSB holdings. Although the selling already starts during the two quarters before the downgrading event, the magnitude is rather small - less than 1% of the offer amount. The selling accelerates dramatically in the downgrading quarter to 5.09% of the offer amount. During the two quarters following the downgrading, the net selling by insurance companies gradually declines to about 2% of the offer amount. This V-shape pattern of net selling is consistent with the finding in Ellul, Jotikasthira, and Lundblad (2011) that regulatory-constrained insurance companies immediately sell a significant portion of their FSB holdings following the downgrade. In contrast, the average net trading volume for the mutual fund industry is positive for all quarters during the event window and exhibits an inverse V-shape pattern peaking at the downgrading quarter. Specifically, the net purchase from mutual funds during the downgrading quarter is 1.21% of the offer amount, accounting for about 24% of the net sell by insurance companies. This provides the first evidence that mutual funds serve as an important liquidity provider to insurance companies during the regulatory-induced fire sale events.

3.2 Diff-in-Diff Analyses

We next conduct diff-in-diff analyses on the trading of FSBs between the insurance industry and the mutual fund industry. We focus on the downgrading quarter when trading is most active. For each bond (FSBs, non-FSBs, or matched bonds), we define an aggregate industry-level trading volume (ATV) as the change in total par value investments by either the insurance or mutual fund industry over a given quarter, scaled by the initial offer amount of the bond. Formally, ATV is defined as following:

$$ATV_{i,j,t} = \frac{\Sigma_k Volume_{i,k,t}, \forall k \in j}{AMT_i} \tag{1}$$

where $Volume_{i,k,t}$ is the par value of bond i traded in quarter t by firm k and AMT_i is the initial offer amount of bond i. We sum up bond i's trading volume, $Volume$, in quarter t over all firms k in industry j, where j is either the insurance or mutual fund industry.

Table 3 separately reports the abnormal trading volumes for FSBs relative to non-FSBs and the matched bonds. Relative to non-FSBs, insurance companies on average sell 1.65% (of the offer amount) more FSBs during the downgrading quarter. On the other hand, mutual funds on average buy 0.67% more FSBs than non-FSBs in the same quarter. The diff-in-diff test based on the abnormal trading volume suggests that mutual funds on average buy 2.32% more FSBs than insurance companies. All differences are statistically significant at the 1 percent level. The results are similar when using the matched bonds as the control group. Insurance companies on average sell 5.15% more FSBs than the matched bonds, while mutual funds on average buy 0.36% more FSBs than the matched bonds. The 5.51% difference in matched-bond adjusted trading volume between the two industries is again statistically significant at the 1 percent level.

Table 4 presents the trading volume dynamics for all quarters during the event window. For brevity, we only report the results using the matched bonds as the control group.[2] Relative to the matched bonds, the FSBs sold by insurance companies increase from 0.96% to 1.35% during the two quarters prior to the downgrading, reach the peak of 5.15% during the downgrading quarter, and then decline to 1.06% two quarters after the downgrading. This is again consistent with the regulatory-induced asset fire sale in Ellul, Jotikasthira, and Lundblad (2011).

Another interesting pattern observed in Table 4 is mutual funds' net purchase of FSBs relative to the matched bonds during the event window. During the two quarters before downgrading, mutual funds actually purchase significantly less FSBs than the matched bonds. During the downgrading quarter, however, mutual funds purchase 0.36% more FSBs than the matched bonds. The over-purchase of FSBs relative to the matched bonds increases to 0.68% in the first quarter following the downgrading and then declines to 0.41% by the second quarter. In untabulated results, we observe that the above reversed pattern is driven by the decrease (increase) of net purchase of the matched bonds (FSBs) during the event window. Note that the matched bonds have similar credit rating and duration to the FSBs. If the investment mandate of mutual funds allocates a fixed proportion of investments to bonds with certain characteristics, then the above pattern may reflect the process of portfolio rebalancing in which mutual funds over-weigh the FSBs and under-weigh other bonds with similar characteristics. This is consistent with the slow-moving capital theories based on the reallocation of limited capital capacity by financial intermediaries to trading opportunities.

3.3 Regression Analyses

As a robustness check, we estimate regressions at the bond/industry level for the downgrading quarter in the following model.

$$ATV_{i,j} = \alpha + \beta_1 FSB_{i,j} + \beta_2 MF_{i,j} + \beta_3 MF_{i,j} * FSB_{i,j} + \beta_4 Ln(AMT)_i + \beta_5 Year_{i,j} + \varepsilon_{i,j} \qquad (2)$$

The dependent variable $ATV_{i,j}$ is the aggregate net trading volume of each bond i during the downgrading quarter for industry j, which is either the insurance or the mutual fund industry. The explanatory

[2] The results using the non-FSBs as the control group are similar.

variables include an indicator variable FSB that equals one if bond i is identified as a fire sale bond and zero otherwise, an indicator variable MF that equals one if the bond-level net trading volume is aggregated for the mutual fund industry and zero for the insurance industry, the interaction of MF and FSB, and the logarithm of the initial offer amount, AMT for each bond i. We also control for year fixed effects in the regression.

We report the regression results in Table 5. The data sample for Models 1 and 2 consists of FSBs and non-FSBs, while the data sample for Models 3 and 4 consists of FSBs and the matched bonds based on credit rating and duration. As shown in Models 1 and 2, the coefficient for FSB is negative and statistically significant at the 1 percent level, suggesting that FSBs on average experience net sale during the downgrading quarter. In contrast, the positive and significant coefficients for MF suggest that mutual funds on average purchase the downgraded bonds. Moreover, the purchasing activity by mutual funds is more intense for FSBs - as indicated by the positive and significant coefficients for the interaction term. We find similar results in Models 3 and 4 when non-FSB bonds are replaced with matched bonds. Overall, the regression results are consistent with the diff-in-diff analysis for the downgrading quarter.

In Table 6, we separately examine the FSB trading by two types of mutual funds: speculative-grade funds and investment-grade funds. We run the same specification as in regression 2 except that the indicator variable MF equals one either for the speculative-grade funds in Models 1 to 4 or for the investment-grade funds in Models 5 to 8.

Models 1 to 4 compare the net trading volume of speculative-grade funds relative to the insurance companies, while Models 5 to 8 investigate the difference in net trading volume between investment-grade funds and insurance companies. The coefficients for MF are positive and significant in all models, suggesting that both types of mutual funds purchase (relative to insurance companies) the downgraded bonds during the downgrading quarters. Similar to what we observe in Table 5, the positive and significant coefficients for the interaction term ($MF * FSB$) indicate that both types of mutual funds purchase significantly more FSBs than the non-FSBs. Hence, the evidence suggests that both speculative-grade and investment-grade funds engage in liquidity provision to insurance companies.

In summary, the diff-in-diff and regression analyses suggest that insurance companies on the net sell large quantity of FSBs and corporate-bond mutual funds (both speculative-grade and investment-grade funds) appear to be on the other side of the trade. Moreover, the cross-trading mainly concentrates in the downgrading quarters. It is thus consistent with the notion that some insurance companies are forced into fire sales due to regulatory pressure following the downgrading events and that corporate-bond mutual funds serve as an important liquidity provider.

4 The Performance Implications of Liquidity Provisions

From previous sections, we observe that bond mutual fund industry on aggregate tend to provide liquidity to falling angel bonds that are experiencing fire sales from insurance industry due to its regulatory constraints. On aggregate, such liquidity provision activity is beneficial as it stabilizes the corporate bond market and helps to ease the capital constraints and reduce capital costs for the down-graded companies. Yet, another interesting and important question is, whether the mutual fund industry, especially corporate-bond funds that actively engage in liquidity provision, gains from such trades. Further, is this a performance strategy skillful managers intentionally follow to add value to their funds? In this section, we investigate the performance implications of bond mutual funds liquidity provision trade involving FSBs.

4.1 Trade Fire sale Bond Measure ($TFSB$)

We introduce a fund-level trade fire sale bond measure ($TFSB$). It captures a fund's tendency to persistently trade fire sale falling-angel bonds. First, for each quarter, we compute the percentage of a fund's dollar-valued trades used to purchase fire sale bonds over the quarter.

$$QTFSB_{j,t} = \frac{\sum_i (max(0, \Delta Shares_{j,i,t}) * Price_{i,t}) | i \in FSB_{t-3,t}}{Total\_Purchases_{j,t}} \tag{3}$$

where $\Delta Shares_{j,i,t}$ is the change in number of shares of bond i by fund j over quarter t, and $Price_{i,t}$ is the price of bond i at the end of quarter t. To identify the timing of changes in bond holdings correctly, *QTFSB* is calculated for all fund-quarters where holdings are reported at both the beginning and the end of the quarter. The dollar-value purchases of *FSBs* are the increases in the number of shares of FSBs during the quarter multiplied by the price of the bond at the end of the quarter. This includes both expanded and new positions. The opportunity set of the trade includes falling angel bonds that are fire sold by insurance companies in the prior year including the current quarter. Finally, to adjust for a fund's trading activities during the quarter, the total dollar purchases of *FSBs* are scaled by the total dollar purchases made by the fund over the quarter.

Next, we then averaged this quarterly percentage trade measure, *QTFSB*, over the past 3 years, or 12 quarters, to construct *TFSB* measure.

$$TFSB_{j,t} = \frac{\sum_{s=t-11}^{t} (QTFSB_{j,t})}{12} \tag{4}$$

TFSB measures captures a fund's persistency in providing liquidity to insurance companies by trading fire sale falling-angel bonds.

4.2 Risk-Adjusted Performance by *TFSB*

This section examines the performance implications of persistent liquidity provision activities ($TFSB$). To avoid any potential issues of reverse causality, we analyze only the future performance of funds after computing the $TFSB$ measure. To facilitate the comparison of performance across funds, we focus on funds that are unconstrained to hold and trade junk bonds. That is, we focus on bond funds which have positive holdings of junk bonds and ever trade fallen angel bonds in the past 3 years. Our sample covers 75% of all corporate bond funds.

Table 7 reports the bond mutual fund performance sorted by their $TFSB$ activities. At the end of each quarter, mutual funds are sorted into quintile portfolios according to their $TFSB$ measure. We then compute the equal weighted average fund returns of all funds for the corresponding portfolios over the next months. The portfolios are rebalanced each quarter. Finally, we compute the average returns using the time-series of fund portfolio returns. Column 2 of Table 7 presents the mean $TFSB$ measure of each bond fund portfolios. Columns 3 to 6 present four different risk-adjusted performance measures of $TFSB$ bond fund portfolios. Specifically, column 3 shows intercept alphas of gross NAV returns of bond portfolios after adjusting for four risk factors that are standard for bond fund risk adjustments (Elton, Gruber, and Blake (2009), Gutierrez, Maxwell, and Xu (2009), and Cici and Gibson (2012)). The four-factor model is specified as follows:

$$R_t = \alpha + \beta_1 STK_t + \beta_2 BOND_t + \beta_3 DEF_t + \beta_1 OPTION_t + \varepsilon_t \tag{5}$$

where t denotes month, R is the portfolio return in excess of the risk-free rate, STK is the excess return on the CRSP value-weighted stock index, $BOND$ is the excess return on the Lehman Aggregate index, DEF is the return difference of the Lehman High-Yield and Intermediate Government indices, and $OPTION$ is the return difference of the Lehman Government National Mortgage Association (GNMA) and intermediate Government indices. [3]

Columns 4 to 6 of Table 7 present three holdings-based performance measures. Column 4 shows four-factor alphas of holdings returns of bond fund portfolios. Columns 5 and 6 of Table 7 further divide the gross holdings return into the Characteristic Selectivity measure (CS) and the Characteristic Timing

[3] Our results remain strong after controlling for 2 additional risk factors, the *SMB* and *HML*, that are prevalent for equity fund risk adjustments.

measure (CT) for bond fund portfolios following Daniel, Grinblatt, Titman, and Wermers (1997) and Cici and Gibson (2012). To form the benchmark bond portfolios, we group all corporate bonds into quintiles according to their durations and 7 groups according to their credit ratings (i.e. AAA, AA, A, BBB, BB, B, and below B). Such sorting results in 35 benchmark bond portfolios.

The CS measure for bond funds denotes a measure of bond selection ability and is used as a benchmark the return of a portfolio of bonds that is matched to each of the bond funds holdings every quarter along the dimensions of duration and credit ratings.

$$CS_{f,t}^{BF} = \sum_{j} w_{f,j,t-1} \left(R_{j,t} - BR_{j,t} \right), \tag{6}$$

where $R_{j,t}$ is the excess return on bond j during period t and $BR_{j,t}$ is the return on a benchmark portfolio during period t to which bond j was allocated at the end of the previous quarter according to its duration and credit rating characteristics.

The variable CT denotes a measure of style-timing ability, which examines whether bond fund managers can generate additional performance by exploiting time-varying expected returns of benchmark portfolios by duration and credit rating:

$$CT_{f,t}^{BF} = \sum_{j} \left(w_{f,j,t-1} BR_{j,t} - w_{j,t-13} BRL_{j,t} \right), \tag{7}$$

where $BRL_{j,t}$ is the return on a benchmark portfolio during period t to which bond j was allocated one year earlier according to its duration and credit rating characteristics.

Examining the results in Table 7, we notice that cross-sectionally bond funds vary a lot in terms of their $TFSB$ activities. While some funds spend only 0.24% of their total buy trades on FSBs, the top group, on average, spends about 3.9% on FSB purchases quarterly and persistently over the past 3 years. Second, Table 7 shows a strong positive relationship between $TFSB$ activities and subsequent fund performance. We observe that funds in the top group with the highest $TFSB$ experience a significant positive NAV return of 10 basis points per month on a four-factor risk-adjusted basis, which is equivalent to 1.2% annually. Holdings-based performance measures show similar results. Top $TFSB$ group exhibits a significant positive holding-based abnormal return of 12 basis points per month (1.44% annually). Further decomposition of holdings returns show that these funds experiences significant CS and CT performance of 8 and 3 basis points per month, respectively. These performance results indicate that bond funds that engage in liquidity provisions to insurance companies benefit from such activities subsequently on a risk-adjusted basis. Therefore, liquidity premium might be the direct motivation behind such cross-industry trading activities.

Further, comparing funds with high and low $TFSB$ activities, we observe that funds in the top $TFSB$ group outperform fund in the bottom group with almost none $TFSB$ activities by 17 basis points per month (2.04% annually) on a four-factor risk-adjusted basis using gross NAV returns.[4] Holdings-based returns confirm the result and show that the top group outperforms the bottom groups by 20 basis points per month on risk-adjusted basis. In addition, decomposing holdings return into CS and CT measures, we observe that bond funds with the highest liquidity provision activities exhibit significantly higher investment skills in both the selectivity and timing dimensions than those with almost none such activities.[5]

Therefore, liquidity provision activities to insurance companies through purchasing FSBs are associated with an overall positive performance effect. Bond funds that persistently engage in such liquidity provision activities tend to outperform bond funds that are less involved in such activities.

4.3 Performance Decompositions - Liquidity Premium and Other Performance

Our performance results show that bond funds that chose to engage in liquidity provision to insurance companies during policy constraints induced fire sale events perform better subsequently. This suggests that liquidity premium from fire sales is a direct motivation for such liquidity provisions and contribute to the better performance. Moreover, beyond liquidity premium, superior performance might come from overall investment skills by these bond fund managers. In this section, we further investigate the sources of superior performance by decomposing holdings return into subcomponents.

In Table 8, we first decompose abnormal holdings performance into speculative- versus investment-grade bond components. We observe that funds with high $TFSB$ activities perform better than funds with low $TFSB$ in both components. Specifically, funds in top $TFSB$ group outperform funds in low $TFSB$ group by 21 and 12 basis points per month on their speculative-grade and investment-grade bond components, respectively. This is the first indication that bond funds that are involved in liquidity provisions to insurance companies have overall skills beyond investing in speculative-grade bonds. Second, within speculative-grade holdings, we further decompose returns into holdings returns associated with FSB purchases and with other junk bonds. Four-factor adjusted abnormal returns of these two components are presented in columns 3 and 4. We observe that top group with the highest $TFSB$ activities outperforms the low $TFSB$ group directly from their FSB component by 32 basis points per month on

[4] Using net NAV return, we confirm the results. Top group outperforms bottom group by 17 basis points monthly.

[5] In unreported test, we eliminate index bond funds, and the results remain similar both qualitatively and quantitatively.

a risk-adjusted basis and 3.8% annually. This indicates that funds in top $TFSB$ group not only engage more in liquidity provisions but also exhibit superior ability in trading these fallen angel bonds, which contribute to their superior performance. On the other hand, the bottom group might trade $TFSB$ for reasons such as portfolio rebalancing rather than performance chasing, and therefore might time the trades poorly. Finally, examining performance from other junk bonds in column 4, we notice that top group also shows outperformance on their other junk-bond holdings by 22 basis points per month and 2.6% annually.

Therefore, our results indicate that top $TFSB$ funds exhibit strong overall abilities in corporate bond investments. TFSB measure can serve as an indicator of overall investment skills.

4.4 Speculative- versus Investment-Grade Mutual Funds

Results in previous sections show that both speculative- and investment-grade bond funds on aggregate engage in providing liquidity to insurance companies during fire sale events. Is performance implication different between the two types of bond funds? Table 8 splits the sample of bond funds (with positive junk bond holdings) into subsamples - speculative-grade fund sample versus investment-grade bond fund sample according to whether their junk-bond holdings are above or below the median level.

In our sample, speculative-grade funds on average hold 96% of junk bonds and 4% of investment-grade bonds. On the other hand, investment-grade bond funds on average hold 26% of junk bonds and 74% of investment-grade bonds. Table 9 shows the risk-adjusted performance for the two subsamples by $TFSB$ activities. First, we notice that for both subsamples, funds differ significantly in their $TFSB$ activities. Specifically, the spreads between top and bottom $TFSB$ groups are 3.5% and 3.3% for speculative-grade and investment-grade bond fund samples, respectively. Moreover, for both groups, we observe significant positive performance impact of TFSB. For example, top $TFSB$ group outperform bottom $TFSB$ group by 9 and 10 basis points per month in gross NAV abnormal returns for speculative-grade funds and investment-grade Funds, respectively. We obtain similar results using holding-based performance measures.

4.5 Multivariate Regression Analyses

In this section, we perform multivariate regression analysis of the performance consequences of $TFSB$ activities. Regression analysis help control various fund characteristics. We run the following Fama-

Macbeth regression:

$$PERF_{f,t} = \alpha_t + \beta_1 TFSB_{f,t-1} + \beta_2 PERF_{f,t-1} + \beta_3 EXP_{f,t-1} + \beta_4 LOG(TNA_{f,t-1}) \\ + \beta_5 AGE_{f,t-1} + \beta_6 TURN_{f,t-1} + \beta_7 JUNK_{f,t-1} + \varepsilon_{f,t}, \quad (8)$$

The dependent variable is $PERF$, the monthly measure of fund performance. For regression analyses, we focus on abnormal holdings returns based on four-factor risk adjustments and various sub-components of the abnormal holdings returns. The main independent variable is $TFSB$, which measures a fund's tendency to persistently engage in liquidity provision trades to insurance company fire sales and is defined in Section 4.1. The coefficient for $TFSB$ captures the relationship between liquidity provision and subsequent bond fund performance. EXP is the funds expense ratio, TNA is the fund size, AGE is the logarithm of fund age plus 1, and $TURN$ is the annual fund turnover. All control variables are lagged by a year. We also control fund returns over prior year. Finally, we add $JUNK$ as an additional control, which is the mean weight of a fund's speculative-grade bond holdings over the past year. We use Fama-Macbeth regression method. In the first step, we run a cross-sectional regression in each month. In the second step, the means of the cross-sectional coefficients are computed over the whole time period. To reduce noise, we exclude quarters when there are no FSBs identified.

To measure risk-adjusted performance, each month, we use the four-factor risk adjustment model to estimate factor loadings for each fund using fund returns over the prior 36 months. We then compute the abnormal returns for each fund in the month as the difference between the actual fund holding return and the expected return based on the estimated factor loadings.

Table 10 presents the regression results. Column 2 presents results where the overall abnormal holding return is the dependent variable. We observe a significant positive relationship between $TFSB$ and subsequent fund performance after controlling for all fund characteristics. The coefficient on $TFSB$ is about 1.9. Therefore, a fund that spends 5% of their quarterly buy trades on FSBs will experience a significant abnormal return of 9.5 basis point per month (1.1% annually) subsequently. The positive performance exists after controlling for all fund characteristics including past fund performance. In addition, to make sure the $TFSB$ is not just the proxy for investments in speculative-grade bonds, we also include prior weight on speculative-grade bonds as an additional control. We observe that coefficient for $JUNK$ itself is not significant and it does not affect the explanatory power of TFSB.

We further decompose the overall holding alpha into various components. Columns 3 and 4 focus on speculative-grade versus investment-grade bond components. We observe that funds with high $TFSB$

tend to achieve superior performance mainly from their speculative-grade holdings. The coefficient on $TFSB$ is about 3.6 for junk-bond holdings. On the other hand, after controlling for past performance and other fund characteristics, the performance implication of $TFSB$ on investment-grade bond returns is no longer significant. Next, we focus on speculative-grade bond holdings exclusively and decompose returns into FSB part and other junk-bond part. Clearly, columns 5 and 6 show that bond funds with high $TFSB$ activities achieve superior performance from both FSB and other junk-bond holdings. The coefficients are about 9.9 and 3.2 for the two components, respectively. Therefore, a fund that follows a liquidity provision strategy and spends 5% of their quarterly buy trades on FSBs will experience a significant subsequent abnormal return of 49.8 basis points per month (6.0% annually) directly from their FSB positions. In addition, from other junk-bond positions, the fund will also experience a significant abnormal return of 16.2 basis points per month (1.9% annually).

These results are largely consistent with our previous findings using portfolio approach and indicate that high $TFSB$ fund managers tend to have overall superior abilities beyond trading fire sale fallen angel bonds.

4.6 Performance Implications of Trading Non-FSBs

As shown in previous sections, trading FSBs is a profitable strategy and earns liquidity premium. Persistent liquidity provision (TFSB) is an indicator of bond funds' overall investment skill. Although FSBs experience large mispricing and subsequent reversal, non-FSBs (fallen angel bonds that do not experience fire sales from insurance companies) do not share the same return pattern. Therefore, trading Non-FSBs should not lead to any superior fund performance.

As a robustness check, in the section, we investigate the performance implications for trading non-FSBs. Similarly, we define a trading Non-FSBs ($TNFSB$) measure which captures the tendency of a bond fund to persistently purchasing fallen angel bonds that do not experience fire sales from insurance companies. For each quarter, we first compute the dollar-amount purchase of Non-FSBs divided by total purchases made by the fund over the quarter. Then, we average the quarterly percentage trade measure over the past 3 years to obtain $TNFSB$ measure. Table 11 reports the multivariate regression results on the performance effect of trading Non-FSBs. Various risk-adjusted performance measures are used as the dependent variables. As expected, we find no significant performance effects for funds that trade Non-FSBs. Therefore, trading fallen angel bonds in general is not a successful strategy. Bond funds that simply pick up fallen angel bonds with no mispricing exhibit no skills and therefore do not generate superior performance.

5 Conclusion

We document that corporate-bond mutual funds provide significant liquidity to insurance companies that are forced to sell downgraded corporate bonds due to regulatory constraints. Specifically, corporate-bond mutual funds purchase about 24% of fire sale bonds from insurance companies during the downgrading quarter. While increasing the holding of fire sale bonds, corporate-bond mutual funds decrease the capital allocated to bonds with similar credit ratings and duration. The evidence is therefore consistent with the slow-moving capital theories based on the reallocation of limited capital capacity to trading opportunities. Performance analysis suggests that corporate-bond mutual funds benefit from liquidity provision to insurance companies through capturing the liquidity premium. Furthermore, fund managers most actively and persistently engaging in liquidity provision demonstrate superior overall selection and timing skills in corporate bond investments.

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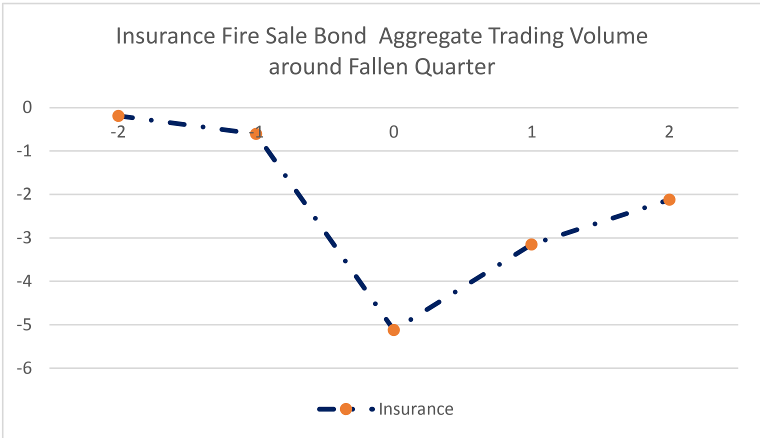
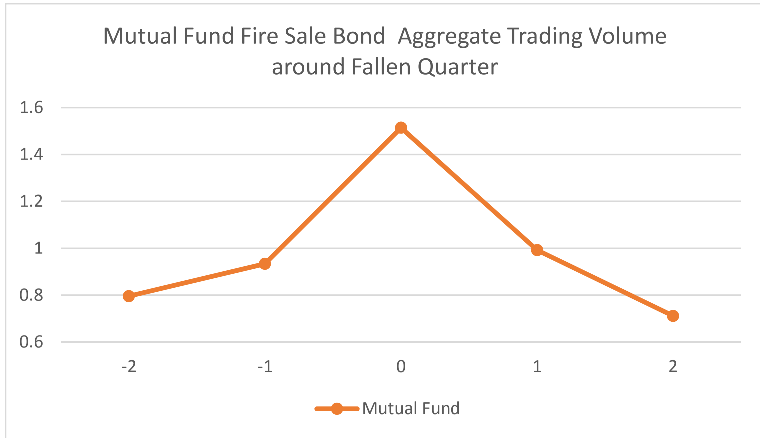


(a) Insurance Firm



(b) Mutual Fund

Figure 1: **Aggregate Trading Volume of FSBs by Insurance and Mutual fund Industries**

This figure shows trading activities of Fire Sale Bonds (FSBs) by insurance and bond mutual fund industries around the downgrade quarter. FSBs are the bonds downgraded from investment grades to non-investment grades and experienced fire sales. They are identified during the period of 2001 to 2012. Vertical axes is bond trading volume scaled by bond initial offering amount. Horizontal axes displays event quarter and quarters before and after it. Event quarter is the downgrade/firesale quarter.

Table 1: **Corporate Bond Sample Summary Statistics**

This table reports summary statistics of fallen angel bonds during 2001 to 2012. Fallen angel bonds are corporate bonds that were downgraded from investment grades to speculative grades. Panel A reports bond level statistics for all 2,115 fallen angel bonds, which include 969 fire sale bonds (FSB) and 1,196 non-fire sale fallen angel bonds (Non-FSB) identified during this period. Panel B reports statistics before and after the event quarter of downgrading. Mutual funds and insurance firms' median holding of those bonds in 2 quarter before and 2 quarters after the event quarter are reported in the first two rows. Average yield and median rating of the month before and the month after the fallen angel event date are reported in the last 2 rows, respectively.

Panel A: Summary Statistics for Downgraded Bonds

	All Downgrade Bonds			Fire Sale Bonds (FSB)			Non-Fire Sale Bonds (Non-FSB)		
	Mean	Median	STD	Mean	Median	STD	Mean	Median	STD
Offering Amount ($MM)	444.855	300.000	475.043	564.905	400.000	509.800	343.346	250.000	417.596
Maturity (Years)	9.244	5.593	10.883	7.970	5.114	9.308	10.322	6.031	11.953
Age (Years)	4.885	3.937	4.013	3.391	2.694	2.687	6.148	5.242	4.488
Rating	10.522	11.000	0.953	10.430	11.000	1.072	10.599	11.000	0.832
Duration	5.549	4.692	4.105	5.303	4.570	4.143	5.833	4.883	4.046

Panel B: Insurance and Bond Mutual Fund Fallen Angel Bond Holding, Rating and Yield

	All Downgrade		FSB		Non-FSB	
	Before	After	Before	After	Before	After
Median Insurance Company Holding (%)	30.707	22.161	27.945	18.305	33.463	28.869
Median Mutual Fund Holding (%)	2.891	4.004	3.334	4.856	2.447	3.153
Median Rating	11.000	12.000	11.000	13.000	11.000	12.000
Average Yield	10.799	14.871	10.840	20.099	10.751	9.262

Table 2: **Bond Mutual Fund Sample Summary Statistics**

This table reports summary statistics for corporate bond mutual funds from 2002 to 2012. Number of observations, mean, standard deviation, 25 percentile, median and 75 percentile statistics are reported.

	Mean	STD	25 Percentile	Median	75 Percentile
TNA (Million Dollars)	1309.450	7688.481	74.688	246.979	757.550
Expense Ratio (in % per year)	0.906	0.369	0.650	0.860	1.145
Turnover (in % per year)	1.234	1.516	0.440	0.740	1.380
Age (Years)	12.615	10.435	5.000	11.000	17.000
Corporate Bond Holdings (% of TNA)	57.226	27.863	34.324	52.612	85.116
Investable Bond Holdings (%)	55.450	41.791	4.486	74.046	96.318
Junk Bond Holdings (%)	44.550	41.791	3.682	25.954	95.514
Trading of FSB (% of Offering Amt)	1.097	1.657	0.000	0.462	1.557
NAV Return (in % per month)	0.491	1.890	−0.101	0.540	1.270
NAV Gross Return (in % per month)	0.584	1.911	−0.023	0.631	1.366
Holding Return (in % per month)	0.716	2.287	−0.117	0.811	1.617

Table 3: **Aggregate Trading Volume of Fire Sale Bonds by Insurance and Mutual Fund Industries**

This table reports aggregate trading volume of fire sale bonds by insurance (INS) and mutual fund (MF) industries during 2002 to 2012. Fire sale fallen angel bonds (FSBs) are corporate bonds that were downgraded from investment grades to speculative grade and fire sold by insurance companies due to regulatory constraints. Aggregate trading volume (ATV) is defined as dollar amount changes in investments in a fallen angel bond by insurance or mutual fund industry over a given quarter scaled by the initial offering amount of the bond as in Equation 1. BENCH is benchmark bond group, which is either fallen angel bonds that did not experience fire sales or the matched bonds that are similar to FSBs in terms of credit rating and duration characteristics. Abnormal trading volume, denoted as $DIFF$ in the table, is the difference between trading volumes towards FSB and its benchmark bond. t-statistics are reported in the parentheses. ***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively.

		BENCH	FSB	DIFF
FSB vs Non-FSB	INS	-3.440^{***}	-5.089^{***}	-1.649^{***}
		(-13.552)	(-15.31)	(-4.005)
	MF	0.534^{***}	1.205^{***}	0.671^{***}
		(8.562)	(12.262)	(5.936)
	DIFF	3.974^{***}	6.293^{***}	2.320^{***}
		(15.204)	(18.158)	(5.433)
FSB vs Matched	INS	0.026	-5.123^{***}	-5.149^{***}
		(0.386)	(-12.358)	(-12.261)
	MF	1.156^{***}	1.514^{***}	0.358^{**}
		(16.823)	(11.663)	(2.438)
	DIFF	1.130^{***}	6.637^{***}	5.507^{***}
		(11.777)	(15.278)	(12.375)

Table 4: **Aggregate Trading Dynamics of Fire Sale Bonds**

This table reports abnormal trading volume of fire sale bonds (FSBs) by both insurance (INS) and mutual fund (MF) industries two quarters before and two quarters after the downgrade quarter for year 2002 to 2012. We use matching bonds as the benchmark group. Abnormal trading volume (ATV) is defined as trading volume toward FSBs minus trading volume toward matching bonds as in Equation 1. All volumes are scaled by bond initial offering amount in percentage terms. t-statistics are reported below in the parentheses. ***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively.

	INS	MF	DIF
Quarter -2	-0.955^{***}	-0.785^{***}	0.170
	(-3.222)	(-5.425)	(0.502)
Quarter -1	-1.350^{***}	-0.455^{***}	0.895^{***}
	(-5.235)	(-3.438)	(3.051)
Quarter 0	-5.149^{***}	$0.358{**}$	5.507^{***}
	(-12.261)	(2.438)	(12.375)
Quarter +1	-2.302^{***}	0.680^{***}	2.981^{***}
	(-10.622)	(6.414)	(12.36)
Quarter +2	-1.064^{***}	0.412^{***}	1.476^{***}
	(-5.133)	(5.013)	(6.619)

Table 5: **Regression Analysis of Aggregate Trading of Fire Sale Bonds**

This table reports the regression analysis of aggregate trading volume of fire sale bonds (FSBs) by insurance and mutual fund industries during the event quarter from 2002 to 2012. Aggregate trading volume (ATV in %) is defined as dollar amount changes in investments in a fallen angel bond by insurance or mutual fund industry over a given quarter scaled by the initial offering amount of the bond as in Equation 1. FSB is fire sale bond dummy, MF is mutual fund industry dummy and offering amt is bond initial offering amount. Regression coefficients are reported and receptive t-statistics are reported below in parentheses. ***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively. Year fixed effect are controlled for all models.

	FSB and Non-FSB		**FSB and Matched Bond**	
	Model 1	**Model 2**	**Model 3**	**Model 4**
FSB	-1.687^{***}	-2.197^{***}	-5.149^{***}	-5.408^{***}
	(-4.058)	(-5.103)	(-12.207)	(-11.873)
MF	3.974^{***}	3.974^{***}	1.131^{***}	1.132^{***}
	(15.095)	(15.093)	(12.949)	(12.951)
MF*FSB	2.320^{***}	2.320^{***}	5.506^{***}	5.504^{***}
	(5.438)	(5.437)	(12.846)	(12.844)
Ln(offering amt)		0.774^{***}		1.187^{***}
		(5.523)		(3.981)
Constant	-1.707^{***}	-11.541^{***}	$0.779{**}$	-14.795^{***}
	(-5.831)	(-6.272)	(2.461)	(-3.823)
Year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.147	0.153	0.218	0.227
N	4,230	4,230	2,499	2,499

Table 6: **Aggregate Trading of FSBs by Speculative-Grade Bond Funds and Investment-Grade Bond Funds**

This table reports the regression analysis results of trading volume toward FSBs by speculative-grade bond mutual funds and investment-grade bond mutual funds comparing to insurance company for the period of 2002 to 2012. Aggregate trading volume (ATV) is defined as dollar amount changes in investments in a fallen angel bonds by insurance or mutual fund industry over a given quarter scaled by the initial offering amount of the bond as in Equation 1. FSB is fire sale bond dummy. MF is either Speculative-Grade Bond Fund or Investment-Grade Bond Fund dummy. AMT is bond initial offering amount. Regression coefficients are reported and receptive t-statistics are reported below in parentheses. ***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively. Year fixed effect is controlled for all models.

	Speculative-Grade Funds and Insurance Company				Investment-Grade Funds and Insurance Company			
	FSB and Non-FSB		FSB and Matched Bond		FSB and Non-FSB		FSB and Matched Bonds	
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**
FSB	−1.674***	−2.148***	−5.149***	−5.368***	−1.702***	−2.089***	−5.149***	−5.360***
	(−4.028)	(−4.987)	(−12.207)	(−11.774)	(−4.096)	(−4.850)	(−12.207)	(−11.751)
MF	3.795***	3.795***	0.820***	0.821***	3.618***	3.618***	0.286***	0.287***
	(14.613)	(14.611)	(10.245)	(10.249)	(14.050)	(14.048)	(4.203)	(4.212)
MF*FSB	2.132***	2.132***	5.441***	5.441***	1.837***	1.837***	5.212***	5.211***
	(5.047)	(5.046)	(12.831)	(12.830)	(4.351)	(4.350)	(12.238)	(12.237)
Ln(AMT)		0.718***		1.006***		0.586***		0.968***
		(5.219)		(3.437)		(4.250)		(3.349)
Constant	−1.657***	−10.779***	0.805**	−12.398***	−1.891***	−9.335***	0.859***	−11.842***
	(−5.512)	(−5.965)	(2.348)	(−3.264)	(−6.172)	(−5.141)	(3.537)	(−3.162)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.139	0.144	0.210	0.217	0.126	0.130	0.184	0.191
N	4,230	4,230	2,499	2,499	4,230	4,230	2,499	2,499

Table 7: **Future Risk-Adjusted Performance of Bond Mutual Fund Portfolios by Trading Fire Sale Bonds ($TFSB$)**

This table reports future risk-adjusted performance of portfolios of bond mutual funds sorted according to the most recent Trading Fire Sale Bonds ($TFSB$) measure. Trade fire sale bond measure ($TFSB$) is the percentage of a fund's dollar-valued trades used to purchase fire sale bonds over the quarter, averaged over the prior 12 quarters (three years). It captures a fund's tendency to persistently trade fire-sale fallen-angel bonds. We report alphas based on gross NAV returns and holdings-based returns from the four-factor risk adjustment model following (Elton, Gruber, and Blake (2009), Gutierrez, Maxwell, and Xu (2009), and Cici and Gibson (2012)). Two additional holdings based measures: the Characteristics Selectivity (CS) and Characteristics Timing (CT) for bond funds following Cici and Gibson (2012)) are also reported. The corresponding t-statistics are reported in parentheses. ***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively.

FSB Portfolio	TFSB	Gross NAV Return Alpha	Holding Return Alpha	Characteristic Selectivity Alpha	Characteristic Timing Alpha
Low	0.24%	-0.076^{**}	-0.075^{*}	0.025^{*}	0.010
		(−2.048)	(−1.93)	(1.678)	(0.989)
P2	0.77%	−0.019	−0.021	0.033^{*}	0.022
		(−0.652)	(−0.562)	(1.84)	(1.43)
P3	1.36%	0.005	0.049	0.064^{***}	0.040^{***}
		(0.156)	(1.164)	(3.049)	(2.895)
P4	2.06%	0.066	0.059	0.022	0.033^{***}
		(1.610)	(1.301)	(0.882)	(2.649)
High	3.90%	0.095^{***}	0.124^{***}	0.077^{***}	0.034^{**}
		(2.621)	(2.984)	(2.835)	(2.539)
High-Low	3.67%	0.171^{***}	0.199^{***}	0.052^{***}	0.024^{***}
		(3.436)	(4.257)	(2.621)	(3.185)

Table 8: **Bond Mutual Fund Performance Decomposition**

This table decomposes holdings returns of bond fund portfolios sorted according to the most recent Trade Fire Sale ($TFSB$) measure into two components: holdings return of speculative-grade bonds and holdings return of investment-grade bond. Within speculative-grade bond component, we further decompose holdings returns into with fire sale bond return and without fire sale bond return. Four factor risk adjusted alphas of holdings return are reported. Corresponding t-statistics are reported in parentheses below. ***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively.

Portfolio	FSB and Non-FSB Component	FSB Holding Component	Other Speculative-Grade Component	Investment -Grade Component
Low	−0.071	−0.146	−0.078	−0.075
	(−1.027)	(−0.835)	(−1.167)	(−1.35)
P2	0.111*	−0.015	0.088	−0.017
	(1.654)	(−0.089)	(1.425)	(−0.368)
P3	0.138***	0.017	0.135***	−0.004
	(2.729)	(0.093)	(2.578)	(−0.07)
P4	0.081	0.004	0.077	0.007
	(1.513)	(0.023)	(1.400)	(0.094)
High	0.137***	0.174	0.139***	0.047
	(2.834)	(0.996)	(2.838)	(0.717)
High-Low	0.208***	0.320**	0.217***	0.122**
	(3.126)	(2.44)	(3.251)	(2.117)

Table 9: **Future Performance of TFSB Portfolios: Investment-Grade Bond Funds and Speculative-Grade Bond Funds**

This table separates bond funds into above (Speculative-Grade Bond Fund) and below (Investment-Grade Bond Fund) median groups based their speculative grade bond holding. In our sample, speculative-grade bond funds on average hold 96% of speculative grade bonds and 4% of investment grade bonds. On the other hand, investment-grade bond funds on average hold 26% of speculative grade bonds and 74% of investment grade bonds.For each group, bond funds are sorted into quantiles based on the most recent $TFSB$. Four different risk adjusted performance are reported: the four-factor adjusted alphas based on *NAV* returns and holdings based returns, Characteristics selectivity (*CS*) and Characteristics Timing (CT) measures. t-statistics are presented in parentheses below.***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Mean $TFSB$		Gross NAV alpha		Holding Return Alpha		Characteristics Selectivity		Characteristics Timing	
Portfolios Sort by FSB Holding	Speculative -Grade Fund	Investment -Grade Fund	Speculative -Grade Fund	Investment -Grade Fund	Speculative -Grade Fund	Investment -Grade Fund	Speculative -Grade Fund	Investment -Grade Fund	Speculative -Grade Fund	Investment -Grade Fund
Low	0.59%	0.14%	0.025	0.106^{**}	0.067	0.091^{*}	0.007	0.034^{*}	0.035^{**}	0.002
			(0.58)	(−2.472)	(1.078)	(−1.933)	(0.181)	(1.822)	(2.395)	(0.26)
P2	1.31%	0.47%	0.093^{**}	0.041	0.147^{***}	0.081^{*}	0.072^{**}	0.034^{*}	0.059^{***}	0.012
			(2.384)	(−1.287)	(2.77)	(−1.958)	(2.364)	(1.839)	(3.354)	(0.655)
P3	1.85%	0.89%	0.086^{*}	0.048	0.104^{*}	0.082^{**}	0.025	0.033^{**}	0.046^{***}	0.015
			(1.848)	(−1.549)	(1.703)	(−2.043)	(0.642)	(2.052)	(3.162)	(0.925)
P4	2.45%	1.45%	0.098^{**}	0.054	0.147^{***}	0.083^{**}	0.052	0.044^{***}	0.042^{**}	0.016
			(2.387)	(−1.208)	(2.714)	(−2.121)	(1.496)	(2.729)	(2.525)	(1.421)
High	4.11%	3.39%	0.111^{**}	0.010	0.166^{***}	0.025	0.072^{**}	0.068^{**}	0.038^{***}	0.013
			(2.55)	(−0.284)	(2.859)	(−0.568)	(2.088)	(2.162)	(2.609)	(0.843)
High-Low	3.52%	3.26%	0.086^{***}	0.095^{***}	0.098^{***}	0.067^{*}	0.065^{**}	0.034	0.002	0.010
			(3.036)	(2.617)	(3.052)	(1.951)	(2.38)	(1.493)	(0.308)	(0.93)

Table 10: **Multivariate Performance Regression of Trading Fire Sale Bond ($TFSB$)**

This table reports results from a multivariate Fama-MacBeth regression. The dependent variable is $PERF$, the monthly measure of fund future performance. For regression analyses, we focus on abnormal holdings returns based on four-factor risk adjustments and various sub-components of the abnormal holdings returns. Specifically, we analyze holdings alphas of speculative-grade versus investment-grade bonds; and holdings alphas of speculative-grade bond component with and without FSBs. The main independent variable is $TFSB$, which is the percentage of a fund's dollar-valued trades used to purchase fire sale bonds over the quarter, averaged over the prior 12 quarters. It captures a fund's tendency to persistently trade fire-sale fallen-angel bonds. EXP is the funds expense ratio, TNA is the log fund size, AGE is the logarithm of fund age plus 1, and $TURN$ is the annual fund turnover. $JUNK$ is the mean weight of a fund's speculative-grade bond holdings over the past year. Regression coefficients are reported and respective t-statistics are reported below in parentheses. ***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Holding Period Return Alpha	Speculative-Grade Fund Return Alpha	Investment-Grade Fund Return Alpha	Speculative-Grade Fund FSB Return Alpha	Speculative-Grade Fund Other Security Return Alpha
Constant	−0.064	−0.335***	0.009	0.212	−0.295**
	(−0.806)	(−2.675)	(0.085)	(0.700)	(−2.360)
FSB Ratio	1.936**	3.584***	0.409	9.957**	3.232***
	(2.348)	(3.781)	(0.278)	(2.549)	(3.438)
RF	0.015***	0.016***	0.014**	−0.001	0.017***
	(3.130)	(2.720)	(2.176)	(−0.057)	(2.717)
Size	0.003	0.002	0.001	−0.023	−0.003
	(0.796)	(0.215)	(0.073)	(−0.879)	(−0.197)
Age	−0.018	−0.003	−0.017	−0.030	0.005
	(−1.459)	(−0.165)	(−0.788)	(−0.558)	(0.234)
Expense Ratio	0.413	1.617***	−0.444	−0.130	1.519**
	(1.562)	(2.644)	(−0.803)	(−0.112)	(2.407)
Turnover	0.000	0.084**	−0.001	−0.019	0.079**
	(0.038)	(2.574)	(−0.133)	(−0.420)	(2.393)
Junk	0.053	0.089	0.027	0.207	0.065
	(0.400)	(0.835)	(0.186)	(0.876)	(0.587)

Table 11: **Further Fund Performance of Trading Non-Fire Sale bonds (*TNFSB*)**

This table investigates the relationship between future fund performance and Trade Non-FSB Fire Sale bonds (*TNFSB*). The dependent variable is a monthly measure of fund future performance. For regression analyses, we focus on abnormal holdings returns based on four-factor risk adjustments. The main independent variable is *TNFSB*, which is the percentage of a fund's dollar-valued trades used to purchase Non-FSBs over the quarter, averaged over the prior 12 quarters. It captures a fund's tendency to persistently trade none fire sale fallen-angel bonds. *EXP* is the funds expense ratio, *TNA* is the log fund size, *AGE* is the logarithm of fund age plus 1, and *TURN* is the annual fund turnover. *JUNK* is the mean weight of a fund's speculative-grade bond holdings over the past year. Regression coefficients are reported and respective t-statistics are reported below in parentheses. ***, ** and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Holding Return Alpha
Constant	−0.055
	(−0.626)
Non-FSB Ratio	0.535
	(0.655)
rf	0.012***
	(2.919)
Size	−0.002
	(−0.585)
Age	−0.011
	(−0.908)
Expense Ratio	0.206
	(0.776)
Turnover	−0.007
	(−0.989)
Junk	0.119
	(0.970)