Rating-based investment constrains-induced trading: other thresholds beyond the investment-grade boundary *

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Abstract

This paper investigates the effect of rating-based portfolio restrictions that many institutional investors face on the trading of their bond portfolios. Formal regulations and informal investment guidelines require limiting or even prohibit from investing in securities rated below a certain rating category. We explore how credit rating downgrades affect to bondholders that are subject to such rating-based constrains in the US corporate bond market. These boundaries go beyond the well-documented investment-grade threshold. We also control for downgrades that cross any of the buckets established in the NAIC's risk-based capital system. We state that the informativeness of rating downgrades will be different according to whether they imply crossing investment-policy thresholds or not. We analyze corporate bond data from TRACE to test our main hypothesis and find a clear response around the announcement date consistent with portfolio adjustments made by institutions in their fulfillment of nonregulatory investment constrains. Downgrades affecting the three subcategories within the "A" rating class have the larger impact on pricing and trading activity.

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1. INTRODUCTION

Many institutional investors face credit rating-based portfolio restrictions. Regulatory and nonregulatory rules contingent on ratings can be found in bank, insurance and broker-dealer capital requirements, suitability requirements in contractual investment mandates and in internal investment procedures, or collateral requirements. First, the Securities and Exchange Commission (SEC) has used the ratings from certain credit rating agencies (CRAs) designated as Nationally Recognized Statistical Ratings Organizations (NRSRO) to implement various kinds of regulations. The capital structure of federal or state banks, mutual funds, broker-dealers and insurance companies is regulated to assure financial solvency. In concrete, the National Association of Insurance Commissioners (NAIC)'s risk-based capital system for insurance companies are based upon six credit quality designations of bonds, from 1 to 6, with a direct correspondence of credit rating scales (AAA to A, BBB, BB, B, CCC, below CCC). Higher capital requirements are imposed when their portfolios contain bonds rated in lower quality categories. Second, most portfolio managers use a wide variety of rating-based guidelines that potentially affect portfolio investments, retentions, disclosures and performance tracking. Among other goals, these investment policy statements (IPS) serve as a policy guide and provide discipline to the investment process. Finally, some covenants and collateral rules are based on ratings. Central bank policies also use external ratings to determine haircuts and the eligibility of securities to be offered as collateral or for outright purchase.

Formal regulations and informal investment guidelines require to limit investments or are even prohibited from investing in securities rated below a certain rating category. The use of credit ratings allows to simplify several processes, such as the portfolio management risk-taking process, capital requirement computations and capital contractual client relationships. This method is easier than defining the criteria for various levels of risk. Ratings provide a convenient way for communicating investment guidelines and standards to portfolio managers.

However, the major CRAs are often criticized for the quality of ratings and the slowness in adjusting them. Unpredicted well-known bankruptcies and mass defaults of highly rated structured finance securities in the recent financial crisis have triggered regulatory reforms all over the world. Rating-based contingent regulation has a number of drawbacks. It delegates the task of risk assessment to CRAs. These private companies may determine the structure of most bondholder portfolios. The rating of a bond affects the clientele of investors willing to hold it and modifies security price and trading regardless of any fundamental information the rating may convey. As regulation favors better-rated securities, theoretical studies analyze potential incentives to provide inflated ratings and to lead to ratings with low informativeness (see, e.g., Opp, Opp and Harris, 2013, Kartasheva and Yilmaz, 2013 and Parlor and Rajan, 2016). The system also reduces the flexibility for managing credit risk at portfolio level. Ratings-based regulations of bond investment affect the cost of debt (e.g., Kisgen and Strahan,

2010) and may lead to market segmentation into high-yield and investment-grade (IG) investor clienteles (see, e.g., Ambastha, Dor, Dynkin, Hyman and Konstantinovsky 2010, Chen, Lookman, Schürhoff and Seppi, 2014). Additionally, rating cuts through IG threshold (“fallen angels” downgrades) may lead to fire sales with price-pressure effects (e.g., Da and Gao, 2009, Ellul, Jotikasthira and Lundblad, 2011, Ambrose, Cai and Helwege, 2012, Spiegel and Starks, 2016). According the Financial Stability Board (FRB, 2010), regulations incentivize large numbers of market participants to act in similar fashion after rating downgrades experienced during the recent crisis, dealing to “cliff effects” and herding behavior. FRB comments that certain downgrades may amplify procyclicality and cause systemic disruptions. In any event, despite these criticisms, credit ratings today remain as a benchmark used in financial contracting and regulation probably because the lack of a clear and good alternative.

In this paper, we explore how credit rating downgrades affect to bondholders that are subject to rating-based contingent investment constrains. We state that their responses to bond rating adjustments that lead to jumps across common rating thresholds should be different than those downgrades that do not involve them. We compare the bond trading activity and price reaction to downgrades crossing boundaries usually used in guidelines with their reaction to downgrades across the well-documented IG threshold. In addition, we control for downgrades involving crossing one of the six credit quality designations or buckets with implications on the NAIC’s risk-based capital requirements for the insurance companies. Each bucket implies a different risk weight. Downgrades involving a jump between buckets (inter buckets) should have a greater impact on insurers’ portfolios than those that do not cross none of them (intra buckets). Additionally, we study if trading before the release of the credit rating cuts could be consistent with informed-based trading. Our purpose is to answer the following questions: Do guidelines and regulations force institutional investors to unwind positions after downgrades that are relevant from these investment constrains? Is there evidence of “cliff effects” after rating downgrades because rated-based contingent guidelines? Do bondholders react to any downgrade in the same way or is their reaction to these common thresholds cuts stronger? Is the potential market reaction significantly relevant in comparison with the well-documented reaction to fallen angels? Is the market reaction exclusively generated by insurance companies that are subject to NAIC’s rating-based capital regulation?

Most concerns about rating-contingent regulation and almost all the literature about this issue are focused on examining the IG threshold. However, from a large survey, Cantor, Gwilym and Thomas (2007) observe that both a threshold of A and the IG cut-off of BBB/Baa are usually used in the US fund managers’ guidelines (80% and 88% respectively). Chen, et al. (2014) observe that portfolio managers and investment committees have incentives to be more conservative than official regulation standards to avoid potential litigation or to simplify contractual client relationships. Cantor and Packer (1994) and Kisgen and Strahan (2010) list a number of rating-based regulations beyond the IG cutoff. For instance, the AA/Aa rating has been used in the mortgage-backed security market, the SEC Rule 2a-7 stated that money market mutual funds are required to limit investments in bonds rated less than A+/A1 and commercial paper rated less than A1/P1/F1,[1] or the Department of Labor instituted a regulation in 1988 permitting pension fund investment in asset-backed securities only rated A or better. Most IPS of local governments, such as departments, counties, districts, cities, or municipalities, adopts or ratifies the prudent investor standards in accordance with the California Government Code Section 53600. This code prohibits California-incorporated insurance companies from investing in bonds rated below A.[2] Similar guidelines are used by banks, bondholders (via loan and bond covenants and collaterals), pension fund trustees and other fiduciary agents.[3] Surprisingly, these "other" thresholds have received little attention. Ultimately, the extent to which rating-based investment guidelines result in the pricing and trading activity in the US corporate bond market is an empirical question.

As far as we know, ours is the first empirical paper that examines the reaction to a large sample of downgrades without regulatory implications in the US corporate bond market. We analyze the impact of downgrades that cross, or even only approach, typical boundaries included in IPS. We examine common nonregulatory rating thresholds included in investment guidelines and private contracts. Most institutional investors face portfolio restrictions to limit conflicts of interest intrinsic in delegated portfolio management. Cantor et al. (2007) emphasizes the importance of ratings within the pension fund portfolio managers outside of a regulatory context. They report that 86% of fund managers indicated that ratings were explicitly referred to in their IPS. This investment community use ratings largely because their clients require them to do so (62% of respondents) and rather less because regulations force them to (20%). Two other papers that consider nonregulatory rating-based investment practices are Chen et al. (2014) and Dick-Nielsen and Rossi (2017). The latter examines natural experiments from the Barclay Capital (formerly Lehman Brothers) investment-grade corporate bond index and it analyzes the liquidity costs around fallen angel bond exclusions from the index. Chen et al. (2014) examine the impact on prices and trading of bonds affected by the 2005 index redefinition. Both papers observe an impact of events without regulatory effects and conclude that credit ratings do segment the bond market thought the IG threshold.

In our analysis, we compare the market reaction, such as forced selling and price concessions, to these "other downgrades" with the impact of IG downgrades. This comparison allows us to highlight

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[1] SEC (2015) states: "*In adopting final amendments to rule 2a-7 and Form N-MFP to implement Section 939A of the Dodd-Frank Act,* (…) (we) *remove references to ratings and adopt a uniform standard to define an eligible security to be a security that has been determined to present minimal credit risks.*" The compliance date of this rule is October 14, 2016.

[2] For instance, Section 9.0 of the City of San Jose Investment Policy states "*All investments shall conform to Sections 53600 et seq. of the California Government Code and as described within the Policy ("Permitted Investments"). (…) Permitted Investments and applicable limitations shall include: (…) 9.8 Corporate Notes, a. Securities eligible for investment must be rated "A3, A-, or A-" or better by two of the three nationally recognized rating services, Moody's, S&P, or Fitch, respectively.*" In similar terms, the Venture County Investment Pool requires "*State law limits investment in medium term notes to a rating of A or better by Standard & Poor's or A2 by Moody's*."

[3] Ratings-based covenants allow to obtain better terms to bond issuers and loan borrowers. For instance, some covenants allow to keep cash equivalent investments (e.g., the Continental Wind, LLC indenture dated as of September 30, 2013, mentions "*Cash Equivalent Investment means: (…) (j) deposit accounts with any bank that is insured by the Federal Deposit Insurance Corporation and whose long-term obligations are rated A2 or better by Moody's and/or A or better by S&P.*").

the relevance of other thresholds related to the fallen angel benchmark. In the event that a bond held by a manager has its rating downgraded below the required rating, the manager must take actions according with the IPS. In most cases, there is a forced selling of the downgraded security.[4] However, forced selling does not necessarily mean fire sale. An automatic selling of downgraded assets might lead to financial turmoil and damage the company's business. Cantor et al. (2007)'s survey shows a flexible response to such credit events. Portfolio managers have some discretion both in respect to the timing of a disposal and its relation to overall portfolio credit quality. In concrete, 26% of fund manager respondents refer to client specific guidelines, 20% "must sell within an unspecified amount of time", 20% conduct an internal review and 16% refer to no formal procedure.[5] In spite of the allowed deferred sale of the downgraded bond, previous literature focused on IG downgrades observes relevant increments on trading activity by insurance companies around the downgrade date. For instance, Ellul et al. (2011), Ambrose et al. (2012) and Spiegel and Starks (2016) documents a forced-selling phenomenon and certain mixed price pressure effects. Therefore, we hypothesize that the announcement of such a credit rating change can trigger an abnormal trading activity in the secondary corporate bond market.

To answer these questions we study a comprehensive sample of 2,082 credit rating downgrades from the US corporate bond market involving 1,250 straight bonds issued by 245 issuers announced by the three biggest global credit rating agencies: Moody's, Standard and Poor's and Fitch Ratings. The sample includes 1,462 "standard" downgrades, i.e., those downgrades that do not have regulatory implications. The sample also includes 620 NAIC credit-rating downgrades, i.e. downgrades trespassing any of the NAIC's classes, from which 320 downgrades are "straight" NAIC cuts and 300 downgrades are "double affected" downgrades, i.e. rating cuts that are simultaneously NAIC and fallen angel downgrades.[6] Our data combines bond trading information reported from the Trade and Reporting Compliance Engine (TRACE) database, with bond's issue, issuer and rating information provided by the Fixed Income Securities Database (FISD) during the period July 2002 to December 2014. We restrict

[4] There are exceptions. For instance, the investment policy statement of the Metropolitan Water District of Southern California states "*If the security matures within 60 days of the rating change, the Treasurer or investment manager may choose not to sell the security.*"

[5] A common rule included in dozens of guidelines states: "*If securities owned by the (…) are downgraded below the quality required by this Policy, it shall be the policy of the (…) to review the credit situation and make a determination as to whether to sell or retain such securities in the portfolio. If a security is downgraded two grades below the level required by the Policy, the security shall be sold immediately. If a security is downgraded one grade below the level required by this Policy, the Treasurer will use discretion in determining whether to sell or hold the security based on its current maturity, the loss in value, the economic outlook for the issuer and other relevant factors.*"

[6] We define as "straight" NAIC credit-rating cuts to those downgrades that cross one or more thresholds of those that the NAIC regulatory system stablish for capital requirements and that are not fallen angel bonds. Analogously, "straight" fallen angel downgrades refer to those downgrades crossing the IG frontier that do not are NAIC credit-rating cuts. Moreover, we define as "standard" downgrades to those downgrades that do not have any regulatory implications, i.e., those that are not a NAIC credit-rating cut or a fallen angel downgrade. Finally, "double affected" downgrades are those downgrades that are simultaneously a NAIC and a fallen angel downgrade, i.e., those that cross almost one of the thresholds that stablishes the NAIC system and that, at the same time, cross the IG frontier.

the sample to institutional-size trades, excluding retail-size transactions, meaning that all transactions below $100,000 are discarded.

Our study contributes to the existing literature in several ways. We test the impact of common rating-based contingent constrains mainly faced by institutional investors on the normal behavior of secondary corporate debt market. Our study also contributes by shedding light onto research into credit rating effects on bond yields, specifically into credit rating downgrades research. We investigate if trading activity around rating downgrades is triggered by nonregulatory guidelines and regulatory rules. It would be of interest to bond market participants, credit risk managers and regulators. Market participants can take advantage if market behavior seems to anticipate downgrade events, especially those bondholders of future downgraded bonds with investment constrain implications.

Our paper tries to shed light in the controversy around the convenience of the credit rating use in regulation and guidelines. As mentioned above, the use of external credit ratings simplify a number of credit risk management tasks, but it has been heavily criticized. The FRB (2010) requests standard setters and regulators to reduce reliance on CRA ratings in laws and regulations. The proposed principles aim to change existing practices, to end mechanistic reliance by market participants and establish stronger internal credit risk assessment practices instead. The Dodd–Frank Wall Street Reform and Consumer Protection Act of 2010, among other dispositions, requires each federal regulatory agency "*to remove any reference to or requirement of reliance on credit ratings and to substitute in such regulations such standard of creditworthiness as each respective agency shall determine as appropriate for such regulations*" (Section 939A). Although the European Commission (2013) also supports the view that sole and mechanistic reliance on the external credit ratings should be reduced, it emphasizes that "*it is important that reducing overreliance on credit ratings does not lead to legal uncertainty*. (…) *The experience in the US has shown that it is difficult to remove references to ratings without having viable alternatives in place*." In this sense, Basel Committee on Banking Supervision (2016), after several proposals in consultative documents for the revisions to the Standardised Approach for credit risk, acknowledges the limitations of removing all references to external ratings. In concrete, "*the Committee proposes, in this second consultative document, to reintroduce external ratings, in a non-mechanistic manner, for exposures to banks and corporates*."[7] The only proposal affecting the "corporates" exposure class consists of considering current risk weight buckets based on external ratings

[7] In December 2014, the Basel Committee releases a consultative document to revise the standardized approach for credit risk (see BIS 2014). Among other changes, the proposal requires more granularity and risk sensitivity. However, the revised proposals in this second consultative document, published in March 2016, summarizes: "*The Committee considered various alternatives to replace external ratings. Nonetheless, these alternatives would result in significant complexity or lack of comparability across banks. Developing a standard risk-weighting methodology that does not refer to external ratings is particularly difficult in the case of corporate exposures, given the material differences in business models, accounting practices and specific industry factors. Taking a balance of all relevant objectives, the Committee proposes to maintain references to external ratings, where available and/or possible, but complementing its use with banks' due diligence processes.*"

as the “base” and considering a higher risk weight if a due diligence analysis requires it. Recently, Brown and Garber (2016) show as NAIC still considers the reliance on ratings to compute capital requirements. They highlight that general consensus in NAIC recommends increasing granularity by expanding the current 6 NAIC designations for statutory accounting and state investment laws to 20 designations.

We highlight a clear policy implication of these findings. A finer granularity both in the rated-based contingent guidelines and in the NAIC’s capital requirement buckets should mitigate market overreactions and fire sales among institutional investors in general and among insurance companies in particular. This result is in line with recent proposals of regulatory changes announced by the Basel Committee and NAIC. A finer granularity should also allow a more accurate risk adjustment.

The remainder of this paper is organized as follows: Section 2 presents a review of the literature about the effects of credit rating announcements on the trading of the corporate bond market, and the most relevant regulatory and nonregulatory rules. Section 3 presents the methodology and the definition of the main variables. Section 4 outlines the data description and the ample selection. Section 5 presents the main results obtained. Finally, Section 6 concludes.

2. BACKGROUND

This section provides a review of related literature about the market response to credit rating changes and it also includes a the most widely used rating-based regulations in terms of capital requirements to bondholders.

2.1. Related literature

In our analysis of a possible market reaction of the US corporate debt market around a credit rating downgrade triggered by rating-based contingent guidelines, our paper is related to different lines of the previous literature. One of these lines is related to the information channel, i.e. one of several channels linking credit ratings to bond prices. There is a long-standing literature that analyzes price adjustments around credit rating changes in the corporate bond markets focusing on the information channel (e.g., Wansley, Glascock and Clauretie, 1992, Hand, Holthausen and Leftwich, 1992, Hite and Warga, 1997; Hand, Holthausen and Leftwich, 1992; Steiner and Heinke, 2001; May, 2010). They examine bond pricing, returns and trading volume variations around bond rating adjustments under the efficient markets hypothesis, which states that prices should respond to events that convey new and surprising information to the market. Overall, they find some mixed evidence about price response depending on the sample period and the frequency of data. In addition, our paper is related to those analyzing different hypothesis of the effects of credit rating downgrades (Norden and Weber, 2004). Finally, our analysis is also closely related to the recent empirical literature that analyzes bond liquidity after cuts in the credit quality of bonds. Using the TRACE dataset, May (2010) and Jankowitsch, Nagler and Subrahmanyam (2014) document evidence of different price, volume and trading frequency impacts from credit rating downgrades with some persistent effects over time. In the case of the last paper, only downgrades to default are examined. Studies on the stock market and Credit Default Swaps (CDS) find also evidence of the effects of credit rating changes.[8] The new information about bond creditworthiness disclosed by rating adjustments must be relevant to any investor in the corporate bond market that will adjust their bond portfolios after these rating changes.

The regulatory channel considers that credit ratings affect market prices for rating-contingent regulation, independent of the information they provide about the riskiness of securities. Most of this literature is almost exclusively focuses on the IG category regulatory cutoff. First, recent theoretical studies highlight that rating-contingent regulation generates that issuers demand and CRA prefer to facilitate potential overoptimistic ratings (inflated), favoring poor informativeness (e.g., Bolton, Freixas and Shapiro, 2012, Opp, Opp and Harris, 2013, Kartasheva and Yilmaz, 2014 and Parlor and Rajan, 2016). Proposed models consider that most investors cannot hold speculative-grade bonds due to restrictions and they also desire high ratings. In addition, issuers need IG ratings to obtain a large investor base and reduce the liquidity component of their cost of debt. These theoretical papers conclude that the use of ratings in regulation has an adverse effect on the quality of the rating, leads to rating inflation and results in excess volatility in bond returns. In these models, welfare is enhanced by reducing the use of ratings in regulation.

Second, a large empirical literature body examines the impact of regulatory constraints through the analysis of bond downgrades from investment- to speculative-grade. Regulatory restrictions on the holding of speculative-grade bonds could force most institutional investors to sell fallen angels, i.e. downgraded IG bonds ending up in the speculative category. The forced-selling phenomenon generates a price pressure effect due to the price concessions that institutional bondholders bear in order to accomplish regulatory mandates. Under these circumstances, other investors chasing for high yield could pick up these bonds at prices substantially below their fundamental values (see, e.g., Fridson and Cherry, 1992; Fridson and Sterling, 2006; Ben Dor and Xu, 2011).[9] Recent papers using NAIC transaction data find mixed evidence of fire sales immediately after downgrades below investment-grade and subsequent price reversals by insurance companies, both originated by the forced selling of downgraded bonds phenomenon (see, e.g., Ambrose, Cai and Helwege, 2012; Ellul, Jotikasthira and Lundblad, 2011). Ellul et al. (2011) show that forced sales and large price concessions are more likely for those insurers that face stringent capital requirements for the holding of speculative-grade bonds, especially when the overall insurance industry is in distress. Overly, they document insignificant price declines despite the increased number of bond sales for non-constrained insurers. Dick-Nielsen and

[8] For instance, Norden and Weber (2004) in the stock and CDS markets, Jorion and Zhang (2007) in the CDS market and Hull, Predescu and White (2004) in the CDS and bond markets.

[9] Using TRACE dataset, Jankowitsch, Nagler and Subrahmanyam (2014), document the price pressure effect on a sample restricted to default events. They find temporally price pressure effects on the default event day itself exclusively.

Rossi (2017) examines dealer inventories and observe that trading activity spikes at the downgrade date despite a grace period of up to two month in which the institutional investors are allowed to hold on to these bonds. Da and Gao (2009) and Spiegel and Starks (2016) examine IG downgrades using the TRACE database. Both find evidence of a persistent price concession, but Da and Gao (2009) highlights little effects on sale activity. Despite the latter, most empirical studies indicate that downgraded bonds crossing the investment-speculative barrier will involve stronger price impacts and liquidity effects than any other downgrade due to the intensified response of those investors subject to rating-specific constraints to downgrades that have regulatory implications.

Spiegel and Starks (2016) is the paper most closely related to ours because they examine the market reactions in terms of trading activity and prices on the US corporate bond market from a large sample of downgrades to speculative-grade using the TRACE database for a period similar to that we consider. However, it is focused on the IG threshold and does not consider other relevant boundaries in regulation and IPS. Our paper offer significant additional insights, given that we carefully consider effects of downgrades in which a bond's rating crosses, or even only approaches, typical boundaries included in IPS. We consider the fallen angels' downgrades as a benchmark to quantify the significance of other thresholds.

Third, other empirical papers examine different rare quasi-natural experiments to investigate how credit ratings can affect bond yields. Several concrete changes in regulation are studied, such as amendments to SEC's Rule 2a-7, in June 1991, restrict investment in securities with medium-grade credit ratings (A2/P2/F2) to 5 percent of a money market mutual fund's assets (Crabbe and Post, 1994), the SEC's Regulation Fair Disclosure, in October 2000, prohibits public companies (including CRA) from making selective, nonpublic disclosures to favored investment professionals (Jorion, Liu and Shi, 2005), SEC's 2003 designation of DBRS as an NRSRO (Kisgen and Strahan 2010), or the Dodd-Frank Act (Dimitrov, Palia and Tang, 2015 and Jankowitsch, Ottonello and Subrahmanyam 2017). As many investors track investment-grade bond indexes, changes in rules to calculate these bond indexes are other natural experiments to examine (e.g., Chen et al., 2014 and Dick-Nielsen and Rossi, 2017). Even the way ratings are expressed (e.g., Kliger and Sarig, 2000), or even after big-name companies' downgrade (e.g., Acharya, Schaefer and Zhang, 2015) [10] are other exploited experiments. Most of these papers document that changes in rules and regulation affect bond yield. Similarly, Dimitrov, Palia and Tang (2015) and Jankowitsch, Ottonello and Subrahmanyam (2017) find controversial results about the impact of the Dodd-Frank Act on the accuracy and informativeness of credit ratings. Anyway, Jean and Lovo (2013) highlight that, besides the Dodd-Frank Act, the credit ratings remain in investment guidelines and private contracts such as collateral agreements.

[10] The General Motors and Ford downgrades of May 2005.

The mentioned Chen et al. (2014)'s paper proposes a noninformational and nonregulatory transmission channel or investment practices channel. They examines a Lehman's index-rating rule redefinition in 2005 that changed the bond demands of passive index replicators. The index is an important benchmark for institutional investors, thus they analyze the impact of this concrete change in two nonregulatory investment practices: indexation and investability. They observe a clear rating-based bond market segmentation.

Our paper has also a certain connection with prior research that analyses the relationship between institutional trading and informed trading in the corporate bond market. Ronen and Zhou (2013) find significant trading activity and price movements before earnings announcements consistent with informed trading. Kedia and Zhou (2014) show the existence of informed trading in the bond market around acquisition announcements, although the introduction of TRACE helps in reducing information asymmetry. Chae (2005) analyzes specific corporate events such as unscheduled Moody's bond rating announcements and finds evidence for dramatically increased trading volume before downgrade announcements. Prior studies find evidence of abnormal trading activity before credit rating announcements in bond markets (Grier and Katz, 1976, Hite and Warga, 1997, Steiner and Heinke, 2001). Using CDS data Hull, Predescu and White (2004) find that the market anticipates negative rating actions. Findings of these papers suggest that institutional investors possess high levels of information-gathering and monitoring skills

In this context, it is expectable that financial institutional investors can anticipate rating change announcements that affects investment limits and/or increases capital requirements. We would expect to observe intensified trading before those downgrades that could involve rating-based investment constrains, as long as informed traders could trade in advance to private information that they manage, trading at better prices than those prices that they will find in the market after downgrade announcements. The prices should drop to incorporate the new information about the bond rating and the lower attractive in terms of investment restrictions. If most financial institutions decide unwinding positions of the just downgraded bond immediately after the release of the new credit rating score, a downward pressure on prices would probably penalize these transactions.

2.2. Rating-based regulation of capital requirements

Two main widely used rating-based regulations of capital requirements can be highlighted. The "Standardized Approach" (SA) developed by Basel II framework for international regulation for bank solvency and the NAIC's Risk-Based Capital (RBC) system for insurance companies in US. Both approaches are used to compute capital requirements based on risk weights buckets determined by external credit ratings. These institutional bondholders are subject to rating-contingent capital requirements on their holdings of risky assets.[11] However, only the NAIC approach is applied in the US because the federal banking agencies only adopt "Internal Ratings-Based" (IRB) approach of the Basel II, which is based on the Value-at-Risk calculation and is only applied to the very largest, internationally active "core" US banks.[12] The rest of US banks must stay on Basel I, in which all loans by a bank to a corporation have a risk weight of 100% and require the same amount of capital. Perhaps, this fact explains that credit rating category buckets have received little attention by the literature.[13]

NAIC's RBC Standards requires insurance companies in the US to maintain minimum levels of capital on a risk-adjusted basis. In parallel to these capital requirements, insurance companies also face restrictions on the amount of speculative grade debt they may hold. The RBC charges are based upon six credit quality designations of corporate bonds with a direct correspondence of credit rating scales (AAA/Aaa to A/A, BBB/Baa, BB/Ba, B/B, CCC/Caa, below CCC/Caa). The risk weights are 0.3% (Class 1, A/A or above), 0.96% (Class 2, BBB/Baa), 3.39% (Class 3), 7.38% (Class 4), 16.96% (Class 5) and 19.50% (Class 6). Becker and Ivashina (2015) point out that "*For each $100 invested in NAIC category 1, the insurer has to have $0.30 in equity capital. For NAIC category 2 (BBB), the insurer has to have $0.96, more than three times the category 1 requirement. A similar investment in NAIC category 5 (CCC) would command $16.96, or nearly 57 times more equity capital*." This six buckets method simplifies computations for insurance companies. On the one hand, whereas capital requirements are homogeneous within each of these buckets, the economic risk of assets assigned to the same risk bucket may vary substantially. This fact gives rise to criticism of this methodology. On the other hand, capital requirements for the portfolio position hold in a concrete bond remain constant after a credit rating change within categories in the same bucket affecting the bond. The requirement is insensible on this seemly change on the bond issuer's creditworthiness. However, a credit rating change among buckets implies a large shift in the risk weight of the position. Therefore, rating deteriorations could have implications for these large bondholders as these events will also affect their investment decisions. In addition, these downgrades also have implications to potential buyers in terms of capital requirements.

[11] In July 1999, the Basel Committee proposes the first version of the rules that have become known as Basel II. A final set of rules was published in June 2004. Basel II rules are applicable to global commercial US banks or "internationally active" US banks in about 2007. The small regional banks in the USA are regulated under Basel IA. In the latter case, all loans by a bank to a corporation have a risk weight of 100% and require the same amount of capital. Later, Basel III is proposed in December 2010 and includes a series of rules concerned with increasing the amount of capital that banks have to keep for credit risk and tightening the definition of capital. Basel III is being phased in over several years. Full implementation is expected to be complete by 2019.

[12] Even in this more sophisticated approach, i.e. IRB, the credit rating determines the probability of default, the loss given default variables and the credit correlation. The credit correlation parameter, which is set by Basel II rules, defines the "worst-case default rate" for a time horizon and a confidence level obtained from the Vasicek's one-factor Gaussian copula model.

[13] For instance, Weber and Darbellay (2008) examines under a critic point of view the role of CRA in Basel II regulation. The empirical literature about Basel II is focused on the IRB approach for credit risk. A number of papers have examined the potential procyclicality of the Value-at-Risk computation underlying in the IRB approach. They study the accurate link between regulatory capital requirement and economic risk (see, e.g., Dangl and Lehar, 2004, Peura and Jokivuolle, 2004, Alexander and Baptista, 2006, Heid, 2007, Adroian and Shin, 2013).

In our analysis, we examine credit rating downgrade announcements involving crossing one of these risk thresholds.[14] All bond downgrades that involve passing from a risk weight bucket to another will force to the bondholder to increase capital levels to adequate to the new credit assessments. This situation does not force insurance companies to sell immediately downgraded bonds, but the increased surplus of capital will make the investment much more expensive as well as less attractive. These institutions will have to decide whether to sell the downgraded bonds at lower prices or to maintain them in the portfolios and face a penalty in terms of capital requirements with the consequent rebalancing of their investment to preserve their credit risk exposure. We hypothesize that the announcement of such a credit rating change can trigger an abnormal trading activity in the secondary corporate bond market.

A paper related to ours is that of Lu, Lai and Ma (2017) which investigates the impact of several factors in the NAIC's RBC requirements on selling downgraded bonds. They examine the impact of these downgrades across NAIC categories on the corporate bond holdings on the life insurance companies' balance sheets at the end of the year and the bonds acquired and sold during the year. They conclude that life insurers sell more "fallen angels" than downgraded bonds remaining at IG and are also slightly less likely to sell downgraded bonds remaining in the same NAIC rating category than bonds downgraded from a higher NAIC rating category to a lower NAIC rating category. As far as we know, this paper presents the first analysis regarding the impact of downgrades through NAIC rating categories. However, it is mainly focused on internal characteristics of life insurance companies. The trading activity generated by all the insurance companies only account for 12.5% of corporate bond trading during the second half of 2002 (Bessembinder, Maxwell and Venkataraman, 2006). By contrast, the TRACE dataset that we use includes all the transactions in the US corporate bond market. Our paper offers wider analysis of all the rating-based investment constrains, in which both the insurance companies' case and the impact of the risk weight buckets are just particular cases.

3. EMPIRICAL METHODOLOGY

This section describes the methodology that we use to test whether rating-based regulation is ahead of abnormal trading activity around credit rating downgrades in the corporate bond market. First, we detail the regression analysis that we conduct in this paper. Second, we present the liquidity measures that we use.

3.1. Regression model

We use the abnormal mean daily liquidity in the month subsequent to the downgrade as dependent variable.[15] The period that we analyze comprises one month in working days starting immediately after the event, where the announcement day is set to Day 0, i.e. the window of days [0,

[14] See Appendix I for a more detailed classification of credit ratings within each NAIC bucket.
[15] The computational details of abnormal liquidity are given in Subsection 3.2.

20]. We expect to find the effects derived from credit rating changes along this month since most of the investors are not forced to sell downgraded bonds immediately after the rating downgrade announcement. Moreover, this period selection is consistent with the analyzed periods in other studies, as for example the works of Da and Gao (2009), May (2010) and Jankowitsch, Nagler and Subrahmanyam (2014), that document evidence of different price, volume and trading frequency impacts from credit rating downgrades with some persistent effects over time.

We run different regressions for the abnormal liquidity, where the exogenous are, on the one side, variables able capture for the existence of regulatory and non-regulatory implications of the CRCs analyzed; and on the other side, a set of variables that control for the main features of both the CRCs and the bonds that could affect in a lesser or extent degree to the market response.

First, most institutional investors face portfolio restrictions to limit conflicts of interest intrinsic in delegated portfolio management. Such restrictions involve that they cannot invest on bonds below certain rating categories. Following Cantor, Gwilym and Thomas (2007) the threshold of A and the IG cut-off of BBB/Baa are usually used in the US fund managers' guidelines (80% and 88% respectively). This nonregulatory rules could force portfolio managers to unwind positions if a rating bond crosses any of these boundaries after a rating downgrade event. To capture this issue, we include a variable that identifies those downgrades crossing boundaries usually used in these guidelines. Moreover, the NAIC's RBC requirements establishes capital requirements for insurance companies, in order to accomplish capital levels for corporate bond investments. The six tranches include ratings from AAA to A, BBB, BB, B, CCC, and below CCC. The capital requirements rise from 0.3% to 19.5%, depending on the tranche in which the corporate bond is included. The increase in capital-level requirements for downgraded bonds crossing one or more tranches may motivate selling transactions, in order to not have to increase capital levels. Therefore, the jump from one tranche to another may affect abnormal liquidity. To control for this effect, we include a variable that captures if a bond rating change crosses any of these buckets.

Second, there are other cross common factors about the credit events that may affect the response of liquidity to rating changes. On first instance, as Jorion and Zhang (2007) state, we expect that the liquidity reaction to rating changes would depend on the prior rating level. To capture for this effect, we include a variable with the numeric value of the credit rating prior to the CRC, that is the average numeric value across agencies assigned by the long term debt rating equivalences (LTDRE), with values from AAA=1 to D=25.[16] Additionally, institutional investors will concentrate on the investment-grade market segment, causing this grade to be more active than the speculative grade. This effect can lead to a lower impact of CRCs on speculative-grade firms than on investment-grade firms. These institutional rigidities can also result in stronger liquidity reactions to CRCs that cross the

[16] See Table AI in Appendix I for details.

investment-grade frontier. To control for this feature we include a variable that take into account if there is a rating grade change after the downgrade event. The size of the rating change, i.e. the number of notches, must be also important in determining abnormal liquidity. We hypothesize that the number of notches downgraded could cause greater impacts on abnormal liquidity. To control for this effect, we include the number of notches that every CRC conveys, where notches have been stablished following the LTDRE. Additionally, the final credit rating could be determinant for the abnormal response. Even if the final rating does not affect to any rating-based regulation, the economic impact in terms of higher credit risk could be also relevant for bondholders that will face a greater risk exposure. To control for this feature, we include the numeric value of the final rating following the LTDRE.

In addition, the liquidity response to the final CRC can be affected by the opening of a rating review process, which may possibly lead to the announcement of an effective rating change. Sometimes CRAs put bonds on their credit-watch lists, providing information to the market. Investors then can modify their position, anticipating the possibility of a rating change. Altman and Rijken (2007) find evidence about that two thirds of the bonds that were listed on negative perspective by the Moody's watchlists ended with a downgrade, something that result in a weaker market reaction. We expect that those CRCs that are the outcome of credit watch procedures will have a smaller impact on liquidity. To control for this issue we include information, when available, about whether bonds have been included in credit watchlists with negative perspective. Moreover, we take into account whether could be an agency-specific effect on the liquidity response to rating actions. Some authors, such as Livingston et al. (2010) and Norden and Weber (2004), find differences in the market reaction to rating announcements by Moody`s and S&P, whereas Guettler and Wahrenburg (2007) find that ratings from these agencies are highly correlated. To include this issue, we use variables that indicates whether the rating change has been announced by one agency or another. Finally, we add bond age at the time to the credit rating event to the regressions.

For each liquidity variable and window, we run separate regressions where the exogenous are on first instance, regulatory and/or nonregualtory related variables, and on second instance, CRC features control variables. The regressions are

$$AL_{i,(0,20)} = \alpha + \gamma_i(Rating - based\ rules)_i + \beta_i Controls_i + \epsilon_{i,(0,t_n)} \qquad (1)$$

where *AL* refers to abnormal liquidity, *i* is the rating change event, and *(0, 20)* is the period to which refers the dependent variable, abnormal mean daily liquidity. We estimate all the econometric models by OLS and compute standard errors by using the White heteroskedasticity-consistent covariance matrix.

3.2. Liquidity measures

Prior empirical literature examining liquidity in bond markets use a wide range of direct liquidity measures, as for example quoted bid-ask spreads, quoted sizes or trade frequencies. In the case of corporate bonds, most of these measures are difficult to estimate either because often there are not available data or due to the computational drawbacks that some measures exhibit. Therefore, we use indirect liquidity measures that also have been used in the prior literature on bond liquidity. We analyze the number of trades, volume, price, yield spread and price performance measures. We compute these variables on a day-by-day basis for each bond and event. In particular, the *number of trades* (NT) for bond-event *i*, on day *t*, is:

$$NT_{i,t} = \sum_{k=1}^{K_t} nt_{i,t,k} \tag{2}$$

where $nt_{i,t,k}$ is the *k*-th transaction, $k = 1, \ldots, K_t$ of bond-event *i* on day *t*. The *trading volume* (TV) is:

$$TV_{i,t} = \sum_{k=1}^{K_t} tv_{i,t,k} \tag{3}$$

where $tv_{i,t,k}$ is the volume of the *k*-th transaction of bond-event *i* on day *t*. It should be highlighted that TRACE do not report exact volumes for trades above $5 million for investment-grade bonds and above $1 million for high-yield bonds. Therefore, trading volume values are expected to be higher than reported in this study.

We compute the *daily price* (PR) of bonds as the average of intraday trading prices in percentage of face value as follows:

$$PR_{i,t} = \frac{1}{K_t} \sum_{k=1}^{K_t} pr_{i,t,k} \tag{4}$$

where $pr_{i,t,k}$ is the price in percentage of face value of the *k*-th transaction of bond-event *i* on day *t*. Finally, the *yield spread* (YS) is computed as:

$$YS_{i,t} = Y_{i,t} - Y_t \tag{5}$$

where Y_t, is the yield of a Treasury bond with the same time to maturity than the bond of bond-event *i* on the same day *t*[17] and $Y_{i,t}$ is the average bond daily yield, computed as:

[17] We use Treasury yields on actively traded non-inflation-indexed issues adjusted to constant maturities reported by the Federal Reserve Statistical Release (http://www.federalreserve.gov/releases/h15/data.htm#fn26) and interpolate if necessary.

$$Y_{i,t} = \frac{1}{K_t}\sum_{k=1}^{K_t} y_{i,t,k} \quad (6)$$

where $y_{i,t,k}$ is the yield of the *k*-th transaction of bond-event *i* on day *t*.

We then compute the values of the liquidity variables within the window of days [0, 20]. $NT_{i,(0,20)}$, $TV_{i,(0,20)}$, $PR_{i,(0,20)}$ and $YS_{i,(0,20)}$ are the average number of trades, trading volume, price and yield spread measures of event *i* in window [0, 20].

Following Corwin and Lipson (2000), we compute abnormal liquidity values for each of the considered measures. First, we use bond-specific past history to compute the expected values of the number of trades, trading volume, prices and yield spreads.[18] We use the one-month period starting two months prior the downgrade (from day t = -41 to day t = -21).[19] This period ends 21 trading days prior the announcement to avoid possible price lead-up preceding it. We compute the expected behavior of liquidity variable *L* for event *i*, defined as a pair bond-downgrade date, as:

$$EL_{i,(-41,-21)} = \frac{1}{20}\sum_{t=-41}^{-21} L_{i,t} \quad (7)$$

where $L_{i,t}$ represents the daily number of trades, volume, price or yield spread of the downgraded bond on day t $\in$[-41, -21]. Second, the abnormal behavior of liquidity variable *L* for event *i* in window [0, 20] is computed then as:

$$AL_{i,(0,20)} = \frac{L_{i,(0,20)} - EL_{i,(-41,-21)}}{EL_{i,(-41,-21)}} \quad (8)$$

where $L_{i,(0,20)}$ refers to the values of the number of trades, volume, price or yield spread of event *i* within the window of days [0, 20].

4. DATA

4.1. Data description

We study the US secondary corporate bond market behavior using two main sources of data: Trace Reporting and Compliance Engine (TRACE) database[20] and the Mergent's Fixed Income Securities Database (FISD). TRACE system collects and disseminates data of corporate bond transactions in the over-the-counter secondary market that includes, among others, information about trade prices, yields

[18] One alternative is consider an appropriate matching portfolio of similar bonds with stable ratings. However, the lack of liquidity in corporate bond markets makes this approach unsuitable.
[19] Our filtering process described in Section 4.2 guarantees stability in the bond rating during this month.
[20] On January 31, 2001, members of the NASD, Financial Industry Regulatory Agency (FINRA) since 2007, were required to report their secondary over-the-counter bond transactions of a specific type of corporate bonds, following the proposed transparency rules by the Securities and Exchange Commission (SEC). In order to fulfill these requirements, the TRACE system was implemented on July 1, 2002, through which all members must report bond transactions within a timeframe of 1 hour and 15 minutes. In July 2002, the reporting time was initially 75 minutes, decreasing to 45 minutes on October 1, 2003, to 30 minutes on October 1, 2004 and finally ending up at 15 minutes on July 1, 2005.

and volumes. We apply the algorithms and procedures proposed by Dick-Nielsen (2009) to eliminate duplicates, reversals and same-day corrections that could bias results.[21] The second dataset, FISD, includes qualitative and quantitative information about features of US fixed income securities as well as rating history information. It contains details on more than 200,000 securities, including among others delivery date, coupon rate, maturity date, issuer, industry, call features and special features.

Following Dick-Nielsen et al. (2012) we identify intraday institutional-sized trades considering a trading volume cutoff of $100,000. The choice of this cutoff point has a twofold justification. On the one hand, this volume level follows the standard literature conventions. The FINRA stablishes the threshold of a trading volume of $100,000 to classify investor's trades. All transactions below $100,000 are considered as retail trades, meanwhile transactions equal to or above $100,000 are set to as institutional trades (Ketchum, 2012).[22] On the second hand, with this restrictive threshold we minimize the risk of loss original institutional trades as it were retail transactions. Institutional traders could disaggregate their large positions, into small trades, i.e., into odd-lot sizes. In the bond market, odd lot sizes are those trades below $100,000 or not divisible by $100,000. Meanwhile, round lot sizes are those positions equal to or divisible by $100,000.[23] In this market, is more probably that institutional investors trade in round- and block-lot sizes and small investors in micro or odd-lot sizes (see, for example, Hendershott and Madhavan, 2015, O'Hara, Wang and Zhou, 2015, or Atanasov, Merrick and Schuster, 2017). Therefore, choosing this threshold of $100,000 we are avoiding the risk of eliminating potential institutional positions and considering them as small ones.

4.2. Sample selection

Matching TRACE and FISD datasets, we collect the trading information for straight corporate bonds[24] with rating downgrades from the main three CRAs, i.e. Moody's, Standard & Poor's and Fitch. We exclude bonds affected by default downgrade events.[25] We use trading information to select bonds that meet some specific trading criteria. To be eligible, one bond should be traded at least once in the 20 working days before the event and once in a similar period after the event.[26] In addition, bonds must be

[21] Dick-Nielsen (2009) shows that TRACE contains almost 7.7% of the errors among total reports. Edwards, Harris and Piwowar (2007) and Dick-Nielsen (2009) show that many errors are due to later corrected or canceled transactions. Appendix I shows the exhaustive debugging and filtering process in detail.

[22] Previous researches in the bond market, as for example the study of Edwards, Harris and Piwowar (2007), also consider this threshold to classify transactions into retail and institutional groups. On the other hand, some other papers choose different limits to identify institutional and retail-sized trades. For example, Ronen and Zhou (2013), in their paper of effects from other corporate events, consider the cutoff point of $500,000.

[23] The standard industry conventions to split the trades into different groups is the following: micro sized trades are those trades in the interval [$1, $100,000), odd-lot within the interval [$100,000, $1,000,000), round-lot within [$1,000,000, $5,000,000) and block in the interval [$5,000,000, +∞).

[24] We exclude zero coupon bonds, variable coupon bonds, bonds that are part of a unit deal, TIPS, STRIPS and either perpetual, putable, callable, tendered, preferred, convertible or exchangeable bonds.

[25] We do not include default bonds in our analysis because of the reduced information provided by TRACE after defaults. Once a CRA announces the default, TRACE stops reporting yield information.

[26] The liquidity level in the US corporate bond market, the world's largest one, is really low. Mahanti, Nashikkar, Subrahmanyam, Chacko and Mallik (2008) report that the percentage of the total number of bonds in their sample (2004-2005) that trade at least once a year is between 22% and 34%, each year. Over 40% of bonds do not even trade once a year.

traded on at least 20% of the trading days in the period starting 41 days prior to the credit announcement and ending 20 days after it.

We filter out also overlapping rating events, i.e. events preceded by other rating announcements in the previous 61 working days are ignored. We consider doubled or tripled rating announcements by two or more CRAs (multiple rating changes) as one unique event whenever changes are in the same direction and grade category (investment or speculative grade).[27] In these cases, we compute initial or final rating values as the average across agencies using the numeric value assigned by the long term debt rating equivalences, with values from AAA=1 to D=25. The final data sample consists of 2,082 credit rating downgrades (CRD) involving 1,250 bonds from 245 issuers. Table 1 shows the composition of our final sample across rating categories and some of the main characteristics of the bonds involved.

[INSERT TABLE 1 ABOUT HERE]

Table 1 displays the number of final ratings after downgrades by CRA and by unique events. Among the 2,082 unique rating downgrades, the largest number of downgrades within a category is equal to 368 and corresponds to bonds ending on BB/Ba grade. The average issue size of the whole sample is equal to $0.70 million, the average coupon rate is equal to 5.86%, the average age is equal to 4.74 years and the average Macaulay duration equals to 2.87.

The transition matrix of the total number of 2,082 rating downgrades across rating groups is showed in Table 2. We cluster in thirteen groups, AA+/Aa1 plus 12 groups according to the standing rating grade before the rating change (in rows) and the final rating grade after the event (in columns).

[INSERT TABLE 2 ABOUT HERE]

Table 2 displays both, the number of downgrades with and without regulatory implications. From the 2,082 credit rating downgrades, 620 are NAIC credit-rating cuts, i.e. downgrades that imply crossing at least one of the classes stablished in the NAIC risk-based capital system, and that hence have capital regulatory implications for insurance companies. We refer to these downgrades as inter-bucket downgrades. From the 620 inter-bucket downgrades, 320 downgrades are simultaneously NAIC cuts and fallen angels (see boxed doted and striped cells in Table 2), meaning that not only trespass almost one NAIC classes, but also they involve crossing the IG frontier. The other 320 inter-bucket downgrades are “straight” NAIC cuts (see boxed doted cells in Table 2), i.e. downgrades that do not cross the IG frontier. Table 2 also shows 1,462 “standard” downgrades, i.e. downgrades that are not subject to any capital regulation. Among the 620 inter-bucket downgrades, the largest number corresponds to jumps from the BBB category to the BB one, specifically 126 rating downgrades. These 126 downgrades represent more than 20% of the total inter-bucket downgrades analyzed.

[27] Multiple rating events in the opposite direction are excluded.

Graphically, Figure 1 displays the final composition of the sample by jump size across rating level for the complete sample. Darker values represent the minimum size of jumps and lighter ones the maximum. The size of the jump goes from 1 notch, i.e. the minimum size to 6 notches, i.e. the maximum size of the jump in our sample. Bonds rated BBB/Baa, BB/Ba and A after downgrades represent nearly 85% of total downgrades and a jump size of one notch accounts for 81.65% of our sample.

[INSERT FIGURE 1 ABOUT HERE]

Table 3 summarizes the main statistics for different CRDs: "standard" or intra-NAIC-bucket downgrades (without regulatory implications), inter-NAIC-bucket downgrades (the rating moves from one NAIC rating class to another and involves an increase in capital requirements for insurance companies), and "fallen angel" downgrades (with several regulatory implications). As commented, for multiple rated bonds we compute prior rating and final rating as the average across agencies using the numeric value assigned by the long term debt rating equivalences.

[INSERT TABLE 3 ABOUT HERE]

We can observe several differences between intra- and inter-bucket downgrades. First, inter-NAIC-bucket downgrades (central panel on Table 3) involve lower ratings, i.e., bonds with inferior creditworthiness, than "standard" downgrades (left panel). In fact, a downgrade between the first NAIC bucket to the second one implies that the rating moves from a category A or better to BBB. The average downgrade in the inter-bucket subsample moves from 9.44 (between BBB/Baa2 and BBB-/Baa3) to 11.33 (between BB+/Ba1 and BB/Ba2). The intra-bucket downgrade subsample shows that, on average, rating moves from 6.06 or rating A-/A3 (original rating) to 7.18 or rating BBB+/BBB1 (final rating). Second, the average and the maximum number of rating notches in the inter-NAIC-bucket downgrades are larger than they are in the "standard" downgrade. Thus, the highest initial rating is 5 (A/A2) and the average jump size is equal to 1.89, representing an average jump close to two notches and ranging from 1 (minimum) to 10 (maximum) notches. The percentage of "Small jumps" (jump size lower than 3 notches) accounts for 44% in the inter-bucket and 89% in the intra-bucket subsamples. Third, the percentage of bonds preceded by their inclusion onto negative watchlists is double in the case of inter-NAIC-buckets, represent 54% and 27% respectively. The inclusion of a bond onto negative watchlists can be important in the predictability of rating downgrades and can be used by investors to rebalance their portfolios before the downgrade itself, especially if final ratings involve regulatory constraints. Finally, right panel on Table 3 presents the main statistics for double affected downgrades, i.e. downgrades that are simultaneously NAIC cuts and fallen angels. Statistics are quite to the inter-NAIC-bucket case.

5. RESULTS

In this section we show the main results from our analysis of the impact of rating-based regulatory and non regulatory rules on bond liquidity. We first present some preliminary insights about the liquidity variables computed and its abnormal values around credit rating changes. Second, we present our main results from the regression analysis.

5.1. Preliminary insights

Table 4 provides statistics for the number of trades, volume, price, yield spread and price performance across rating grades by windows and sorted by kind of downgrades. Panel A displays the statistics for the average liquidity measures in the window [-41, -21] and Panel B in the window of days [0, 20]. Bonds ending on BBB+/Baa1 group category present the largest mean average number of trades, with a value equal to 3.76 trades per day in the window control period. And it rises to 3.81 trades on average in the window [0, 20]. However, the bonds that present the highest mean average number of trades after downgrades, are bonds ending on A-/A3 category, with a value of 3.87 trades per day on average in this window of days. In the case of the trading volume, the highest mean average trading volume in the post-announcement period is for bonds ending on AA+/Aa1 grade ($5.03 million), although their number of trades is substantially lower (2.50 trades) than for the rest of the categories. The largest drop on prices is for bonds ending on A-/A3 grade, with a mean average price equal to 94.02% after the downgrade, compared with the same value in the [-41, -21] window, that is equal to 99.12% of its face value. The same but in opposite sign can be observed if we look at the yield spread. The mean average yield spread for bonds ending on A-/A3 grade in the window [-41, -21] is equal to 278 basis points, and they experiment a rise after suffer a downgrade until a mean of 621 basis points.

[INSERT TABLE 4 ABOUT HERE]

Figure 2 shows daily values of the abnormal liquidity computed. We observe increasing abnormal levels around the announcement date. The increase in abnormal trading activity is much more pronounced around the announcement date, where the number of trades increases by nearly 50% on average immediately after the downgrade (see upper right side of Figure 2). Abnormal trading volume (see upper left side of Figure 2) also increases dramatically around the days of the credit rating change announcement. It should be noted that the volumes traded are expected to be larger than reported in this paper since TRACE do not provide exact volumes for trades above $5 million for investment-grade bonds and above $1 million for high-yield bonds. During the weeks before announcements, abnormal prices (see down left side panel of Figure 2) are close to zero or follow a slightly downward-trend. From one day before the downgrade, we observe a clear drop in prices, and on the event day, the price falls more than 3%. This fall in abnormal prices stabilizes on the following days and from day +4 it seem to recover to normal price levels. From this day forward, abnormal prices remain at a more or less stable level, 3% below the average price in the control period and it seems to follow a price reversal at the end of the period as prices return to the values observed one month before the downgrade event. The down right panel of Figure 2 shows abnormal yield spread behavior. The daily average abnormal yield spread is systematically higher around the announcement day, corroborating the drop in abnormal prices that we find.

5.2. Regression analysis results

Tables 5 and 6 shows the main results of the regression analysis. The dependent variable in all models is the mean abnormal liquidity in the window of days [0, 20], where the liquidity variables are the number of trades, the trading volume, the price and the yield spread.

In Table 5, we present the results including rating-based variables that control for the prior rating before the rating change. Particularly, the variables defined are those that affecting the last subcategory of the "AA" class, the three subcategories within the "A" rating class and the first two subcategories within the "BBB" class. Meanwhile, in Table 6, the control variables are related with the final rating of the bond after the credit rating change. In particular, the variables defined are those that affecting the three subcategories within the "A" and "BBB" rating classes. Additionally, we include other control variables that capture for characteristics of the rating change. For example, *FALLEN_ANGEL* is a dummy variable equal to one for downgrades from investment to speculative grade; *NAIC* is a dummy variable equal to one for downgrades involving changes across NAICs system buckets; *FIN_RATING* is the numeric value of the rating after the CRC where values are assigned following the long term debt rating equivalences from 1 to 25; *JUMP_SIZE* represent the numeric value of the jump between the prior rating and the final rating; *MOODYS* is a dummy variable equal to one for downgrades by Moody's, and zero otherwise; and *WNEG* is a dummy equal to one for downgraded bonds after their inclusion in the credit watch lists and zero otherwise. We also include other control variables to capture the features of the bonds involved in the CRC. The variables included are: *LOG_OFFER* is the log of the issue size; *TIME TO MATURITY* is the time to maturity at the moment of the CRC announcement; and *COUPON* is the coupon rate of the bond.

We estimate the model separately for each liquidity variable considered, including and excluding the control variables, by OLS and test for parameter significance with the White heteroscedasticity consistent covariance matrix.

As showed in Tables 5 and 6, the coefficients of variables related with rating limits included in policy guidelines present the correct sign for each of the models, and are highly significant. For example, in the second Model of Table 5, where the dependent variable is the number of trades, the coefficient of the variable that captures if a bond is downgraded below A-/A3, which is a limit included in most of the guidelines, is positive and equal to 0.296 and statistically significant at 10% level. In the case of the price, the fifth Model of Table 5, present a coefficient equal to 0.046 and highly significant at 1% level.

6. CONCLUSIONS

This paper investigates the impact of credit rating downgrades on the liquidity and trading activity of institutional traders in the over-the-counter US corporate bond market. We study the effects on trading of rating-based regulatory and nonregulatory rules. Our findings show that the increased trading activity and price concessions after downgrades seem to be triggered by rating-specific constraints and nonregulatory rules of the institutional constrained segment. Downgrades affecting the three subcategories within the "A" rating class have the larger impact on pricing and trading activity. Fire sales seems to occur after the disclosure of credit news, as long as large price pressure is detected after downgrades and trading volume is presumably larger than reported.

This study contributes by shedding light onto research into credit rating effects and specifically into credit rating downgrades research. It should be of interest to bond market participants, credit risk managers and regulators. Our results suggest that trading patterns after credit rating downgrades are an important source of information for market participants. These results could also be of interest to regulators. We highlight a clear policy implication of these findings. A finer granularity both in the rated-based contingent guidelines and in the NAIC's capital requirement buckets should mitigate market overreactions and fire sales among institutional investors in general and among insurance companies in particular. This result is in line with recent proposals of regulatory changes announced by the Basel Committee and NAIC. A finer granularity should also allow a more accurate risk adjustment.

References

Acharya, V. V., Schaefer, S., Zhang, Y., 2015. Liquidity risk and correlation risk: A clinical study of the General Motors and Ford Downgrade of May 2005. *The Quarterly Journal of Finance*, 5(02), 1550006.

Acharya, V.V., Schaefer, S., Zhang, Y. (2015), Liquidity Risk and Correlation Risk: A Clinical Study of the General Motors and Ford Downgrade of May 2005, Quarterly Journal of Finance, Vol. 5, No. 2, 1550006 (51 pages)

Adrian, T., Shin, H.S. (2014), “Procyclical Leverage and Value-at-Risk”, The Review of Financial Studies, Volume 27, Issue 2, 1 February 2014, Pages 373–403

Alexander, G.J, Baptista, A.M. (2006). “Does the Basle Capital Accord reduce bank fragility? An assessment of the value-at-risk approach”, Journal of Monetary Economics, Volume 53, Issue 7, Pages 1631-1660

Ambastha, M., Dor, A. B., Dynkin, L., Hyman, J., Konstantinovsky, V. (2010). Empirical duration of corporate bonds and credit market segmentation. The Journal of Fixed Income, 20(1), 5-27,3.

Ambrose, B.W., Cai, N., Helwege, J., 2012. Forced selling of fallen angels, *Journal of Fixed Income,* 18, 72-85.

Atanasov, V., Merrick Jr, J. J., Schuster, P. (2016). Why do dealers buy high and sell low? An analysis of persistent crossing in extremely segmented markets. *Review of Finance*, *21*(2), 719-760.

Bank for International Settlements (2014), “Revisions to the standardised approach for credit risk: Basel Committee issues consultative document,” Basel Committee on Banking Supervision. December 22, 2014

Bank for International Settlements (2016), “Revisions to the Standardised Approach for credit risk: second consultative document,” Basel Committee on Banking Supervision. March 11, 2016

Barber, B. M., Lee, Y. T., Liu, Y. J., Odean, T., 2009. Just how much do individual investors lose by trading?. *Review of Financial studies*, 22(2), 609-632.

Barber, B. M., Odean, T., Zhu, N., 2009. Do retail trades move markets?. *Review of Financial Studies*, 22(1), 151-186.

Basel Committee on Banking Supervision, 2004. International Convergence of Capital Measurement and Capital Standards, a Revised Framework. Bank for International Settlements, Basel, Switzerland.

Basel Committee on Banking Supervision. Long-term Rating Scales Comparison. Bank for International Settlements, Basel, Switzerland. http://www.bis.org/bcbs/qis/qisrating.htm

Becker, B., Ivashina, V. (2015). Reaching for yield in the bond market. The Journal of Finance, 70(5), 1863-1902.

Ben Dor, A., & Xu, Z. (2011). Fallen angels: characteristics, performance and implications for investors. The Journal of Fixed Income, 20(4), 33-58.

Ben Dor, A., Xu, Z., 2011. Fallen angels: characteristics, performance and implications for investors. *The Journal of Fixed Income*, 20(4), 33-58.

Benford, J., Nier, E. W. (2007). Monitoring cyclicality of Basel II capital requirements.

Bessembinder, H., Kahle, K. M., Maxwell, W. F., Xu, D., 2009. Measuring abnormal bond performance. *Review of Financial Studies,* 22(10), 4219-4258.

Bessembinder, H., Maxwell, W., Venkataraman, K., 2006. Market transparency, liquidity externalities and institutional trading costs in corporate bonds, *Journal of Financial Economics,* 82, 251-288.

Bolton, P., Freixas, X., Shapiro, J. (2012), The Credit Ratings Game. The Journal of Finance, 67: 85–111

Brown, C., Garber, J. (2016), Risk-Based Capital Update, Insurance Summit, Investment RBC (E) Working Group, National Association of Insurance Commissioners (NAIC)Campbell, J. Y., Taksler, G. B., 2003. Equity volatility and corporate bond yields. *The Journal of Finance,* 58(6), 2321-2349.

Cantor, R., Gwilym, O. A., & Thomas, S. H. (2007). The use of credit ratings in investment management in the US and Europe. The Journal of Fixed Income, 17(2), 13-26.

Chae, J., 2005. Trading volume, information asymmetry and timing information. *The Journal of Finance*, 60(1), 413-442.
Chen, Z., Lookman, A. A., Schürhoff, N., Seppi, D. J. (2014). Rating-based investment practices and bond market segmentation. The Review of Asset Pricing Studies, 4(2), 162-205.
Corwin, S. A., Lipson, M. L., 2000. Order flow and liquidity around NYSE trading halts, *The Journal of Finance*, 55(4), 1771-1805.
Crabbe, L., Post, M. A. (1994). The effect of a rating downgrade on outstanding commercial paper. The Journal of Finance, 49(1), 39-56.
Da, Z., Gao, P., 2009. Clientele change, persistent liquidity shock and bond return reversals after rating downgrades, SSRN http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1280834.
Dangl, O., Lehar, A. (2004) "Value-at-risk vs. building block regulation in banking", Journal of Financial Intermediation, Volume 13, Issue 2, Pages 96-131
Dick-Nielsen, J., Rossi, M. (2017). The cost of immediacy for corporate bonds. Available at SSRN: https://ssrn.com/abstract=2139403
Dick-Nielsen, J., 2009. Liquidity biases in TRACE, *The Journal of Fixed Income* 19 (2), 43-55.
Dick-Nielsen, J., Feldhütter, P., Lando, D., 2012. Corporate bond liquidity before and after the onset of the subprime crisis, *Journal of Financial Economics*, 103, 471-492.
Dimitrov, V., Palia, D., Tang, L. (2015). Impact of the Dodd-Frank act on credit ratings. Journal of Financial Economics, 115(3), 505-520.
Easley, D., O'Hara, M., 1987. Price, trade size and information in securities markets. *Journal of Financial Economics*, 19, 69-90.
Easley, D., O'Hara, M., 2004. Information and the cost of capital. *The Journal of Finance* 59(4), 1553-1583.
Edwards, A.K., Harris, L.E., Piwowar, M.S., 2007. Corporate bond market transaction costs and transparency, *Journal of Finance*, 62(3), 1421-1451.
Ellul, A., Jotikasthira, C., Lundblad, C.T., 2011. Regulatory pressure and fire sales in the corporate bond markets, *Journal of Financial Economics*, 101(3), 596-620.
European Commission (2013). New rules on credit rating agencies (CRAs) enter into force – frequently asked questions. Press Release Database. Available at http://europa.eu/rapid/press-release_MEMO-13-571_en.htm
Financial Stability Board (2010). Principles for reducing reliance on CRA ratings, October.
Fitch Ratings, 2017. Rating Definitions. Fitch Group, New York, NY.
Frazzini, A., Lamont, O. A., 2008. Dumb money: Mutual fund flows and the cross-section of stock returns. *Journal of Financial Economics*, 88(2), 299-322.
Fridson, M., Cherry, M., 1992. Are There Bargains in Fallen Angels?. *Journal of High Yield Bond Research*, Merrill Lynch & Co, 4-15.
Fridson, M., Sterling, K., 2006. Fallen angels: A separate and superior asset class. *Journal of Fixed Income*, 16(3), 22-29.
Goldstein, M. A., Hotchkiss, E. S., Sirri, E. R., 2007. Transparency and liquidity: A controlled experiment on corporate bonds. *Review of Financial Studies*, 20(2), 235-273.
Grier, P., Katz, S., 1976. The differential effects of bond rating changes among industrial and public utility bonds by maturity. *Journal of Business* 49, 226-239.
Grossman, S. J., Miller, M. H., 1988. Liquidity and market structure. *The Journal of Finance*, 43(3), 617-633.
Han, S., Zhou, X., 2014. Informed bond trading, corporate yield spreads and corporate default prediction. *Management Science*, 60(3), 675-694.
Hand, J. R., Holthausen, R. W., Leftwich, R. W., 1992. The effect of bond rating agency announcements on bond and stock prices. *The Journal of Finance*, 47(2), 733-752.

Harris, L., Piwowar, M., 2006. Secondary trading costs in the Municipal bond market. *Journal of Finance*, 61(3), 1361-1397.
Heid, F. (2007). The cyclical effects of Basel II capital requirements. Journal of Banking & Finance. 31. 3885-3900.
Heid, F. (2007). The cyclical effects of the Basel II capital requirements. *Journal of Banking and Finance*, 31, 3885–3900.
Hendershott, T., Madhavan, A. (2015). Click or Call? Auction versus Search in the Over□the□Counter Market. *The Journal of Finance*, *70*(1), 419-447.
Hite, G., Warga, A., 1997. The effect of bond-rating changes on bond price performance. *Financial Analysts Journal* 53(3), 35-51.
Hull, J., Predescu M., White, A., 2004. The relationship between credit default swap spreads, bonds yields and credit rating announcements, *Journal of Banking and Finance,* 28(11), 2789-2811.
Jankowitsch, R., Nagler, F., Subrahmanyam, M. G., 2014. The determinants of recovery rates in the US corporate bond market. *Journal of Financial Economics,* 114, 155-177.
Jankowitsch, R., Ottonello, G., Subrahmanyam, M.G. (2017), The Rules of the Rating Game: Market Perception of Corporate Ratings. Available at SSRN: https://ssrn.com/abstract=2655684
Jeon, D. S., Lovo, S. (2013). Credit rating industry: A helicopter tour of stylized facts and recent theories. International Journal of Industrial Organization, 31(5), 643-651.
Jorion, P., Liu, Z., Shi, C. (2005). Informational effects of regulation FD: evidence from rating agencies. Journal of financial economics, 76(2), 309-330.
Jorion, P., Zhang, G., 2007. Good and bad credit contagion: Evidence from credit default swaps, *Journal of Financial Economics*, 84, 860-883.
Kaniel, R., Liu, S., Saar, G., Titman, S., 2012. Individual investor trading and return patterns around earnings announcements. *The Journal of Finance*, 67(2), 639-680.
Kaniel, R., Saar, G., Titman, S., 2008. Individual investor trading and stock returns. *The Journal of Finance*, 63(1), 273-310.
Kartasheva, V., Yilmaz, B. (2013). The Precision of Ratings. Available at SSRN: https://ssrn.com/abstract=2232998
Kashyap, A. K., Stein, J. C. (2004). Cyclical implications of the Basel II capital standards. Economic Perspectives-Federal Reserve Bank Of Chicago, 28(1), 18-33.
Kedia, S., Zhou, X., 2014. Informed trading around acquisitions: Evidence from corporate bonds. *Journal of Financial Markets* 18, 182-205.
Ketchum, G. R., 2012. Speech: Bond Dealers Association Annual Conference. Chicago, IL, October 11, 2012. Available at: http://www.finra.org/newsroom/speeches/ketchum/p187314.
Kim, O., Verrecchia, R.E., 1994. Market liquidity and volume around earnings announcements. *Journal of Accounting and Economics,* 17, 41-67.
Kisgen D, Strahan P. (2010) Do Regulations Based on Credit Ratings Affect a Firm's Cost of Capital?. Review of Financial Studies. December, 23(12), 4324-4347.
Lu, E. P., Lai, G. C., Ma, Q. (2017). Organizational structure, risk-based capital requirements and the sales of downgraded bonds. Journal of Banking & Finance, 74, 51-68.
Mahanti, S., Nashikkar, A., Subrahmanyam, M.G., Chacko, G, Mallik, G., 2008. Latent liquidity: A new measure of liquidity, with an application to corporate bonds, *Journal of Financial Economics*, 88(2), 272-298.
May, A. D., 2010. The impact of bond rating changes on corporate bond prices: New evidence from the over-the-counter market, *Journal of Banking and Finance,* 34(11), 2822-2836.
Moody's Investors Service, 2016. Rating Symbols and Definitions. Moody's, New York, NY.
Ng, L., Wu, F., 2007. The trading behavior of institutions and individuals in Chinese equity markets. *Journal of Banking & Finance*, 31(9), 2695-2710.

Norden, L., Weber, M., 2004. Informational efficiency of credit default swap and stock markets: The impact of credit rating announcements, *Journal of Banking and Finance,* 28, 2813-2843.

O'Hara, M., Wang, Y., Zhou, X., 2015. *The best execution of corporate bonds*. Working paper.

Opp, C. C., Opp, M. M., Harris, M. (2013). Rating agencies in the face of regulation. Journal of Financial Economics, 108(1), 46-61.

Parlour, C. A., Rajan, U. (2016). Contracting on credit ratings: Adding value to public information. Available at SSRN: https://ssrn.com/abstract=2516940

Peura, S., Jokivuolle, E. (2004). Simulation based stress tests of banks' regulatory capital adequacy, Journal of Banking & Finance, Volume 28, Issue 8, 2004, Pages 1801-1824

Peura, S., Jokivuolle, E. (2004). Simulation based stress tests of banks' regulatory capital adequacy. *Journal of Banking & Finance*, 28(8), 1801-1824.

Ronen, T., Zhou, X., 2013. Trade and information in the corporate bond market. *Journal of Financial Markets,* 16, 61-103.

Sheskin, D. J., 1997. Handbook of parametric and nonparametric statistical procedures, CRC Press. New York.

Spiegel, M., Starks, L. (2016). Institutional rigidities and bond returns around rating changes. WP, University of Texas and Yale School of Management.

Standard & Poor's Financial Services, 2017. S&P Global Ratings Definitions, Standard and Poor's, New York, NY.

Steiner, M., Heinke, V. G., 2001. Event study concerning international bond price effects of credit rating actions, *International Journal of Finance and Economics,* 6, 139-157.

Wansley, J. W., Glascock, J. L., Clauretie, T. M., 1992. Institutional bond pricing and information arrival: The case of bond rating changes. *Journal of Business Finance & Accounting,* 19(5), 733-750.

Weber, R. H., Darbellay, A. (2008). The regulatory use of credit ratings in bank capital requirement regulations. *Journal of banking regulation*, 10(1), 1-16.

Weber, R.H., Darbellay, A. (2008), The regulatory use of credit ratings in bank capital requirement regulations, Journal of Banking Regulation, 10.1, November, 1-16.

Wei, J., Zhou, X., 2016. Informed Trading in Corporate Bonds Prior to Earnings Announcements. *Financial Management*, 641-674.

Appendix I

Table AI. Long-term debt rating equivalences. This table shows the alpha-numerical rating codes and their correspondent numerical values assigned to each of the tree main credit rating agencies. It also exhibits their correspondence to grade categories, and the different NAIC's risk-based classes for insurance companies. Actually, some of these standing categories do not apply nowadays, as for example 'Aa' Moody's rating currently corresponds to 'Aa2' rating. The reason to include them here is that we find them along our data sample. Sources: Standard & Poor's Financial Services (2017), Moody's Investors Service (2016), Fitch Ratings (2017), and NAIC's Risk-Based Capital (RBC) system http://www.naic.org/documents/svo_naic_aro.pdf.

Credit rating agency			Numerical value	Grade	NAIC's classes
Standard & Poor's	Moody's	Fitch			
AAA	Aaa	AAA	1	Investment	1
AA+	Aa1	AA+	2		
AA	Aa Aa2	AA	3		
AA-	Aa3	AA-	4		
A+	A1	A+	5		
A	A A2	A	6		
A-	A3	A-	7		
BBB+	Baa1	BBB+	8		2
BBB	Baa Baa2	BBB	9		
BBB-	Baa3	BBB-	10		
BB+	Ba1	BB+	11	Speculative	3
BB	Ba Ba2	BB	12		
BB-	Ba3	BB-	13		
B+	B1	B+	14		4
B	B B2	B	15		
B-	B3	B-	16		
CCC+	Caa1	CCC+	17		5
CCC	Caa Caa2	CCC	18		
CCC-	Caa3	CCC-	19		
CC	Ca	CC	20		6
C	C	C	21		
CC-	Ca3		22		
C+	C1	DDD	23		
C	C2	DD	24		
D	C3	D	25		
SUSP	SUSP	SUSP	26		
NR	NR	NR	27		

Appendix II

TRACE data goes through three phases: the first phase started in July 2002 and only included the larger and higher credit quality issues; the second phase included not only higher-quality issues but also the smaller investment-grade issues; and the third phase started in October 2004 and reported all secondary market transactions for corporate bonds. Thus, not all trades reported to TRACE were initially disseminated at the launch of TRACE on July 1, 2002. Since October 2004, trades in almost all bonds, except some lightly traded bonds, are disseminated. Comparing TRACE with the NAIC data used in previous studies focused on insurance companies, the latter represents a small part of the US corporate bond market. Even during the second half of 2002, when TRACE showed a partial coverage, Bessembinder *et al.* (2006) indicate that insurance companies completed 12.5% of the dollar trading volume in TRACE-eligible securities.

Following Edward *et al.* (2007) and Dick-Nielsen (2009) with minor alterations, we debug the data set in several steps:

1. Deleting records with transaction hour equal to zero, trade volumes under zero, or traded prices over $500 or below $0.001.
2. Deleting true duplicates, same-day corrections (cancelations and corrections), reversals and when-issued trades. The information is obtained from the sequence numbers.
3. When the transaction is an agency transaction, it requires three reports to be submitted to the TRACE system and two of the reports will be disseminates. Once we have found triple transactions, in contrast to Dick-Nielsen (2009) who eliminates only same prices, widening the timeframe to 60 seconds, we eliminate couples of same price, widening the timeframe to 300 seconds.
4. Applying reversal filters to eliminate those trades that have an absolute price, or yield change deviation from the lead and average price, or yield change by at least 10%.
5. Using median filters to eliminate those trades with price deviations more than 20% from the daily median.

Figure 1. Jump size across final ratings distribution.
This figure shows final ratings after downgrades across rating categories and by jump size. Darker colors indicates the lower size of jump size and contrary lighter ones higher jump sizes. . The dataset includes 2,082 credit rating downgrades involving 1,250 straight bonds issued by 245 issuers. Bond trading information is reported by the TRACE database and rating information is provided by FISD. The dataset covers the period from July 1, 2002 to December 31, 2014.

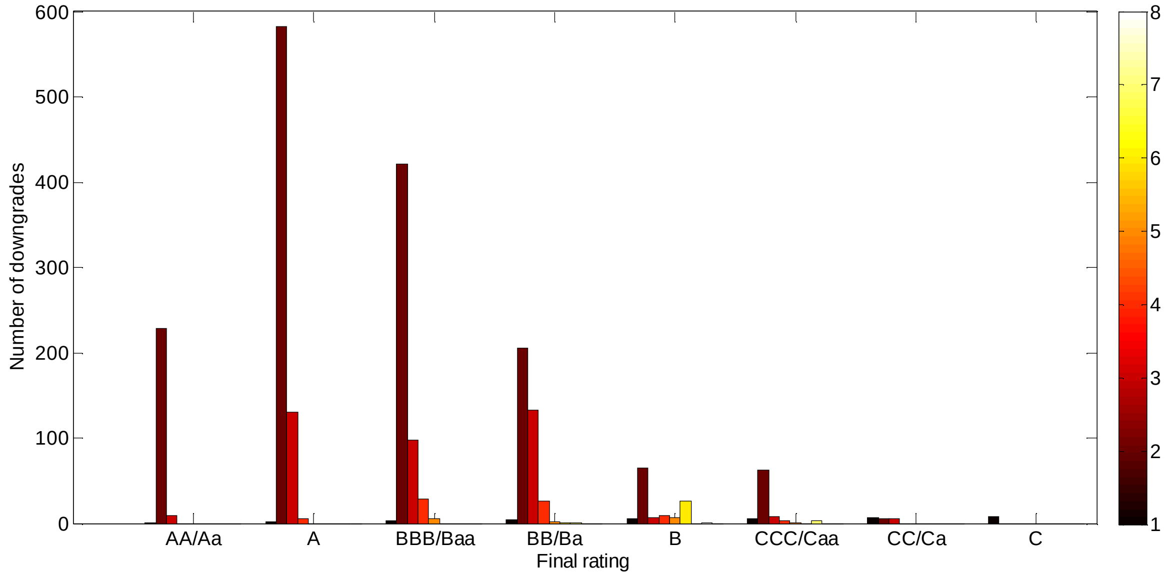

Figure 2. Abnormal trading behavior around credit rating downgrades.
This figure shows average abnormal values across working days to announcement, where abnormal values are computed as $AL_{i,\tau} = \frac{L_{i,\tau}-EL_i}{EL_i}$ in a daily basis by bond i, on day τ only for days with non-zero EL_i. Abnormal values are then averaged across days for all N downgrades in the sample. The dataset includes 2,082 credit rating downgrades involving 1,250 straight bonds issued by 245 issuers. Bond trading information is reported by the TRACE database and rating information is provided by FISD. The dataset covers the period from July 1, 2002 to December 31, 2014.

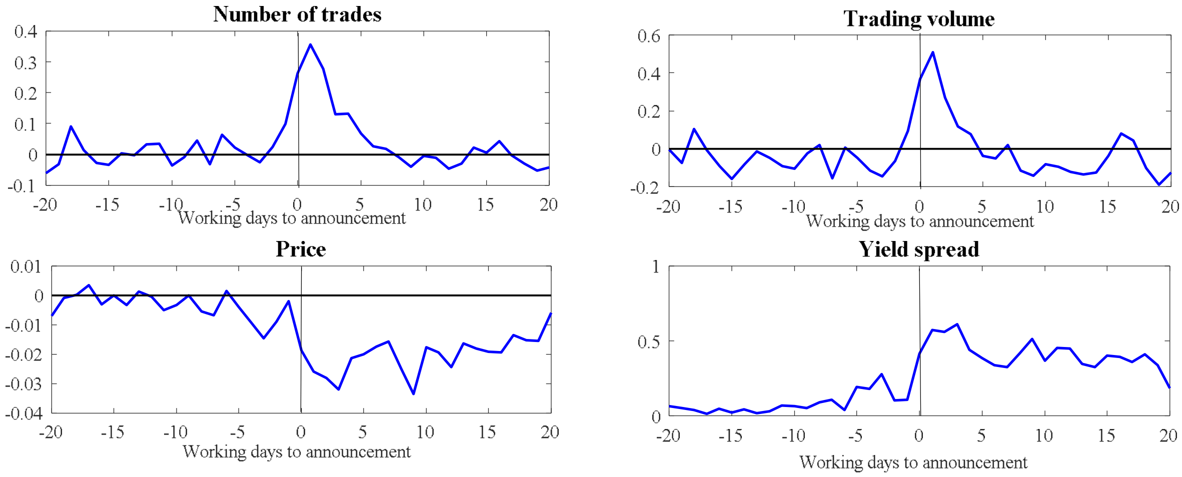

Table 1. Final credit rating after downgrades by agency across rating categories and summary statistics of bond characteristics.

This table shows final ratings after downgrades for different CRAs and for the whole sample across the final rating grade. *Issue size* is the value of the amount outstanding in millions of dollars. *Coupon* is the coupon rate for the bond in percentage. *Age* is the age of the bond in years. *Duration* is the Macaulay duration in years. The dataset includes 2,082 unique downgrade events involving 1,250 straight bonds issued by 245 issuers. It covers the period from July 1, 2002 to December 31, 2014 and includes bond's issue, issuer and rating information based on data from the Fixed Income Securities Database (FISD).

	AA+/ Aa1	AA/ Aa2	AA-/ Aa3	A+/ A1	A/ A2	A-/ A3	BBB+/ Baa1	BBB/ Baa2	BBB-/ Baa3	BB/ Ba	B	CCC/ Caa	CC/Ca or below	All
Fitch	4	6	32	132	91	34	17	40	196	81	26	11	1	671
Moody's	4	30	45	94	78	112	62	67	53	214	48	50	6	863
S&P	98	12	17	85	109	60	60	41	22	80	43	17	5	649
Agg. Total	106	48	94	311	278	206	139	148	271	375	117	78	12	2,183
Unique Total	**106**	**43**	**89**	**266**	**270**	**183**	**149**	**137**	**266**	**368**	**116**	**77**	**12**	**2,082**
Avg. issue size	2.59	1.00	0.85	1.00	0.91	0.70	0.87	0.76	0.23	0.17	0.50	0.22	0.45	0.70
Avg. coupon	5.43	5.01	5.77	5.59	6.08	5.89	5.65	5.87	5.55	5.80	6.97	6.78	7.45	5.86
Avg. age	3.06	4.16	4.89	4.11	5.31	5.11	4.90	5.19	3.68	4.48	6.06	7.63	8.36	4.74
Avg. duration	1.08	3.74	4.58	3.19	3.54	2.85	2.62	3.00	2.80	2.43	3.06	2.13	1.21	2.87

Table 2. Transition total rating downgrades matrix.

This table shows the total number of final ratings after the downgrade announcements, clustered by prior and final ratings. It displays, in rows, the standing prior rating before the rating downgrade and in columns, the final rating after the rating downgrade. Striped cells indicates downgrades crossing any of the NAIC's classes, i.e. inter-bucket downgrades, and add up to 620 downgrades. Combinations of cells with boxed doted cells and striped cells indicate downgrades that are simultaneously NAIC cuts and fallen angels downgrades. The rest of the cells refer to standard downgrades, i.e. downgrades without regulatory implications to their bondholders. The dataset includes 2,082 unique downgrade events involving 1,250 straight bonds issued by 245 issuers. It covers the period from July 1, 2002 to December 31, 2014 and includes bond's issue, issuer and rating information based on data from the Fixed Income Securities Database (FISD).

From / to	AA+/ Aa1	AA/ Aa2	AA/ Aa3	A+/ A1	A/ A2	A-/ A3	BBB+/ Baa1	BBB/ Baa2	BBB- / Baa3	BB/ Ba	B	CCC/ Caa	CC/Ca or below	Total
AAA	106	8	0	0	0	0	0	0	0	0	0	0	0	114
AA+/Aa1	0	35	1	0	0	0	0	0	0	0	0	0	0	36
AA/Aa2	0	0	88	42	1	0	0	0	0	0	0	0	0	131
AA-/Aa3	0	0	0	224	43	5	0	0	0	0	0	0	0	272
A+/A1	0	0	0	0	226	45	15	5	0	0	0	0	0	291
A/A2	0	0	0	0	0	133	53	11	0	0	1	0	0	198
A-/A3	0	0	0	0	0	0	81	36	2	3	0	0	0	122
BBB+/Baa1	0	0	0	0	0	0	0	85	9	21	1	0	0	116
BBB/Baa2	0	0	0	0	0	0	0	0	255	126	0	0	0	381
BBB-/Baa3	0	0	0	0	0	0	0	0	0	123	25	0	0	148
BB/Ba	0	0	0	0	0	0	0	0	0	95	45	4	0	144
B	0	0	0	0	0	0	0	0	0	0	44	58	0	102
CCC/Caa	0	0	0	0	0	0	0	0	0	0	0	15	10	25
CC/Ca or below	0	0	0	0	0	0	0	0	0	0	0	0	2	2
Total	106	43	89	266	270	183	149	137	266	368	116	77	12	2,082

Table 3. Summary statistics for "standard" downgrades (without regulatory implications), NAIC credit-rating cuts downgrades, and "fallen angels" downgrades.

This table shows summary statistics for rating downgrades. Left panel shows the statistics for *Intra-bucket downgrades,* or "standard" downgrades, i.e. those bond downgrades without regulatory implications. Central panel displays the statistics for *Inter-bucket downgrades,* that refers to downgrades that crosses almost one of the NAICs tranches and hence with regulatory implications for insurance companies. Right panel shows the statistics for simultaneous NAIC cuts and fallen angel downgrades, i.e. those downgrades which have capital regulatory implications and that crosses the IG frontier.

Prior rating represent the numeric value of the rating immediately before the downgrade, i.e. in the case of S&P a prior rating AAA is equal to 1. *Jump size* represent the numeric value of the jump measured in rating notches crossed, i.e. a downgrade of S&P from AAA to A is equal to a jump size of 2. *Final rating* indicates the final rating after the downgrade, i.e. the final rating of A is equal to 3. For multiple rated bonds we compute these values as the average across agencies using the numeric value assigned and then we end up with a unique sample. *Big jump* represent the number of downgrades with jump size of more than 2 notches. *Small jump* represent the number of downgrades with a jump size equal to 1 notches. *Negative watch* indicates the number of bonds included on negative credit watch lists prior to the downgrade. For the final sample, we compute the average numeric values when simultaneously double or triple rated in the same event. The dataset includes 620 unique inter-bucket and 1,462 unique intra-bucket events. It covers the period from July 1, 2002 to December 31, 2014 and includes bond's issue, issuer and rating information based on data from the Fixed Income Securities Database (FISD).

	Intra-NAIC-bucket downgrades or without regulatory implication (N=1,462)			*Inter-NAIC-bucket downgrades* (N=620)			*Fallen Angel downgrades (also Inter-NAIC-bucket)* (N=320)		
	Prior rating	Jump size	Final rating	Prior rating	Jump size	Final rating	Prior rating	Jump size	Final rating
$Q_{0.05}$	1.00	1.00	2.00	6.00	1.00	8.00	5.00	1.00	8.00
$Q_{0.25}$	4.00	1.00	5.00	7.00	1.00	9.00	6.00	1.00	8.00
$Q_{0.5}$	5.00	1.00	6.00	9.00	2.00	11.00	7.00	1.00	9.00
$Q_{0.75}$	9.00	1.00	10.00	10.00	2.00	12.00	13.00	2.00	16.00
$Q_{0.95}$	11.95	2.00	13.00	16.00	5.00	17.00	16.00	4.00	17.05
Average	6.06	1.12	7.18	9.44	1.89	11.33	9.49	1.75	11.24
Std. Dev	3.38	0.34	3.35	3.04	1.13	3.03	4.18	0.95	4.07
Min	1.00	1.00	2.00	5.00	1.00	8.00	5.00	1.00	8.00
Max	20.00	3.00	21.00	19.00	10.00	20.00	19.00	6.00	20.00
Big Jump		0.41%			18.39%			17.81%	
Small jump		88.58%			44.52%			50.31%	
Negative watch		27.22%			54.19%			53.13%	

Table 4. Summary statistics of bond trading across final rating category and window.

This table shows summary statistics of the liquidity average values within each window across different rating groups. Liquidity average values within each window are computed as the average from daily values included in the window for each of the liquidity variables (see details of implementation in Section 3.2). *Panel A* displays the statistics for the liquidity average values within the windows [-41, -21], and *Panel B* in the windows [0, 20]. *NT* is the number of trades, *TV* is the trading volume is in million dollars, *PR* is the price and it is in percentage of face value, and *YS* is the yield spread and it is in percentage. The dataset includes 2,082 unique downgrade events involving 1,250 straight bonds issued by 245 issuers. It covers the period from July 1, 2002 to December 31, 2014 and includes bond's issue, issuer and rating information based on data from the Fixed Income Securities Database (FISD) and trading information based on data from the Trade Reporting and Compliance Engine (TRACE) database.

		Event category – final rating after downgrade													
		AA+/ Aa1	AA/ Aa2	AA/ Aa3	A+/ A1	A/ A2	A-/ A3	BBB+/ Baa1	BBB/ Baa2	BBB /Baa3	BB/ Ba	B	CCC/ Caa	CC/Ca or below	All
Panel A. Window [-41,-21]															
NT	Mean	2.85	2.96	2.66	2.92	3.01	2.84	3.76	3.26	2.31	2.02	2.39	1.68	2.72	2.76
	Median	2.35	2.20	2.11	2.12	2.11	2.00	2.44	2.20	1.81	1.50	2.00	1.40	2.67	2.00
	Std. Dev.	2.61	2.10	2.13	2.52	3.01	3.22	3.78	4.26	2.54	1.58	1.86	1.12	1.42	2.82
TV	Mean	6.18	4.01	3.09	3.28	3.79	2.93	4.79	3.62	1.90	1.32	1.51	0.94	1.76	3.09
	Median	4.09	2.13	2.08	2.09	2.12	2.05	2.81	2.32	0.54	0.40	1.18	0.69	1.83	1.73
	Std. Dev.	8.44	5.24	3.39	4.26	6.14	4.55	6.22	5.61	3.48	2.46	1.34	0.89	0.79	4.99
PR	Mean	103.40	100.97	102.29	102.71	101.89	99.12	92.99	98.68	94.55	95.19	88.19	78.53	67.12	97.51
	Median	102.01	100.79	101.46	101.35	101.06	100.40	97.98	100.85	98.75	96.72	90.45	80.32	83.29	99.82
	Std. Dev.	3.73	6.65	6.43	7.94	9.23	10.21	13.36	12.12	10.78	7.21	10.82	15.64	28.76	11.66
YS	Mean	-0.62	1.22	1.43	1.44	2.05	2.78	6.41	3.34	3.80	4.30	6.82	16.56	29.06	3.66
	Median	0.08	1.44	1.58	1.22	1.76	2.40	3.27	1.63	1.77	3.65	6.10	11.02	27.11	2.07
	Std. Dev.	1.25	1.60	1.46	2.09	2.00	2.84	8.06	5.40	4.27	4.30	3.56	12.73	18.94	5.97
Panel B. Window [0, 20]															
NT	Mean	2.50	2.97	2.58	2.75	2.81	3.87	3.81	3.44	2.31	2.48	2.54	2.05	4.10	2.88
	Median	2.15	2.31	2.03	2.00	2.00	2.48	2.42	2.28	1.77	1.75	2.00	1.47	4.56	2.00
	Std. Dev.	2.20	1.93	1.81	2.17	2.13	4.48	4.19	3.57	2.13	2.55	2.10	1.26	1.87	2.85
TV	Mean	5.03	3.69	2.84	3.39	3.32	4.62	4.56	3.91	1.79	1.39	1.63	1.23	3.02	3.13
	Median	3.89	2.66	2.46	2.12	2.17	2.75	3.32	2.50	0.31	0.34	1.24	1.05	3.34	1.76
	Std. Dev.	7.80	3.72	2.58	4.29	4.17	7.64	5.11	4.88	3.14	3.03	1.67	1.06	1.59	4.78
PR	Mean	103.57	102.18	102.07	102.56	100.58	94.02	90.19	97.36	91.46	92.52	88.31	74.26	58.87	954
	Median	102.05	101.57	102.31	101.55	100.92	98.24	97.21	99.79	95.26	93.93	90.77	78.79	67.60	99.00
	Std. Dev.	3.84	4.85	6.60	8.45	13.40	13.61	16.93	12.13	10.70	8.49	10.75	21.38	24.29	13.50
YS	Mean	-0.26	1.21	1.61	1.65	2.97	6.21	8.31	4.29	5.03	5.83	7.24	19.34	30.82	4.76
	Median	0.15	1.52	1.56	1.25	2.06	4.17	3.96	2.41	3.44	4.77	6.23	11.61	24.53	2.62
	Std. Dev.	1.09	1.41	2.06	2.96	5.13	7.18	11.62	5.59	4.83	5.34	4.79	17.89	19.50	7.55

Table 5. Results from the regression analysis.

This table shows the main results for different models where the dependent variable is the mean abnormal liquidity in window [0, 20]. *NT* is the number of trades, *TV* is the trading volume is in million dollars, *PR* is the price and it is in percentage of face value, and *YS* is the yield spread and it is in percentage. *PRI_AA-_FIN_ANY, PRI_A1_FIN_ANY*, *PRI_A2_FIN_ANY* and *PRI_A3_FIN_ANY* are dummy variables that take value 1 if the prior rating before the change is equal to AA-/Aa3, A+/A1, A/A2 and A-/A3 grades respectively jointly with if the final rating after the rating change is any of the grades, and zero otherwise. *PRI_BBB+_FIN_ANY* (*PRI_BBB_FIN_ANY*) is a dummy variable that takes value 1 if the prior rating before the change is equal to BBB+/Baa1 (BBB/Baa2) grade and if the final rating after the rating change is any of the grades, and zero otherwise. *FALLEN ANGEL* is a dummy variable that takes value 1 if the rating change is a fallen angel, and zero otherwise. *NAIC* is a dummy variable that takes value 1 if the rating change involve a NAIC change, and zero otherwise. *FIN_RATING* is the numeric value of the final rating after the rating change. *JUMP SIZE* is the number of notches of the rating change. *MOODYS* is a dummy variable that takes value 1 if rating change is from Moody's, and zero otherwise. *WNEG* is a dummy variable that takes value 1 if the bond is in negative watchlists before the rating change, and zero otherwise. *LOG_OFFER* is the log of the issue size. *TIME TO MATURITY* is the time to maturity at the event date. *COUPON* is the coupon rate in percentage. The dataset includes 2,082 unique downgrade events involving 1,250 straight bonds issued by 245 issuers. It covers the period from July 1, 2002 to December 31, 2014 and includes bond's issue, issuer and rating information based on data from the Fixed Income Securities Database (FISD) and trading information based on data from the Trade Reporting and Compliance Engine (TRACE) database. In parenthesis the *p*-values. The significance is indicated as follows: $^{*} < 0.1$, $^{**} < 0.05$, and $^{***} < 0.01$.

	NT	NT	TV	TV	PR	PR	YS	YS
C	0.170***	-0.861*	0.369***	2.667*	-0.007	0.212****	0.273***	-1.560
	(0.000)	(0.070)	(0.000)	(0.066)	(0.282)	(0.002)	(0.000)	(0.267)
PRI_AA-_FIN_ANY	-0.131**	-0.003	0.113	0.159	-0.004	-0.020**	-1.001	0.297
	(0.011)	(0.964)	(0.525)	(0.537)	(0.659)	(0.027)	(0.313)	(0.166)
PRI_A1_ FIN _ANY	0.041	0.120*	0.594***	0.668**	-0.039***	-0.058***	0.540**	0.956***
	(0.455)	(0.059)	(0.006)	(0.013)	(0.001)	(0.000)	(0.015)	(0.000)
PRI_A2_ FIN _ANY	0.265*	0.480**	0.451**	0.558*	-0.023***	-0.031**	1.516	0.783**
	(0.063)	(0.027)	(0.021)	(0.064)	(0.006)	(0.017)	(0.168)	(0.031)
PRI_A3_ FIN _ANY	0.065	0.296*	0.625**	0.676	-0.046***	-0.053	0.681**	0.449
	(0.455)	(0.065)	(0.023)	(0.118)	(0.002)	(0.139)	(0.031)	(0.381)
PRI_BBB+_ FIN _ANY	0.075	0.041	0.136	0.133	-0.005	-0.020	-0.320	-0.323
	(0.288)	(0.632)	(0.412)	(0.596)	(0.549)	(0.133)	(0.156)	(0.390)
PRI_BBB_ FIN _ANY	0.015	-0.092	0.185	-0.111	-0.020*	-0.012	-0.528	-0.778
	(0.869)	(0.394)	(0.475)	(0.700)	(0.068)	(0.491)	(0.446)	(0.314)
FALLEN_ANGEL		0.180		-0.398		0.055		-0.352
		(0.257)		(0.246)		(0.100)		(0.545)
NAIC		-0.309*		-0.353		0.010		0.213
		(0.063)		(0.293)		(0.746)		(0.666)
FIN_ RATING		0.033***		0.031		-0.003		0.077**
		(0.003)		(0.161)		(0.400)		(0.013)
JUMP_SIZE		0.084*		0.224*		-0.025*		0.266
		(0.063)		(0.088)		(0.053)		(0.117)
MOODYS		0.185***		0.297		-0.038***		0.395
		(0.009)		(0.105)		(0.000)		(0.150)
WNEG		0.160*		0.189		-0.046***		0.770***
		(0.070)		(0.292)		(0.000)		(0.004)
LOG_OFFER		0.063**		-0.129		-0.008*		0.130
		(0.049)		(0.155)		(0.084)		(0.200)
TIME TO MATURITY		-0.008*		-0.012		0.001		-0.010
		(0.052)		(0.194)		(0.361)		(0.445)
COUPON		-0.036		-0.164***		-0.008**		-0.213**
		(0.139)		(0.006)		(0.040)		(0.028)
#Obs.	1,268	890	1,268	890	1,268	890	1,265	890
Adjusted R^2	0.012	0.042	0.008	0.022	0.037	0.140	0.003	0.050

Table 6. Results from the regression analysis.

This table shows the main results for different models where the dependent variable is the mean abnormal liquidity in window [0, 20]. *NT* is the number of trades, *TV* is the trading volume is in million dollars, *PR* is the price and it is in percentage of face value, and *YS* is the yield spread and it is in percentage. *PRI_ANY_FIN_A1, PRI_ANY_FIN_A2, PRI_ANY_FIN_A3, PRI_ANY_FIN_BBB*+ and are *PRI_ANY_FIN_BBB* are dummy variables that take value 1 if the prior rating before the change is any jointly with if the final rating after the rating change is equal to A+/A1, A/A2, A-/A3, BBB+/Baa1, BBB/Baa2 and BBB-/Baa3 grades respectively, and zero otherwise. *FALLEN ANGEL* is a dummy variable that takes value 1 if the rating change is a fallen angel, and zero otherwise. *NAIC* is a dummy variable that takes value 1 if the rating change involve a NAIC change, and zero otherwise. *FIN_RATING* is the numeric value of the final rating after the rating change. *JUMP SIZE* is the number of notches of the rating change. *MOODYS* is a dummy variable that takes value 1 if rating change is from Moody's, and zero otherwise. *WNEG* is a dummy variable that takes value 1 if the bond is in negative watchlists before the rating change, and zero otherwise. *LOG_OFFER* is the log of the issue size. *TIME TO MATURITY* is the time to maturity at the event date. *COUPON* is the coupon rate in percentage. The dataset includes 2,082 unique downgrade events involving 1,250 straight bonds issued by 245 issuers. It covers the period from July 1, 2002 to December 31, 2014 and includes bond's issue, issuer and rating information based on data from the Fixed Income Securities Database (FISD) and trading information based on data from the Trade Reporting and Compliance Engine (TRACE) database. In parenthesis the *p*-values. The significance is indicated as follows: * < 0.1, ** < 0.05, and *** <0.01.

	NT	NT	TV	TV	PR	PR	YS	YS
C	0.198***	-0.663	0.342***	2.887*	-0.007	0.226***	0.285***	-1.082
	(0.000)	(0.165)	(0.000)	(0.053)	(0.272)	(0.001)	(0.000)	(0.451)
PRI_ANY_FIN_A1	-0.176***	-0.049	0.057	-0.119	0.008	0.001	-0.230**	0.048
	(0.000)	(0.422)	(0.569)	(0.489)	(0.254)	(0.891)	(0.010)	(0.799)
PRI_ANY_FIN_A2	-0.108	0.090	0.419	0.764*	-0.008	-0.030***	0.067	0.678***
	(0.049)	(0.261)	(0.114)	(0.069)	(0.400)	(0.008)	(0.633)	(0.007)
PRI_ANY_ FIN _A3	0.355**	0.503	0.805***	0.837***	-0.049***	-0.052***	-0.821	1.354***
	(0.020)	(0.015)	(0.000)	(0.005)	(0.000)	(0.000)	(0.616)	(0.000)
PRI_ANY_ FIN _BBB+	-0.035	-0.038	0.355*	-0.045	-0.011	-0.043	2.191	0.002
	(0.674)	(0.804)	(0.077)	(0.918)	(0.389)	(0.181)	(0.137)	(0.997)
PRI_ANY_ FIN _BBB	0.106	0.125	0.676**	0.566	-0.003	-0.008	0.304	0.149
	(0.226)	(0.171)	(0.022)	(0.117)	(0.785)	(0.676)	(0.352)	(0.719)
PRI_ANY_ FIN _BBB-	0.050	-0.003	0.297	-0.070	-0.024**	-0.007	-0.450	-0.514
	(0.582)	(0.976)	(0.269)	(0.812)	(0.022)	(0.689)	(0.540)	(0.524)
FALLEN_ANGEL		-0.006		-0.682**		0.018		-0.922*
		(0.961)		(0.046)		(0.632)		(0.051)
NAIC		0.001		0.179		0.069**		0.749*
		(0.994)		(0.641)		(0.031)		(0.068)
FIN_ RATING		0.021**		0.008		-0.003		0.043
		(0.024		(0.691)		(0.337)		(0.166)
JUMP_SIZE		0.056		0.182		-0.036***		0.305
		(0.198)		(0.140)		(0.008)		(0.117)
MOODYS		0.155**		0.264		-0.031***		0.296
		(0.022)		(0.158)		(0.000)		(0.293)
WNEG		0.144*		0.243		-0.046***		0.802***
		(0.083)		(0.217)		(0.000)		(0.003)
LOG_OFFER		0.058*		-0.013		-0.008***		0.111
		(0.067)		(0.155)		(0.053)		(0.272)
TIME TO MATURITY		-0.008*		-0.129		0.001		-0.009
		(0.053)		(0.162)		(0.450)		(0.491)
COUPON		-0.040		-0.173***		-0.007*		-0.224**
		(0.124)		(0.005)		(0.050)		(0.025)
#Obs.	1,268	890	1,268	890	1,268	890	1,265	890
Adjusted R^2	0.026	0.045	0.013	0.033	0.021	0.125	0.003	0.053