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Mathematical and Statistical Methods for Actuarial Sciences and Finance

MAF 2016

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Editors
Marco Corazza
Department of Economics
Ca' Foscari University of Venice
Venezia, Italy

Florence Legros
Département Finance, Audit, Comptabilité et Contrôle
ICN Business School
Nancy, France

Cira Perna
Department of Economics and Statistics
University of Salerno
Fisciano (SA), Italy

Marilena Sibillo
Department of Economics and Statistics
University of Salerno
Fisciano (SA), Italy

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Preface

This volume is a collection of referred papers from the several tens that were presented at the international conference *MAF 2016—Mathematical and Statistical Methods for Actuarial Sciences and Finance*.

The conference was held in Paris (France), from March 30 to April 1, 2016, at the Université Paris-Dauphine. It was organized by the Executive MBA CHEA—Centre des Hautes Etudes d'Assurances and by the Department of Economics of the Ca' Foscari University of Venice (Italy), with the collaboration of the Department of Economics and Statistics of the University of Salerno (Italy).

The conference was the seventh of an international biennial series which began in 2004. It was born out of the idea that enhanced cooperation between mathematicians and statisticians working in actuarial sciences, in insurance, and in finance can result in improved research in these fields.

The wide participation at all the conferences in the series constitutes proof of the merits of this idea.

The papers published in this volume present theoretical and methodological contributions and their applications to real contexts.

Of course, the success of *MAF 2016* would not have been possible without the valuable help of all members of the Scientific Committee, the Organizing Committee, and the Local Committee.

Finally, we are pleased to inform readers that the organizing machine for the next edition is already in action: the conference *MAF 2018* will be held in Madrid (Spain), from April 4 to 6, 2018 (for details visit the website http://www.est-econ.uc3m.es/maf2018/).

We look forward to seeing you there.

Venezia, Italy — Marco Corazza
Nancy, France — Florence Legros
Fisciano (SA), Italy — Cira Perna
Fisciano (SA), Italy — Marilena Sibillo
August 2017

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The Effects of Credit Rating Announcements on Bond Liquidity: An Event Study

Pilar Abad, Antonio Diaz, Ana Escribano, and M. Dolores Robles

Abstract This paper investigates liquidity shocks on the US corporate bond market around credit rating change announcements. These shocks may be induced by the information content of the announcement itself, and abnormal trading activity can be triggered by the release of information after any upgrade or downgrade. Our findings show that: (1) the market anticipates rating changes, since trends liquidity proxies prelude the event, and additionally, large volume transactions are detected the day before the downgrade; (2) the concrete materialization of the announcement is not fully anticipated, since we only observe price overreaction immediately after downgrades; (3) a clear asymmetric reaction to positive and negative rating events is observed; (4) different agency-specific and rating-specific features are able to explain liquidity behavior around rating events; (5) financial distress periods exacerbate liquidity responses derived from downgrades and upgrades.

1 Introduction

Information on rating actions has been a permanent subject of debate. Credit rating agencies (CRAs) state that they consider insider information when assigning and revising ratings, without disclosing specific details to the public at large. The literature examines prices and/or returns responses to rating events. However, the information about the creditworthiness of issuers disclosed by rating actions can not only affect prices. Besides this, it can induce specific market dynamics concerning the liquidity of the re-rated bonds. One important role of ratings is to reduce the information asymmetry between lenders and borrowers. As this asymmetry is

P. Abad
Universidad Rey Juan Carlos de Madrid, Madrid, Spain
e-mail: pilar.abad@urjc.es

A. Diaz • A. Escribano (✉)
Universidad de Castilla-La Mancha, Albacete, Spain
e-mail: antonio.diaz@uclm.es; ana.escribano@uclm.es

M.D. Robles
Universidad Complutense de Madrid, Madrid, Spain
e-mail: mdrobles@ccee.ucm.es

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inversely related to liquidity, if credit rating changes (CRCs) release specific news about the financial situation of firms, they will affect firms' bond liquidity.

In order to analyze this question, we go beyond the traditional price analysis by analyzing corporate bond liquidity patterns around CRC announcements. We examine different dimensions of corporate bond liquidity, and compute different adaptations of traditional microstructure-based liquid measures on stock markets to bond markets, as well as other traditional bond market liquidity measures.[1]

Our paper relates to several strands of the literature. First, we contribute to research that seeks to better understand the liquidity of corporate bond markets (e.g. [1, 8] and Chen et al. [3]). Second, to the literature that studies the information content of rating announcements and their impact on bond market (e.g. Steiner and Heinke [18] and May [15]) and on stock markets (e.g. Norden and Weber [16]).

We study a comprehensive sample of 2727 CRCs in the whole US corporate bond market, using TRACE transaction data from 2002 to 2010. We also study the impact of the recent global financial crisis on the response of the different liquidity aspects to CRC announcements. We consider the default of Lehman Brothers in mid-2008 to be the starting point of the financial turmoil.

Our results indicate three clear patterns in liquidity and prices, depending on the time period around the announcement when we consider the whole sample period. First, we observe trends in prices and liquidity deterioration before the announcement. Additionally, nervousness emerges in the market the day before downgrades. Second, there is price pressure for a few days after the downgrades. This fact could imply transaction prices below fundamental values. Third, we observe that 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 no price impact.

Aside from analyzing impacts on liquidity derived from credit rating migrations, we examine the determinants of abnormal liquidity observed before and after the announcements. To find the drivers of abnormal liquidity, we carry out a cross-sectional analysis including as key factors different characteristics of the rating event, the issue, and the issuer, to explain liquidity responses to rating changes. Our premise is that rating changes that provide more relevant information to the market must cause stronger impacts on liquidity.

Our results should enable market participants to manage portfolios, given that they need to have an understanding of the way in which the liquidity and the liquidity premium on prices behave around CRC.

The remainder of the paper is arranged as follows: Sect. 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 Sect. 5. Section 6 includes the cross-sectional analysis. Finally, Sect. 7 concludes.

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[1]Recent papers using some of these measures corroborate the liquidity effects on prices (see, e.g., Bao et al. [1], Dick-Nielsen et al. [8] and Friewald et al. [10]).

2 The Expected Response of Liquidity to Rating Actions

We consider that the effects of rating changes can be explained by different possible hypotheses. The main hypothesis states that CRAs are supplied with considerable non-public information about firms, such as information about the total firm value and its organizational effectiveness. In the liquidity literature, the market microstructure models indicate that trading activity responses to news releases are related to the existence of asymmetric information among informed traders, uninformed traders, and market-makers. Kim and Verrecchia [14] 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. A rating revision may provide additional information about the firm. Different investors' risk perception can induce portfolio rebalancing processes. In this context, higher trading activity after CRCs will be expected.

The second theory we analyze is the reputation hypothesis. This hypothesis (Holthausen and Leftwich [11]) states that rating agencies face asymmetric loss functions, and that 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. Reputation costs create an incentive for CRAs to truthfully reveal the investment quality, since investors can eventually learn and punish the agency.

The last hypothesis points out that the usual liquidity premium on prices widens after a CRC. We examine whether the liquidity impact on prices is exacerbated after a CRC. If rating announcements disclose new and relevant information about the default risk of a bond, then prices should immediately incorporate this information. Independently of price adjustment, liquidity may drive additional price changes. The traditional literature considers liquidity to be a key component of corporate bond prices. Recent papers corroborate this result. For instance, [1] conclude that illiquidity explains a substantial part of the yield spreads of high-rated bonds, overshadowing the credit risk component. Chen et al. [3] and Friewald et al. [10] also observe that the economic impact of liquidity is significantly larger for speculative-grade bonds.

3 Data Description

We use two main sources of data in our analysis: the NASD's Trade Reporting and Compliance Engine (TRACE) transactions data for corporate bonds and the Mergent Fixed Income Securities Database (FISD), with complete information on the characteristics of each bond.[2] According with FISD bond information, we limit the sample to straight corporate bonds.[3] FISD data set also provides rating information per bond from the main three CRAs, i.e. Moody's, Standard and Poor's, and Fitch, from which we compute more than 225,000 CR changes.

Matching both data sets, we select those CR announcements which meet certain criteria. First, a minimum trading activity level. The bond should be traded at least once in the 20 working days before the event, and once in a similar period after the event. Second, bonds must be traded for at least 20% of the trading days in the period of 1 month starting 2 months prior the CRC. Third, events preceded by other rating announcements in the previous 61 working days, are also ignored.

The final data sample consists of 2620 unique CRC, involving 1342 bonds from 286 issuers; and with nearly 4.5 million trades, it forms approximately 10.6% of the total number of trades reported by TRACE during the period July 1, 2002 to March 31, 2010.[4] It comprises 907 upgrades and 1713 downgrades.

4 Proxies of Liquidity

We consider liquidity proxies that focus on three aspects of liquidity, i.e. price impact, market impact, and trading frequency, and select some of the most used measures in the existing empirical literature on liquidity. As price impact measures, we compute the 'Amivest' ratio (*AV*), the 'Bao' et al. measure (*Bao*), the imputed roundtrip cost measure (*IRC*) and the 'price dispersion' measure (*PD*). As proxies of market impact, we consider both the 'market share' (*MS*) and the 'trading volume' (*TV*). Finally, we compute the 'number of trades' (*NT*) as trading frequency measure.

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[2]The use of the TRACE data set for research purposes requires previous filtering. Edwards et al. [9] and Dick-Nielsen [7] propose using algorithms to filter out the reporting errors, and we apply these, introducing minor variations. From the original 45 million transactions, we include in our sample about 4.5 million.

[3]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.

[4]Bonds double- or triple-rated by more than one CRAs, are set as unique events. We compute the final rating as the average rating using the numeric value assigned by the long-term debt rating equivalences, with values from AAA = 1 to D = 25. CRCs in the opposite direction are ignored.

4.1 Amivest

$$AV_{i,t} = \frac{1}{D_{i,t}} \sum_{k=1}^{D_{i,t}} \frac{TV_{i,k}}{|r_{i,k}|} \tag{1}$$

The Amivest liquidity ratio proposed by Cooper et al. [4] is a liquidity proxy. Following this 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.

4.2 Bao

$$Bao_{i,t} = -Cov(\triangle p_t, \triangle p_{t+1}) \tag{2}$$

The [1] measure is a illiquidity measure. Following this measure, an illiquid bond is traded with a large bid-ask spread, which implies highly negatively correlated consecutive prices and hence a high positive value of the *Bao* measure.

4.3 Imputed Roundtrip Cost

$$IRC_{i,t} = \frac{P_{i,t}^{max} - P_{i,t}^{min}}{P_{i,t}^{max}} \tag{3}$$

Dick-Nielsen et al. [8] proposes the *IRC* measure. According to this illiquidity measure, higher values represent large differences between the maximum and minimum prices, which can be interpreted as large transaction costs. Therefore, bonds with high *IRC* values are less liquid bonds.

4.4 Price Dispersion

$$PD_{i,t} = \sqrt{\frac{1}{\sum_{k=1}^{N_{i,t}} TV_{i,k,t}} \sum_{k=1}^{N_{i,t}} (p_{i,k,t} - \overline{p}_{i,t})^2 \cdot TV_{i,k,t}} \tag{4}$$

The price dispersion measure proposed by Jankowitsch et al. [12] is an illiquidity measure. It can be interpreted as the volatility of the price dispersion, hence a low level of *PD* measure indicates high liquidity, i.e. the bond can be traded close to its fair value.

4.5 Market Share

$$MS_{i,t} = \frac{\sum_{k=1}^{N_{i,t}} TV_{i,k,t}}{TTV_k} \tag{5}$$

Following Diaz et al. [6] we compute market share as the ratio of the trading volume of a bond in a day to the total trading volume in the whole market, including any transaction involving any outstanding issue. The larger the market share, the higher the bond liquidity.

Finally, we also include the trading volume (TV) as a market activity measure and the number of trades (NT) as a trading frequency measure. A larger volume as well as a large number of trades indicates large liquidity.

5 Effects of Rating Change Announcements on Liquidity

5.1 Methodology

To analyze the effects of CRC announcements we carry out an event study. We compare liquidity around the rating-change days to normal liquidity days. We define the date of the announcement as day $t = 0$, and compute the observed liquidity in a window around the CRC, from day $t = t_1$ to day $t = t_2$ (CRC window) for each CRC in the sample as the averaged liquidity proxy:

$$OL_{i(t_1,t_2)} = \frac{\sum_{t=t_1}^{t_2} l_{i,t}}{T_O} \tag{6}$$

where $OL_{i(t_1,t_2)}$ is the observed liquidity for bond i in the window (t_1, t_2), T_O is the number of days in (t_1, t_2) and $l_{i,t}$ is the liquidity proxy computed in a day-by-day basis for the CRC i.

We compare this observed liquidity to the expected liquidity in "stable-rating times".[5] We consider 2 months prior the CRC announcement without any other

[5]Following Corwin and Lipson [5] we use the firm-specific past history to compute the expected liquidity in a period of typical liquidity. Other alternative is considering an appropriate matching portfolio of similar bonds with stable ratings. However, the lack of liquidity in corporate bond markets makes this approach unsuitable. Bessembinder et al. [2] indicate that construct abnormal bond returns using the matching portfolio models (the benchmark is a matching portfolio designed

credit event. Then, we define the stability-rating window from day $t = -41$ to day $t = -21$. The window ends 21 trading days prior to the announcement day, in order to avoid possible price lead-up preceding the shocks. The expected liquidity, EL_i, for CRC i is computed as the averaged liquidity proxy in this benchmark window:

$$EL_{i(t_1,t_2)} = \frac{1}{N}\sum_{t=-41}^{-21} l_{i,t} \tag{7}$$

To taking into account the different scales of liquidity proxies across different bonds, we compare the liquidity around the rating change and the expected liquidity in logarithms. Then, the abnormal liquidity in a specific event window (t_1, t_2) for the CRC i is obtained as the difference between observed liquidity in that rating-change window and the expected liquidity both in logs:

$$AL_{i(t_1,t_2)} = ln(OL_{i(t_1,t_2)}) - ln(EL_{i(t_1,t_2)}) \tag{8}$$

where $ln(.)$ indicates the 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:

$$AAL_{(t_1,t_2)} = \frac{1}{N}\sum_{i=1}^{N} AL_{i(t_1,t_2)} \tag{9}$$

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 must be zero.

To test the statistical significance we first compute the well-known t-ratio test, asymptotically normally distributed under the null hypothesis. Second, we compute two non-parametric tests (the 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 calculates 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.[6]

We study different width windows to analyze the behavior of abnormal liquidity before and after the release date: $[-10, -6]$, $[-5, -1]$, $[0, 5]$, $[6, 10]$, and $[11, 20]$. Besides, we examine separately the effects from both, downgrades and upgrades.

to adjust risk and time-to-maturity) or the mean-adjusted model (the benchmark is Treasury security with the most similar maturity date) induces a bias.

[6] See Sheskin [17] for details.

5.2 Event Study Results for Downgrades and Upgrades

The left-hand side of Table 1 presents results for rating downgrades.[7] In the case of price impact proxies (Panel A), results suggest that liquidity becomes scarce both before and after the event. In the case of the *AV* liquidity measure, the mean abnormal value estimated is negative and statistically significant in all the pre- and post-announcement day event windows. This result suggests an increase of the cost of demanding liquidity around a downgrade event. This result is robust to the method that we use (mean and median abnormal liquidity, parametric and non-parametric tests). The abnormal value of the *Bao* illiquidity measure is only statistically significant for the last two windows, with positive estimated coefficients. This 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. transaction costs higher than usual. Finally, the *PD* illiquidity measure shows positive and statistically significant abnormal values after the event. The price dispersion increases after a downgrade. These results are in line with those in [18], that find significant bond price reactions after downgrades.

Panel B shows the market impact measures. *MS* and *TV* show a decrease in abnormal trading activity in the previous days to the downgrade and in the second post-announcement week, while these measures are positive and significant in the first week after. We highlight that mean and median abnormal liquidity are negative and particularly low in the weeks previous to the event. Trading activity drops again during the second post-announcement week $[6, 10]$ and converges to regular values from the second fortnight after the downgrade $[11, 20]$. Abnormal TV is insignificant for the first week $[0, 5]$. These findings are consistent with results in [15], that find increasing trading activity after CR downgrade announcements.

Finally, Panel C of Table 1 displays the results for the trading frequency measure, *NT*. In this case, there is a significantly abnormal number of trades after the event, in the $[0, 20]$ window. The estimated coefficient is especially high immediately after the event $[0, 5]$. These results are also robust to the tests applied.

The right-hand side of Table 1 presents the results for upgrades. Panel A shows the effects on liquidity, measured by the price impact measures. In general, mean and median abnormal values of the four proxies are statistically significant, but their signs are a little confusing. Liquidity level becomes abnormally high during all the periods $[-10, 20]$ according to three proxies (*Bao*, *IRC* and *PD*), but we observe 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 periods, but a higher price impact of new transactions. Results show inappreciable differences of these proxies between each week around the event.

[7] Other results for different subsamples and periods are available upon request.

Table 1 Event study results for Downgrades and Upgrades

		Downgrades (N = 1713)					Upgrades (N = 907)				
Event window		[−10, −6]	[−5, −1]	[0, 5]	[6, 10]	[11, 20]	[−10, −6]	[−5, −1]	[0, 5]	[6, 10]	[11, 20]
Panel A: Price impact measures. H_0: Abnormal liquidity = 0											
AV	Mean	−0.737*	−0.666*	−0.426*	−0.671*	−0.332*	−0.766*	−0.699*	−0.419*	−0.807*	−0.282*
	Median	−0.732+◇	−0.685+◇	−0.446+◇	−0.619+◇	−0.329+◇	−0.716+◇	−0.601+◇	−0.414+◇	−0.750+◇	−0.211+◇
	% > 0	35.0%	35.5%	40.8%	36.6%	42.8%	35.5%	37.3%	41.8%	34.5%	45.9%
Bao	Mean	0.031	0.008	0.027	0.048*	0.107*	−0.019	−0.025	−0.078*	−0.070*	−0.115*
	Median	−0.008	−0.015	0.024	0.044	0.095+◇	−0.010	−0.027	−0.099+◇	−0.086◇	−0.122+◇
	% > 0	49.4%	49.2%	50.9%	51.2%	53.7%	48.8%	49.4%	46.1%	47.3%	46.6%
IRC	Mean	0.001*	0.003*	0.009*	0.005*	0.004*	−0.000*	−0.001*	−0.001*	−0.001*	−0.001*
	Median	−0.001+	−0.000◇	0.002◇	0.001◇	0.001◇	−0.001◇	−0.001◇	−0.000◇	−0.001◇	−0.001◇
	% > 0	45.6%	48.5%	57.3%	53.8%	55.4%	42.3%	41.9%	45.4%	40.4%	42.4%
PD	Mean	−0.083*	−0.003	0.180*	−0.022	0.144*	−0.103*	−0.204*	−0.180*	−0.225*	−0.274*
	Median	0.015	0.048◇	0.188◇	0.159◇	0.144◇	−0.084◇	−0.110◇	−0.129◇	−0.092◇	−0.141◇
	% > 0	50.9%	52.2%	58.8%	57.5%	56.9%	44.4%	45.7%	42.9%	45.2%	42.5%
Panel B: Market impact measures. H_0: Abnormal liquidity = 0											
MS	Mean	−0.367*	−0.253*	0.102*	−0.112*	−0.034	−0.505*	−0.381*	−0.170*	−0.405*	−0.144*
	Median	−0.292+◇	−0.188+◇	0.154+◇	−0.051◇	0.004	−0.377+◇	−0.231+◇	−0.120+◇	−0.294+◇	−0.101+◇
	% > 0	39.7%	43.7%	55.0%	48.5%	50.2%	36.5%	43.0%	45.4%	40.5%	45.0%
TV	Mean	−0.395*	−0.272*	0.019	−0.195*	−0.061*	−0.472*	−0.407*	−0.131*	−0.371*	−0.173*
	Median	−0.312+◇	−0.205+◇	0.050	−0.119+◇	−0.014	−0.333+◇	−0.267+◇	−0.109+◇	−0.247+◇	−0.115+◇
	% > 0	39.2%	41.7%	51.5%	45.6%	49.6%	37.8%	40.0%	46.0%	40.5%	43.4%

(continued)

Table 1 (continued)

		Downgrades (N = 1713)					Upgrades (N = 907)				
Event window		[−10, −6]	[−5, −1]	[0, 5]	[6, 10]	[11, 20]	[−10, −6]	[−5, −1]	[0, 5]	[6, 10]	[11, 20]
Panel C: Trading frequency measures. H_0: Abnormal liquidity = 0											
NT	Mean	−0.048*	0.001	0.141*	0.027*	0.032*	−0.035*	−0.044*	0.016*	−0.056*	−0.045*
	Median	$-0.050^{+\diamond}$	−0.018	$0.128^{+\diamond}$	0.020	$0.034^{+\diamond}$	$-0.039^{+\diamond}$	$-0.057^{+\diamond}$	−0.022	$-0.033^{+\diamond}$	$-0.049^{+\diamond}$
	% > 0	45.9%	47.9%	58.0%	50.4%	52.3%	44.8%	44.9%	48.1%	45.8%	43.3%

This table shows T-ratio and non-parametric tests, for the Average Abnormal Liquidity (*AAL*). Results for downgrades are on the left side and for upgrades on the right side. *AV*, *Bao*, *IRC*, *PD*, *MS*, *TV* and *NT* represent the Amivest, Bao, Imputed Roundtrip Costs, Price Dispersion, Market Share, Trading Volume and Number of Trades. The time period covered is July 2002 to March 2010. The subsample for downgrade events involves 1050 different bonds from 223 different issuers, and for upgrades, 621 different bonds issued by 150 different issuers. *, + and ◇ indicates significance at 10% or lower level for the t-ratio, Sign and Rank tests respectively