Changes in Corporate Debt Ratings and Stock Liquidity: Evidence from the Spanish Market*

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This study examines the existing relationship between announcements of debt rating changes for companies listed on the Spanish stock exchange and the liquidity of their stocks for the period of 2000 to 2010. Liquidity around the announcement day is analyzed using different liquidity measures proposed by the equity market literature. The study also examines the factors that determine the intensity of the announcement's effect on liquidity. The evidence shows that both positive and negative announcements (of improvement and decline in credit rating) lead to an increase in liquidity, which is anticipated by the market in both cases. Regarding the factors that determine intensity, it is observed that investors combine the information included in the announcement with the characteristics of the issuing company. Still, the recent economic and financial crisis, in which the role of the rating agencies has been greatly questioned, has not changed the intensity of these effects on liquidity.

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1. Introduction

The information content hypothesis states that rating agencies handle confidential information and that rating revisions therefore contain new information. In an efficient market, this new information must be rapidly included into prices. A number of studies have examined the informative content of rating announcements, most of which focus on analyzing the effects of those announcements on stock prices. The main conclusion is that returns are influenced by bond rating changes, especially downgrades (e.g., Hand, Holthausen and Leftwich, 1992; Matolcy and Lianto, 1995; Barron, Clare and Thomas, 1997; Elayan, Hsu and Meyer, 2001; Abad and Robles, 2006, 2007; Purda, 2007 or Jorion and Zang, 2007). Other studies find similar evidence concerning corporate debt prices (e.g., Hit and Warga, 1997; Kliger and Sarig, 2000; Steiner and Heinke, 2001; Gropp and Richards, 2001 or May, 2010). In both cases, the results demonstrate the importance of rating change announcements in revealing specific company information that is relevant to price formation.

However, although the literature has demonstrated the important role that revealed information plays in determining liquidity (for example Kyle, 1985, Kim and Verrecchia, 1994 or Balduzzi, Elton and Green, 2001), there are almost no studies that analyze the relationship between rating changes and the liquidity of the issuing company's stocks. [1] Odders-White and Ready (2006) created a theoretical model of the relationship between rating level and liquidity and found that it is positive, but they did not analyze the effect that rating changes would have on liquidity.[2] This analysis was conducted by Abad, Díaz and Robles (2011, 2012) for the Spanish commercial paper and corporate bond markets using a combination of liquidity measures based on market conditions. In both cases, these researchers find significant effects, indicating that these announcements provide relevant information.

[1] There is a broad literature related to the effect on liquidity of other relevant events, such as dividend announcements, stock splits and recommendations of financial analysts or voluntary disclosure by companies.

[2] He, Wang and Wei (2011) find that bond rating changes affect the information asymmetry of stock trading and other measures of information risk.

The main objective of this paper is to fill this research gap by examining the role of rating agencies as information providers. We analyze the impact of credit rating action announcements on stock liquidity. According to the information hypothesis, it could be expected that the inclusion of new information about firm solvency is associated with higher activity in the market. Market microstructure models assert that the liquidity response after the disclosure of new information is related to the existence of asymmetric information among agents and market makers (e.g., see Balduzzi *et al.*, 2001). Kyle (1985) states that liquidity is inversely proportional to the quantity of information held by the "insider" related to the demand of liquidity traders. A higher level of public information should imply lower adverse selection and therefore greater liquidity. The liquidity of re-rated firm stocks may also improve due to an increase in its visibility, as well as in the degree of market monitoring of the firm. These factors most likely increase the flow of public information regarding the stock. In this context, if the rating announcement contains new information, it should reduce adverse selection and increase market liquidity.

Prior studies on corporate credit ratings have shown that they have an asymmetrical impact on financial markets. Steiner and Heinke (2001) and Hull, Predescu and White (2004) indicate that to safeguard their reputations, agencies may prefer to proceed slowly so as not to make mistakes. The loss of reputation associated with giving a good rating to a high-risk company is more serious than that resulting from assigning a poor rating to a low-risk company because the first error could mean economic losses for investors. According to Holthausen and Leftwich (1986) and Ederington and Goh (1998), this asymmetry means that the agencies allocate greater resources to revealing negative information than positive information. Therefore, the impact on liquidity will be greater in the case of downgrades than upgrades.

However, agency behavior could reflect a "moral hazard risk problem" that would undermine the reliability of their ratings. Almost all rating agency revenue comes from rating fees. Steiner and Heinke (2001) show that agencies may systematically overrate issuers to gain market share or maintain leadership. As Covitz and Harrison (2003) state, one method for acting in the interest of issuers is to delay ratings downgrades. With this behavior, the market would not value rating changes, and they would not affect stock liquidity.

In this paper, we consider changes in debt ratings and their issuers announced by three primary agencies: Moody's, Fitch and Standard & Poor's, in the Spanish market. In addition to effective rating changes, we analyze outlook reviews and credit watch listings. Agencies state that they make these different rating-related decisions to offer up-to-date and accurate information concerning solvency before deciding on whether to change the credit rating of a firm.[3] According to Steiner and Heinke (2001), Hull *et al.* (2004), Boot, Milbourn and Schmeits (2006)[4] or Altman and Rijken (2007), these announcements convey even more useful information than do effective rating changes.

We studied abnormal liquidity around rating change announcements using an event study. We approximated liquidity using the measures proposed by Amihud (2002), Chan, Hong and Subrahmanyam (2008) and Hui and Heuble (1984). We also examined which factors determine the sign and intensity of the observed effects on liquidity via cross-section analysis. As such authors as Hand *et al.* (1992), Barron *et al.* (1997) and May (2010) suggest, we focused on characteristics related to the rating change announcements, the issuing agency and the economic environment, paying special attention to the effects of the financial turbulence beginning in 2007.

We find a close association between rating actions and liquidity. We show the presence of higher liquidity after announcements, independent of their sign. We also find that investors pay more attention to the analyzed factors in the case of negative announcements than positive ones. Concretely, relevant factors for investors in terms of

[3] Watch list additions occur after special events (e.g., changes in regulation and unexpected changes in management) and indicate that the rating is under review for a likely short-term change. Outlooks indicate the credit worthiness trend in a medium-term time frame.

[4] Boot *et al.* (2006) provide a model based on an implicit contract between the credit rating agency and the firm that should prevent further downgrades. An agency initiates a monitoring regime through the credit watch procedure, and the issuer implicitly promises to initiate specific actions to mitigate the possible decline of its rating.

the intensity of the liquidity response include the degree of debt monitoring, the degree of agreement or disagreement between rating agencies following the same issuer, whether the announcement is expected, whether it is part of a trend, the initial rating level and the range of the jump represented by the new rating. For announcements of improved credit ratings, the intensity of liquidity increases is lower after the 2007 crisis. In this period, there is greater risk aversion among investors, who are more conservative regarding positive news and who perceive the agencies to have less credibility.

The remainder of the study is structured as follows. Section 2 presents the data. Section 3 details the methodology used to study events and the employed liquidity measures. Section 4 presents the main results. The cross section analysis is detailed in section 5. Finally, the main conclusions are presented in section 6.

2. Data

We analyzed businesses listed on the Spanish Continuous Market that have received changes in credit ratings over the period of January 2000 to December 2010. The information regarding changes came from the web pages of Fitch, Standard & Poor's and Moody's and was supplemented with information from the *Reuters* database. Information regarding debt ratings and the issuer was considered, as well as changes in issuer perspective and entries into watch lists. The initial sample was made up of a total of 359 announcements.

Figure 1 shows the annual evolution of announcements grouped into negative changes (implying a decrease in credit quality) and positive changes (implying an improvement in credit quality). Two periods with the total number of announcements falling well above the annual mean of 33 announcements were observed: 2002 with 58 announcements and 2009 with 43. In both cases, the upturn came after periods of crisis: the dot-com crisis in 2001 and the subprime mortgage crisis in 2007-2008, which led to a global financial crisis. This financial turmoil led to a great number of negative announcements, which represented 70% of the sample.

[Insert Figure 1]

Table 1 shows rating changes by sector and scoring agency. Moody's is the agency with the greatest number of announcements, and the Petroleum and Energy and Financial sectors are those that receive the greatest amount of monitoring. During the study period, 41% of announcements pertained to the Financial sector, 52.7% of which were negative. This high percentage is observed because this sector includes the greatest number of Spanish companies that issue debt. Moreover, it is a sector that has implemented many changes as a result of the crisis. The Petroleum and Energy sector represents 35% of the announcements in the sample, with 82.4% of these being negative.

3. Measures of Abnormal Liquidity in the Event Study

Despite the interest in the study of liquidity, there is no consensus on how to measure it (Kamara, Lou and Sadka, 2008). Liquidity is not observable, tends to be associated with the impact of transactions on prices and is related to the idea of continued low-cost negotiation. Ericsson and Renault (2006) define liquidity as the capacity to exchange a cash asset for a price that is close to its value in a disturbance-free market. Sarr and Lybek (2002) show that liquidity is related to five factors: tightness, immediacy, depth, breadth and resilience. Tightness refers to low transaction costs, immediacy to the speed at which orders are executed, depth to the number of orders, breadth to the volume of orders, and resilience to the capacity of the market to recover from unexpected events.

Given the difficulty of defining liquidity, different methods have been proposed based on one of these factors.[5] Several procedures seek to quantify transaction costs with measures based on the bid-ask spread; others attempt to compute the impact of price, such as the measurements used by Brennan and Subrahmanyam (1996) or Sadka (2006); other methods are based on transaction volume, such as turnover ratio. In this study, we use measurements proposed in the literature that allow us to obtain liquidity measures based

[5] Goyenko, Holden and Trzcinka (2009) offer an extensive review on liquidity measures.

on daily data.[6, 7] In particular, we use measurements proposed by Amihud (2002), Kamara *et al.* (2008), Chan, Hong and Subrahmanyam (2008) and Hui and Heuble (1984).

The Amihud (2002) measure (AM) relates performance and negotiation volume in monetary value. AM begins with the hypothesis that performance tends to increase in the presence of illiquidity. We apply the adaptation to daily data proposed by Kamara *et al.* (2008). The AM daily illiquidity measurement is

$$AM_{it} = \frac{\left|r_{it}\right|}{P_{it} \times Vol_{it}}, \tag{1}$$

where r_{it} is the return calculated as the rate of logarithmic price variation, P_{it} is the price, and Vol_{it} is the number of negotiated units of asset i on day t. To calculate this measurement, the mean of the maximum and minimum prices on that day are used.[8] When AM has a high value, the negotiation volume greatly affects prices, and as such, there is little liquidity.

The second liquidity measurement analyzed is the Turnover Ratio (TR), which is also based on the volume of monetary unit negotiation. This ratio measures the frequency with which the volume in circulation changes hands over a set period. We use the adaptation of daily data proposed by Chan *et al.* (2008):

$$TR_{it} = \frac{Vol_{it}}{C_{it}}, \tag{2}$$

where C_{it} is the number of assets in circulation for asset i on day t. This ratio is a simple measurement for estimating changes in liquidity because it establishes the negotiated volume relative to the number of assets in circulation as a barometer of liquidity: the

6 Several of these measures are not used in this study because our database does not include the necessary information to calculate them (for example, bid-ask spread).

7 Goyenko *et al.* (2009) provide evidence that the effort of computing high-frequency measures is simply not worth the cost.

8 The AM was obtained via a different method, substituting P_{it} for the closing price of asset i on day t. The results, which are similar, are not shown in the interest of saving space.

greater the negotiated volume in relation to total assets, the greater the liquidity of the asset.

Third, we analyze the Hui and Heuble (1984) (HH) ratio of illiquidity:

$$HH_{it} = \frac{\left(\dfrac{P_{\max_{it}} - P_{\min_{it}}}{P_{\min_{it}}}\right)}{TR_{it}}, \tag{3}$$

where $P\max_{it}$ and $P\min_{it}$ are the maximum and minimum prices of asset i on day t, respectively. This measure has also been adapted to the daily frequency along the same lines as the two previous ones. The greater the rotation of assets in relation to the proportional variation in prices – that is, the lower HH is – the greater the liquidity.

To analyze the effects of rating change announcements, we carried out an event study. This consists of examining abnormal liquidity behavior around the date of the rating change announcement. To calculate abnormal liquidity, we must define the concept of "normal", i.e., control liquidity. In our case, the level of control liquidity for company i (CL_i) is estimated as the mean liquidity of company assets in the period before the announcement. To calculate CL_i, we used liquidity information from two months prior to the rating change announcement. In particular, if t=0 indicates the day of the announcement[9], control liquidity is calculated as

$$CL_i = \frac{\sum_{t=-40}^{-20} l_{it}}{20}, \tag{4}$$

where l_{it} is the liquidity of asset i on day t as approximated by one of the three previously mentioned measures (AM_{it}, TR_{it} or HH_{it}).

This control liquidity for asset i should be compared with liquidity around the date when the rating change announcement is made. For this, event liquidity is calculated as the mean liquidity in a window (t_1, t_2) around the announcement, $EL_{i,(t_1,t_2)}$:

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

$$EL_{i,(t_1,t_2)} = \frac{\sum_{t=t_1}^{t_2} l_{it}}{T}, \tag{4}$$

where T is the number of days in the window (t_1, t_2) that is created around the announcement day.

Finally, abnormal liquidity $AL_{i,(t_1,t_2)}$ is obtained by comparing event liquidity, $EL_{i,(t_1,t_2)}$, and control liquidity, CL_i,:

$$AL_{i,(t_1,t_2)} = EL_{i,(t_1,t_2)} - CL_i, \tag{5}$$

In this study, we analyzed ten different event windows: four symmetrical windows and three pre- and post-event windows. The symmetrical windows, (-1,1), (-5,5), (-10,10), (-15,15), are intervals around the day of the event, whereas the previous, (-15,-1), (-10,-1), (-5,-1), and subsequent windows, (1,5), (1,10), (1,15), do not include the day of the event. The use of different windows allows us to analyze the impact of the event throughout a particular period of time. The main advantage of using previous (subsequent) windows for an event is that they allow for the analysis of whether the market has anticipated the effects of the event (if the event was instantaneous, or if it lasts for a few days after the announcement.)

The contrast to the null hypothesis for an absence of effects for the rating change announcement on liquidity (H_0: $AL_{i,(t_1,t_2)} = 0$) is carried out via three contrasts: t-ratio, sign test and range test. The first test is a parametric contrast with an asymptotic normal distribution under the null hypothesis. The others are non-parametric robust contrasts to non-normality. The Fisher sign test statistic equals the number of times it is positive. Under the null hypothesis, this statistic follows a binomial distribution (n, p) with p=0.5.The Wilcoxon rank test accounts for information of both magnitudes and signs. The contrast statistic is the sum of all ranks associated with positive signs with absolute values of $AL_{i,(t_1,t_2)}$ that were previously ordered from smallest to largest. We used normal approximation in this study.

To carry out this study, we use daily data on asset prices, negotiated volume and number of assets in circulation for the re-rated company[10]. Prior to analysis, different filters are applied to the sample that lead to the elimination of events that: (1) do not have a minimum number of observations in the total window (-40, +15); (2) have a rating event for the same issuer within the total window; or (3) have another event for the same issuer within the total window that might have affected liquidity.[11] This filtering leads to the exclusion of 87 announcements from the sample. The final sample has 272 events affecting 32 issuers in 6 different sectors. Table 2 shows that the distribution of the final sample with regard to the 6 analyzed categories (upgrade/downgrade, positive/negative outlook and positive/negative watch listing) coincide with that of the initial sample.

4. Rating Event Effects on Liquidity

We consider the impact of announcements for deteriorated credit quality actions (Table 3) and for improved credit quality actions (Table 4). Both tables present the results for three liquidity measures in three panels. We calculate the mean and median abnormal liquidity jointly with an indicator for the sign of effects. Because we have two variables that measure illiquidity (AM and HH) and one that measures liquidity (TR), we add ↑(↓) to indicate that the estimated result implies higher (lower) liquidity related to the announcement. The tables show the three statistics used to test the significance of these effects.

4.1. Effects of Negative Rating Announcements on Liquidity

Table 3 presents the results for announcements of deteriorated credit quality rating actions. The mean and median abnormal liquidities are significant when we consider the turnover ratio in the symmetric and pre-event windows. The parametric and non-

[10] These are daily closing prices that are corrected for dividends, stock splits, equity offerings and merger effects. Preferred stocks have been excluded from this study.

[11] Such as fusions, acquisitions, splits and grouped stocks.

parametric tests indicate that abnormal liquidity is significantly positive, as proxied by turnover ratio. Furthermore, we detect an increment in liquidity before the announcement of the lower credit quality that persists for just few days (less than 5) after the announcement. This effect is confirmed in some of these windows when liquidity is approximated by the AM or HH measures. This evidence indicates (1) that the negative announcements contain relevant news for market participants and (2) a certain degree of anticipation of the negative news by the market.

4.2. **Effects of Positive Rating Announcements on Liquidity**

Table 4 shows the results for announcements of improved credit quality. For the negative rating announcement, we find significant and positive abnormal liquidity. In this case, the effect of the positive rating event is detected through the AM and HH measures and with the nonparametric tests. The tests indicate that the abnormal illiquidity median is significant and negative in all considered event windows (symmetric, pre- and post-event windows) and implies that an increase of liquidity is observed around the positive announcement. This result indicates that positive rating actions 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 announcements 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 Spanish market investors. As Kyle (1985) stated, this new information seems to diminish informational asymmetry, thereby causing higher levels of liquidity. 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 corporate bond market. Our results seem to contrast 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). However, 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.

5. Determinants of the Abnormal Liquidity Reaction to Rating Changes

Many researchers, such as Altman and Rijken (2007), assert that rating refinements – outlooks and reviews – may be even more useful than effective rating changes in transmitting relevant information concerning the issuer's default risk to the markets. According to their hypothesis, it must be expected that higher liquidity relates to these refinements than to effective credit changes. Additionally, we expect that rating changes that are the resolution of credit watch procedures be less informative. Watch listing increases the firm's visibility and the market expectations of a rating change,[12] which could diminish the liquidity response. Conversely, Boot *et al.* (2006) state that the announcement of a credit watch most likely increases the information content of effective rating changes because it discloses more private information. This hypothesis implies a stronger liquidity response to rating changes announced after inclusion in a credit watch list.

Looking at the agency, Livingston, Wei, and Zhou (2010) find that the impact of Moody's ratings on market reactions is stronger compared to Standard & Poor's. Guettler and Wahrenburg (2007) find that bond ratings by Moody's and Standard & Poor's are highly correlated. Along these lines, we also analyze if there is an agency-specific effect on the liquidity response to rating actions. In our sample, 45.4% of rating actions are made by Moody's, 29.5% by Fitch and 25.1% by Standard & Poor's.

Furthermore, because many credit issues are rated by more than one agency, in certain situations, we can find split ratings. These splits could be related to differences in methodology or to the importance that each agency gives to relevant variables or particular matters. It could be expected that disagreements among agencies about the solvency of a firm could increase the level of asymmetric information in the market,

[12] In our total sample, 31% of rating drops and 4% of rises were preceded by entry into a watch list belonging to the same rating agency.

causing lower liquidity around split-rating announcements. In contrast, certain rating events generate consensus among agencies, reflecting agreement in the firms' default risk as perceived by the different agencies. This type of announcement might lead to lower information asymmetries and higher liquidity. Similarly, the number of agencies that rate each firm would also be important.[13] We hypothesize that rating actions affecting highly monitored firms could be less informative because these firms are more visible to market participants, who will already have more information about them. If this hypothesis is the case, the impact on liquidity of rating actions that reflect the opinion of more agencies could be lower than for less monitored firms.

Conversely, 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 develops, 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.

The characteristics of investors are also important in determining the liquidity response. Institutional investors are constrained by clauses that force them to make decisions based on the observed rating[14]. These forced trades could influence the effects caused by rating changes even though these changes contain no new information for the market. In this context, we expect that the liquidity reaction to rating actions would depend on the prior rating level. Institutional investors will concentrate on the investment-grade level, 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

[13] Bolton, Freixas and Shapiro (2012) model the different conflict of interests of rating agencies and conclude that a monopoly of one rating agency would be more efficient than a duopoly in some circumstances.

[14] For example, pension funds are often allowed to deal only with investment-grade issues. Similarly, certain markets, such as the Eurobond market, may simply require the presence of a particular minimum rating before listing the debt issue.

firms.[15] These institutional rigidities can also result in stronger liquidity reactions to rating changes that cross the investment-grade frontier.

Additionally, as Covitz and Harrison (2003) indicate, a moral hazard risk problem may arise because although ratings users are investors, agency income comes from rated firms. This fact might lead agencies to act in favor of issuers by delaying the date of publicizing a downgrade, thus providing the issuer with time to correct its credit quality. Along these lines, we hypothesize that the number of degrees downgraded is a signal of the amount of information that this rating change conveys. It is more probable that market participants anticipate the information when a firm is suffering a large change in its default risk than when this change is small because the delay of the agency in announcing the new rating could be greater. The time that an agency takes in the case of large improvements might be longer because of the possible loss of reputation associated with the bankruptcy of a highly rated business.[16] In this sense, we expect a negative reaction between abnormal liquidity and the degree to which the rating is changed.

The sample period we analyze covers the recent economic recession, which originated due to the collapse of the housing bubble. We can trace the beginning of the financial market tensions to September 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 the crisis. For example, Jorion, Liu and Shi (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 of rating agencies' credibility due to their central role in the sub-prime mortgage crisis or

[15] Jorion and Zang (2007) indicate that we should expect greater stock price impact for lower initial ratings.

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

their failure to predict the Lehman Brothers default in 2008.[17] 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 on the value of 1 (or 0) depending on whether the rating announcements involve: outlook reports, reviews, Fitch or Standard & Poor's decisions, split ratings, consensus rating actions[18], trend-ratings[19], cases in which the previous rating is in the speculative grade or decisions in times of crisis. We also consider the number of agencies that monitor the firm. In the case of the effective rating change subsample, we also consider the number of grades of the jump and dummy variables that take on the value of 1 (or 0), depending on whether the rating announcements involve expected rating changes[20] and border crossing[21].

We analyze AM, TR and HH abnormal liquidity proxies in the (-1,1) and (-5,5) windows. We also consider the narrower pre- and post-event windows, (-5,-1) and (1,5), to study the reaction when the market anticipates the effect on liquidity or when the effect persists after the announcement. All models are estimated by OLS with the White heteroskedasticity-consistent covariance matrix. We consider a 10% significance level for the tests.

5.1. Determinants of Reactions to Announcements of Deterioration in Credit Quality

The results for announcements of credit quality deterioration are shown in Table 5. Contrary to the hypothesis of Altman and Rijken (2007), few differences are observed in

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

[18] We consider two different kinds of consensus rating actions. We refer to those rating actions by more than one agency in the same direction and date as s*imultaneous rating*, and those by one agency that follow a rating action in the same direction by other agency in the preceding 12 months as s*econd mover*.

[19] We define *trend-rating* as any announcement that has been preceded by three rating announcements in the same direction over the past 12 months.

[20] Rating changes that are the resolution of a credit watch.

[21] There are only two downgrades with this property in our sample.

the impact of rating events on liquidity that imply a refining of information regarding effective changes. We only detect more abnormal illiquidity associated with bear market perspectives with the AM in the largest symmetrical window and in the period following the event.

In general, evidence of possible differences in liquidity reactions related with the agency making the announcement is not conclusive. We observe a greater impact of events announced by Fitch than those by Moody's, but only in the post-announcement window and using the TR measure, which would indicate that this agency is more informative. We do not detect differences between Standard & Poor's and Moody's, which would be in line with the results of Guettler and Wahrenburg (2007).

Rating events that affect poorly monitored companies cause greater increases in liquidity; this effect is significant in the pre- and post-event windows and in the broadest symmetrical window using the AM measure. The effect is positive and significant, indicating greater illiquidity levels, when the company is more monitored. This result supports our hypothesis that the market holds more information on these companies than on those that are followed by fewer agencies. Thus, the rating events appear to be less informative when more agencies rate the firm.

We also found that when several agencies simultaneously announce a rating event in the same direction, the increase in liquidity is greater. This effect can be observed in all windows but only with TR. In the case of second mover events, which assume that an agency announces a rating event in the same direction and confirms a previous announcement by a different agency, the results are contradictory. The effect is of a different sign depending on the measure. HH indicates a lower abnormal liquidity response, whereas AM indicates the opposite effect because the parameter in this case is significantly negative. Conversely, the results regarding split rating were as expected. The effect on abnormal liquidity in this case is significantly lower. The estimated parameter is positive and significant in all windows with the AM or HH measures. These results are in line with our hypothesis. It would appear that although simultaneous events lead to a reduction in informational asymmetry in the market, discrepancies in agency opinions tend to increase it.

With regard to trend-ratings, the results confirm the initial hypothesis. The impact on liquidity of this type of announcement is lower because the effect is significant in the (-5,5) and (1,5) windows with two different liquidity measures. This effect indicates that newly incorporated information decreases when rating actions are included in a streak of announcements, implying a continued decrease in the solvency of a company.

We also found lower abnormal liquidity after negative rating actions that affect speculative-grade debt relative to those that affect investment-grade debt. The parameter is positive and significant with the AM measure of liquidity in all windows except (-1,1). Our hypothesis is that institutional investors participate less in this segment of the market, and consequently, the effect on liquidity is lower.

Finally, differential effects in abnormal liquidity associated with announcements that take place before and after the start of the financial and economic crisis in 2007 were not found. This result indicates that, although rating agencies have been questioned about their role in the crisis, markets continue to use their negative ratings in the same ways.

5.2. Determinants of Reactions to Announcements of Improved Credit Quality

Table 6 shows the estimated models in the case of announcements that imply an improvement in the credit rating. The evidence on the relationship between abnormal liquidity and the different analyzed factors is much weaker than in the case of those implying a decrease in quality. Basically, significant differences associated with the majority of analyzed factors are not detected, nor the type of announcement or rating agency making the announcement. In this sense, although liquidity is higher after both positive and negative news, the intensity of the abnormal liquidity response to different factors is asymmetrical.

As in the case of reductions in ratings, we find that differential effects are associated with the degree of monitoring of companies. Greater monitoring implies lower effects on abnormal liquidity. The estimated coefficient always has the proper sign (in all windows and using all measures) and is significant in the narrowest symmetrical window with HH and in the previous window with AM.

In this case, regardless of whether the event implies consensus or discrepancy among agencies, it does not appear to be relevant in determining the intensity of the liquidity response. We only find lower abnormal liquidity with the AM measure in the window prior to the announcement in the case of second mover ratings. The event also does not appear to be relevant if it fits within a trend or is a starting rating level.

With regard to the crisis, the results show differences in the intensity of liquidity responses to improvements in previous or subsequent ratings. The abnormal liquidity response decreases when the announcement comes after the beginning of the crisis. The effect is significant with the TR measure in the widest symmetrical window and in the pre- and post-event windows. The evidence, which is in favor of our hypothesis, indicates that the market finds positive announcements to be less credible, whether because of a more uncertain economic environment or because of a loss in agency credibility.

5.3. **Determinants of Reactions to Announcements of Effective Changes**

Tables 7 and 8 show the results for effective downgrade or upgrade announcements. We add rating change characteristics to the analysis: if the change is expected (result of an earlier entry in a watchlist), the size of the change or whether the investment-speculation limit has been crossed.

As we can see in Table 7, the abnormal liquidity caused by a downgrade is lower according to the increase in monitoring of the company. The effect is detected with AM in all windows, except the narrowest symmetrical one.

Simultaneous downgrades appear to be more informative, although a significant effect is only observed in the post-event window using the TR measure. For the second mover effective downgrades, the increase in liquidity is greater, even though the evidence is weak (only in the case of the AM measure, in the previous window and in the widest symmetrical window.) As indicated, this type of announcement leads to lower information asymmetries and, as consequence, higher liquidity.

For those expected downgrades, normal liquidity is lower when measured with TR in the broadest symmetrical window and in the post-event window. This phenomenon appears to indicate that a lower rotation of the issuer's stocks is produced. This result coincides with the hypothesis of Altman and Rijken (2007) and contradicts the hypothesis of Boot *et al.* (2006) because it appears that expected downgrades are less informative. Thus, their impact on liquidity is lower.

The liquidity reaction to a downgrade appears to be related to the size of the jump in rating and the fact that the downgrade implies a jump in the speculative grade. Thus, we find lower impact on liquidity belonging to those downgrades that imply a greater leap. The effect is observed in the post-event window using the TR measure. This result supports our initial hypothesis and suggests that the quantity of non-public-information-revealing downgrades is lower according to the amount of solvency lost by the company and thus the greater the rating drop. This result might be related to the fact that agencies take longer to announce this type of downgrade is due to the importance that it may have for the issuing agency, which is in line with the hypothesis of Covitz and Harrison (2003). This delay makes it more probable that the market will have the relevant information before the announcement. We also find evidence of the importance of the downgrade implying a jump in speculative grade. In this case, we only find a significant and negative effect with the AM measure in the subsequent and widest symmetrical windows. In the same way as with the size of the leap, this lower intensity of increase in liquidity is related to whether these events are less informative. It is probable that companies with difficulties discovered soon after entering speculative grade are followed more closely by the market; thus, these downgrades have likely been anticipated.

This study confirms the hypothesis that the impact on liquidity of announcements that are part of a trend is lower given that new information incorporated by successive downgrades decreases. This effect is detected with the AM and TR measures in all studied windows, except for the narrowest.

For upgrades (Table 8), the liquidity reaction is significantly lower as the grade of monitoring by the issuing agency increases. The effect is only observed with measures AM and HH because the parameter is positive and significant in the four analyzed windows. It is also the case for upgrades that announcements appear to incorporate less new information when debt held by the business is rated by more agencies.

When several agencies announce a simultaneous upgrade, this announcement does not significantly affect the liquidity response. We find only a negative pre-event effect with the HH measure, indicating a greater liquidity response. We do not find any effect related to whether it is a second mover upgrade, although we do find a greater liquidity response in the case of expected upgrades. This effect can be observed with the TR measure in three of the four considered windows. Contrary to results for downgrades, this result lends support to the hypothesis of Boot *et al.* (2006). It appears that the prior review process leads to an increase in the credibility of the announcement when it is an upgrade.

The effect of jump size points to a reduction of the normal liquidity response. We find negative and significant effects in all windows using the TR measure. This result is in line with what is observed for effective downgrades and points to the idea that non-public information contained in these upgrades is lower; thus, the liquidity response is also lower. Regarding trend-upgrades, as was already observed in the complete sample of positive news, there are no effects on liquidity different than those caused by the remainder of the positive changes.

The beginning of the August 2007 crisis lead to announcements having lower effects on abnormal liquidity relative to those of the prior period. The impact of upgrades on abnormal liquidity is significantly less intense in all analyzed windows using the TR measure. This result indicates that the market offers perceives less credibility of corporate debt upgrades after the crisis, reflecting a potential diminishment of the reputation of the agencies.

6. Conclusions

This paper studies the effect of rating announcements on the liquidity of stocks belonging to issuing companies. Although there is a great deal of literature on the effect of these events on the prices of stocks and bonds, there is no evidence on their effects on liquidity in the stock market. Thus, this study fills a gap in the literature. We analyzed the effect of three different types of rating actions by the three primary international rating agencies. The results of this study are crucial for market participants. On the one hand, these results allow for the evaluation of whether rating announcements offer new information to investors. On the other hand, these findings demonstrate the degree to which investors respond to the different characteristics of these announcements.

We carried out an event study with the goal of evaluating the existence of effects on abnormal liquidity. Three standard measures of liquidity were used, considering several window periods around the rating announcement date. To identify which factors determine the effect on liquidity, a cross-section analysis was carried out, accounting for characteristics of the rating announcement, of the debt issuer and of the economic environment.

The provided evidence supports the information content hypothesis. We find effects on stock's liquidity in response to rating announcements. Both positive and negative announcements result in an increase in liquidity. This demonstrates that both types of announcements contain relevant information in the Spanish stock market. Moreover, the market is capable of anticipating the announcement, exhibiting effects on liquidity before the announcement. In the case of announcements that imply an increase in credit rating, there is also a persistent effect for the week following the announcement.

Regarding determinants of the intensity of the liquidity response, the cross-section analysis results indicate that for both positive and negative news, rating refinements do not appear to incorporate distinct information than what is contained in effective changes. There also does not appear to be a differential effect between agencies. The factors that imply a greater probability that the market already has the information that has led to the rating action, therefore leading to a lower impact of the announcement on liquidity response. Among these factors are the degree of debt monitoring, whether the announcement is simultaneous, and the size of the leap.

The intensity of responses to certain factors differs between announcements with different signs. Thus, to determine the liquidity response in the case of negative news, important factors include if an event is agreed upon, if it shows discrepancy among agencies or if it fits within a trend or the initial rating level; however, these factors do not apply to positive news.

The contrary effect is observed during crises. The informational content of announcements showing an improvement in credit rating appears to be lower once the crisis has begun, whereas it does not appear to be important for explaining abnormal liquidity caused by downgrade announcements. This phenomenon may be related to the role that agencies have played in the crisis. Agencies offered excessively high ratings to organizations that later went bankrupt. These decisions may have affected the credibility of positive ratings, thus resulting in lower liquidity responses after the beginning of the crisis. However, the fact that issuers pay agencies for ratings makes it less likely that they would provide excessively low ratings. As a result, investors grant the same credibility to negative ratings, independent of the economic environment we find ourselves in, thus justifying the irrelevance of the crisis factor in the case of downgrades.

Response intensity is clearly asymmetrical with respect to expected changes. In the case of effective downgrades, liquidity responds to a lesser extent to change announcements preceded by entering into a watch list. A downgrade may signify economic losses to investors (Steiner and Heinke, 2001; Hull *et al.*, 2004), who increase their alertness after the announcement of watch listings. These investors will look for the necessary information to anticipate the downgrade, causing a lower liquidity response when it is confirmed. On the other hand, the intensity is greater after expected upgrades. In this case, the economic consequences are not as severe, which is why investors prefer to wait and see if the new rating is confirmed before changing their positions. In this case, as indicated by Boot *et al.*

(2006), the review process incorporates a greater amount of information in upgrade confirmation, increasing the effect on liquidity.

Finally, as with any empirical paper, two limitations should be mentioned. First, we do not know whether our conclusions can be generalized to international markets. Second, we consider three standard liquidity measures, but we do not know where our evidence can be inferred from other measures. These limitations suggest avenues for future research.

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Figure 1. Annual evolution of rate change announcements of credit ratings.

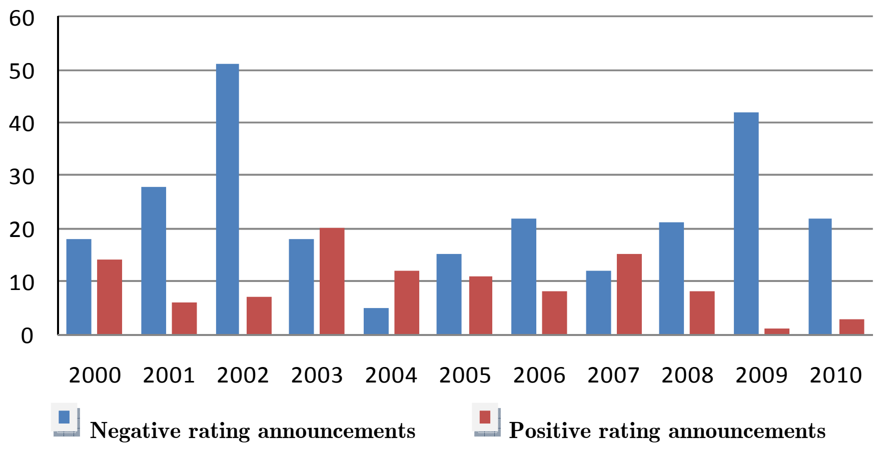

Table 1. Announcements by sector and rating agency

	Agency			
	Fitch	Moody's	Standard & Poor's	Total
Consumer goods	3	4	2	9
Financial	43	70	35	148
Raw materials, industry and construction	6	14	1	21
Petroleum and energy	33	55	37	125
Consumer services	13	10	3	26
Telecommunications	8	10	12	30
Total	106	163	90	359

Table 2. Types of analyzed announcements

	Complete Sample	Analyzed Sample
Negative rating announcements:	254	192
- Effective Downgrade	131	96
- Negative Outlook Assignment	33	30
- Review for Downgrade	90	66
Positive rating announcements	105	80
- Effective Upgrade	56	41
- Positive Outlook Assignment	37	33
- Review for Upgrade	12	6
Total	359	272

Note: The analyzed sample is derived by filtering the complete sample to eliminate events (1) that do not have a minimum number of data in the total window (-40, +15); (2) for which there was some event for the same business within the total window period; (3) for which there was another incident for the same business within the total window that could affect liquidity.

Table 3. Effects of negative rating announcements on liquidity (N=192)

Event window	**(-1,1)**	**(-5,5)**	**(-10,10)**	**(-15,15)**	**(-15,-1)**	**(-10,-1)**	**(-5,-1)**	**(1,5)**	**(1,10)**	**(1,15)**
					AM					
Mean	-2.119 ↑	-1.169 ↑	-0.792 ↑	-1.157 ↑	-0.492 ↑	0.135 ↓	-0.835 ↑	-1.667 ↑	-1.764 ↑	-1.877 ↑
t-ratio	-0.857	-0.451	-0.364	-0.610	-0.321	0.051	-0.303	-0.576	-0.588	-0.634
(p-value)	(0.392)	(0.653)	(0.716)	(0.543)	(0.748)	(0.959)	(0.762)	(0.566)	(0.557)	(0.527)
Median	-0.010 ↑	-0.010 ↑	-0.004 ↑	0.001 ↓	0.004 ↓	0.001 ↓	-0.006 ↑	-0.030 ↑	-0.008 ↑	0.000 ↓
Sign	82 *	88	92	95	93	95	88	78 *	89	96
(p-value)	(0.051)	(0.279)	(0.613)	(0.942)	(0.718)	(0.942)	(0.279)	(0.012)	(0.348)	(1.000)
Rank	-0.767	-1.724 *	-0.445	-0.030	-0.135	-0.228	-1.144	-2.370 *	-1.283	-0.089
(p-value)	(0.443)	(0.085)	(0.656)	(0.976)	(0.893)	(0.819)	(0.253)	(0.018)	(0.200)	(0.929)
					TR					
Mean	1.473 ↑	0.644 ↑	0.430 ↑	0.320 ↑	0.249 ↑	0.377 ↑	0.496 ↑	0.483 ↑	0.308 ↑	0.266 ↑
t-ratio	3.477 *	2.705 *	2.238 *	1.744 *	1.673 *	2.273 *	2.405 *	1.904 *	1.402	1.161
(p-value)	(0.001)	(0.007)	(0.026)	(0.083)	(0.096)	(0.024)	(0.017)	(0.058)	(0.162)	(0.247)
Median	0.114 ↑	0.124 ↑	0.117 ↑	0.093 ↑	0.049 ↑	0.089 ↑	0.027 ↑	0.086 ↑	0.053 ↑	0.029 ↑
Sign	84 *	82 *	79 *	80 *	86	86	91	87	85	88
(p-value)	(0.097)	(0.051)	(0.017)	(0.025)	(0.170)	(0.170)	(0.516)	(0.220)	(0.130)	(0.279)
Rank	-3.468 *	-2.686 *	-2.411 *	-2.139 *	-1.816 *	-1.886 *	-1.163	-1.677 *	-1.305	-1.102
(p-value)	(0.001)	(0.007)	(0.016)	(0.032)	(0.069)	(0.059)	(0.245)	(0.094)	(0.192)	(0.270)
					HH					
Mean	-0.022 ↑	-0.019 ↑	-0.017 ↑	-0.017 ↑	-0.015 ↑	-0.015 ↑	-0.016 ↑	-0.019 ↑	-0.017 ↑	-0.018 ↑
t-ratio	-1.221	-1.059	-1.023	-1.062	-1.011	-0.961	-0.902	-1.012	-0.972	-1.019
(p-value)	(0.223)	(0.291)	(0.308)	(0.290)	(0.313)	(0.338)	(0.368)	(0.313)	(0.332)	(0.309)
Median	0.000 ↑	0.000 ↑	0.000 ↑	0.000 ↓	0.000 ↓	0.000 ↑	0.000 ↓	0.000 ↑	0.000 ↑	0.000 ↑
Sign	82 *	88	93	94	94	89	94	88	82 *	95
(p-value)	(0.051)	(0.279)	(0.718)	(0.829)	(0.829)	(0.348)	(0.829)	(0.279)	(0.051)	(0.942)
Rank	-2.751 *	-1.091	-1.027	-0.498	-0.420	-1.370	-0.682	-1.601	-1.529	-0.569
(p-value)	(0.006)	(0.275)	(0.304)	(0.618)	(0.674)	(0.171)	(0.495)	(0.109)	(0.126)	(0.569)

Note: In all cases, * indicates rejection of the null hypothesis that no effects were due to rating announcements at the 10% significance level or lower. P-values in parentheses. Mean (Median) is the abnormal liquidity mean (median). t-ratio is t-ratio test for the null hypothesis of abnormal liquidity mean is zero. Sign (Rank) is the Fisher's Sign test (Wilcoxon's Rank test) for the null hypothesis of abnormal liquidity median is zero. AM (TR) [HH] denotes that abnormal liquidity was calculated using the Amihud liquidity measure (Turnover ratio liquidity measure) [Hui and Heubel liquidity measure]. ↑ (↓) denote that the effect of announcement is an increase (decrease) in liquidity in the event window.

Table 4. Effects of positive rating announcements on liquidity (N=80)

Event window	**(-1,1)**	**(-5,5)**	**(-10,10)**	**(-15,15)**	**(-15,-1)**	**(-10,-1)**	**(-5,-1)**	**(1,5)**	**(1,10)**	**(1,15)**
					AM					
Mean	-4.332 ↑	-1.731 ↑	-2.033 ↑	-1.778 ↑	-1.995 ↑	-1.733 ↑	-2.402 ↑	-0.890 ↑	-2.278 ↑	-1.506 ↑
t-ratio	-1.303	-0.710	-1.132	-0.803	-1.556	-1.489	-1.351	-0.255	-0.730	-0.411
(p-value)	(0.196)	(0.480)	(0.261)	(0.424)	(0.124)	(0.140)	(0.180)	(0.799)	(0.467)	(0.682)
Median	-0.020 ↑	-0.011 ↑	-0.007 ↑	-0.009 ↑	-0.009 ↑	-0.015 ↑	-0.017 ↑	-0.025 ↑	-0.032 ↑	-0.013 ↑
Sign	30 *	35	34	33	34	32 *	29 *	26 *	26 *	30 *
(p-value)	(0.033)	(0.314)	(0.219)	(0.146)	(0.219)	(0.093)	(0.018)	(0.002)	(0.002)	(0.033)
Rank	-2.696 *	-1.588	-1.751 *	-2.048 *	-1.871 *	-2.034 *	-2.259 *	-2.585 *	-2.590 *	-2.211 *
(p-value)	(0.007)	(0.112)	(0.080)	(0.041)	(0.061)	(0.042)	(0.024)	(0.010)	(0.010)	(0.027)
					TR					
Mean	0.273 ↑	0.120 ↑	0.052 ↑	0.044 ↑	-0.111 ↓	-0.077 ↓	0.078 ↑	0.157 ↑	0.172 ↑	0.193 ↑
t-ratio	1.098	0.749	0.369	0.328	-0.883	-0.521	0.361	0.899	1.033	1.156
(p-value)	(0.275)	(0.456)	(0.713)	(0.744)	(0.380)	(0.604)	(0.719)	(0.372)	(0.305)	(0.251)
Median	-0.087 ↓	0.015 ↑	0.003 ↑	-0.018 ↓	-0.094 ↓	0.001 ↑	-0.031 ↓	-0.005 ↓	0.009 ↑	0.010 ↑
Sign	35	38	40	37	38	40	36	39	39	39
(p-value)	(0.314)	(0.738)	(1.000)	(0.576)	(0.738)	(1.000)	(0.434)	(0.911)	(0.911)	(0.911)
Rank	-0.772	-0.662	-0.365	-0.043	-1.050	-0.652	-0.552	-0.600	-0.767	-0.892
(p-value)	(0.440)	(0.508)	(0.715)	(0.966)	(0.294)	(0.514)	(0.581)	(0.549)	(0.443)	(0.372)
					HH					
Mean	-0.042 ↑	0.004 ↓	-0.015 ↑	-0.018 ↑	-0.027 ↑	-0.035 ↑	-0.038 ↑	0.052 ↓	0.006 ↓	-0.009 ↑
t-ratio	-1.391	0.077	-0.398	-0.566	-0.894	-1.210	-1.260	0.523	0.102	-0.210
(p-value)	(0.168)	(0.938)	(0.691)	(0.573)	(0.374)	(0.230)	(0.211)	(0.603)	(0.919)	(0.834)
Median	-0.001 ↑	0.000 ↑	0.000 ↑	0.000 ↑	0.000 ↑	-0.001 ↑	0.000 ↑	-0.001 ↑	0.000 ↑	-0.001 ↑
Sign	30 *	31 *	31 *	30 *	32 *	29 *	31 *	26 *	30 *	26 *
(p-value)	(0.033)	(0.057)	(0.057)	(0.033)	(0.093)	(0.018)	(0.057)	(0.002)	(0.033)	(0.002)
Rank	-2.374 *	-2.067 *	-2.307 *	-2.293 *	-1.856 *	-2.264 *	-2.494 *	-3.060 *	-2.672 *	-2.374 *
(p-value)	(0.018)	(0.039)	(0.021)	(0.022)	(0.063)	(0.024)	(0.013)	(0.002)	(0.008)	(0.018)

Note: In all cases, * indicates rejection of the null hypothesis that no effects were due to rating announcement at the 10% significance level or lower. P-values in parentheses. Mean (Median) is the abnormal liquidity mean (median). t-ratio is t-ratio test for the null hypothesis of abnormal liquidity mean is zero. Sign (Rank) is the Fisher's Sign test (Wilcoxon's Rank test) for the null hypothesis of abnormal liquidity median is zero. AM (TR) [HH] denotes that abnormal liquidity was calculate using the Amihud liquidity measure (Turnover ratio liquidity measure) [Hui and Heubel liquidity measure]. ↑ (↓) denote that the effect of announcement is an increase (decrease) in liquidity in event window.

Table 5. Determinants of the liquidity response to negative rating announcements

	(-1,1)			(-5,5)			(-5,-1)			(1,5)		
	AM	***TR***	***HH***	***AM***	***TR***	***HH***	***AM***	***TR***	***HH***	***AM***	***TR***	***HH***
Intercept	3.441	-1.776	-0.036	-15.24*	-0.206	0.021	-16.55*	0.907	0.038	-19.60*	-0.389	0.051
	(0.783)	(0.512)	(0.593)	(0.009)	(0.897)	(0.621)	(0.013)	(0.53)	(0.498)	(0.004)	(0.811)	(0.663)
Review	-0.396	0.901	-0.008	1.127	-0.154	-0.007	0.502	-0.649	0.009	1.524	-0.039	-0.02
	(0.856)	(0.499)	(0.491)	(0.3)	(0.828)	(0.343)	(0.643)	(0.166)	(0.296)	(0.249)	(0.96)	(0.17)
Outlook report	3.567	0.161	0.018	2.629*	0.339	0.009	2.159	0.228	0.005	2.811*	0.388	0.017
	(0.117)	(0.835)	(0.185)	(0.04)	(0.462)	(0.365)	(0.106)	(0.677)	(0.373)	(0.061)	(0.424)	(0.428)
Fitch	1.333	0.396	0.007	0.931	0.653	-0.002	1.535	0.607	-0.003	-0.151	0.815*	-0.007
	(0.56)	(0.573)	(0.461)	(0.516)	(0.159)	(0.664)	(0.295)	(0.233)	(0.646)	(0.932)	(0.07)	(0.631)
S&P	-2.071	0.054	-0.015	0.747	0.445	-0.011	1.184	0.133	-0.005	0.404	0.968	-0.016
	(0.384)	(0.966)	(0.266)	(0.47)	(0.528)	(0.15)	(0.276)	(0.807)	(0.373)	(0.744)	(0.214)	(0.149)
# agencies	-2.66	0.435	0.003	3.475*	0.027	-0.011	4.239*	-0.108	-0.017	4.941*	-0.082	-0.019
	(0.466)	(0.482)	(0.887)	(0.038)	(0.945)	(0.451)	(0.033)	(0.801)	(0.299)	(0.017)	(0.834)	(0.608)
Simultaneous-rating	0.961	7.227*	0.016	-0.511	3.825*	0.008	0.033	2.96*	0.004	-1.317	3.261*	0.009
	(0.651)	(0.005)	(0.207)	(0.606)	(0.008)	(0.23)	(0.978)	(0.057)	(0.323)	(0.219)	(0.007)	(0.362)
Second mover	0.855	1.305	0.013*	-2.308*	0.378	0.009*	-2.109*	0.085	0.008*	-3.188*	0.295	0.01*
	(0.574)	(0.162)	(0.093)	(0.033)	(0.487)	(0.051)	(0.047)	(0.833)	(0.062)	(0.044)	(0.632)	(0.093)
Split-rating	3.763	-0.749	0.023*	0.431	-0.214	0.02*	3.225*	-0.168	0.001	-2.047	-0.152	0.045*
	(0.185)	(0.431)	(0.097)	(0.762)	(0.71)	(0.009)	(0.01)	(0.799)	(0.868)	(0.182)	(0.77)	(0.004)
Trend-rating	1.935	-1.092	0.006	1.982*	-0.716*	0.002	0.49	-0.645	0.003	3.147*	-0.51	0.002
	(0.172)	(0.108)	(0.385)	(0.069)	(0.084)	(0.565)	(0.594)	(0.108)	(0.443)	(0.043)	(0.255)	(0.771)
Starting grade	1.666	0.877	0.01	3.002*	0.201	0.005	2.701*	-0.24	0.004	3.254*	0.266	0.003
	(0.356)	(0.429)	(0.199)	(0.047)	(0.732)	(0.357)	(0.073)	(0.533)	(0.589)	(0.044)	(0.688)	(0.789)
Subprime	0.58	-0.455	0.009	-0.405	0.018	0.002	-0.715	0.292	0.001	0.052	0.002	0.00
	(0.762)	(0.481)	(0.237)	(0.729)	(0.962)	(0.745)	(0.509)	(0.425)	(0.899)	(0.972)	(0.996)	(0.972)
R^2	0.042	0.162	0.056	0.135	0.136	0.061	0.139	0.119	0.058	0.142	0.1	0.05
F	0.709	3.089*	0.946	2.5*	2.519*	1.035	2.584*	2.163*	0.985	2.641*	1.786*	0.847
	(0.729)	(0.001)	(0.498)	(0.006)	(0.006)	(0.417)	(0.005)	(0.018)	(0.462)	(0.004)	(0.059)	(0.593)

Note: All models are estimated by OLS, with robust covariance matrix adjusted for heteroskedasticity, p-values in parentheses. * indicates significance at the 10% significance level or lower. *Review* (*Outlook reports*) is a dummy variable equal to one if the rating action is a watch listing (outlook review) and zero otherwise, *Fitch* (*S&P*) is a dummy variable equal to one if the rating action is announced by Fitch (S&P) and zero otherwise, *# agencies* is a variable that takes the value of 1, 2 or 3 depending on the number of agencies that rate the firm *Simultaneous-rating* is a dummy variable equal to one if the rating action is by more than one agency in the same direction and date and zero otherwise, *Second mover* is a dummy variable equal to one if the rating action follows an action by other agency in the same direction in the preceding twelve months and zero otherwise, *Split-rating* is a dummy variable equal to one if the rating action follows an action by other agency in the opposite direction and zero otherwise, *Trend-rating* is a dummy variable equal to one if the rating action is preceded by three or more actions in the same direction in the preceding twelve months and zero otherwise, *Starting grade* is a dummy variable equal to one if the old rating is in the speculative level and zero otherwise, *Subprime crisis* is a dummy variable equal to one if the rating action is announced after august 2007 and zero otherwise.

Table 6. Determinants of the liquidity response to positive rating announcements

	(-1,1)			(-5,5)			(-5,-1)			(1,5)		
	AM	***TR***	***HH***	***AM***	***TR***	***HH***	***AM***	***TR***	***HH***	***AM***	***TR***	***HH***
Intercept	-9.562	1.692	-0.118*	-10.60	1.071	-0.06	-10.92*	0.96	-0.069	-12.07	1.23	-0.043
	(0.239)	(0.329)	(0.062)	(0.209)	(0.178)	(0.13)	(0.004)	(0.238)	(0.12)	(0.369)	(0.177)	(0.299)
Review	-3.292	0.758	0.02	-2.392	0.229	0.005	-2.378	0.366	0.006	-1.826	0.134	0.003
	(0.187)	(0.609)	(0.2)	(0.338)	(0.737)	(0.608)	(0.232)	(0.617)	(0.627)	(0.639)	(0.852)	(0.774)
Outlook report	0.349	0.533	0.013	1.004	-0.115	0.006	-0.808	-0.296	0.008	2.801	-0.133	0.004
	(0.809)	(0.332)	(0.197)	(0.489)	(0.746)	(0.271)	(0.444)	(0.533)	(0.267)	(0.224)	(0.767)	(0.45)
Fitch	-0.131	0.364	0.015	2.278	-0.456	0.011	1.608	-0.218	0.01	3.419	-0.746	0.013
	(0.958)	(0.72)	(0.243)	(0.375)	(0.412)	(0.147)	(0.262)	(0.729)	(0.232)	(0.428)	(0.249)	(0.174)
S&P	-0.823	0.314	-0.003	-0.099	0.327	-0.002	0.055	0.93	-0.003	-0.118	-0.213	0.00
	(0.235)	(0.663)	(0.56)	(0.877)	(0.505)	(0.527)	(0.934)	(0.223)	(0.473)	(0.899)	(0.678)	(0.976)
# agencies	3.359	-0.454	0.035*	3.541	-0.205	0.018	4.019*	-0.226	0.021	3.636	-0.184	0.012
	(0.222)	(0.53)	(0.067)	(0.197)	(0.517)	(0.138)	(0.002)	(0.501)	(0.122)	(0.41)	(0.602)	(0.339)
Simultaneous-rating	0.064	-0.853	-0.005	-1.05	-0.422	-0.003	-1.314	-0.724	-0.006	-1.2	-0.187	0.00
	(0.966)	(0.363)	(0.526)	(0.467)	(0.53)	(0.566)	(0.188)	(0.375)	(0.353)	(0.591)	(0.768)	(0.949)
Second mover	-0.481	-1.083	0.005	-0.848	-0.256	0.002	-0.93*	-0.711	0.001	-0.881	0.236	0.001
	(0.263)	(0.15)	(0.399)	(0.18)	(0.648)	(0.564)	(0.064)	(0.302)	(0.748)	(0.38)	(0.707)	(0.699)
Split-rating	0.079	-0.647	0.001	-1.169	0.094	0.00	-0.952	-0.372	0.00	-1.768	0.703	-0.001
	(0.94)	(0.495)	(0.91)	(0.367)	(0.905)	(0.994)	(0.271)	(0.656)	(0.998)	(0.38)	(0.486)	(0.82)
Trend-rating	0.006	0.074	0.016	0.238	-0.157	0.008	-0.472	0.255	0.008	1.03	-0.541	0.006
	(0.993)	(0.922)	(0.111)	(0.807)	(0.783)	(0.121)	(0.598)	(0.69)	(0.207)	(0.475)	(0.393)	(0.169)
Starting grade	-0.394	-0.363	0.00	-0.063	-1.034	-0.001	-0.647	-1.498	-0.002	0.62	-0.847	0.00
	(0.59)	(0.614)	(0.982)	(0.942)	(0.176)	(0.662)	(0.557)	(0.201)	(0.656)	(0.598)	(0.145)	(0.977)
Subprime	-0.249	-0.949	-0.035	0.613	-1.186*	-0.016	0.545	-0.952*	-0.02	0.974	-1.494*	-0.003
	(0.691)	(0.107)	(0.23)	(0.622)	(0.032)	(0.168)	(0.572)	(0.081)	(0.21)	(0.627)	(0.02)	(0.411)
R^2	0.206	0.129	0.321	0.215	0.16	0.282	0.353	0.134	0.264	0.145	0.164	0.173
F	1.459	0.833	2.66*	1.543	1.072	2.216*	3.071*	0.872	2.025*	0.954	1.108	1.179
	(0.171)	(0.608)	(0.007)	(0.139)	(0.398)	(0.024)	(0.002)	(0.571)	(0.041)	(0.497)	(0.371)	(0.32)

Note: All models are estimated by OLS, with robust covariance matrix adjusted for heteroskedasticity, p-values in parentheses. * indicates significance at the 10% significance level or lower. *Review* (*Outlook reports*) is a dummy variable equal to one if the rating action is a watch listing (outlook review) and zero otherwise, *Fitch* (*S&P*) is a dummy variable equal to one if the rating action is announced by Fitch (S&P) and zero otherwise, *# agencies* is a variable that take the value of 1, 2 or 3 depending on the number of agencies that rate the firm, *Simultaneous-rating* is a dummy variable equal to one if the rating action is by more than one agency in the same direction and date and zero otherwise, *Second mover* is a dummy variable equal to one if the rating action follows an action by other agency in the same direction in the preceding twelve months and zero otherwise, *Split-rating* is a dummy variable equal to one if the rating action follows an action by other agency in the opposite direction and zero otherwise, *Trend-rating* is a dummy variable equal to one if the rating action is preceded by three or more actions in the same direction in the preceding twelve months and zero otherwise, *Starting grade* is a dummy variable equal to one if the old rating is in the speculative level and zero otherwise, *Subprime crisis* is a dummy variable equal to one if the rating action is announced after august 2007 and zero otherwise.

Table 7. Determinants of the liquidity response to downgrades

	(-1,1)			(-5,5)			(-5,-1)			(1,5)		
	AM	***TR***	***HH***	***AM***	***TR***	***HH***	***AM***	***TR***	***HH***	***AM***	***TR***	***HH***
Intercept	-5.843	1.427	-0.067	-17.92*	0.861	0.027	-16.70*	0.756	-0.022	-26.93*	0.776	0.098
	(0.733)	(0.375)	(0.352)	(0.046)	(0.327)	(0.422)	(0.065)	(0.527)	(0.577)	(0.017)	(0.202)	(0.329)
# agencies	0.456	0.357	0.016	5.484*	0.22	-0.015	5.471*	0.169	0.002	8.046*	0.159	-0.04
	(0.936)	(0.576)	(0.533)	(0.05)	(0.535)	(0.209)	(0.073)	(0.704)	(0.872)	(0.016)	(0.559)	(0.254)
Simultaneous -rating	-2.954	8.153	0.004	-0.357	2.606	-0.003	1.578	0.369	0.002	-3.216	2.518*	-0.01
	(0.529)	(0.163)	(0.795)	(0.902)	(0.22)	(0.784)	(0.33)	(0.702)	(0.896)	(0.509)	(0.08)	(0.433)
Second mover	-0.622	0.042	0.002	-2.918*	0.154	0.009	-4.223*	0.379	0.002	-2.381	0.12	0.019
	(0.812)	(0.951)	(0.894)	(0.099)	(0.711)	(0.213)	(0.042)	(0.387)	(0.817)	(0.205)	(0.801)	(0.159)
Expected	-3.778	-1.276	-0.027	-1.055	-0.88*	0.001	-2.899	-0.68	-0.018	1.758	-0.793*	0.026
	(0.316)	(0.175)	(0.211)	(0.655)	(0.045)	(0.911)	(0.212)	(0.14)	(0.148)	(0.479)	(0.036)	(0.377)
# grades	3.708	-1.028	0.017	0.826	-0.448	0.007	1.317	-0.258	0.011	1.12	-0.391*	0.002
	(0.312)	(0.223)	(0.208)	(0.488)	(0.155)	(0.335)	(0.256)	(0.253)	(0.274)	(0.468)	(0.092)	(0.792)
I. to S.	10.189	-2.408	0.02	15.092*	-0.542	0.001	3.086	0.263	0.01	29.718*	-0.303	-0.01
	(0.191)	(0.279)	(0.16)	(0.083)	(0.567)	(0.899)	(0.291)	(0.837)	(0.268)	(0.051)	(0.7)	(0.595)
Trend-rating	2.478	-0.888	0.011	3.126*	-0.859*	0.004	1.733	-0.738*	0.01	4.077*	-0.833*	-0.003
	(0.274)	(0.145)	(0.315)	(0.084)	(0.027)	(0.604)	(0.376)	(0.071)	(0.26)	(0.034)	(0.043)	(0.788)
R2	0.062	0.245	0.12	0.194	0.166	0.072	0.141	0.069	0.088	0.326	0.146	0.116
F	0.816	4.038*	1.693	2.993*	2.466*	0.96	2.037*	0.924	1.202	6.02*	2.12*	1.639
	(0.577)	(0.001)	(0.121)	(0.007)	(0.023)	(0.465)	(0.059)	(0.492)	(0.311)	(0)	(0.05)	(0.135)

Note: All models are estimated by OLS, with robust covariance matrix adjusted for heteroskedasticity, p-values in parentheses. * indicates significance at 10% significance level or lower. *# agencies* is a variable that take the value of 1, 2 or 3 depending on the number of agencies that rate the firm, *Simultaneous-rating* is a dummy variable equal to one if the rating action is by more than one agency in the same direction and date and zero otherwise, *Second mover* is a dummy variable equal to one if the rating action follows an action by other agency in the same direction in the preceding twelve months and zero otherwise, *Expected* is a dummy variable equal to one if the upgrade was the resolution of a review process and zero otherwise, *# grades* is the number of notches the rating is decreased, *I. to S.* is a dummy variable equal to one if the downgrade move the debt from the investment grade to the speculative grade and zero otherwise, *Trend-rating* is a dummy variable equal to one if the rating action is preceded by three or more actions in the same direction in the preceding twelve months and zero otherwise.

Table 8. Determinants of the liquidity response to upgrades

	(-1,1)			(-5,5)			(-5,-1)			(1,5)		
	AM	***TR***	***HH***	***AM***	***TR***	***HH***	***AM***	***TR***	***HH***	***AM***	***TR***	***HH***
Intercept	-13.47*	1.096*	-0.174*	-18.54*	1.449*	-0.09	-13.08*	1.123	-0.111*	-25.44*	1.813*	-0.055
	(0.097)	(0.015)	(0.064)	(0.035)	(0.018)	(0.131)	(0.018)	(0.109)	(0.09)	(0.054)	(0.08)	(0.4)
# agencies	5.1*	-0.03	0.059*	6.989*	-0.031	0.031	5.373*	0.102	0.039*	9.058*	-0.14	0.019
	(0.033)	(0.892)	(0.063)	(0.014)	(0.89)	(0.119)	(0.005)	(0.669)	(0.081)	(0.038)	(0.714)	(0.388)
Simultaneous -rating	-0.756	-0.234	-0.009	-0.912	-0.463	-0.004	-1.31	-0.617	-0.01*	-0.704	-0.471	0.004
	(0.394)	(0.781)	(0.243)	(0.339)	(0.339)	(0.406)	(0.271)	(0.272)	(0.084)	(0.44)	(0.311)	(0.562)
Second mover	-1.416	-1.49	-0.008	-1.454	-0.704	-0.006	-1.675	-1.117	-0.009	-1.259	-0.206	-0.002
	(0.154)	(0.134)	(0.491)	(0.174)	(0.283)	(0.355)	(0.128)	(0.154)	(0.239)	(0.331)	(0.787)	(0.731)
Expected	0.13	1.874*	0.044	0.494	1.289*	0.019	0.006	1.458*	0.025	1.171	1.054	0.006
	(0.904)	(0.001)	(0.102)	(0.829)	(0.031)	(0.125)	(0.997)	(0.011)	(0.126)	(0.763)	(0.195)	(0.59)
# grades	-0.578	-0.425*	-0.002	-0.785	-0.56*	-0.002	-0.675	-0.629*	-0.002	-0.867	-0.533*	-0.003
	(0.325)	(0.074)	(0.574)	(0.187)	(0)	(0.289)	(0.211)	(0.037)	(0.354)	(0.206)	(0.023)	(0.366)
Trend-rating	0.114	0.419	0.017	0.04	-0.08	0.008	-0.788	0.325	0.009	0.889	-0.493	0.006
	(0.91)	(0.639)	(0.176)	(0.973)	(0.9)	(0.204)	(0.486)	(0.664)	(0.254)	(0.571)	(0.523)	(0.27)
Subprime crisis	-0.482	-1.418*	-0.057	0.904	-1.766*	-0.025	0.37	-1.486*	-0.033	1.856	-2.104*	-0.004
	(0.694)	(0.063)	(0.174)	(0.683)	(0.026)	(0.114)	(0.817)	(0.043)	(0.145)	(0.599)	(0.025)	(0.479)
R2	0.327	0.256	0.442	0.478	0.361	0.398	0.406	0.225	0.42	0.47	0.329	0.182
F	2.149*	1.52	3.511*	4.055*	2.501*	2.932*	3.023*	1.284	3.203*	3.928*	2.174*	0.989
	(0.067)	(0.197)	(0.007)	(0.003)	(0.037)	(0.018)	(0.015)	(0.291)	(0.011)	(0.004)	(0.065)	(0.458)

Note: In all cases, * indicates significance 10% significance level or lower. P-values in parentheses. *# agencies* is a variable that take the value of 1, 2 or 3 depending on the number of agencies that rate the firm, *Simultaneous-rating* is a dummy variable equal to one if the rating action is by more than one agency in the same direction and date and zero otherwise, *Second mover* is a dummy variable equal to one if the rating action follows an action by other agency in the same direction in the preceding twelve months and zero otherwise, *Expected* is a dummy variable equal to one if the upgrade was the resolution of a review process and zero otherwise, *# grades* is the number of notches the rating is upgraded, *Trend-rating* is a dummy variable equal to one if the rating action is preceded by three or more actions in the same direction in the preceding twelve months and zero otherwise, *Subprime crisis* is a dummy variable equal to one if the rating action is announced after august 2007 and zero otherwise.