Downgrades, Dealer Funding Constraints, and Bond Price Pressure

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Abstract: Regulatory constraints imposed on insurance companies can induce a collective need to divest downgraded bond issues. Upon a downgrade, corporate bond dealers act as middlemen and provide liquidity by absorbing temporary order-flow imbalances. Limited access to inventory financing can temporarily limit dealers' inventory and risk-bearing capacities though and, at least in the short run, impair liquidity provision. Using insurance company transaction data, I investigate if dealer funding constraints (as proxied by their CDS spreads) amplify price declines and stall subsequent reversals of downgraded bonds. I find that higher dealer CDS spreads are associated with substantially larger and abrupt declines and slower reversals of abnormal returns around a downgrade.

Keywords: Corporate Bond Downgrades, Price Pressure, Dealer Inventory Constraints, TRACE, NAIC

JEL Classification: G01, G14, G18, G22, G24

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1 Introduction

This paper investigates the impact of corporate bond dealers' financial constraints on bond price pressures in downgraded corporate bond issues held by insurance companies. Insurers constitute an important group of investors in corporate bond markets holding over a quarter of all outstanding corporate bonds. At the same time, they operate under regulations that either prohibit or impose large capital requirements on the holdings of non-investment grade bonds.[1] As documented by Ellul, Jotikasthira, and Lundblad (2011), a rating downgrade from investment-grade to speculative grades (a rating of BB+ or below) can induce insurance companies to immediately and collectively divest at least part of their holdings in downgraded bond issues.

The forced selling of corporate bond issues temporarily generates substantial order flow imbalances.[2] Upon a downgrade, corporate bond dealers provide liquidity by temporarily absorbing these order-flow imbalances before re-selling the positions to other investors. Dealers' ability take the role of middlemen is closely linked to the ease with which they can establish and maintain inventory positions. Speculative bond inventories hold substantial price risks, require higher risk-based capital charges, and are costly in terms of financing. As a dealer's cost of holding risky inventory increases, she can become increasingly hesitant to take on additional inventory, and may quote smaller quantities at less attractive prices. Regulatory induced selling pressure in downgraded bond issues provides an appropriate environment in which to study the impact of dealers' financial constraints on bond price pressures.

Despite dealers' crucial role in corporate bond markets, we still know relatively little about how their financial constraints impact the provision of liquidity during times of intense selling pressures. Up to now, data limitations, in particular the lack of dealer identities, have hampered efforts to link bond dealers' financial constraints with their liquidity provision. To empirically test whether dealers' financial constraints affect the price pressure around a downgrade, I construct a dataset of all the corporate bond downgrades and insurance companies' trade records from the *National Association of Insurance Commissioners* (NAIC) from 2002 to 2014 while identifying the dealer behind each individual bond transaction.

In this paper, I show empirically that dealers' financial constraints (as proxied by their

[1]Insurance companies are regulated at the state level where many states follow the guidelines of the National Association of Insurance Commissioners (NAIC). Holdings in non-investment grade bonds come with capital requirements of 4.6% and 10% for BB-rated and B-rated bonds, respectively. The same requirement is only 1.3% for BBB-rated bonds and 0.4% for bonds rated A or above. Total holdings in non-investment grade bonds cannot exceed 20% for the entire portfolio where Ellul et al. (2011) find almost all insurance companies have less than 10% of their assets in non-investment grade bonds.

[2]Regulations and self-imposed risk management practices may force the sale of bond issues and simultaneously prevent other buy-side investors facing similar regulatory constraints, such as pension funds or other insurance companies, from stepping in as buyers.

CDS spreads) have a statistically and economically meaningful negative impact on the bond price patterns surrounding a downgrade. By focusing on the role of dealers in fire sales, the paper makes two contributions: First, I find a striking pattern of large price drops and partial reversals around the downgrade, similar to the patterns in related studies (e.g., Ellul et al. (2011), Han and Wang (2014), Spiegel and Starks (2016)) Importantly, these return patterns are markedly different for bonds handled by unconstrained versus bonds handled by constrained dealers. The latter experience substantially larger return deviations, as exhibited by more negative and abrupt declines in abnormal returns, which appears to be consistent with the idea that dealers' financial constraints limit their risk-bearing capacities. Second, in a bond-level cross-sectional analysis I find that a one standard deviation increase in the ratio of a bond's volume-weighted average dealer CDS spread over the median dealer CDS spread at the time is associated with a significant negative average (median) CAR of 3.55% (1.71%). I find the negative impact on CARs to be stronger when measuring dealer constraints at the issuer instead of the bond-level. Comparing the pre- with the post-event window, the empirical evidence suggests that the negative impact of dealers' inventory constraints on CARs is stronger in the weeks following the downgrade. That is, as selling pressures peak and dealer inventory limits become binding. Overall, the empirical evidence suggests that higher inventory costs limit dealers' risk-bearing capacities making them less willing to establish growing inventory imbalances without substantial price markdowns. All these findings are robust to controlling for various bond, market, and dealer characteristics as well as when using median regressions.

The empirical approach in this paper follows an event study methodology, particularly using *matching portfolios* as proposed by Bessembinder et al. (2009) and further adapted by Ederington et al. (2015).[3] Arguably, the latter can be understood as a simplified special case of the approach recently proposed by Spiegel and Starks (2016). It is a simplification to the extent that I do not explicitly estimate daily returns using a dummy variable approach. And, it is a special case in the sense that bond returns contributing to a portfolio on a particular trading day are generally equally-weighted. In comparison, I am matching based on a bond's rating and its time-to-maturity while Spiegel and Starks (2016) group on a bond's yield and its industry classification. Importantly, as in Spiegel and Starks (2016), the approach yields an average univariate regression coefficient of one when regressing bond returns on the matching portfolios.

Using cross-sectional regressions, I relate bonds' cumulative abnormal returns (CAR)

[3]My results do not depend on the method for computing abnormal returns. I find very similar CAR patterns (i.e., in terms of timing and magnitude) when using a modified regression-based approach that is based on Ellul et al. (2011), as well as when using a simple market-return model as used in Han and Wang (2014).

around a downgrade to the volume-weighted average CDS spread of the five most-active dealers per bond and issuer respectively. In doing so, I control for various bond, market, and other dealer characteristics. Quantifying dealers' financial constraints requires dealer identities. The choice for dealers' CDS spreads as proxies for their inventory constraints is motivated by the following argument: In the process of liquidity provision dealers establish inventory positions for which they strongly rely on short-term collateralized loans (so-called "repos").[4] This dependence on short-term funding exposes dealers to debt runs, rollover risk, and wider financial contagion. Since direct measures of dealers' effective short-term funding costs are either difficult to come by or not available at all,[5] I make use of their credit default swap (CDS) spreads, which exhibit variation across dealers and represent a plausible indicator of credit risk based on which risk managers and lenders evaluate financing terms, credit lines, and position limits. To the extent that adverse changes in borrower credit risk increase monitoring concerns and prompt lenders to demand higher interests or curtail lending (Calomiris and Kahn (1991); Rochet and Tirole (1996)) dealer CDS spreads appear as a suitable proxy for dealer-specific changes in funding costs.

My work draws on theoretical models of dealers' market making behavior. Standard market microstructure models with inventory frictions have (risk-averse) dealers absorbing temporary imbalances in order flow to end up with (suboptimal) inventory positions. Stoll (1978), Amihud and Mendelson (1980), and Ho and Stoll (1981, 1983) are the first to formalize that increased inventory risks require a compensation in terms of larger discounts and markups respectively to fundamental values. In more recent work that accounts for the decentralized trading in over-the-counter markets, Duffie et al. (2005) show that higher search costs and therefore limited outside options reduce investors' bargaining position and have them engage in transactions at larger discounts. Theoretical work that combines market making behavior and financing constraints shows that the latter can limit dealer liquidity provision to suboptimal levels (see, e.g., Gromb and Vayanos (2002) and Gromb and Vayanos (2010)). Brunnermeier and Pedersen (2009) highlight that funding limits amplify shocks to asset values and ultimately lead to adverse liquidity spirals and reinforcing feedback loops. Within a search model, Weill (2007) shows that insufficient access to capital adversely affects dealers' ability to supply liquidity.

Dealers' willingness and ability to commit capital can be limited, which has been doc-

[4]Repurchase agreements make up, on average, 60% of dealers' liabilities between the years 2002 to 2014 (see Rosengren (2014)).

[5]Following the SEC's money market fund reforms in 2010 monthly tri-party repo data is available only after November 2010. Using this data, Hu et al. (2015) show that dealers' CDS spreads are weakly positively related to repo spreads.

umented empirically, e.g., in stock markets. Comerton-Forde et al. (2010) show that specialists' inventories and trading revenues have a significant impact on the width of bid-ask spreads. Hendershott and Menkveld (2014) find that price pressures increase with higher inventories reflecting dealers' unwillingness or inability to provide additional inventory capacity.

While the empirical literature on fire sales provides several examples in which transaction prices deviate from fundamental values (see, e.g., Coval and Stafford (2007) for open-end mutual fund redemptions in equity markets; Mitchell et al. (2007) for hedge fund redemptions in convertible bonds; Pathak et al. (2009) for foreclosures on real estate prices), the impact of market makers funding constraints has not been directly studied yet. In empirical work focusing on the bond trading of insurance companies, Ambrose et al. (2008) use aggregate data to show that, in the absence of information effects (i.e., no stock price reaction to the news of a downgrade), there is not much price pressure among downgraded bonds. Price reversals only exist for bonds that contain negative information effects. They argue that there is less downward price if dealers know that insurers are not informed traders. Using more granular data on the insurance company level from 2000 to 2005, Ellul et al. (2011) find that insurers that are more constrained by regulation are more likely to immediately sell downgraded bond issues. In addition, downgraded bonds held by constrained insurance companies experience significantly larger selling pressure and subsequent price reversals. Spiegel and Starks (2016) propose a modified repeated sales methodology to study a large sample of downgrades covering over 8,000 bonds between the years 2002 to 2015. Upon a bond rating change between the investment and non-investment classification, they document significant negative (or positive) abnormal returns followed by partial recoveries that are consistent with microstructure models of limited dealer inventory capacities. None of the above-mentioned papers, however, explicitly considers the impact of dealers financial constraints. Thus, what sets my paper apart is to examine periods of increased selling pressure among insurance companies while focusing on the role of dealers and their ability and willingness to temporarily assume bond positions.

There are two papers that tackle related issues: First, using a proprietary dataset that contains dealer identities, Han and Wang (2014) employ an event-study methodology and link directly link dealer CDS spreads to transaction prices. They exclusively investigate the price and volume dynamics of *defaulted* corporate bonds. They document that defaults trigger more active trading, wider bid-ask spreads, and lower abnormal returns. They show that higher dealer CDS spreads are associated with a zero-balance exposure to defaulted bond issues, suggesting that more constrained dealers are less willing to take positions in defaulted bonds. My paper further investigates this notion but differs from in a number of ways that add a unique contribution: For one, and most importantly, I focus on the rating downgrade from investment to non-investment grades (excluding outright defaults), which represents the crucial rating event for regulated institutional investors, such as insurance companies and mutual funds holding close to 65% of outstanding corporate debt. That is, the downgrade to speculative grades constitutes the stress event that drives portfolio decisions for a substantial fraction of the market. By the time an actual (expected) default occurs, institutional investors would have had to sell their positions in distressed bonds leaving the ground for specialized investors (e.g., unregulated hedge funds) for whom a default event does not need to trigger a sell off. For another, there are methodological differences between the papers. I am comparing bond returns to the portfolio return of a basket of matched bonds rather than marking to the market index (e.g., the Barclay's U.S. high-yield and investment-grade corporate bond indices). Within my sample, find the latter to over-/underestimate expected or normal bond returns respectively. Moreover, given the high degree of concentration in the market-making of a particular bond or issuer (O'Hara et al. (2016)), I find that volume-weighting dealer constraints, as compared to simple averages (Han and Wang (2014)), is important and may explain differences in our approaches. Second, Bao, O'Hara, and Zhou (2016) have similar data access and study dealer liquidity provision in individual bonds following the downgrade to speculative grades. Specifically, they account for the regulatory changes following the implementation of the Volcker Rule. Exploiting dealer identities, their measure of dealer constraints is a distinction into Volcker-affected and non-Volcker-affected dealers. Within a difference-in-differences framework Bao et al. (2016) document reduced liquidity provision by Volcker-affected dealers and an overall reduction in the liquidity of downgraded bonds after the implementation of the Volcker Rule.[6]

The remainder of the paper is organized as follows: Section 2 outlines the sample construction and provides a general description of the data. Section 3 introduces the event study methodology and describes the use of matching portfolios. Section 4 starts with a graphical inspection of the bond price patterns around a downgrade and continues with the baseline results using cross-sectional regressions of cumulative abnormal returns on bond, market, and dealer characteristics. Subsections 4.2.2 and 4.2.3 hold robustness checks when accounting for bonds recent trading frequencies and insurer constraints respectively. Section 5 concludes.

[6]In a related paper (that cannot exploit data on dealer identities), Anderson and Stulz (2017) argue that in recent post-crises years liquidity around bond downgrades has not diminished in comparison to the pre-crisis period.

2 Data

2.1 Sample Construction

The dataset primarily builds on four databases: First, the insurance companies' transaction data from the National Association of Insurance Commissioners (NAIC). The latter records the identity of the dealer engaged in each transaction. As reports are manually coded, counterparty entries need extensive cleaning with respect to name variations and misspellings. Importantly, with dealer identification comes the ability to link cross-sectional differences in dealer characteristics to abnormal returns surrounding a downgrade.[7] Second, all relevant bond-level characteristics (such as issue date, issuance size, coupon rate, credit ratings, option features, etc.) are taken from Mergent's Fixed Income Securities Database (FISD). I work with credit ratings from Moody's, Standard & Poor's (S&P), and Fitch to identify downgrades from the investment-grade to the non-investment-grade classification. Third, as a proxy for dealers' effective (short-term) funding costs I use credit default swap (CDS) spreads, which I retrieve from Bloomberg and Datastream/CMA respectively. Fourth, for the computation of normal returns I use data from the Financial Industry Regulatory Authority's (FINRA) Trade Reporting and Compliance Engine (TRACE) to calculate value-weighted *matching portfolios* in style of Bessembinder et al. (2009). The sample period stretches over 12 years and ranges from July 1, 2002 to June 30, 2014.

The NAIC requires insurance companies to self-report security transactions in their financial statements. Each entry contains detailed transaction information including the CUSIP, the date and par value of the transaction, the (clean) price on a $100-par-basis, and the buy/sell indicator.[8] There are a number of steps required to process the raw data: A first major step is to filter bonds using bond-level characteristics (such as issue date, issuance size, coupon rate, credit ratings, option features, etc.) where I essentially stick to the literature (e.g., Asquith et al. (2013)). A second major round of filters apply to records with potential data issues concerning their price (missing, negative, or unreasonably large prices and sharp reversals), volume (trades <$1,000 or >50% of the issuance amount are dropped), or timing (trades on a bond's offering or maturity date, and trades on trading holidays). The steps taken are outlined in Table XZY in the Data Appendix.

[7] Analyzing dealers' participation in trading downgraded bonds is strictly limited to NAIC trades though. All subsequent, potentially offsetting trades of the same dealers are not observed within the NAIC data (and the TRACE data available to me is anonymous with respect to dealer identities).

[8] In my dataset the identification of counterparties is one-sided. That is, the names of the insurance companies involved in the transactions, as available to Ellul et al. (2011) and O'Hara et al. (2016), are not given.

In the calculation of returns I take into account that the NAIC database exhibits a systematic error from a disaggregation of trades due to the reporting process (as pointed out by Asquith et al. (2013)), which leads to an over-reporting in the number of trades and an under-reporting of the true price dispersion.[9] To correct for the disaggregation I group NAIC trades per bond CUSIP when trade execution date, counterparty, and buy/sell indicator are identical, and the difference in price is smaller or equal to one cent (i.e., $\leq |0.01|$ on a \$100-par-basis).[10] Lastly, the NAIC transaction data do not contain transaction time, which renders time ordering of trades impossible. Following Bessembinder et al. (2006), in case of multiple trades per day I calculate returns based on the NAIC trade of the previous trading day.[11]

To specify the downgrade event I use FISD's rating history file, which details credit ratings and rating changes for each bond at each point in time. I use the lower of Moody's, S&P's, or Fitch's rating and, following Ellul et al. (2011), define the rating change event as the date of the downgrade announcement by the rating agency that acts *first*.[12] They argue that the de facto downgrade date of a bond should corresponds to the first downgrade for several reasons: First, in case of multiple rating agencies per bond one sees accordance in downgrades (i.e., 78.5% (64.1%) of bonds with multiple rating agencies see accordance in ratings of two (three) agencies) and initial downgrades by one agency are quickly followed by the others (i.e., 38.9% of downgraded bonds with multiple agencies see a subsequent downgrade within a week[13]). Second, prior to July 2005, Lehman Brothers' corporate bond indices (now the Barclays corporate bond indices) based their index constituency on the first downgrade of a rating agency.[14] To mutual bond funds, which according to the Federal Reserve's Flow of Funds statement increased their holdings from \$0.5 trillion in 2002 (i.e., ca. 7% of outstanding corporate bonds) to \$2 trillion in 2014 (i.e., ca.

[9] Specifically, multiple NAIC transactions match a single TRACE trade using CUSIP, trade execution date, price, and counterparty but taken separately show a discrepancy with the reported volume.

[10] Not grouping on insurer type accounts for the possibility that an insurance company may book and report portions of the same trade under their respective divisions or subsidiaries.

[11] In case there are multiple NAIC trades on consecutive trading days I opt for the last "institutional" TRACE trade (i.e., $\geq$\$100,000) of the previous day to calculate returns. This difficulty only applies to a small number of trades though.

[12] In comparison, the NAIC considers a bond to be in the non-investment grade classification if it no longer holds *any* investment-grade rating (i.e., corresponding to the date of the *last* rating downgrade). As in Ellul et al. (2011) I find the results to remain unchanged when defining the event as the last downgrade.

[13] The median number of days between the first and the subsequent downgrade is 21 days.

[14] After the classification change securities are deemed to fall into the non-investment grade classification if, in case of three rating agencies, the median rating justifies a downgrade, or, in case of two agencies, the lower rating justifies a downgrade.

25% of outstanding corporate bonds), these Barclays bond indices are important return benchmarks. The same holds for corporate bond exchange traded funds (ETFs), which since their introduction in the year 2007 have seen rapid growth to roughly $0.45 trillion in 2014. Given the rules for constituency both bond mutual funds and ETFs may start buying downgraded bonds from constrained insurers even before all three agencies rate a bond non-investment grade. Third, for an insurance company holding on to downgraded bonds for too long may come at a reputational cost from regulators, rating agencies, and industry bodies (such as the NAIC), who require stringent (self-imposed) risk management practices and screen for investments in high-yield bonds as a source of potential credit losses.

With dealer identification comes the ability to link dealer characteristics to NAIC transaction data. For this, I determine a dealer's parent company and then gather CDS and credit rating data using Bloomberg and Datastream/CMA respectively. Using CDS spreads comes with three limitations: First, overall CDS coverage is not complete. While CDS contracts are available for bigger institutions there are often no contracts for smaller dealer boutiques or investment firms. Second, I do not have access to all data providers (e.g., the Markit database). Third, some series only start after July 1, 2002, end before June 30, 2014, have gaps, or show periods of stale prices (i.e., treated as missing if the spread does not update for more than two weeks). To retain the widest possible cross-sectional coverage with respect to dealer-specific inventory costs I fall back on long-term issuer ratings obtained from Moody's in case I do not have a dealer's CDS spread. Then, based on a dealer's rating, I *impute* a CDS spread. Specifically, I compute the average CDS spread on a given day for a given rating class (see Data Appendix) using the sample of dealers with both a CDS spread and a credit rating. I then map the average CDS spread per ratings class to the dealers for whom I lack a CDS spread. Out of the 74,108 NAIC trades in the eligible downgrade sample I am able to pair 55,385 (56,899) trades with a credit rating (CDS spread). Using *imputed*, rating-based average CDS spreads leaves me with data for 64,846 trades instead (corresponding to close to 100% of matched TRACE trades of the 10 most active dealers, and 98.46% (93.17%) of trades of the 25 (50) most active firms).

The value-weighted *matching portfolios* used as normal returns in the computation of abnormal returns are based on U.S. corporate bond trades reported to the Financial Industry Regulatory Authority's (FINRA) and disseminated through the Trade Reporting and Compliance Engine (TRACE). I use Enhanced TRACE data, which includes both disseminated and non-disseminated transaction records and captures full trade sizes, starting from TRACE's initiation in July 2002 (but only available with an 18-month lag).

To reduce the effects of infrequent, non-consecutive daily trading and to obtain a sizable sample within each portfolio partition, I impose less restrictive requirements with respect to bond characteristics than Bessembinder et al. (2009). Specifically, I include corporate bonds of financial institutions, and all coupon types (with the exception of perpetual bonds) independent of their security level. In order not to suffer from a cross-correlation problem I make sure that the TRACE data does not contain any of the downgraded bonds under consideration in this study. Again, I apply several data filters (see the Data Appendix for details) where majority of filters involve eliminating erroneous trade reports such as cancellations, modifications, reversals, or duplicates (Dick-Nielsen, 2014, 2009).

In calculating bond returns within the event window (i.e., the period from -20 weeks before to +35 weeks after the downgrade) I require that bonds trade (i) at least once between weeks -20 and -1, and (ii) at least once between weeks 0 and +35. In addition, bonds that trades less than ten times during the sample period (i.e., highly illiquid bonds with potentially unreliable prices) are excluded from the analysis. These screens are similar to those applied in Ellul et al. (2011) but do not require trades outside the event window (as with matching portfolios I have no need for estimation windows).[15] This leaves me with a final sample of 1,078 eligible downgrades in 968 distinct bonds that are downgraded from investment to speculative grades during the sample period. These bonds are issued by 423 issuers, accounting for 74,108 transactions with 375 distinct counterparties.

2.2 Bond Characteristics

Table 1 reports the annual number of downgrades from investment to non-investment grades over the sample period. There are two peaks in terms of the number of downgrade events: in the year 2005 when the two car manufacturers Ford and General Motors were downgraded from investment to speculative grades; and in the years 2008 and 2009 when, as a consequence of the subprime crisis, the credit ratings of many financial companies were lowered substantially.[16] Table 1 further illustrates that as of the year 2010 the number of downgrades in the sample drops markedly. This decline is likely the result of two developments: First, following more stringent post-crisis risk management frameworks insurance companies appear to have cut down their exposure to high-yield bonds and those issues in imminent danger of being downgraded (CRO Forum, 2009). Second, after the

[15]The relaxation of trade screens increases the sample from 59,313 trades in 706 distinct bonds to 74,108 trades in 968 bonds.

[16]In some cases, for instance Lehman Brothers, this ultimately ended in the collapse of the company.

crisis-induced high in corporate default rates the lessened volatility in the years 2010 to 2014 along with extraordinarily loose monetary policy showed comparably low corporate defaults both in numbers and volume (Ou et al., 2017).

Table 2 describes the summary statistics for the total NAIC sample, the sample of all bond issuers experiencing at least one downgrade in one of their bond issues, the sample of all downgraded bonds, and, finally, the sample of downgraded bonds that are eligible for the analysis (i.e., those bonds that pass the trade screens). Close to 8.5% of bonds within the insurance company corporate bond universe are affected by downgrades, which represents roughly 12.3% of total trades within NAIC. These bonds are typically large with an average issuance size of around $400 million, having on average a 6.5% offering yield. In comparison to the typical insurer bond the average issue size of downgraded bonds is slightly smaller. As a consequence of the trade screens though (i.e., excluding highly illiquid bonds with potentially unreliable prices) the eligible downgrade sample contains slightly bigger bonds than the sample of all downgraded bonds. This suggests that after the uncertainty surrounding the downgrade has been resolved, the bonds in the eligible downgrade sample may be more liquid and frequently traded than other non-investment grade as well as typical high-yield bonds.[17] Given that the focus is to study the significance of dealer inventory constraints around downgrades, the overrepresentation toward more liquid downgraded bonds, although not ideal, will only help to strengthen the results if they show up for the more liquid bonds. As expected, insurers tend to hold long-term bonds where the average maturity is close to 12 years and the average bond age when traded on the secondary market is 3.5 for the total and 5 years for the downgrade samples respectively. Most bonds held and traded by insurance companies are investment-grade bonds and carry an investment-grade rating of 8 (i.e., a Moody's rating of Baa1 (upper- to lower-medium grade)). Bonds that are to be downgraded hold a median rating of 9 (i.e., a Moody's rating of Baa2 (lower-medium grade)). This is within two steps of the non-investment-grade classification where in the period leading up to the official downgrade rating agencies oftentimes put the respective bond "on watch" in the sense that a downgrade may very well be anticipated by the market.

In terms of trading activity, the downgraded bonds trade more frequently and in larger size (i.e., higher turnover and number of trades) than the typical insurer bond of the total NAIC sample. This is likely due to the increased trading activity surrounding the downgrade. The median monthly turnover – the bond's monthly trading volume as a percentage of

[17]Houweling et al. (2005) show that the amount issued appears to be a good proxy for corporate bond liquidity.

its issuance size – is 6.1% for downgraded bonds (4.3% for all bonds in the total NAIC sample), and the median number of trades per downgraded bond is 103 (80 for all bonds in the total NAIC sample). Insurance companies become net sellers in the period leading up to the downgrade (i.e., on average 50.1% of all trades are sells) and keep on selling heavily after the first downgrade announcement (i.e., on average 68.8% of all trades are sells). Given the higher sell frequencies before the downgrade it appears that the selling pressure in downgraded issues increases in the weeks before the official downgrade. This points to the fact that the risk managemnet constraints imposed on insurance companies (e.g., large capital requirements on the holdings of non-investment grade bonds) induce a collective need to divest downgraded bond issues.

2.3 Dealer Characteristics

A. CDS Spreads

Insurers' collective need to divest downgraded bond issues leads to substantial selling pressure. At this, bond dealers are called for temporarily absorbing order-flow imbalances onto their own balance sheets before eventually offsetting the positions with other counterparties. Importantly, establishing and maintaining such inventories requires financing where dealers strongly rely on short-term collateralized loans (so-called "repos"). As dealers' effective (short-term) funding costs are not publicly available I use their credit default swap (CDS) spreads. This proxy maintains cross-sectional variation and represents a plausible indicator of credit risk based on which lenders and risk managers evaluate financing terms and position limits. As higher credit risk increases monitoring concerns and prompts lenders to demand higher interest rates (Calomiris and Kahn, 1991; Rochet and Tirole, 1996) a dealer's CDS spreads appears as a suitable proxy for dealer-specific changes in funding costs.[18] In the subsequent cross-sectional analysis of cumulative abnormal returns, the main empirical goal is to link differences in dealers' inventory financing constraints (as proxied by their CDS spreads) to price patterns surrounding a downgrade.

The eligible downgrade sample holds 74,108 bond trades with 375 distinct dealer firms of which, in terms of transactions, the most-active five dealers account for 37.7%, the most-active ten (25) dealers make up 63.3% (84.3%).[19] These dealers show a median

[18] The haircuts/initial margins in a repurchase agreement (i.e., lender imposed adjustments to the quoted market value of pledged collateral intended to hedge collateral risk) also vary with credit risk, albeit weakly.

[19] Around 200 dealers make up 99% of all transactions where the 200^{th} dealer accounts for 10 trades

(average) CDS spread of close to 33 (62) basis points (hereafter *bpts*) with a standard deviation of 74 bpts (i.e., a coefficient of variation of 1.19). Figure 1 depicts the daily average dealer CDS spread as well as the lowest and highest CDS quintiles over the sample period. Notably, the three series co-move strongly but show considerable cross-sectional variation in levels, clearly highlighted in the spread difference between the first (least constrained) and the fifth (most constrained) quintile.[20] The series closely reflect the aggregate market condition at the time (e.g., the 2007-2009 subprime mortgage crisis, and the years 2010-2012 of the European sovereign debt crisis). Overall, dealer CDS spreads appear to be a reasonable substitute for short-term funding rates[21] in that they increase during periods with heightened credit concerns.

B. Market Shares

Distinguishing bonds with respect to the trading activity of their market-making dealers offers another dimension for cross-sectional variation. In the subsequent cross-sectional analyses of cumulative abnormal returns, I use dealers' annual market shares in terms of trading volume in a particular bond (or issuer) to compute the Herfindahl index as a proxy indicator for their bargaining power and the amount of competition. These dealers show a median (average) market share of 6.2% (16.8%) at the bond- and a market share of 2.9% (10.9%) at the issuer-level where the standard deviations are given by 2.9% and 2.9% respectively (i.e., coefficient of variations of 1.44 and 1.77). To illustrate the cross-sectional differences in dealers' trading activity the panel in Figure 2 reports the share in monthly trading activity in the downgraded bonds in terms of trading volume for the most active 5, 10, 25, and 50 dealer firms. The most-active five dealers account, on average, for 50% of volume highlighting the striking concentration of trading activity among only a small number of dealers handling a major share in the overall trading of downgraded bonds. The most-active 10 firms make up just below 70% of the volume, the most-active 25 firms close to 95% of the volume, and the most-active 50 firms for close to 100% of the volume in downgraded U.S. corporate bond markets.

over the 12-year sample period. This indicates a skewed distribution with a long tail of dealers who only marginally contribute to the sample.

[20] Similarly, there is substantial cross-sectional variation in dealer credit ratings. The quarterly average rating is at 6.3 (i.e., A2 (upper-medium grade)) with a standard deviation of 3 rating steps. The first rating quintile is at 4.1 (i.e., Aa3 (high grade)) while the fifth quintile is at 11.3 (i.e., Ba1 (non-investment grade)).

[21] Dealer CDS spreads show a significant correlation (+0.25) with the TED spread (i.e., the difference between the three-month LIBOR and the three-month T-bill interest rates), which is generally used as a proxy for credit risk in the banking sector and closely related to financial institutions' short-term funding markets.

3 Event Study Methodology

3.1 Matching Portfolios

To investigate whether cross-sectional differences in liquidity providers' financing constraints explain the extent of price pressures upon a downgrade I employ an event study methodology. Specifically, I compute cumulative abnormal returns (CARs) to examine the return patterns of downgraded bonds and relate them to bond and dealer characteristics using cross-sectional regressions.

In spirit of Bessembinder et al. (2009), abnormal returns are measured using a matching portfolio approach where one compares the return of a particular bond i at time t with the average return on a portfolio of bonds at time t which *matches* bond i along a finite number of relevant risk factors (generally proxied for by observable bond characteristics). For a long-horizon event study, as is the case in this paper, constructing a benchmark return that equals the portfolio return on a small group of bonds with similar characteristics appears particularly appropriate as it assures a more reliable risk adjustment than a pure "*market return model*" that might potentially omit important risk factors. Thus, in an effort to appropriately match bonds along the most relevant risk dimensions I control for two risk factors: namely the default risk (proxied by bond ratings), the maturity risk of a bond (proxied by time-to-maturity). This yields 10 matching portfolios – five rating classes (AAA to AA-, A+ to A-, BBB+ to BBB-, BB+ to B, B- to C) times two time-to-maturity groupings (1 to 5 years (52^{th} percentile), and over 5 years). Matching along two dimensions is motivated by the balance between ensuring roughly similar portfolio sizes (with a sufficient number of trades) and creating matching portfolios that offer a reasonably close and reliable risk adjustment on a daily basis. For robustness, I also compute a set of matching portfolios based on a bonds' credit rating and its amount issued where the latter characteristic proxies for potential liquidity risks of high-yield bonds (Houweling et al., 2005).[22] For brevity and because the results are qualitatively similar I focus on the findings using rating/time-to-maturity matched portfolios. The results using rating/issued amount matched portfolios are relegated to the Appendix (important differences will be pointed out in the main text though).

In comparison to a "*market return model*", which is typically sufficient for short horizon

[22] In case of rating/issued amount matched portfolios I group bonds into five rating classes and a set of liquid ($1 to $500 million issuance size; i.e., the 65^{th} percentile) versus illiquid bonds (above $500 million issuance size).

event studies, these matching portfolios are segmented on finer partitions and therefore constitute a more reliable risk adjustment than broader market indices (e.g., the Barclay's U.S. high-yield and investment-grade corporate bond indices). This appears to be critical, since the assumption that bonds of different ratings load equally on aggregate bond returns is inaccurate at least within my sample. A univariate regression of bond on index returns produces an average β on the investment-grade (high-yield) index of 1.2 (0.74) before (after) the downgrade. That is, a "market return model" (where $\beta = 1$ by assumption) would underestimate (overestimate) expected or normal bond returns. Intuitively, the loading on the index should depend on a bond's default risk relative to the average default risk of the index. The majority of bonds hold a BBB- rating (i.e., the lowest investment-grade rating) in the weeks before the downgrade and a BB+ rating (i.e., the highest high-yield rating) in the weeks after the downgrade, which explains the over (under) exposure on the respective indices.

As an alternative to matching portfolios, one could also use a "*market-model approach*" to estimate bond- or portfolio-specific loadings on various risk factors. For instance, Ellul et al. (2011) estimate a bond's exposure to changes in the government bond yield, in both the investment-grade and the high-yield corporate spreads, as well as the issuer and aggregate stock market returns using bond portfolios. Since a considerable number of issuers do not have stock price data employing their particular estimation methodology would unnecessarily restrict the sample size though. Still, as a robustness check, I replicate my results employing their approach using a slightly modified regression setup. I replace replace an issuer's stock return with the return of the relevant SIC industry portfolio (using the Fama-French 49 industry classifications). This exercise does not change the overall conclusions of the paper and in fact produces comparable CAR patterns (see Figures 5, 6, and 7 in the Appendix).

Bond trades are usually irregularly spaced: some bonds trade on a daily basis, but the majority of bonds trade infrequently. Thus, focusing solely on daily-traded bonds when creating the matching portfolios would only reflect the return on the most liquid bonds and thus potentially omit illiquidity return premia. Likewise, excluding non-consecutive trades drastically reduces the number of bond trades per portfolio. Hence, to keep a sizable sample I include both consecutive and non-consecutive bond trades. In case a bond trades non-consecutively I linearly interpolated its prices in order to calculate a daily bond return.[23] To reduce the effects of highly infrequent trading within a bond I require that trades are 15 or fewer trading days apart (96^{th} percentile). Finally, on a given trading day each matching portfolio must contain at least two bond returns. Otherwise, I compute the portfolio return

[23]Suppose there is a trade at $t = 0$ for \$100, and no trade at $t = 1$, but there is a trade at $t = 2$ for \$105. Then, I calculate the daily return from $t = 1$ to $t = 2$ using prices \$102.5 and \$105.

on trading day t as a weighted average of the trading returns from days $t-1$, t, and $t+1$.[24] These requirements can lead to artificial smoothing in the returns of the matching portfolios, which, although not ideal, should not further affect the analysis of CARs. Lastly, the composition of each portfolio may change from day to day, which is partly mitigated by using value-weighted returns.

Arguably, my matching portfolios can be understood as a simplified special case of the approach proposed by Spiegel and Starks (2016). It is a simplification to the extent that I do not explicitly estimate daily returns using a dummy variable approach. And, it is a special case in the sense that bond returns contributing to a portfolio on a particular trading day are generally equally-weighted. In comparison, I am matching based on a bond's rating and its time-to-maturity while Spiegel and Starks (2016) group on a bond's yield and its industry classification. Importantly, as in Spiegel and Starks (2016), the approach yields an average univariate regression coefficient, β, of *one* when regressing bond returns on the matching portfolios.

3.2 Computing Abnormal Returns

In the calculations of bond returns I use simple returns (reported in %). That is, bond i's return at trading day t is calculated as

$$\mathrm{R}_t^i = \frac{\mathrm{P}_t^i - \mathrm{P}_{t-1}^i}{\mathrm{P}_{t-1}^i} \tag{1}$$

where P_t^i (P_{t-1}^i) is the clean price of bond i on trading day t ($t-1$).[25]

I denote the simple return on a corresponding matching portfolio over the event period $t-1$ to t as NR_t^i (i.e., the normal or expected bond return for R_t^i). Then, the abnormal return, AR_t^i, for bond i on event day t is calculated as the difference between the observed return and the normal bond return:

$$\mathrm{AR}_t^i = \mathrm{R}_t^i - \mathrm{NR}_t^i \tag{2}$$

Following Ellul et al. (2011) I define the downgrade event as the first downgrade announcement and the event period as the period from event weeks -20 to $+35$. When tracing

[24] Notably, this difficulty is mostly prevalent in *marginal* portfolios (e.g., portfolios with AAA to AA- or B- to C ratings.

[25] The clean price is preferred over the dirty price (i.e., with accrued interest) as it does not vary with coupon payments such that "clean" returns will not show an abrupt negative return on the coupon payment date. Arguably, the clean price only captures a bond price but not its interest return though.

abnormal returns over weeks -20 to $+35$, I constrain the sample to bonds that trade (i) at least once between weeks -20 and -1, (ii) at least once between weeks 0 and $+35$, and (iii) at least ten times during the sample period (i.e., excluding highly illiquid bonds with potentially unreliable prices). To obtain cumulative abnormal returns $\text{CAR}^i_{[t_1,t_2]}$ for event period $[t_1, t_2]$, I aggregate AR^i_t for each bond by event week and accumulate weekly CAR between event weeks t_1 and t_2. In case of multiple trades per bond i on trading day t and given the lack of time stamps in NAIC I use the median abnormal return of the particular day. Finally, I normalize CARs for each bond to zero at week -20.

I calculate the median (average) cumulative abnormal return, $\text{MCAR}_{[t_1,t_2]}$ ($\text{ACAR}_{[t_1,t_2]}$), as the median (average) of the normalized CARs across all available bonds in the each event week. That is, as in Ellul et al. (2011), MCARs and ACARs only contain the CARs of those bonds that actually trade in a particular event week. Consequently, the number of bonds used in the calculation of the aggregate statistics varies from week to week. Due to the potentially large, negative outliers surrounding a downgrade ACARs tend to be more noisy whereas the MCARs are more robust.[26] Since the mean better reflects the experience of insurers in aggregate though I report both statistics for the remainder of the paper.

4 Results

4.1 Return Patterns Around The Downgrade

The main empirical goal is to establish whether or not the financing constraints limiting liquidity providers' risk-bearing and inventory capacities negatively affect bond price patterns around a downgrade. I start with a graphical inspection of CARs. Using the volume-weighted average CDS spread of the five most-active dealers per bond and issuer respectively, I compare CARs for bonds with average dealer CDS spreads above the median (i.e., *constrained* dealers with high inventory financing costs) with those for bonds with average dealer CDS spreads below the median (i.e., *unconstrained* dealers with high inventory financing costs). Figure 3 plots ACAR and MCAR patterns at the bond-level whereas Figure 4 plots them at the issuer-level. I find a striking pattern of large price drops and reversals around the downgrade, similar to the pattern documented in the literature (see, e.g., Spiegel and Starks (2016), Ellul et al. (2011)). However, dealer constraints appear to have a substantial impact on these price patterns.

[26] In fact, Bessembinder et al. (2009) find that skewness in abnormal returns leads to excessive Type I errors (over-rejections of the null) using t-statistics.

Insert Figures 3 and 4 here

Consistent with the financial constraints hypothesis, those bonds with dealers showing high credit risks and thus potentially more severe inventory financing constraints experience substantially larger return deviations, as exhibited by more negative and abrupt declines in abnormal returns. This provides graphical support for the idea that higher inventory financing costs limit dealers' risk-bearing capacities making them less willing to establish growing inventory imbalances without substantial price markdowns.

In these plots three observations stand out. Consider, for example, Figure 3: First, CARs are increasingly declining from as early as week -20 where ACARs (MCARs) have dropped by 6.8% (5.3%) before the first downgrade announcement. This suggests that markets are likely anticipating adverse rating changes (e.g., due to the deterioration of issuer fundamentals) resulting in strong negative bond price momentum. The price decline steepens as the downgrade event approaches suggesting that the speed with which capital moves out of the distressed bonds is likely increasing. Since bond prices should incorporate the probability of a downgrade, the more rapid drop in returns appears to be are result of growing order-flow imbalances rather than changes in the prediction of issuer credit risks. Notably, before the actual downgrade the bond returns of constrained and unconstrained dealers do not diverge significantly.

Second, after the downgrade CARs continue to fall and reach their lowest point in the short period before event week $+5$. At this point MCARs have dropped by close to 6.9% while ACARs have fallen by 9.7%. By this point the bonds of constrained dealers have dropped significantly more than those of unconstrained dealers. That is, bond of dealers with higher financing constraints are experiencing larger price declines and thus appear to be transacting positions at larger markdowns. These return differences are significant in particular in the period immediately following the downgrade (see Tables 3 and 4).

Third, in the period from event week $+5$ to $+10$, ACARs show signs of modest price reversals moving upward by 1.8%. MCARs, on the other hand, more or less stabilize and improve by 1.4% up to week $+25$. Clearly, the reversals are steeper and thus faster for bond of unconstrained dealers suggesting that because these dealers can finance trading positions at lower costs they are able to rebalance inventories faster at potentially lower transaction costs than their constrained competitors. For the period after event week $+15$ the return patterns generally tend to stabilize for the following 20 weeks where bond prices have dropped by roughly 6.5% (6.1%) in terms of ACARs (MCARs). Notably, in this period the return differences between bonds of constrained and unconstrained dealers is not significant different from zero anymore (see Tables 3 and 4). Overall, these return patterns are consistent with the findings of Spiegel and Starks (2016) who show that downgrades lead to significant negative abnormal returns to be followed by partial prices recoveries.

As reported in Figures 5, 6 and 7 in the Appendix I find similar CAR patterns (i.e., in terms of timing and magnitude) when using the modified regression-based approach of Ellul et al. (2011), the simple market-return model used in Han and Wang (2014), or when using rating/issued amount matched portfolios. All plots are consistent with the notion that temporary risk-bearing limits depress bond prices beyond fundamentals until inventory imbalances abate and the negative price pressure partially dissipates. Importantly, the effects are clearly in line with the financial constraints hypothesis where bonds handled by constrained dealers are associated with substantially more negative and abrupt declines in abnormal returns and slower reversals.

To check whether the return differences between bond of constrained and unconstrained dealers illustrated in Figures 3 and 4 are indeed statistically significant I test the significance of CARs over 5-week periods before and after the downgrade. Tables 3 and 4 hold these CAR statistics. I find the CAR difference between bonds with constrained dealers and those with unconstrained to be statistically significant in particular in the period immediately following the downgrade.

Insert Tables 3 and 4 here

Consider Tables 3 measuring dealer constraints at the bond level: In the downgrade week the MCAR difference is given by -3.73% (t-stat= -2.37) highlighting their statistical and economic significance. In the weeks following the downgrade (i.e., weeks $+1$ to $+15$) this return difference remains significant at -3.63% on average. For ACARs the results are similarly negative and given by -3.21% (t-stat= -1.65) in the downgrade week where I tend to obtain strong statistical significance only as of week $+5$. That is, between weeks $+5$ to $+20$ the ACAR return difference is strongly significant and given by -6.64% (t-stat= -3.16) on average. Notice that these CAR differences in bonds of constrained and unconstrained dealers are strongly negative and highly significant particularly within the short period after the downgrade while they tend to be statistically insignificant in weeks before and long after the downgrade. This suggests that cross-sectional differences in dealers' financing constraints matter exactly when selling pressure is the highest. And, that the negative price effects tend to be eventually comparable in magnitude as selling pressure dissipates and inventories constraints abate over time.

Measuring dealer constraints at the issuer instead of the bond level, the CAR statistics are slightly more noisy such that I obtain less significance but similar in terms of timing and magnitude (see Table 4). Market making at the issuer level entails handling more trading volume with a potentially wider clientele such that dealers could potentially be able to better offset trading positions. Also, hedging adverse price movements of held inventories *within the same bond issuer* (e.g., long downgraded bond A_1 and short another investment-grade bond A_2 of issuer A) allows dealers to partially avoid some of the inventory (price) risks. Thus, one could expect that market-making at the issuer level increases dealers' risk-management and hedging possibilities. However, as dealers receive no capital relief from hedges within the same bond issuer under Basel rules such within-issuer price hedges come at the cost of increased capital and financing needs. Even at the issuer level this can intensify inventory effects for constrained dealers in particular under intense selling pressure.

Overall, downgrades from the investment to the non-investment grade classification appear to lead to permanent devaluations of bond prices, which, through the perspective of microstructure models, reflect lasting changes in investors' expectations. The fact that CARs partially reverse in the long run suggests that the collective need to divest downgraded bonds may, at least in the short-term, be limited by dealers' inventory capacities. That is, downgrades tend to depress bonds prices beyond fundamental values (i.e., prices overshoot their new long run equilibrium value) where part of the overly negative price effects eventually dissipate over time as aggregate dealer inventories revert to their long-term averages. Importantly, the above analysis highlights that these return patterns are different for bonds handled by constrained versus those handled by unconstrained dealers and that these differences appear to be consistent with the idea that dealers' financial constraints limit their risk-bearing capacities around a downgrade.

4.2 Cross-Sectional Regressions of Downgraded Bonds

In what follows I run bond-level cross-sectional regressions to relate CARs to bond, trading, and dealer characteristics. Beside $CAR_{[-20,+35]^i}$ (spanning the entire event window) I study $CAR_{[-20,-1]^i}$ to capture the downward return pressure up to the rating change as well as $CAR_{[0,+35]^i}$ to capture the effect following the actual downgrade. I employ two estimation procedures: first, to reflect the average trading experience of an insurer I use regular OLS, and, second, due to potentially large, negative outliers I also use median regressions for robustness.

The regression equation relating the cross-section of CARs to bond, trading, and dealer characteristics is given by

$$\mathrm{CAR}^i_{[t_1,t_2]} = \alpha + \beta_D D^i_{[t_1,t_2]} + \beta_T T^i_{[T_1,T_2]} + \beta_B B^i + \sum_{k=2003}^{2014} \gamma_k \delta^i_k + \gamma_{\mathrm{fin}} \delta^i_{\mathrm{fin}} + \gamma_{\mathrm{int}} \left(\delta^i_{\mathrm{fin}} \times \delta^i_{\mathrm{crisis}} \right) + \epsilon^i \,. \tag{3}$$

In equation (3) the vectors B^i, $T^i_{[T_1,T_2]}$, and $D^i_{[t_1,t_2]}$ hold *bond*-specific characteristics, a set of measures capturing bond i's *trading* activity, as well as *dealer*-specific attributes that proxy for the market presence and the inventory constraints of the most-active five dealers per bond (issuer).

Specifically, the vector $D^i_{[t_1,t_2]}$ holds the following regressors: Relative to the downgrade date and corrected for the trading within the event window I construct a bond's annual Herfindahl index where a higher index points to a reliance on a small number of key market makers, potentially rendering the bond trading imperfectly competitive.[27] To make the measure comparable across bonds (issuers) and time I compute the ratio of each respective Herfindahl index over the median Herfindahl index per calendar year. In case of an industry-wide sell-off of a downgraded bond issue one would expect the selling pressure to be partially alleviated if it can be shared among more (unconstrained) market makers. Similarly, using primary market data, I identify a bond's (issuer's) lead underwriters and compute their market share (in %) per event year where higher figures around the downgrade would point to a sustained issuer-dealer relationship and a potential commitment to market-making for a particular bond (issuer). Lastly, and of primary interest, I construct the weekly volume-weighted average CDS spread of the five most-active dealers per bond and issuer respectively.[28] For comparison across bonds (issuers) and time I then compute the ratio of weekly dealer CDS averages over the median dealer CDS average per calendar week and accumulate the resulting ratio between event weeks t_1 and t_2. Consistent with the financial constraints hypothesis, bonds with more constrained dealers as their most-active market-makers should experience substantially larger price pressure, as exhibited by more negative and abrupt declines in abnormal returns.

The vector $T^i_{[T_1,T_2]}$ contains bond-specific trading characteristics computed between weeks $T_1 = -75$ to $T_2 = -20$ preceding the downgrade. All of these measures primarily proxy for the liquidity in a bond (issuer). For each bond, insurers' net trading volume (in \$ millions) using NAIC transactions is calculated as the buy volume minus the sell volume

[27]In that the measure closely follows O'Hara et al. (2016).

[28]The weighting of CDS spreads by trading volume is based on dealers' trading activity per event year in a particular bond (issuer). The results remain qualitatively unchanged when I correct for the trading within the event window.

during weeks −75 to −20, divided by the bond issue size.[29] A positive net volume identifies the insurance industry as a net buyer where larger figures could suggest more severe selling pressure. Using TRACE data, I compute the total non-insurer trading volume of a bond (in $ millions) over weeks −75 to −20 as the sum of all TRACE trading volume minus the equivalent NAIC trading volume where the difference is then divided by the bond issue size. Beside liquidity this measure also captures potential buyer capital where more frequent and higher trading of non-insurance companies would suggest a more liquid market with a potentially larger client base. The latter could make it easier for dealers to offset trading positions after a downgrade. Capturing the ability to readily offset trading positions in a particular bond in a short period of time, I compute the average time (in minutes) between consecutive customer-dealer trades within TRACE in the weeks −75 to −20. Moreover, as a proxy for an active inter-dealer market, I compute the share (in %) of inter-dealer trades relative to all trades (i.e., customer-dealer plus inter-dealer trades) in TRACE in the weeks −75 to −20. A more liquid inter-dealer market may ensure that positions can be acquired and subsequently passed along to other dealers.

Captured in B^i I control for a range of bond characteristics. For instance, the natural logarithm of a bond's offering amount (in $ million)[30] and the natural logarithm of a bond's age (i.e., the time since issuance) measured at the time of downgrade. Also, I include a dummy that flags bonds if they do not have seniority in order of repayment (i.e., all forms of junior and subordinate debt). Similarly, I include a dummy for bonds with credit enhancements (e.g., guarantees, letter of credit, etc.). As a measure of rating dispersion I use the maximum rating difference measured in the week before t_1 (i.e., the difference between the highest and the lowest rating in case of multiple agencies; in case of only one agency this measure is zero by definition).

Finally, I include a dummy, δ^i_{fin}, flagging an issuer's SIC industry code as related to finance or banking (i.e., using the Fama-French 49 industry portfolio classifications). These issuers may have experienced more severe pressure in case of downgrades during the 2007-2009 subprime crisis. I also add year fixed-effects, δ^i_k,[31] and include an interaction term, $\delta^i_{\text{fin}} \times \delta^i_{\text{crisis}}$, that captures downgrades of financials during the 2007-2009 subprime crisis period (particularly August 2007 to March 2009).

[29] This measure does not taking primary market trading into account (i.e., trades executed on a bond's offering date).

[30] For matching portfolios based on bond ratings and issue amount the natural logarithm of the (remaining) time-to-maturity at the time of the downgrade is used instead.

[31] For instance, Ellul et al. (2011) find the year 2002 to be the most likely to result in fire sale prices since insurers are found to be more "impaired" and thus likely to heavily sell downgraded issues.

In the particular regression settings it makes sense to de-mean (de-median) *all* independent variables in order to give the regression constant the interpretation of the mean (median) cumulative abnormal return. Thus, all variables have to be interpreted as deviation from the mean (median) such that I will report the marginal effect of a particular regressor in terms of a one standard deviation increase.

The error term ϵ^i in equation (3) is assumed to be zero on average and uncorrelated with the explanatory variables. Econometric issues may be the following: As captured in Table 1, the majority of firms have only a handful of bonds affected by a rating event while there is a small number of large issuers with a lot of bonds being downgraded in close proximity of time.[32] For one, this may lead to a (potentially) skewed distribution of downgrades across issuers. Given that the focus is to study the significance of dealer inventory constraints, the overrepresentation of issuers with multiple downgraded issues, although not ideal, will strengthen the point that insurers' collective need to suddenly divest downgraded issues can temporarily overexert dealers' risk bearing and inventory capacities. Actually, median regressions as well as using subsamples (e.g., excluding Lehman Brothers) suggest that the results are not driven by only a handful of issuers. For another, downgrades may be clustered (i.e., downgrades in close proximity with potentially highly correlated bond and dealer characteristics) and have overlapping event windows, which violates the assumption of independent observations and leads to inflated t-statistic. To overcome these issues I correct the standard errors by clustering observations at the issuer×downgrade-year level.

4.2.1 Baseline Findings

With the bond-level cross-sectional analysis I want to confirm that the impact of dealers' inventory constraints on CARs documented in the graphical analysis is indeed valid after controlling for various bond and trading characteristics. Table 5 reports the average and median regression estimates for the full, the pre, and the post event period for abnormal returns computed against a rating/time-to-maturity matched portfolio and dealer constraints measured for the five most-active dealers at the bond-level. Table 6 holds the regression results when dealer constraints are measured at the issuer-level.

Insert Tables 5 and 6 here

To begin with, the regression results confirm the observed patterns of the graphical inspection: dealers' inventory financing constraints (as proxied by their CDS spreads) have

[32]In the years 2005 and 2008 big issuers such as Ford and General Motors as well as Lehman Brothers experience downgrades in most (if not all) of bond their issues on the same calendar date.

a negative, economically meaningful, and highly significant effect on CARs over the entire event window (i.e., weeks -20 to $+35$). Even though OLS estimates are more pronounced than the median regression results, the negative impact on CARs is consistent independent of the regression procedure. Consider the regression results for the whole event period [-20,+35] where dealer constraints are measured for the five most-active dealers at the bond-level: the average (median) estimate of -12.11% (-5.82%) implies that a one standard deviation increase in the ratio of a bond's volume-weighted average dealer CDS spread over the median dealer CDS spread at the time is associated with a significant negative average (median) CAR of 3.55% (1.71%).

I find the negative impact on CARs to be stronger when measuring dealer constraints at the issuer instead of the bond-level. Table 6 suggests that for a one standard deviation increase the average (median) estimate of -17.39% (-7.04%) implies a negative CAR of 4.24% (1.71%). This suggests that bonds and particularly issuers with constrained dealers (i.e., an average volume-weighted dealer CDS spreads above the median) exhibit more negative cumulative abnormal returns around a downgrade.

Comparing the pre- with the post-event window when measuring dealer constraints at the issuer-level, the empirical evidence suggests that the negative impact of dealers' inventory constraints on CARs is stronger in the weeks following the downgrade (i.e., weeks 0 to $+35$). Using OLS, the coefficients on the dealer CDS ratio are -6.90 for the pre-event and -10.29 for the post-event window. Moreover, in the median regressions, the coefficient on the dealer CDS ratio is of lower magnitude and does not obtain statistical significance in the period leading up to the event (i.e., weeks -20 to -1). This indicates that inventory financing constraints appear to matter more after the rating change occurs, the insurance industry is constrained to selling the bond issue, and dealers' inventory limits become binding. When dealer constraints are measured at the bond-level this effect is much less pronounced.

Overall, these findings provide strong support for the financing constraint story: bonds handled by dealers with higher inventory financing constraints and therefore limited risk-bearing capacities show a higher price pressure around a downgrade. The effect on CARs is negative and substantially larger for bonds with dealers showing high credit risks, which suggests that constrained dealers are less willing to establish growing inventory imbalances without substantial price markowns.

Among the remaining dealer characteristics the market share of a bond's lead underwriters (LU) has a positive, significant and economically meaningful effect on ACARs in particular in the pre-event period (i.e., weeks -20 to -1). The coefficient of 0.13 implies that a one standard deviation increase results in an increase of ACARs of approximately 1.15%. This suggests that in the weeks leading up to the downgrade higher involvement of lead underwriters in the market-making of a bond is associated with less price pressure (e.g., due to a valuable issuer-dealer relationship resulting in an implicit commitment to a bond). This appears to be in line with a finding by Dick-Nielsen et al. (2012) who show that bonds become more illiquid if two particular lead underwriters, potentially still serving as market-makers in secondary market trading, are facing financial distress (i.e., Bear Stearns in March 2008, and Lehman Brothers in September 2008). Admittedly, when measured at the issuer level or using median regressions the effect of LU market share on CARs is not statistically significant though.

A bond's Herfindahl ratio (i.e., the Herfindahl index scaled by the median Herfindahl index at the time) has a significant and negative effect on ACAR in the pre-event period (i.e., weeks -20 to -1). This effect is significant both at the bond- and the issuer-level where coefficients imply that a one standard deviation increase leads to decrease in ACARs of 1.00% and 1.35% respectively. That is, a reliance on a small number of key market makers, potentially rendering the bond trading imperfectly competitive, decreases CARs in particular in the weeks leading up to the downgrade. Using median regressions, this effect does not obtain statistical significance.

Over the entire event-window the regression constants are significant and well below zero throughout all specifications. As reported in Table 5, the average (median) constant is -11.26% (-4.53%). Comparing the pre- and the post-event windows, the constants show a noticeable pattern: CARs in the pre-event period are significantly lower. This is the case because the post-event period is associated with return reversals where overly negative price pressure is partially reversed through positive returns after event week 10. Using median regressions, the constant for the weeks following the downgrade, 0.59%, is even slightly positive.

Unreported in the Tables 5 and 6, year dummies barely obtain statistical significance. With the exception of the years 2003, 2005, 2008 and 2009, these dummy estimates have a positive effect on CARs. Zooming in on the crisis period, I do not find that CARs of bonds experiencing a downgrade during the years 2007 to 2009 are per se lower. However, I find the interaction effect between the crisis period and the financial industry dummy to be very negative and strictly different from zero at any reasonable level of significance. The coefficients suggests that bond ACARs (MCARs) of financial firms are depressed by 9.87% (15.18%) for a one standard deviation increase over the entire event period. The effect is similar in magnitude for estimates in Table 6. That is, bond downgrades of financial companies during the 2008 subprime crisis period are associated with highly negative CARs. This appears to be, among other things, driven by the Lehman Brothers default in September

2008 but still holds (in unreported results) for subsamples excluding Lehman Brothers.

Considering the remaining control variables in Table 5, I find that only a small number of regressors is associated with significant and economically meaningful effects. Among the bond characteristics, credit enhancements (e.g., guarantees, letter of credit, etc.) significantly reduce price pressure such that bonds with enhancement features fair better and, for a one standard deviation increase, are associated with a positive ACAR of 2.08%. In a similar spirit, I find that juniority in order of repayment (i.e., all forms of junior and subordinate debt) points toward strongly negative ACAR. However, the effect does not obtain statistical significance. The variable rating dispersion is associated with a positive effect on ACARs. That is, wider disagreement between agencies, measured as the difference between the highest and the lowest available rating, leads to lower price pressure, especially leading up to a downgrade. Comparing the pre- with the post-event window coefficient, a one standard deviation increase in rating dispersion increases ACARs by 3.74% and 1.54% respectively. Thus, rating dispersion appears to capture the strength of a sell-off and thus the decline of returns in the period leading up the event, which is likely associated with insurers being less pressured into selling downgraded issues quickly. Using median regressions, the effects of the various bond controls oftentimes obtain less statistical significance. I find bond age to have a negative and significant effect on MCARs where a one standard deviation increase reduces MCARs by 0.90% over the entire event window.

Among a bond's trading characteristics, the coefficient on the share of inter-dealer trading is significant and negative and tends to decrease ACARs by 1.07% for a one standard deviation increase. Using median regressions, I find that MCARs negatively affected if a bond shows a higher TRACE trading volume (excluding NAIC trades). A one standard deviation increase significantly decreases MCARs by 0.84%. Similarly, the average TRACE time stamp difference between customer-dealer trades obtains statistical significance and depressed MCARs by 0.72% for a one standard deviation increase. All of these trading characteristics proxy for a bond's liquidity. Surprisingly, my findings suggests that more bonds with higher trading activity, in terms of volume and trades, experience higher price pressure. In what follows I investigate this aspect further by running cross-sectional regression on various liquidity subsamples.

4.2.2 Accounting for Recent Bond Liquidity

On top of inventory price risks, high-yield bond inventories are costly in terms of financing and require higher risk-based capital charges. In the process of acquiring downgraded bond positions, dealers' expected inventory costs are therefore a function of the expected illiquidity of a particular bond position. For instance, Goldstein and Hotchkiss (2017) find that inventory positions in high-yield bonds are oftentimes quickly offset within the same trading day (i.e., as consequence of dealer search efforts) to mitigate inventory risks and costs associated with holding inventory positions. Thus, dealers' propensity to offset trading positions within a short period of time rather than to establish inventory is, among other things, determined by their liquidity. Besides bond characteristics such as the amount issued and bond age, which have been shown to be good proxies for liquidity by Houweling et al. (2005),[33] a bond's recent (in)frequency of trading, measured by a bond's non-zero trading days, provides a good proxy for expected near term trading activity (see, e.g., Goldstein and Hotchkiss (2017)). Typically the number of non-zero trading days will be higher for bonds with bigger buyer interest rendering these bonds more liquid.

Thus, in the subsequent analysis, I re-run the cross-sectional regressions while exploiting the non-zero trading days measure. Besides including the variable as another control variable, I form subsamples of the data by splitting all downgraded bonds into a group of liquid and one of illiquid bonds. In case the number of non-zero trading days in the weeks -75 to -20 preceding the downgrade is less (more) than 72 a bond is categorized as illiquid (liquid). The cutoff point for non-zero trading days is the median. Tables 7 and 8 hold the regression results.

Insert Tables 7 and 8 here

To start with, the results are robust to the direct inclusion of the non-zero trading days liquidity measure as another control variable in regression equation (3). The liquidity proxy yields a positive but statistically insignificant coefficient of 0.017 (0.019) with t-stat$=1.21$ (t-stat$=1.32$) when dealer constraints are measured at the bond-level (issuer-level), which translates into a increase of CARs of 1.27% (1.36%) for a one standard deviation increase in a bond's trading frequency. That is, illiquid bonds show lower ACARs over the full event window. Importantly, the coefficient on the dealer CDS ratio is not affected by the inclusion and remains at -12.40 with t-stat$=-3.63$ at the bond-level (-17.71 with t-stat$=-4.20$ at the issuer-level). As reported in Table 8 median regression coefficients are also robust (i.e., the magnitude and significance of the coefficient on Dealer CDS ratio does not change markedly) to the inclusion of the non-zero trading days variable. The latter yields a positive coefficient of 0.018 (0.020) with t-stat$=1.55$ (t-stat$=1.75$) when dealer constraints are measured at the bond-level (issuer-level), which translates into a increase of CARs of 1.40% (1.32%) for a one standard deviation increase in a bond's trading frequency.

[33]The non-zero trading days measure is significantly positively correlated (0.69) with the issued amount and significantly negatively correlated (-0.16) with bond age.

The positive effect of higher (recent) bond liquidity on CARs is also picked up in the subsample regressions: the regression constants across the subsamples indicate that illiquid bonds show a highly significant negative ACARs over the entire event window (i.e., weeks -20 to $+35$) whereas the constant is not significant for liquid bonds. Consider, for example, the *LoLiq* specifications when dealer constraints are measured at the bond-level: the ACAR is -11.35% (-11.73%) for illiquid (liquid) bonds where the constant in the low liquidity subsample is highly statistically significant, t-stat$= -9.18$, while the one in the high liquidity subsample does not obtain statistical significance, t-stat$= -1.60$. Using median regression, I find all constant to be insignificantly different from zero across both subsamples.

The subsample regression results are consistent with the financing constraint story: bonds handled by dealers with higher inventory financing constraints show lower CARs around a downgrade. The effect remains negative, and economically meaningful. However, CARs in liquid bonds appear to be more affected by constrained dealers than illiquid bonds. That is, the subsample regression coefficients suggest that CARs of liquid bonds are more negatively affected by dealers' inventory financing constraints than illiquid bonds. The estimates imply that a one standard deviation increase in the dealer CDS ratio decreases ACARs by -4.86% (-1.75%) for liquid (illiquid) bonds when dealer constraints are measured at the bond-level. When measured at the issuer-level, the impact on ACARs is given by by -6.15% (-1.93%) for liquid (illiquid) bonds. For MCARs this effect is given by -2.72% (-1.20%) for liquid (illiquid) bonds when dealer constraints are measured at the issuer-level.

Interestingly, the return difference between liquid and illiquid bonds will be reduced when the latter show more frequent inter-dealer trading. The inter-dealer market allows dealers to pass along trading positions to other dealers who are indicating a better fit for the particular trading position. Only the subsample of illiquid bonds exhibit significantly lower CARs when there is a higher share of inter-dealer trades in total trading. The coefficients imply that for a one standard deviation increase in the variable ACARs of illiquid bonds decrease by -1.39% when dealer constraints are measured at the bond-level (-1.29% at the issuer-level). Using median regressions, this effect on illiquid bonds is of similar significance but less pronounced: MCARs increase by -0.66% (-0.64%) when dealer constraints are measured at the bond-level (issuer-level). This suggests that whenever a dealer cannot re-sell illiquid bond position within her client base and turns to the inter-dealer market these bonds experience more substantial price pressure. Increased inter-dealer trading appears to be an indication of smaller buyer interest in a particular bond issue such that price markdowns associated with illiquid bonds appear to be affected by a trade-off between retaining inventory risks and search efforts.

4.2.3 Accounting for Insurer Constraints

Ellul et al. (2011) show that more constrained insurance companies are more likely to sell at least part of their holdings of a downgraded bonds. This oversupply can amplify selling pressures especially in periods when the insurance industry as a whole is more constrained. To control for insurer constraints I take into account three insurer-specific variables as employed by Ellul et al. (2011) in Section 3.1 “Probability of selling around the downgrade”.[34] First, the holdings of the entire insurance industry in a particular bond (in %) measured in the quarter before the downgrade. Second, the holdings of property insurance companies (in %) in the quarter before the downgrade in order to account for the fact that property insurance companies, in comparison to life insurers, face relatively short-term and more uncertain liabilities, which prompts them to divest downgraded bonds more rapidly (Ellul et al. (2011)). Third, as a direct measure of regulatory constraints, the average NAIC risk-based capital ratio (RBC ratio) of all insurers’ holding the respective bond. This ratio is defined as the ratio of total adjusted capital to NAIC risk-based capital (RBC). RBC is the minimum amount of capital that the insurance company must maintain based on the inherent risks in its operations. Higher RBC ratios represent better capitalization and ratios below 2.0 trigger supervisory interventions. As documented in Ellul et al. (2011) this proxy is a strong predictor of a bond’s selling probability upon a downgrade.

As their data ranges from 2001 to 2005 whereas my data ranges from 2002 to 2014 I can only include downgrades during the years 2002 to 2005 (i.e., fully excluding the 2007-2009 subprime crisis period). This reduces the sample from roughly 882 feasible downgrades to 234 downgrades. As Ellul et al. (2011) only include bonds that exhibiting zero-issuer-stock returns upon the downgrade this subsample investigates downgraded in absence of information effects (see Ambrose et al. (2009)). All bond with insurer-specific characteristics are senior debt which means I drop the juniority dummy. The years from 2002 to 2005 when cross-sectional differences in dealer CDS spreads are at their lowest (see Figure 1) and the quintile spread is at merely 30 bps. During this period markets become increasingly more liquidity close to its all-time high in year 2006 (Bao et al. (2011)) and dealers start scaling up their balance sheets with cheap short-term funding (Rosengren (2014)). The empirical strategy is straightforward: I include the RBC ratio as another independent variable in my cross-sectional regression to check whether the coefficient on dealer financing constraints retains its strength and significance. Table 9 holds the regression results.

[34] I thank Chotibhak Jotikasthira for sharing data on bonds’ selling probabilities. Ellul, Jotikasthira, and Lundblad (2011) employ several measures of insurer constraints to predict the probability of insurer sells surrounding a downgrade.

Insert Table 9 here

The results in Table 9 are consistent with the financial constraint hypothesis: bonds with more constrained dealers experience significantly lower CARs around a downgrade where the average effect is more pronounced than the median effect. Consider specification 2, the estimate of -13.55 implies that for a one standard deviation increase in the dealer CDS ratio decreases ACARs by -2.55%. Likely due to the lack of power given the limited number of observation, I obtain less statistical significance. Using OLS, the coefficients are still highly significant when measuring dealer constraints at the issuer-level and slightly less significant at the bond-level. In median regressions, the effect has the right sign and economic magnitude but the effect is not significant anymore. Overall, the impact of dealers constraints on CARs is robust to the inclusion of insurer constraints. Upon a downgrade, dealer constraints, on average, still amplify downward price pressure in downgraded bonds.

The insurer-specific variables do not obtain statistical significance throughout all specifications. The direction of the coefficients on insurer holdings and the RBC ratio are in line with expectations. Higher insurance holdings result in more negative CAR. And, better bonds held by better capitalized insurers experience less price pressure. Surprisingly, the coefficient on property insurer holdings is positive suggesting that bonds with higher property companies holding them show increasing CAR.

Among the remaining control variables, a bond's age tends to significantly depress CARs within this subsample. A one standard deviation increase in bond age decreases ACARs by 3.64%. Surprisingly, rating dispersion before a downgrade now has a significantly negative impact on CARs leading to a decrease of 3.64% for a one standard deviation increase in the variable. Similar to the findings in Subsection 4.2.2, a one standard deviation increase in the share of inter-dealer trading in a downgrade issue decreases ACARs by 1.36%. The coefficient flagging financial firms is positive and significant, which implies an increase in ACARs of 3.83% for a one standard deviation increase. The effect predominantly captures the trading in the Ford and General Motors subsidiaries General Motors Acceptance Corporation (GMAC) and Ford Motor Credit Company (FMCC) respectively, which handle the auto financing and loans in support of their parent companies. Thus, in comparison to the average CAR, which is around -9%, financials firms show significantly higher ACARs within the event period.

5 Conclusion

This paper investigates the impact of dealers' financial constraints on fire sales of corporate bonds by insurance companies. As insurance companies operate under regulations that constrain their risk-taking capacity, a bond downgrade from investment-grade to non-investment-grades can induce a collective need to immediately and collectively divest downgraded bond issues (see, Ellul et al. (2011)).

Since regulated insurance companies as a group hold over a quarter of all outstanding corporate bonds, the forced selling of downgraded bond issues temporarily generates substantial order flow imbalances. Upon a downgrade, corporate bond dealers provide liquidity by absorbing these temporary order-flow imbalances onto their own balance sheets. Dealers' ability to take the role of middlemen is closely linked to the ease with which they can establish and maintain inventory positions. Speculative bond inventories hold substantial inventory price risks, require higher risk-based capital charges, and are costly in terms of financing. At least in the short-term, a dealer's financial constraints can create temporary limits in her risk-bearing capacities. As the cost of liquidity provision increases, a dealer can become increasingly hesitant to take on additional inventory, and may quote smaller quantities at less attractive prices.

I show empirically that dealers' financing constraints (as proxied by dealers CDS spreads) have a statistically and economically meaningful negative impact on the bond price patterns surrounding a downgrade. Consistent with the financial constraints hypothesis, bonds that are handled by constrained dealers experience substantially larger return deviations, as exhibited by more negative and abrupt declines in abnormal returns. The empirical evidence suggests that higher inventory costs limit dealers' risk-bearing capacities making them less willing to establish growing inventory imbalances without substantial price markdowns. These findings are robust to controlling for various bond, market, and dealer characteristics as well as when using median regressions.

Figure 1: Cross-Sectional Dispersion in Dealer CDS Spreads

Note: This figure illustrates the daily average dealer CDS spread as well as the lowest and highest dealer CDS quintiles.

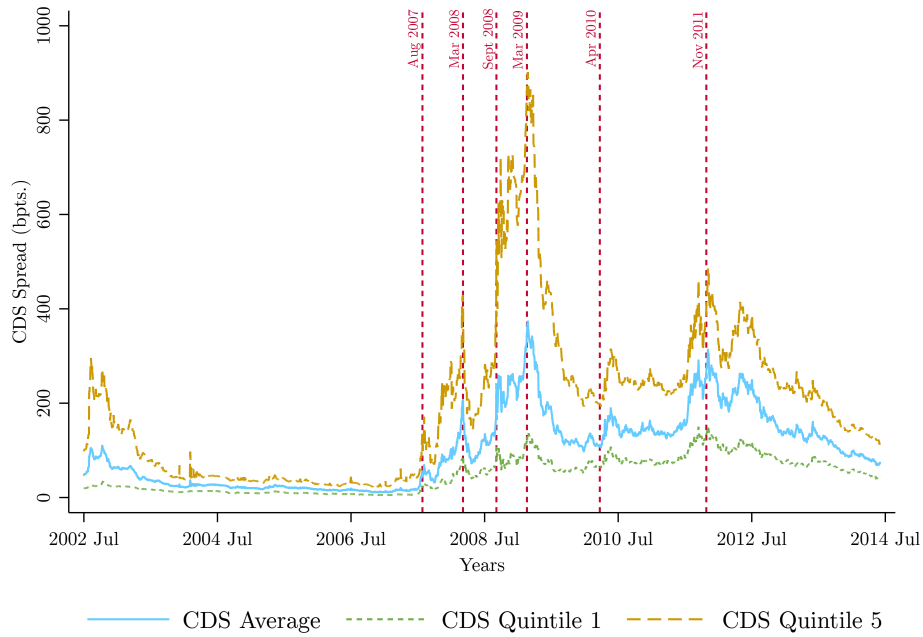


Figure 2: Dealer Trading Activity in Downgraded Bonds (by Volume)

Note: This figure illustrates the annual trading volume of the most-active 5, 10, 25, and 50 dealer firms.

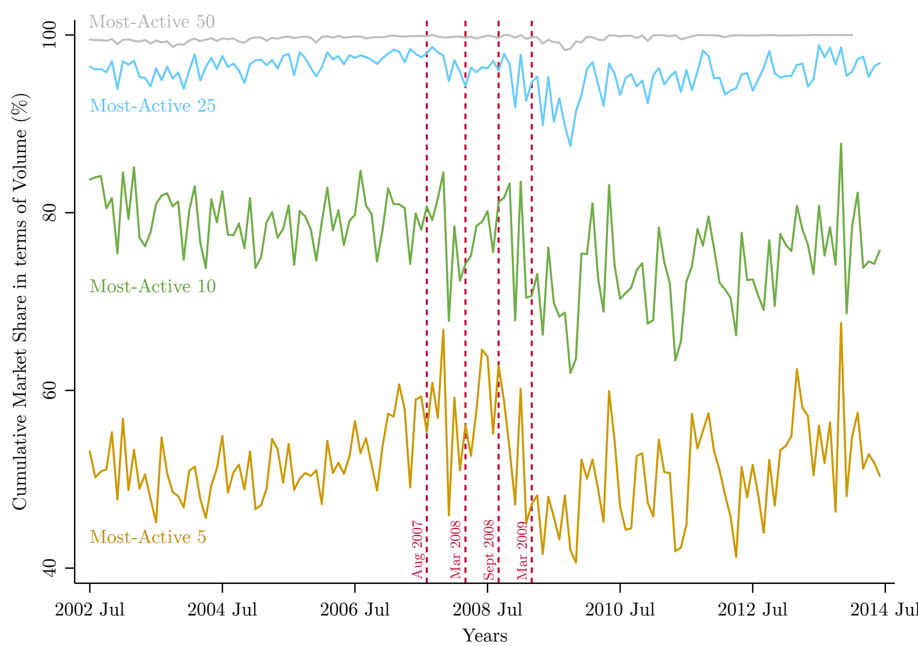
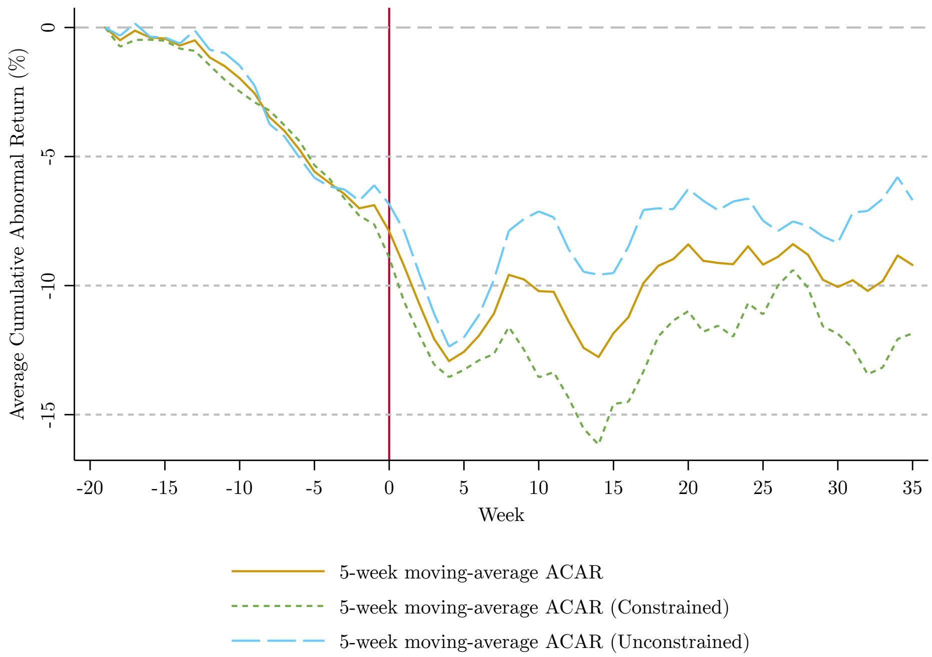


Figure 3: CARs around Downgrade (*bond-level*)

Note: Dealer CDS spreads are measured at the ***bond-level***.



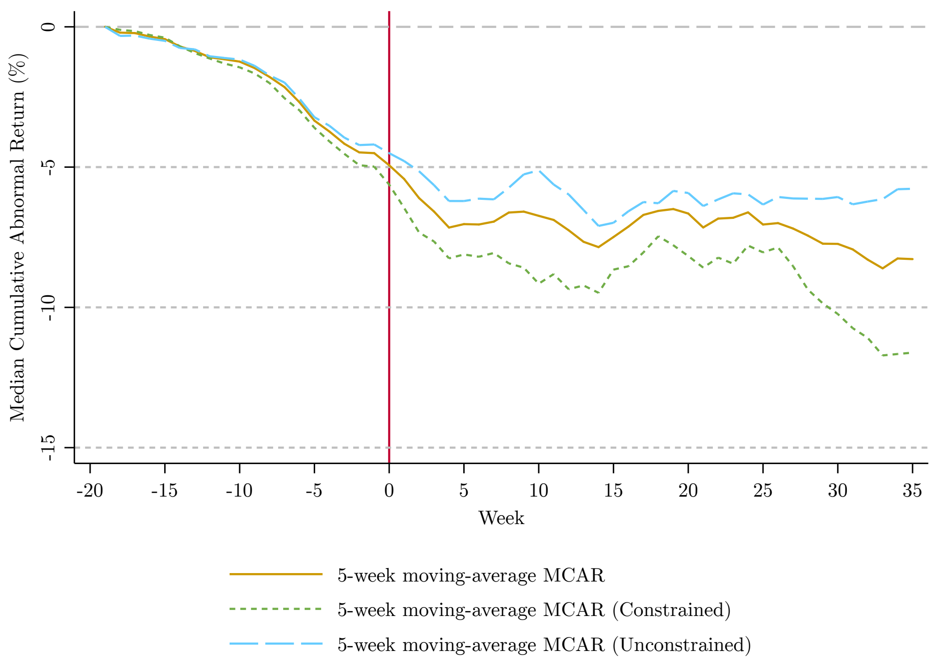
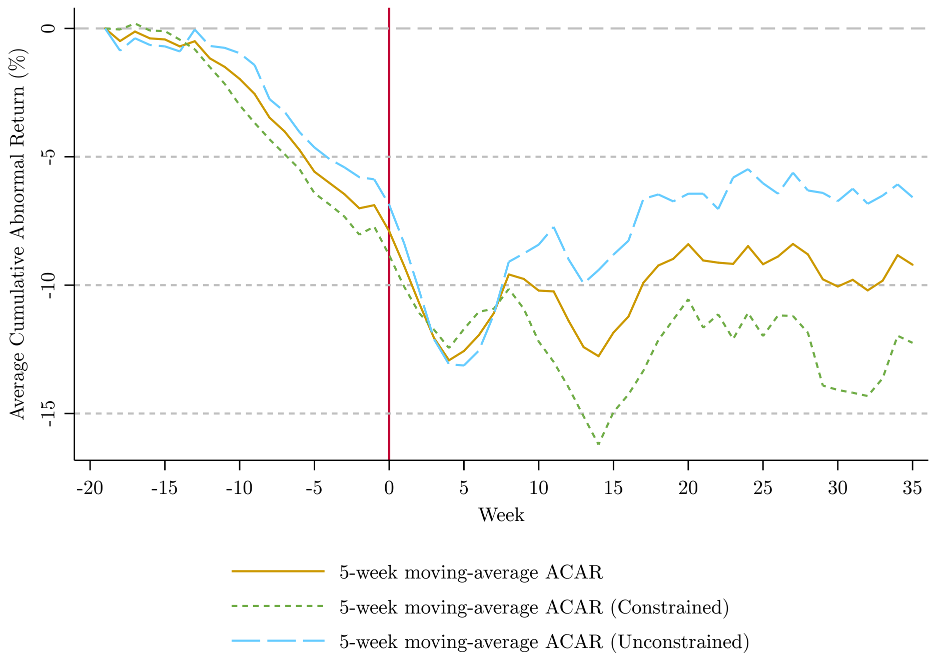


Fig. 3. The upper (lower) panel holds average (median) cumulative abnormal return, ACAR (MCAR), of downgraded bonds. CARs are based on ***rating/time-to-maturity*** matched portfolios. Event week is in the X-axis and week 0 is the downgrade announcement week. CARs are grouped by above-median (*constrained*) and below-median (*unconstrained*) dealer CDS spreads of the most-active five dealers.

Figure 4: CARs around Downgrade (*issuer-level*)

Note: Dealer CDS spreads are measured at the ***issuer-level***.



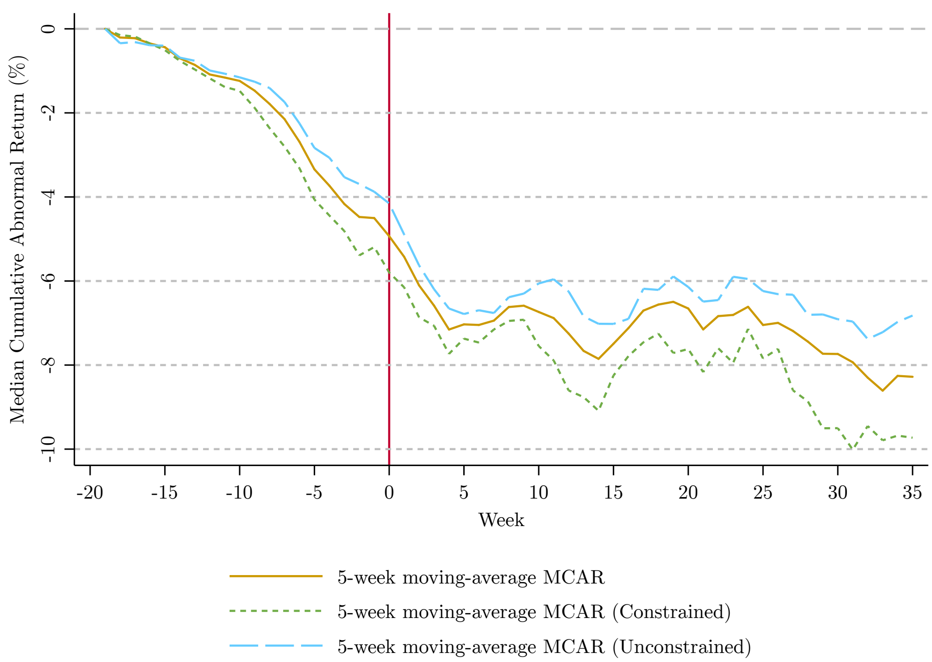


Fig. 4. The upper (lower) panel holds average (median) cumulative abnormal return, ACAR (MCAR), for downgraded bonds. CARs are based on ***rating/time-to-maturity*** matched portfolios. Event week is in the X-axis and week 0 is the downgrade announcement week. CARs are grouped by above-median (*constrained*) and below-median (*unconstrained*) dealer CDS spreads of the most-active five dealers.

Table 1: Number of Downgrades from Investment to Non-Investment Grades

	Downgraded Bonds (all)				Downgraded Bonds (eligible[1])			
Year	*#Bonds*	*#Issuers*	*Mean B/I*	*Median B/I*	*#Bonds*	*#Issuers*	*Mean B/I*	*Median B/I*
2002	349	125	5.6	4	103	54	5.2	4
2003	178	72	4.4	3	103	48	5.2	3
2004	120	46	4.3	4	72	34	4.2	4
2005	537	69	52.5	23	133	40	11.8	13
2006	154	54	6.0	4	101	37	5.8	4
2007	155	53	5.5	4	96	33	6.5	6.5
2008	314	64	26.5	10	117	39	21.2	8
2009	484	81	31.1	18	148	50	12.5	6
2010	88	33	5.2	4	46	21	5.2	4
2011	55	22	4.3	3	34	14	4.6	3
2012	54	27	4.7	3	40	19	5.4	3
2013	89	31	5.5	5	61	22	6.0	6
2014	67	29	3.6	3	24	12	3.7	3
Total	2,644	706	22.1	7	1,078	423	8.8	5

This table reports the number of downgraded bonds per issuer and year over the sample period (i.e., July 1, 2002 to June 30, 2014). As specified in Section 2, the columns captioned ***Total Downgrades*** hold the total number of downgrades from investment to non-investment grade over the sample period after cleaning the data (e.g., bond screens; price, volume, and timing screens; excluding NAIC portfolio events; discarding outliers). The columns captioned ***Eligible Downgrades*** hold the number of downgraded bonds that are eligible for the event study analysis (i.e., the passed the trade screens – see [1]). ***#Bonds*** is the number of bonds. ***#Issuers*** is the number of issuers. ***Mean B/I*** gives the mean of downgraded bonds per issuer. ***Median B/I*** gives the median of downgraded bonds per issuer. In the years 2005 and 2008 big issuers such as Ford and General Motors as well as Lehman Brothers experience downgrades in several of bond issues on the same calendar date, which explains the spike in the bonds per issuers statistics.

1 Eligible bonds are those that trade (i) at least once between weeks -20 and -1, (ii) at least once between weeks 0 and +35, and (iii) at least ten times during the sample period (i.e., excluding highly illiquid bonds with potentially unreliable prices).

Table 2: Summary Statistics for the Downgrade Sample

							Downgrades (all)						Downgrades (eligible[1])					
	Total NAIC Sample			Downgraded Issuers			Before Downgrade			After Downgrade			Before Downgrade			After Downgrade		
	Mean	*Med*	*Std*	*Mean*	*Med*	*Std*	*Mean*	*Med*	*Std*	*Mean*	*Med*	*Std*	*Mean*	*Med*	*Std*	*Mean*	*Med*	*Std*
#Obs	774,627			151,859			62,969			32,238			51,287			22,821		
#Bonds	24,235			4,491			2,024			2,024			968			968		
Issuance	424	250	531	392	250	492	340	200	469	340	200	469	567	400	555	567	400	555
Maturity	11.6	10.1	9.6	11.9	10.1	9.9	13.7	10.2	11.0	13.7	10.2	11.0	13.7	10.2	10.1	13.7	10.2	10.1
Yield	5.9	6.0	2.2	6.4	6.5	2.3	6.7	6.7	2.6	6.7	6.7	2.6	6.7	6.8	1.3	6.7	6.8	1.3
Rating	8.0	8.0	3.6	9.9	10.0	3.2	8.6	9.0	1.6	13.4	12.0	3.1	8.6	9.0	1.6	13.1	12.0	2.8
Bond Age	3.3	2.4	3.2	4.9	4.4	3.4	5.2	4.8	3.2	4.2	3.4	3.6	5.0	4.6	2.9	4.0	3.3	3.1
Time-to-Maturity	8.3	6.3	7.9	9.0	6.0	9.3	8.2	5.3	8.9	10.6	7.5	9.9	8.0	5.2	8.2	10.2	7.3	9.2
Turnover	4.3	2.7	5.5	4.9	3.3	5.7	6.1	4.3	6.6	4.7	3.2	5.2	5.9	4.3	5.8	4.8	3.5	4.8
Trade Size	2,466	987	4,609	2,639	1,000	4,499	3,042	1,000	4,887	2,466	1,000	4,494	2,991	1,000	4,881	2,453	1,000	4,394
#Trades per bond	121.7	80.0	125.3	116.5	78.0	111.6	147.4	103.0	128.6	111.4	74.0	111.9	166.7	123.0	132.0	133.8	87.0	122.8
#Trades p.m.	11.8	8.0	11.6	11.4	8.0	10.6	14.2	10.0	12.3	10.8	7.0	10.3	15.9	12.0	12.7	12.7	9.0	11.3
#Trades p.d.	1.3	1.0	0.9	1.4	1.0	0.9	1.4	1.0	1.1	1.3	1.0	0.8	1.5	1.0	1.1	1.3	1.0	0.8
Sells	48.3	Buy	50.0	53.9	Sell	49.9	50.1	Sell	50.0	68.8	Sell	46.3	50.5	Sell	50.0	70.0	Sell	45.8

This table reports summary statistics regarding the samples used in the empirical analyses (i.e., cross-sectional means, medians, and standard deviations). The sample period is from July 1, 2002 to June 30, 2014. The ***All NAIC Sample*** holds all NAIC bond trades that pass the initial cleaning process detailed in the Appendix. The ***Downgraded Issuers*** sample includes all trades in issuers that have experienced at least one of their bond issues to be downgraded. The ***Downgraded Bonds (all)*** sample includes only trades on bonds that are downgraded from the investment-grade (BBB- and above) to non-investment grade (BB+ and below) classification during the sample period. The ***Downgraded Bonds (eligible[1])*** sample only holds trades in downgraded bonds, which also pass the additional trade screens. The summary statistics for the downgraded bond samples are calculated separately for the periods before and after the downgrade. ***#Obs*** is the number of observations (i.e., trades). ***#Bonds*** is the number of bonds. ***Issuance*** is a bond's issued amount in $ millions. ***Maturity*** is the bond's time to maturity at issuance (in years). ***Yield***, reported only for fixed coupon bonds, is the bond's offering yield in %. The last three statistics are calculated across all bond issues, taking each issue as one observation. The following statistics are calculated across bond issues, taking each trade as one observation. ***Rating*** is a numerical translation of Moody's rating: 1=Aaa and 21=C. ***Bond Age*** is the time since issuance at the downgrade (in years); or time since issuance at the trade for the total NAIC sample. ***Bond Age*** is the (remaining) time-to-maturity at the downgrade (in years); or time-to-maturity at the trade for the total NAIC sample. ***Turnover*** is the bond's monthly trading volume as a percentage of its issuance. ***Trade Size*** is the average trade size of the bond in thousands of dollars of face value. ***#Trades per bond*** is the bond's total number of trades over the sample period. ***#Trades p.m. (p.d.)*** is the bond's total number of trades in a month (day). ***Sells*** gives the share of customer sell orders in %.

1 Eligible bonds are those that trade (i) at least once between weeks -20 and -1, (ii) at least once between weeks 0 and +35, and (iii) at least ten times during the sample period (i.e., excluding highly illiquid bonds with potentially unreliable prices).

Table 3: CARs of Downgraded Bonds (Bond Level)

Weeks	All downgraded bonds		*Above*-median dealer CDS		*Below*-median dealer CDS		Difference		
	(4) H0: ACAR = 0		(5) H0: ACAR = 0		(6) H0: ACAR = 0		H0: (5) - (6) = 0		N
[-19, -15]	-0.34	(-0.73)	-0.28	(-0.38)	-0.39	(-0.68)	0.11	(0.12)	574
[-14, -10]	-2.65	(-4.47)	-3.56	(-4.60)	-1.94	(-2.37)	-1.62	(-1.50)	555
[-9, -5]	-5.82	(-9.03)	-5.56	(-6.44)	-6.03	(-7.24)	0.47	(0.42)	570
[-4, -0]	-9.60	(-7.60)	-11.92	(-5.74)	-7.50	(-7.49)	-4.42	(-2.13)	646
Week 0	-13.16	(-5.63)	-14.85	(-4.92)	-11.73	(-5.83)	-3.12	(-1.60)	427
[1, 5]	-11.94	(-7.12)	-13.31	(-6.98)	-10.89	(-5.83)	-2.41	(-1.39)	707
[6, 10]	-10.49	(-6.98)	-14.66	(-6.05)	-6.92	(-5.59)	-7.74	(-3.23)	620
[11, 15]	-10.80	(-5.35)	-13.85	(-5.16)	-8.42	(-4.62)	-5.43	(-2.63)	561
[16, 20]	-9.29	(-7.00)	-12.90	(-7.11)	-6.08	(-4.28)	-6.83	(-3.53)	500
[21, 25]	-8.77	(-7.78)	-10.39	(-7.53)	-7.40	(-5.33)	-2.99	(-1.85)	485
[26, 30]	-10.49	(-6.68)	-14.16	(-7.04)	-7.23	(-3.74)	-6.93	(-2.82)	464
[31, 35]	-9.62	(-6.51)	-12.72	(-6.81)	-7.15	(-4.16)	-5.57	(-2.69)	421
[-20, -1]	-7.47	(-10.79)	-9.25	(-7.71)	-6.16	(-9.73)	-3.09	(-2.49)	1,024
[1, 35]	-10.39	(-6.97)	-13.38	(-7.31)	-8.16	(-5.53)	-5.22	(-3.70)	1,043
[-20, 35]	-10.45	(-9.30)	-12.92	(-6.11)	-8.61	(-9.83)	-4.31	(-2.01)	1,049
	(1) H0: MCAR = 0		(2) H0: MCAR = 0		(3) H0: MCAR = 0		H0: (2) - (3) = 0		N
[-19, -15]	-0.76	(-4.62)	-0.73	(-3.59)	-0.83	(-3.81)	0.10	(0.36)	574
[-14, -10]	-1.51	(-6.32)	-1.91	(-4.94)	-1.35	(-4.93)	-0.56	(-1.29)	555
[-9, -5]	-3.39	(-8.31)	-3.39	(-5.89)	-3.37	(-6.75)	-0.02	(-0.03)	570
[-4, -0]	-5.52	(-8.75)	-6.11	(-5.24)	-5.06	(-8.54)	-1.05	(-0.89)	646
Week 0	-6.92	(-7.75)	-9.29	(-6.58)	-5.46	(-6.97)	-3.83	(-2.77)	427
[1, 5]	-6.80	(-10.13)	-8.45	(-8.43)	-6.00	(-8.41)	-2.45	(-2.26)	707
[6, 10]	-6.48	(-9.51)	-9.15	(-7.01)	-5.45	(-7.55)	-3.70	(-2.65)	620
[11, 15]	-6.60	(-9.39)	-7.96	(-6.35)	-5.69	(-7.67)	-2.27	(-1.75)	561
[16, 20]	-7.20	(-9.52)	-8.88	(-7.40)	-6.00	(-6.89)	-2.88	(-2.19)	500
[21, 25]	-6.65	(-9.09)	-7.55	(-7.14)	-5.37	(-5.96)	-2.19	(-1.77)	485
[26, 30]	-8.02	(-8.19)	-11.71	(-8.31)	-6.54	(-6.29)	-5.17	(-3.16)	464
[31, 35]	-7.95	(-7.88)	-11.49	(-8.78)	-5.47	(-4.88)	-6.01	(-3.97)	421
[-20, -1]	-3.84	(-10.31)	-4.27	(-6.25)	-3.65	(-9.58)	-0.61	(-0.86)	1,024
[1, 35]	-6.45	(-11.23)	-8.44	(-7.86)	-5.49	(-10.32)	-2.95	(-2.77)	1,043
[-20, 35]	-6.50	(-11.98)	-6.64	(-7.50)	-6.45	(-10.53)	-0.20	(-0.20)	1,049

This table reports the average (median) cumulative abnormal returns, MCAR (ACAR), based on *rating/time-to-maturity* matched portfolios grouped by above- and below-median dealer CDS spreads of the most-active five dealers measured at the ***bond-level***. Week 0 is the downgrade announcement from investment to non-investment grade. In squared brackets are 5-week periods before and after the downgrade as well as the full, pre, and post period. The upper panel holds ACAR and the lower panel MCAR statistics where specifications (1) to (3) give averages, and columns (4) to (6) give medians and t-statistics are reported in brackets. The t-statistics are for the tests of (a) the null hypothesis that CARs are equal to zero and (b) the null hypothesis that the CARs of the two dealer CDS spread groups are equal. Standard errors are clustered on the issuer-month level (and robust to other time horizons or the use of bootstrapped standard errors). For each bond abnormal returns are computed using matching portfolios and accumulated over time. Cumulative abnormal returns for each bond are then normalized to zero in week -20. ACARs (MCARs) are measured as across-bond averages (medians) of CARs using simple returns for each five-week period relative to the event.

Table 4: CARs of Downgraded Bonds (Issuer Level)

Weeks	All downgraded bonds		*Above*-median dealer CDS		*Below*-median dealer CDS		Difference		
	(4) H0: ACAR = 0		**(5) H0: ACAR = 0**		**(6) H0: ACAR = 0**		**H0: (5) - (6) = 0**		**N**
[-19, -15]	-0.34	(-0.73)	-0.10	(-0.14)	-0.54	(-0.93)	0.44	(0.50)	574
[-14, -10]	-2.65	(-4.47)	-4.13	(-6.05)	-1.36	(-1.49)	-2.78	(-2.48)	555
[-9, -5]	-5.82	(-9.03)	-6.57	(-6.44)	-5.12	(-6.38)	-1.46	(-1.12)	570
[-4, -0]	-9.60	(-7.60)	-11.48	(-5.27)	-7.82	(-7.39)	-3.65	(-1.57)	646
Week 0	-13.16	(-5.63)	-13.22	(-5.01)	-13.12	(-5.18)	-0.11	(-0.05)	427
[1, 5]	-11.94	(-7.12)	-11.10	(-6.25)	-12.47	(-5.21)	1.37	(0.48)	707
[6, 10]	-10.49	(-6.98)	-13.90	(-7.36)	-7.49	(-4.57)	-6.41	(-3.39)	620
[11, 15]	-10.80	(-5.35)	-13.28	(-5.39)	-8.71	(-3.81)	-4.57	(-1.81)	561
[16, 20]	-9.29	(-7.00)	-12.45	(-6.25)	-6.14	(-4.18)	-6.31	(-2.68)	500
[21, 25]	-8.77	(-7.78)	-11.28	(-6.54)	-6.49	(-4.59)	-4.79	(-2.16)	485
[26, 30]	-10.49	(-6.68)	-15.49	(-6.47)	-6.42	(-3.47)	-9.07	(-3.10)	464
[31, 35]	-9.62	(-6.51)	-12.73	(-5.19)	-7.19	(-4.97)	-5.54	(-2.09)	421
[-20, -1]	-7.47	(-10.79)	-9.14	(-6.91)	-6.22	(-9.93)	-2.92	(-2.03)	1024
[1, 35]	-10.39	(-6.97)	-13.18	(-7.74)	-8.43	(-4.80)	-4.76	(-2.65)	1043
[-20, 35]	-10.45	(-9.30)	-13.66	(-6.07)	-8.04	(-9.27)	-5.62	(-2.37)	1049
	(1) H0: MCAR = 0		**(2) H0: MCAR = 0**		**(3) H0: MCAR = 0**		**H0: (2) - (3) = 0**		**N**
[-19, -15]	-0.76	(-4.62)	-0.73	(-3.91)	-0.83	(-3.01)	0.10	(0.30)	574
[-14, -10]	-1.51	(-6.32)	-1.86	(-5.09)	-1.27	(-4.24)	-0.59	(-1.25)	555
[-9, -5]	-3.39	(-8.31)	-3.85	(-5.89)	-3.05	(-6.23)	-0.80	(-0.99)	570
[-4, -0]	-5.52	(-8.75)	-6.50	(-5.64)	-4.77	(-7.63)	-1.73	(-1.34)	646
Week 0	-6.92	(-7.75)	-6.92	(-4.89)	-6.99	(-6.95)	0.07	(0.04)	427
[1, 5]	-6.80	(-10.13)	-6.62	(-6.46)	-7.04	(-8.16)	0.41	(0.31)	707
[6, 10]	-6.48	(-9.51)	-8.69	(-7.75)	-5.36	(-6.64)	-3.33	(-2.51)	620
[11, 15]	-6.60	(-9.39)	-6.81	(-6.43)	-6.52	(-7.56)	-0.29	(-0.22)	561
[16, 20]	-7.20	(-9.52)	-8.79	(-6.49)	-5.93	(-6.97)	-2.87	(-1.82)	500
[21, 25]	-6.65	(-9.09)	-7.92	(-6.13)	-5.37	(-6.33)	-2.55	(-1.65)	485
[26, 30]	-8.02	(-8.19)	-10.34	(-6.72)	-6.77	(-5.88)	-3.57	(-1.89)	464
[31, 35]	-7.95	(-7.88)	-9.09	(-5.16)	-6.76	(-5.32)	-2.33	(-1.09)	421
[-20, -1]	-3.84	(-10.31)	-4.82	(-6.71)	-3.42	(-9.60)	-1.40	(-1.78)	1024
[1, 35]	-6.45	(-11.23)	-7.29	(-6.73)	-6.14	(-9.95)	-1.15	(-0.96)	1043
[-20, 35]	-6.50	(-11.98)	-7.19	(-6.64)	-6.16	(-10.24)	-1.03	(-0.84)	1049

This table reports the average (median) cumulative abnormal returns, MCAR (ACAR), based on *rating/time-to-maturity* matched portfolios grouped by above- and below-median dealer CDS spreads of the most-active five dealers measured at the ***issuer-level***. Week 0 is the downgrade announcement from investment to non-investment grade. In squared brackets are 5-week periods before and after the downgrade as well as the full, pre, and post period. The upper panel holds ACAR and the lower panel MCAR statistics where specifications (1) to (3) give averages, and columns (4) to (6) give medians and t-statistics are reported in brackets. The t-statistics are for the tests of (a) the null hypothesis that CARs are equal to zero and (b) the null hypothesis that the CARs of the two dealer CDS spread groups are equal. Standard errors are clustered on the issuer-month level (and robust to other time horizons or the use of bootstrapped standard errors). For each bond abnormal returns are computed using matching portfolios and accumulated over time. Cumulative abnormal returns for each bond are then normalized to zero in week -20. ACARs (MCARs) are measured as across-bond averages (medians) of CARs using simple returns for each five-week period relative to the event.

Table 5: Cross-Sectional Regressions (bond-level)

	OLS			**Median Regressions**		
	[-20, +35]	[-20, -1]	[0, +35]	[-20, +35]	[-20, -1]	[0, +35]
Log Offering Amount	-0.78	-1.59	-0.65	0.27	-0.29	-0.05
	(-0.71)	(-1.77)	(-0.63)	(0.38)	(-0.42)	(-0.08)
Log Bond Age	-1.19	-0.09	-0.69	-1.10	0.06	-0.84
	(-1.25)	(-0.13)	(-0.85)	(-1.99)	(0.10)	(-1.71)
Juniority Dummy	-9.78	-2.98	-15.87	-4.72	2.98	-8.98
	(-1.16)	(-0.46)	(-2.45)	(-1.20)	(0.58)	(-1.59)
Enhancement Dummy	5.53	2.60	5.12	-0.32	-0.28	0.65
	(2.19)	(1.42)	(2.16)	(-0.31)	(-0.25)	(0.65)
Rating Dispersion	5.33	4.21	1.79	-0.24	0.50	0.07
	(3.02)	(3.31)	(1.75)	(-0.26)	(0.56)	(0.16)
Finance Dummy	0.90	-0.34	2.11	1.38	-0.78	1.25
	(0.28)	(-0.17)	(0.83)	(0.68)	(-0.33)	(0.78)
Finance x Crisis	-35.69	-12.21	-35.58	-54.87	-12.49	-48.15
	(-4.72)	(-2.36)	(-5.13)	(-7.16)	(-1.34)	(-6.50)
NAIC Net Volume	-8.90	-14.06	10.54	-5.65	-7.47	1.22
	(-1.04)	(-1.67)	(1.68)	(-1.10)	(-1.34)	(0.42)
TRACE Volume	-0.19	-0.22	0.41	-0.56	-0.32	0.18
	(-0.50)	(-0.84)	(1.29)	(-3.26)	(-2.05)	(0.65)
TRACE Time Elapsed	-0.02	0.00	-0.03	-0.03	0.00	-0.05
	(-1.14)	(-0.07)	(-1.13)	(-2.82)	(-0.01)	(-2.83)
TRACE ID Share	-0.05	0.00	-0.09	-0.02	0.01	-0.05
	(-1.66)	(-0.02)	(-1.94)	(-2.07)	(0.77)	(-2.92)
Herfindahl Ratio	-1.88	-2.27	-1.10	-0.34	-0.55	-0.43
	(-0.94)	(-1.82)	(-0.81)	(-0.29)	(-0.64)	(-0.83)
LU Market Share	0.19	0.13	0.13	0.01	0.03	0.02
	(1.89)	(2.43)	(2.29)	(0.19)	(0.76)	(1.40)
Dealer CDS Ratio	-12.11	-3.35	-3.72	-5.82	-0.30	-1.31
	(-3.56)	(-1.94)	(-1.14)	(-3.06)	(-0.23)	(-1.37)
Constant	-11.26	-8.03	-3.98	-4.53	-3.10	0.59
	(-14.77)	(-10.57)	(-4.99)	(-2.24)	(-1.74)	(0.49)
Observations	870	855	882	870	855	882
Adjusted R^2	0.37	0.24	0.33	0.32	0.20	0.31
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

This table reports regression coefficients of CARs on bond, trading, and dealer characteristics using OLS and median regressions. CARs are in % and based on rating/time-to-maturity matched portfolios. The event is defined as the first downgrade announcement (i.e., week 0) where the downgrade is from investment to non-investment grades. The sample period is July 2002 to June 2014. Dealer characteristics are measured at the ***bond-level*** for the most-active 5 dealers. The independent variables are measured up to the week preceding the event window (see Section 4.2 for definitions): year dummies range from 2003 to 2014 (2002 is omitted). A bond's log offering amount is in $ millions. A bond's log bond age is in years. The juniority dummy flags bonds without seniority in order of repayment. The enhancement dummy marks bonds with credit enhancements. Rating dispersion is the difference between the highest and the lowest available credit rating at the time (and 0 in case of only one agency). The finance dummy flags issuers in the banking/financial industry. The finance times crisis interaction flags downgrades of financials during the 2007-2009 subprime crisis period. NAIC Net Volume is the buy minus the sell volume divided by a bond's issued amount and given in $ millions. TRACE Volume is the total trading volume (excluding all NAIC trading volume) scaled by a bond's issued amount and measured in $ millions. The variable TRACE Time Elapsed gives the average number of days between consecutive customer-dealer trades within a bond in TRACE. TRACE ID Share gives the share of inter-dealer trading in total trading volume in %. The Herfindahl Ratio represents a bond's annual Herfindahl index scaled by the overall median Herfindahl index in that year. LU (or Lead Underwriter) Market Share gives the average annual market share in total NAIC trades of a bond's lead underwriters. Dealer CDS Ratio is the mean of the weekly volume-weighted dealer CDS average of the most-active dealers scaled by the median weekly volume-weighted dealer CDS. Standard errors are clustered at the issuer-times-year level and the respective t-statistics are reported in parentheses.

Table 6: Cross-Sectional Regressions (issuer-level)

	OLS			Median Regressions		
	[-20, +35]	[-20, -1]	[0, +35]	[-20, +35]	[-20, -1]	[0, +35]
Log Offering Amount	-0.05	-1.14	0.13	0.49	-0.03	0.15
	(-0.04)	(-1.24)	(0.13)	(0.78)	(-0.04)	(0.27)
Log Bond Age	-0.91	-0.12	-0.65	-1.01	0.11	-0.83
	(-1.03)	(-0.17)	(-0.79)	(-1.83)	(0.20)	(-1.53)
Juniority Dummy	-10.87	-3.50	-16.72	-5.00	4.08	-9.01
	(-1.32)	(-0.56)	(-2.59)	(-1.22)	(1.06)	(-2.04)
Enhancement Dummy	4.67	2.35	4.57	-0.20	-0.25	0.32
	(1.92)	(1.35)	(1.89)	(-0.20)	(-0.23)	(0.31)
Rating Dispersion	5.37	4.17	1.93	0.14	0.38	0.16
	(2.97)	(3.30)	(1.90)	(0.16)	(0.45)	(0.35)
Finance Dummy	1.79	0.27	2.48	1.47	-0.34	0.74
	(0.60)	(0.14)	(1.02)	(0.66)	(-0.19)	(0.50)
Finance x Crisis	-35.81	-11.80	-35.46	-54.81	-13.30	-48.22
	(-4.87)	(-2.64)	(-5.15)	(-5.59)	(-1.62)	(-6.01)
NAIC Net Volume	-9.22	-13.43	10.03	-6.74	-9.15	1.03
	(-1.09)	(-1.67)	(1.60)	(-1.35)	(-1.39)	(0.36)
TRACE Volume	-0.18	-0.22	0.46	-0.54	-0.30	0.08
	(-0.51)	(-0.90)	(1.41)	(-3.20)	(-1.87)	(0.27)
TRACE Time Elapsed	-0.01	0.00	-0.03	-0.03	-0.01	-0.03
	(-0.57)	(0.01)	(-1.44)	(-2.25)	(-0.16)	(-1.85)
TRACE ID Share	-0.05	-0.01	-0.08	-0.02	0.01	-0.05
	(-1.53)	(-0.32)	(-1.80)	(-1.97)	(0.90)	(-2.62)
Herfindahl Ratio	-0.70	-2.79	1.41	-0.35	-0.22	-0.16
	(-0.40)	(-1.86)	(1.10)	(-0.33)	(-0.26)	(-0.29)
LU Market Share	0.41	0.14	0.15	-0.03	0.07	0.02
	(1.47)	(0.95)	(0.90)	(-0.22)	(1.02)	(0.14)
Dealer CDS Ratio	-17.39	-6.90	-10.29	-7.04	-1.96	-2.92
	(-4.16)	(-2.85)	(-3.00)	(-2.46)	(-1.11)	(-1.89)
Constant	-11.21	-8.13	-3.94	-3.97	-3.73	0.55
	(-15.04)	(-11.02)	(-4.99)	(-1.84)	(-2.18)	(0.50)
Observations	870	855	882	870	855	882
Adjusted R^2	0.38	0.25	0.34	0.33	0.20	0.32
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

This table reports regression coefficients of CARs on bond, trading, and dealer characteristics using OLS and median regressions. CARs are in % and based on rating/time-to-maturity matched portfolios. The event is defined as the first downgrade announcement (i.e., week 0) where the downgrade is from investment to non-investment grades. The sample period is July 2002 to June 2014. Dealer characteristics are measured at the ***issuer-level*** for the most-active 5 dealers. The independent variables are measured up to the week preceding the event window (see Section 4.2 for definitions): year dummies range from 2003 to 2014 (2002 is omitted). A bond's log offering amount is in $ millions. A bond's log bond age is in years. The juniority dummy flags bonds without seniority in order of repayment. The enhancement dummy marks bonds with credit enhancements. Rating dispersion is the difference between the highest and the lowest available credit rating at the time (and 0 in case of only one agency). The finance dummy flags issuers in the banking/financial industry. The finance times crisis interaction flags downgrades of financials during the 2007-2009 subprime crisis period. NAIC Net Volume is the buy minus the sell volume divided by a bond's issued amount and given in $ millions. TRACE Volume is the total trading volume (excluding all NAIC trading volume) scaled by a bond's issued amount and measured in $ millions. The variable TRACE Time Elapsed gives the average number of days between consecutive customer-dealer trades within a bond in TRACE. TRACE ID Share gives the share of inter-dealer trading in total trading volume in %. The Herfindahl Ratio represents a bond's annual Herfindahl index scaled by the overall median Herfindahl index in that year. LU (or Lead Underwriter) Market Share gives the average annual market share in total NAIC trades of a bond's lead underwriters. Dealer CDS Ratio is the mean of the weekly volume-weighted dealer CDS average of the most-active dealers scaled by the median weekly volume-weighted dealer CDS. Standard errors are clustered at the issuer-times-year level and the respective t-statistics are reported in parentheses.

Table 7: Accounting for Recent Bond Liquidity (OLS)

	OLS					
	Issuer-Level Constraints			Bond-Level Constraints		
	CAR_[-20, +35]			CAR_[-20, +35]		
	All Bonds	HiLiq	LoLiq	All Bonds	HiLiq	LoLiq
Log Offering Amount	-1.06	-0.41	-1.11	-1.68	-1.66	-1.64
	(-0.84)	(-0.20)	(-0.69)	(-1.33)	(-0.79)	(-1.06)
Log Bond Age	-1.17	-2.01	-0.64	-1.45	-2.41	-0.69
	(-1.34)	(-0.71)	(-0.69)	(-1.53)	(-0.83)	(-0.74)
Juniority Dummy	-10.66	-9.95	-7.26	-9.46	-9.11	-7.09
	(-1.29)	(-0.72)	(-1.45)	(-1.12)	(-0.63)	(-1.45)
Enhancement Dummy	4.64	10.13	-1.94	5.53	10.45	-1.31
	(1.91)	(2.44)	(-0.84)	(2.19)	(2.37)	(-0.57)
Rating Dispersion	5.26	8.39	-0.19	5.22	8.75	-0.27
	(2.94)	(2.91)	(-0.18)	(3.01)	(3.18)	(-0.25)
Finance Dummy	1.94	-1.17	6.05	0.99	-2.83	6.07
	(0.66)	(-0.22)	(2.83)	(0.31)	(-0.49)	(2.69)
Finance x Crisis	-36.15	-32.61	-44.42	-36.00	-33.23	-44.66
	(-4.93)	(-3.41)	(-5.55)	(-4.77)	(-3.36)	(-5.37)
NAIC Net Volume	-8.38	-7.18	-6.45	-8.20	-8.92	-7.79
	(-0.98)	(-0.51)	(-0.73)	(-0.95)	(-0.66)	(-0.88)
TRACE Volume	-0.47	-0.62	1.71	-0.44	-0.61	1.51
	(-1.20)	(-1.36)	(1.26)	(-1.08)	(-1.24)	(1.15)
TRACE Time Elapsed	-0.01	-0.14	-0.02	-0.01	-0.20	-0.02
	(-0.45)	(-0.11)	(-1.42)	(-0.99)	(-0.15)	(-1.59)
TRACE ID Share	-0.06	-0.10	-0.05	-0.06	-0.13	-0.06
	(-1.55)	(-0.81)	(-2.37)	(-1.69)	(-1.08)	(-2.60)
Herfindahl Ratio	-0.39	-3.15	0.67	-1.38	-3.46	-1.54
	(-0.22)	(-0.66)	(0.47)	(-0.67)	(-0.90)	(-0.75)
LU Market Share	0.41	0.52	0.05	0.19	0.35	0.06
	(1.46)	(0.97)	(0.23)	(1.91)	(0.98)	(0.76)
Dealer CDS Ratio	-17.71	-28.56	-7.40	-12.40	-18.40	-5.55
	(-4.20)	(-3.95)	(-1.54)	(-3.63)	(-2.90)	(-1.79)
Non-Zero Trading Days	0.019			0.017		
	(1.32)			(1.21)		
Constant	-11.13	-11.73	-11.35	-11.18	-11.87	-11.35
	(-14.73)	(-1.60)	(-9.18)	(-14.45)	(-1.60)	(-9.34)
Observations	870	452	418	870	452	418
Adjusted R^2	0.38	0.39	0.44	0.37	0.38	0.44
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

This table reports regression coefficients of CARs on bond, trading, and dealer characteristics using OLS for liquidity subsamples. Subsamples are formed in a bond's non-zero trading days where bonds' above (below) 72 non-zero trading days are considered liquid (illiquid). tba. (...)

Table 8: Accounting for Recent Bond Liquidity (Median Regressions)

	Median Regressions					
	Issuer-Level Constraints			Bond-Level Constraints		
	CAR_[-20, +35]			CAR_[-20, +35]		
	All Bonds	HiLiq	LoLiq	All Bonds	HiLiq	LoLiq
Log Offering Amount	-0.45	0.82	0.00	-0.84	0.49	0.16
	(-0.51)	(0.70)	(0.00)	(-0.87)	(0.39)	(0.14)
Log Bond Age	-1.06	-1.89	-0.48	-1.36	-2.18	-0.16
	(-2.11)	(-1.49)	(-0.73)	(-2.60)	(-1.67)	(-0.23)
Juniority Dummy	-4.76	-6.47	-2.58	-3.90	-5.11	-2.64
	(-1.36)	(-0.61)	(-0.73)	(-1.07)	(-0.83)	(-0.78)
Enhancement Dummy	-0.40	0.29	-1.28	-0.34	-0.04	0.57
	(-0.35)	(0.19)	(-0.66)	(-0.31)	(-0.02)	(0.32)
Rating Dispersion	0.35	1.71	-1.04	0.06	2.17	-1.04
	(0.44)	(1.96)	(-1.34)	(0.07)	(2.27)	(-1.53)
Finance Dummy	2.18	-0.94	3.68	2.11	-1.99	3.63
	(1.26)	(-0.34)	(2.42)	(1.29)	(-0.74)	(2.36)
Finance x Crisis	-57.55	-54.90	-32.07	-57.13	-52.85	-27.13
	(-5.64)	(-6.93)	(-2.90)	(-5.61)	(-4.38)	(-2.26)
NAIC Net Volume	-4.35	-3.89	-3.24	-6.38	-1.83	-1.99
	(-0.87)	(-0.37)	(-0.35)	(-1.18)	(-0.16)	(-0.25)
TRACE Volume	-0.78	-0.61	0.57	-0.71	-0.57	0.76
	(-3.95)	(-2.63)	(0.60)	(-3.54)	(-2.00)	(0.86)
TRACE Time Elapsed	-0.03	0.04	-0.02	-0.03	-0.34	-0.02
	(-2.84)	(0.05)	(-1.83)	(-3.14)	(-0.47)	(-2.11)
TRACE ID Share	-0.04	-0.09	-0.03	-0.05	-0.11	-0.03
	(-0.62)	(-1.03)	(-2.39)	(-0.78)	(-1.54)	(-2.55)
Herfindahl Ratio	-0.40	-4.65	-0.06	-0.07	-0.17	-0.76
	(-0.33)	(-2.18)	(-0.06)	(-0.06)	(-0.08)	(-0.57)
LU Market Share	0.00	0.18	0.01	0.01	-0.21	0.01
	(-0.01)	(0.86)	(0.06)	(0.39)	(-1.21)	(0.19)
Dealer CDS Ratio	-7.58	-12.67	-4.63	-5.45	-8.73	-3.54
	(-2.79)	(-3.01)	(-1.62)	(-2.94)	(-1.85)	(-2.01)
Non-Zero Trading Days	0.018			0.020		
	(1.55)			(1.75)		
Constant	-4.70	-3.87	-2.91	-4.51	-4.27	-3.88
	(-2.19)	(-1.17)	(-1.29)	(-2.23)	(-0.91)	(-1.66)
Observations	870	452	418	870	452	418
Adjusted R^2	0.33	0.32	0.44	0.33	0.31	0.43
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

This table reports regression coefficients of CARs on bond, trading, and dealer characteristics using median regressions for liquidity subsamples. Subsamples are formed in a bond's non-zero trading days where bonds' above (below) 72 non-zero trading days are considered liquid (illiquid). tba. (...)

Table 9: Regressions incl. insurer selling probability from Ellul et al. (2011)

	OLS				Median Regressions			
	Issuer-Level		Bond-Level		Issuer-Level		Bond-Level	
	[-20, -1]	[0, +35]	[-20, -1]	[0, +35]	[-20, -1]	[0, +35]	[-20, -1]	[0, +35]
Log Offering Amount	-1.13	3.09	-1.55	3.86	-0.91	1.65	-0.87	0.93
	(-1.24)	(-2.62)	(-1.53)	(-2.86)	(-0.69)	(-1.55)	(-0.66)	(-1.10)
Log Bond Age	-0.89	-3.41	-0.87	-3.56	-0.29	-3.09	-0.14	-2.65
	(-1.20)	(-2.54)	(-1.14)	(-2.61)	(-0.27)	(-3.05)	(-0.15)	(-3.34)
Enhancement Dummy	-7.09	3.42	-7.32	3.50	-4.38	-0.44	-4.50	-1.16
	(-2.56)	(-0.72)	(-2.64)	(-0.70)	(-1.98)	(-0.13)	(-2.37)	(-0.40)
Rating Dispersion	-1.38	-1.03	-1.54	-0.25	-1.86	-1.19	-1.90	-0.64
	(-1.76)	(-0.94)	(-1.95)	(-0.21)	(-2.00)	(-0.91)	(-2.27)	(-0.56)
Finance Dummy	4.60	3.92	5.22	2.31	3.33	4.01	2.77	2.95
	(-2.54)	(-1.61)	(-2.70)	(-0.79)	(-1.09)	(-0.91)	(-1.27)	(-0.74)
NAIC Net Volume	3.68	-13.46	3.01	-10.12	0.44	-6.64	0.67	-4.28
	(-0.36)	(-1.49)	(-0.29)	(-1.09)	(-0.03)	(-0.76)	(-0.05)	(-0.48)
TRACE Volume	0.10	-0.28	0.06	-0.28	-0.20	-0.24	-0.28	-0.19
	(-0.50)	(-0.96)	(-0.32)	(-0.85)	(-0.98)	(-1.24)	(-1.42)	(-1.08)
TRACE Time Elapsed	-0.05	0.07	-0.05	0.02	-0.08	0.03	-0.06	-0.02
	(-0.89)	(-0.91)	(-1.17)	(-0.20)	(-1.66)	(-0.55)	(-1.14)	(-0.50)
TRACE ID Share	-0.12	-0.10	-0.13	-0.14	-0.13	-0.05	-0.10	-0.07
	(-2.22)	(-1.39)	(-2.40)	(-1.94)	(-1.51)	(-0.66)	(-1.49)	(-0.94)
Herfindahl Ratio	-0.94	-1.47	-1.99	2.26	-1.84	-0.28	-0.89	1.88
	(-0.68)	(-0.93)	(-1.14)	(-1.63)	(-1.42)	(-0.24)	(-0.44)	(-1.84)
LU Market Share	0.10	-0.06	-0.09	0.00	0.10	-0.09	-0.07	0.00
	(-0.56)	(-1.23)	(-1.55)	(-0.06)	(-0.59)	(-2.18)	(-1.59)	(-0.03)
Dealer CDS Ratio	**-2.06**	**-13.28**	**0.19**	**-5.21**	**-2.69**	**-7.89**	**2.73**	**-1.70**
	(-0.64)	(-3.04)	(-0.08)	(-1.57)	(-0.62)	(-1.91)	(-1.08)	(-0.91)
Bond Selling Probability	1.42	-2.45	2.41	-4.89	-1.94	1.09	-0.95	-1.58
	(0.25)	(-0.32)	(0.41)	(-0.62)	(-0.33)	(0.23)	(-0.15)	(-0.37)
Constant	-9.02	5.66	-11.12	9.78	-1.65	-5.56	-4.54	-0.51
	(-0.75)	(-0.34)	(-0.92)	(-0.57)	(-0.14)	(-0.54)	(-0.37)	(-0.05)
Observations	237	242	237	242	237	242	237	242
Adjusted R^2	0.13	0.16	0.14	0.13	0.15	0.18	0.14	0.13
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports regression coefficients of CARs on bond, trading, and dealer characteristics using OLS and median regressions including the variables insurer selling probability used in Ellul at al. (2011). The variables is available for downgraded bonds between 2002 and 2005. tba. (...)

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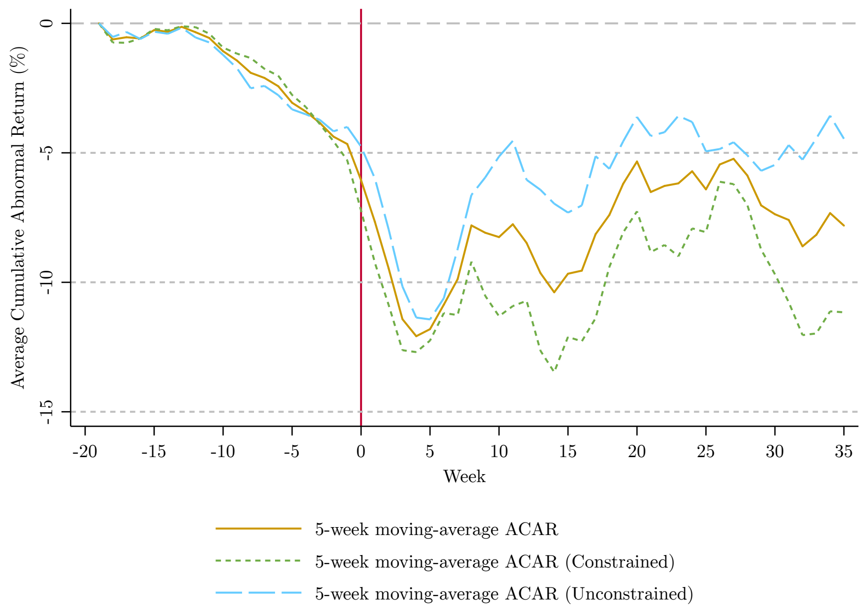
A.1 Appendix

Figure 5: CARs around Downgrade (*bond-level*)

Note: Dealer CDS spreads are measured at the ***bond-level***.



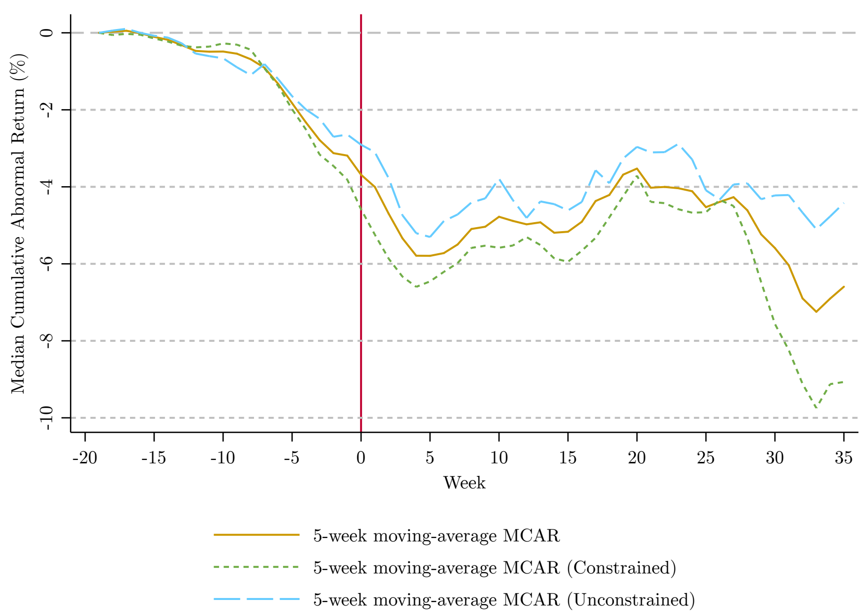
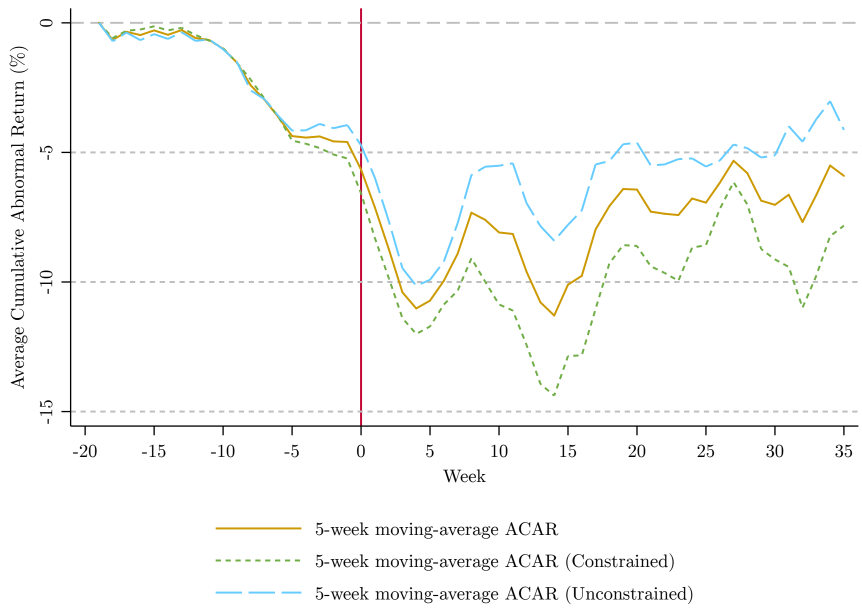


Fig. 6. The upper (lower) panel holds average (median) cumulative abnormal return, ACAR (MCAR), of downgraded bonds. CARs are computed using the ***market model approach*** of Ellul et al. (2011). Event week is in the X-axis and week 0 is the downgrade announcement week. CARs are grouped by above-median (*constrained*) and below-median (*unconstrained*) dealer CDS spreads of the most-active five dealers.

Figure 6: CARs around Downgrade (*bond-level*)

Note: Dealer CDS spreads are measured at the ***bond-level***.



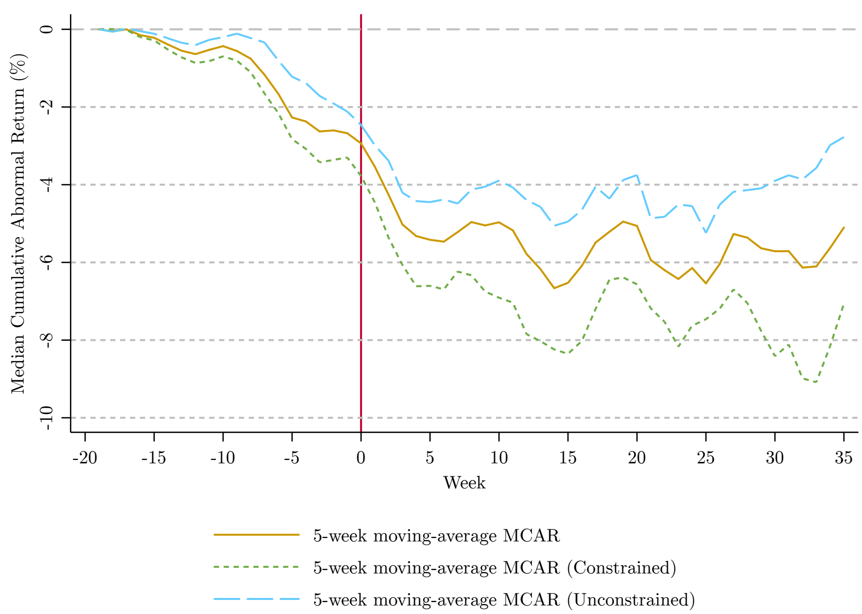
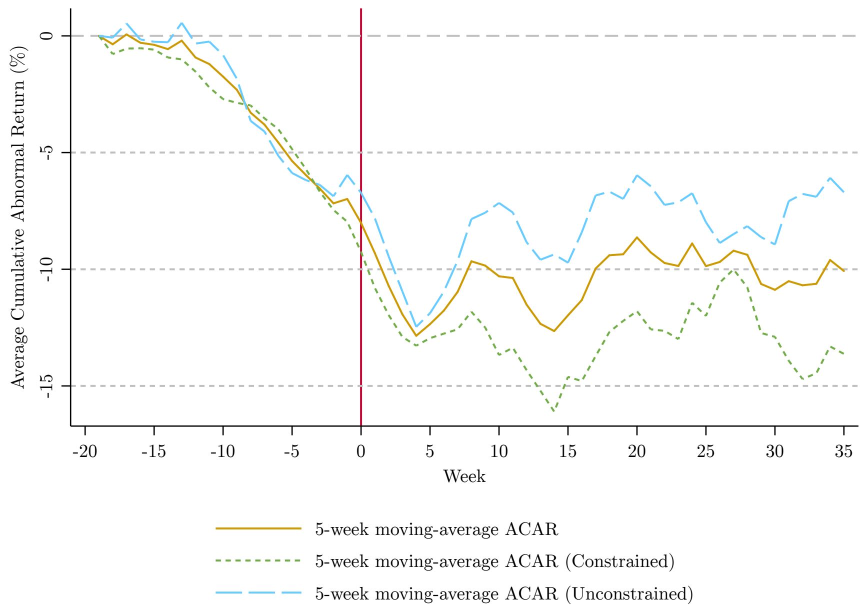


Fig. 7. The upper (lower) panel holds average (median) cumulative abnormal return, ACAR (MCAR), of downgraded bonds. CARs are computed using a simple ***market-return model***. Event week is in the X-axis and week 0 is the downgrade announcement week. CARs are grouped by above-median (*constrained*) and below-median (*unconstrained*) dealer CDS spreads of the most-active five dealers.

Figure 7: CARs around Downgrade (*bond-level*)

Note: Dealer CDS spreads are measured at the ***bond-level***.



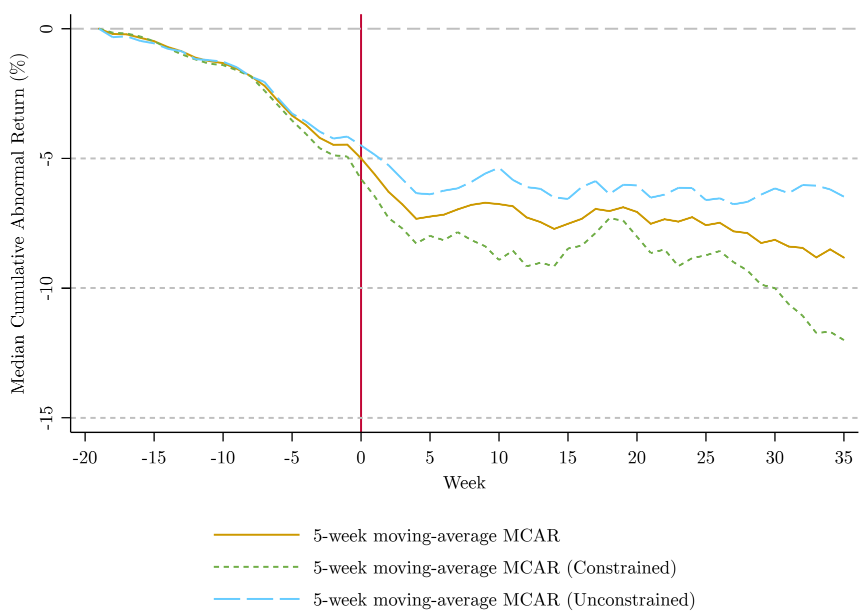


Fig. 5. The upper (lower) panel holds average (median) cumulative abnormal return, ACAR (MCAR), of downgraded bonds. CARs are based on ***rating/time-to-maturity*** matched portfolios. Event week is in the X-axis and week 0 is the downgrade announcement week. CARs are grouped by above-median (*constrained*) and below-median (*unconstrained*) dealer CDS spreads of the most-active five dealers.