Credit Rating Announcements and Bond Liquidity*

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Abstract:

This paper investigates liquidity shocks on the US corporate bond market induced by the information content of the credit rating change announcements and by regulatory constraints. Abnormal trading activity can be triggered by the release of information after any upgrade or downgrade but, even if the event conveys no new information to the market, changes on liquidity can be originated if the credit note change involves implications on capital requirements for institutional investors or on bond holding restrictions. We show that: (1) market anticipates rating changes since institutional-size trading activity slows down days before the event, and large size transactions are detected the day before the downgrade; (2) the concrete materialization of the announcement is not fully anticipated since we observe price overreaction immediately after downgrades; (3) the combination of high price impact and large institutional trading activity exacerbate the overreaction in prices; (4) no evidence of massive fire sales is obtained, i.e. institutional bondholders wait price convergence to fundamentals values to rebalance portfolios, (5) a clear asymmetric reaction to positive and negative rating events is observed.

Keywords: Credit rating agencies; rating changes; event study; liquidity; trading activity; regulatory constraints; corporate bond market

JEL Classification: G12, G14, C34.

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1. Introduction

Information on rating actions has been a permanent subject of debate. Credit rating (CR) agencies state that they consider insider information when assigning ratings without disclosing specific details to the public at large. Thus, their actions should have some effect on market returns. Earlier studies, such as Weinstein (1977), Wakeman (1978, 1990) and Zaima and McCarthy (1988), report that CR agencies only summarize public information, and changes in bond ratings convey no new information to the market. More recent studies obtain evidence that negative rating announcements, particularly reviews for downgrade and downgrades, do in fact disclose information relevant to the formation of stocks and bonds prices and credit default swap spreads (e.g., Norden and Weber, 2004, Hull *et al.*, 2004, and Jorion and Zhang, 2007). All this literature examines prices and/or returns. In this paper, we go beyond the traditional price analysis by analyzing the behavior of different liquidity faces around a CR announcement and their interactions with prices and yield spreads.

We address several research questions from a comprehensive sample of 2,727 CR changes in the whole US corporate bond market using transaction data. Can liquidity patterns before the event help to predict its occurrence? An abnormal behavior of liquidity proxies before an unscheduled CR announcement could indicate that market anticipates the event. In the case of a fall in liquidity with stable prices, it could be interpreted as the market expects an imminent announcement without knowing its specific realization. Do liquidity shocks or even fire sales occur after a downgrade announcement? Regulatory constraints could imply a forced selling phenomenon. A downgrade can also breach risk limits, determined by risk appetite and by regulatory capital, but bondholders can delay sales of part of the holdings avoiding fire sale prices. Do the different liquidity proxies evolve in the same way? We analyze separately the behavior of several price dispersion and trading activity proxies. We consider the price impact, proxied by four different popular measures, and the trading activity, proxied by two variables depending of the trading volume, and by one variable depending of the trading frequency. Results of this analysis are helpful to answer the next question. To what extent is the usual liquidity's effect on price and yield spread intensified after the event? We study if liquidity behavior around the event drives the price behavior or, at least, a significant proportion of it.

The effects of fallen angel downgrades on the corporate bond market have also been subject of analysis, especially focusing on the impact on prices. Most institutions (such as insurance companies, pension funds or investment-grade bond mutual funds) face varying degrees of restrictions on holding speculative-grade corporate bonds or junk bonds. The forced selling of downgraded bonds induced by these regulatory constrains would allow other investors (such as hedge funds and high-yield mutual funds) to pick up the bonds at transaction prices that are significantly below fundamental values (see Fridson and Cherry, 1992, or Fridson and Sterling, 2006).

Recent papers investigate bond transactions around rating downgrades motivated by regulatory pressure on insurance companies. They observe price pressure and limited liquidity shock as consequence of a forced selling phenomenon. They use actual National Association of Insurance Commissioners (NAIC) transaction data. Meanwhile they observe large price concessions immediately after the downgrade and persistent price reversals (Ambrose *et al.*, 2008, Da and Gao, 2009, Ellul *et al.*, 2011), the effects on sales activity for fallen angels is reduced. Only a small portion of the insurance companies' overall holdings of downgraded corporate bonds are sold. Ellul *et al.* (2011) point out that the selling pressure depends on the financial health of the insurance companies. Da and Gao (2009) also find increased transaction cost during the first six months after the event. This evidence is not consistent with the hypothesis that regulations force insurance companies to sell off these bonds, causing further disruptions in the credit markets.

We consider five different hypotheses to explain the possible impact of the CR announcement on liquidity. The information content hypothesis assumes that these events are supplied with considerable non-public information about firms. A rating revision may provide additional information about the total firm value and its organizational effectiveness. A different investors' risk perception can induce portfolio rebalancing processes.

The second hypothesis to test assumes that regulatory constraints may also motivate abnormal trading activity. As mentioned, downgrades from investment grade categories to speculative grade categories have regulatory implications for many institutional investors in terms of restrictions on holding these bonds, e.g. pension funds, investment-grade bond mutual funds, money market funds.

The risk limits hypothesis considers that not only fallen angel downgrades involve regulatory constraints. Any downgrade can induce a breach in the risk tolerance of a bondholder. This motivates them to liquidate positions in those bonds, but this is in itself no assurance of a fire sales phenomenon. They can wait selling without price concessions. In the case of financial institutions, they set a risk limit in the risk appetite framework to constrain risk-taking. Risk capacity is determined by regulatory capital and liquidity needs, and by obligations from a conduct perspective. Additionally risk-based capital regulations compel banks and insurance companies to hold more capital (surplus) when they invest in riskier assets. A credit rating downgrade (upgrade) may increase (reduce) capital requirements making the bond much less (more) attractive. The Standardized Approach of the Basel II rules for financial institutions establish capital adequacy requirements based on external credit ratings.[1] In the case of corporate credits, the risk weights are 20% (AAA to AA-), 50% (A+ to A-), 100% (BBB+ to BB-, and unrated), and 150% (below BB-). The NAIC's risk-based capital system for insurance companies depend also on credit ratings.[2]

The fourth hypothesis, i.e. the reputation hypothesis, proposes an asymmetric reaction to positive and negative rating events. Downgrades represent information not yet known by the market, whereas upgrades confirm information that is already available.

An additional hypothesis to test proposes that price reaction immediately after the CR announcement is mainly driven by the behavior of some of the faces of liquidity regardless of the price adjustment due to the new information. We examine whether the liquidity impact on prices and yield spreads is exacerbated after the CR announcement.

We observe shocks in liquidity with three clear patterns: before, immediately after and during one-month from the rating change. First, the trading activity slows down days before the announcement. This market anticipation is not fully consistent with the hypothesis that CRA supply non-public information about firms. On the one hand, bond trading activity fades away while the market is waiting for the imminent event. The theoretically unexpected CRA seems to be anticipated by the market. However, the concrete materialization of the announcement is not anticipated since we observe price overreaction after downgrades. Second, there is a price pressure and abnormal high institutional trading volumes during few days after the downgrades. This investors' overreaction could imply transaction prices below fundamental values. This is consistent with the regulatory constraints hypothesis, but no massive fire sales are detected since trading frequency shows

[1] Basel II rules are applicable to global commercial US banks. 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.

[2] The NAIC capital charges are based upon six credit quality designations of bonds: 1 corresponds to credit rating AAA, AA or A, 2 to BBB, 3 to BB, 4 to B, 5 to CCC, 6 to "in or near default".

lower levels than normal. Third, prices converge to the correct value and the level of trading activity clearly rises during the second fortnight. In the case of upgrades, there is not a price impact.

Our analysis contributes to the understanding of the information value and regulatory implications of credit ratings in several ways. First, we focus the analysis on the effects of rating change announcements on liquidity by using event study methodology. Traditional literature studies if rating actions disclose information relevant to the price formation. Other recent papers analyze price pressure and trading activity shocks after downgrades to junk status in the case insurance companies holding the bond, or after a default event. We investigate both hypotheses, i.e. the regulatory pressure and the information-motivated trading. Inside the regulatory pressure hypothesis, we analyze the particular case of fire sales after downgrades to speculative grade. Traditional market microstructure models predict that liquidity will deteriorate around the time new information is released and return to normal afterwards (Kim and Verrecchia, 1994). This price pressures typically do not last for more than a few days in the equity market, but liquidity shocks in the corporate bond market are likely to be larger and more persistent (Ambrose *et al.*, 2008, Da and Gao, 2009, Ellul *et al.*, 2011). These studies also obtain weak results about liquidity shocks from a dataset restricted to insurance companies' transactions. In the case of a default event, Jankowitsch *et al.* (2014) document temporally high trading activity and price pressure on the default event day itself exclusively.

Second, we analyze a comprehensive data set covering all the intraday transactions in the whole US corporate bond market during almost eight years. We use TRACE (Trade Reporting and Compliance Engine) transactions data for corporate bonds which allows us to accurately calculate liquidity proxies. We consider all the transactions involving straight bonds with trading enough to compute liquidity measures. After debugging and filtering the data set, we consider nearly 4.5 million trades involving 1,342 straight bonds from 286 different issuers that are affected by 2,727 rating changes over the period July 2002– March 2010. Besides Jankowitsch *et al.* (2014) that uses a similar sample from TRACE but restricted to default events, previous research in this topic analyses a small part of the US corporate bond market, i.e. the insurance companies' transactions from NAIC data.

Third, we consider all the liquidity faces using a set of popular liquidity proxies and their interaction with prices. Traditional literature on fixed income markets highlights liquidity as a relevant component of bond prices. TRACE data set availability has originated the appearance of new proposes of adaptations to the bond market of traditional microstructure-based based liquid measures on stock markets. Recent papers using these measures corroborate the liquidity effects on prices (see, e.g., Bao, Pan, and Wang, 2011; Dick-Nielsen, Feldhütter, and Lando, 2012; Friewald, Jankowitsch, and Subrahmanyam, 2012). Among others, some of these proxies are the Amivest liquidity ratio (Cooper *et al.*, 1985), the Amihud (2002) price impact of a trade per unit traded, the Imputed Roundtrip Cost (IRC) proposed by Dick-Nielsen *et al.* (2012), or the Roll (1984) and Bao *et al.* (2011) measures based on the serial price covariance. For each single straight bond affected by a rating change, we daily compute the Amivest, the Bao, the IRC, and the price dispersion measures together with other traditional trading activity proxies. We include two proxies of the trading volume, i.e. the raw trading volume and the market share, and one proxy of the trading frequency, i.e. the number of trades.

Four, we examine the different role of institutional and retail players in the market. We observe as the trading activity and transaction prices of typical uninformed retail investors remain insensible of the CR changes. The institutional investors lead the behavior of the market around the announcements and partially anticipate the event.

The remainder of the paper is arranged as follows: Section 2 explains the hypotheses to be tested. Section 3 presents the data description. Section 4 examines different measures of abnormal liquidity. The main results are presented in Section 5. Finally, Section 6 concludes.

2. Data description

We use two main sources of data in our analysis, the NASD's TRACE transactions data for corporate bonds and the Mergent FISD (Fixed Income Securities Database) with complete information on the characteristics of each bond. TRACE covers transactions data for corporate bonds which allow us to calculate liquidity proxies accurately. Since January 2001, members of the FINRA (Financial Industry Regulatory Authority) are required to report their secondary over-the-counter corporate bond transactions through TRACE, following the proposed transparency rules by the Securities and Exchange Commission (SEC).

TRACE data goes through three phases: first phase started in July 2002 and only included the larger and higher credit quality issues; second phase included not only higher quality issues but also the smaller investment grade issues; and third phase started in October 2004 reported all secondary market transactions for corporate bonds. So not all trades reported to TRACE are 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 uses in previous studies focused on insurance companies, the later represents a small part of the US corporate bond market. Even during the second half of 2002 when TRACE shows a partial coverage, Bessembinder *et al.* (2006) indicate that insurance companies completed 12.5% of the dollar trading volume in TRACE-eligible securities.

The use of TRACE dataset for research purposes requires previous filtering. Dick-Nielsen (2009) shows that TRACE contain almost 7.7% of errors among total reports. Edwards *et al.* (2007) and Dick-Nielsen (2009) show as many errors are due to later corrected or canceled transactions. They propose algorithms to filter out the reporting errors.

Introducing minor variations to Edward *et al.* (2007) and Dick-Nielsen (2009) filtering purposes, 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. Information is obtained from the sequence numbers.
3. When the transaction is an agency transaction, it requires three reports to be filled 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.

We complete the bond qualitative information from FISD. This database ranges from April 1920 to August 2010 and allow us to obtain qualitative information such as delivery date, coupon rate, maturity date, issuer, industry, call features, special features, etc. We limit the sample to straight corporate bonds. We exclude zero or variable coupon bonds, TIPS, STRIPS, perpetual bonds and bonds with embedded options, such as putable, callable, tendered, preferred, convertible or exchangeable bonds. Additionally we ignore municipal bonds, international bonds and Eurobonds. We also eliminate those bonds that are part of a unit deal.[3] Our sample covers almost eight years, from July 2002 to March 2010.

FISD data set also provides rating information per bond from the main three CRA, i.e. Moody's, Standard & Poor's, and Fitch. During the sample period of our TRACE data set, there are more than 225,000 CRA announcements reported by FISD. From the both data sets, we match announcements with bond transactions which meet three criteria. The first filter consists of requiring a minimum trading activity level of the bond involved in the announcement during an event window. The bond should be traded at least once on the 20 working days before the event and once on a similar period after the event.[4] As the second filter, bonds must be traded at least a 20% of the trading days in the control window. And finally, events preceded by other rating announcement on the previous 61 working days, i.e., in the control window, are also ignored.

Table 1 shows the progressive reduction of the considered number of transactions during the debugging and filtering process. From the original 45 million transactions, we include in the event study analysis about 4.5 million. Right column of Table 1 and Panels B, C, D and E of Table 2 show the composition of our sample in terms of transactions (Table 1) and in terms of CRA announcements (Table 2). The final data sample consisting of 2,727 CRA events (2,620 unique credit rating announcements) involving 1,342 bonds from 286 issuers, and with nearly 4.5 million trades, approximately 10.6% of the total number of trades reported by TRACE during the period July 1, 2002 to March 31, 2010. From those 2,727 rating changes, 73 are doubled rated by two CRA and 17 are tripled rated by the three CRA. We only take into account changes in the same direction, and into the same grade category (investment or speculative grade). For doubled or tripled rated bonds final rating is computed as the average rating using the numeric value assigned by the long term debt rating equivalences, with values from AAA=1 to D=25. Rating events in opposite direction are ignored, so we finally end up with 2,620 unique credit rating changes from which 907 are upgrades and 1,713 are downgrades. Figure 1 shows the final composition of our events set shorted by CR. We highlight that most of downgrades establish the CR in the threshold between investment- and speculative-grade (ratings BBB and BB). This is a very sensitive border with a number of financial implications. In the case of the upgrades, the changes drive to AA or A ratings. Table 3 shows summary statistics for final sample.

[INSERT TABLES 1, 2 AND 3 AND FIGURE 1 ABOUT HERE]

[3] In a unit deal the bond is sold as part of a package of securities; those bonds that are secured lease obligation issues, i.e., those issues secured by one or more leases issued in a sales leaseback transaction by an electric utility

[4] This level of trading should seem negligible but general liquidity level in the US corporate bond market, the world's largest one, is really low. Mahanti et al. (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.

3. The expected response of liquidity to rating actions

In the liquidity literature, the market microstructure models indicate that trading activity responses to news release are related to the existence of asymmetric information among informed traders, uninformed traders, and market-makers. Kim and Verrecchia (1994) state that the fact that some traders are able to make better decisions than others, based on the same information, leads to information asymmetry and positive abnormal trading volume despite a reduction in liquidity after the release of new information about the firm. In this context, higher trading activity after the rating action will be expected. However, low liquidity of corporate debt markets may prevent this kind of effect.

Almost all large corporate bond issues are rated by at least one CR agency. Agencies assign an initial CR to new issues based on the solvency of the issuers and other related industry and macroeconomic factors. Subsequently, agencies reevaluate corporate bonds, as some of these relevant conditions change. When the CR is solicited, the issuers pay a fee to be rated since CR are a compulsory entry condition in the market. Issuing non-rated corporate bonds is virtually impossible. CR are also crucial for determining the issuer borrowing cost and the issue marketability.

Previous research has proposed and tested several sometimes conflicting theories about the role of credit ratings and the effects of CR change announcements. They establish the expected behavior of re-rated bond returns around the announcement date, but they indicate little about the expected liquidity behavior.

We consider that the effects of rating changes can be explained by five possible hypotheses: the information released by the CR announcement, fire sales from downgrades to speculative grade, risk limits, reputation, and widening of the liquidity premium. The main hypothesis concerning CR change effects states that CR announcements are supplied with considerable non-public information about firms, such as information about the total firm value and its organizational effectiveness. According to this hypothesis, we expect trading activity involving these securities to temporarily rise.

A number of papers are focused on providing theories that explain why CR changes are relatively seldom, such as the rating stability hypothesis related to the through-the-cycle approach (Howe, 1995, Cantor, 2001 or Altman and Rijken, 2006) and the policy of rating bounce avoidance (Cantor, 2001, or Löffler, 2004, 2005). They argue that agencies prefer to be slow and right rather than fast and wrong to preserve their reputation. CR agencies are intended to measure the default risk over long investment horizons. In addition, they find that a rating change is triggered when the difference between the actual agency rating and the rating predicted by the agency-rating model exceeds a certain threshold level. Thus, CR agencies avoid frequent rating reversals. This lower timeliness of agencies conflicts with the point-to-time perspective of most investors, who can search current information, although Löffler (2004) concludes that this policy is beneficial to bond investors. If rating agencies are slow to react to new information, bond price and liquidity reactions to CR changes would not be expected. There are other factors that also support this line of reasoning. For instance, institutional investors often use a passive buy-and-hold strategy of investing. As a result, information disclosed in rating actions may be of little importance in monitoring firms, being the effects on the debt market limited. Evidence from previous research on other European bond markets indicates a lack of reaction (Gropp and Richards, 2001 or Dallocchio *et al.*, 2006) or a weak reaction (Steiner and Heinke, 2001).

One alternative hypothesis is the fire sales hypothesis. Regulatory mandates forces most institutional investors to fire sell downgraded bonds from investment-grade to speculative categories. These downgrades simultaneously prevent other institutional investors from buying these bonds. The main players in the corporate bond markets are involved in this process. Most institutions (such as insurance companies, pension funds or investment-grade bond mutual funds) face varying degrees of restrictions on holding junk bonds. The forced selling of downgraded bonds induced by these regulatory constrains would allow other investors (such as hedge funds and high-yield mutual funds) to pick up the bonds at transaction prices significantly below fundamental values (see Fridson and Cherry, 1992, Fridson and Sterling, 2006, or Dor and Xu, 2011). Therefore, downgrades from investment- to speculative-grade can imply greater price impact and greater liquidity effect than other downgrades.

Recent papers observe price pressure and limited liquidity shock in the case of insurance companies caused by the forced selling phenomenon. They use actual NAIC transaction data. Meanwhile, they observe large price concessions immediately after the downgrade event and persistent price reversals (Ambrose *et al.*, 2008, Da and Gao, 2009, Ellul *et al.*, 2011), the effects on sales activity for fallen angels is reduced. Only a small portion of the insurance companies' overall holdings of downgraded corporate bonds are sold. Ellul *et al.* (2011) point out that the selling pressure depends on the financial health of the insurance companies. Da and Gao (2009) also observe an increased transaction cost during the first six months after the event. This evidence is not consistent with the hypothesis that regulations force insurance companies to sell off these bonds, causing further disruptions in the credit markets.

The overall approach, including policies, processes, controls, and systems through which risk appetite is established, communicated, and monitored. It includes a risk appetite statement, risk limits, and an outline of the roles and responsibilities of those overseeing the implementation and monitoring of the risk appetite framework.

A third hypothesis is the risk limits hypothesis. As the previous hypothesis, it involves regulatory constraints but there are two main differences between them. It does not imply forced selling at fire sale discounts and it is not restricted to jumps from investment- to speculative-grade ratings. Any bondholder has certain risk tolerance that can be breached after a downgrade. This motivates them to liquidate positions, but this is in itself no assurance of a fire sales. They can wait selling without price concessions. In the case of financial institutions, they set a risk level to constrain risk-taking within their risk appetite framework,[5] as well as capital and other regulatory requirements. Campbell and Taksler (2003) highlights that institutions that are subject to rating-based restrictions on their holdings hold more than half of all corporate bonds. The risk appetite framework includes policies, processes, controls, and systems through which risk appetite is established, communicated, and monitored. Risk capacity is determined, on the one hand, by regulatory capital and liquidity needs, and, on the other hand, by obligations from a conduct perspective, to depositors, policyholders, other customers, and shareholders. The chief financial officer should act in a timely manner to mitigate risk exposures that exceed the approved risk limits.

The Basel Committee on Banking Supervision proposes capital requirements associated with credit risk. The three approaches, i.e. the standardized, the foundation internal-rating and the advanced internal-rating approaches, calculate minimum regulatory capital for credit risk from risk weights. The risk weighted assets in the standardized approach are calculated as the amount of exposures times the supervisory determined risk weights. These weights are determined by the category of the borrower (sovereign, bank, or corporate) and by the credit assessment (credit rating). In the case of corporate credits they

[5] However, the October 2011 Financial Stability Board progress report on enhanced supervision noted that effective risk appetite frameworks that are actionable and measurable by both firms and supervisors have not yet been widely adopted.

are 20% (AAA to AA-), 50% (A+ to A-), 100% (BBB+ to BB-, and unrated), and 150% (below BB-). In the foundation and internal-rating approaches the risk weights are functions of the type of exposure and four variables: the probability of default, the loss given default, the maturity, and the exposure at default. Even in these more sophisticated approach, the credit rating determines the probability of default, the loss given default variables, and the credit correlation, ρ. This 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.

The credit rating not only determines the capital adequacy requirements for global commercial banks in the Basel rules, but also establishes the NAIC's risk-based capital system for insurance companies. The NAIC capital charges are based upon six credit quality designations of bonds with a direct correspondence of credit rating scales (AAA to A, BBB, BB, B, CCC, below CCC). The capital requirements are 0.4% (A or above), 1.3% (BBB), 4.6% (BB), 10% (B) and 20% (speculative grade bonds). Therefore a change in the credit rating of a bond from one of these scales to another has relevant implication for most bondholders and potential buyers in terms of capital requirements. These institutional investors could need to compute more than double the amount of exposure to this bond. Also the holding of an upgraded bond could appear more attractive since the required capital should be lower than it was before the credit rating change. This third hypothesis does not necessarily imply instant trading. The attractive of maintaining a bond in portfolio reduces (increases) after a downgrade (upgrade) but it does not necessarily require a fast sale (purchase). Investors could wait until bond price converges to the fundamental values.

A well-documented phenomenon is the asymmetric reaction to positive and negative rating events. The reputation hypothesis (Holthausen and Leftwich, 1986) states that rating agencies face asymmetric loss functions, and they allocate more resources to revealing negative credit information than positive information because the loss of reputation is more severe when a false rating is too high than when it is too low. As a result, downgrades represent information not yet known by the market, whereas upgrades confirm information that is already available. Also, the price pressure subsequent to rating actions is different for downgrades and upgrades. Although downgrades force selling transactions, upgrades do not force buying transactions. Under this hypothesis, we expect a stronger reaction on liquidity in the case of downgrades. The same effects are affirmed by the moral hazard risk problem (Covitz and Harrison, 2003). Whereas the market is the end customer of rating agencies, almost all their revenues come from rating fees paid by the rated firms. The agencies may act in the interest of issuers delaying rating downgrades to give the firm time to correct its credit quality.

The last hypothesis to test suggests that the usual liquidity premium on prices widens after a CR announcement. If CR announcements disclosure new and relevant information about the default risk of a bond, then price level should immediately incorporate this information. Independently of this price adjustment, liquidity may drive additional price changes. Traditional literature considers liquidity as a key component of corporate bond prices. Recent papers corroborate this result using TRACE transaction data. For instance, Bao et al. (2011) conclude that illiquidity explain a substantial part of the yield spreads of high-rated bonds overshadowing the credit risk component. Acharya et al. (2009), Chen et al. (2007), or Friewald et al. (2012) also observe that the economic impact of liquidity is significantly larger for speculative grade bonds.

Liquidity premium of each bond has a permanent component, which depends on issue characteristics, such as amount outstanding (Fisher, 1959), age (Sarig and Warga, 1989), and other features, and risk characteristics, such as credit rating. Literature on liquidity risk distinguishes permanent and transitory components of price impact. The permanent liquidity component is the change in the price of the asset that is independent of the rate at which the asset is traded. It depends on the level of asymmetric information, i.e. a higher-rated bond have a lower permanent component than a lower-rated bond, which involves more asymmetric information. The temporary component consists of the instantaneous and reversible price pressure that results from trading. This component is higher for bonds with low trading volumes and short amounts outstanding. Both the permanent and temporary price impact of trading increase in magnitude with the size of the traded block. A fall in the asymmetric information after a CR announcement triggers predatory trading. Adapting the terminology of Carlin et al. (2008), some "distressed traders" may require to sell a large block of the asset in a short time horizon after a CR downgrade. The "predators traders" compete strategically in the market to exploit the price impact of the distressed traders' selling. The predators can return to their original positions in the bond days later. We assume that the liquidity effect on prices and yield spread exacerbates from the disclosure of new CR information.

4. Proxies of liquidity

Liquidity is not observable. It is related to capacity of a market to absorb a large number of transactions without causing big movements on prices. According to Sarr and Lybek (2002) liquidity has five dimensions: tightness (low transaction costs), immediacy (the speed at which orders are executed), depth (number of orders), breadth (volume of orders) and resilience (the capacity of the market to recover from unexpected events).

The different methods proposed in the literature to measure liquidity usually focus on one of these factors. A number of market condition variables and security-specific characteristics have been traditionally used as liquidity proxies in debt markets. Most of these measures are independent of an eventual rating action and are clearly inappropriate in our study. This is the case of measures such as the amount outstanding (Fisher, 1959), the age of the bond (Sarig and Warga, 1989), the status (Warga, 1992), the time to maturity (Amihud and Mendelson, 1991), the trading volume (Elton and Green, 1998), the number of trades (Fleming, 2001), the expected liquidity over the full life of the issue (Goldreich *et al.*, 2005), the trading activity life cycle (Díaz *et al.*, 2006), the trade size and issue size (Edwards *et al.*, 2007), or the accessibility of a security by dealers (Mahanti *et al.*, 2008).

Recent accessibility of TRACE transaction database has enabled the emergence of a number of papers that adapt widely used liquidity proxies in equity markets to the fixed income markets. Some of these liquidity proxies for debt markets are price impact measures. Literature defines "price impact" as the cost of demanding additional instantaneous liquidity. It can be interpreted as the first derivative of the effective spread with respect to the transaction size. Amihud (2002) measure relates the price impact of a trade to the trade volume. It is defined as the price impact of a trade per unit traded. Cooper *et al.* (1985) and Amihud *et al.* (1997) propose the "Amivest" liquidity measure as a measure of price impact as far as it seems to be a good indicator of market depth. It is the average ratio of the trading volume and absolute return per transaction. A larger value of this measure implies a lower price impact. The "Bao" illiquidity measure, from Bao *et al.* (2011), is an adaptation of the Roll (1984) measure to quantify transaction costs.[6] Bao measure is computed as the negative covariance between the price change from a time and the price change from the previous

[6] Roll (1984) finds that, under certain assumptions, consecutive returns can be interpreted as a bid-ask bounce. Thus, the covariance in price changes provides a measure of the effective bid-ask spread.

period. The negatively serially correlated price changes are leaded by a transitory component in price because of the lack of liquidity. According its authors, it is an illiquidity measure that captures the broader impact of illiquidity on prices, above and beyond the effect of bid-ask spread. The Imputed Roundtrip Costs (IRC) measure, proposed by Dick-Nielsen *et al.* (2012), is the difference between the largest price of a bond on a day and the smallest price on the same day, over the largest price of the bond on that day. It is calculated only for "imputed roundtrip trades", that they define as those transactions with only two or three trades in the same day that have the same trade size, without another transaction in the same day. They propose this measure as proxy of bid-ask spreads. The "Price dispersion" (PD) is an illiquidity measure, proposed by Jankowitsch *et al.* (2011), that is computed as the volume-weighted volatility of the traded prices around the fair price value. They compute the root mean squared difference between the TRACE prices and the respective Markit quotation. We proxy the fair price with the average transaction price for each bond during the day. A low dispersion of traded prices around its market-wide valuation implies transactions near the fair value and lower transaction costs. We consider liquidity proxies that focus in three different faces of liquidity, i.e. price impact, market impact, and trading frequency (see the Appendix for mathematical details). As price impact measures, we analyze the "Amivest" ratio, the "Bao" measure, the IRC measure and the "Price dispersion" measure. The first measure is a liquidity proxy and the rest of measures are illiquidity ones. Following the Amivest ratio, larger liquidity implies lower price impact of new transactions. Bonds with high levels of this ratio are the most liquid bonds, i.e. those bonds with less price impact. In the case of the Bao measure, an illiquid bond is traded with a large bid-ask spread that implies highly negative correlated consecutive prices and a high positive value of the Bao measure. According to the IRC measure, higher values represent large differences between maximum and minimum prices that can be interpreted as large transaction costs. Therefore, bonds with high IRC values are less liquid bonds. Finally, a low level of the PC measure indicates liquidity, i.e. the bond can be traded close to its fair value.

As proxies of market impact, we consider both the "Market share" (MS) and the "Trading volume" (TV). Following Diaz *et al.* (2006), we compute market share as the ratio of the trading volume of a bond in a day over total trading volume in the whole market, including any transaction involving any outstanding issue. The second measure, TV, is the traditional trading volume of the bond in a day. The larger the trading volume, the higher the bond liquidity.

Finally, we compute as trading frequency measure the "Number of trades" (NT) for a bond in a day. A large number of trades means high liquidity. In the presence of bonds with low number of trades, it is difficult to sell or buy those bonds without incurring in high transaction costs.[7]

5. Effects of rating change announcements

5.1. Prices and yield spreads behavior

In this section, we study the patterns of prices and yield spreads of bonds affected by a CR change during the time around the event. We compare traded prices and the corresponding yield spreads on the pre-event period represented by the time window from

[7] There are other trading frequency measures based on the concept of "runs" (Sarig and Warga, 1989) or zero-trading. They compute the number of zero-trading days in a firm or a bond level (e.g., Chen, Lesmond, and Wei, 2007, Goyenlo *et al.*, 2009, Dick-Nielsen *et al.*, 2012, Friewald *et al.*, 2012).

41 to 1 working days before the announcement, to the values on the following 20 working days (from 1 to 20 days post-event). We examine whether, from our comprehensive data set, there is evidence of phenomena, such as price corrections before the event (or market anticipation), price impact on the event day (or informational content of the CR announcement), price pressure or even fire sales after the event (or price overreactions). All this information is key to understand the interrelation of prices and liquidity in our later study of the behavior of the different faces of liquidity around the announcement.

The analysis of the price impact of different assets, such as stocks, bonds or credit default swaps, is the main subject of an extensive literature about the information content on CR announcements. Recent papers obtain evidence that negative CR announcements, particularly reviews for downgrade and downgrades, do in fact disclose information relevant to the formation of stocks and bonds prices and credit default swap spreads (e.g., Norden and Weber, 2004, Hull et al., 2004, and Jorion and Zhang, 2007).

We propose a descriptive analysis of the average transaction prices in the period around the CR event. We expand the study by including yield spreads. This measure should be less noisy than prices or returns. It is independent on the level of interest rates at each time since it is computed as the yield to maturity of the corporate bond less the yield to maturity of a similar US government bond. The yields of the risk-free bonds are obtained from the US Department of the Treasury data set,[8] which provides daily market yields at fixed maturities calculated from composites of quotations of on-the-run securities obtained by the Federal Reserve Bank of New York. These on-the-run Treasury bonds are the just-issued bonds of a particular maturity. By far, they are the most liquid securities in the market since most of the trading took place in on-the-run issues (e.g. Sarig and Warga, 1989, Sack and Elsasser, 2004). We select the yield to maturity of the 5-year Treasury bond since this is the average term to maturity of the corporate bonds involved in CR changes in our sample (see Table 3).

Figure 2 depicts the behavior of the average traded prices and yield spreads per day for all the transactions involving downgraded bonds. We highlight three relevant results. First, there is a clear declining trend in prices (left side of the figure), and the corresponding upward trend in yield spreads (right side). The average price is 96.35 percent of the face value during the control window [-41,-21] we use in the event study, 94.82 during the 10 working days before the announcement, and 93.12 during the 20 working days after. Same pattern is observed in yield spreads, i.e. 346 b.p. in [-41,-21], 399 b.p. in [-10,-1], and 432 b.p. in [+1,+20]. The normality Kolmogorov-Smirnov tests of Lilliefors and the equality of median Wilcoxon tests for comparing the periods [-10,-1] and [+1,+20] reveal the statistical significance of the differences between the pre-event and post-event period.[9] Second, there is a relevant reaction of prices and yield spreads on the event day and/or a few following days. Other interesting pattern is that the slope of the trend seems flattening or even slightly reversing after the first post-event week. During this period immediately after the event [+1,+5] we observe the most extreme values, i.e. average price of 92.14 and yield spread of 431 b.p.. These results support the idea that CR downgrade announcements are partially anticipated by the market, since there is a downward trend on prices in the period preceding the event. However, the announcement also contains new information, since there is an overreaction in the first days after the event that is corrected later.

[INSERT FIGURE 2 ABOUT HERE]

[8] http://www.treasury.gov/resource-center/data-chart-center/interest-rates/Pages/TextView.aspx?data=yield

[9] Results of these tests are available upon request from the authors.

In the case of upgrades, Figure 3 provides the evolution of the average traded prices and yield spreads per day for all the transactions. Results are less convincing than in the downgrades case. For the full sample of upgrades, we observe an upward trend in prices before the event (average price is 99.94 in [-41,-21] and 100.79 in [-10,-1]), a peak immediately after the event (102.85 at the event day), and a stabilization after the event (101.22 in in [+1,+20]). Upgrades to or within investment grade categories seems to be an erratic impact in prices and yield spreads. Besides results of this simple and intuitive analysis, Kolmogorov-Smirnov and Wilcoxon tests obtain statistical significance differences between the pre-event and post-event period except for rising starts sample. Thus, we observe pattern for upgrades similar to that obtained for downgrades.

[INSERT FIGURE 3 ABOUT HERE]

The downward (upward) peak that average prices show in the downgrade (upgrade) announcement day and in the few following days deserves further attention. We examine the role of retail-sized trades in this behavior. Do uninformed retail traders drive the price behavior in the first week after the announcement? We fix the threshold between retail and institutional transaction in 100 bonds or 100,000 dollars (e.g. Alexander et al., 2000, Edwards et al., 2007 among others). Around 79% transactions per day in our sample of rerated bonds can be considered as retail size trades. This percentage is almost double the number reported by Edwards et al. (2007) for the period January 2003 to January 2005.[10]

[INSERT FIGURE 4 ABOUT HERE]

Figure 4 depicts the average price behavior around the announcement distinguishing institutional-size and retail-size trades. In the downgrade events (left panels), the fall in the average price and the jump in its volatility during the first week become drastic in the sample of institutional trades. The retail-size trades also show a decrease (increase) in the average (standard deviation) of the price but this pattern is much more moderate than in the institutional-size case. A simple comparison between both kind of trades shows that daily prices of institutional trades are 55 b.p. higher than the retail ones during the days previous the event, 186 b.p. lower during the first week after, and 54 b.p. lower from the second to the fourth week after. This result suggests that price pressure after a downgrade event is generated by institutional trades.

In the case of upgrade events (Figure 4 right panel), average and volatility of daily prices show a smooth trend in which prices are adjusted to the new rating category and volatility decreases. The price spread between institutional- and retail-size trades remains stable around 94 b.p. No evidence of price pressure is observed in this simple analysis.

5.2. Preliminary analysis of the liquidity proxies

In this section, we show a descriptive analysis of the liquidity proxies from the day 41 before the event to the day 20 after the event. Table 4 depicts the mean and median values of the four proxies of the price impact, the two proxies of the market impact, and the proxy of the trading frequency during the five event windows we examine in the next sections through an event study analysis. In addition, Figure 5 shows the temporal evolution of the average values.

[INSERT FIGURE 5 AND TABLE 4 ABOUT HERE]

10 Using TRACE data for a different period and using different filters, Edwards et al. (2007) observe that the average percentage of retail-sized transactions is approximately 45% and their average trading volume is 1% of the total traded volume.

We stress the peak that the average PD, TV and NT show after the downgrade announcement (left side of the Figure 5). The event triggers roughly a doubling in value in the average of the three liquidity proxies. This behavior analyzed jointly with the price impact we observe in Figure 2 suggests that fire sales happen. Particularly high price dispersion indicates that some transactions are crossed at extreme prices. These pattern are only partially observed in the upgrades sample (right side of Figure 5) but in a much more smooth way. All these figures are commented in depth to interpret the results of the event study analysis.

An interesting point to consider is the huge difference between the mean and the median values of these liquidity proxies (see Table 4). In concrete, the relative median TV (in relation to its value in the control window [-41, -21]) in the window immediately after the event [1, 5] is 73%, i.e. half the value of the average (140%). Simultaneously the trading frequency remains 21% higher than usual. This result suggests that there are a small number of extremely large size transactions but most of the trades are retail transactions that drop the median of the TV.

As in previous section, we examine the role of the trade size in this behavior. Above we comment that the extreme drop in prices on the downgrade event day and following days is mainly observed for institutional-size trades. In Figure 6, we examine the composition of the trading activity by separating retail-size trades (below 100,000 dollars) and institutional-size trades.

[INSERT FIGURE 6 ABOUT HERE]

The average trade size in the institutional segment increases 25% at the downgrade event day ($1.32 million) and the day after in relation with the average trade size in the previous month ($1.05) (see upper left panel of Figure 6). The increment in the total number of trades in the full market for bonds around a downgrade (TNT) is even larger (61%), from an average of 2,100 institutional trades in the period before the downgrade to 3,400 trades immediately after the event. Both components of the trading activity, i.e. average trade size and number of trades, imply a large increment in the trading activity during the first week after the downgrade in the institutional segment. Lower left panel in Figure 6 clearly shows the peak of activity in the market around the CR announcement. The institutional trading volume the day after the event is more than doubled (214%) the average value during the previous month. This figure means a large increment in the usual trading activity, but it is not large enough to indicate the presence of massive fire sales. Additionally the institutional trading activity returns to conventional values after the first week.

In the case of retail-size trades (central left panel of Figure 6), the evolution of the trading volume per trade and the total number of trades provides little evidence to support a retail investors reaction to the downgrades. There are a bit more retail trades in days 1 and 2 after the downgrade than usual in preceding days, but their average size remains constant. Anyway, the graph suggests an upward trend in the number of retail trades until day 1 that changes to a downward trend after this day.

A puzzling result is that institutional trading activity triggers the day previous the announcement. Total trading volume coming from institutional-size trades for all the issues involved in downgrades is 43% higher the day before a downgrade ($3.21 billion) than the average value of this variable during the previous month ($2.24 billion). However, institutional prices remain stable until the event; they just drop after the announcement. This suggests that market could anticipate a downgrade, but it is not able to know the specific rating change.

Results for upgrades announcements (right panel of Figure 6) are less impressive than in the case of downgrades. Average trading volume per institutional trade remains quite stable during the period. Number of institutional trades raises 17% the upgrade day in relation the previous month. This amount is far away of the 61% observed in the case of downgrades. The total trading volume for institutional-size trades in the sample increases after the upgrade (30%) and keeps relatively high during the three weeks after (lower right panel of Figure 6).

5.3. Event study analysis of liquidity

5.3.1. Methodology

To analyze the effects of CR change announcements, we carried out an event study test. We compare liquidity on the rating-change days to the same characteristics on normal liquidity days. We examine liquidity around the date of the announcement, that we define as day $t = 0$.[11] We compute the "liquidity around the rating-change" from day $t = t_1$ to day $t = t_2$ around $t = 0$, as the averaged liquidity proxy:

$$OL_{i(t_1,t_2)} = \frac{\sum_{t=t_1}^{t_2} l_{it}}{T} \tag{1}$$

that we call rating-change window, and T is the number of days in this window (t_1,t_2). Previously, each liquidity proxy has been computed in a day-by-day basis.

We compare liquidity around rating-changes to the expected liquidity of bond i (EL_i) in "stable-rating times". Following Corwin and Lipson (2000), we use the firm-specific past history to compute the expected liquidity for bond i in a period of typical liquidity.[13] We consider two months prior to the rating change announcement without any other credit event. Then, we define the stability-rating window as the day $t = -41$ to day $t = -21$ window. The window ends 20 trading days prior to the announcement day in order to avoid possible price lead-up preceding the shocks.[14] EL_i is computed as the averaged liquidity proxy in this benchmark window:

$$L_{i(t_1,t_2)} = \frac{1}{N}\sum_{t=-40}^{-21} l_{it} \tag{2}$$

To taking into account for different scales of liquidity proxies across different bonds, we compare the liquidity around the rating change and the expected liquidity in logarithms. Then, the bond i abnormal liquidity in a specific event window (t1, t2) is obtained as the difference between observed liquidity in that rating-change window and the expected liquidity both in logs:

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11 In case the CRA announce the rating change on a holiday day, we consider as $t = 0$ the next business day.

13 Bessembinder, Kahle, Maxwell and Xu (2009) indicate that the use of the firm-specific past history as benchmark could be less powerful than create a matching portfolio of stable rating bonds. However, the second approach implies to create an appropriate portfolio with characteristics related to liquidity as similar as possible to the re-rated bond to avoid biased results. To find such a good matching portfolio is very difficult in the case of corporate bonds, due to infrequent trading observed even in the most liquid markets such as the U.S.

14 We discard those re-rated bonds with other confounding rating event in the [-41, t_2] window. We also require that the re-rated bond trades at least 20% of the days in this control period.

$$AL_{i,(t_1,t_2)} = \log(OL_{i,(t_1,t_2)}) - \log(EL_i) \tag{3}$$

where ln(.) indicates natural logarithm.

In order to test the null hypothesis of no effects on liquidity due to rating changes, we compute the Averaged Abnormal Liquidity as:

$$AAL_{(t_1,t_2)} = \frac{1}{N}\sum_{i=1}^{N} AL_{i,(t_1,t_2)} \tag{4}$$

where N is the number of rating changes in the considered subsample of events (upgrades or downgrades). Under the null, the expected value of $AAL_{(t_1,t_2)}$ must be zero. To test statistical significance of $AAL_{(t_1,t_2)}$ we apply different methods. First, we compute the well-known t-ratio test, asymptotically normal distributed under the null hypothesis. Second, we compute two non-parametric tests (Fisher sign test and Wilcoxon rank test) that are robust to non-normality, skewness and other statistical characteristics of liquidity data that may affect the t-ratio properties. The Fisher sign test equals the number of times abnormal liquidity is positive. The Wilcoxon rank test accounts for information of both magnitudes and signs. We report *p*-values for the asymptotic normal approximation to these tests. See Sheskin (1997) for details.

We study different rating-change windows to analyze the behavior of abnormal liquidity before and after the release date: Three post-announcement windows, [0,5], [6,10], [11,20], to analyze the impact on liquidity and its duration; and two pre-announcement windows, [-10,-6], [-5,-1], to detect if market participants anticipate the rating information in days before the rating change take place.

5.3.2 Event study results

We analyze separately the impact on liquidity both for CR downgrades and for CR upgrades. We analyze three faces of liquidity through the three groups of liquidity measures: price impact measures (the "Amivest" ratio, the "Bao" measure, the IRC measure and the PD measure), market impact measures (the MS and the TV) and trading frequency measures (NT). All these measures are liquidity proxies, except Bao, IRC and PD that are illiquidity proxies. For each measure, we test the hypothesis of abnormal liquidity equal to zero for the different width windows. We show mean and median abnormal liquidity and the results for the Fisher sign test and the Wilcoxon rank test.

Downgrades

Table 5 presents results for CR downgrades for the three groups of liquidity proxies. In the case of the four price impact proxies (Panel A), results suggest that liquidity becomes scarce both before and after the event. The price impact, price dispersion and transaction costs are especially high after the event, period in which the four proxies indicate the poorest liquidity.

[INSERT TABLE 5 ABOUT HERE]

In the case of the Amivest liquidity measure, the mean abnormal value estimated is negative and statistically significant in the entire pre- and post-announcement day event windows. This result suggests an increase of the cost of demanding liquidity around a downgrade event as far as Amivest is considered a proxy of the price impact. Investors incur in large price concessions to trade these bonds. The mean and median of the abnormal liquidity are especially low in relation to the control window in the days before the event and during the second week after. This result is robust with the analysis method that we use (abnormal liquidity in mean and median, and parametric and non-parametric tests).

The abnormal value of the Bao illiquidity measure is only statistically significant for the last two windows showing positive estimated coefficients. Thus, the result suggests larger effective bid-ask spreads, i.e. a liquidity deterioration, during the period [6, 20]. The analysis for the IRC illiquidity proxy depicts significant positive abnormal values for all the windows, with higher mean and median values after the event. Results indicate a fall of liquidity around the event, i.e. transactions suffer higher than usual transaction costs. Finally, PD illiquidity measure shows positive and statistically significant abnormal values after the event. The price dispersion increases after the downgrade.

Panel B shows the market impact measures. The two considered measures, MS and TV, show a decrease in abnormal trading volumes in previous days to the downgrade announcement day and in the second post-announcement week, while these measures are positive and significant in the first week after. This result is robust with the test we use and corroborate the difference between mean and median values we comment in section 5.2. We highlight that coefficients of abnormal liquidity are negative and particularly low in the weeks previous the event [-10, -1]. Trading activity drops again during the second post-announcement week [6, 10] and converges to regular values from the second fortnight after the downgrade [11, 20].

Finally, Panel C Table 4 displays the results for the trading frequency measure NT. In this case, there are a significant abnormal number of trades after the event, in the [0, 20] window. The estimated coefficient is especially high immediately after the event [0, 5]. Those results are also robust to the tests used.

From these results, we can highlight four clear patterns around a downgrade. First, during the days previous the announcement, we observe a behavior of liquidity proxies that we interpret as an episode of calm tense in the market prelude to the announcement. Institutional investors modify trading patterns meanwhile retail investor's activity remains relatively insensible. Institutional investors should have access to more information than retail ones. These main players in the marketplace trade more often lower size transactions until the day before the announcement and the liquidity deteriorates. This is a period of abnormally low liquidity in the market. The two market impact proxies, i.e. the TV and the MS, and three price impact proxies, Amivest, IRC and PD, show unusual low liquidity levels. Trading frequency and Bao have a "normal" behavior during this period. In this week previous the downgrade, the median TV level only reaches the 58% of its usual value meanwhile the median number of trades is 9% higher than usual (see Table 4). However, the mean TV is slightly higher than usual (7%), which implies some extreme values in the tail of the distribution. This suggest a lower participation of institutional investors in the trading of these bonds. The descriptive analysis in Section 5.2 (see Figure 6) helps to understand this low trading activity in the week before the downgrade. First, the trading volume of institutional-size trades keeps a decreasing trend during the month before the downgrade (it is 8% lower on average than in the control window). Second, the number of institutional trades in the week previous the event [-5, -1] shows upward trend (17% higher than in the control window).

Second, nervousness emerges the day before the announcement [-1] but transaction prices remain stable (see Section 5.1). The institutional trading activity considerable raises the day before the announcement. In concrete for these institutional transactions, average trade size (number of trades) is 17% (27%) higher in this day than during the previous month [-20, -2]. The activity of retail investors still keep constant. As suggested above, institutional investors seem to anticipate a downgrade, but they are not able to know the specific rating change.

The third result we stress is that the downgrade event exacerbates trading activity, prices overreact, and transaction price impact deteriorates during the announcement day and the following week [0, 5]. Thus, one face of liquidity improves, there is much more activity in the market, but other face of liquidity worsen, there is a high price dispersion and transaction costs increases. Result is a clear price overreaction leaded by some institutional investors. After that, the price progressively converges to the fundamental value.

IRC and PD proxies show the worst levels in the full-analyzed period. In fact, the average of both proxies is around 50% higher than in the control window (see Table 4). However, trading activity clearly raises. As commented in Section 5.2, institutional-size trades lead this growth. Number of transactions increases for both kind of investors, 80% in the case of institutional and 42% in the case of retail the day after the event in relation to the control window, and TV rises 19% for institutional trades and just 2% for retail ones. As in the day before the event, proxies of price impact and proxies of trading activity move to opposite directions. However, in this case there is a price pressure that slumps prices. As commented in Section 5.1, the extreme values of prices and yield spreads are observed during the begging of this week, especially in the day after the announcement (91.46). The average price drops 4.1% respect to the control window (from 96.33 to 92.44)

Results for the third period [6, 20] suggest that price pressure banishes. All price impact and market impact proxies show lower levels than usual. Only the NT is larger than in the control window. Besides price impact, transaction costs, and price dispersion are higher than usual, prices increase and converge to the fundamental value after incorporating the new information about the CR.

From these three clear patterns, we can summarize some conclusions. First, it seems that the market partially anticipates the CR announcement during the two weeks previous the event. In this period, prices steadily drop and the trading activity of the main players slows waiting to know exactly the magnitude of the rating migration. Large size transactions are detected the day before the downgrade. Second, there is a considerable price pressure accompanied by an increase in retail trades that keep exceptionally low the TV during the first week after the downgrade. Besides we observe large size transactions in this period, no evidence of massive fire sales is found. This result is partially consistent with literature that suggests forced selling induced by regulatory constraints which implies prices below fundamental values. Third, the trading activity measured by the TV clearly increases from the second week after the announcement and the number of transactions remains larger than normal. The price pressure diminishes and the median trading volumes and number of transactions are larger than normal. Bondholders forced to unwind positions wait until this period in which prices probably converge to its equilibrium level according the new credit rating.

Upgrades

Table 6 presents the results for upgrades. Panel A shows the effects in liquidity, measured by the price impact measures, due to a rating change. In general, mean and median abnormal values of the four proxies are statistically significant but are a little confusing.

Liquidity level becomes abnormally high during all the period [-10, 20] according three proxies (Bao, IRC and PD), but with the opposite result in the case of Amivest. This suggests shorter effective bid-ask spreads, lower transaction costs, and lesser price dispersion during all the period, but a higher price impact of new transactions. Results show inappreciable differences of these proxies between each week around the event.

[INSERT TABLE 5 ABOUT HERE]

Panel B and C show the results for the market impact and trading frequency. According to the results, the abnormal liquidity behavior of MS, TV, and NT indicates a drop in the trading activity around the upgrade, except an increase of the average number of trades immediately after the upgrade. Analysis of Section 5.2 detects a slightly increment of institutional investor activity immediately after the upgrade and during the second fortnight. Retail investor activity remain insensible to the upgrade event. Prices follow a smooth upward trend during the period without any notable movement.

From these results in the case of upgrade events, we stress that both faces of liquidity evolve in opposite direction around the event. We observe an improvement on price impact liquidity and a worsening of trading activity liquidity. The consequence is a progressive and smooth increase of prices. As in the case of downgrades, it seems that the market partially anticipates the CR announcement during the two weeks previous the event.

5.3.3. Addressing the research questions

In the introduction, we consider several research questions and hypothesis. Now we summarize results and some conclusions about.

1. Can liquidity patterns before the event help to predict its occurrence?

Results suggest that the market partially anticipates the CR announcement during the week previous the event. In the case of downgrades, prices steadily drop and the trading activity of the main players slows waiting to know exactly the magnitude of the rating migration. We call this period as an episode of calm tense prelude to the announcement. Institutional investors reduce the participation in the trading. Surprisingly nervousness emerges the day before the downgrade involving a large increment of institutional-size transactions before. However, prices remain stable the day before. Only after the release of information the prices drop. We conclude that market expects an imminent announcement without knowing its specific realization.

These results for downgrades can be interpreted as evidence that both the information content hypothesis and the reputation hypothesis are partially corroborated. The fact that market seems to anticipate the CR announcement supports the idea that CR agencies modify CR too slow to preserve their reputation and avoiding rating bounces. However, the CR event triggers large trading activity and even generates price overreactions. That means that these events supply with considerable non-public information. The new information is probably not the event itself but the number of steps the rating category changes.

Additionally we observe the typical asymmetric reaction to positive and negative rating events. In the case of upgrades, prices steadily rise and institutional trading activity decreases during all the period. Only a small increment in trading size immediately after the upgrade is detected. There is no evidence of any reaction in the market. Our results seem to agree with studies that analyze the impact of rating changes on stock and bond prices (e.g., Holthausen and Leftwich, 1986; Ederington and Goh, 1998 or Abad and Robles, 2006, 2007). These studies find asymmetries in the effects caused by negative and positive rating changes in prices, which must necessarily be accompanied by a symmetrical effect (increase) in liquidity.

2. Do liquidity shocks or even fire sales occur after a downgrade announcement?

We observe a large increment of institutional-size trades the day and the day after the downgrade. The total trading volume for all the downgraded bonds the day after is double the daily value during the control window. Transaction size remains in normal levels but trading frequency increases. Some institutional investors lead a transitory price overreaction. However, this increase in the trading activity is not large enough to evidence a forced selling phenomenon. Literature documents that a large proportion of the corporate bond issues is usually kept in inactive portfolios until maturity. Thus, the daily turnover of these bonds is really low. A trading activity twice as common do not imply massive fire sales. Institutional bondholders can wait a more favorable price after prices converge to the fundamental values to rebalance the portfolio. This is evidence against our third hypothesis of regulatory constraints.

3. Do the different liquidity proxies evolve in the same way? To what extent is the usual liquidity's effect on price and yield spread intensified after the event?

We group our liquidity proxies in price impact proxies and market impact, including trading frequency, proxies. On the one hand, we observe two periods in which both groups indicate abnormal low liquidity levels. In the first period, the week before a downgrade [-5, -2], prices moderately decrease, and in the second, from the second week after the downgrade [6, 20], prices moderately increase. On the other hand, there are also two periods in which both faces of liquidity move in opposite direction. First, price impact proxies show low liquidity level and trading activity is higher than usual after the downgrade [0, 5] implying a fall in prices. Second, the complete period for upgrades in which high liquidity in terms of price impact and low trading activity [-10, 20] involves a smooth rise in prices. Only the combination of high price impact and large trading activity seems to exacerbate the liquidity component of price and yield spread.

6. Conclusions

This paper examines liquidity behavior in the market for US corporate bonds around credit rating changes. Using a large sample of nearly 4.5 million trades involving 1,342 straight bonds from 286 different issuers that are affected by 2,620 rating changes over the period July 2002– March 2010, we observe shocks in liquidity with three clear patterns: before, immediately after and during one-month from the rating downgrade. First, the trading activity and liquidity slows down days before the announcement with prices slightly decreasing. However, large size transactions are detected the day before the downgrade without impact on prices. This market anticipation is not fully consistent with the hypothesis that CR agencies supply non-public information about firms. Institutional trading activity fades away while the market is waiting for the imminent event. However, the concrete materialization of the announcement is not anticipated since we only observe price overreaction after downgrades. Second, there is a price pressure and abnormal high trading volumes, transaction costs, and price dispersion during the first days after the downgrades. Institutional-size trades lead this behavior. This institutional investor overreaction could imply transaction prices below fundamental values. This is consistent with the regulatory constraints hypothesis, but no massive fire sales are detected. Third, prices converge to the correct value with low impact price liquidity and normal level of trading activity during the second fortnight. Bondholders forced to unwind positions wait until this period in which prices probably converge to its equilibrium level according the new credit rating. In the case of upgrades, proxies of price impact show higher than usual liquidity levels meanwhile trading activity remains below the common level. Prices follow a smooth upward trend during the period around the upgrade. Any liquidity or prices reaction is observed. This corroborates the asymmetric reaction to positive and negative rating events. Finally, we observe some periods in which our price impact proxies and market impact proxies evolve in the same direction and other ones in which they moves in opposite direction. Only the combination of high price impact and large trading activity seems to exacerbate the liquidity component of price and yield spread.

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Appendix

This appendix describes in details the liquidity measures we analyse in this paper.

A.1. Amivest

$$Amivest_{i,t} = \frac{1}{N_{i,t}} \sum_{k=1}^{N_{i,t}} \frac{TV_{i,k}}{r_{i,k}}$$

The Amivest Liquidity ratio (1985) is the average of daily ratio of trading volume to absolute return (divided by 10^6). In empirical research on stock exchange markets, this measure is considered to show how well an asset is able to absorb trading volumes without a significant move in its price. A high ratio means that large amounts of asset can be traded with little effect on prices. We compute an average for each day for each bond where $N_{i,t}$ is the number of returns for bond i on day t; $TV_{i,k}$ is the trading volume for bond i on day t for each return; and $|r_{i,k}|$ are the absolute returns of bond i on day t. In the event study, we compute the average Amivest on each window.

A.2. Bao *et al.*

$$\gamma_{i,t} = -cov(\Delta p_t, \Delta p_{t+1})$$

The Bao *et al.* (2011) measure is the negative covariance between the price change from $t-1$ to t and the price change from t to $t+1$. If the bond trades with large changes in transaction prices on subsequent days, the covariance between prices enlarges. The sign's change implies a lower negative value of the covariance, lower values of $\gamma_{i,t}$ and then more illiquid bond. The price p_t is the last price for bond i on day t, and we compute this covariance in a rolling window of maximum 20 days. In the event study, we compute the average $\gamma_{i,t}$ on each event window.

A.3. Imputed Roundtrip Cost

$$IRC_{i,t} = \frac{P_{i,t}^{max} - P_{i,t}^{min}}{P_{i,t}^{max}}$$

We compute this measure daily as the difference between the largest price and the smallest price for bond i on day t. We obtain the value of this measure for each event window by averaging over daily estimates.

A.4. Price dispersion

$$d_{i,t} = \sqrt{\frac{1}{\sum_{k=1}^{N_{i,t}} v_{i,k,t}} \sum_{k=1}^{N_{i,t}} (p_{i,k,t} - \bar{p}_{i,t})^2 \cdot v_{i,k,t}}$$

This measure is an estimation of the volatility of the price dispersion. When the value of $d_{i,t}$ is high for a bond, it would indicate that investors cannot trade the bond near its fundamental value, so they have to incur in large transaction costs. In our case, the price dispersion is measured through the difference between traded prices and the average volume-weighted prices. For each bond i we find $N_{i,t}$ transactions on day t with volume $v_{i,k,t}$ at prices $p_{i,k,t}$. We compute the difference between $p_{i,k,t}$ traded prices and the volume-weighted average price for bond i on day t. After compute daily $d_{i,t}$, we average for each window in the event study.

A.5. Market Share

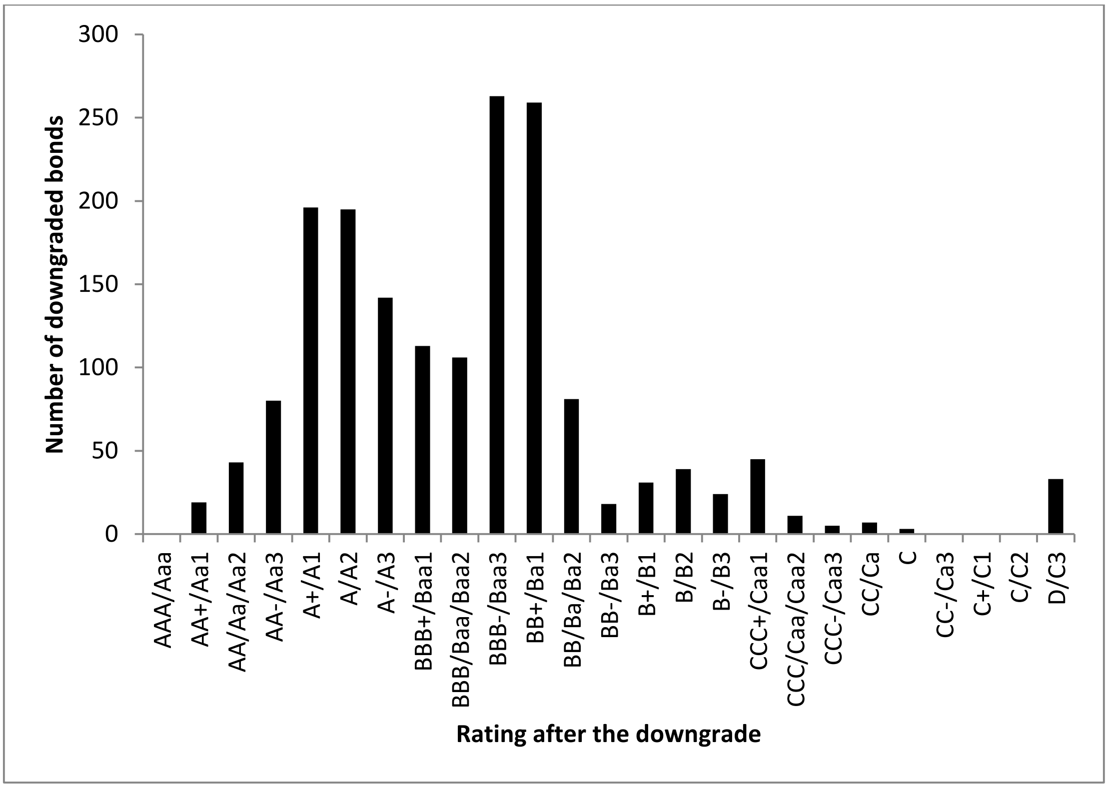
$$MS_{i,t} = \frac{TV_{i,t}}{TTV_t}$$

The market share for a bond i at day t ($MS_{i,t}$) is computed as the ratio of the trading volume of the bond during the day ($TV_{i,t}$) to the total trading volume in the whole market ($MS_{i,t}$), including any transaction involving any outstanding issue, during the day t. It is also computed in a day-by-day basis, and averaged depending on the days of the window to the event study.

A.6. Number of Trades

The Number of Trades (NT) is the sum of trades for bond i on day t. We also compute it on a day-by-day basis, and in the event study, we take the average for each window.

Figure 1. Distribution of our final sample of downgrade events (upper panel) and upgrade events (lower panel) across rating grades. The rating grade is the final rating after the announcement. We take this information from the FISD database that collects ratings from Fitch, Moody's and Standard and Poor's. The number of downgraded bonds represent the total number of downgrade events by rating grade, where we distinguish grades by rating agency. For bonds doubled or tripled rated we compute the average rating using the numeric value assigned by the long term debt rating equivalences, with values from AAA=1 to D=25.The data set is for 1,713 unique downgrade events of US corporate bonds from July 2002 to March 2010.



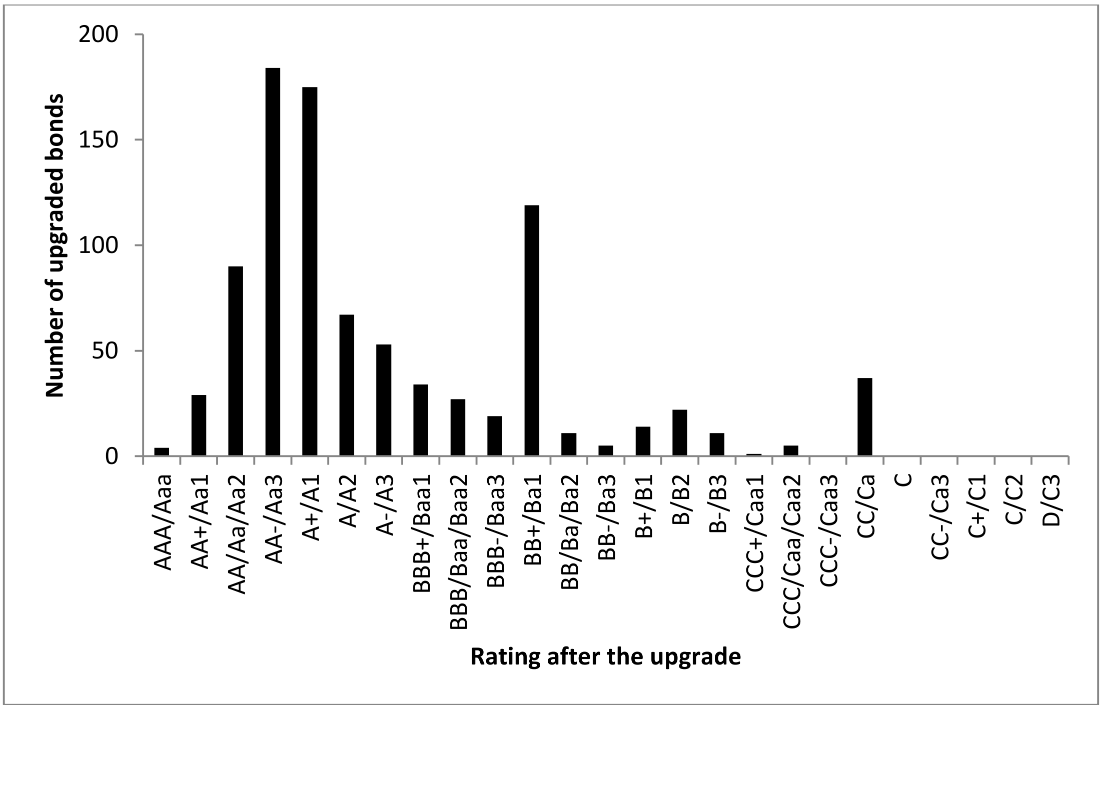


Figure 2. Prices (left side) and yield spreads (right side) behaviour around Downgrades. This figure shows mean prices in percentage of face value and yield spreads in basis points around the CR announcement. The yield spread is computed as the difference between the yield reported by TRACE for each transaction and for each bond and day, and the yield to maturity at the same day for the 5-year US Treasury bond (the average age of our bonds set is 5 years). In first place it plots mean yield spreads for all the 1,713 downgrade announcements, while bellow it plots different samples: downgrades by speculative grade (excluding fallen angels and defaulted bonds), investment grade, fallen angels (bonds for which a downgrade implies a change from investment grade to speculative grade). The data set is reported by TRACE and covers the period July 2002 to March 2010. The credit rating announcements are collected from the FISD database, as well as the qualitative information. The 5-year Treasury yields are reported from the U.S. Department of the Treasury web page.

Figure 3. Prices (left side) and yield spreads (right side) behaviour around Upgrades. This figure shows mean prices in percentage of face value and yield spreads in basis points around the CR announcement. The yield spread is computed as the difference between the yield reported by TRACE for each transaction and for each bond and day, and the yield to maturity at the same day for the 5-year US Treasury bond (the average age of our bonds set is 5 years. In first place it plots mean transaction prices for all the 907 upgrade announcements, while bellow it plots different samples: upgrades by speculative grade, investment grade (excluding rising stars), rising stars (bonds for which an upgrade implies a change from speculative grade to investment grade. The data set is reported by TRACE and covers the period July 2002 to March 2010. The credit rating announcements are collected from the FISD database, as well as the qualitative information. The 5-year Treasury yields are reported from the U.S. Department of the Treasury web page.

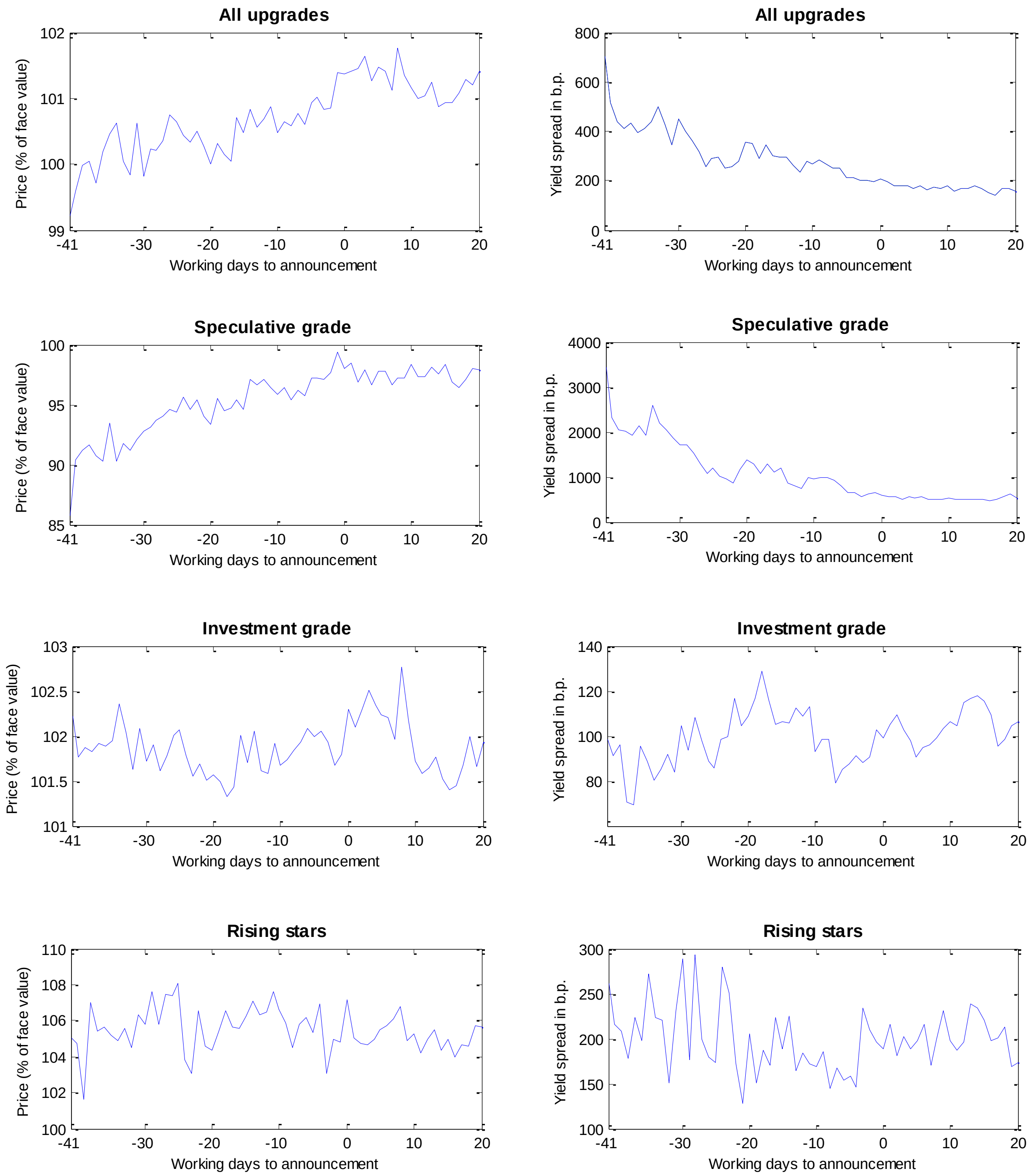


Figure 4. Prices behaviour around the CR event for institutional- and retail-size trades. This figure shows average and standard deviation of prices in percentage of face value around the CR announcement. Retail-size trades involve less than 100 bonds or 100,000 dollars. The data set is reported by TRACE and covers the period July 2002 to March 2010. The credit rating announcements are collected from the FISD database, as well as the qualitative information.

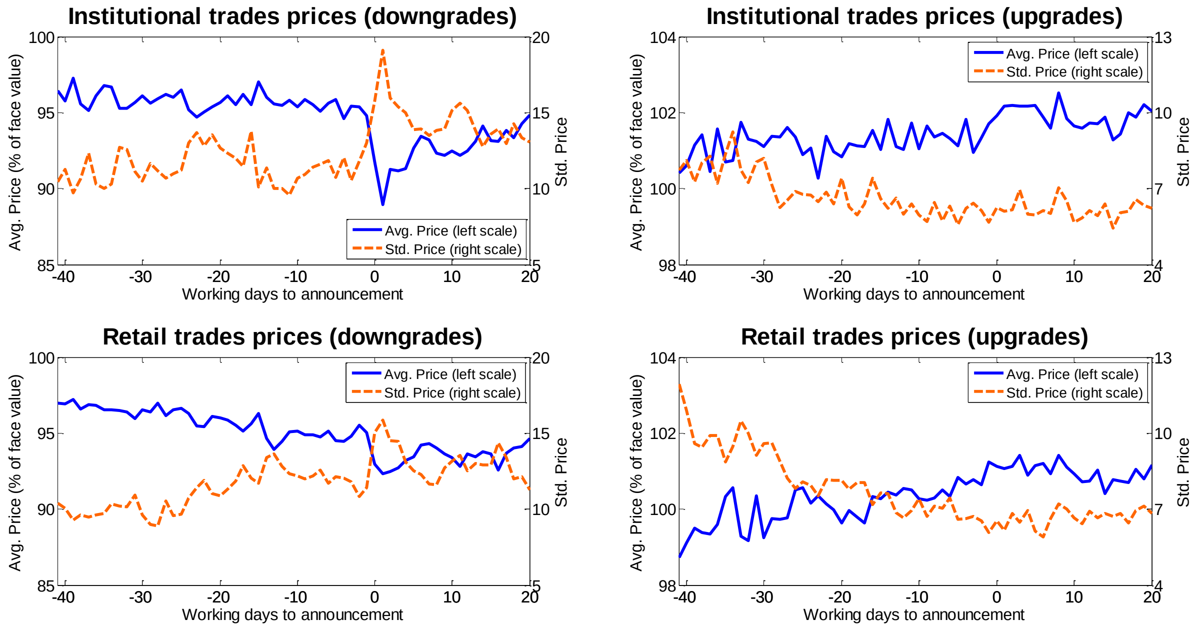


Figure 5. Liquidity proxies behaviour around CR announcement. This figure shows the average evolution of four liquidity proxies: Amivest, price dispersion (PD), trading volume (TV) and total number of trades (TNT). Downgrade announcements are on the left side and upgrade events are on the right side of the figure. The data set is reported by TRACE and covers the period July 2002 to March 2010. The credit rating announcements are collected from the FISD database, as well as the qualitative information.

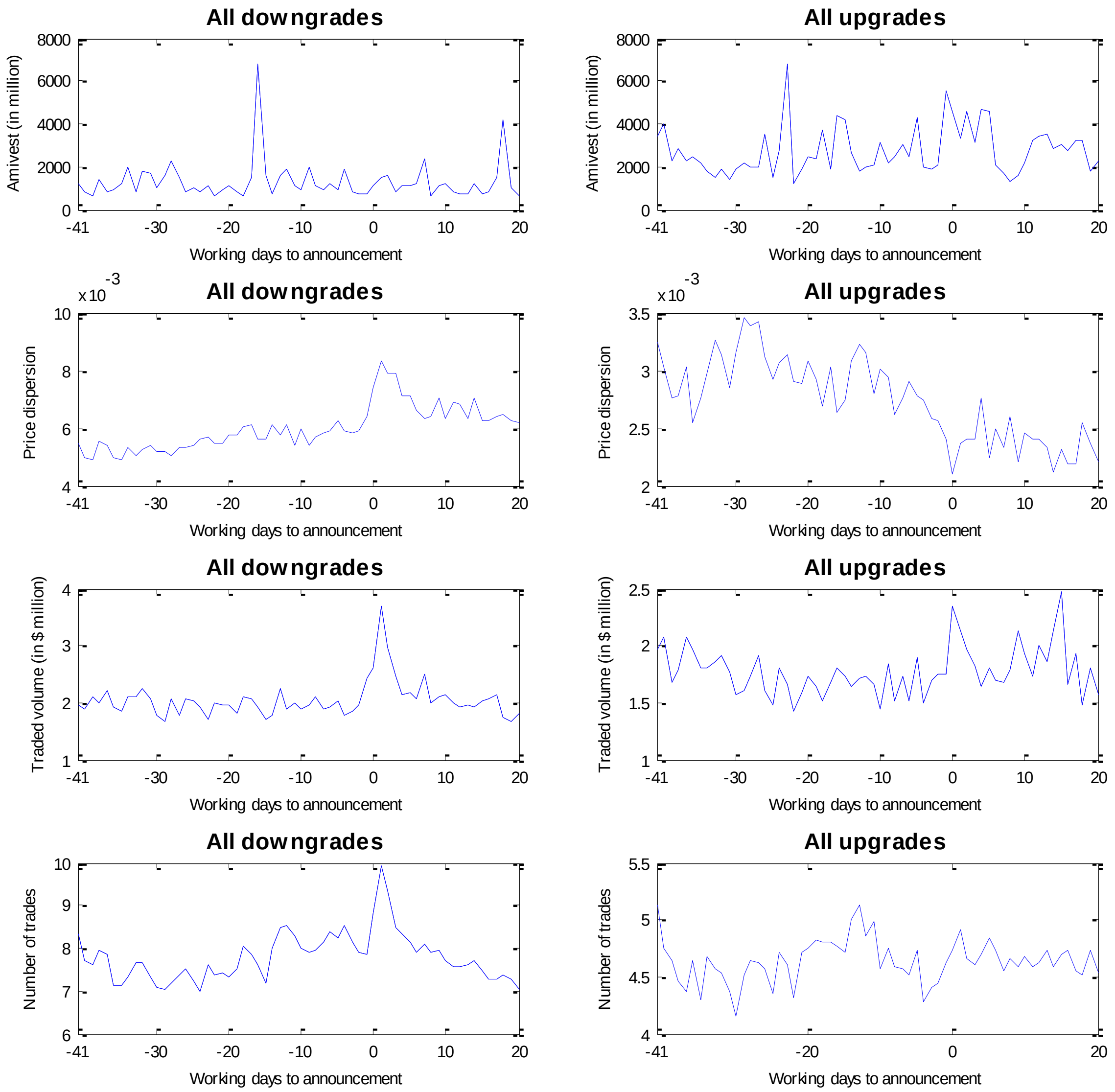


Figure 6. Trading activity around the CR event for institutional- and retail-size trades. This figure shows average trading volume per trade, number of trades, and total trading volume per issue around the CR announcement. Retail-size trades involve less than 100 bonds or 100,000 dollars. The data set is reported by TRACE and covers the period July 2002 to March 2010. We include 1,713 downgrade events (1,050 different bonds issued by 223 different issuers) and 907 upgrade events (621 different bonds issued by 150 different issuers). The credit rating announcements are collected from the FISD database, as well as the qualitative information.

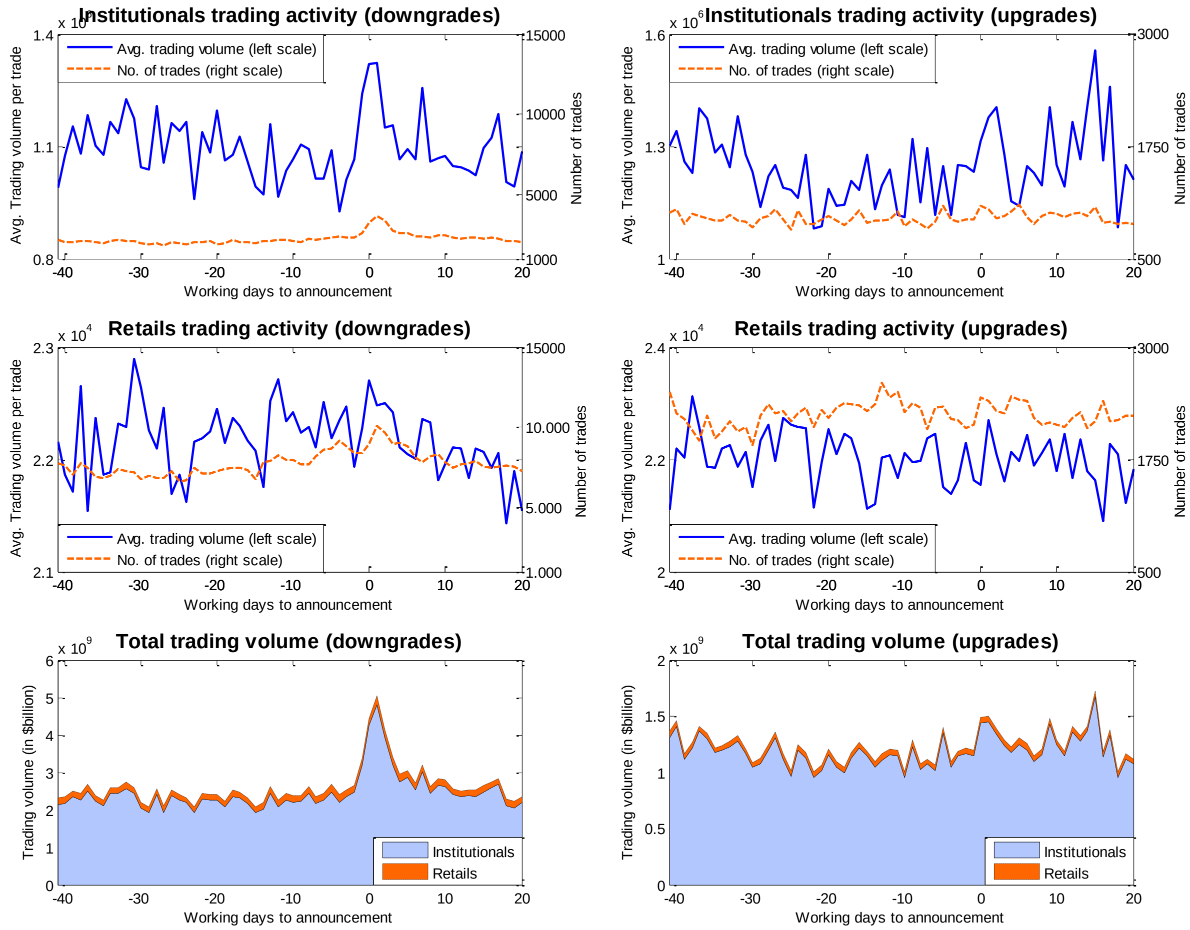


Table 1. TRACE Sample Debugging and Filtering Process. This table shows the evolution of the number of trades after each step of the debugging and filtering process. Intraday data of all the transactions ranges from July 2002 to March 2010. Thereby we obtain the subtotal number of trades of straight bonds, which represents approximately the 13.2% of the original total number of trades reported by TRACE during the period from July 1, 2002 to March 31, 2010. Right column shows the result of filtering transactions from bonds without trading during the event window before and after the announcement or affected by overlapping events. The minimum liquidity requirement is at least one transaction on the 20 working days before the event and on a similar period after the event. Events preceded by other rating announcement on the previous 61 working days, i.e., in the control window, are also ignored.

Year	All #trades in TRACE master files	#trades after debugging errors	#trades only straight corporate bonds	#trades of bonds involved in credit rating events	#trades final sample
2002 (Jul-Dec)	1,129,107	775,819	215,837	169,335	125,592
2003	3,026,807	2,167,348	727,040	553,113	413,132
2004	3,476,809	2,508,118	825,289	633,392	488,573
2005	6,191,729	4,328,809	1,245,287	966,317	724,658
2006	5,503,111	3,776,245	1,007,504	815,979	622,526
2007	5,101,009	3,398,844	820,050	681,241	556,382
2008	6,693,708	4,175,458	1,103,568	841,634	742,033
2009	11,326,563	6,820,586	1,684,292	1,089,355	919,918
2010 (Jun-Mar)	2,706,172	1,657,954	370,112	219,208	174,937
Total	45,155,015	29,609,181	7,998,979	5,969,574	4,767,751

Table 2. Credit Rating Announcements Composition. This table shows the composition of our final sample of 2,727 announcements by credit rating (CR) agency. The Aggregate Total column includes simultaneous announcements for more than one agency in the same direction, into the same grade category (investment- or speculative-grade) at the same day. Right column shows final values where events are triggered by an only CR agency. Panel A depicts the full number of CR announcements during the sample period (from July 2002 to March 2010) provided by Mergent FISD. Panel B shows the result of filtering these events by excluding announcements involving not liquid enough bonds and overlapping events. The minimum liquidity requirement is at least one transaction on the 20 working days before the event and on a similar period after the event. Events preceded by other rating announcement on the previous 61 working days, i.e. in the control window, are also ignored. Panels C and D show the final composition by industry and CR category. Panel E include information about "Fallen angels" that involve downgrades from investment grade to speculative grade and about "Rising stars" that represent upgrades to investment categories.

	Fitch	Moody's	S&P	Agregate Total	**Unique Total**
Panel A: Original sample (Mergent FISD)					
Rated bonds (Jul.2002 – Mar.2010)	152,826	155,746	119,798	428,370	**392,063**
CR announcements (Jul.2002 – Mar.2010)	52,955	96,149	86,332	235,436	**225,398**
Panel B: Matched sample with liquid straight corporate bonds					
CR announcements	778	960	989	2727	**2,620**
Issues	650	724	719	2093	**1,342**
Issuers	137	194	185	516	**286**
Upgrades	189	282	442	913	**907**
Downgrades	589	678	547	1814	**1,713**
Panel C: Composition by Industry					
Industrial	195	225	173	593	**579**
Financial	573	728	793	2094	**2,002**
Utility	10	7	23	40	**39**
Miscellaneous	0	0	0	0	**0**
Panel D: Composition by credit rating category					
AAA/Aaa	0	4	1	5	**4**
AA/Aa	110	153	195	458	**445**
A	257	289	360	906	**828**
BBB/Baa	280	148	143	571	**562**
BB/Ba	90	227	184	501	**493**
B	30	57	55	142	**141**
CCC/Caa	9	46	13	68	**67**
CC/Ca	1	41	5	47	**47**
C	1	0	0	1	**0**
D/Other or NA Grade	0	0	33	33	**33**
Panel E: Composition by credit rating grade					
Investment Grade	647	592	699	1938	**1,839**
Speculative Grade	131	368	290	789	**781**
"Fallen Angels"	63	162	72	297	**294**
"Rising Stars"	10	11	3	24	**22**

Table 3. Summary Statistics. This table shows the summary statistics for bond variables Macaulay duration, age, maturity, coupon and issue size, and for rating changes for each agency, where the number for the rating has been assigned following a long term debt rating equivalences where AAA=1 to D=25. For bonds simultaneously doubled or tripled rated in the same event we compute the average final numeric rating. In panel A the statistics are calculated over the 2,620 unique rating changes, and in panel B, as we distinghish by rating agency, the statistics are calculated over the 2,727 credit rating announcements. The sample includes 1,342 different bonds issued by 286 different issuers. The time period covered is July 2002 to March 2010.

	Mean	25th Percentile	Median	75th Percentile	Std. Dev.	Min	Max
Panel A. Bond Variables Summary Statistics							
Duration	3.444	1.363	2.602	4.393	2.938	0.003	15.065
Age (yrs)	5.005	2.175	3.838	7.176	3.874	0.096	20.058
Term to maturity (yrs)	4.683	1.408	2.826	5.211	5.540	0.003	39.279
Coupon	5.900	5.000	5.750	6.750	1.410	1.000	12.000
Issue size (million $)	0.344	0.071	0.168	0.337	0.803	0.002	10.850
Panel B. Bond Rating Summary Statistics							
Fitch Rating	7.995	5.000	8.000	10.000	3.239	2.000	21.000
Moody's Rating	9.222	5.000	9.000	12.000	4.629	1.000	21.000
S&P Rating	7.873	5.000	6.000	11.000	4.767	1.000	25.000

Table 4. Relative values of liquidity proxies. This table shows the ratio of the liquidity proxies during event window to their respective value in control window [-41,-21]. The time period covered is July 2002 to March 2010. Panel A includes 1,713 downgrade events that involves 1,050 different bonds issued by 223 different issuers. Panel B includes 907 upgrade events that involves 621 different bonds issued by 150 different issuers.

Panel A. Downgrades

		[-10, -6]	[-5, -1]	[0, 5]	[6, 10]	[11, 20]
Amivest	Average	1.02	0.96	1.09	1.08	1.03
	Median	0.44	0.44	0.50	0.46	0.62
Bao	Average	1.19	1.17	1.21	1.22	1.29
	Median	0.98	1.00	1.00	1.05	1.13
Imputed Roundtrip Cost (IRC)	Average	1.08	1.16	1.52	1.30	1.26
	Median	1.03	1.01	1.33	1.26	1.27
Price Dispersion (PD)	Average	1.07	1.16	1.47	1.26	1.27
	Median	0.95	0.98	1.24	1.14	1.24
Trading Volume (TV)	Average	0.97	1.07	1.47	1.10	0.98
	Median	0.57	0.58	0.78	0.68	0.88
Market Share (MS)	Average	0.96	1.03	1.41	1.12	0.96
	Median	0.58	0.57	0.81	0.75	0.87
Number of Trades (NT)	Average	1.06	1.14	1.26	1.07	1.01
	Median	1.02	1.09	1.27	1.16	1.13

Panel B. Upgrades

		[-10, -6]	[-5, -1]	[0, 5]	[6, 10]	[11, 20]
Amivest	Average	0.96	1.25	1.64	0.67	1.17
	Median	0.39	0.43	0.60	0.48	0.73
Bao	Average	0.99	0.95	0.88	0.87	0.80
	Median	0.94	0.96	0.88	0.91	0.92
Imputed Roundtrip Cost (IRC)	Average	0.96	0.92	0.92	0.85	0.85
	Median	0.96	0.90	1.00	0.92	0.92
Price Dispersion (PD)	Average	0.94	0.89	0.84	0.79	0.77
	Median	0.84	0.80	0.88	0.82	0.83
Trading Volume (TV)	Average	0.91	1.00	1.11	1.03	1.03
	Median	0.51	0.53	0.92	0.76	0.91
Market Share (MS)	Average	0.90	0.97	1.08	0.99	1.01
	Median	0.50	0.56	0.89	0.71	0.89
Number of Trades (NT)	Average	1.00	1.00	1.07	0.99	0.98
	Median	0.99	0.99	1.05	0.99	0.95

Table 5. Event study results for Downgrades. This table shows the results for the t-ratio and non-parametric tests, for the average abnormal liquidity ($ALL_{(t1,t2)}$) measured by the average of the difference between the logarithm for the liquidity measure in the event window and the logarithm for the liquidity measure in the control window for all measures except to IRC for which we compute ($ALL_{(t1,t2)}$) as the average of the difference between the liquidity measure in the event window and the liquidity measure in the control window. We present the results by group of liquidity proxies: price impact measures, market impact measures and trading frequency measures, shorted by different width window. The time period covered is July 2002 to March 2010, and the subsample is for 1,713 downgrade events, that involves 1,050 different bonds issued by 223 different issuers.. In parenthesis p-value. * Indicates significance at 10% or lower level.

Panel A: Price impact measures. H_0: Abnormal liquidity = 0					
Event Window	[-10,-6]	[-5,-1]	[0,5]	[6,10]	[11,20]
AAL-Amivest					
Mean	-0.737	-0.666	-0.426	-0.671	-0.332
t-ratio	-18.562*	-17.078*	-11.555*	-17.215*	-9.114*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Median	-0.732	-0.685	-0.446	-0.619	-0.329
Sign test	12.273*	11.984*	7.587*	10.956*	5.954*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rank test	14.274*	14.040*	9.347*	13.462*	7.171*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% >0	35.0%	35.5%	40.8%	36.6%	42.8%
AAL-Bao					
Mean	0.031	0.008	0.027	0.048	0.107
t-ratio	1.602	0.375	1.060	1.802*	3.745*
	(0.109)	(0.707)	(0.289)	(0.072)	(0.000)
Median	-0.008	-0.015	0.024	0.044	0.095
Sign test	0.444	0.594	0.698	0.974	2.986*
	(0.657)	(0.553)	(0.485)	(0.330)	(0.003)
Rank test	0.878	0.104	1.063	1.604	2.982*
	(0.380)	(0.917)	(0.288)	(0.109)	(0.003)
% >0	49.4%	49.2%	50.9%	51.2%	53.7%
AAL-IRC					
Mean	0.001	0.003	0.009	0.005	0.004
t-ratio	3.714*	8.223*	15.220*	11.236*	11.472*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Median	-0.001	0.000	0.002	0.001	0.001
Sign test	3.495*	1.185	6.018*	3.140*	4.456*
	(0.001)	(0.236)	(0.000)	(0.002)	(0.000)
Rank test	1.108	2.499*	10.534*	6.729*	8.243*
	(0.268)	(0.012)	(0.000)	(0.000)	(0.000)
% >0	45.6%	48.5%	57.3%	53.8%	55.4%
AAL-Price dispersion					
Mean	-0.083	-0.003	0.180	-0.022	0.144
t-ratio	-1.999*	-0.103	4.829*	-0.398	4.920*
	(0.046)	(0.918)	(0.000)	(0.691)	(0.000)
Median	0.015	0.048	0.188	0.159	0.144
Sign test	0.630	1.724*	7.054*	5.846*	5.520*
	(0.528)	(0.085)	(0.000)	(0.000)	(0.000)
Rank test	0.232	2.284*	8.782*	6.249*	6.910*
	(0.817)	(0.022)	(0.000)	(0.000)	(0.000)
% >0	50.9%	52.2%	58.8%	57.5%	56.9%

Table 5. Event study results for Downgrades (continued). This table shows the results for the t-ratio and non-parametric tests, for the average abnormal liquidity ($ALL_{(t1,t2)}$) measured by the average of the difference between the logarithm for the liquidity measure in the event window and the logarithm for the liquidity measure in the control window for all measures except to IRC for which we compute ($ALL_{(t1,t2)}$) as the average of the difference between the liquidity measure in the event window and the liquidity measure in the control window. We present the results by group of liquidity proxies: price impact measures, market impact measures and trading frequency measures, shorted by different width window. The time period covered is July 2002 to March 2010, and the subsample is for 1,713 downgrade events, that involves 1,050 different bonds issued by 223 different issuers.. In parenthesis p-value. * Indicates significance at 10% or lower level.

Panel B: Market impact measures. H_0: Abnormal liquidity = 0					
Event Window	[-10,-6]	[-5,-1]	[0,5]	[6,10]	[11,20]
AAL-Market Share					
Mean	-0.367	-0.253	0.102	-0.112	-0.034
t-ratio	-13.987*	-9.829*	3.928*	-4.155*	-1.431
	(0.000)	(0.000)	(0.000)	(0.000)	(0.152)
Median	-0.292	-0.188	0.154	-0.051	0.004
Sign test	8.400*	5.219*	4.107*	1.168	0.145
	(0.000)	(0.000)	(0.000)	(0.243)	(0.885)
Rank test	10.256*	7.235*	4.056*	2.005*	0.212
	(0.000)	(0.000)	(0.000)	(0.045)	(0.832)
% >0	39.7%	43.7%	55.0%	48.5%	50.2%
AAL-Traded volume					
Mean	-0.395	-0.272	0.019	-0.195	-0.061
t-ratio	-15.038*	-10.655*	0.713	-7.389*	-2.546*
	(0.000)	(0.000)	(0.476)	(0.000)	(0.011)
Median	-0.312	-0.205	0.050	-0.119	-0.014
Sign test	8.747*	6.862*	1.281	3.529*	0.339
	(0.000)	(0.000)	(0.200)	(0.000)	(0.735)
Rank test	11.106*	8.118*	1.055	4.630*	0.922
	(0.000)	(0.000)	(0.292)	(0.000)	(0.357)
% >0	39.2%	41.7%	51.5%	45.6%	49.6%
Panel C: Trading frequency measures. H_0: Abnormal liquidity = 0					
AAL-Number of trades					
Mean	-0.048	0.001	0.141	0.027	0.032
t-ratio	-4.164*	0.072	10.909*	2.158*	2.752*
	(0.000)	(0.943)	(0.000)	(0.031)	(0.006)
Median	-0.050	-0.018	0.128	0.020	0.034
Sign test	2.755*	1.215	7.123*	0.956	2.212*
	(0.006)	(0.224)	(0.000)	(0.339)	(0.027)
Rank test	4.092*	1.127	8.531*	1.495	2.573*
	(0.000)	(0.260)	(0.000)	(0.135)	(0.010)
% >0	45.9%	47.9%	58.0%	50.4%	52.3%

Table 6. Event study results for Upgrades. This table shows the results for the t-ratio and non-parametric tests, for the average abnormal liquidity ($ALL_{(t1,t2)}$) measured by the average of the difference between the logarithm for the liquidity measure in the event window and the logarithm for the liquidity measure in the control window window for all measures except to IRC for which we compute ($ALL_{(t1,t2)}$) as the average of the difference between the liquidity measure in the event window and the liquidity measure in the control window.. We present the results by group of liquidity proxies: price impact measures, market impact measures and trading frequency measures, shorted by different width window. The time period covered is July 2002 to March 2010, and the subsample is for 907 upgrade events that involves 621 different bonds issued by 150 different issuers. In parenthesis p-value. * Indicates significance at 10% or lower level.

Panel A: Price impact measures. H_0: Abnormal liquidity = 0					
Event Window	[-10, -6]	[-5, -1]	[0, 5]	[6, 10]	[11, 20]
AAL-Amivest					
Mean	-0.766	-0.699	-0.419	-0.807	-0.282
t-ratio	-18.719*	-17.432*	-10.781*	-20.015*	-7.472*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Median	-0.716	-0.601	-0.414	-0.750	-0.211
Sign test	8.653*	7.637*	4.914*	9.254*	2.433*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.015)
Rank test	10.336*	9.611*	6.153*	11.134*	4.008*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% >0	35.5%	37.3%	41.8%	34.5%	45.9%
AAL-Bao					
Mean	-0.019	-0.025	-0.078	-0.070	-0.115
t-ratio	-0.905	-1.043	-2.979*	-2.631*	-4.050*
	(0.365)	(0.297)	(0.003)	(0.009)	(0.000)
Median	-0.010	-0.027	-0.099	-0.086	-0.122
Sign test	0.674	0.338	2.294*	1.550	1.989*
	(0.500)	(0.736)	(0.022)	(0.121)	(0.047)
Rank test	0.615	0.817	2.293*	2.076*	2.556*
	(0.539)	(0.414)	(0.022)	(0.038)	(0.011)
% >0	48.8%	49.4%	46.1%	47.3%	46.6%
AAL-IRC					
Mean	0.000	-0.001	-0.001	-0.001	-0.001
t-ratio	-2.791*	-4.871*	-4.603*	-8.157*	-8.511*
	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)
Median	-0.001	-0.001	0.000	-0.001	-0.001
Sign test	4.515*	4.787*	2.628*	5.652*	4.407*
	(0.000)	(0.000)	(0.009)	(0.000)	(0.000)
Rank test	3.880*	4.278*	2.339*	5.074*	4.729*
	(0.000)	(0.000)	(0.019)	(0.000)	(0.000)
% >0	42.3%	41.9%	45.4%	40.4%	42.4%
AAL-Price dispersion					
Mean	-0.103	-0.204	-0.180	-0.225	-0.274
t-ratio	-2.647*	-4.371*	-4.422*	-4.304*	-5.842*
	(0.008)	(0.000)	(0.000)	(0.000)	(0.000)
Median	-0.084	-0.110	-0.129	-0.092	-0.141
Sign test	3.073*	2.397*	4.064*	2.634*	4.340*
	(0.002)	(0.017)	(0.000)	(0.008)	(0.000)
Rank test	2.860*	3.110*	4.147*	2.999*	5.229*
	(0.004)	(0.002)	(0.000)	(0.003)	(0.000)
% >0	44.4%	45.7%	42.9%	45.2%	42.5%

Table 6. Event study results for Upgrades (continued). This table shows the results for the t-ratio and non-parametric tests, for the average abnormal liquidity ($ALL_{(t1,t2)}$) measured by the average of the difference between the logarithm for the liquidity measure in the event window and the logarithm for the liquidity measure in the control window window for all measures except to IRC for which we compute ($ALL_{(t1,t2)}$) as the average of the difference between the liquidity measure in the event window and the liquidity measure in the control window.. We present the results by group of liquidity proxies: price impact measures, market impact measures and trading frequency measures, shorted by different width window. The time period covered is July 2002 to March 2010, and the subsample is for 907 upgrade events that involves 621 different bonds issued by 150 different issuers. In parenthesis p-value. * Indicates significance at 10% or lower level.

Panel B: Market impact measures. H_0: Abnormal liquidity = 0					
Event Window	[-10, -6]	[-5, -1]	[0, 5]	[6, 10]	[11, 20]
AAL-Market Share					
Mean	-0.505	-0.381	-0.170	-0.405	-0.144
t-ratio	-18.762*	-14.451*	-6.780*	-14.594*	-6.422*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Median	-0.377	-0.231	-0.120	-0.294	-0.101
Sign test	8.051*	4.184*	2.723*	5.676*	2.998*
	(0.000)	(0.000)	(0.007)	(0.000)	(0.003)
Rank test	9.896*	7.115*	3.662*	7.672*	3.248*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
% >0	36.5%	43.0%	45.4%	40.5%	45.0%
AAL-Traded volume					
Mean	-0.472	-0.407	-0.131	-0.371	-0.173
t-ratio	-17.551*	-15.594*	-5.347*	-13.245*	-7.768*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Median	-0.333	-0.267	-0.109	-0.247	-0.115
Sign test	7.249*	5.977*	2.391*	5.676*	3.900*
	(0.000)	(0.000)	(0.017)	(0.000)	(0.000)
Rank test	9.192*	8.121*	2.708*	6.887*	4.136*
	(0.000)	(0.000)	(0.007)	(0.000)	(0.000)
% >0	37.8%	40.0%	46.0%	40.5%	43.4%
Panel C: Trading frequency measures. H_0: Abnormal liquidity = 0					
AAL-Number of trades					
Mean	-0.035	-0.044	0.016	-0.056	-0.045
t-ratio	-4.080*	-5.183*	1.945*	-6.147*	-5.799*
	(0.000)	(0.000)	(0.052)	(0.000)	(0.000)
Median	-0.039	-0.057	-0.022	-0.033	-0.049
Sign test	2.596*	2.802*	0.801	2.052*	3.369*
	(0.009)	(0.005)	(0.423)	(0.040)	(0.001)
Rank test	2.686*	3.661*	0.118	3.705*	3.437*
	(0.007)	(0.000)	(0.906)	(0.000)	(0.001)
% >0	44.8%	44.9%	48.1%	45.8%	43.3%