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 there is a credit rating changes from one main credit rating category to another involving implications on capital requirements for most institutional investors or on bond holding restrictions. We show that: (1) market anticipates rating changes since trading activity slows down days before the event, (2) there is a price pressure and high trading volume during two weeks after, but trading frequency is below normal values, (3) price converges to the fundamentals values and the level of trading activity clearly rise during the second fortnight, (4) among other characteristics of the rating change, the migration between investment- and speculative-grade categories involves further liquidity shocks.

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 agencies (CRA) 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 CRA 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).

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 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 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 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.

In this paper we analyze if liquidity shocks occur in the market for US corporate bonds after credit rating changes and what factors determine the liquidity behavior around the event. Previous studies provide evidence of price impact during long periods after downgrades and weak results about liquidity shocks from a dataset restricted to insurance companies' transactions. Using a large sample of 8,630 rating changes, we investigate bond liquidity behavior around rating change announcements in the whole corporate bond market. Different faces of the liquidity concept are considered. We consider the price impact, proxied by the Amivest measure, and the trading activity, proxied by two variables depending of the trading volume and other two variables depending of the trading frequency.

We consider four different hypotheses to explain the possible impact of the announcement on liquidity. The information content hypothesis assumes that CRA announcements 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 capital requirement hypothesis considers that not only fallen angel downgrades involve regulatory constraints. Additionally risk-based capital regulations force 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 ratings by 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 BBB-, 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.

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. Bond 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 observe price overreaction after downgrades. Second, there is a price pressure and abnormal high trading volumes with low trading frequency during the first fortnight after the downgrades. This invertor 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 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 and trading volumes only increases over the normal levels from two weeks after the event. Trading frequency maintains below normal levels during all the period around the upgrade.

The cross sectional analysis show that the main impact is caused by rating changes that imply the bond becomes a fallen angel or a rising star. Other factors that explain the liquidity behavior around the event are the prior rating, the fact of belonging to the speculative-grade, a large jump in number of categories, a simultaneous rating change, or a second-mover change. No evidence of the impact of rating changes that imply a break of the rating trend, or the economic environment is obtained.

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. 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

[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".

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 (Da and Gao, 2009).

Second, we analyze an extensive 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 5.5 million trades involving 4,106 straight bonds from 526 different issuers that are affected by 8,630 rating changes over the period July 2002– March 2010. 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 analyze popular liquidity proxies used in recent papers. 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. Among others, this is the case of the Amivest liquidity ratio (Cooper *et al.,* 1985), the Amihud (2002) price impact of a trade per unit traded, the Dick-Nielsen *et al.* (2012) Imputed Roundtrip Cost (IRC), or 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 measure together with other traditional trading activity proxies. We include two proxies of the trading volume, the market share and the turnover, and two proxies of the trading frequency, the number of trades, the number of trading days.

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, and Section 6 presents a cross sectional analysis of the determinants of liquidity impacts. Finally, Section 7 concludes.

2. The expected effect of rating actions

In the liquidity literature, the market microstructure models indicate that trading activity responses to a 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 credit rating agency. Agencies assign an initial rating to new issues on the basis of the solvency of the issuing firms and other related industry and macroeconomic factors. Subsequently, agencies reevaluate corporate bonds, as some of these relevant conditions change. When the rating is solicited, the issuers pay a fee to be rated since credit rating are a compulsory entry condition in the market. Issuing non-rated corporate bonds is virtually impossible. Ratings 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 rating change announcements. They establish the expected behavior of re-rated firm 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 four possible hypotheses: the information released by the CRA, fire sales from downgrades to speculative grade, capital requirements and reputation. The main hypothesis concerning rating change effects states that CRA 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 rating 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. They observe that CRAs 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, CRAs 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 rating 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, and the effects on the debt market may be 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 that are 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 than other downgrades and greater liquidity effect.

Recent papers observe price pressure and limited liquidity shock in the case of insurance companies as consequence of a 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.

A third hypothesis is the capital requirement hypothesis. As the previous hypothesis, it involves regulatory constraints but there are two main differences between them. It does not imply forced selling and it is not restricted to jumps from investment- to speculative-grade ratings. The Basel Committee on Banking Supervision proposes capital requirements associated with credit risk. The three approaches, i.e. the standardized approach, and the foundation 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 product of the amount of exposures and supervisory determined risk weights. These risk 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 in the standardized approach, the risk weights are 20% (AAA to AA-), 50% (A+ to A-), 100% (BBB+ to BBB-, and unrated), and 150% (below BB-). In the 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 approaches, the credit rating determines the probability of default, the loss given default variables, and the credit correlation. This parameter ρ, 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 immediate 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.

3. 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 contains 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 428,000 CRA announcements reported by FISD. From the both data sets, we match announcements with bond transactions which meet two 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, 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 5.5 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 2,636 CRA events involving o1,345 bonds from 286 issuers, and with nearly 4.8 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 2,636 rating changes, 915 are upgrades and 1,721 downgrades. Table 3 shows summary statistics for final sample.

[INSERT TABLES 1, 2 AND 3 ABOUT HERE]

4. Proxies of liquidity

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 accessibility of a security by dealers (Mahanti *et al.*, 2008).

Among other traditionally suggested proxies are: 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).

As proxies of trading activity, we consider both the Market Share and the Turnover. Market share has been used, among others, by Goldreich *et al.* (2005) and Diaz *et al.* (2006). The measure is the ratio of the trading volume of a bond during a day over total trading volume in the whole market including any transaction involving any outstanding issue, (see the Appendix for mathematical details). Meanwhile, Turnover is the ratio of bond traded volume on day over the amount outstanding of that bond. Turnover has been used in

[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.

previous research in corporate debt by among others Dick-Nielsen *et al.* (2012). Both measures are computed by day.

The frequency measures that we use are the Total Days Traded (TDT) and the Total Number of Trades (TNT), both used among others by Nashikkar *et al.* (2011) or Fleming (2001). TDT is computed as the number of days which the bond has trading activity, while TNT is a bond number of trades in a particular day. We calculate the TDT measure by event window and the TNT in a day-by-day basis.[5]

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. This is the case of Roll (1984) and Bao *et al.* (2011) measures to quantify transaction costs. 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. However, these measures required computing the price serial covariance and this is only possible for extremely liquid corporate bonds.[6]

Some of the recently proposed liquidity proxies for debt markets are price impact measures. 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. The Bao, Pan and Wang (2011) illiquidity measure is the negative covariance between the price change from a time and the price change from the previous period. 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. Among others, Cooper *et al.* (1985) and Amihud *et al.* (1997) propose the Amivest measure as a measure of price impact as far as it seems to be a good indicator of market depth.

We consider the Amivest Liquidity ratio (1985) as a measure of the price impact. A 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. It is computed as average of the daily ratio of trading volume and absolute return. It is only computed for bonds with nonzero returns.

5. Effects of rating change announcements

To analyze the effects of rating change announcements, we carried out an event study. This consists of examining abnormal liquidity around the date of the rating change announcement, that we define as day $t = 0$.[7] We compute the observed liquidity in a specific "event window", from day $t = t_1$ to day $t = t_2$ around the announcement date $OL_{i,(t_1,t_2)}$. We study different event windows to better understand the impact of the rating announcement. To analyze the behavior of abnormal liquidity before and after the release date, we use different width windows; three post-announcement windows, [1,5], [1,10], [1,20], to analyze the duration of the rating announcement impact; and two pre-announcement windows, [-5,-1], [-10,-1], to detect if market participants anticipate the rating information in days before the rating change announcement take place.

[5] 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).

[6] In general, a typical stock is traded several times per minute, a typical government bond is traded several times per day, and a typical off-the-run corporate bond is traded several times per year.

[7] In case the announcement takes place on a holiday day, we consider t=0 to be the next business day.

To calculate abnormal liquidity, we must define a benchmark to measure the expected liquidity of bond *i* (EL_i). Instead of create a sample of bonds that exactly matches the characteristics of bonds in our sample, we use historical data for each bond. We compute the expected liquidity for bond *i* two months prior to the rating change announcement, from day t=-40 to day t=-20. We refer to this period as the "control window". The bond *i* abnormal liquidity in a specific event window (t_1, t_2), $AL_{(t_1,t_2)}$, is obtained as the logarithm difference between observed liquidity, $OL_{i(t_1,t_2)}$ in that window and the expected liquidity, EL_i:

$$AL_{(t_1,t_2)} = \log\left(OL_{i(t_1,t_2)}\right) - \log(EL_i) \tag{1}$$

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

$$AAL_{(t_1,t_2)} = \frac{1}{N}\sum_{i=1}^{N} AL_{i(t_1,t_2)} \tag{2}$$

where N is the number of rating changes in the sample. 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 statistic. 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 consider the impact on liquidity from deteriorations in credit quality (Table 5) and the impact on liquidity due to an improvement in credit quality (Table 6). We present results for the three groups of liquidity measures in each table: price impact measures, market impact measures and trading frequency measures, both for upgrades and downgrades. In Panel A we present the results for the price impact measure Amivest; in Panel B we show the market impact Market Share and Turnover measures; meanwhile in Panel C we display the trading frequency measures Total Days Traded and Total Number of Trades. For each kind of measures 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.

[INSERT TABLES 5 AND 6 ABOUT HERE]

5.1. Results for downgrades

Table 5 presents results for downgrades for the three groups of liquidity proxies. Regarding to price impact Amivest measure (Panel A), the mean abnormal liquidity estimated is negative in the entire pre- and post-announcement day event. The t-ratio indicates statistically significant decreases in this liquidity proxy related to the announcement of downgrades in the prior days to a rating change announcement, and during the two weeks after the announcement. This result is robust with the analysis method that we use (abnormal liquidity in mean and median, and parametric and non-parametric tests). The effect is not significant in the case of the larger post-event window, indicating that the effect disappears after three weeks. Results for the median are similar. The estimated median is negative in all event windows and the two non-parametric tests generally rejects the null hypothesis of abnormal liquidity equal to zero, except to the [1,20] window.

Panel B shows the market impact measures. The two considered measures, Market Share and Turnover show a decrease in abnormal liquidity in previous days to the downgrade announcement day, while these measures are positive and significant in the post-announcement windows. In this case, the two non-parametric tests generally rejects the null hypothesis of abnormal liquidity equal to zero, except to the [1,5] window. This result is robust with the test we use.

Finally, Panel C Table 5 displays the results for the trading frequency measures Total Days Traded (TDT) and Total Number of Trades (TNT). In this case, it also seems to be a decrease in liquidity two weeks before the rating change announcement, followed by an increase in liquidity in the [1,20] window. Those results are also robust to the tests used.

From these results we can highlight three clear patterns around a downgrade. During the days previous the announcement, we observe an abnormally low liquidity in the market. The two considered dimensions of the trading activity, i.e. the trading frequency and the trading volume, show unusual low levels. Also results for the price impact proxy are similar. The Amivest measure is computed as the ratio between trading volume and return in absolute terms. Thus, we hypothesize that the lesser than normal value of this ratio does not show a price impact but it is conditioned by the lower trading volume. Anyway, everything points to a decline in liquidity.

During the two weeks after the announcement, i.e. [1,5] and [1,10] windows, results suggest an increase in the "normal" volume traded by the downgraded bond that is triggered by the rating event. From this result, the interpretation of the statistically significant negative sign of the Amivest measure change completely. Only an extreme reaction on returns (denominator) originated by the downward correction on prices could compensate the rise in the trading volume (numerator). It shows a clear price reaction after the announcement. However, the trading frequency maintains abnormal low levels.

In the case of considering the whole month after the downgrade, i.e. [1,20] windows, results imply a new pattern in the market that completely change behavior in the first fortnight. As abnormal Amivest is not statistically significant, price pressure decreases but the trading volume (numerator) is still higher than normal. In the last two weeks of the month after the event is when the trading frequency clearly rises.

From these three clear patterns, we can summarize some conclusions. First, it seems that the market anticipates the rating announcement during the two weeks previous the event. In this period, the trading activity slows waiting to know exactly the magnitude of the rating migration. Second, there is a considerable price pressure accompanied by an increase in trading volume during the two weeks after the downgrade. This result is partially consistent with literature that suggests forced selling induced by regulatory constraints which implies prices below fundamental values. However, we do not observe the expected massive sales since the trading frequency maintains in levels below the normal ones. Third, the trading activity measured by the number of transactions clearly increases in the second fortnight of the month after the announcement. The price pressure diminishes and the trading volumes and the 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.

5.2. Results for Upgrades

Table 6 presents the results for upgrades. Panel A shows the effects in liquidity measured by the price impact measure Amivest, due to a rating change. The mean and median abnormal liquidities are negative and significant in all event windows, except in the window [1,20]. Parametric and non-parametric tests indicate that mean and median liquidity decreases around the announcement day, both the two pre-event weeks and the two post-event weeks. The effect for longer term seems to be positive, since we found an increase in liquidity in the fourth week post-event window [1,20] after the upgrade in rating announcement. So the impact in liquidity of an upgrade announcement persists for several days (a month) after the announcement.

Panel B shows the results for the market impact. According to the results, the abnormal liquidity behavior is the same as the abnormal liquidity measured by Amivest. Either Market Share or Turnover presents the same results in all the different width windows. Furthermore, in those cases the results are robust to the tests used. Likewise in Panel A, the two non-parametric tests generally rejects the null hypothesis of abnormal liquidity equal to zero, except to the post-event windows [1,10] and [1,20].

And finally, Panel C table 6 displays the results for the trading frequency measures Total Days Traded (TDT) and Total Number of Trades (TNT), where we find a decrease in the abnormal liquidity in every analyzed width window. Even in the most width window, we do not find rises in liquidity.

Summarizing results for five liquidity proxies, the evidence indicates that there are price impacts in liquidity related to rating change announcements, regardless to the kind of change (downgrade or upgrade). Besides we find that the impact is asymmetric, because there are a few differences among upgrades and downgrades. Both changes we observe a decrease in liquidity two weeks before the announcement day, so that would indicate that markets are expected to rating changes. The long term effect is positive on both cases. However, for rating improvements there is a decrease in liquidity immediately after the announcement, and the rise in liquidity only occurs after several weeks. In the case of downgrades, we find an increase in liquidity that occurs immediately after the announcement and that persists some weeks after the change, although the moment depends on the liquidity measure analyzed.

These results indicate that downgrades contain relevant information for market participants and the effects are anticipated by the market and persist after the announcement. Overall, our findings indicate that both types of rating changes cause a significant increase in liquidity. In accordance with the informative content hypothesis, the evidence reveals that both types of announcements contain relevant information about issuer solvency that is important for market investors. This evidence is similar to that found by Abad *et al*. (2011, 2012), who find an increase of liquidity around positive and negative rating events in the Spanish corporate bond market.

We also find certain degree of asymmetry on the effect. Whereas changes in both directions increase liquidity, the impact is weaker for upgrades. 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.

6. Cross sectional analysis

We expect to find stronger reactions of abnormal liquidity in the case of events that provide more information to the market. Different characteristics of the rating event, the agency, the issuer and the economic environment could contain relevant information to explain liquidity responses to rating changes.

First, we analyze whether there is an agency-specific effect on the liquidity response to rating actions or not. Some authors as Livingston, Wei, and Zhou (2010) find that the impact of Moody's ratings on market reactions is stronger compared to Standard & Poor's. Conversely, Morgan (2002) analyzes split ratings and finds Moody's was more likely to take the more conservative side of the split compared to S&P. Grande and Parsley (2005) and Norden and Weber (2004) find that S&P tends to provide the earliest and the most thorough market assessment. Finaly, Guettler and Wahrenburg (2007) find that bond ratings by Moody's and Standard & Poor's are highly correlated, pointing to no differences among agencies. In our sample, Moody's is responsible for 966 of the rating actions. Consequently, to test this hypothesis we include an indicator variable to distinguish between S&P and the other two agencies.

Jorion and Zang (2007) indicate that the prior rating is the most important factor in explaining the stock returns reaction after downgrades. Institutional investors are constrained by clauses that force them to make decisions based on the observed rating. These forced trades could influence the effects caused by rating changes even though these changes contain no new information. In this context, we expect that the liquidity reaction to rating actions would depend on the prior rating level. Additionally, institutional investors will concentrate on the investment-grade market segment, causing this grade to be more active than the speculative-grade. This effect can lead to a lower impact of rating events on speculative-grade firms than investment-grade firms. These institutional rigidities can also result in stronger liquidity reactions to rating changes that cross the investment-grade frontier.

The size of the rating change, i.e. the number of notches, must be also important to determine abnormal liquidity. We hypothesize that the number of notches downgraded (or upgraded) acts as a signal of the amount of information that this rating change conveys. Large rating changes will be more informative, causing higher impacts on abnormal liquidity.

There are other factors that may affect the change in liquidity due to rating changes. Some of them are related to the fact that several agencies rate the bonds of the same company (multirating company).[8] Sometimes, different agencies give different initial rating to a company issues. Besides, they do not change the assigned rating at the same time. These splits could be related to differences in methodology or to the importance that each agency gives to relevant variables or particular matters (Cantor and Packet, 1997). That is why the information that contains a rating change will be different depending on whether the change represents a unanimous decision on the default risk. That is, whether the rating change is announced simultaneously by different agencies or whether the agencies disagree announcing a rating change only one of them. It could be expected that agreements among agencies about the solvency of a firm may cut the level of asymmetric information in the market, causing higher liquidity around simultaneous rating announcements.[9]

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[8] Cantor and Packer (1997), Bongaerts *et al.* (2012), or Peña-Cerezo *et al.* (2013), study different aspects of multirating.

[9] We consider two different kinds of consensus rating actions. First we define simultaneous rating change as those by more than one agency in the same direction and date as, and Second-mover change as those by one agency that follow a rating change in the same direction by another agency in the preceding 3 months.

In the same way, it is likely that the market does not immediately detect when a company's solvency begins to change. If a continuous decrease (improvement) in solvency happens, agencies will carry out a series of successive downgrade (upgrade) announcements regarding the rating of the issuer's debt. In this situation, it is expected that the informational content of each successive rating action will be lower than the previous one. As such, our hypothesis is that events included in an issuer's solvency trend would cause lower levels of abnormal liquidity than those that indicate a break of the rating trend.

The economic environment may be relevant to explain the liquidity responses to rating changes. The sample period we analyze covers the recent economic recession, which originated by the collapse of the housing bubble in the middle 2007. This period has been characterized by a more uncertain informational environment and high levels of volatility. Several authors find significant differences in rating action effects due to different financial crisis. For example, Jorion *et al.* (2005) find less negative effects of downgrades on stock returns during the 2001 stock market crisis, and May (2010) finds a more negative reaction to downgrades in the US corporate bond market after 2007. We expect this increased uncertainty after the crisis began to cause higher levels of informational asymmetries, leading to lower liquidity responses to rating actions. Another important effect of the financial turmoil is the loss credibility of rating agencies decisions due to their central role in the sub-prime mortgage crisis or their failure to predict the Lehman Brothers default in 2008.[10] This loss of reputation should undermine the reliability of rating actions after the crisis, thereby causing lower liquidity response to rating actions after the crisis.

To test these hypotheses, we run a regression of the abnormal liquidity against a set of dummy variables that take value 1 (or 0), depending on whether the rating announcements involve S&P's decision, issues in speculative-grade prior the change, a large size change, crossing of the investment/speculative barrier,[11] a simultaneous rating change, a second-mover change,[12] a break in the rating trend,[13] or a change after September 2007. We also include a variable coded from 1 to 26 to measure the rating prior the event, being 1 the best category (AAA/Aaa), 2 the second best (AA+/Aa1), etc. We include in each regression as control variables the natural log of the bond age at the announcement date, the log of the offering amount and their illiquidity level prior the rating change measured as the number of days with zero returns four weeks before the announcement. Finally, we include dummy variables for firms in the industrial or financial industries and for multirated firms.

<u>Market reaction</u>

To analyze the determinants of the reaction of liquidity, we study abnormal liquidity computed by the five liquidity measures before the event, i.e., in the [1, 20] post-event window. We estimate the regression parameters by OLS and compute standard errors by using the White heteroskedasticity-consistent covariance matrix. We consider 10% or lower significance level for the tests.

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10 See Crouchy et al. (2008) for an analysis of the role played by rating agencies in the subprime mortgage crisis.

11 As is usual in the literature, we call Falling Angels to those firms that a rating change makes them falling in the speculative grade from the investment grade, and Rising Stars to the opposite movement.

12 We consider that a second mover occurs after a downgrade from other agency three months before.

13 We define Rating trend changes as those preceded by three rating announcements in the same direction over the past 12 months. Break rating trend changes are those preceded by three rating announcements in the opposite direction over the past 12 months.

Table 7 shows the results for the impact of rating changes in liquidity during four weeks after the change rating announcement. Panel A display the results after downgrades and Panel B after upgrades.

[INSERT TABLE 7 ABOUT HERE]

In first place, we analyze the event study results in the case of downgrades (Table 7, Panel A). In previous section, we observe that trading volume and frequency are higher than normal during the month after the change rating announcement, i.e. [1,20] window. Amivest measure shows abnormally low levels during the first fortnight, showing a clear price pressure, but it maintains a normal level if the full month period is considered.

Prior rating variable has a statistically significant impact in the behavior of four liquidity proxies after the announcement. Since we define each rating category as an integer that increases in value as the credit quality worsens, the worse the initial rating, the larger the increase in liquidity after a downgrade. This result is consistent with results reported by Joriong and Zang (2007). This effect is mitigated in the case of speculative debt. For these bonds, downgrades cause lower liquidity than normal regardless of the liquidity measure used. This result is according with the null hypothesis. The impact in liquidity is stronger for investment grade debt, which shows that this sector of the market is more active and then the rise in liquidity is higher after a downgrade. According to the regulation constraints' hypothesis, we can also see that downgrades going through the investment/speculative threshold appear to be related with a greater rise in liquidity that we find in four measures. Regarding with the jump size, we can see that when downgrades involve large drops in rating, the liquidity answer is higher. It seems that, as we expect, the information contained is higher when the jump is important in terms of size, although we can only see this answer in the case of the trading frequency measures total days traded (TDT) and total number of trades (TNT).

When we analyze the features of the agency that announces a downgrade event, there are scarce differences in the impact on liquidity of downgrades released by S&P respect to the announced by the other agencies. We only observe a stronger positive impact on abnormal liquidity measured by TNT after S&P announcements. On the other hand, we observe a positive response of abnormal liquidity with simultaneous downgrade announcements from different agencies. That is the case of trading volume measures (MS and TN) and TNT, whose values indicate a large increase in liquidity after a simultaneous announcement. This result indicates that simultaneous rating changes from different agencies contain more information. In the case of downgrades preceded by a downgrade from other agency during the three previous months (second mover), we observe a significant increase in trading volumes together with a decrease in trading frequency. Contrary to the initial hypothesis, we do not observe effects of downgrades that break a positive rating trend.

Otherwise, it seems that the beginning of the crisis do not affect the abnormal liquidity that causes a downgrade, except for a greater impact of the downgrade announced after September 2007, when liquidity is measured as the number of days on which the bond is traded. Respect to other control variables like age, prior liquidity and issue size, a downgrade has an isolate effect in liquidity in the case of financial issuers and multirating companies.

In second place, we analyze the event study results in the case of upgrades for the post-event [1,20] window (Table 7, Panel B). In the previous event study analysis we observe a decrease in all the analyzed liquidity proxies during the first two weeks after the upgrade announcement. Results for the one-month length window show a relevant increment of trading volume and Amivest meanwhile trading frequency maintains lower levels than normal.

In this case, prior rating is very important in order to explain the liquidity behavior after an upgrade, although its sign is the opposite than for downgrades. The worse the initial rating (higher values for prior rating variable) the lower the liquidity increment. This result is according with institutional investor's behavior just because they are more involved in the case of credit quality deteriorations. In this case we can also see differences in bonds starting on speculative level, but due only in trading measures. The effect that we observe indicates that there is a stronger liquidity impact when it leads with speculative debt, though given the prior rating level effect; this increase is smaller as prior rating worsens. Respect to rising stars, i.e. those bonds jumping to investment grade after an upgrade, a further increase in liquidity after the announcement reflected on all measures occurs, except Amivest (AV). This finding suggests that the activity around these bonds increases, which may be related to the fact that those bonds belongs to the set of eligible bonds by institutional investors. The same seems to occur when the improved rating is large because we can see a positive and significant effect of the jump size over abnormal liquidity always with two measures, TN and TDT.

Regarding to the agency, we do not see significant differences between S&P and other agencies in the case of upgrades. Neither seems to be relevant that several agencies announce a rating improve simultaneously. Conversely, a second mover upgrade announcement appears to provide less information to the market, because the response of liquidity is lower in this case. This suggests that the effect on liquidity of an upgrade is higher in the first announcement and smaller in the second, while the effect of the second announcement is higher in case of a downgrade. Those effects are detected by four liquidity measures. The response to changes that break the trend is also different between upgrades and downgrades. For the latter, this factor does not seem to be relevant, while for upgrades it has a positive and significant effect for three measures. This outcome would indicate that a rating improve following a downtrend contains more new information than other upgrades, so that the increase in liquidity is higher.

Finally, upgrade announcements after the current crisis beginning lead to a large increase in liquidity, though we can only detect it in two liquidity measures. Respecting to control variables effect, the findings are similar as for downgrades. The bond's age, the prior illiquidity, the issue size and the multirating company variables varies in some cases the intensity of the effect on liquidity.

Market anticipation

The information content of rating actions is sometimes anticipated by the market. Covitz and Harrison (2003) show that a moral hazard risk problem may arise because ratings users are investors but agency income comes from rated firms. This fact might lead agencies to favor issuers by delaying the announcement of a downgrade, thus providing the issuer time to react. The period needed by agencies could be longer in the case of large improvements due to the loss of reputation in the event of the bankruptcy of a highly rated business.[14] In any case, the delay of the agency in announcing the new rating could be greater when firms suffer a large change in their default risk than when this change is small, increasing the probability that market participants anticipate the information.

[14] Recall the default of Enron in 2001 or that of Lehman Brothers in 2008 for example.

In previous section, we observe signals of anticipation in the liquidity behavior one week before the rating change. All the considered liquidity proxies show values lower than the normal ones. We interpret this result as market dries since it is waiting for an upcoming event. Table 8 shows the analysis of which factors contribute to this anticipation during the [-5,-1] pre-event window. Panel A displays the results before downgrades and Panel B before upgrades.

[INSERT TABLE 8 ABOUT HERE]

In Table 8 Panel A we observe that only the big jumps and S&P downgrades imply liquidity improvements in a period of abnormal low liquidity. The uncertainty regarding the scope of the event seems not to depend on most of the different characteristics of the rating change. Thus the market anticipates the proximity of the downgrade and the level of trading activity decreases regardless of the kind of downgrade. Only a significant deterioration in the creditworthiness that leads to a fall in bond's rating several notches is able to increase liquidity.

Respect to upgrades, the intensity of the effect on abnormal liquidity the week before the announcement varies respect to a wide range of features (see Table 8 Panel B). Regarding to features related with change, the prior rating level and the speculative status are relevant variables. Specifically, the worse rating the higher anticipated decrease in abnormal liquidity, but if it deals with speculative debt, the decrease in liquidity before the announcement is smooth. Finally, big jumps themselves are previously discounted by the market; the greater the big jump is, the larger the decrease in liquidity before the announcement is.

In the case of agency features, S&P announcements are dealing with a greater decrease in liquidity before an upgrade, suggesting that investors interpret in a different way the information from the different agencies. When Moody's or Fitch are going to upgrade some debt, market participants anticipate the movement causing a less pronounced decrease in liquidity than when it is S&P. We see that although there were a simultaneous upgrade by several agencies, liquidity before the announcement does not change, except to the positive response in case of Amivest. When it is a second mover announcement, there is a smooth drop in volatility in the prior window.

Finally, differences in the improvements related to the onset crisis impacts were detected. In this case, the decrease in liquidity before the announcement is more pronounced than in the previous time.

The results presented are in agreement with Covitz and Harrison (2003), since more differential effects on upgrades are anticipated. This is so probably because the agencies need more time in the case of large improvements due to the loss of reputation in the event of the bankruptcy of a highly rated business; and when the jumps are big, because the delay of the agency in announcing the new rating could be greater when firms suffer a large change in their default risk than when this change is small, increasing the probability that market.

7. Conclusions

This paper examines if liquidity shocks occur in the market for US corporate bonds after credit rating changes and what factors determine the liquidity behavior around the event. Using a large sample of nearly 5.5 million trades involving 4,106 straight bonds from 526 different issuers that are affected by 8,630 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 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. Bond 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 observe price overreaction after downgrades. Second, there is a price pressure and abnormal high trading volumes with low trading frequency during the first fortnight after the downgrades. This invertor 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 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 and trading volumes only increases over the normal levels from two weeks after the event. Trading frequency maintains below normal levels during all the period around the upgrade.

The cross sectional analysis show that the main impact is caused by rating changes that imply the bond becomes a fallen angel or a rising star. Other factors that explain the liquidity behavior around the event are the prior rating, the fact of belonging to the speculative-grade, a large jump in number of categories, a simultaneous rating change, or a second-mover change. No evidence of the impact of rating changes that imply a break of the rating trend, or the economic environment is obtained.

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Appendix

In the appendix we describe in detail each one of the liquidity measures computed that we use in this work.

A.1. Amivest

$$Amivest_{i,t} = \frac{1}{D_{i,t}} \cdot \sum_{j=1}^{Di,t} \frac{TV_{i,j}}{\left| r_{i,j} \right|}$$

The Amivest Liquidity ratio (1985) is the average of daily ratio of trading volume to absolute return. 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 bond where $D_{i,t}$ is the number of days in which the bond *i* is traded in the last week (five working days) from the day *t*; $TV_{i,t}$ is the trading volume for bond *i* on day *t*; and $|r_{i,t}|$ is the absolute return of bond *i* on day *t*.

A.2. Bond Zero-Trading Days:

$$BondZero_i = \frac{db_i}{D} \cdot 100$$

This measure represents the percentage of days where the bond *i* doesn't trade into the window. db_i is the number of days where the bond does not trade respect to *D* that is the total number of laborer days into the event window or into the control window. Bond zero-trading days is similar to other liquidity proxies measures based on number of traded days, such as Zeros used among others by Lesmond *et al.* (1999), Zero return, used by Friewald *et al.* (2012), among others, or Zeros2, used by Goyenko *et al.* (2009). All of them are used as trading activity measures, and the use of each one depends primarily on the availability data.

A.3. 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*.

A.4. Total Days Traded

$$TDT_{i,t} = \sum_{j=1}^{n} d_j$$

Total Days Traded (TDT) is the number of trading days for bond *i* into a specific window *t*, where d_j is a trading day for bond *i* in window *t*.

A.5. Total Number of Trades

$$TNT_{i,t} = \sum_{j=1}^{n} t_j$$

Total Number of Trades (TNT) is the number of trades for bond *i* in day *t*, where t_j is a trade for bond *i* in day *t*.

A.6. Turnover:

$$Turnover_{i,t} = \frac{TTV_{i,t}}{AmOt_i}$$

Where $TTV_{i,t}$ is the total traded volumen of bond *i* on day t and $AmOt_i$ is the amount outstanding of bond *i*.

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	133,270
2003	3,026,807	2,167,348	727,040	553,113	463,633
2004	3,476,809	2,508,118	825,289	633,392	551,939
2005	6,191,729	4,328,809	1,245,287	966,317	861,054
2006	5,503,111	3,776,245	1,007,504	815,979	743,081
2007	5,101,009	3,398,844	820,050	681,241	639,494
2008	6,693,708	4,175,458	1,103,568	841,634	813,579
2009	11,326,563	6,820,586	1,684,292	1,089,355	1,045,679
2010 (Jun-Mar)	2,706,172	1,657,954	370,112	219,208	207,035
Total	45,155,015	29,609,181	7,998,979	5,969,574	5,458,764

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.

	Fitch	Moody's	S&P	Total
Panel A: Original sample (Mergent FISD)				
CRA announcements (Jul.2002 – Mar.2010)	152,826	155,746	119,798	428,370
Panel B: Matched sample with liquid straight corporate bonds				
CRA announcements	781	966	996	2,743
Issues	651	727	722	2,100
Issuers	138	194	185	517
Upgrades	191	284	446	921
Downgrades	590	682	550	1,822
Panel C: Composition by Industry				
Industrial	195	229	174	598
Financial	576	730	799	2,105
Utility	10	7	23	40
Miscellaneous	0	0	0	0
Panel D: Composition by credit rating category				
AAA/Aaa	0	3	1	4
AA/Aa	112	155	197	464
A	258	288	364	910
BBB/Baa	280	150	144	574
BB/Ba	90	227	184	501
B	30	57	55	142
CCC/Caa	9	46	13	68
CC/Ca	1	40	5	46
C	1	0	0	1
Other or NA Grade	0	0	33	33
Panel E: Composition by credit rating grade				
Investment Grade	650	597	706	1,953
Speculative Grade	131	369	290	790
“Fallen Angels” (Downloads to speculative grade)	63	163	72	298
“Rising Stars” (Upgrades to investment grade)	10	12	3	25

Table 2: **Credit Rating Announcements Composition**: This table shows the composition of our final sample of 2,743 announcements by credit rating agency (CRA), which affects 1,345 different bonds issued by 286 different issuers. 2,636 events are triggered by one only CRA. Panel A depicts the full number of CRA 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 also 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.

	Mean	25th Percentile	Median	75th Percentile	Std. Dev.	Min	Max
Panel A. Bond Variables Summary Statistics							
Duration	3.453	1.366	2.606	4.434	2.941	0.003	15.065
Age (yrs)	5.010	2.175	3.849	7.185	3.874	0.096	20.058
Time to maturity (yrs)	4.696	1.416	2.830	5.238	5.545	0.003	39.279
Coupon	5.901	5.000	5.750	6.750	1.411	1.000	12.000
Issue size (million $)	0.478	0.059	0.300	0.650	0.554	0.000	5.500
Panel B. Bond Rating Summary Statistics							
Fitch Rating	7.980	5.000	8.000	10.000	3.243	2.000	21.000
Moody's Rating	8.975	5.000	9.000	11.000	4.512	1.000	21.000
S&P Rating	8.052	5.000	6.000	11.000	4.746	1.000	25.000

Table 3: **Summary Statistics**: This table shows the summary statistics for bond variables duration, age, maturity, coupon and issue size, and for rating changes for each agency, where the numerical number for the rating has been assigned following a long term debt rating equivalences. In panel A the statistics are calculated over the 2,636 unique rating changes, and in panel B, as we distinghish by rating agency, the statistics are calculated over the 2,743 credit rating announcements. The sample includes 1,345 different bonds issued by 286 different issuers. The time period covered is July 2002 to March 2010.

Event Window	[1, 5]	[1, 10]	[1, 20]	[-5, -1]	[-10, -1]
Panel A: Price impact measures. H0: Abnormal liquidity = 0					
AAL-Amivest					
Mean (million)	-0.633	-0.275	-0.014	-0.720	-0.367
t-ratio	-13.698*	-5.825*	-0.310	-16.259*	-8.222*
	(0.000)	(0.000)	(0.757)	(0.000)	(0.000)
Median	-0.557	-0.262	-0.052	-0.664	-0.293
Sign test	11.715*	5.592*	1.639	12.197*	6.219*
	(0.000)	(0.000)	(0.101)	(0.000)	(0.000)
Rank test	12.594*	6.396*	1.024	14.059*	8.066*
	(0.000)	(0.000)	(0.306)	(0.000)	(0.000)
% >0	35.9%	43.2%	48.0%	35.3%	42.5%
Panel B: Market impact measures. H0: Abnormal liquidity = 0					
AAL-Market Share					
Mean	0.057	0.193	0.240	-0.249	-0.091
t-ratio	2.102*	8.421*	11.847*	-9.674*	-4.162*
	(0.036)	(0.000)	(0.000)	(0.000)	(0.000)
Median	0.135	0.231	0.248	-0.181	-0.079
Sign test	3.519*	6.798*	8.003*	5.158*	2.411*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.016)
Rank test	2.680*	7.340*	9.719*	7.075*	3.267*
	(0.007)	(0.000)	(0.000)	(0.000)	(0.001)
% >0	54.3%	58.2%	59.7%	43.8%	47.1%
AAL-Turnover					
Mean	-0.041	0.099	0.177	-0.271	-0.119
t-ratio	-1.486	4.347*	8.856*	-10.617*	-5.450*
	(0.137)	(0.000)	(0.000)	(0.000)	(0.000)
Median	0.011	0.121	0.156	-0.202	-0.117
Sign test	0.289	3.834*	5.785*	6.798*	3.712*
	(0.772)	(0.000)	(0.000)	(0.000)	(0.000)
Rank test	0.653	3.850*	7.047*	8.070*	4.445*
	(0.514)	(0.000)	(0.000)	(0.000)	(0.000)
% >0	50.4%	54.6%	57.0%	41.8%	45.5%
Panel C: Trading frequency measures. H0: Abnormal liquidity = 0					
AAL-TDT					
Mean (million)	-1.297	-0.634	0.034	-1.318	-0.669
t-ratio	-184.923*	-99.946*	5.919*	-203.683*	-107.824*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Median (million)	-1.386	-0.693	0.000	-1.386	-0.742
Sign test	41.461*	38.010*	4.216*	41.461*	38.380*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rank test	35.968*	35.070*	3.403*	35.967*	35.295*
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
% >0	0.0%	3.5%	39.7%	0.0%	3.1%
AAL-TNT					
Mean (million)	-1.165	-0.503	0.158	-1.317	-0.647
t-ratio	-70.269*	-33.744*	11.720*	-87.124*	-46.569*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Median (million)	-1.185	-0.550	0.120	-1.335	-0.668
Sign test	34.710*	21.953*	6.524*	37.494*	28.755*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rank test	33.854*	23.997*	9.054*	34.849*	28.828*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% >0	8.0%	22.9%	57.2%	4.6%	15.0%

Table 5. **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. We present the results by group of liquidity proxies: price impact measures, market impact measures and trading frequency measures, shorted by different width window, where TDT and TNT are the Total Days Traded and Total Number of Trades measures respectively. The time period covered is July 2002 to March 2010, and the subsample is for 1,822 downgrade events: 590 from Fitch, 682 from Moody's and 550 from Standard&Poors. In parenthesis p-value. * Indicates significance at 10% or lower level.

Event Window	[1, 5]	[1, 10]	[1, 20]	[-5, -1]	[-10, -1]
Panel A: Price impact measures. H0: Abnormal liquidity = 0					
AAL-Amivest					
Mean (million)	-0.485	-0.101	0.282	-0.717	-0.248
t-ratio	-10.674*	-2.234*	5.959*	-15.553*	-5.247*
	(0.000)	(0.025)	(0.000)	(0.000)	(0.000)
Median	-0.460	-0.138	0.136	-0.628	-0.201
Sign test	5.951*	2.314*	2.116*	8.860*	3.636*
	(0.000)	(0.021)	(0.034)	(0.000)	(0.000)
Rank test	7.096*	2.316*	2.720*	10.184*	4.643*
	(0.000)	(0.021)	(0.007)	(0.000)	(0.000)
	40.1%	46.1%	53.6%	35.3%	43.9%
Panel B: Market impact measures. H_0: Abnormal liquidity = 0					
AAL-Market Share					
Mean	-0.228	-0.067	0.058	-0.382	-0.210
t-ratio	-8.560*	-2.933*	3.047*	-14.497*	-9.385*
	(0.000)	(0.003)	(0.002)	(0.000)	(0.000)
Median	-0.141	-0.023	0.043	-0.231	-0.152
Sign test	2.843*	0.727	1.587	4.232*	3.769*
	(0.005)	(0.467)	(0.113)	(0.000)	(0.000)
Rank test	4.721*	1.621	1.537	7.179*	4.891*
	(0.000)	(0.105)	(0.124)	(0.000)	(0.000)
	45.2%	48.7%	52.7%	43.0%	43.7%
AAL-Turnover					
Mean	-0.203	-0.036	0.064	-0.403	-0.201
t-ratio	-7.743*	-1.614	3.409*	-15.419*	-9.132*
	(0.000)	(0.106)	(0.001)	(0.000)	(0.000)
Median	-0.127	-0.012	0.032	-0.265	-0.175
Sign test	2.645*	0.264	1.124	5.884*	4.760*
	(0.008)	(0.791)	(0.261)	(0.000)	(0.000)
Rank test	4.014*	0.784	1.587	8.045*	4.980*
	(0.000)	(0.433)	(0.113)	(0.000)	(0.000)
	45.6%	49.5%	51.9%	40.2%	42.1%
Panel C: Trading frequency measures. H_0: Abnormal liquidity = 0					
AAL-TDT					
Mean (million)	-1.363	-0.697	-0.033	-1.383	-0.696
t-ratio	-215.993*	-121.869*	-6.167*	-223.938*	-127.533*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Median (million)	-1.386	-0.693	-0.049	-1.386	-0.693
Sign test	30.216*	28.799*	7.607*	30.216*	29.016*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rank test	26.226*	25.916*	4.486*	26.226*	25.946*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% >0	0.0%	1.9%	31.1%	0.0%	1.5%
AAL-TNT					
Mean (million)	-1.364	-0.687	-0.027	-1.428	-0.702
t-ratio	-113.504*	-63.379*	-2.734*	-126.937*	-72.208*
	(0.000)	(0.000)	(0.006)	(0.000)	(0.000)
Median (million)	-1.386	-0.712	-0.039	-1.449	-0.724
Sign test	29.173*	23.967*	2.785*	29.521*	25.814*
	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)
Rank test	26.037*	23.874*	1.917*	26.086*	24.713*
	(0.000)	(0.000)	(0.055)	(0.000)	(0.000)
% >0	1.6%	10.2%	43.9%	1.1%	6.8%

Table 6. **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. We present the results by group of liquidity proxies: price impact measures, market impact measures and trading frequency measures, shorted by different width window, where TDT and TNT are the Total Days Traded and Total Number of Trades measures respectively. The time period covered is July 2002 to March 2010, and the subsample is for 921 upgrade events: 191 from Fitch, 284 from Moody's and 446 from Standard&Poors. In parenthesis p-value. * Indicates significance at 10% or lower level.

	Panel A. Downgrades					Panel B. Upgrades				
	AV	MS	TN	TDT	TNT	AV	MS	TN	TDT	TNT
Constant	-0.396	0.310	0.291	-0.974*	-1.293*	0.740	-1.057	-0.517	-1.432*	-1.646*
	(0.713)	(0.529)	(0.553)	(0.000)	(0.000)	(0.736)	(0.346)	(0.617)	(0.000)	(0.000)
Prior rating	0.024	0.055*	0.038*	0.018*	0.059*	-0.049	-0.035*	-0.054*	-0.012*	-0.034*
	(0.387)	(0.000)	(0.004)	(0.000)	(0.000)	(0.301)	(0.064)	(0.004)	(0.009)	(0.002)
Speculative grade	-0.506*	-0.579*	-0.567*	-0.202*	-0.664*	0.154	0.191	0.182	0.140*	0.298*
	(0.069)	(0.000)	(0.000)	(0.000)	(0.000)	(0.714)	(0.298)	(0.300)	(0.001)	(0.000)
Fallen angel/Rising star	0.312	0.285*	0.296*	0.081*	0.302*	0.324	0.576*	0.643*	0.177*	0.329*
	(0.213)	(0.025)	(0.018)	(0.008)	(0.000)	(0.501)	(0.035)	(0.019)	(0.001)	(0.005)
Big jump	0.034	0.062	0.123	0.075*	0.150*	0.456	0.154	0.463*	0.141*	0.369
	(0.861)	(0.464)	(0.147)	(0.001)	(0.009)	(0.412)	(0.497)	(0.074)	(0.091)	(0.118)
S&P	-0.048	-0.049	-0.041	0.013	-0.066*	0.036	-0.014	0.034	0.004	0.037
	(0.735)	(0.416)	(0.484)	(0.356)	(0.081)	(0.840)	(0.843)	(0.629)	(0.804)	(0.242)
Simultaneous	-0.357	0.254*	0.249*	-0.007	0.273*	0.036	0.190	-0.006	0.087	-0.024
	(0.233)	(0.086)	(0.095)	(0.795)	(0.001)	(0.964)	(0.640)	(0.990)	(0.592)	(0.948)
Second mover	-0.676	0.556*	0.961*	-0.019	-0.319*	-0.473*	-0.061	-0.282*	-0.070*	-0.440*
	(0.208)	(0.034)	(0.000)	(0.692)	(0.049)	(0.036)	(0.382)	(0.000)	(0.000)	(0.000)
Break trend	0.159	0.057	-0.112	-0.035	-0.062	0.952*	0.169	0.293*	0.126*	0.192
	(0.582)	(0.706)	(0.424)	(0.273)	(0.452)	(0.009)	(0.250)	(0.040)	(0.005)	(0.118)
Crisis	-0.209	0.042	-0.046	0.029*	0.055	0.249	0.268*	0.031	0.109*	0.034
	(0.127)	(0.489)	(0.446)	(0.038)	(0.166)	(0.482)	(0.072)	(0.830)	(0.020)	(0.775)
Age	0.162*	0.015	0.010	-0.017*	0.017	-0.020	0.041	0.037	-0.023*	-0.044*
	(0.017)	(0.627)	(0.747)	(0.011)	(0.381)	(0.839)	(0.312)	(0.349)	(0.016)	(0.029)
Iliquidity	0.004	0.002	0.003*	0.009*	0.013*	0.005	0.005*	0.005*	0.009*	0.012*
	(0.201)	(0.117)	(0.094)	(0.000)	(0.000)	(0.330)	(0.010)	(0.008)	(0.000)	(0.000)
Offering ammount	-0.018	-0.035	-0.013	0.054*	0.055*	-0.001	0.047	0.037	0.096*	0.135*
	(0.692)	(0.141)	(0.585)	(0.000)	(0.001)	(0.991)	(0.257)	(0.331)	(0.000)	(0.000)
Financial	-0.546	-0.241	-0.332*	0.025	-0.122	0.252	0.147	0.057	-0.006	-0.032
	(0.183)	(0.182)	(0.074)	(0.630)	(0.314)	(0.817)	(0.839)	(0.931)	(0.960)	(0.867)
Industrial	-0.327	-0.218	-0.189	-0.001	-0.154	0.318	0.220	0.162	-0.023	0.062
	(0.428)	(0.237)	(0.319)	(0.984)	(0.206)	(0.771)	(0.762)	(0.805)	(0.837)	(0.739)
Multirating	-0.088	0.087	0.056	0.084*	0.112*	-0.689	-0.088	-0.053	0.092*	0.094
	(0.749)	(0.428)	(0.608)	(0.001)	(0.085)	(0.115)	(0.570)	(0.726)	(0.002)	(0.145)
R^2	0.015	0.034	0.040	0.376	0.183	0.020	0.052	0.062	0.377	0.235
F-stat	1.763*	4.021*	4.733*	68.346*	25.477*	1.196	3.283*	3.943*	36.302*	18.411*
p-value	(0.035)	(0.000)	(0.000)	(0.000)	(0.000)	(0.269)	(0.000)	(0.000)	(0.000)	(0.000)
#Obs.			1721					915		

Table 7. **Determinants of abnormal post event liquidity [1, 20].** All models are estimated by OLS, with the robust covariance matrix adjusted for heteroskedasticity, p-values in parentheses. * indicates significance at 10% significance level or lower. S&P is a dummy variable equal to one if the rating action is announced by S&P and zero otherwise, Prior rating is a variable encoding the rating categories of the previous rating of the firm, assigning value 1 to AAA, …and 26 to D. Speculative grade is a dummy variable equal to one if the prior rating of the firm is on speculative level and zero otherwise, Big jump is a dummy variable equal to one if the jump between the prior rating and new rating is higher than 2 notches and zero otherwise. Simultaneous is a dummy variable equal to one if the rating action has been announced by two or more agencies the same day and zero otherwise, Second mover is a dummy variable equal to one if there are other action announced by other agency in same direction during 3 previous month and zero otherwise, Break trend is a dummy variable equal to one if the rating action has been preceded by two rating announcements in the opposite direction over the past 12 months and zero otherwise. Crisis is a dummy variable equal to one if the rating action is announced after the beguining of the ongoing crisis, September 14, 2008, and zero otherwise. Age is the age of the bond measured in days as the dirrefence between the issue date and the rating change announcement. Illiquidity takes the value of the illiquidity measure Bond Zero-Trading Day in the control window [-20, -1]. Offering amount the initial amount offered by each bond, Financial (Industrial) is a dummy variable equal to one if the rating action involves financial (industrial) sector firms, Multirating is a dummy variable equal to one if there are more than one agency following the issuer.

	Panel A. Downgrades					Panel B. Upgrades				
	AV	MS	TN	TDT	TNT	AV	MS	TN	TDT	TNT
Constant	-0.403	0.240	0.289	-2.212*	-3.061*	6.321*	2.062	1.850	-2.436*	-2.748*
	(0.708)	(0.741)	(0.688)	(0.000)	(0.000)	(0.012)	(0.130)	(0.174)	(0.000)	(0.000)
Prior rating	-0.011	0.013	-0.002	0.006*	0.015	-0.179*	-0.089*	-0.072*	-0.010*	-0.020
	(0.710)	(0.445)	(0.888)	(0.093)	(0.122)	(0.006)	(0.001)	(0.008)	(0.058)	(0.128)
Speculative grade	0.100	0.109	0.215	-0.043	-0.074	0.965*	1.092*	0.701*	0.133*	0.332*
	(0.731)	(0.547)	(0.231)	(0.212)	(0.461)	(0.032)	(0.000)	(0.005)	(0.007)	(0.003)
Fallen angel/Rising star	0.050	-0.022	-0.123	0.016	-0.019	0.531	0.491	0.377	-0.083	-0.05
	(0.848)	(0.894)	(0.441)	(0.612)	(0.831)	(0.331)	(0.192)	(0.312)	(0.297)	(0.703)
Big jump	0.379*	0.144	0.205*	0.125*	0.346*	-1.382*	-1.122*	-1.686*	-0.103	-0.405*
	(0.078)	(0.215)	(0.075)	(0.000)	(0.000)	(0.085)	(0.078)	(0.006)	(0.343)	(0.001)
S&P	-0.144	0.036	0.056	0.044*	0.112*	-0.261	-0.195*	-0.191*	-0.046*	-0.126*
	(0.289)	(0.648)	(0.482)	(0.003)	(0.010)	(0.139)	(0.051)	(0.058)	(0.020)	(0.002)
Simultaneous	-0.475*	0.044	0.027	0.042	0.132	1.618*	0.528	0.813	0.048	0.228
	(0.099)	(0.783)	(0.867)	(0.185)	(0.168)	(0.023)	(0.453)	(0.232)	(0.724)	(0.299)
Second mover	0.169	0.242	0.332	-0.112	-0.220	1.836*	1.453*	1.491*	0.056*	0.433*
	(0.671)	(0.452)	(0.286)	(0.136)	(0.246)	(0.000)	(0.000)	(0.000)	(0.005)	(0.000)
Break trend	0.295	-0.164	-0.082	0.004	-0.088	0.335	-0.083	-0.325	-0.010	-0.074
	(0.315)	(0.376)	(0.659)	(0.919)	(0.376)	(0.300)	(0.683)	(0.125)	(0.851)	(0.588)
Crisis	-0.173	0.051	-0.074	-0.017	-0.045	-0.926*	-0.147	-0.344*	-0.118*	-0.157
	(0.195)	(0.525)	(0.350)	(0.252)	(0.322)	(0.036)	(0.485)	(0.100)	(0.013)	(0.236)
Age	0.049	-0.071*	-0.059	-0.019*	-0.002	-0.122	-0.097*	-0.093	-0.010	-0.031
	(0.497)	(0.064)	(0.124)	(0.010)	(0.938)	(0.178)	(0.092)	(0.100)	(0.394)	(0.218)
Iliquidity	0.005	0.002	0.002	0.011*	0.015*	-0.005	-0.002	-0.002	0.009*	0.012*
	(0.126)	(0.377)	(0.258)	(0.000)	(0.000)	(0.311)	(0.539)	(0.508)	(0.000)	(0.000)
Offering ammount	-0.003	0.021	0.025	0.049*	0.100*	-0.228*	-0.024	-0.011	0.077*	0.126*
	(0.958)	(0.532)	(0.464)	(0.000)	(0.000)	(0.032)	(0.665)	(0.843)	(0.000)	(0.000)
Financial	-0.676*	-0.573*	-0.580*	0.055	-0.029	-0.985	-0.553	-0.431	0.079	-0.025
	(0.043)	(0.036)	(0.031)	(0.353)	(0.799)	(0.219)	(0.392)	(0.495)	(0.519)	(0.903)
Industrial	-0.558*	-0.725*	-0.672*	0.048	-0.091	-0.128	-0.367	-0.177	0.075	-0.014
	(0.098)	(0.009)	(0.013)	(0.415)	(0.429)	(0.869)	(0.573)	(0.781)	(0.542)	(0.947)
Multirating	0.06	0.128	0.083	0.046	0.06	-0.163	-0.205	-0.183	0.011	-0.043
	(0.774)	(0.398)	(0.583)	(0.104)	(0.453)	(0.572)	(0.277)	(0.337)	(0.757)	(0.505)
R^2	0.012	0.018	0.015	0.371	0.141	0.030	0.043	0.034	0.280	0.147
F-stat	1.409	2.070*	1.710*	67.180*	18.733*	1.861*	2.721*	2.135*	23.267*	10.302*
p-value	(0.134)	(0.009)	(0.043)	(0.000)	(0.000)	(0.024)	(0.000)	(0.007)	(0.000)	(0.000)
#Obs.			1721					915		

Table 8. Determinants of abnormal pre event liquidity [-5, -1]. All models are estimated by OLS, with the robust covariance matrix adjusted for heteroskedasticity, p-values in parentheses. * indicates significance at 10% significance level or lower. S&P is a dummy variable equal to one if the rating action is announced by S&P and zero otherwise, Prior rating is a variable encoding the rating categories of the previous rating of the firm, assigning value 1 to AAA, …and 26 to D. Speculative grade is a dummy variable equal to one if the prior rating of the firm is on speculative level and zero otherwise, Big jump is a dummy variable equal to one if the jump between the prior rating and new rating is higher than 2 notches and zero otherwise. Simultaneous is a dummy variable equal to one if the rating action has been announced by two or more agencies the same day and zero otherwise, Second mover is a dummy variable equal to one if there are other action announced by other agency in same direction during 3 previous month and zero otherwise, Break trend is a dummy variable equal to one if the rating action has been preceded by two rating announcements in the opposite direction over the past 12 months and zero otherwise. Crisis is a dummy variable equal to one if the rating action is announced after the beguining of the ongoing crisis, September 14, 2008, and zero otherwise. Age is the age of the bond measured in days as the dirrefence between the issue date and the rating change announcement. Illiquidity takes the value of the illiquidity measure Bond Zero-Trading Day in the control window [-20, -1]. Offering amount the initial amount offered by each bond, Financial (Industrial) is a dummy variable equal to one if the rating action involves financial (industrial) sector firms, Multirating is a dummy variable equal to one if there are more than one agency following the issuer.