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Clientele Change, Persistent Liquidity Shock, and Bond Return Reversals After Rating Downgrades*

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Abstract

Analysis of the actual holdings of bond mutual funds and transaction data of insurance companies during the period between 2003 and 2007 confirms a clientele change when a corporate bond is initially downgraded to "junk" status. Investment-grade bond funds and insurance companies are forced to sell to meet their investment constraints, creating a persistent price concession of around 2%; prices recover partially after almost three months. High-yield bond funds and hedge funds specializing in distressed securities benefit from providing liquidity during these downgrade events. The clientele change is greater for bonds held by more constrained mutual funds. We do not find a persistent liquidity shock around similar downgrades when the threshold between investment grade and speculative grade is not crossed.

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1 Introduction

Short-term return reversals in security prices are well documented. The reversals in stock prices noted by Fama (1965) have been shown to be both robust and economically important (Jegadeesh, 1990; and Lehman, 1990). One explanation for return reversals is the price pressure that can occur when the short-term demand curve of a stock is downward sloping. In the model of Campbell, Grossman, and Wang (1993), for example, non-informational trades lead to a temporary price concession that, when absorbed by liquidity providers, results in a reversal in price that serves as compensation for those who provide liquidity. Nevertheless, there remain many outstanding questions with regard to price reversals. How long does it take the market to absorb such price pressure? How are market structure and the identity of the market participants related to the resolution of such price pressure? What motivates the trades of different market participants? That is, why do many agents decide to trade a considerable amount of a particular asset at the same time for non-informational reasons?[1] We attempt to shed some light on these questions by examining the link between persistent liquidity shocks and return reversals in the market for US corporate bonds. Answers would help us better understand asset pricing under frictions and aid in security market design.

Corporate bonds are an important asset class. As of the end of 2007, the US corporate bond market exceeded $5.8 trillion, or more than one-third the size of the US stock market.[2] This market has several advantages over the equity market for the purpose of analyzing persistent liquidity shocks and their impact on asset prices. First, it is on average much less liquid than the equity market, suggesting a more downward-sloping demand curve for the securities. Price pressures typically do not last for more than a few days in the equity market, but liquidity shocks in the corporate bond market are likely to be larger, more persistent, and easier to detect. Second, the corporate bond market tends to be dominated by large institutional investors who are arguably more sophisticated and better informed than individual investors. Consequently, return reversals are less likely to be

[1] One example of a "pure" liquidity shock in the equity market is related to S&P index additions and deletions. Lynch and Mendenhall (1997) document that index funds trade heavily around the effective date of the index change to minimize their tracking errors. Such abnormal trading triggers a non-information-motivated liquidity shock which in turn causes a short-term return reversal.

[2] Source: Securities Industry and Financial Markets Association (SIFMA): http://www.sifma.org/research/statistics/statistics.html.

driven by behavioral-based overreaction.[3] Finally, and perhaps most important, we are able in this market to identify a clear cause of the liquidity shocks that lead to return reversal.

Table 1 tabulates the corporate bond holdings of different types of investors for 2003 – 2007. As of 2007, individual investors held 14% of corporate bonds and institutions held the remaining 86%. Most institutions face varying degrees of restrictions on holding non-investment-grade corporate bonds or "junk" bonds (bonds rated Ba and below by Moody's, or BB and below by S&P). Savings and loans have been prohibited from holding junk bonds since 1989 (see Cantor and Packer, 1997). In 1991, the National Association of Insurance Commissioners (NAIC) imposed higher reserve requirements on insurance companies' holdings of junk bonds, specifying a 20% cap on the assets insurers may hold in junk bonds. Many pension funds place limits on the fraction of a portfolio that can be invested in junk bonds. Investment-grade bond mutual funds can hold up to only 5% of assets in junk bonds and must sell any security if it falls below a "B" rating (see Kisgen, 2007). A similar 5% cap is imposed on money market funds because of the Investment Company Act of 1940 (see Yago, 1991).

These investment restrictions mean that a clientele change is likely to happen when a corporate bond is downgraded to junk status — institutions that are affected by investment restrictions are forced to sell such bonds. If there are no ready buyers on the other side of the market, a liquidity shock will occur.[4] The liquidity shock can be particularly persistent for downgraded corporate bonds for at least two reasons. First, it takes time and human capital for an investor to identify a profitable opportunity and then act on it (see Berndt, Douglas, Duffie, Ferguson, and Schranzk, 2005 and Weill, 2007). Such "capital immobility" is especially relevant for junk bonds. Second, the over-the-counter nature of the corporate bond market could further prolong the dissipation of a liquidity shock (Duffie, Garleanu, and Pedersen, 2005 and 2007). As a result, the bond price will be temporarily depressed and will recover only over time after more buyers come to the market. Such price recovery compensates the buyers for providing liquidity at a time it is most needed.

In a comprehensive sample of almost 2,300 bonds issued by 126 distinct issuers during 2003

[3] See Gebhardt, Hvidkjaer and Swaminathan (2005) for such an arguement.

[4] There is some anecdotal evidence that selling pressures due to credit constraints or investment constraints. For example, Glenn Schorr, an analyst at UBS AG, described market conditions after Lehman Brothers was filing for bankruptcy, "There have been tough situations like Long-Term Capital Management and the crash of 1987, but the problem here is there is leverage in the securities under the microscope and in the banks that own them. *And to try and unwind it all at once creates a one-way market where there are only sellers, and no buyers.*" (Wall Street Journal, September 15, 2008, A1; italics added.)

and 2007, we document a large and persistent price concession followed by a gradual price recovery after a bond is downgraded from investment grade ("Baa" by Moody's) to non-investment grade ("Ba" by Moody's). During the first three months after announcement of the downgrade, the bond price drops by 2% on a risk-adjusted basis, to recover gradually by about 1% during the next three months. We show that such prolonged price reversal is statistically significant even after controlling for contemporaneous and lagged stock returns and many bond-specific characteristics. The price recovery is also economically significant. A calendar portfolio formed to take advantage of post-downgrade price recovery produces a significant abnormal return of about 50 bps per month after accounting for systematic risk.

Interestingly, such a sizeable and prolonged price reversal occurs only when the threshold between investment grade and non-investment grade is crossed. When bonds are downgraded either from "A" to "Baa" (investment grades) or from "Ba" to "B" (non-investment grades), the initial price concession after announcement of the downgrade is much smaller (50 bps at most), and the price quickly reverses within a month.

We also provide evidence of a significant liquidity shock immediately after a bond is downgraded from investment grade to non-investment grade. Using actual National Association of Insurance Commissioners (NAIC) transaction data for insurance companies, and following the methodology in Bessembinder, Maxwell and Venkataraman (2006), we find that the one-way trade execution cost increases by almost 18 bps (from 28 bps) during the first six months after announcement of a downgrade. No such liquidity shock in terms of increased transaction cost is observed for the other two types of downgrades.

Analysis of the quarterly holdings of bond mutual funds and transaction data of insurance companies during the same period reveals a clientele change on bonds downgraded from investment grade to non-investment grade. In the case of insurance companies, we find significant selling pressure on the downgraded bonds. Investment-grade bond mutual funds similarly reduce their holdings of these bonds on average. These institutional sales reflect the companies' investment constraints.

When one group of investors is forced to sell bonds because of investment constraints, investors without investment constraints can benefit by taking the other side of the trades. High-yield bond mutual funds investing in junk bonds seem to be the natural candidates to provide this liquidity.

When we examine holding changes of high-yield bond mutual funds, we indeed uncover strong buying activities on downgraded bonds.

Another potential group of buyers of recently downgraded bonds is hedge funds that specialize in distressed securities. While information on their actual transactions is not available, we can infer their trades by examining returns. Return on a calendar portfolio formed to take advantage of post-downgrade price recovery is significantly positively correlated with the return to a hedge fund index tracking the performance of hedge funds specializing in distressed security investment. Abnormal returns on the calendar portfolio can also be largely explained by the hedge fund index return. This indirect evidence supports our conjecture that hedge funds specializing in distressed securities indeed benefit from liquidity provision in downgrade scenarios.

Finally, we obtain two pieces of evidence from cross-sectional analysis of individual downgraded bonds, further supporting the notion that the large and persistent price concession on bonds recently downgraded to junk status is a result of clientele change attributable to the investment constraints of financial institutions. We find that (1) downgraded bonds held by institutions with more binding investment constraints are more likely to be sold; and (2) bonds experiencing more selling pressure will encounter larger price concessions immediately after downgrade events.

Overall, our findings support the notion that liquidity can disappear quickly, making it very costly for those forced to sell, and generating a persistent price impact (Shleifer and Vishny, 1992). Coval and Stafford (2007) document such a persistent liquidity shock in the equity market when mutual funds are forced to transact for fund flow reasons. We show that the liquidity shocks can occur in the bond market following a bond downgrade. Our work is also related to that of Gebhardt, Hvidkjaer, and Swaminathan (2005), who documents short-term bond return reversals among investment-grade bonds. We point out that such return reversals can be much stronger following a downgrade event that crosses the investment-grade threshold. While Gebhardt et al. focus exclusively on quoted bond prices of investment-grade bonds, we use transaction prices and trading volume information, which allows us to analyze the liquidity aspects of bond trading more precisely. More recently, Acharya, Schaefer, and Zhang (2008) identify significant liquidity risk following the rating downgrades of GM and Ford in 2005. They focus, however, on correlation risk due to the commonality in market making activities.

Our research contributes to several other strands of literature. First, the fact that bonds downgraded from investment grade to non-investment grade experience an average permanent excess return of 1% is consistent with a long-term downward-sloping demand curve for bonds. If the new bond holders, such as high-yield mutual funds and hedge funds, trade more frequently than the previous bond holders such as high-grade mutual funds and insurance companies, such a clientele change would increase the supply of bonds in circulation, putting downward pressure on the market clearing price. Note also that the permanent price impact takes effect gradually after the downgrade announcement, a price pattern that cannot easily be explained by information content associated with the downgrade, which should predict a permanent price impact on the announcement day but no post-announcement drift. Shleifer (1986), Lynch and Mendenhall (1997), and Wurgler and Zhuravskaya (2002) have documented the downward-sloping demand curve in the equity market, we show it might also obtain in the bond market.

Second, the large and persistent price concession on the trading of downgraded bonds and the subsequent price reversals have important implications for future empirical research on bond returns. Our work complements recent methodological synthesis of Bessembinder, Kahle, Maxwell, and Xu (2008) who provide general guidance on event study using actual bond returns. If the initial price concession can last up to three months after certain corporate events, then examining post-event returns over a short window might not be sufficient. Da and Gao (2008) highlight the important role of short-term stock price reversals in studying the returns on financially distressed stocks. One must take care to account for the effect of short-term return reversal in studying bond price reactions to news, especially in relation to stock price reactions.

Finally, this paper is related to the literature on the trade-offs between timeliness and stability of ratings (Fons, Cantor and Mahoney, 2002).[5] The usual argument for the stability of ratings is that frequent rating changes can be disruptive to the operation of underlying economic entities (see Boot, Milbourn, and Schmeits, 2006). We provide empirical support for another rationale. That is, maintaining relatively stable ratings limits the effect of temporary price pressure induced by trades related to investment constraints of some classes of institutional investors. In another words, maintaining relatively stable ratings benefits not just the bond issuers but also institutional

[5] Fons, Cantor and Mahoney (2002) argues: "Issuers want stability in ratings and the opportunity to make changes in their financial condition, if possible, to avoid changes in ratings. Investors want ample notice of potential rating changes, in part because of investment requirements and restrictions that may be placed on them by owners of funds or their representatives such as endowments and pension fund sponsors, and especially with respect to rating changes resulting in changes in indices against which the investors may be measured."

bond investors and other participants in the bond market.

The rest of the paper is organized as follows. Section 2 describes the sources of data and how we construct our sample. Section 3 illustrates a large and persistent price concession followed by a gradual price recovery on the bonds recently downgraded from investment grades to non-investment grades and such price reversal coincides with a liquidity shock. Section 4 provides collaborating evidence consistent with the existence of a clientele change which triggers the liquidity shock. Section 5 presents the results of cross-sectional analysis. Section 6 concludes.

2 Data Sources and Construction

We obtain data from several sources. We provide here some detailed descriptions of these data sources and how we construct our sample.

2.1 Corporate Bond Returns and Bond Characteristics

To the best of our knowledge, we are the first to use actual transaction data to examine bond returns around rating downgrades. We obtain tick-by-tick bond transaction data from Trade Reporting and Compliance Engine (TRACE). Since July 2002, TRACE has consolidated transaction data for all eligible corporate bonds — investment-grade, high-yield and convertible-debt. TRACE is an over-the-counter (OTC) corporate bond market real-time price dissemination service. Its coverage of bond transactions improves over time as regulatory reporting requirements on average increase. By the end of 2007, individual investors and market professionals could access on TRACE information on all OTC activity, representing over 99% of the total US corporate bond market activity in over 30,000 securities.[6] TRACE provides bond identification information in both Committee on Uniform Security Identification Procedures (CUSIP) codes and the National Association of Securities Dealers Automated Quotation System (NASDAQ) symbols, as well as information on the date and time of trade execution, the price and the yield. It does not completely report the trade size information. For investment-grade bonds, the trade size reported by TRACE is truncated at $5 million; for non-investment-grade bonds, the trade size reported is truncated at $1 million. From an academic

[6] Bessembinder, Maxwell, and Venkataraman (2006), Edwards, Harris, and Piwowar (2006), and Goldstein, Hotchkiss, and Sirri (2007) provide a complete description of TRACE. They also show that introduction of TRACE enhances bond market transparency, and on average reduces transaction costs.

research point of view, one important limitation of TRACE data is lack of a buy-sell indicator. Furthermore, we cannot even indirectly infer the direction of trades because the quote data are not available.

TRACE data do allow us to construct actual transaction price-based bond returns and increase the power of statistical tests as shown in Bessembinder, Kahle, Maxwell, and Xu (2008). Note also that there are a number of problematic trades in the TRACE database that likely represent data errors. Following the Bessembinder et al. data cleaning procedure, we eliminate cancelled, corrected, commission trades from TRACE, and trades with extreme returns. TRACE reports the "clean" price; i.e., the traded price of bonds does not include the accrued interest payable at settlement. For research on bond returns around a short event window, using bond returns based on clean prices can be justified because the associated accrued interest is typically low. To examine bond returns for periods up to six months, however, it is necessary to consider accrued interest. Furthermore, incorporating accrued interest is consistent with our use of the benchmark bond return indices constructed by Lehman Brothers, which are total return indices including accrued interest.

Following Bessembinder, Kahle, Maxwell, and Xu (2008), we compute bond returns as

$$R_{t-1:t} = \frac{(P_t - P_{t-1}) + AI_{t-1:t}}{P_{t-1}} \tag{1}$$

where $R_{t-1:t}$ is bond return including accrued interest during period $[t-1, t]$, P is the price of the bond and $AI_{t-1:t}$ denotes the accrued interest. The bond price on day t (P_t) is the trade-size-weighted-average of all trade prices during that day. To calculate the accrued interest, we use bond issuer and bond characteristics information from the Mergent's Fixed Income Security Database (FISD), which provides detailed information on coupon rates, payment schedule (for floating-rate bonds), payment frequency and bond denomination. Following Campbell and Taksler (2003), we also eliminate from our sample bonds with special features (preferred stocks, pass-throughs, convertible bonds, callable bonds, puttable bonds and bonds denominated in foreign currencies) using the bond characteristic file.

To obtain risk-adjusted bond returns, we use the Lehman Brothers bond indices, obtained from the Datastream.

2.2 Credit Rating and Rating Changes

We obtain credit rating information from Moody's. We focus on three types of "Downgrade" events. "dg1" refers to a Moody's downgrade from "A" to "Baa"; "dg2" refers to a downgraded from "Baa" to "Ba"; and "dg3" refers to a downgraded from "Ba" to "B". Event "dg2" is of particular interest to us, as this is when a bond is downgraded from investment grade to junk status. At the same time, "dg1" and "dg3" serve as good control events. In the first case, both pre- and post-ratings are investment grades; and in the second case, both pre- and post-ratings are non-investment grades. Neither of these cases should lead to a clientele change.

To be able to relate downgrade events to bond transactions, we include in our sample only bonds covered by TRACE at the time the downgrade event occurs. Specifically, we include bonds only when the entire [-1, 120] event window is covered by TRACE, where day zero is the date of the bond downgrade. In addition, to ensure the set of bonds we consider is relatively liquid, the bond has to be traded at least once during the week prior to the event to be included in our sample.

Table 2 reports some sample statistics for the event bonds between 2003 and 2007. There are 3014 "dg1" event bonds issued by 127 distinct issuers, 2288 "dg2" event bonds issued by 126 distinct issuers and 828 "dg3" event bonds issued by 144 distinct issuers. A large percentage of these bonds were issued by GM or Ford. For example, GM had 1006 bonds downgraded from "A" to "Baa" on November 4, 2004, and 1207 bonds downgraded from "Baa" to "Ba" on August 24, 2005. Ford had 550 bonds downgraded from "A" to "Baa" on May 12, 2005, 552 bonds downgraded from "Baa" to "Ba" on January 11, 2006, and 469 bonds downgraded from "Ba" to "B" on September 19, 2006. The other larger issuers in our sample are SLM Corp (568 bonds downgraded from "A" to "Baa on August 14, 2007) and DaimlerChrysler (323 bonds downgraded from "A" to "Baa" on September 15, 2006). To ensure that our results are not driven by these large issuers, we conduct our analysis mainly at the issuer level. In a robustness check, we also carry out analyses by excluding bonds issued by GM and Ford, and the results are the same.

2.3 Stock Returns

In the empirical analysis, we include stock returns of the issuer obtained from the Center for Research in Security Prices (CRSP) database as a control variable. This requires us to match each bond to the corresponding firm in CRSP. The Mergent-FISD database usually records only the original issuer's (or its subsidiary's) name, but after corporate transactions such as mergers, acquisitions and spin-offs, the original bonds will be integrated into the new company's capital structure. Therefore, special care must be taken to ensure all bonds are matched to the appropriate company.[7]

To ensure an accurate match between stock information from CRSP and bond information from Mergent-FISD, we verify each match, and make corrections using a variety of information sources, including Factiva News Wire, Security and Data Corporation (SDC) corporate transaction data and internet searches. Most often when we cannot find a valid CRSP return during the event window, these are privately held companies, stocks not traded on the main exchanges or not common shares.

2.4 Insurance Company Corporate Bond Transactions

Insurance companies are important players in the corporate bond market. We examine their corporate bonds transactions using the National Association of Insurance Commissioners (NAIC) transaction data. NAIC data provide detailed transaction information, including date, price and size of trade. We link NAIC transaction data to other databases using issue CUSIP, and go through the same cross referencing process as detailed before.

Insurance companies consistently held more than 20% of all US corporate bonds during our sampling period from 2003 to 2007 (see Table 1). According to Bessembinder, Maxwell, and Venkataraman (2006), insurance companies represented 12.5% of the dollar trading volume in TRACE-eligible bonds during the second half of 2002.

Panel A of Table 3 provides summary statistics about insurance company trades in the three types of events. Overall, insurance companies as a group sell more event bonds than they buy, particularly in the case of the two groups receiving non-investment grades ("dg2" and "dg3"). In our sample of corporate bond downgrade events, insurance company transactions within a one year event-window before and after bond downgrades amount to more than $144 billion (in par

[7] An example illustrates this point. In our sample, Tenneco Packaging was a subsidiary of Tenneco Inc. (NYSE: TEN). On October 5, 1999, the Tenneco Packaging issued bonds with CUSIP numbers 880394AB7, 880394AD3, and 880394AE1. On November 4, 1999, Tenneco Packaging underwent a tax-free spin-off from Tenneco Inc., and the new company was traded on the NYSE under name Pactiv Corp. (NYSE: PTV). In the Mergent-FISD database, all of these bonds are recorded under the issuer name Tenneco Packaging. Without taking into account the spin-off transactions, one would erroneously conclude the corresponding stock should be Tenneco Inc.

value) of corporate bonds. Of these transactions, \$52 billion was in buyer-initiated transactions (about 37%), and \$92 billion in seller-initiated transactions. About 42% of the insurance company transactions involve bonds downgraded from investment grade to non-investment grade for the first time; 40% of them involve bond downgrades within the investment grades, and the remaining 18% of the transactions involve non-investment bond downgrades.

There are some noticeable differences in the distribution of buyer-initiated versus seller-initiated transactions. For the "dg2" category (bonds downgraded from investment grades to non-investment grades), 66% of the trades (68% of the dollar volume) are seller-initiated, resulting in considerable selling pressure. For the "dg1" category (bonds downgraded within the investment grades), however, 56% of the trades (53% of the dollar volume) are seller-initiated. For the "dg3" category (bonds downgraded from Ba to B), there is significant selling from the insurance companies as a group. For this category, however, the total dollar volume of transactions or the net selling in dollar volume is much lower than for the other two categories, consistent with insurance company constraints on holding junk bonds.

2.5 Bond Mutual Fund Holdings

We obtain the bond mutual fund holdings from the CRSP US Survivor-Bias-Free Mutual Fund Database. We separate the set of bond mutual funds into two groups based on the bonds they hold. The first group is more likely to hold high-yield bonds, or bonds with lower credit ratings. The second group is more likely to hold investment-grade bonds. To identify the high-yield bond mutual funds, we use the Standard &Poor's style classification code (available since July 2003) provided by the CRSP database.[8]

We can identify 77 unique high-yield bond funds and 269 unique investment-grade bond funds. We exclude all bond funds specializing in emerging markets, municipal bonds and money market funds. In theory, money market funds should not be excluded from our sample, because, like other investment-grade bond funds, they must invest in bonds with ratings above a certain investment threshold. CRSP coverage of the holdings of the money market funds is sparse and sporadic, however; it has only four money market funds with consecutive quarters of portfolio holdings.

[8] Specifically, the high-yield funds include all bond funds with Standard & Poor's style code "FJI". To identify the set of investment-grade funds, we retain the set of bonds with S&P style codes "FHI", "FHL", "FHS".

Thus, we eliminate the money market funds.

We know relatively little about bond mutual fund holding characteristics because there have been limited holdings data available. We therefore provide some initial descriptive statistics of bond mutual fund holding characteristics in Panel B of Table 3. We report the equally weighted and value-weighted bond mutual fund holding characteristics such as bond rating, age (years since issuance of the bonds), offering size (in thousands of dollars), average offering yield (in percentage), offering maturity (in years), time until maturity (in years, as of the portfolio reporting date), as well as number of bonds in the portfolio. When we compute the value-weighted characteristics of the bond portfolios, we use the end of quarter market value of the holding positions recorded by CRSP. To obtain these summary statistics, we first aggregate all bond positions by the end of the quarter, and then take the time-series average of these characteristics. Panel B reports the cross-sectional means of these time-series averages.

Several patterns emerge in the figures. First, our sample of bond mutual funds holds relatively unseasoned bonds. Average age of bonds in the portfolios is about four years. Bond maturity, measured from the date of issuance, is about seven years (value-weighted) to ten years (equally weighted). Second, the bond funds in our sample tend to hold relatively large bond issues; average offering sizes range from \$1 billion to \$4 billion, depending on how offering size is computed (equally weighted vs. value-weighted; mean or median). To put these numbers into perspective, we also compute the average offering size decile breakpoints for all the bonds in the Mergent-FISD database. Median offering size in this case is about \$32 million — the bonds held by the funds are above 90th percentile of the bond offering size at the time of issuance. The bond funds' preference for larger and unseasoned bonds may reflect liquidity concerns. Warga (1992) suggests that as a bond becomes more seasoned, it becomes less liquid, because inactive investors progressively absorb the original issues, and trading of the bond becomes thinner. Hong and Warga (2000) also show that larger bond issues have significantly narrower bid-ask spreads.

Breaking the full sample of bond mutual funds into high-yield bond funds and investment-grade bond funds shows that these two groups of funds prefer different sets of bonds. The most salient difference between the high-yield and investment-grade funds is of course the average credit rating of the bonds. As expected, the average credit rating of bonds held by high-yield bond funds is about 6 (where 1 is "Aaa" and 10 is "D"), while the average credit rating of bonds held by the investment-grade bond funds is about 3. The average offering yield (at time of issuance) of the high-yield bond funds is about 8% per year, compared to average offering yields for investment-grade funds of about 6%. The offering size of bonds held by high-yield bond funds is about $500 million, compared to about $2.0 to 4.4 billion for the investment-grade bond funds. The difference in offering size is consistent with the observed difference in credit risk, as larger offerings tend to have lower credit risk and higher credit ratings. The significant differences in average credit rating, offering yield and offering size of these two classes of bond funds illustrate that our style-based classification scheme does a reasonably good job in separating the high-yield funds from the investment-grade funds.

3 Return Reversal and Liquidity Shock

First we analyze bond returns after the announcement of downgrades across the three event types. We then use both event-time and calendar-time portfolio regressions to examine the economic and statistical significance of our results.[9] Finally, we provide evidence consistent with a liquidity shock during a period that coincides with the price reversal.

3.1 Event-Time Evidence

We compute cumulative event returns on each of the three event portfolios for an event window starting from the last trading day before the announcement to the 120th trading day (about 6 months) after the announcement ([-1, 120] event window). The bond returns (including accrual interest) are first size-weighted at the issuer level using the offering amount of the bond as the weight, and then equal-weighted across issuer. This procedure ensures that our event portfolio returns are not driven by large issuers. Finally, to account for different systematic risk exposures associated with bonds with different credit ratings, we risk-adjust the event portfolio returns using the returns on the appropriate Lehman Brothers bond index. For example, the risk-adjusted return on "dg1" event portfolio is computed in excess of the return on Lehman Brothers US credit "Baa" index.

[9] Using both calendar-time and event-time approaches ensures our results are not subject to the criticism of Fama (1998) and Loughran and Ritter (2000). Fama (1998) advocates a calendar-time approach. Loughran and Ritter (2000) provide an analysis on the statistical power of calendar-time versus event-time portfolio approaches to identify abnormal returns.

Figure 1 plots the cumulative risk-adjusted returns on the three event portfolios during the $[-1, 120]$ event window. The most striking result occurs for bonds downgraded from investment grade to non-investment grade. We see persistent price pressure, with an average cumulative price concession of 200 basis points by the end of the first quarter. The price starts to recover after 60 days, and recovers by about 50% (or 100 basis points) at the end of the event window.

Such large and persistent price concession, followed by a gradual price recovery, is not observed for the other two downgrade announcements. Bonds that are downgraded from "A" to "Baa" ("dg1" bonds), experience a much smaller and much quicker reversal. This price drops by less than 40 bps in about 7 days and recovers to its pre-announcement level within 20 days. Bonds that are downgraded from "Ba" to "B" ("dg3" bonds) experience a slightly prolonged price reversal of approximately 50 bps. Both the large persistent price concession and subsequent gradual price recovery following Baa to Ba downgrades stand in sharp contrast to the short-term price reversals on the other two types of bonds. The cumulative risk-adjusted returns across all three types of bonds become flat after 6 months and therefore are not plotted in Figure 1.

Table 4 confirms these price patterns and shows their statistical significance. We first compute the cumulative excess returns for each individual event bond during various event windows. These excess returns (including the accrued interest) are again size-weighted at the issuer level (using the offering amount of the bond as the weight). We then report the average excess returns across issuers for each event type and the associated t-values.[10] First, all three types of event bonds significantly underperform their respective benchmarks during the $[-120, -1]$ pre-announcement event window (corresponding to the six months prior to the downgrade announcements). The underperformance is worse for "dg3" bonds (-1.85%) than for "dg1" bonds (-0.65%), and "dg2" bonds (-1.70%). Underperformance of these downgraded bonds relative to their benchmarks prior to the rating change announcements is consistent with findings elsewhere that bond markets anticipate rating changes. For instance, Hite and Warga (1997) document significantly negative abnormal returns in the 6 months before actual downgrades. Consistent with the pattern in Figure 1, we find that the "dg2" bonds experience an initial price drop of about -1.80% (with a t-value of -2.64) during

[10] Since we compute cumulative event-window bond returns for individual bonds first before averaging them in the cross section, the resulting cumulative event portfolio returns could differ from those plotted in Figure 1 where we compute average daily event portfolio returns first before compounding them over time to arrive at the cumulative returns.

the $[1, 60]$ event window (or the first three months after the downgrade), the price then recovers by about 80 basis points (with a t-value of 1.85) during the next three months. Overall, the "dg2" bonds experience a net permanent price impact of 1.43% during the $[-1, 120]$ event window as a result of the downgrade announcement. We do not observe such a large and persistent price reversal or a significant price impact in the other two event categories.

Table 4 also reports abnormal trading volume after the downgrade announcements. Abnormal trading volume is defined as the average monthly dollar trading volume during the event window after the announcement scaled by the average monthly dollar trading volume before the announcement (during the event window $[-120, -1]$), minus one. In other words, it reflects the percentage change in the dollar trading volume. As expected, trading volume increases significantly after the downgrade announcement for all three types of events. The abnormal trading volume is lower for "dg2" bonds, which is in part due to the truncation issue with TRACE: the dollar trading volume is truncated at $5 million for an investment-grade bond but at $1 million for a non-investment-grade bond. The truncation problem creates a downward bias in the calculation of abnormal trading volume only for the "dg2" bonds, so these reported abnormal dollar volumes are likely to be understated.

To formally estimate the economic magnitude and the statistical significance associated with the return reversal, we conduct various regressions. Motivated by the empirical price reversal pattern observed in Figure 1, we regress the cumulative risk-adjusted bond returns during the second half of the event window [61, 120] on the cumulative risk-adjusted bond returns during the first half of the event window ([1, 60]).

All regressions control for the stock returns during these first and second event-windows for different reasons. First, to ensure our results are not driven by potential delayed reflection of stock market information in the bond market, we include the first-period stock returns as a control variable. Kwan (1996) finds that lagged stock returns have explanatory power for current bond yield changes, but not vice versa, and suggests the stocks lead bonds in reflecting firm-specific information. Using intraday transaction data on stocks and high-yield bonds, Hotchkiss and Ronen (2002) find stocks and bonds seem to reflect firm-specific information at roughly the same time, and one does not lead or lag the other. Gebhardt, Hvidkjaer, and Swaminathan (2005) show lagged stock returns are related to future bond returns in the so-called stock momentum spillover effect.

Using a more comprehensive sample of high-frequency bond transaction data, Downing, Underwood and Xing (2007) show the corporate bond market is less informationally efficient than the stock market despite the reduction of transaction costs and increase in market transparency.

Second, to sort out the net impact of lagged bond returns on current bond returns, we control for current stock returns in the regression. Dichev and Piotroski (2001) show that there seems to be some prolonged downward drifts in stock prices after bond downgrades. On the one hand, if both stock and bond returns respond to new information about the value of the issuing firm's underlying assets, as reported by Hotchkiss and Ronen (2002) and Bessembinder, Maxwell, and Venkataraman (2006), then bond prices should also exhibit a downward drift. On the other hand, if deteriorating credit conditions trigger creditor intervention that improves the performance of the firm, the bond value could increase. For instance, Nini, Sufi and Smith (2008) provide some evidence that private credit arrangements usually impose credit rating-sensitive covenants that improve firms' performance after rating downgrades.

We report the regression results in Table 5. In Panel A bond returns are aggregated at the issuer level first using the offering amount of bonds at issuance as the weights. Regressions (1) through (4) are ordinary least square (OLS) regressions, where the standard errors are computed using White's (1980) procedure. Although this sample of bonds is relatively large in terms of both number of issuers and number of issues, from a statistical point of view, the number of issuers is small. To guard against potential undue impact of outliers, we also carry out robustness checks using the median regressions in columns (5) to (8).

The OLS regression in (1) and the median regression in (5) show that across all the bonds in our sample, there is an economically sizable and statistically significant return reversal effect after bond downgrades. The regression coefficients on the lagged bond return are -0.28 to -0.32, depending on the regression model. In general, current stock returns are positively and statistically significantly correlated with concurrent bond returns. After controlling for the concurrent stock returns, the lagged stock returns are not reliably related to the current bond returns. Lagged stock returns are low and statistically insignificant.

Both OLS and median regressions confirm a significant price reversal, and the reversal is driven entirely by the first downgrades to non-investment grade, the "dg2" event bonds. Among this set of bonds, the later bond event window ([61, 120]) returns are significantly negatively related to the first bond event window ([1, 60]) returns. The regression coefficients on the lagged bond return are -0.48 to -0.49, and significant at the 1% level. Thus, almost half of the first-period bond returns are reversed by the end of the second period. This is consistent with the return reversal pattern in Figure 1. We also should emphasize the goodness of fit of the regressions on the "dg2" event bonds. The R-square in the OLS regression is about 0.44, double that of the "dg1" event bonds (about 0.22), and much higher than that of the "dg3" event bonds (about 0.01). The pseudo R-square in the median regression displays a similar pattern.

From Table 2, we know there are some time-series variations in bond downgrade events across years. To ensure our results are not driven by a specific calendar year, in Panel B of Table 5 we include the year fixed effect. The results of these fixed-effect regressions are similar to the regression results in Panel A, which suggests that the large and persistent price reversal on "dg2" event bonds is not driven by any particular calendar year.

In Panel C, we carry out the OLS regressions at the individual bond issue level, which allows us to control for individual bond-specific characteristics such as number of trades prior to the rating change (*LogPriorTradesNum*) and issue size in terms of the face values of the bonds (*LogBondSize*). The standard errors of OLS regressions are clustered at the issuer level following Petersen (2008). These issue-level regressions lead to the same conclusion: There is a large and persistent price concession followed by subsequent gradual price recovery only when a bond is downgraded from investment grade to non-investment grade. The return reversal at the issue-level is greater than return reversal estimated at the issuer-level. The regression coefficients on the lagged bond return are -0.76 to -0.86, significant at the 1% level. If one views the offering size of the bond as related to the average liquidity level of the bond, as suggested by Hong and Warga (2000), the high regression coefficients on the lagged bond return (in absolute values) illustrates that bonds with smaller offering sizes, and consequently less liquid bonds, experience stronger return reversal effects.

3.2 Calendar-Time Evidence

We also provide calendar-time evidence that bonds downgraded to junk status later experience price reversals that are both statistically and economically significant. We form a calendar portfolio for each event as follows. During each trading day, we include a bond in the portfolio if the trading day falls in the [61, 120] post-event window for the bond. The portfolio returns are computed by first size-weighting bond returns at the issuer level (using the offering amount of the bond as the weight), and then equal-weighting issuer-level returns. On any trading day the portfolio includes no bond, we assume the return to be equal to the risk-free rate on that day. Once the calendar portfolio is constructed, we regress the resulting monthly calendar portfolio returns (in excess of the risk-free rate) on various monthly excess return factors. Bond factor denotes the bond index return (with comparable credit rating) minus the risk-free rate. MKTRF, SMB and HML are the Fama-French (1993) three factors. The regression results are provided in Table 6.

The calendar-time portfolio results confirm that bonds recently downgraded to junk status ("dg2" bonds) experience on average a positive and significant monthly abnormal return during the [61, 120] event window after the downgrade announcement. When we use only the Lehman Brothers bond index in the risk adjustment model, the average risk-adjusted return or alpha on the "dg2" calendar portfolio is 58 bps per month (t-value = 2.65) between July 2003 and September 2007. When we add the market excess return factor, the alpha goes down slightly to 56 bps per month (t-value = 2.41). Finally, when we also include the other Fama-French factors (SMB and HML), the alpha goes down further, to 50 bps per month, but is still significant with a t-value of 2.06. The size of the alpha is consistent with what we observe in Figure 1. The factor loadings are in general small and statistically insignificant, with the exception of the high-yield bond factor itself, which is 0.31 and marginally significant (t-value = 1.89).

The return on the "dg1" calendar-time portfolio, however, ranging between 1 to 12 basis points per month and is close to zero after risk adjustments. The "dg1" bond portfolio returns load positively and significantly on the investment-grade bond index return factor (point estimates range from 0.68 to 0.74, and t-values range from 6.65 to 7.10). For the "dg3" bond portfolio, the factor model-adjusted returns are positive but not statistically significant at a conventional level. The "dg3" bond portfolio returns load positively on high-yield bond index, market and SMB factors, but statistically significantly only on the SMB factor. The "dg3" bond portfolio returns are strongly correlated with the high-yield bond factor by itself (point estimate = 0.68, t-value = 2.29). The SMB factor seems to subsume the high-yield bond index return in explaining the "dg3" portfolio returns. The factor loading on the high-yield bond return factor drops to 0.36 (t-value = 1.03), and the factor loading on the SMB factor is 0.47 (t-value = 2.50). The calendar-time portfolio regression results confirm overall that the price reversal following a downgrade is economically significant.

3.3 Liquidity Shock

A plausible explanation of the return reversal phenomenon may be based on the equilibrium model of Campbell, Grossman, and Wang (1993), where non-information-motivated trades trigger a liquidity shock and cause temporary price movements that, when absorbed by liquidity providers, result in a price reversal. Do price reversals coincide with a liquidity shock? Note that we would anticipate significant liquidity shock as illustrated by increased transaction costs after the downgrades for "dg2" bonds, but not for either "dg1" or "dg3" bonds. Bond rating changes represent public news widely disseminated to market participants. We would further anticipate increases in transaction costs for "dg2" bonds to arise mainly from the dealer inventory component, rather than the adverse selection component of total trading costs.

Several recent authors, including Edwards, Harris, and Piwowar (2006), and Goldstein, Hotchkiss, and Sirri (2007), have developed transaction cost estimates using the TRACE database. One crucial data requirement is that there be some version of daily dealer quote data, information not currently available to us. Chen, Lesmond and Wei (2006) propose a version of a "zero-volume" day model to estimate transaction costs, but their model may not apply to our context. This is because their model assumes that if there is a mechanical increase in trading volume due to an exogenous shock, there will be on average a decline in trading costs by construction. In another words, their model may estimate the average transaction costs well, but may not estimate the event-driven change of transaction costs well.

To measure the changes of bond liquidity around rating downgrades, we adopt the transaction costs estimation model of Bessembinder et al. (2006). By relaxing the requirement of dealer quote data, Bessembinder et al. (2006) extend the bond transaction cost model developed by Warga (1991) and Schultz (2001). The main idea is to incorporate observable public information that affects bond value, much like Huang and Stoll (1997) and Madhavan Richardson, and Roomans (1997). The underlying assumption of the empirical implementation is that the public information serves as sufficient statistics for the dealer quote. To save on space, we do not discuss their procedure in detail.

We estimate a two-stage model using NAIC transactions. For data availability reasons, the sampling period ends at 2006 for this estimation. The first stage is estimated as:

$$Q_t = a + bQ_{t-1} + \varepsilon_t, \tag{2}$$

where Q_t denotes an indicator variable that equals 1 if the time t trade is a customer buy and 1 if it is a customer sell. Characterizing ε_t as Q_t^*, the second stage is then estimated as:

$$\Delta P_t = a + wX_t + \gamma S Q_t^* + \alpha S \Delta Q_t + \omega_t. \tag{3}$$

These regressions include three public information variables that are measured from the date of the most recent transaction on a day before the date of the current transaction. The first variable is the change in the interest rate for the on-the-run Treasury security matched to the corporate bond based on maturity (*TreasuryReturn*). The second is the returns of the bond issuer's common stock (*StockReturn*). The third is the change in the spreads between Moody's BAA-rated bonds and Treasury securities (Δ*(BAA-Treasury Spreads)*). To account for potential differences in their sensitivities to the underlying public information variables, these three public information variables are interacted with investment-grade and non-investment-grade indicator variables when such interaction is applicable. To measure the impact of bond rating changes on bond market liquidity, we interact ΔQ with a binary indicator variable (*PeriodDummy*), which equals one if the time period is during the first six months after the rating change; and zero otherwise. All regressions are estimated using weighted least squares (WLS), where the weight is a function of the fraction of time between two trades. We report the regression results for the three event types in Table 7.

Consistent with the findings in Bessembinder et al. (2006), we find generally significant estimated coefficients on the control variables that measure public information flow in (3), highlighting the contribution of public information flow to transaction cost estimation. Coefficient estimates on the stock return variable are positive and statistically significant in all regressions. This is consistent with the notion that both bonds and stocks react to common information about the underlying issuer. For the "dg2" event bonds (downgrades from investment to non-investment grade), the coefficient on stock returns is slightly higher when explaining returns on non-investment-grade bonds but the difference is not statistically significant. A comparison of "dg1" and "dg3" bonds shows that the coefficient on stock returns is slightly higher when explaining returns on "dg3" bonds, but a formal statistical test shows no statistically reliable differences. The "dg1" and "dg2" event bonds exhibit strong correlations with overall interest rates. Coefficient estimates on the treasury return are positive and statistically significant in these two categories of bonds, although the coefficient estimates on the "dg3" bond is not statistically significant. The coefficients on the change of BAA bond and Treasury spreads, which potentially captures the increase in default risk (Fama and French, 1989), are negative and significant for the "dg3" bonds, but generally close to zero for the "dg1" and "dg2" bond.

Several regression results are evident for the level of and the change in transaction costs. First, the coefficient on ΔQ estimates one-way trade execution costs (half-spread) during the no-event period. We find that the half-spreads during the no-event period on "dg2" bonds (28 bps) and "dg3" bonds (25 bps) are higher on average than that on the "dg1" bonds (16 bps). There is some evidence from the equity market that transaction costs increase with financial distress (see Da and Gao, 2008) or bond rating changes (see Odders-White and Ready, 2005). Since our sample of bonds and the insurance company transactions are constructed by explicitly choosing bonds with rating changes around downgrade events, we anticipate higher transaction costs than what is usually reported in the literature. Indeed, the estimates of the half-spreads are generally higher than previously reported in Schultz (2001) or Bessembinder et al. (2006). For instance, Schultz (2001) reports the full spreads in his sample of high credit quality bond are about 27 basis points. Depending on model specification, Bessembinder et al. (2006) report the full spreads in their sample (approximately 70% high credit quality bond) are about 15 to 18 basis points after establishment of the TRACE system.

Second, the coefficient on ΔQ interacted with the *PeriodDummy* measures the additional one-way trade execution costs during the six-month period after the downgrade event. We find that the trade execution cost increases significantly after the downgrade events only for "dg2" bonds. On average, the execution cost goes up by almost 18 bps for these bonds during the six months immediately after the announcement of downgrade. For "dg1" and "dg3" bonds, the execution costs actually decline although not significantly.

Finally, we find the coefficient estimates of the information asymmetry component of the spreads, i.e., the surprise in order flow Q^* in regression (3) are low and statistically insignificant.[11] This result is not entirely surprising. After public announcements of bond rating downgrades, the insurance companies in the NAIC sample transact for portfolio balancing reasons, and not on the basis of private information.

We document overall a significant increase in trading costs— particularly in the inventory costs— after a downgrade announcement, but only for bonds that are downgraded from investment grades to non-investment grades.

4 Clientele Change

We have said that one would expect a downgrade from investment grade to non-investment grade to trigger forced selling of the downgraded bonds by investors who operate under quality restrictions, leading to a clientele change. We can confirm such a clientele change by examining different types of institutional investors' holdings changes. The results are in Table 8 which reports the bond holding changes of insurance companies (Panel A), investment-grade bond funds (Panel B) and high-yield bond funds (Panel C) around the time of bond downgrades. [-1:0], [0:1] and [1:2] denote holding changes concurrent with the quarter of rating downgrades, one quarter after that quarter and two quarters after the bond rating downgrade.

The transactions of insurance companies in Panel A show that they are on average selling all three types of downgraded bonds, but selling junk bonds a lot more heavily. The t-values associated with the sales of junk bonds are all higher than 5. The heavier selling of junk bonds is strongly consistent with the investment constraints that these institutional investors face.

We document that investment-grade bond mutual funds reduce their holdings on downgraded bonds on average. Due to the small sample of bond mutual funds, however, most of the declines in holdings are not significant. The only exceptions are in the case of bonds downgraded from investment grade to non-investment grade.

There are several reasons why the forced selling of junk bonds is unlikely to be absorbed by ready outside buyers, thereby causing a large and persistent liquidity shock. First, it takes time and human capital for an investor to identify a profitable opportunity and then act on it (see

[11] Bessembinder, Maxwell, and Venkataraman (2006) also report similar results.

Berndt, Douglas, Duffie, Ferguson, and Schranzk, 2005). We believe such "capital immobility" to be especially relevant for the trading of junk bonds. The results of junk bond investing depend on an investor's efficiency in uncovering and analyzing all the variables specific to the distressed company. The junk bond investor: "will not only know everything about the company and its financials but will have studied the creditors involved in the reorganization as well: their numbers, their willingness to compromise, and the complexity of their claims help indicate how long the reorganization will last, what the asset distributions will be, and whether the expected returns are worth the wait."(Friedland, 2005).

Second, one needs to take into account the market structure of corporate bonds. Like many other assets, corporate bonds are traded over the counter (OTC). Until recently, there has been limited transparency in this market, both before and after transactions. After introduction of the TRACE, post-trade market transparency has increased but is still limited. Traders in the OTC markets search for counterparties in order to transact. As Duffie, Garleanu, and Pedersen (2005, 2007) show, a market structure like this often exhibits large price reactions to supply shock and slow price recovery. Therefore, it is not entirely surprising that we find a prolonged dissipation of liquidity shock and recovery of bond prices in the corporate bond market.

The sudden selling by one group of investors with no immediate offsetting increase in the demand from other investors results in an order imbalance. This imbalance explains the liquidity shock we have documented in the trading of "dg2" bonds. In this case, liquidity providers have to step in and a considerable price concession is needed to attract them. Prices will bounce back once outside investors recognize an opportunity and redeploy capital. We conclude that the clientele change is likely to explain the large and persistent price concession followed by subsequent gradual price recovery that we observe on bonds recently downgraded from investment grades to non-investment grades.

4.1 Liquidity Providers

When one group of investors is forced to sell junk bonds due to their investment constraints, investors without investment constraints can benefit from liquidity provision by taking the other side of trades when liquidity is most needed. High-yield bond mutual funds that focus on the junk bond sector seem to be natural candidates. When we examine the holding changes of the high-yield bond mutual funds, we indeed document strong buying activities from them on the "dg1" and "dg2" bonds. Take the "dg2" bond as an example. While investment-grade bond mutual funds significantly reduce their holdings during the three quarters around the downgrade events, high-yield bond mutual funds significantly increase their holdings (associated t-values are higher than 3). We also document some selling of "dg3" bonds by high-yield bond mutual funds, although these holding declines are not statistically significant.

Another potential group of buyers of bonds recently downgraded to junk status is hedge funds that specialize in distressed securities. While information on their actual transactions is not available, we can still make inferences on their trades by comparing their returns to the return on the "dg2" calendar portfolio.[12]

Figure 2 plots the calendar portfolio return ("dg2") against the distressed hedge fund index return provided by the Hedge Fund Research (HFR) Institute (both in excess of the risk-free rate). These two returns in general move closely with each other. Their correlation is about 0.20 during our sampling period from 2003 through 2007, indicating that some hedge funds might indeed have benefited by providing liquidity to financial institutions that are facing investment constraints. More formally, if we regress the excess calendar portfolio returns on the excess hedge fund index return, we find that the excess calendar portfolio return that cannot be explained by bond and stock return factors can be largely explained by the single hedge fund return factor. The alpha is now reduced to 40 bps and is no longer significant (t-value = 1.60).

5 Cross-Sectional Analysis

So far we have argued that the investment constraints faced by one group of financial institutions contribute to the observed clientele change, which in turn causes the large and persistent price reversal for the "dg2" bonds. If this argument is indeed true, in the cross-section, we would expect that: (1) downgraded bonds held by institutions with more binding investment constraints are more likely to be sold; and (2) bonds experiencing more selling pressure will encounter larger price

[12] A similar return-based inference approach is also adopted by Brunnermeier and Nagel (2004) and Chen, Hanson, Hong, and Stein (2007). Brunnermeier and Nagel (2004) provide an analysis of hedge fund equity investment around the internet "bubble" period, where they cannot observe the short position. Chen, Hanson, Hong, and Stein (2007) investigate whether the long-short equity hedge funds benefits from mutual fund flow-induced liquidation of stocks by front-running.

concessions immediately after the downgrade announcements.

We measure the importance of the investment constraint using a variable called *junk_ratio*. The *junk_ratio* variable is constructed in two steps. First, on each holding report date, and for each investment-grade bond mutual fund with at least 50% of its holdings receiving a credit rating, we compute the percentage of bond holdings (market value) receiving ratings below investment grade (as a percentage of market value of all bonds receiving ratings). Second, for each bond, we value-weight the percentages across all investment-grade mutual funds holding the bond to calculate the *junk_ratio*. Intuitively, a high *junk_ratio* means that the bond is held by mutual funds that already have many junk bonds in their holdings, so the investment constraint will be more binding for them.

For each event type, we sort all bonds into quintiles on the basis of their most recent *junk_ratios* during the quarter prior to the event. For each quintile, we compute the average holding changes on the bonds from the quarter before the event to the second quarter after the event ([-1:2]). We report the results in Panel A of Table 9. Consistent with our conjecture, for the two events where the investment constraint on investment-grade bond mutual funds is likely to be binding ("dg2" and "dg3"), the holding changes decline monotonically with the *junk_ratio*, and the difference between the average holding changes of the two extreme quintiles is statistically significant. This finding implies that a bond held by institutions with more binding investment constraints is more likely to be sold, which in turn suggests that the binding investment constraint is likely behind the clientele change.

To relate the clientele change to the initial price concession in the cross-section, we use a regression analysis. Panel B of Table 9 presents the results for regression of bond returns during the quarter after the downgrade event on contemporaneous institutional transactions from insurance companies and investment-grade mutual funds (Inst_Holding_Chang[1, 60], regressions 1 – 4), or the contemporaneous number of transactions recorded by the TRACE system (LogNumTrades[1,60]). Because of investment constraints, the variable institutional transactions (Inst_Holding_Chang[1, 60]) is a direct proxy of the selling pressure on the bond. In addition, to the extent that most of the trades after downgrades are likely seller-initiated, the total number of transactions (LogNumTrades[1,60]) is also an indirect proxy for the selling pressure on the bond. Using both proxies, we document a strong positive relation between price concession and the selling pressure. This direct relation is driven mostly by "dg2" event bonds. These regression results suggest that the large and persistent price concession on bonds recently downgraded from investment grades to non-investment grades is likely caused by the forced selling of constrained financial institutions.

Overall, these two additional cross-sectional results provide further support for our explanation. The large and persistent price concession on bonds recently downgraded to junk status is a result of clientele change originating out of the investment constraints faced by financial institutions.

6 Conclusion

In theory, liquidity shocks can be persistent and generate short-term return reversals on financial assets. Most empirical studies of stock market data document that liquidity shocks are typically short-lived and their economic causes cannot be easily identified. We examine the link among clientele change, persistent liquidity shocks and return reversals in the market for US corporate bonds, which offers a better setting for analysis of liquidity events.

The investment restrictions faced by many financial institutions give natural rise to a liquidity shock when bonds are downgraded from investment grade to non-investment grade. We use the actual quarterly holdings of bond mutual funds and transaction data of insurance companies during the period between 2003 and 2007 to document a clientele change when a corporate bond is initially downgraded to "junk" status. Investment-grade bond funds and insurance companies are forced to sell, creating a persistent price concession of around 200 bps, although the prices recover gradually in almost three months and on average by half by the end of six months. High-yield bond funds and hedge funds specializing in distressed securities, which are taking the other side of the trade, benefit from providing liquidity during these events. We do not observe such persistent liquidity shocks around similar downgrades where the dividing line between investment grade and non-investment grade is not crossed.

Besides documenting an interesting and prevalent channel where clientele change can trigger large and persistent liquidity shocks, our results have other important implications for empirical asset pricing. First, the permanent price impact following the clientele change suggests that the long-term demand curve of a corporate bond is likely to be downward sloping. While downward-sloping demand curve has been documented for stocks, we find that it might also exist for bonds.

Second, we show that liquidity shocks are particularly relevant for bonds with high credit risk, and must be accounted for in the empirical examination of bond returns.

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Table 1: US Corporate Bond Investors

This table reports the holdings of US corporate bonds across different types of investors. The numbers are aggregated from Table L.212 Z.1 of the flow of funds accounts from Federal Reserve.

	2003	2004	2005	2006	2007
	Dollar Holdings (in billions of dollars)				
Household sector	1,108.3	1,254.8	1,285.9	1,469.4	1,504.7
Mutual funds (1)	807.0	883.8	962.4	1,181.6	1,349.4
Insurance companies (2)	1,839.1	2,013.3	2,103.5	2,118.9	2,199.7
Other institutions (3)	3,239.5	3,717.6	4,245.1	4,991.3	5,669.5
Total	6,993.9	7,869.5	8,596.9	9,761.2	10,723.3
	Percentage Holdings				
Household sector	15.85%	15.95%	14.96%	15.05%	14.03%
Mutual funds (1)	11.54%	11.23%	11.19%	12.11%	12.58%
Insurance companies (2)	26.30%	25.58%	24.47%	21.71%	20.51%
Other institutions (3)	46.32%	47.24%	49.38%	51.13%	52.87%
Total	100.00%	100.00%	100.00%	100.00%	100.00%

(1) Includes money market mutual funds.
(2) Includes property-casualty insurance companies and life insurance companies.
(3) Includes state and local governments, rest of the world, commercial banking, savings institutions, credit unions, private pension funds, federal, state and local government retirement funds, closed-end funds, exchange-traded funds, government-sponsored enterprises, REITs, brokers and dealers and funding corporations.

Table 2: Sample Summary Statistics

This table reports some summary statistics on the "event" bonds in our sample. The events include: (1) dg1 (downgrades from "A" to "Baa"); (2) dg2 (downgrades from "Baa" to "Ba"); and (3) dg3 (downgrades from "Ba" to "B"). Ratings are obtained from Moody's. The sampling period is from 2003 through 2007.

year	Number of bonds	Number of issuers	Number of bonds per issuer		Offering size (in thousand dollars)		
			median	max	Q1	Median	Q3
			Downgrades from "A" to "Baa" (dg1)				
2003	92	19	3	22	150,000	300,000	500,000
2004	1,060	16	3	1,006	10,819	21,821	38,590
2005	639	26	3	550	7,324	13,314	29,219
2006	447	32	3	323	3,002	6,963	50,000
2007	776	34	2	568	1,386	3,135	25,000
			Downgrades from "Baa" to "Ba" (dg2)				
2003	25	15	1	5	300,000	400,000	550,000
2004	46	15	3	11	200,000	400,000	750,000
2005	1,397	32	3	1,207	8,323	19,622	38,470
2006	657	37	2	552	5,964	11,791	25,990
2007	163	27	3	56	3,118	250,000	350,000
			Downgrades from "Ba" to "B" (dg3)				
2003	22	8	2	6	100,000	500,000	900,000
2004	15	8	1	8	200,000	375,000	600,000
2005	102	32	2	15	200,000	301,189	500,000
2006	637	69	1	469	7,265	14,021	125,000
2007	52	27	2	5	150,000	200,000	350,000

Table 3: Transactions of Insurance Companies and Holdings of Bond Mutual Funds

Panel A provides information on the characteristics of the trading volume of insurance companies within a 25-month window before and after the bond downgrading events. Panel B describes equally weighted and value-weighted bond mutual fund holding characteristics such as rating, age (years since issuance of the bonds), offering size (in thousands of dollars), average offering yield (in percentage), initial maturity (in years), and time until maturity (in years, as of the portfolio reporting date) of the bonds, as well as the number of bonds in the portfolio. We only retain bonds which we can match with the Mergent-FISD database. When we compute the value-weighted characteristics of the bond portfolios, we use the CRSP recorded end of the quarter market value of the holding positions. To obtain these summary statistics, we first aggregate all bond positions by the end of the quarter, and then take the time-series average of these characteristics. The cross-sectional means of these time-series average are reported. There are 77 unique portfolios for the high-yield bond funds, and 269 unique portfolios for the investment-grade bond funds.

Panel A: Insurance company bond transactions

Event Category	"A" to "Baa" (dg1)			"Baa" to "Ba" (dg2)			"Ba" to "B" (dg3)			All Downgrading Events		
Transaction Type	Buy	Sell	All	Buy	Sell	All	Buy	Sell	All	Buy	Sell	All
Trade price (% of par value)												
Average trade price	103.23	101.75	102.39	100.30	97.14	98.21	97.43	93.28	94.64	101.15	97.94	99.15
Median trade price	102.16	101.39	101.69	100.20	99.50	99.90	99.62	97.45	98.45	100.89	100.00	100.00
Trade Size												
Average trade size (in $MM)	3.02	2.73	2.85	3.01	3.30	3.20	1.90	2.65	2.41	2.81	2.94	2.89
Median trade size (in $MM)	1.00	1.00	1.00	0.75	1.00	1.00	0.47	0.78	0.63	0.75	1.00	0.88
Average trade size (% of offering size)	0.65	0.59	0.62	0.49	0.73	0.65	0.40	0.71	0.61	0.55	0.67	0.63
Median trade size (% of offering size)	0.14	0.13	0.13	0.09	0.12	0.10	0.09	0.16	0.13	0.11	0.13	0.13
Total number of trades	8,930	11,534	20,464	6,365	12,412	18,777	3,531	7,298	10,829	18,826	31,244	50,070
Cumulative trading volume (in $MM)	26,924	31,453	58,377	19,181	40,951	60,132	6,712	19,332	26,044	52,817	91,736	144,553

Panel B: Bond Mutual Fund Holdings

	Equally Weighted						Value Weighted						
	Rating	Bond Age	Offering Size	Offering Yield	Offering Maturity	Time to Maturity	Rating	Bond Age	Offering Size	Offering Yield	Offering Maturity	Time to Maturity	Number of Bonds
B1: High Yield Bond Fund Holding Characteristics													
Q1	5.59	2.82	422,804	7.75	9.04	6.65	5.60	2.87	446,059	7.85	8.70	6.54	29
Mean	5.71	3.22	1,141,505	8.27	9.43	7.10	5.66	3.19	1,282,039	8.34	9.39	6.98	145
Median	5.86	3.28	457,788	8.38	9.57	7.37	5.84	3.19	511,040	8.32	9.55	7.32	128
Q3	5.95	3.61	541,534	8.84	10.23	7.87	5.93	3.76	645,202	8.88	10.25	7.91	227
B2: Investment Grade Bond Fund Holding Characteristics													
Q1	2.63	3.52	1,204,445	5.60	7.08	3.64	1.94	3.43	2,163,157	5.44	6.45	3.39	34
Mean	3.21	4.36	3,242,946	6.30	10.70	7.28	2.66	4.44	5,734,613	6.17	10.65	7.10	108
Median	3.14	4.16	1,953,073	6.09	10.37	7.44	2.46	4.11	4,474,404	5.96	10.63	7.40	74
Q3	3.75	5.02	3,340,291	6.84	13.11	9.70	3.14	5.08	7,422,378	6.74	13.23	9.47	136
B3: All Bond Fund Holding Characteristics													
Q1	2.77	3.30	717,623	5.76	7.42	4.52	2.10	3.19	798,451	5.54	6.97	4.15	34
Mean	3.74	4.11	2,776,715	6.70	10.44	7.25	3.30	4.17	4,742,417	6.62	10.39	7.09	118
Median	3.45	3.97	1,511,287	6.43	9.97	7.43	2.81	3.85	3,114,628	6.31	10.00	7.34	79
Q3	5.39	4.63	2,750,403	7.65	12.60	9.11	5.00	4.83	6,933,528	7.59	12.73	8.93	158

Table 4: Event Window Returns and Trading Volumes

This table reports the average event portfolio returns in excess of the returns on the appropriate bond index from in several event windows. The bond returns (including the accrual interests) are first size-weighted at the issuer level (using the offering amount of the bond as the weight), then equal-weighted across issuer. We also report the abnormal dollar volumes during the first two quarters after the downgrade events. The abnormal dollar volume is defined as: the average monthly dollar trading volume during the event window / the average monthly dollar trading volume during the event window [-120,-1] -1. The *t*-values are reported in *italics*. Sampling period is from 2003 to 2007.

Event Type	Number of bonds	Number of issuers	Event_window excess return				Abnormal Dollar Vol	
			[-120, -1]	[1, 60]	[61, 120]	[-1, 120]	[1, 60]	[61, 120]
"A" to "Baa" (dg1)	2114	68	-0.0065	-0.0011	-0.0004	-0.0019	3.71	6.91
			-2.10	*-0.41*	*-0.17*	*-0.51*	*19.56*	*16.79*
"Baa" to "Ba" (dg2)	2066	76	-0.0170	-0.0180	0.0079	-0.0143	0.17	0.88
			-3.29	*-2.64*	*1.85*	*-2.55*	*5.85*	*2.44*
"Ba" to "B" (dg3)	719	97	-0.0185	-0.0040	-0.0020	-0.0048	0.63	0.69
			-3.00	*-1.02*	*-0.49*	*-0.72*	*5.32*	*2.66*

Table 5: Regression Analysis of Return Reversal after Downgrading

This table reports the results from regressing the cumulative bond returns during the fourth month to the six month against the cumulative bond returns during the first month to the third month after downgrading events. Panel A and Panel B report the regressions in which the bond returns are aggregated at issuer level using offering amount of bonds. In Panel A, regressions (1) to (4) are ordinary least square (OLS) regressions, and regressions (5) to (8) are median regressions. Panel B is similar to Panel A, except these regressions include year fixed effects. Panel C reports OLS regressions in which the bond returns are at the individual issue level. The standard errors of OLS regressions in Panels A and B are White (1982) standard errors; the standard errors of the median regressions in Panels A and B are bootstrapped standard errors using 500 replications. The standard errors of OLS regressions in Panel C are clustered at the issuer level. *, **, and *** denote the regression coefficients are statistically significant at 10, 5 and 1% levels.

Panel A: Return reversal regression by issuer

	(1) full sample	(2) dg1	(3) dg2	(4) dg3	(5) full sample	(6) dg1	(7) dg2	(8) dg3
AdjBondReturn [1, 60]	-0.324***	0.014	-0.483***	-0.012	-0.280***	-0.026	-0.489***	-0.023
	(0.113)	(0.203)	(0.107)	(0.195)	(0.088)	(0.162)	(0.095)	(0.254)
StockReturn [1, 60]	0.013	-0.000	0.024	0.019	0.001	0.008	0.014	0.009
	(0.015)	(0.027)	(0.030)	(0.023)	(0.018)	(0.038)	(0.028)	(0.035)
StockReturn [61, 120]	0.034**	0.099***	0.043**	-0.004	0.034*	0.078**	0.044**	0.019
	(0.016)	(0.033)	(0.018)	(0.032)	(0.018)	(0.030)	(0.018)	(0.041)
Intercept	-0.003	-0.006*	-0.006	-0.000	-0.003	-0.005	-0.000	0.002
	(0.002)	(0.003)	(0.004)	(0.005)	(0.003)	(0.004)	(0.005)	(0.007)
Year Fixed Effect	NO	NO	NO	NO	NO	NO	NO	NO
N	154	56	48	50	154	56	48	50
Adjusted R^2	0.157	0.224	0.438	0.012	0.036	0.072	0.113	0.011

Panel B: Return Reversal Regression with year fixed effect, by issuer

	(1) full sample	(2) dg1	(3) dg2	(4) dg3	(5) full sample	(6) dg1	(7) dg2	(8) dg3
AdjBondReturn [1, 60]	-0.315***	-0.013	-0.420***	0.012	-0.177***	-0.133	-0.500***	-0.019
	(0.111)	(0.190)	(0.114)	(0.162)	(0.046)	(0.147)	(0.124)	(0.179)
StockReturn [1, 60]	0.015	0.005	0.017	0.015	0.027***	0.014	0.045	0.026
	(0.015)	(0.024)	(0.027)	(0.024)	(0.009)	(0.040)	(0.034)	(0.022)
StockReturn [61, 120]	0.039**	0.102***	0.055**	0.006	0.033***	0.054*	0.056**	0.026
	(0.016)	(0.035)	(0.021)	(0.034)	(0.010)	(0.030)	(0.022)	(0.027)
Intercept	0.002	0.002	-0.011	0.033	0.004	0.002	-0.000	0.024
	(0.006)	(0.007)	(0.011)	(0.020)	(0.004)	(0.007)	(0.012)	(0.016)
Year Fixed Effect	YES	YES	YES	YES	YES	YES	YES	YES
N	154	56	48	50	154	56	48	50
Adjusted R^2	0.189	0.363	0.495	0.079	0.122	0.2167	0.169	0.082

Panel C: Return reversal estimates by issue

	(1) full sample	(2) full sample	(3) full sample	(4) dg1	(5) dg1	(6) dg2	(7) dg2	(8) dg3	(9) dg3
AdjBondReturn [1, 60]	-0.255*	-0.207	-0.193	0.088	-0.177	-0.757***	-0.862***	-0.073	-0.039
	(0.141)	(0.153)	(0.161)	(0.239)	(0.168)	(0.146)	(0.142)	(0.091)	(0.089)
StockReturn [1, 60]	-0.129***	-0.123***	-0.132***	0.002	-0.037	0.122**	0.065**	-0.025	-0.014
	(0.035)	(0.039)	(0.040)	(0.059)	(0.029)	(0.054)	(0.031)	(0.043)	(0.028)
StockReturn [61, 120]	0.082***	0.132***	0.120***	0.116*	0.122***	0.045	0.058*	0.154**	0.205***
	(0.027)	(0.032)	(0.031)	(0.058)	(0.025)	(0.051)	(0.035)	(0.069)	(0.070)
LogPriorTradesNum	0.004	0.010***		-0.009*	-0.004	0.013***	0.007	-0.002	-0.002
	(0.003)	(0.003)		(0.005)	(0.004)	(0.004)	(0.005)	(0.003)	(0.003)
LogBondSize	-0.001	-0.007**		0.008***	0.004***	-0.015***	-0.010	-0.001	-0.001
	(0.002)	(0.003)		(0.002)	(0.001)	(0.005)	(0.007)	(0.003)	(0.003)
Intercept	-0.004	0.069**	0.027***	-0.082***	0.008	0.181***	0.118*	0.027	-0.003
	(0.027)	(0.029)	(0.008)	(0.026)	(0.018)	(0.039)	(0.067)	(0.027)	(0.032)
Year Fixed Effect	YES	NO	NO	NO	YES	NO	YES	NO	YES
Observations	10547	10547	10568	1814	1814	1450	1450	485	485
Adjusted R^2	0.359	0.218	0.200	0.138	0.326	0.701	0.728	0.237	0.387

Clustered standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6: Calendar Portfolio Returns

This table reports results of time-series regressions using calendar portfolio returns. The calendar portfolio for each event is constructed as follows. During each trading day, we include a bond in the portfolio if the trading day falls in the [61, 120] post-event window for the bond. The portfolio returns are computed by first size-weighting bond returns at the issuer level (using the offering amount of the bond as the weight), then equal-weighting issuer-level returns. On a trading day when our portfolio contains zero bond, we assume the return to be equal to the risk-free rate on that day. We then regress the resulting monthly calendar portfolio returns (in excess of risk free rate) on various monthly excess return factors. Bond Factor denotes the bond index return (with comparable credit rating) minus the risk free risk. MKTRF, SMB and HML are the Fama-French three factors. dg1 denotes downgrades from "A" to "Baa"; dg2 denotes downgrades from "Baa" to "Ba"; and dg3 denotes downgrades from "Ba" to "B". Ratings are obtained from Moody's. The sampling period is 2003- 2007.

	Intercept (%)	Bond Factor	MKTRF	SMB	HML	R2
			"A" to "Baa" (dg1)			
Estimate	0.0406	0.6833				0.4794
t-value	*0.27*	*6.65*				
Estimate	0.0140	0.6847	0.0292			0.4818
t-value	*0.09*	*6.60*	*0.46*			
Estimate	0.1227	0.7415	-0.0355	0.1181	-0.1269	0.5293
t-value	*0.74*	*7.10*	*-0.49*	*1.54*	*-1.42*	
			"Baa" to "Ba" (dg2)			
Estimate	0.5819	0.3095				0.0677
t-value	*2.65*	*1.89*				
Estimate	0.5587	0.2838	0.0338			0.0699
t-value	*2.41*	*1.56*	*0.34*			
Estimate	0.5038	0.2656	0.1082	-0.1313	0.0320	0.0988
t-value	*2.06*	*1.39*	*0.93*	*-1.17*	*0.23*	
			"Ba" to "B" (dg3)			
Estimate	0.3779	0.6752				0.1109
t-value	*0.99*	*2.29*				
Estimate	0.2090	0.3434	0.3124			0.1589
t-value	*0.53*	*0.95*	*1.53*			
Estimate	0.3492	0.3609	0.0505	0.4741	-0.0401	0.2754
t-value	*0.91*	*1.03*	*0.23*	*2.50*	*-0.18*	

Table 7: Spreads changes after bond downgrading

In this table, we examine the half-spread for the set of corporate bonds around rating downgrades events between 2003 and 2006 using NAIC transactions. Following Bessembinder, Maxwell and Venkataraman (2006), we estimate a two-stage model with the first stage estimated as,

$$Q_t = a + bQ_{t-1} + \varepsilon_t.$$

Referring to ε_t. from the previous equation as Q_t*, the second stage is then estimated as,

$$\Delta P = a + wX_t + \gamma SQ_t^{*} + \alpha S\Delta Q_t + \omega_t.$$

These regressions include three public information variables which are measured from the data of the most recent transaction on a day prior to the date of the current transaction. The first variable is the change in the interest rate for the on-the-run Treasury security matched to the corporate bond based on maturity (i.e., *TreasuryReturn*). The second is the returns of bond issuer's common stocks (i.e., *StockReturn*). The third is the change in the spreads between Moody's BAA-rated bonds and Treasury securities (i.e., *Δ(BAA-Treasury Spreads)*). To account for potential differences in their sensitivities to the underlying public information variables, these three public information variables are interacted with investment-grade and noninvestment-grade indicator variable when such interaction is applicable. To measure the impact of bond rating change on the bond market liquidity in terms of transaction costs, we interact ΔQ with the a binary indicator variable (i.e., *PeriodDummy*), which takes value of one if the time period is during the six months after bond downgrades occur; and zero otherwise. All regressions are estimated using the weighted least squared (WLS), where the weight is a function of the fraction of time between two trades. Regressions 1, 2 and 3, and 4 present regression results from different subsamples, where dg1 denotes downgrades from "A" to "Baa"; dg2 denotes downgrades from "Baa" to "Ba"; and dg3 denotes downgrades from "Ba" to "B". Ratings are obtained from Moody's. The standard errors are clustered at issuer level, and provided in parenthesis. *, ** and *** denote the regression coefficients are statistically significant at 10%, 5% and 1% respectively.

	(1) dg1	(2) dg2	(3) dg2	(4) dg3
StockReturn	3.037***	3.894***	4.250***	3.049***
	(0.403)	(0.479)	(0.835)	(0.417)
StockReturn x Investment			-0.500	
			(1.020)	
TreasuryReturn	25.745***	12.988***	5.857	-9.551
	(3.554)	(5.002)	(9.018)	(7.542)
TreasuryReturn x Investment			10.243	
			(10.837)	
Δ(BAA-Treasury Spreads)	-37.920	-38.479	-29.681	-179.645***
	(33.222)	(44.253)	(76.770)	(66.973)
Δ(BAA-Treasury Spreads) x Investment			-14.419	
			(93.459)	
ΔQ	0.156***	0.283***	0.284***	0.250***
	(0.024)	(0.038)	(0.038)	(0.055)
ΔQ x *PeriodDummy*	-0.014	0.179**	0.178**	-0.156
	(0.044)	(0.080)	(0.080)	(0.120)
Q*	0.032	-0.029	-0.029	-0.009
	(0.025)	(0.040)	(0.040)	(0.055)
Intercept	-0.026	-0.064**	-0.065**	-0.025
	(0.021)	(0.032)	(0.032)	(0.044)
N	9912	12393	12393	6203
Adjusted R^2	0.022	0.014	0.014	0.014

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8: Holding Changes of Insurance Companies and Bond Mutual Funds

This table reports the bond holding changes of insurance companies (Panel A), investment grade bond funds (Panel B), and high yield bond funds (Panel C) around the time of bond downgrades. Among the set of bond downgrades we consider dg1 denotes downgrades from “A” to “Baa”; dg2 denotes downgrades from “Baa” to “Ba”; and dg3 denotes downgrades from “Ba” to “B”. [-1:0], [0:1], [1:2] and [2, 3] denote the holding changes of bond mutual funds, or selling of insurance companies concurrent to the quarter of rating downgrades, one and two quarters after the quarter of bond rating downgrade. The sampling period is 2003- 2006.

Panel A: Insurance Company bond holding changes around downgrading events

Statistic	Holding Changes [-1:0]	Holding Changes [0:1]	Holding Changes [1:2]
Downgrading Event: "A" to "Baa" (dg1)			
Mean	-1.04%	-1.04%	1.05%
t-statistics	-2.38	-2.19	1.61
N	349	403	203
Downgrading Event: "Baa" to "Ba" (dg2)			
Mean	-5.48%	-3.94%	-3.61%
t-statistics	-7.45	-7.18	-5.11
N	240	382	353
Downgrading Event: "Ba" to "B" (dg3)			
Mean	-4.55%	-5.42%	-6.35%
t-statistics	-6.31	-9.14	-5.28
N	139	189	99

Panel B: Investment-grade bond fund holding change around downgrading events

Statistic	Holding Changes [-1:0]	Holding Changes [0:1]	Holding Changes [1:2]
Downgrading Event: "A" to "Baa" (dg1)			
Mean	0.05%	-0.01%	-0.06%
t-statistics	1.82	-0.33	-0.60
N	219	217	217
Downgrading Event: "Baa" to "Ba" (dg2)			
Mean	-0.15%	-0.13%	-0.12%
t-statistics	-2.35	-2.03	-2.34
N	191	181	168
Downgrading Event: "Ba" to "B" (dg3)			
Mean	-0.07%	-0.11%	-0.09%
t-statistics	-1.06	-1.82	-1.90
N	172	165	146

Panel C: High-yield bond fund holding change around downgrading events

Statistic	Holding Changes [-1:0]	Holding Changes [0:1]	Holding Changes [1:2]
Downgrading Event: "A" to "Baa" (dg1)			
Mean	0.18%	0.21%	0.13%
t-statistics	2.85	2.63	1.56
N	26	35	39
Downgrading Event: "Baa" to "Ba" (dg2)			
Mean	0.23%	0.18%	0.30%
t-statistics	3.48	3.56	3.65
N	81	85	96
Downgrading Event: "Ba" to "B" (dg3)			
Mean	-0.21%	-0.24%	-0.21%
t-statistics	-1.95	-1.21	-1.44
N	192	182	179

Table 9: Cross-Sectional Analysis

Panel A examines the relation between bond holding change and a measure of investment constraint (*junk_ratio*). The junk_ratio variable is constructed in two steps. First, on each holding report date, and for each investment-grade bond mutual fund that has at least 50% of its holdings receiving credit rating, we compute the percentage of bond holdings (market value) receiving ratings below investment grades (as a percentage of market value of all bonds receiving ratings). Second, for each bond, we value-weigh the percentages across all investment-grade mutual funds holding the bond to calculate the junk ratio. For each event type, we then sort all bonds into quintiles based on their most recent junk_ratios during the quarter prior to the event. For each quintile, we compute the average holding changes on the bonds from the quarter prior to the event to the second quarter after the event. We consider three events: dg1 denotes downgrades from "A" to "Baa"; dg2 denotes downgrades from "Baa" to "Ba"; and dg3 denotes downgrades from "Ba" to "B". Sampling period is from 2003 to 2007. Panel B regresses first quarter bond returns on contemporaneous institutional transactions from insurance companies and investment-grade mutual funds (regressions 1 to 4), or contemporaneous number of transactions recorded by the TRACE system. The standard errors are clustered at issuer level, and provided in parenthesis. *, ** and *** denote the regression coefficients are statistically significant at 10%, 5% and 1% respectively.

Panel A: Bond holding changes and the junk ratio

	"A" to "Baa" (dg1) (N = 176)		"Baa" to "Ba" (dg2) (N = 106)		"Ba" to "B" (dg3) (N = 37)	
rank	junk_ratio	hd_chg	junk_ratio	hd_chg	junk_ratio	hd_chg
1	0.00%	-0.91%	0.00%	2.26%	0.59%	8.83%
2	0.00%	-2.14%	0.34%	-1.07%	3.09%	0.36%
3	0.56%	0.76%	1.37%	-1.20%	5.78%	0.72%
4	2.04%	-1.16%	3.44%	-1.67%	7.00%	2.54%
5	6.52%	-0.30%	8.28%	-3.88%	9.43%	-7.46%
1-5		-0.61%		6.14%		16.29%
t-value		*-0.86*		*2.28*		*2.65*

Panel B: Bond transactions and returns after downgrading

	(1) full sample	(2) dg1	(3) dg2	(4) dg3	(5) full sample	(6) dg1	(7) dg2	(8) dg3
StockReturn [1, 60]	0.245***	0.109***	0.137***	0.145***	0.179***	0.107***	0.136***	0.143***
	(0.090)	(0.036)	(0.028)	(0.049)	(0.059)	(0.036)	(0.029)	(0.046)
StockReturn [1, 60] x DG2	0.019							
	(0.098)							
StockReturn [1, 60] x DG3	-0.064							
	(0.123)							
Inst_Holding_Change[1, 60]	-0.096	0.004	0.059*	-0.053				
	(0.071)	(0.033)	(0.032)	(0.055)				
Inst_Holding_Change[1, 60] x DG2	0.156**							
	(0.079)							
Inst_Holding_Change[1, 60] x DG3	0.089							
	(0.144)							
LogNumTrades[1, 60]					-0.004	0.001	-0.018***	0.011**
					(0.004)	(0.002)	(0.006)	(0.004)
LogNumTrades[1, 60] x DG2					-0.009**			
					(0.004)			
LogNumTrades[1, 60] x DG3					-0.004			
					(0.004)			
Intercept	0.074***	-0.003	0.067***	0.008*	0.109***	-0.006	0.137***	-0.047**
	(0.013)	(0.004)	(0.005)	(0.005)	(0.018)	(0.010)	(0.021)	(0.022)
Year Fixed Effect	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
Observations	2800	1358	1359	83	2800	1358	1359	83
Adjusted R^2	0.450	0.498	0.456	0.255	0.482	0.498	0.508	0.308

Figure 1: Cumulative Event-window Returns Following Downgrades

We plot the cumulative event portfolio returns in excess of the returns on the appropriate bond index from the trading day immediate prior to the event to the 120th trading day after the event ([-1,120] event window). We only include bonds where the entire [-1, 120] event window is covered in TRACE. In addition, the bond has to be traded at least once during the week prior to the event. The bond returns (including the accrual interests) are first size-weighted at the issuer level (using the offering amount of the bond as the weight), then equal-weighted across issuer. We consider three events: dg1 denotes downgrades from “A” to “Baa”; dg2 denotes downgrades from “Baa” to “Ba”; and dg3 denotes downgrades from “Ba” to “B”. Sampling period is 2003-2007.

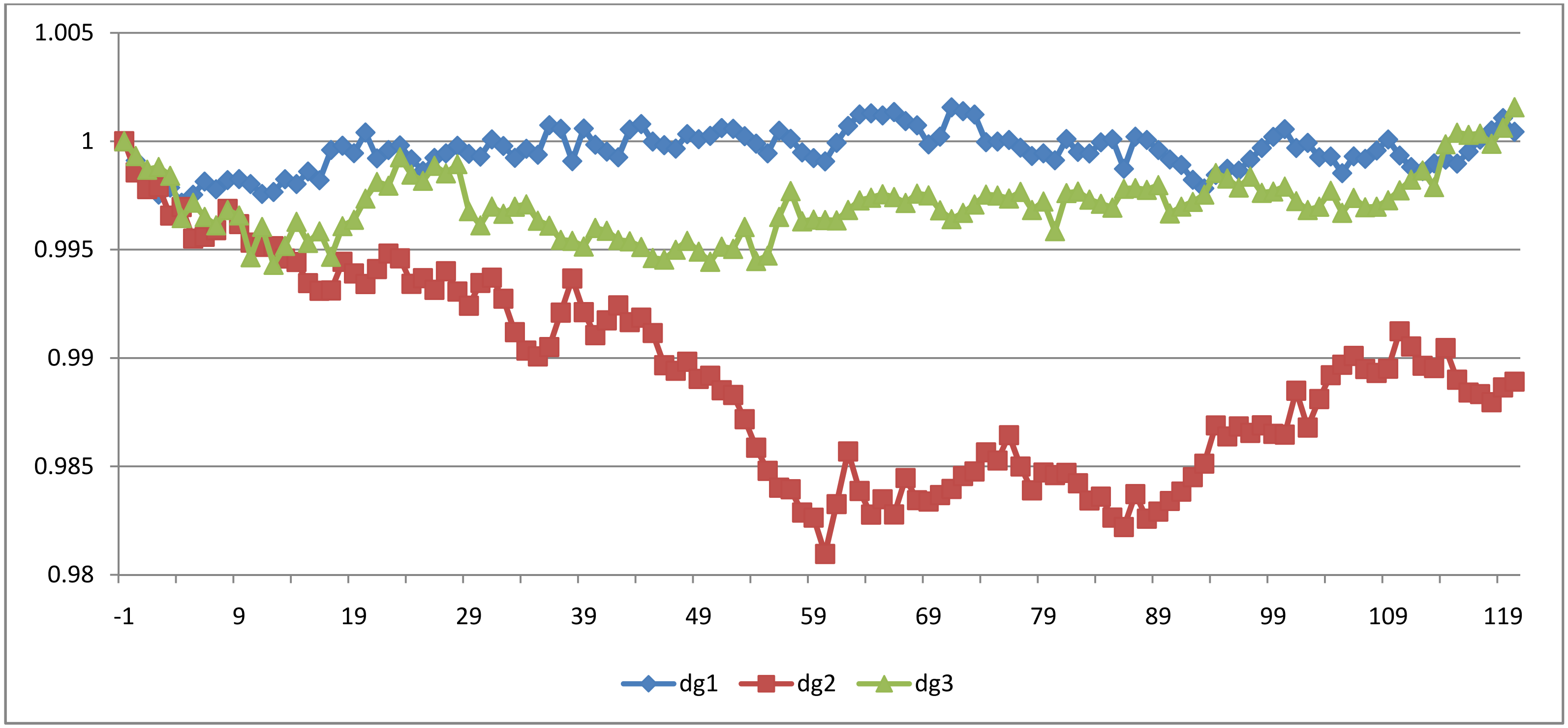

Figure 2: Calendar Portfolio Return (dg2) and Hedge Fund Return

We plot the calendar portfolio return (dg2) against the distressed hedge fund index return (both in excess of risk-free rate). The calendar portfolio for dg2 event is constructed as follows. During each trading day, we include a bond in the portfolio if the trading day falls in the [61, 120] post-event window for the bond. The portfolio returns are computed by first size-weighting bond returns at the issuer level (using the offering amount of the bond as the weight), then equal-weighting issuer-level returns. On a trading day when our portfolio contains zero bond, we assume the return to be equal to the risk-free rate on that day. The distressed hedge fund returns are provided HFR. The sampling period is from Jul 2003 through September 2007.