Intra-industry Spillover Effects of Debt Rating News: Risks and Returns

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Abstract

The aim of this study is to analyze the effect of credit rating announcements on its industry stock returns and on systematic and idiosyncratic risk of the sector. We develop the analysis considering companies listed on the Spanish market on the period 2000-2014 under credit events announced by the Credit Rating Agencies DBRS, Fitch, Moody's and Standard and Poor's. We use an extension of the event study dummy approach that includes effects on its sector estimated return, beta and volatility. We find effects on the sector return and on the sector volatility indicating that Credit Rating Agencies provide new information to the market. Results suggest that rating announcements spillover beyond the affected firm and extend to its sectorial firms on the same direction concluding that the contagion effect is the predominant effect on the Spanish market. Our main finding is that there is a spillover effect after rating events on the sector return and on its unsystematic risk which is a previously unexplored issue, we also find a bigger effect in watch change events It may have important implications for the valuation and risk management of portfolios on baskets of shares. In addition, and consistent with the literature, these effect are found asymmetric and point that market is more sensitive to negative news.

Keywords: Credit Rating Agencies, CRA, Rating, Market Model, GARCH, Sector returns, Systematic risk, Unsystematic risk.

1. INTRODUCTION

Since the Lehman Brothers default in 2008 the role of Credit Rating Agencies (CRAs) on the markets have been under deep scrutiny by Governments and Regulators. On the European Union it has been implemented a regulation [1] that resulted on the European Securities and Market Authority (ESMA) being responsible for the registration and supervision of CRAs. The main reason for this increase on the regulation is because any rating action by CRAs trends to be accepted and influences the markets.

There are a huge literature on how a rating action on a company affects to its own stock price, for example Wansley and Clauretie (1985), Holthausen and Leftwith (1986) and Cornell *et al.* (1989) find evidence of negative returns under downgrades of debt. The effect of review announcements for potential downgrades has also been studied for example by Followill and Martell (1997). Other authors like Impson, Karafiath and Glascock (1992) and Abad and Robles (2014) find that there is a linkage between risk and downgrades depending on the size of the firm. More recently, Abad and Robles (2006) analyze the effect of rating changes on Spanish stocks and find evidence of negative returns around the date of the downgrade announcement.

Also, the effect of bond rating changes and its transferring effects has been studied by Caton and Goh (2003) and Akhigbe, Madura, and Whyte (1997). More recently Jorion and Zhang (2010) present an analysis of the contagion and competition effects after announcements of bond credit downgrades in the USA markets.

The main objective of our study is to contribute to the literature that analyzes the contagion and competition effects of credit rating events in several ways. First, we analyze the intra-industry transmission effects in the Spanish market for the first time. Second, we complete earlier analysis based on the assumption that the CAPM is the model that reflects the industry stock returns behavior, by not only considering the effects of firm's rating events on their sector returns instead focusing on the changes on their sector systematic and idiosyncratic risks. Third, we focus on six different types of rating actions (upgrades, downgrades, positive and negative outlook reports and positive and negative watch-listing) announced by four global credit rating agencies. Fourth, we analyze these effects in three different time periods: days around the announcement date; days before the release date, to study if market anticipates the news; and several weeks after that date, to analyze the duration of the effects. Finally, we analyze if the effects found depend on sector characteristics on the smallest symmetric window considered.

Rating agencies give a rating grade that is periodically reviewed. These reviews occasionally entail a change in rating grade, which reflects the consideration that the credit solvency of the firm has improved or deteriorated. Moreover, the rating change may be between or within classes and may affect different kinds of debt. In this study we consider two different kinds of rating actions: Standard rating changes (effective rating changes) and rating refinements or modifier actions (Rating outlook and Rating Watch actions). Also, the changes analyzed will be separated in both directions, the ones that suppose a credit enhancement or conversely the credit deteriorations.

[1] the EU Regulation 1060/09 on CRAs

This work will be structured as follows: in section 2 we will set our initial expectations or base hypothesis. In section 3 we will describe the data and the way of filtering it. In section 4 we will set the methodology we will follow, in section 5 we will present the main results obtained. On section 6 we will analyze the determinants of return and risk reaction to rating changes. The work closes with several conclusions in section 7.

2. INITIAL EXPECTATIONS

A number of studies have examined the informative content of rating announcements. Their main purpose is to analyze the effects of rating events on bond and stock prices. The main conclusion is that stock returns of the re-rated firms are influenced by bond rating changes, especially downgrades (e.g., Elayan, Hsu and Meyer, 2001; Abad and Robles, 2006, 2007; Purda, 2007 or Jorion and Zhang, 2007b). Steiner and Heinke, (2001); Gropp and Richards (2001) or May (2010) find similar evidence concerning corporate debt prices. In both cases, the results demonstrate the importance of rating change announcements in revealing specific company information that is relevant to price formation.

Other related studies have focused on the information transfer effects of corporate events such as dividend announcements, bankruptcies, etc. According these studies, the release of new relevant information about a firm may also disclose relevant information about their industry peers/rivals. Under this intra-industry information transfer hypothesis, one may observe a significant effect on one sector after the announcement of relevant events affecting one of its firms. This effect may be one of two types: contagion or competition. The contagion effect implies that the industry respond negatively (positively) to negative (positive) news about one of their firms whereas the competition effect implies movements in the opposite direction.

On one hand, contagion effect can arise due to common factors affecting across the industry, that is, due to the extent to which firms in the industry share inputs, outputs, production processes, and labor markets (Laux, Starks and Yoon, 1998). Also, it can reflect the existence of counterparty risk within the industry associated to close business ties among the industry firms (Jorion and Zhang, 2010). On the other hand, competition effect may occur on industries when the demand for the product is fixed. The rivals can benefit from reduced firm's capacity; they can capture new clients from the displaced firm; or have more market power in more concentrated industries (Jorion and Zhang, 2010).

The contagion and competition effect has been widely analyzed on different kind of events. Balachandran, Faff and Nguyen (2004) find differences on the reaction of Australian energy, industrial and financial firms to special dividend announcements. Goins and Gruca (2008) study the contagion and competition effect of layoffs. Lee, Lin, Chiang and Kuo (2012) find contagion effect on real estate investment trusts dividend events. Jorion and Zhang (2009) find transfer effect of different kind of bankruptcies on the firm's creditors Hertzel, Li, Officer, and Rodgers (2008) study the effect of financial distress along the supply chain on the US market.

In the case of rating news, Lang and Stulz (1992), Akhigbe et al. (1997), Caton and Goh (2003) and Jorion and Zhang (2010) analyze the effect of rating changes on the re-rated company peers/rivals. Jorion and Zhang (2010) find intra-industry transfer effects after bond rating downgrades. Burghof, Schneider and Wenger (2012) study the CDS spreads reaction to rating events and find different behaviors depending on the industry.

This literature has focused mainly on the study of industry returns. The general conclusion in this way is that when there is a negative credit event on a firm, its total value must be lower than prior to the news because to obtain the same expected return it would require a bigger risk premium. That would result on expected return on that firm decreasing at the date of the event. Then, if contagion is the dominant mode of interaction in the sector, the effect of credit events within a group of firms on the same sector should be in the same direction of the announcing enterprise. In the other way, when firms compete on the same sector, they try to obtain the maximum profit and the maximum number of clients, if the firm loses clients favoring same industry firms, it may appear the competition effect. If competition is the dominant mode of interaction in the sector, the effect of credit events within a group of firms competing, should be in the opposite direction of the announcing enterprise

In our paper we consider also the Industry risks: systematic and idiosyncratic. Some authors have shown evidence concerning the effects of rating changes on the re-rated firm risks: Impson et al.(1992); Chandra and Nayar (1998); Barron, Clare and Thomas (1997); Abad and Robles (2006); Hubler, Louargant, Ory and Raimbourg (2013). In general terms, these authors find that downgrades are associated with an increase in beta. There is no evidence that movement within or across rating categories, the number of grades changed, or a change across the investment grade category have a differential impact on the change in beta. Further, the increase in beta is positively correlated with firm size. In that sense, Favara, Schroth and Valta (2012) determined that firms' systematic risk may reflect insolvency risk. Taking this into consideration, we can conclude that the market beta of the firms is inversely related to its financial health, if there are negative news on the market and it is found the contagion-effect to its sector, it will be seen an increase on the systematic risk of the firms belonging to that sector. Instead, if the competition effect is found, and the firms on the sector look stronger after the negative news for the firm, it is expected to be found a decrease on the systematic risk of firms belonging to the same sector.

Considering the effects on idiosyncratic risk, Dierkins (1991) found a positive relationship between volatility and asymmetric information in the markets. Tang (2009) and Opp, Opp and Harris (2013) observed that the role of credit ratings is to mitigate the information asymmetry in credit markets. Barron et al. (1997) analyzed the impact on idiosyncratic risk on rating assignment to new issues and Hubler et al. (2013), and Abad and Robles (2014) found a reduction on stocks price volatility due to any rating actions indicating a lower level of risk. Taking these studies into account, we can expect that if the new information about the rating change contains information that is relevant to its industry, no matter if positive or negative, a spillover effect is produced, so we must expect volatility reductions, independently on the sign of the effect (contagion or competence)

Our initial expectations are summarized on Table 1:

Table1. Spanish Market Firm parameters* hypothesis of change on Sector Parameters* under a firm credit event.

	SECTOR PARAMETERS		
Effect	ALPHA *	BETA *	VOLATILITY *
Contagion	↑	↓	↓
Competition	↓	↑	↓
Contagion	↓	↑	↓
Competition	↑	↓	↓

*based on the return behavior model CAPM

3. DATA SELECTION

3.1 Rating changes on the Spanish Market

We consider rating actions by the most important and active Credit Rating Agencies (CRA) in the Spanish markets: Moody's, Standard and Poor's, Fitch and DBRS. The analyzed sample covers all the companies listed on the Spanish Stock Exchange that have received a rating/perspective/watch-status change from January 2000 to February 2014. [2] We have discarded other rating agencies like Japan Credit Rating Agency and Egan-Jones Ratings Company that are gaining importance on the markets because on the considered period this agencies have a very few number of events in Spanish companies.

We use several sources to identify the announcement date and the classification of the rating action:

- Two news databases. Baratz (Servicios de Teledocumentación, S.A.) and Hemeroteca El País.

- Two on-line databases of financial information: Finanzas (www.finanzas.com, Ya.com Internet Factory) and Invertia (www.invertia.com, Terra Networks, S.A.)

- Additionally, we use direct public information provided by Fitch and Moody's on their websites. (www.fitchratings.com and www.moodys.com)

- We have completed the database by searches on Bloomberg (Bloomberg PLC).

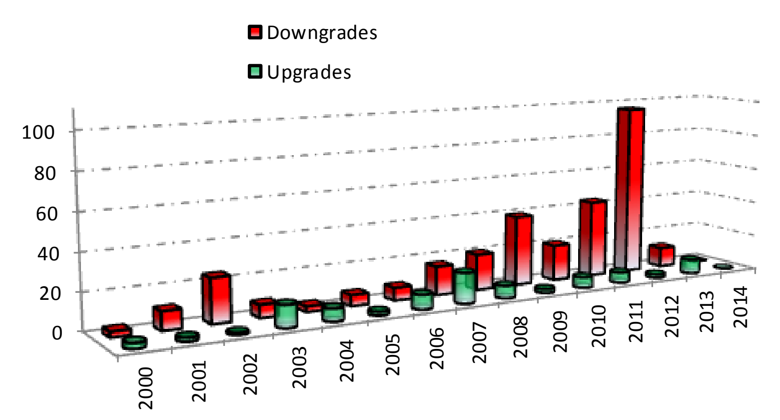
The initial sample was made up of a set of 912 announcements of rating actions that have affected to debt issues or to the issuer, corresponding to 54 issuers. These rating actions are the first rating assignment and the subsequent rating changes or rating refinements (outlook reports and watch listings). We distinguish between positive and negative

[2] This information has been taken from the site www.bolsamadrid.es. We have included firms that were listed but for some reason have been unlisted (mergers and acquisitions, or other events).

announcements. As we are interested in the effect of rating changes we discard first rating assignments. Our final sample accounts with 704 event dates corresponding to 43 issuers. On an event date there may be a rating upgrade/downgrade, an outlook enhancement/deterioration, a watch listing enhancement/deterioration or a mix of them.

The annual evolution of the effective rating changes (upgrades and downgrades) based on our sample is presented in Fig. 1. The period of analysis is characterized by a growing number of rating changes where there are a high number of downgrades (on a ratio of 3:1 against upgrades), being 2012 the year with the greatest number of rating changes. On our sample we have a total of 305 rating downgrades against 83 rating upgrades

Figure 1. Number of rating upgrades and downgrades

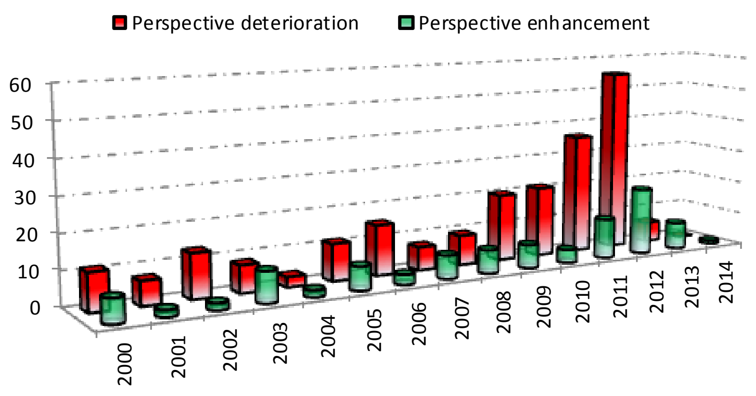


Rating changes may be between or within classes and may affect different kinds of debt. We have used the classification of the changes as presented in the Appendix on Table A.1, grouping them in four main concepts: rating events related to firm specific issues, rating events related to firm financial strength, events related to its short term debt and events related with its long term debt.

The final sample includes 320 events that don't involve an effective rating change but affect to the perspective or credit outlook. This rating action reflects what the CRA expects that is going to happen with the firm rating on a mid-term[3]. This implies an evaluation of the firm's tendencies or risks and their potential impact on the direction of the credit rating of the issuer. Our sample presents 222 perspective deteriorations and 98 perspective enhancements. These rating actions are shown in Fig 2. We find a ratio close to 2:1 negative rating perspective against positive rating perspective. As on the rating changes case, the period from 2010 to 2012 was the one with the hugest amount of perspective changes, being 2012 the year with the biggest number of perspective changes.

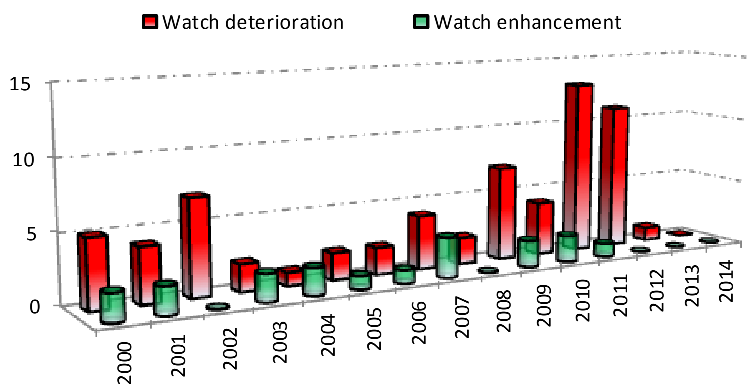
[3]According Fitch website "Rating Outlooks indicate the direction a rating is likely to move over a one- to two-year period"

Figure 2. Number of changes on credit perspective



Our sample includes a second category of rating refinement: Rating Watch[4]. Our analysis includes 83 events of this kind (65 negatives and 18 positives) that have happened as shown on Fig 3

Figure 3. Number of changes on credit watch



In this case the ratio is close to 4:1 (4 watch negative for each watch positive), being 2011 and 2012 the more active years on terms of watch events.

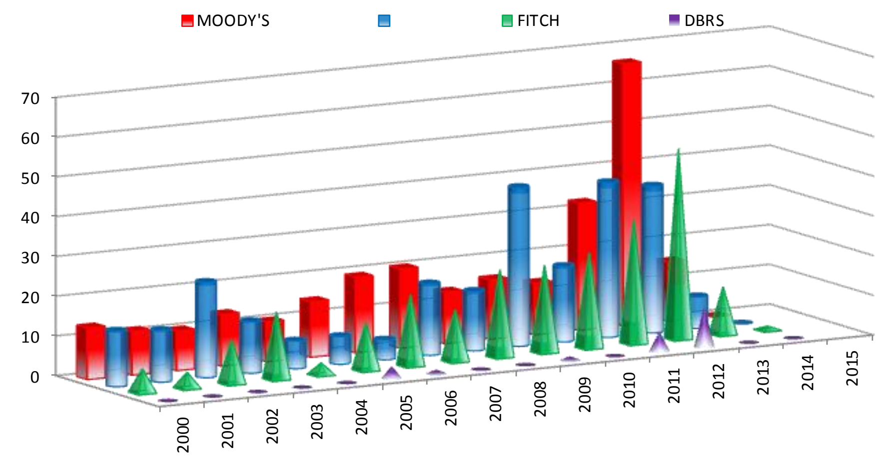
The number of effective rating changes in the sample is almost equal to the number of outlook reports plus watch-listings.

Following Jorion and Zhang (2006), we consider that there may be some events contaminating the sample because they overlap each other. Taking this into account, we identify all consecutive events on a firm and only keep the first observation within the period [-250, +30] working days around the event. The only exclusion to this rule is on the window [0, +3] working days where we decide to join these events to the first observation. Our final

[4] Fitch describes them on its website as they "indicate that there is a heightened probability of a rating change and the likely direction of such a change"

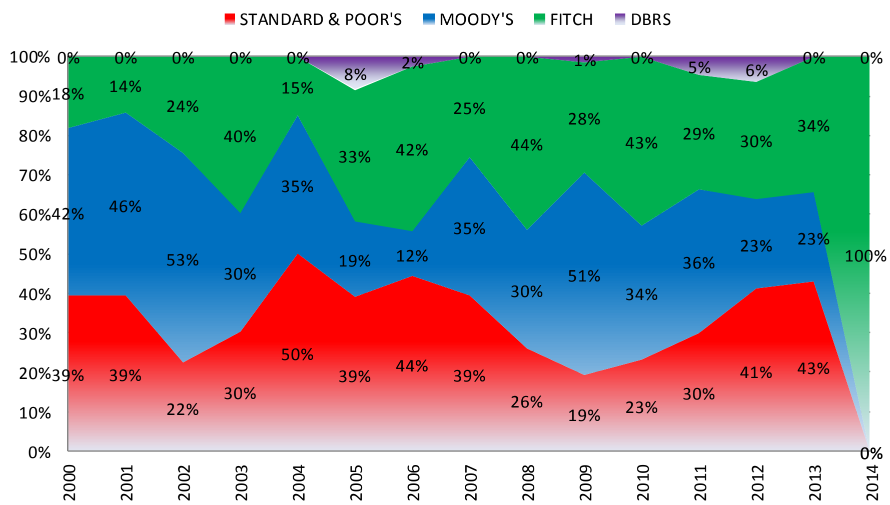
sample includes 704 events[5], 509 deteriorations and 195 enhancements. Considering the deteriorations we divide them as follows 238 rating downgrades, 147 perspective deteriorations and 43 watch deteriorations. The enhancements are divided counting with 79 rating upgrades, 97 perspective enhancements and 15 watch enhancements. In our sample, upgrades and downgrades are sometimes accompanied by a change in the outlook and occasionally a review for a potential future rating change. We decide not to classify these multiple rating actions in any of these subdivisions because this may lead to contaminating our sample.

Figure 4. Number of events by year and Credit Rating Agency



On Fig 4[6] we have considered the evolution of rating events by agency[7] and year. We find that Standard & Poor's is the more active CRA on our sample in the Spanish market, with a total of 264 events, closely followed by Moody's with 259 credit events and Fitch with 244 events. DBRS follows far behind with 20 events. There are only data available from DBRS from 2005.

Figure 5. Percentage of Yearly events by Credit Rating Agency



[5] On each event date it may happen more than one kind of rating actions, for example a deterioration change in perspective and in rating. It can also be affected by one or more agencies (for example Standard and Poor's and Moodys at the same event date)

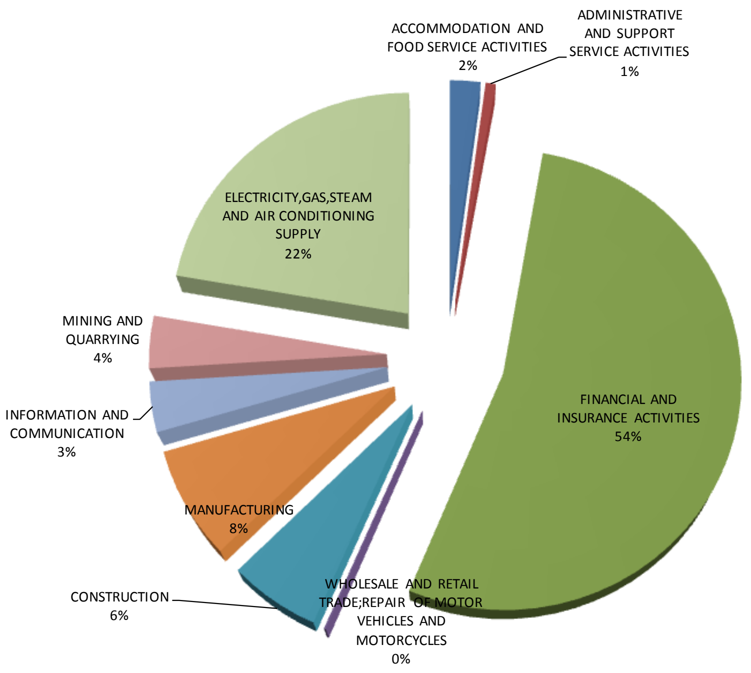
[6] On Figure 4: The data presented shows the number of events grouped by date. (no matter what kind of rating event, if it is a watch or a perspective or a rating effective change) .

[7] There are some dates when more than one agency present an event on one firm at the same time, this events count like one of the events in our sample of 704 events.

At Fig 5 we present the same information provided at Fig 4 but focusing on the evolution of the activity of the different rating agencies on the Spanish market relative to the total yearly number of events based on our initial sample. The more active agency until 2002 was Moody's (during the "dot com" crisis). During the period 2008-2010 (the start of the "liquidity" crisis) the more active CRAs were Fitch and Moody's. Finally, since 2012 the more active CRA has been Standard and Poor's.

The industrial distribution of the events[8] to be considered in our analysis is presented on Figure 6 :

Figure 6. Sectorial distribution of events dates



Based on our sample, as can be seen on the sectorial distribution of events, most the events considered come from the Financial and Insurance sector representing more than half of the events, followed by the Utilities sector.

3.2 Spanish Market data

Our initial database counted on with 351 firms. We exclude those firms whose main operating market is not the Spanish market[9]. We assume that their impact on the Spanish

[8] On Figure 6: Total Number of event dates 704

[9] Firms listed on the Spanish Market excluded of the analysis because their ISIN does not start by ES or their core of the business comes from abroad of Spain: Banco Santander RIO,BBVA Banco Frances SA, Impsat Fiber Networks INC, Aracruz Celulose SA, Banco Bradesco SA, Bradespar SA, Braskem SA, CIA Energetica, Minas GER, Cia Paranaense de Energia, Centrais Electricas Brasileiras, Gerdau SA,NET Servicos de Comuni., Petrobras Petroleos Bras., Cia Suzano de Papel e Celulo., Quattor Petroquimica SA, Usinas Sideerminas Ger., Vale SA, Net Servicos de com., Distribucion y Servicio D&S, Banco de Chile, Empresa Nacional de Elec., Enersis SA, Grupo de Inv. Suramericana, Lafarge SA, Airbus Group NV, Volkswagen AG, Commerzbank AG, Bayer AG, Enel Green Power SPA, Volcan CIA Minera, Santander Bancorp, TV Azteca SAB de CV., Grupo Elektra SAB de CV, Grupo Financiero BBVA Banco, Sare Holding SAB de CV, Alfa SAB, America Movil SAB, Grupo Financiero BBVA Probu, Corporacion GEO SAB, Grupo Financiero Banorte, Grupo Modelo SABm teléfonos de Mexico SAB and Melia Inversiones Americanas. We

industry indexes is not as relevant as other firms that operate in Spain. Conversely, we include other listed firms whose primary market is not the Spanish one, but can be relevant on their respective sectors[10]. This leaves us with 301 firms for our analysis. Furthermore, we check how many of these 301 firms have traded at least one share on the market on the considered period, and it leaves us with 274 firms for our analysis of which, as we pointed out earlier, 43 are affected by credit events.

In order to compute the sector indexes we have decided to classify the sector of the firms according to the NACE classification, for being the European Community standard classification of economic activities[11].

The 274 firms considered are classified as follows[12]:

- Financial and insurance activities, it accounts with 377 event dates on our analysis with 53 firms included on this sector[13] of which 21 are affected by credit rating events.
- Electricity, gas, steam and air conditioning supply, it has 157 credit event dates and 21 different companies considered on this sector of which 8 are affected by credit rating events.
- Manufacturing, with 55 credit event dates with a total of 75 companies on this sector (being the industry with the biggest amount of firms) of which 4 are affected by credit rating events.
- Construction , with 43 credit event dates, with 25 enterprises forming this sector and 4 firms affected by credit rating events
- Mining and quarrying, with a sum of 26 credit event dates and with 8 firms included on this sector with 8 firms on this sector and 2 firms affected by credit rating events.
- Information and communication, accounting 25 event dates to take in our analysis, with 21 enterprises on this sector and only 1 firm affected by credit rating events.
- Accommodation and food service activities, with 15 event dates on our analysis, with just 4 companies belonging to this sector and only 1 firm affected by credit rating events.
- Administrative and support service activities, with 5 event dates taken into consideration, with only 2 enterprises on this sector and only 1 firm affected by credit rating events.
- Wholesale and retail trade, with just one credit event date to take into consideration with 14 companies on this sector and only 1 firm affected by credit rating events.
- Other sectors without credit rating events, we have here 51 firms.

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also have excluded from our sample first time rating events and some certain firms as can be seen on the footnote 10, also some events that happened very close between them have been merged or omitted to ensure our sample is not contaminated

[10] Firms included on the analysis that have an ISIN not starting by ES: Jazztel PLC, Reno de Medici, Tavex Algodonera, Edreams ODIGEO, Arcelor, ArcelorMittal and APERAM

[11] There are other classifications that also represented a high percentage of our firms that we could have used like the ICB or BICS but we have decided to use the NACE classification to create our sectorial indexes

[12] Table A2 at Appendix presents the complete classification

[13] At Tables A3 at Appendix are presented the members on this sector and the number of event dates for each member

4. MODELLING AND TESTING STRATEGY

Under the intra-industry information transfer hypothesis credit announcements by CRAs affecting one firm will cause a significant effect on its sector. Rating changes affecting one firm will spread to the sector causing changes in the sector returns, in the sector risks (systematic and idiosyncratic) or simultaneous movements in all factors.

We assume that the sector stock returns follow the widely used Capital Asset Pricing Model (CAPM). This model calculates the expected return of a sector based on its risk as follows[14]:

$$\dot{R}_{it} = \alpha_i + \beta_i \; R_{Mt} + \dot{e}_{it} \qquad \text{(Equation 1)}$$

Being $\dot{R}_{it}$ the return of sector i at date t, α_i is the expected excess return of sector i considering its risk profile. β_i is the systematic risk of sector i, R_{Mt} is the market premium and $\dot{e}_{it}$ is the idiosyncratic risk of the sector of firm i. According to equation (1), the total variance of the returns can be splitted into two terms:

$$var(\dot{R}_{it}) = \beta_i^2 var(R_t) + var(\dot{e}_{it}) \qquad \text{(Equation 2)}$$

The first one captures the systematic risk which depends on the beta parameter and the market volatility. The second one captures the diversifiable or idiosyncratic risk and depends on the error term volatility.

Model (1) allows us to analyze whether or not changes in the credit risk profile of a firm are transmitted in some way to its sector, as this new information should affect at least one of its parameters. If the new information affects the sector return we will find changes in α_i , if it affects the systematic risk we will find changes in β_i , and we will find changes in volatility of the error term if the effect is on idiosyncratic risk, it also can affect a combination of parameters at the same time.

To test this hypothesis, we proceed as follows. First, we denote t=0 to the announcement date. For each firm and rating event we estimate the extended version of Model (1) proposed by Abad and Robles (2014)[15]:

$$R_{i,t} = \alpha_i + \beta_i \; R_{M,t} + \alpha_{i,s} D_{s,t} + \beta_{i,s} R_t \; D_{s,t} + e_{i,t} \qquad t=-250\ldots T \qquad \text{(Equation 3)}$$

where the rating firm event i is announced in $t = 0$, $R_{i,t}$ is the sector return index (calculated as seen on equation (A.4.3) on Appendix 4, excluding firm i return) at time t from day -250 to day $+T$; R_t is the return on the global return index at time t, which we calculate using an equal weight index as seen on equation (A.4.4) on Appendix 4; $D_{s,t}$ is a dummy variable taking on the value of one on the days at window s = (L, T) and zero otherwise. We study the impact of rating changes on returns and on the two kinds of risk by analyzing different windows around the event date to determine when these effects take place:

[14] As is usual, we consider the Market Model formulation.

[15] At Appendix A4 it is shown the methodology used to build the index

- five symmetric windows around the announcement date: [-1,1], [-5,5], [-10,10], [-15,15] and [-30,30];
- four post-event windows: [1,5], [1,10], [1,15] and [1,30]
- four pre-event windows: [-5,-1], [-10,-1], [-15,-1] and [-30,-1].

In equation (3), as we explained earlier, α_i is the average daily amount by which the stock outperforms the benchmark portfolio on days -250 to L and $\alpha_i + \alpha_{i,s}$ is the average daily amount by which the stock outperforms the benchmark portfolio in the event window. Similarly, β_i is the stock's beta with respect to the benchmark portfolio on days -250 to L and $\beta_i + \beta_{i,s}$ is the stock's beta with respect to the benchmark portfolio on the event i on the window s. Finally, $e_{i,t}$ is the error term that we will assume to be a random variable independent and identically distributed (iid) and normally distributed. We consider $var(e_{i,t})$ in equation (3) to be a time-dependent variance with a direct effect of rating change in the variance equation.

To estimate it we will use models nested on the GJR-GARCH (1, 1, 1) [16]

We take into account the possibility that a credit rating change could have a direct effect on idiosyncratic risk. We include the dummy variable in the variance, D_{st} defined above, which indicates if day t is in the event window:

$$e_{i,t} \sim N(0, \sigma_{i,t})$$
$$\sigma_{i,t}^2 = \omega_{0,i} + \varphi_i \ \sigma_{i,t-1}^2 + \omega_i \ (e_{i,t-1})^2 + \phi_i \ S_{t-1}^{-}(e_{i,t-1})^2 + \delta_{i,s} D_{st} \qquad \text{(Equation 4)}$$

Being S_{t-1}^{-} a variable that equals 1 if $e_{i,t-1} < 0$ and 0 otherwise. If a debt rating change adds new information about firm's i industry idiosyncratic risk, then $\delta_{i,s} \neq 0$ otherwise, if the event does not add any new information about firms i industry idiosyncratic risk, then $\delta_{i,s} = 0$.

To analyze the effect of firm credit rating change announcements on sector return and risk, we have to consider the three components of risk:

- if the average daily amount of outperforms is affected by the event, implies that $\alpha_{i,s} \neq 0$ in equation (3).
- if a credit rating change conveys new information to the market about a change in the sector systematic risk, implies that $\beta_{i,s} \neq 0$ in equation (3).
- if a credit rating change conveys new information to the market about a change in the sector idiosyncratic risk, implies that $\delta_{i,s} \neq 0$ in equation (4).

[16] Based on the wider model GJR-GARCH (1,1,1), GARCH (1,1), ARCH (1)

5. RESULTS

First, we estimate the sector returns model represented by equations (3) and (4) for each event in the sample and for each window by Quasi Maximum Likelihood. We use the Bollerslev and Wooldridge covariance matrix to test the significance of the relevant parameters. Under the null hypothesis that there is no spillover-effect, the parameters accompanying the dummy variables should be equal to zero. For that reason we run three different Wald test taking into consideration individually each event to check if the parameters are significant:

1. Hypothesis 1: there is not spillover-effect. i.e. $\alpha_{i,s} = \beta_{i,s} = \delta_{i,s} = 0$

2. Hypothesis 2: there is not spillover-effect on returns and systematic risk, i.e. $\alpha_{i,s} = \beta_{i,s} = 0$

3. Hypothesis 3: there is not spillover-effect on systematic and idiosyncratic risks, i.e. $\beta_{i,s} = \delta_{i,s} = 0$.

For each rating action in the sample we check if we can reject the null hypothesis based on a 10% confidence and then we take the average number of scenarios where we have rejected the null hypothesis (so there may be a spillover effect). The results for these Wald tests are shown on Table 2

Table 2. Wald tests: Percentage of scenarios where reject the null hypothesis for credit deterioration scenarios (N=509) and credit enhancement scenarios (N=195)

	$\alpha_{i,s} = \beta_{i,s} = \delta_{i,s} = 0$		$\alpha_{i,s} = \beta_{i,s} = 0$		$\beta_{i,s} = \delta_{i,s} = 0$	
Window	deterioration	enhancement	deterioration	enhancement	deterioration	enhancement
[-1,1]	95%	93%	92%	89%	85%	82%
[-5,5]	92%	94%	89%	93%	74%	75%
[-10,10]	92%	92%	90%	90%	62%	66%
[-15,15]	92%	94%	90%	91%	53%	57%
[-30,30]	92%	94%	92%	95%	49%	52%
[1,5]	94%	98%	92%	93%	85%	95%
[1,10]	93%	95%	92%	90%	76%	78%
[1,15]	94%	94%	93%	92%	70%	69%
[1,30]	94%	92%	92%	91%	53%	56%
[-5,-1]	94%	96%	91%	95%	85%	91%
[-10,-1]	93%	90%	91%	89%	78%	72%
[-15,-1]	93%	92%	91%	91%	65%	66%
[-30,-1]	91%	88%	91%	90%	50%	53%

For rating actions related with credit quality deteriorations we find strong evidence about the existence of a spillover effect. In the case of the first hypothesis, $\alpha_{i,s} = \beta_{i,s} = \delta_{i,s} = 0$ the parameters associated with the dummies are relevant the great majority of rating actions and windows considered with a rejection of the null hypothesis on at least 91 When we analyze results for returns and beta ($\alpha_{i,s} = \beta_{i,s} = 0$) we find that the dummies are relevant on the regressions between 89%-92% of the rating events considered. Finally, considering that the spillover effect only on systematic and idiosyncratic risks ($\beta_{i,s} = \delta_{i,s} = 0$) we find lower evidence supporting this hypothesis since the percentages vary between 49%-85% of the cases. We find the lower figures in the wider symmetric, post- and pre-event windows.

On rating actions related with credit enhancements we find something very similar to the case of credit deteriorations: strong evidence about the existence of a spillover effect. In the case of the first hypothesis, ($\alpha_{i,s} = \beta_{i,s} = \delta_{i,s} = 0$), the parameters associated with the dummies are relevant the great majority of rating actions and windows considered with a rejection of the null hypothesis on at least 88%. When we analyze results for returns and beta, ($\alpha_{i,s} = \beta_{i,s} = 0$), where we find that the dummies are relevant on the regressions between 89%-95% of the rating events considered. Finally, considering that the spillover effect only on systematic and idiosyncratic risks, ($\beta_{i,s} = \delta_{i,s} = 0$), we find lower evidence supporting this hypothesis since the percentages vary between 52%-91% of the cases. As the case of credit deteriorations, we find the lower figures in the wider symmetric, post- and pre-event windows.

The effects seen earlier reflect some spillover effect that is bigger when the alpha parameter is on the null hypothesis than when it is out of it. This is our first evidence of the spillover effect. As this contrast does not lead us to find out if there is a contagion or a competence effect, we will try to study it on our next step, the events study.

5.1. Test for Returns.

To draw inferences for the returns, the estimated parameter, $\alpha_{i,s}$, or Cumulative Change in Alpha (CCA) for sector of firm that presents the event, is used to find the Average Cumulative Change in Alpha (ACCA) for a specific window.

$$\mathrm{ACCA_s} = \frac{1}{N}\sum_{\dot{\imath}=1}^{N} \alpha_{\imath,s} \qquad \text{(Equation 5)}$$

where N is the number of credit events in the sample and $\alpha_{i,s}$ is the estimated parameter on the event of firm i on the window s.

The null hypothesis of zero abnormal performance due to rating action announcements implies that ACCA must be zero. To test the statistical significance of the ACCA, we use a standard t-test. Non-normality (skewness, fat tails) can affect the properties of this parametric test. To overcome this problem, we compute two nonparametric tests. First, we use the Fisher-sign test. This test counts the number of times that CCA is positive. Under the null hypothesis, the statistic follows a binomial distribution with p=0.5. Second, the Wilcoxon-signed-rank test is computed. This test assumes that there is information contained in the magnitudes, as well as the signs. To calculate the statistic, we take the series of CCA and rank it from smallest to largest by absolute value. Next, we add the ranks associated with positive values. We report p-values for the asymptotic normal approximation to the test. See Sheskin (1997) for details.

Tables 3 to 6 present the effects of credit deterioration events on the ACCA, on abnormal variations on return. We first analyze the whole sample of negative rating news (Table 3) and then we analyze the subsamples of upgrades, negative reports and negative watch listings in Tables 4, 5 and 6 respectively. Tables 7 to 10 present the effect on ACCA of credit enhancements. As in the case of deterioration, we analyze first the general effect in Table 7, and then we will take a look if the effect differs depending on the kind of event, rating downgrade / upgrade, perspective deterioration / enhancement and finally watch deterioration / enhancement in Tables 8, 9 and 10 respectively..

As we saw earlier our initial hypothesis is that under credit deteriorations, if there is a contagion effect, the ACCA and M-ACCA should be negative. If there is a competition effect the ACCA and M-ACCA should be positive. On this step we will analyze the impact of negative credit events on the abnormal return of the sector

The first thing we find in Table 3 is that the estimated values of the mean and median changes in alpha are negatives in all considered windows. They are also significant in all cases. The t-test giving significant results on rejecting the null hypothesis of ACCA equals 0. On the rank tests we get that it is a robust measure rejecting that the value of M-ACCA equals 0. Finally the sign test also confirms the significance of the negative sign obtained.

This result is in line to those detected in Table 2 confirming the existence of an intra-industry spillover effect of negative rating announcement. The negative sign of abnormal returns indicate that the sector is affected negatively by bad news about the credit risk of one of its firms pointing, a risk contagion effect. This result is consistent with prior studies like the ones obtained by Elayan, Hsu and Meyer, 2001, Abad and Robles, 2006, 2007, Purda, 2007 and Jorion and Zhang, 2007b

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Table 3. Deteriorations: Average Cumulative Change in Alpha. (N=509)

Window	ACCA	t-test	p-val	%sig	M-ACCA	%+	Sign test	p-val	Rank test	p-val
[-1,1]	-0.027*	-3.069	0.002	72%	-0.0036	38%	318*	0.000	6.371*	0.000
[-5,5]	-0.024*	-3.241	0.001	77%	-0.0082	35%	329*	0.000	8.020*	0.000
[-10,10]	-0.032*	-4.472	0.000	79%	-0.0116	34%	338*	0.000	8.949*	0.000
[-15,15]	-0.034*	-5.029	0.000	78%	-0.0155	32%	346*	0.000	9.560*	0.000
[-30,30]	-0.037*	-5.511	0.000	82%	-0.0205	31%	349*	0.000	9.949*	0.000
[1,5]	-0.030*	-3.932	0.000	74%	-0.0091	34%	338*	0.000	7.887*	0.000
[1,10]	-0.028*	-4.034	0.000	79%	-0.0110	35%	333*	0.000	8.299*	0.000
[1,15]	-0.029*	-3.977	0.000	83%	-0.0132	33%	341*	0.000	8.796*	0.000
[1,30]	-0.037*	-5.798	0.000	81%	-0.0176	34%	336*	0.000	9.517*	0.000
[-5,-1]	-0.027*	-3.777	0.000	77%	-0.0078	33%	342*	0.000	8.522*	0.000
[-10,-1]	-0.029*	-4.304	0.000	78%	-0.0117	30%	356*	0.000	9.714*	0.000
[-15,-1]	-0.034*	-4.994	0.000	79%	-0.0132	29%	361*	0.000	9.708*	0.000
[-30,-1]	-0.040*	-6.097	0.000	79%	-0.0172	30%	354*	0.000	9.951*	0.000

ACCA is the Average Cumulative Change in Alpha, * indicates rejection of the null hypothesis that there is no effects due to rating actions (ACCA=0) at least to a 10% significance level. The p-val is the p value that tests the statistical significance of ACCA, the sign test and the rank test respectively. The %sig is the percentage of scenarios where we reject the null hypothesis that the dummy alpha is equal to 0 at a 10% significance level. M-ACCA is the median of ACCA, %+ is the percentage of the scenarios where the dummy alpha is positive, on the sign test * indicates rejection of the null hypothesis that it follows a binomial with p=0.5 at 10% significance level. On the Wilcoxon signed Rank test * indicates rejection of the null hypothesis that M-ACCA is equal to 0 at 10% significance level

The market behavior of the sector prior to the credit event found leads us to believe that the market anticipates the deterioration in credit quality on the previous weeks. The deterioration in credit quality effect on the sector remains at least 30 working days (one month and a half). We also find that the effect on the mean change in alpha, in general terms, increases when we increase the window size around the event, and it is seen the same effect on the median change in alpha.

Table 4. Downgrades: Average Cumulative Change in Alpha. (N=238)

Window	ACCA	t-ratio	p-val	%sig	M-ACCA	%+	Sign test	p-val	Rank test	p-val
[-1,1]	-0.006	-0.472	0.637	74%	-0.0001	42%	139*	0.011	3.099*	0.002
[-5,5]	-0.020*	-1.916	0.055	75%	-0.0077	37%	149*	0.000	5.267*	0.000
[-10,10]	-0.027*	-2.769	0.006	79%	-0.0122	37%	150*	0.000	5.639*	0.000
[-15,15]	-0.025*	-2.940	0.003	79%	-0.0072	37%	149*	0.000	5.599*	0.000
[-30,30]	-0.034*	-3.801	0.000	80%	-0.0171	36%	153*	0.000	6.363*	0.000
[1,5]	-0.018	-1.552	0.121	76%	-0.0074	34%	157*	0.000	4.664*	0.000
[1,10]	-0.015	-1.473	0.141	79%	-0.0045	39%	144*	0.001	4.458*	0.000
[1,15]	-0.019*	-1.861	0.063	82%	-0.0058	38%	147*	0.000	4.498*	0.000
[1,30]	-0.031*	-3.336	0.001	82%	-0.0109	35%	154*	0.000	6.063*	0.000
[-5,-1]	-0.021*	-2.057	0.040	77%	-0.0068	37%	151*	0.000	5.277*	0.000
[-10,-1]	-0.026*	-3.007	0.003	77%	-0.0101	30%	167*	0.000	6.602*	0.000
[-15,-1]	-0.026*	-2.804	0.005	77%	-0.0102	30%	167*	0.000	6.391*	0.000
[-30,-1]	-0.040*	-4.855	0.000	77%	-0.0134	33%	160*	0.000	6.701*	0.000

See Table 3 note

Table 5. Credit outlook deterioration: Average Cumulative Change in Alpha. (N=147)

Window	ACCA	t-ratio	p-val	%sig	M-ACCA	%+	Sign test	p-val	Rank test	p-val
[-1,1]	-0.042*	-2.507	0.012	65%	-0.0036	35%	95*	0.001	3.880*	0.000
[-5,5]	-0.018	-1.233	0.218	73%	-0.0043	35%	95*	0.001	3.787*	0.000
[-10,10]	-0.024*	-1.729	0.084	75%	-0.0008	35%	95*	0.001	3.923*	0.000
[-15,15]	-0.032*	-2.398	0.016	73%	-0.0093	31%	101*	0.000	4.801*	0.000
[-30,30]	-0.031*	-2.328	0.020	80%	-0.0126	31%	102*	0.000	4.528*	0.000
[1,5]	-0.033*	-2.450	0.014	69%	-0.0005	35%	96*	0.000	4.097*	0.000
[1,10]	-0.023*	-1.833	0.067	75%	-0.0056	35%	96*	0.000	4.097*	0.000
[1,15]	-0.019	-1.294	0.196	81%	-0.0095	33%	99*	0.000	4.661*	0.000
[1,30]	-0.030*	-2.501	0.012	75%	-0.0016	36%	94*	0.001	4.342*	0.000
[-5,-1]	-0.024*	-1.811	0.070	74%	-0.0059	29%	104*	0.000	4.665*	0.000
[-10,-1]	-0.021	-1.551	0.121	73%	-0.0059	33%	98*	0.000	4.282*	0.000
[-15,-1]	-0.032*	-2.752	0.006	78%	-0.0067	30%	103*	0.000	4.623*	0.000
[-30,-1]	-0.034*	-2.526	0.012	78%	-0.0067	32%	100*	0.000	4.571*	0.000

See Table 3 note

Table 6. Credit watch deterioration: Average Cumulative Change in Alpha. (N=43)

Window	ACCA	t-ratio	p-val	%sig	M-ACCA	%+	Sign test	p-val	Rank test	p-val
[-1,1]	0.010	0.478	0.633	74%	-0.0056	40%	26	0.222	1.081	0.280
[-5,5]	-0.002	-0.079	0.937	84%	-0.0057	40%	26	0.222	1.746*	0.081
[-10,10]	-0.017	-0.710	0.478	79%	-0.0097	37%	27	0.126	2.458*	0.014
[-15,15]	-0.022	-0.899	0.369	81%	-0.0158	30%	30*	0.014	2.760*	0.006
[-30,30]	-0.013	-0.526	0.599	81%	-0.0129	35%	28*	0.066	2.410*	0.016
[1,5]	-0.019	-1.357	0.175	63%	0.0000	42%	25	0.360	1.770*	0.077
[1,10]	-0.040*	-2.907	0.004	79%	-0.0117	28%	31*	0.005	3.244*	0.001
[1,15]	-0.043*	-3.244	0.001	86%	-0.0238	26%	32*	0.002	3.268*	0.001
[1,30]	-0.044*	-2.215	0.027	77%	-0.0223	44%	24	0.542	2.495*	0.013
[-5,-1]	-0.006	-0.289	0.773	81%	-0.0078	37%	27	0.126	1.818*	0.069
[-10,-1]	0.000	-0.007	0.995	81%	-0.0297	35%	28*	0.066	2.253*	0.024
[-15,-1]	-0.004	-0.196	0.844	81%	-0.0179	40%	26	0.222	1.782*	0.075
[-30,-1]	-0.012	-0.543	0.587	84%	-0.0282	30%	30*	0.014	2.193*	0.028

See Table 3 note

When we zoom into the effect of effective rating downgrades on Table 4 we find that the median estimate change in alpha (M-ACCA) is significantly negative in all windows. The mean (ACCA) is significant in all the pre event windows and most of the post and symmetric windows. On the post event windows it is significant on the two longer windows. As happened in the general credit deterioration situation, we find a negative impact in ACCA and in M-ACCA, and, in general terms it reflects the effect seen earlier of the wider the window the bigger the effect. The main conclusion we can obtain from the downgrades results is that it reflects the contagion effect seen on the general deterioration.

Considering the effect on perspective changes shown on Table 5, we only find 3 windows where the ACCA is not significant. It maintains the negative sign in all windows, and in terms of the M-ACCA we find that it is significant and negative in all windows, with both statistics being robust measures of non-normality. The first result that shocks our expectation is that the greatest impact on ACCA is on the closest symmetric window. In the M-ACCA, the greatest impact happens on the wider symmetric window. On this scenario we do not find the increasing effect on the wider windows that we found under the rating change.

The effect of watch deterioration on Table 6 we find that M-ACCA is significant in almost all windows and we only find 3 scenarios significant on ACCA terms. As we have found on other credit deteriorations events, there is a significant and negative effect, resulting in a contagion effect. This effect is significant in fewer windows than in rating downgrades and perspective deteriorations. It is also interesting to emphasize that the effect on M-ACCA and on ACCA when they are significant under watch deteriorations is bigger than the one seen on the other kind of credit deterioration events. It is important to note that the sample is rather lower for this kind of announcements (only 43 cases).

i) Results obtained on ACCA for credit enhancements

Now we are going to analyze the results on the abnormal return of the sector obtained for credit quality enhancements announcements presented in Table 7.

Table 7. Improvement in credit quality: Average Cumulative Change in Alpha. (N=195)

Window	ACCA	t-ratio	p-val	%sig	M-ACCA	%+	Sign test	p-val	Rank test	p-val
[-1,1]	0.001	0.071	0.943	68%	0.0000	55%	108	0.152	1.031	0.303
[-5,5]	-0.004	-0.409	0.683	76%	0.0000	49%	100	0.775	0.022	0.982
[-10,10]	-0.002	-0.244	0.807	73%	0.0000	49%	99	0.886	0.126	0.900
[-15,15]	0.000	-0.050	0.960	76%	0.0000	48%	102	0.567	0.257	0.798
[-30,30]	0.011	1.031	0.303	78%	0.0000	49%	99	0.886	0.282	0.778
[1,5]	-0.006	-0.510	0.610	76%	0.0000	49%	100	0.775	0.369	0.712
[1,10]	0.003	0.385	0.700	75%	0.0000	51%	100	0.775	0.249	0.803
[1,15]	0.011	1.092	0.275	77%	0.0000	51%	99	0.886	0.134	0.894
[1,30]	0.013	1.029	0.304	77%	0.0000	47%	104	0.390	0.274	0.784
[-5,-1]	-0.001	-0.138	0.890	77%	0.0000	46%	106	0.252	0.497	0.619
[-10,-1]	-0.001	-0.066	0.948	70%	0.0000	46%	106	0.252	0.622	0.534
[-15,-1]	0.004	0.406	0.685	75%	0.0000	49%	99	0.886	0.110	0.913
[-30,-1]	0.002	0.245	0.806	75%	0.0000	53%	104	0.390	0.655	0.513

ACCA is the Average Cumulative Change in Alpha, * indicates rejection of the null hypothesis that there is no effects due to rating actions (ACCA=0) at least to a 10% significance level. The p-val is the p value that tests the statistical significance of ACCA, the sign test and the rank test respectively. The %sig is the percentage of scenarios where we reject the null hypothesis that the dummy alpha is equal to 0 at a 10% significance level. M-ACCA is the median of ACCA, %+ is the percentage of the scenarios where the dummy alpha is positive, on the sign test * indicates rejection of the null hypothesis that it follows a binomial with p=0.5 at 10% significance level. On the Wilcoxon signed Rank test * indicates rejection of the null hypothesis that M-ACCA is equal to 0 at 10% significance level

In this case, we do not find significant levels on ACCA nor on M-ACCA. This result seems to indicate that the market do not consider that positive news about the credit risk of one company be relevant for it sector. Focusing on the upgrades subsample (Table 8), the ACCA and M-ACCA are significant in four windows; two of them are prior to the event and two symmetric windows. The effect seen is robust on the measure used (mean and median) using the t-test and the Wilcoxon rank test. The positive sign found here leads us again to a contagion effect.

Positive rating refinements' affecting the rating of a firm (perspective and watch enhancements) seems to not cause any response in the returns of its sector (Tables 9 and 10).

Table 8. Improvement in credit rating: Average Cumulative Change in Alpha. (N=79)

Window	ACCA	t-ratio	p-val	%sig	M-ACCA	%+	Sign test	p-val	Rank test	p-val
[-1,1]	0.024*	1.710	0.087	63%	0.0000	57%	45	0.260	1.899*	0.058
[-5,5]	0.014	1.022	0.307	65%	0.0000	51%	40	1.000	0.775	0.439
[-10,10]	0.018	1.493	0.136	61%	0.0000	53%	42	0.653	1.356	0.175
[-15,15]	0.016	1.324	0.185	66%	0.0000	53%	42	0.653	1.034	0.301
[-30,30]	0.032*	1.754	0.079	67%	0.0000	54%	43	0.500	1.395	0.163
[1,5]	0.010	0.565	0.572	67%	0.0000	54%	43	0.500	1.195	0.232
[1,10]	0.021*	1.725	0.084	63%	0.0000	57%	45	0.260	1.948*	0.052
[1,15]	0.041*	2.086	0.037	67%	0.0000	59%	47	0.115	2.207*	0.027
[1,30]	0.034	1.451	0.147	66%	0.0000	49%	40	1.000	0.921	0.357
[-5,-1]	0.015	1.201	0.230	65%	0.0000	43%	45	0.260	0.183	0.855
[-10,-1]	0.017	1.320	0.187	54%	0.0000	46%	43	0.500	0.012	0.990
[-15,-1]	0.016	1.237	0.216	61%	0.0000	52%	41	0.822	0.721	0.471
[-30,-1]	0.021	1.453	0.146	65%	0.0000	56%	44	0.368	1.151	0.250

See Table 7 note

Table 9. Improvement in credit outlook: Average Cumulative Change in Alpha. (N=97)

Window	ACCA	t-ratio	p-val	%sig	M-ACCA	%+	Sign test	p-val	Rank test	p-val
[-1,1]	-0.016	-1.391	0.164	73%	0.0000	55%	53	0.417	0.385	0.700
[-5,5]	-0.018	-1.533	0.125	85%	0.0000	46%	52	0.543	0.997	0.319
[-10,10]	-0.017	-1.551	0.121	81%	-0.0021	45%	53	0.417	1.306	0.192
[-15,15]	-0.016	-1.420	0.156	85%	-0.0068	42%	56	0.155	1.493	0.135
[-30,30]	-0.015	-1.410	0.158	89%	-0.0038	43%	55	0.223	1.288	0.198
[1,5]	-0.014	-1.318	0.188	86%	-0.0001	43%	55	0.223	0.623	0.534
[1,10]	-0.012	-1.107	0.268	84%	0.0000	48%	50	0.839	1.213	0.225
[1,15]	-0.017	-1.591	0.112	84%	-0.0001	45%	53	0.417	1.742*	0.082
[1,30]	-0.010	-0.676	0.499	86%	-0.0007	44%	54	0.310	1.745*	0.081
[-5,-1]	-0.017	-1.435	0.151	87%	0.0000	46%	52	0.543	0.993	0.321
[-10,-1]	-0.016	-1.441	0.150	80%	-0.0035	43%	55	0.223	1.367	0.172
[-15,-1]	-0.015	-1.361	0.173	87%	-0.0021	45%	53	0.417	1.033	0.302
[-30,-1]	-0.017	-1.429	0.153	86%	0.0000	49%	49	1.000	0.738	0.461

See Table 7 note

Table 10. Improvement in credit watch: Average Cumulative Change in Alpha. (N=15)

Window	ACCA	t-ratio	p-val	%sig	M-ACCA	%+	Sign test	p-val	Rank test	p-val
[-1,1]	-0.082	-1.071	0.273	53%	0.0000	47%	8	1.000	0.540	0.590
[-5,5]	-0.069	-1.171	0.284	73%	0.0000	47%	8	1.000	0.483	0.629
[-10,10]	-0.078	-0.993	0.241	73%	0.0000	47%	8	1.000	0.653	0.514
[-15,15]	-0.054	0.275	0.321	73%	0.0000	47%	8	1.000	0.369	0.712
[-30,30]	0.004	-1.360	0.783	67%	0.0065	53%	8	1.000	0.312	0.755
[1,5]	-0.093	-1.447	0.174	53%	0.0000	47%	8	1.000	0.369	0.712
[1,10]	-0.049	-1.056	0.148	87%	-0.0017	33%	10	0.302	1.278	0.201
[1,15]	-0.017	0.205	0.291	87%	-0.0046	33%	10	0.302	0.880	0.379
[1,30]	0.003	-0.569	0.837	73%	-0.0001	40%	9	0.607	0.028	0.977
[-5,-1]	-0.043	-0.207	0.569	80%	0.0000	47%	8	1.000	0.256	0.798
[-10,-1]	-0.017	0.797	0.836	73%	0.0000	53%	8	1.000	0.142	0.887
[-15,-1]	0.046	0.984	0.425	80%	0.0000	47%	8	1.000	0.028	0.977
[-30,-1]	0.014	0.000	0.325	67%	0.0041	67%	10	0.302	1.221	0.222

See Table 7 note

5.2. Test for systematic risk effects

To draw inferences for the systematic risk term, the estimated parameter, $\beta_{i,s}$, or Cumulative Change in Beta (CCB) for sector of firm that presents the even in the window, is used to find the Average Cumulative Change in Beta (ACCB):

$$ACCB_s = \frac{1}{N}\sum_{i=1}^{N} \dot{\beta}_{i,s} \qquad \text{(Equation 6)}$$

where N is the number of events in the sample and $\beta_{i,s}$ is the estimated parameter on the event of firm i on the window s.

The null hypothesis of absence of spillover effect on the systematic risk component of the total risk of the sector due to rating action announcements implies that ACCB must be zero. As in the case of abnormal returns, we test the statistical significance of the ACCB, by computing the *t-ratio* test, the Fisher-sign test and the Wilcoxon-signed-rank test again.

The effects of credit quality deteriorations on ACCB are shown on Tables 11 to 14. Results for the whole negative rating actions sample are presented in Table 11, for downgrades, negative outlook reports and negative watch listing in tables 12, 13 and 14 respectively. The effects of credit quality improvements on ACCB, for upgrades and the two positive rating refinements are presented on Tables 15 to 18.

i. Results obtained on ACCB for credit deteriorations

As Table 11 shows, for credit quality deteriorations the evidence about the spillover effect is rather weaker. We do not find significant abnormal systematic risk in any window. The median estimate change in beta (M-ACCB) is significant only in symmetric windows (up to 15 days), pre event windows (up to 15 days prior to the event) and after event on the biggest window considering the rank test p-values. The estimated sign of the abnormal beta risk depends on the analyzed window, being significant and negative unless on the narrower symmetric window.

Table 11. Deterioration in credit quality: Average Cumulative Change in Beta. (N=509)

Window	ACCB	t-ratio	p-val	%sig	M-ACCB	%+	Sign test	p-val	Rank test	p-val
[-1,1]	0.009	1.155	0.248	52%	0.0002	55%	279*	0.033	1.664*	0.096
[-5,5]	-0.001	-0.797	0.426	48%	-0.0001	48%	267	0.287	2.118*	0.034
[-10,10]	0.000	0.579	0.563	50%	-0.0001	48%	266	0.330	1.919*	0.055
[-15,15]	0.000	-0.370	0.712	42%	-0.0001	47%	268	0.249	1.801*	0.072
[-30,30]	-0.001	-0.912	0.362	44%	0.0000	49%	260	0.658	1.323	0.186
[1,5]	0.001	0.257	0.797	54%	0.0001	54%	275*	0.076	0.503	0.615
[1,10]	0.003	1.450	0.147	53%	0.0001	51%	261	0.595	0.034	0.973
[1,15]	0.000	-0.156	0.876	49%	0.0001	52%	266	0.330	0.060	0.952
[1,30]	-0.001	-1.174	0.240	43%	-0.0002	45%	280*	0.027	2.708*	0.007
[-5,-1]	-0.001	-0.697	0.486	56%	-0.0003	46%	277*	0.051	2.881*	0.004
[-10,-1]	-0.001	-1.026	0.305	51%	-0.0002	48%	267	0.287	2.339*	0.019
[-15,-1]	0.000	-0.164	0.869	44%	0.0000	48%	263	0.478	1.776*	0.076
[-30,-1]	0.001	0.748	0.454	45%	0.0001	53%	272	0.132	0.092	0.927

ACCB is the Average Cumulative Change in Beta, * indicates rejection of the null hypothesis that there is no effects due to rating actions (ACCB=0) at least to a 10% significance level. The %sig is the percentage of scenarios where we reject the null hypothesis that the dummy beta is equal to 0 at a 10% significance level. M-ACCB is the median of ACCB, %+ is the percentage of the scenarios where the dummy beta is positive, on the sign test * indicates rejection of the null hypothesis that it follows a binomial with p=0.5 at 10% significance level. On the Wilcoxon signed Rank test * indicates rejection of the null hypothesis that M-ACCB is equal to 0 at 10% significance level

When we look closer to the phenomenon distinguishing among the three different types of positive rating events results are similar. We find significant effects for a few windows and the sign depends on the window

Table 12. Rating Downgrades: Average Cumulative Change in Beta. (N=238)

Window	ACCB	t-ratio	p-val	%sig	M-ACCB	%+	Sign test	p-val	Rank test	p-val
[-1,1]	0.005	0.848	0.397	48%	0.0001	53%	126	0.400	0.595	0.552
[-5,5]	-0.002	-0.896	0.370	41%	0.0000	49%	122	0.746	0.928	0.353
[-10,10]	0.002*	2.052	0.040	47%	0.0002	53%	126	0.400	0.731	0.465
[-15,15]	0.001	1.084	0.278	42%	0.0001	54%	129	0.218	1.229	0.219
[-30,30]	0.000	0.580	0.562	50%	0.0001	51%	121	0.846	0.123	0.902
[1,5]	0.003	0.824	0.410	55%	0.0006	63%	149*	0.000	2.860*	0.004
[1,10]	0.004*	2.240	0.025	59%	0.0004	58%	139*	0.011	2.909*	0.004
[1,15]	0.000	-0.034	0.973	51%	0.0002	56%	134*	0.060	1.603	0.109
[1,30]	0.000	0.179	0.858	40%	-0.0001	47%	126	0.400	0.537	0.591
[-5,-1]	-0.001	-0.180	0.857	54%	-0.0005	42%	137*	0.023	2.667*	0.008
[-10,-1]	-0.001	-0.278	0.781	48%	-0.0001	49%	122	0.746	1.230	0.219
[-15,-1]	0.000	-0.031	0.975	42%	0.0001	51%	122	0.746	0.332	0.740
[-30,-1]	0.003*	1.886	0.059	46%	0.0002	55%	131	0.136	1.182	0.237

See Table 11 note

Table 13. Credit outlook deterioration: Average Cumulative Change in Beta. (N=147)

Window	ACCB	t-ratio	p-val	%sig	M-ACCB	%+	Sign test	p-val	Rank test	p-val
[-1,1]	0.025	1.492	0.136	52%	0.0002	55%	81	0.248	1.049	0.294
[-5,5]	0.003	1.100	0.271	53%	-0.0001	48%	77	0.621	1.072	0.284
[-10,10]	0.000	0.408	0.683	52%	0.0000	50%	74	1.000	1.171	0.242
[-15,15]	-0.001*	-1.769	0.077	43%	-0.0003	42%	85*	0.069	2.169*	0.030
[-30,30]	-0.001	-1.242	0.214	38%	0.0000	52%	76	0.742	0.351	0.726
[1,5]	0.006	1.096	0.273	54%	-0.0003	45%	81	0.248	1.701*	0.089
[1,10]	0.000	0.145	0.884	46%	-0.0001	47%	78	0.510	1.351	0.177
[1,15]	-0.005	-1.053	0.292	49%	0.0000	48%	76	0.742	1.264	0.206
[1,30]	-0.001	-1.428	0.153	46%	-0.0001	47%	78	0.510	1.277	0.202
[-5,-1]	-0.003*	-1.920	0.055	55%	0.0000	50%	74	1.000	0.935	0.350
[-10,-1]	-0.001	-0.603	0.547	52%	0.0000	50%	74	1.000	0.372	0.710
[-15,-1]	0.000	-0.421	0.674	49%	-0.0001	46%	80	0.322	1.420	0.156
[-30,-1]	-0.001	-1.346	0.178	40%	0.0000	52%	76	0.742	1.237	0.216

See Table 11 note

Table 14. Credit watch deterioration: Average Cumulative Change in Beta. (N=43)

Window	ACCB	t-ratio	p-val	%sig	M-ACCB	%+	Sign test	p-val	Rank test	p-val
[-1,1]	-0.044	-0.856	0.392	60%	0.0037	72%	31*	0.005	2.724*	0.006
[-5,5]	-0.010	-1.032	0.302	40%	-0.0005	44%	24	0.542	0.695	0.487
[-10,10]	-0.003	-0.570	0.569	42%	-0.0007	33%	29*	0.032	1.721*	0.085
[-15,15]	-0.002	-0.544	0.587	26%	-0.0005	33%	29*	0.032	1.697*	0.090
[-30,30]	-0.001	-0.153	0.878	44%	-0.0009	33%	29*	0.032	2.096*	0.036
[1,5]	-0.028	-1.017	0.309	60%	-0.0039	37%	27	0.126	0.912	0.362
[1,10]	0.018	0.699	0.484	58%	-0.0042	33%	29*	0.032	1.975*	0.048
[1,15]	0.015	0.702	0.483	49%	-0.0006	42%	25	0.360	0.695	0.487
[1,30]	-0.006	-0.868	0.385	60%	-0.0009	37%	27	0.126	1.891*	0.059
[-5,-1]	0.014*	1.982	0.047	65%	0.0002	58%	25	0.360	1.685*	0.092
[-10,-1]	-0.001	-0.278	0.781	53%	-0.0005	44%	24	0.542	0.900	0.368
[-15,-1]	0.001	0.513	0.608	44%	-0.0004	40%	26	0.222	0.876	0.381
[-30,-1]	0.003	0.881	0.378	56%	-0.0008	42%	25	0.360	0.562	0.574

See Table 11 note

On table 12 we analyze the effect on Beta due to effective rating downgrades. We find only 3 significant windows in terms of ACCB, one intermediate window symmetric, one intermediate window post event and one pre event. As there is not a lot of evidence, only on some windows, we cannot take any conclusions on the sign. Taking into consideration the M-CACCB rank test we find a positive significant effect on the after event windows what would imply, a contagion effect, in opposite to the evidences from the general credit deterioration situation.

Under perspective deteriorations, on Table 13, the evidence about the existence of systematic risk spillover is rather weak: there are only 2 cases where the ACCB is statistically significant, one symmetrical window and the shortest pre event window. Considering the M-ACCB we also find 2 significant cases, the symmetrical window and the shortest post event window.

The results of the effect of watch deterioration on ACCB are presented on Table 14. On M-ACCB we find statistical significance on almost all the symmetric windows and in two post event windows and on one pre event window.

In general terms, results for systematic risk transmission hypothesis indicate that the announcement of an increases in solvency risk of one firm do not convey new information about the systematic risk of its sector.

ii. Results obtained on ACCB for credit enhancements

As we found on Table 11 for credit deteriorations, the results obtained for credit quality enhancements on Table 15 present evidence about the spillover effect rather weak. We do not find significant abnormal systematic risk in any window. If a firm presents less systematic risk, this does not indicate (at least it does not inform) that its sector presents less systematic risk.

Table 15. Improvement in credit quality: Average Cumulative Change in Beta. (N=195)

Window	ACCB	t-ratio	p-val	%sig	M-ACCB	%+	Sign test	p-val	Rank test	p-val
[-1,1]	0.003	0.251	0.802	48%	-0.0002	47%	104	0.390	0.419	0.675
[-5,5]	0.003	1.005	0.315	50%	-0.0003	43%	112*	0.045	1.069	0.285
[-10,10]	0.002	0.817	0.414	47%	-0.0004	39%	118*	0.004	2.406*	0.016
[-15,15]	0.002	1.217	0.224	42%	-0.0001	48%	102	0.567	0.391	0.696
[-30,30]	0.000	0.297	0.767	38%	-0.0003	45%	107	0.197	0.639	0.523
[1,5]	-0.006	-0.909	0.363	55%	-0.0001	48%	101	0.668	0.576	0.565
[1,10]	0.000	-0.014	0.989	49%	-0.0004	42%	113*	0.031	2.127*	0.033
[1,15]	-0.001	-0.655	0.512	39%	-0.0003	44%	110*	0.085	1.457	0.145
[1,30]	-0.001	-0.486	0.627	39%	-0.0004	41%	115*	0.015	1.583	0.113
[-5,-1]	0.011*	2.090	0.037	61%	-0.0001	47%	103	0.474	0.372	0.710
[-10,-1]	0.003	0.916	0.359	47%	0.0000	51%	99	0.886	0.857	0.391
[-15,-1]	0.003	1.277	0.202	47%	-0.0001	48%	101	0.668	0.096	0.924
[-30,-1]	-0.001	-0.387	0.699	44%	-0.0002	45%	107	0.197	1.121	0.262

ACCB is the Average Cumulative Change in Beta, * indicates rejection of the null hypothesis that there is no effects due to rating actions (ACCB=0) at least to a 10% significance level. The p-val is the p value that tests the statistical significance of ACCB, the sign test and the rank test respectively. The %sig is the percentage of scenarios where we reject the null hypothesis that the dummy alpha is equal to 0 at a 10% significance level. M-ACCB is the median of ACCB, %+ is the percentage of the scenarios where the dummy alpha is positive, on the sign test * indicates rejection of the null hypothesis that it follows a binomial with p=0.5 at 10% significance level. On the Wilcoxon signed Rank test * indicates rejection of the null hypothesis that M-ACCB is equal to 0 at 10% significance level

Under credit enhancements the ACCB is only statistically significant on the shortest pre event window, the M-ACCB is significant on one symmetrical window and on one post event window, and the negative sign is found significant in 5 windows what could reflect a contagion effect under credit enhancements.

Table 16. Rating Upgrades: Average Cumulative Change in Beta. (N=79)

Window	ACCB	t-ratio	p-val	%sig	M-ACCB	%+	Sign test	p-val	Rank test	p-val
[-1,1]	-0.019	-1.235	0.217	59%	-0.0003	41%	47	0.115	1.591	0.112
[-5,5]	-0.004	-0.835	0.404	57%	-0.0003	42%	46	0.177	1.356	0.175
[-10,10]	0.002	0.724	0.469	57%	-0.0004	44%	44	0.368	1.136	0.256
[-15,15]	0.003	0.908	0.364	51%	-0.0003	46%	43	0.500	0.462	0.644
[-30,30]	-0.001	-0.229	0.819	51%	-0.0003	46%	43	0.500	0.193	0.847
[1,5]	-0.014	-1.169	0.242	63%	-0.0003	44%	44	0.368	0.736	0.462
[1,10]	0.001	0.321	0.748	57%	-0.0003	43%	45	0.260	0.990	0.322
[1,15]	-0.005*	-1.757	0.079	51%	-0.0003	41%	47	0.115	1.654*	0.098
[1,30]	-0.001	-0.366	0.714	56%	-0.0003	48%	41	0.822	0.017	0.986
[-5,-1]	0.011	1.103	0.270	70%	-0.0002	46%	43	0.500	0.428	0.669
[-10,-1]	0.005	1.102	0.271	54%	0.0001	53%	42	0.653	0.784	0.433
[-15,-1]	0.003	0.710	0.477	56%	-0.0001	44%	44	0.368	0.496	0.620
[-30,-1]	-0.001	-0.243	0.808	53%	0.0001	51%	40	1.000	0.208	0.836

See Table 15 note

Table 17. Improvement in credit outlook: Average Cumulative Change in Beta. (N=97)

Window	ACCB	t-ratio	p-val	%sig	M-ACCB	%+	Sign test	p-val	Rank test	p-val
[-1,1]	0.019	0.908	0.364	41%	0.0000	51%	49	1.000	0.392	0.695
[-5,5]	0.009	1.644	0.100	45%	-0.0005	41%	57	0.104	0.666	0.506
[-10,10]	0.000	0.082	0.934	42%	-0.0007	35%	63*	0.004	2.065*	0.039
[-15,15]	0.000	-0.051	0.960	37%	-0.0001	45%	53	0.417	0.871	0.384
[-30,30]	0.000	0.376	0.707	29%	-0.0004	42%	56	0.155	1.029	0.303
[1,5]	0.005	0.995	0.320	55%	0.0001	53%	51	0.685	0.320	0.749
[1,10]	0.000	-0.049	0.961	44%	-0.0010	39%	59*	0.042	2.163*	0.031
[1,15]	0.001	0.238	0.812	33%	-0.0003	43%	55	0.223	1.371	0.170
[1,30]	-0.003	-0.616	0.538	28%	-0.0005	34%	64*	0.002	2.396*	0.017
[-5,-1]	0.003	0.986	0.324	56%	-0.0005	44%	54	0.310	0.709	0.478
[-10,-1]	-0.001	-0.257	0.797	45%	-0.0005	46%	52	0.543	0.295	0.768
[-15,-1]	0.000	-0.316	0.752	40%	-0.0002	45%	53	0.417	0.453	0.650
[-30,-1]	-0.002	-1.314	0.189	37%	-0.0007	41%	57	0.104	1.447	0.148

See Table 15 note

Table 18. Improvement in credit watch: Average Cumulative Change in Beta. (N=15)

Window	ACCB	t-ratio	p-val	%sig	M-ACCB	%+	Sign test	p-val	Rank test	p-val
[-1,1]	0.016	0.331	0.741	40%	0.0027	60%	9	0.607	0.483	0.629
[-5,5]	0.005	0.927	0.354	53%	0.0031	60%	9	0.607	0.937	0.349
[-10,10]	0.011	0.737	0.461	40%	-0.0012	40%	9	0.607	0.540	0.590
[-15,15]	0.013*	1.898	0.058	40%	0.0005	73%	11	0.119	1.959*	0.050
[-30,30]	0.005	0.630	0.528	40%	0.0008	67%	10	0.302	1.448	0.148
[1,5]	-0.030	-1.017	0.309	20%	-0.0043	40%	9	0.607	1.278	0.201
[1,10]	-0.006	-0.578	0.563	53%	0.0001	53%	8	1.000	0.085	0.932
[1,15]	0.006	1.317	0.188	27%	0.0050	67%	10	0.302	1.675*	0.094
[1,30]	0.000	0.042	0.966	20%	-0.0002	47%	8	1.000	0.199	0.842
[-5,-1]	0.058*	1.686	0.092	40%	0.0033	67%	10	0.302	1.505	0.132
[-10,-1]	0.008	1.555	0.120	20%	0.0001	53%	8	1.000	1.051	0.293
[-15,-1]	0.017	1.246	0.213	47%	0.0018	73%	11	0.119	1.221	0.222
[-30,-1]	0.006	0.777	0.437	33%	-0.0001	47%	8	1.000	0.085	0.932

See Table 15 note

In general terms, under credit enhancements there is a little evidence of the changes in sector Beta, detecting it on some windows for each kind of change. But these windows are not the same on all the tests.

5.3. Test for idiosyncratic risk effects

Considering the idiosyncratic risk, the contagion effect is mostly indistinguishable from the competition effect. The most relevant aspect for the volatility is that the new information about the firm is something relevant for its sector. As we have found that it is relevant for the sector returns it is expected to find evidence of reductions on sector volatility.

To test the hypothesis of the absence of abnormal performance due to rating action announcements, we use the estimated $\delta_{i,s}$ or Cumulative Change in Idiosyncratic Risk (CCIR) for the industry of the firm affected by the event in the window around the event, to find the Average Cumulative Change in Idiosyncratic Risk (ACCIR):

$$ACCIR_s = \frac{1}{N}\sum_{A=1}^{N} \delta_{i,s} \qquad \text{(Equation 7)}$$

where N is the number of events in the sample and $\delta_{i,s}$ is the estimated parameter on the event of firm i on the window s.

To test the statistical significance of the ACCIR, we use the *t-ratio* test, the Fisher-sign test and the Wilcoxon-signed-rank test again.

The effects of credit quality deteriorations on ACCIR are presented on Tables 19 to 22. Results for the whole negative rating actions sample are presented in Table 19, for downgrades, negative outlook reports and negative watch listing in tables 20, 21 and 22 respectively. The effects of credit quality improvements on ACCIR, for upgrades and the two positive rating refinements are presented on Tables 23 to 26.

i. Results obtained on ACCIR for credit deteriorations

As we saw earlier, our initial hypothesis is that under credit deteriorations, if there is a spillover effect, the ACCIR and M-ACCIR should be negative. On this step we will analyze the impact of negative credit events on the abnormal volatility of the sector

Table 19. Deterioration in credit quality: Average Cumulative Change in volatility. (N=509)

Window	ACCIR	t-ratio	p-val	%sig	M-ACCIR	%+	Sign test	p-val	Rank test	p-val
[-1,1]	-0.007*	-4.915	0.000	65%	-0.0004	2%	499*	0.000	18.486*	0.000
[-5,5]	-0.004*	-4.016	0.000	53%	-0.0001	9%	462*	0.000	15.118*	0.000
[-10,10]	-0.004*	-4.573	0.000	39%	-0.0001	14%	436*	0.000	13.503*	0.000
[-15,15]	-0.004*	-4.458	0.000	34%	0.0000	19%	414*	0.000	11.961*	0.000
[-30,30]	-0.003*	-3.039	0.002	26%	0.0000	37%	322*	0.000	4.359*	0.000
[1,5]	-0.006*	-2.887	0.004	68%	-0.0002	5%	482*	0.000	17.632*	0.000
[1,10]	-0.005*	-5.199	0.000	57%	-0.0001	9%	463*	0.000	15.816*	0.000
[1,15]	-0.005*	-5.000	0.000	50%	-0.0001	17%	420*	0.000	12.604*	0.000
[1,30]	-0.007*	-2.921	0.003	34%	0.0000	25%	384*	0.000	9.906*	0.000
[-5,-1]	-0.003*	-4.205	0.000	68%	-0.0002	6%	477*	0.000	17.009*	0.000
[-10,-1]	-0.004*	-4.607	0.000	59%	-0.0001	11%	455*	0.000	15.500*	0.000
[-15,-1]	-0.005*	-4.923	0.000	45%	-0.0001	15%	431*	0.000	13.769*	0.000
[-30,-1]	-0.004*	-4.733	0.000	32%	0.0000	26%	375*	0.000	9.780*	0.000

ACCIR is the Average Cumulative Average Change in Idiosincratic Risk, * indicates rejection of the null hypothesis that there is no effects due to rating actions (ACCIR=0) at least to a 10% significance level. The p-val is the p value that tests the statistical significance of ACCIR, the sign test and the rank test respectively. The %sig is the percentage of scenarios where we reject the null hypothesis that the dummy alpha is equal to 0 at a 10% significance level. M-ACCIR is the median of ACCIR, %+ is the percentage of the scenarios where the dummy alpha is positive, on the sign test * indicates rejection of the null hypothesis that it follows a binomial with p=0.5 at 10% significance level. On the Wilcoxon signed Rank test * indicates rejection of the null hypothesis that M-ACCIR is equal to 0 at 10% significance level

In the case of the whole sample of negative rating news (Table 19) we find statistically significant abnormal volatility in all the windows, and the effect is robust to the measure used (mean and median) using the t-test and the Wilcoxon rank test. The negative sign implies that there is some spillover effect. In M-ACCIR, and in some cases on ACCIR, there is a smaller effect as long as the windows size increases

Table 20. Rating Downgrades: Average Cumulative Change in volatility. (N=238)

Window	ACCIR	t-ratio	p-val	%sig	M-ACCIR	%+	Sign test	p-val	Rank test	p-val
[-1,1]	-0.008*	-3.670	0.000	66%	-0.0004	2%	233*	0.000	12.690*	0.000
[-5,5]	-0.004*	-2.831	0.005	58%	-0.0001	11%	213*	0.000	9.954*	0.000
[-10,10]	-0.004*	-2.884	0.004	44%	-0.0001	14%	205*	0.000	9.431*	0.000
[-15,15]	-0.005*	-2.747	0.006	37%	0.0000	18%	195*	0.000	7.983*	0.000
[-30,30]	-0.002	-1.366	0.172	29%	0.0000	36%	153*	0.000	3.688*	0.000
[1,5]	-0.004*	-1.826	0.068	68%	-0.0002	3%	230*	0.000	12.207*	0.000
[1,10]	-0.005*	-3.763	0.000	62%	-0.0001	5%	226*	0.000	11.938*	0.000
[1,15]	-0.005*	-3.466	0.001	54%	-0.0001	13%	206*	0.000	9.604*	0.000
[1,30]	-0.005*	-3.469	0.001	41%	0.0000	21%	188*	0.000	8.021*	0.000
[-5,-1]	-0.003*	-2.246	0.025	66%	-0.0002	7%	221*	0.000	11.127*	0.000
[-10,-1]	-0.003*	-2.434	0.015	56%	-0.0001	12%	210*	0.000	10.008*	0.000
[-15,-1]	-0.004*	-3.066	0.002	47%	-0.0001	14%	204*	0.000	9.448*	0.000
[-30,-1]	-0.004*	-3.086	0.002	32%	0.0000	26%	177*	0.000	6.316*	0.000

See Table 19 note

Table 21. Credit outlook deterioration: Average Cumulative Change in volatility. (N=147)

Window	ACCIR	t-ratio	p-val	%sig	M-ACCIR	%+	Sign test	p-val	Rank test	p-val
[-1,1]	-0.005*	-1.801	0.072	59%	-0.0003	2%	144*	0.000	9.919*	0.000
[-5,5]	-0.002	-1.337	0.181	48%	-0.0001	11%	131*	0.000	7.792*	0.000
[-10,10]	-0.003*	-2.115	0.034	37%	-0.0001	14%	126*	0.000	7.021*	0.000
[-15,15]	-0.002*	-1.760	0.078	33%	0.0000	19%	119*	0.000	6.270*	0.000
[-30,30]	-0.002*	-1.832	0.067	21%	0.0000	37%	93*	0.002	1.792*	0.073
[1,5]	-0.003*	-2.637	0.008	65%	-0.0001	6%	138*	0.000	9.361*	0.000
[1,10]	-0.002	-1.607	0.108	52%	-0.0001	12%	130*	0.000	7.802*	0.000
[1,15]	-0.003*	-2.087	0.037	44%	-0.0001	20%	117*	0.000	6.069*	0.000
[1,30]	-0.002*	-1.797	0.072	26%	0.0000	31%	102*	0.000	3.563*	0.000
[-5,-1]	-0.003*	-2.149	0.032	65%	-0.0002	8%	135*	0.000	8.951*	0.000
[-10,-1]	-0.003*	-2.396	0.017	63%	-0.0001	10%	133*	0.000	8.697*	0.000
[-15,-1]	-0.003*	-2.535	0.011	46%	-0.0001	16%	124*	0.000	7.264*	0.000
[-30,-1]	-0.001	-1.364	0.173	33%	0.0000	25%	110*	0.000	5.576*	0.000

See Table 19 note

Table 22. Credit watch deterioration: Average Cumulative Change in volatility. (N=43)

Window	ACCIR	t-ratio	p-val	%sig	M-ACCIR	%+	Sign test	p-val	Rank test	p-val
[-1,1]	-0.013*	-2.524	0.012	70%	-0.0003	2%	42*	0.000	5.297*	0.000
[-5,5]	-0.011*	-2.080	0.037	65%	-0.0001	7%	40*	0.000	4.754*	0.000
[-10,10]	-0.007*	-1.943	0.052	35%	-0.0001	23%	33*	0.001	2.519*	0.012
[-15,15]	-0.010*	-2.527	0.012	26%	0.0000	30%	30*	0.014	2.652*	0.008
[-30,30]	-0.007*	-2.454	0.014	28%	0.0000	23%	33*	0.001	2.785*	0.005
[1,5]	-0.033	-1.629	0.103	79%	-0.0003	2%	42*	0.000	5.623*	0.000
[1,10]	-0.012*	-2.559	0.011	58%	-0.0001	5%	41*	0.000	5.140*	0.000
[1,15]	-0.009*	-1.920	0.055	53%	-0.0001	33%	29*	0.032	2.241*	0.025
[1,30]	-0.036	-1.377	0.169	42%	-0.0001	14%	37*	0.000	4.198*	0.000
[-5,-1]	-0.010*	-2.307	0.021	70%	-0.0002	5%	41*	0.000	5.201*	0.000
[-10,-1]	-0.014*	-2.494	0.013	53%	-0.0001	9%	39*	0.000	4.874*	0.000
[-15,-1]	-0.016*	-2.427	0.015	37%	-0.0001	21%	34*	0.000	3.461*	0.001
[-30,-1]	-0.015*	-2.696	0.007	33%	0.0000	33%	29*	0.032	2.712*	0.007

See Table 19 note

When we analyze the effect on the volatility divided by the kind of event, we find the same results that we got on the general case of credit deteriorations: the effects seen are robust on the measure used (mean and median) using the t-test and the Wilcoxon rank test and in general terms the effect is a reduction on returns volatilities what would imply the contagion effect seen earlier. As we found in the general deterioration scenario, we see that the effect on the M-ACCIR that the bigger the window size considered the smaller the effect, this can present that the reduction in volatility effect becomes diluted as time goes by. Another effect we find on the effective rating downgrades is a bigger impact on the post event windows than on the pre event windows. We would like to highlight also, as seen with ACCA and M-ACCA that under credit deteriorations the kind of event that produces a bigger impact reducing volatility in general terms is the watch deterioration.

ii. Results obtained on ACCIR for credit enhancements

Based on our initial hypothesis, under credit enhancements, we expect that the change in volatility will be negative if there is a spillover effect.

Table 23. Rating Upgrades: Average Cumulative Change in volatility. (N=195)

Window	ACCIR	t-ratio	p-val	%sig	M-ACCIR	%+	Sign test	p-val	Rank test	p-val
[-1,1]	-0.004*	-4.461	0.000	59%	-0.0003	3%	190*	0.000	11.625*	0.000
[-5,5]	-0.004*	-3.265	0.001	54%	-0.0001	8%	180*	0.000	10.528*	0.000
[-10,10]	-0.003*	-3.047	0.002	42%	-0.0001	15%	166*	0.000	8.352*	0.000
[-15,15]	-0.002*	-2.246	0.025	33%	0.0000	20%	156*	0.000	7.104*	0.000
[-30,30]	-0.001	-0.454	0.650	30%	0.0000	27%	143*	0.000	4.837*	0.000
[1,5]	-0.005*	-4.015	0.000	72%	-0.0003	3%	189*	0.000	11.264*	0.000
[1,10]	-0.003*	-1.930	0.054	57%	-0.0001	9%	177*	0.000	9.635*	0.000
[1,15]	-0.002	-1.472	0.141	47%	-0.0001	15%	166*	0.000	8.343*	0.000
[1,30]	-0.004*	-3.069	0.002	38%	0.0000	17%	162*	0.000	7.772*	0.000
[-5,-1]	-0.005*	-3.871	0.000	67%	-0.0003	4%	188*	0.000	11.382*	0.000
[-10,-1]	-0.002*	-2.162	0.031	54%	-0.0001	7%	181*	0.000	10.443*	0.000
[-15,-1]	-0.003*	-2.616	0.009	46%	-0.0001	12%	172*	0.000	8.884*	0.000
[-30,-1]	-0.002	-1.593	0.111	36%	0.0000	21%	155*	0.000	6.656*	0.000

ACCIR is the Average Cumulative Change in Idiosincratic Risk, * indicates rejection of the null hypothesis that there is no effects due to rating actions (ACCIR=0) at least to a 10% significance level. The p-val is the p value that tests the statistical significance of ACCIR, the sign test and the rank test respectively. The %sig is the percentage of scenarios where we reject the null hypothesis that the dummy alpha is equal to 0 at a 10% significance level. M-ACCIR is the median of ACCIR, %+ is the percentage of the scenarios where the dummy alpha is positive, on the sign test * indicates rejection of the null hypothesis that it follows a binomial with p=0.5 at 10% significance level. On the Wilcoxon signed Rank test * indicates rejection of the null hypothesis that M-ACCIR is equal to 0 at 10% significance level

In the case of the whole sample of positive rating news (Table 23) we find statistically significant abnormal volatility in the great majority of windows, and the effect is robust to the measure used (mean and median) using the t-test and the Wilcoxon rank test. We find again the same results that we found for credit deteriorations on M-ACCIR, the biggest the window considered the fewer effect found on sector equity returns volatility, indicating that he effect on volatility is diluted as long as time goes by. This result is in line to Abad and Robles (2014) and seems to indicate that the news about the deterioration of credit quality of one firm convey new relevant information for its sector. The reduction on volatility observed may be related to diminish in the uncertainty level about the sector. This relationship connects with the studies of Tang (2009) and Opp et al. (2013) who found that credit ratings mitigate the information asymmetry in credit markets.

Table 24. Improvement in credit rating: Average Cumulative Change in volatility. (N=79)

Window	ACCIR	t-ratio	p-val	%sig	M-ACCIR	%+	Sign test	p-val	Rank test	p-val
[-1,1]	-0.003*	-2.034	0.042	48%	-0.0002	1%	78*	0.000	7.577*	0.000
[-5,5]	-0.003	-1.407	0.159	41%	0.0000	9%	72*	0.000	6.165*	0.000
[-10,10]	-0.002*	-1.677	0.093	25%	0.0000	13%	69*	0.000	5.359*	0.000
[-15,15]	-0.003*	-1.966	0.049	20%	0.0000	16%	66*	0.000	4.890*	0.000
[-30,30]	0.001	0.403	0.687	25%	0.0000	20%	63*	0.000	3.966*	0.000
[1,5]	-0.004*	-2.034	0.042	57%	-0.0001	6%	74*	0.000	6.546*	0.000
[1,10]	-0.003	-1.508	0.132	42%	0.0000	10%	71*	0.000	5.696*	0.000
[1,15]	0.000	0.051	0.960	38%	0.0000	8%	73*	0.000	6.097*	0.000
[1,30]	-0.002	-1.290	0.197	29%	0.0000	10%	71*	0.000	5.794*	0.000
[-5,-1]	-0.005*	-2.382	0.017	58%	-0.0002	0%	79*	0.000	7.719*	0.000
[-10,-1]	-0.003*	-2.091	0.036	43%	0.0000	8%	73*	0.000	6.370*	0.000
[-15,-1]	-0.002	-1.349	0.177	28%	0.0000	15%	67*	0.000	4.787*	0.000
[-30,-1]	-0.002	-1.490	0.136	22%	0.0000	16%	66*	0.000	4.538*	0.000

See Table 23 note

Table 25. Improvement in credit outlook: Average Cumulative Change in volatility. (N=97)

Window	ACCIR	t-ratio	p-val	%sig	M-ACCIR	%+	Sign test	p-val	Rank test	p-val
[-1,1]	-0.003*	-3.467	0.001	65%	-0.0004	4%	93*	0.000	8.046*	0.000
[-5,5]	-0.003*	-2.670	0.008	61%	-0.0001	8%	89*	0.000	7.650*	0.000
[-10,10]	-0.003*	-2.068	0.039	54%	-0.0001	18%	80*	0.000	6.034*	0.000
[-15,15]	-0.003*	-2.113	0.035	40%	-0.0001	24%	74*	0.000	4.994*	0.000
[-30,30]	-0.003*	-1.804	0.071	35%	0.0000	30%	68*	0.000	3.113*	0.002
[1,5]	-0.004*	-2.687	0.007	84%	-0.0004	1%	96*	0.000	8.240*	0.000
[1,10]	-0.001	-0.312	0.755	69%	-0.0001	8%	89*	0.000	6.981*	0.000
[1,15]	-0.003*	-1.667	0.096	53%	-0.0001	22%	76*	0.000	5.451*	0.000
[1,30]	-0.003*	-2.060	0.039	43%	-0.0001	24%	74*	0.000	4.858*	0.000
[-5,-1]	-0.004*	-2.672	0.008	73%	-0.0004	6%	91*	0.000	8.010*	0.000
[-10,-1]	-0.002*	-3.228	0.001	59%	-0.0001	6%	91*	0.000	8.021*	0.000
[-15,-1]	-0.004*	-2.396	0.017	59%	-0.0001	8%	89*	0.000	7.308*	0.000
[-30,-1]	-0.003*	-2.006	0.045	44%	0.0000	22%	76*	0.000	5.347*	0.000

See Table 23 note

Table 26. Improvement in credit watch: Average Cumulative Change in volatility. (N=15)

Window	ACCIR	t-ratio	p-val	%sig	M-ACCIR	%+	Sign test	p-val	Rank test	p-val
[-1,1]	-0.014*	-2.441	0.015	73%	-0.0012	0%	15*	0.000	3.379*	0.001
[-5,5]	-0.011*	-2.680	0.007	73%	-0.0010	0%	15*	0.000	3.379*	0.001
[-10,10]	-0.010*	-2.195	0.028	60%	-0.0002	7%	14*	0.001	2.868*	0.004
[-15,15]	0.002	0.282	0.778	60%	-0.0002	13%	13*	0.007	1.789*	0.074
[-30,30]	0.001	0.318	0.751	33%	0.0000	33%	10	0.302	0.824	0.410
[1,5]	-0.013*	-2.230	0.026	73%	-0.0012	0%	15*	0.000	3.379*	0.001
[1,10]	-0.014*	-2.527	0.012	60%	-0.0003	13%	13*	0.007	2.925*	0.003
[1,15]	-0.008*	-2.048	0.041	60%	-0.0002	13%	13*	0.007	2.641*	0.008
[1,30]	-0.010*	-1.800	0.072	47%	-0.0002	7%	14*	0.001	2.925*	0.003
[-5,-1]	-0.007	-1.068	0.286	67%	-0.0004	7%	14*	0.001	2.584*	0.010
[-10,-1]	-0.008	-1.435	0.151	80%	-0.0002	7%	14*	0.001	2.641*	0.008
[-15,-1]	-0.004	-1.170	0.242	67%	-0.0002	13%	13*	0.007	2.073*	0.038
[-30,-1]	0.008	1.031	0.303	47%	0.0000	33%	10	0.302	0.312	0.755

See Table 23 note

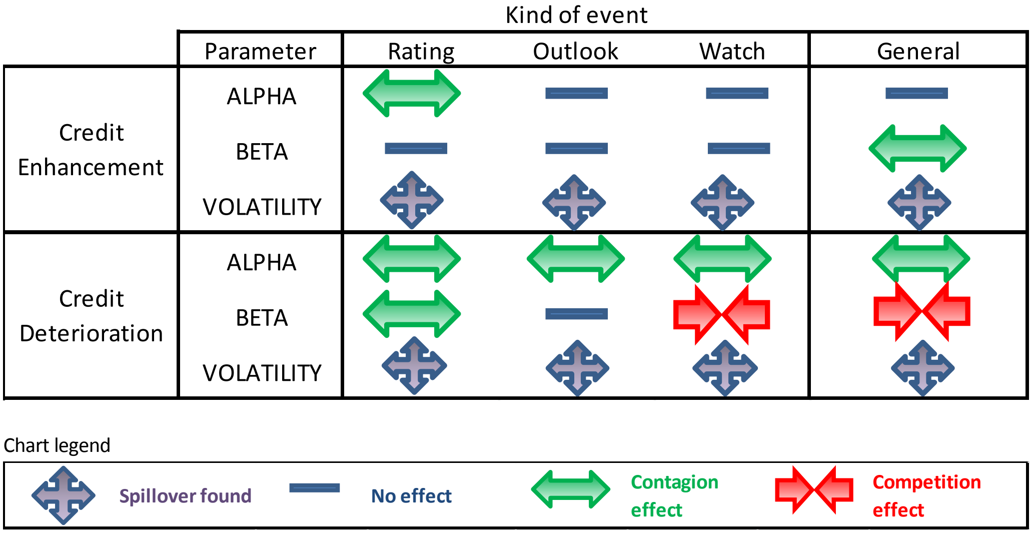
Under effective rating improvements (Table 24), there are 5 windows statistically significant on ACCIR, 3 symmetrical, the shortest window post event and the 2 shortest pre event windows. The effect is robust on the median using the Wilcoxon rank test and there is a predominance of negative signs, what would confirm that downgrade news about a firm is relevant for its peers.

This intra-industry transmission effect is also observed in the case of positive rating refinements. For perspective enhancements (Table 25) we find that almost all windows are statistically significant, the effect is robust on the measure used (mean and median) using the t-test and the Wilcoxon rank test. The effect on ACCIR and on M-ACCIR is bigger than the one found under effective upgrades, showing a bigger contagion effect on volatility under this kind of events.

For positive watch listings (Table 26) we find that due to the few observations considered, there is not a lot of statistical significance on ACCIR, being significant the smaller symmetric windows and all the post event windows. On the M-ACCIR and on the sign tests we have statistical significance unless on the wider symmetric window and on the biggest pre event window.

In general terms we still find the transmission effect we found on the general enhancement scenario and on credit deteriorations, the reduction on volatility affects more to the shortest windows and the reason can be a transfer from uncertainty on the volatility to certainty on the expected return.

Table 27. Summary of effects found divided by Enhancement-deterioration and the kind of event considered



On Table 27 we summarize the results obtained. We find intra-industry information transmission of corporate debt rating news. The information is relevant and cause abnormal returns and volatility whereas there is not systematic risk transmission. Looking at returns the effect that predominates over our results in our analysis is the contagion effect. As expected, there is more evidence found of effects under credit deteriorations than under credit enhancements. This can be because the information contained on credit negative events is less expected by the market than the one found on credit enhancements.

The evidence we find for the sector idiosyncratic risk signals that all kind of announcements convey relevant information to the sector that cause lower volatility, finding an spillover effect.

Another effects found is that, in general terms, the impact of credit watch listing is bigger than the effect under perspective and rating changes. It is also interesting to highlight the effect found on the volatility parameter: the impact is bigger the closer the window around the event date. That can be happening due to an effect of less uncertainty thanks to the new information added with the event.

6. DETERMINANTS OF RETURN AND RISK REACTION TO RATING CHANGES

In section 5 we found that there is a spillover-effect under credit deteriorations to the firm sector. Nevertheless, the intensity of the spillover-effect does not have to affect equally to all industries. There may be some industry specific characteristics that can affect the intensity of the effect resulting on a bigger or less effect. For that reason, in this section we would like to try to identify the determinants of the intensity of this spillover-effect. For that reason, we have taken into consideration the following variables:

- The Sector of the firm, there have been prior evidences where the firm industry is a driver of the effects (Balachandran, Faff and Nguyen 2004, found different impacts depending on the industry or Bughof, Schneider and Wengner 2012 that found that the degree of reaction on CDS spreads under rating changes depends on the industry).

There are industries, like the banking one, where we would expect a bigger contagion effect (considering a bankruptcy on one may derive to a bankruptcy of the competence).

- Competence Level on the markets, we will approximate it by comparing the number of firms considered on the sector relative to the number of firms on the market. If we expect to find a competition effect we should be having a bigger number of firms (as is less probably that one firm dominates the market, and if one falls there are many choices). Under contagion effect we would expect it to be bigger when there are less firms on the market (if there are a few firms on the market it probably be due to access to the industry limitations, and if one firms profile gets worse it is probably that there is a problem in the sector that will spread).

- The sector Economic Importance on the market, measured as an average firm capitalization on the sector compared with the average capitalization per firm. We expect to find that the more important the sector the bigger the contagion effect. Happening the opposite considering competition effect, the less important the sector the bigger the competence effect.

- Two measures of Sector Risk, sector volatility relative to the market volatility and by its Beta. We expect that the bigger the risk the bigger the contagion effect, and if competence effect is found, the less risk the bigger the competence effect.

- It is also considered the effect of the Last Financial Crisis after the Lehman Brothers default, it seems reasonable to expect to find a greater contagion effect after the crisis started.

To test these hypotheses, we run a regression of the abnormal return and risks in the [-1, 1] window against a set of the variables referred to above. We estimate the regression parameters by Ordinary Least Squares (OLS) and calculate the standard errors by the White heteroskedasticity-consistent covariance matrix. We consider 10% or lower significance level for the tests. With the aim of analyzing if results are robust or they are contaminated by the existence of omitted variables, the models will be re-estimated again including some control variables that traditionally have been considered as intensity determinant factors (see for example Abad and Robles 2014). These variables are the number of notches of the change, if the firm is changed from investment grade to speculative grade, if the Firm was a member of the IBEX by the rating change time, if there has been a prior refinement and the Credit Rating Agency that announces the event.

Table 28. Determinants of factor reactions to rating change. Base model and extended model with control variables

	Alpha				Systematic (Beta)				Idiosyncratic (Volatility)			
	Downgrades		Upgrades		Downgrades		Upgrades		Downgrades		Upgrades	
	Model	E. Model	Model	E.Model	Model	E. Model	Model	E. Model	Model	E. Model	Model	E. Model
Constant	-3.251	-3.801	1.110	0.715	5.420	5.635	-1.707	-2.229	-0.472	-0.373	1.018*	0.998*
	(0.482)	(0.401)	(0.780)	(0.870)	(0.473)	(0.460)	(0.364)	(0.259)	(0.373)	(0.471)	(0.000)	(0.000)
Financial	0.097*	0.076	-0.004	-0.038	-0.056	-0.052	-0.020	-0.039	0.014	0.016	-0.007*	-0.004
	(0.097)	(0.173)	(0.943)	(0.504)	(0.220)	(0.225)	(0.472)	(0.213)	(0.387)	(0.313)	(0.041)	(0.218)
Manufacturing	0.253*	0.236*	0.045	-0.035	-0.071	-0.065	-0.103	-0.143	0.049	0.054	-0.010	-0.007
	(0.043)	(0.057)	(0.772)	(0.827)	(0.402)	(0.443)	(0.225)	(0.167)	(0.139)	(0.105)	(0.155)	(0.374)
Utilities	0.011	-0.010	0.014	0.017	0.010	0.024	-0.030	-0.037	-0.004	0.000	0.000	0.002
	(0.717)	(0.721)	(0.525)	(0.507)	(0.650)	(0.352)	(0.156)	(0.153)	(0.545)	(0.978)	(0.803)	(0.409)
Systematic	3.319	3.884	-1.171	-0.880	-5.504	-5.695	1.651	2.156	0.480	0.374	-1.010*	-1.001*
	(0.475)	(0.394)	(0.767)	(0.839)	(0.467)	(0.458)	(0.378)	(0.270)	(0.365)	(0.468)	(0.000)	(0.000)
Idisyncratic	-0.018*	-0.026*	0.013	0.019	0.013	0.017	0.006	0.002	-0.003*	-0.001	0.000	0.001
	(0.060)	(0.010)	(0.315)	(0.215)	(0.209)	(0.146)	(0.438)	(0.821)	(0.016)	(0.329)	(0.843)	(0.422)
Competence Level	-0.011*	-0.012*	0.003	0.006	0.007	0.008	0.003	0.003	-0.002*	-0.002*	0.000	0.000
	(0.067)	(0.045)	(0.628)	(0.336)	(0.308)	(0.269)	(0.333)	(0.236)	(0.080)	(0.100)	(0.424)	(0.368)
Economic Importance	0.019*	0.023*	-0.002	-0.001	0.009*	0.008	0.003	0.003	0.004*	0.003	-0.001	-0.001
	(0.025)	(0.013)	(0.893)	(0.965)	(0.096)	(0.204)	(0.849)	(0.829)	(0.036)	(0.182)	(0.216)	(0.326)
After Financial Crisis (FC)	11.290*	11.674*	-6.289	-5.637	-4.524	-4.717	-2.432	-2.364	0.516	0.427	-1.409*	-1.420*
	(0.038)	(0.027)	(0.349)	(0.395)	(0.560)	(0.546)	(0.662)	(0.680)	(0.590)	(0.641)	(0.000)	(0.000)
After FC Relative Volatility	0.053*	0.052*	0.021	0.003	-0.005	-0.002	-0.041	-0.033	0.007	0.008	0.001	0.000
	(0.011)	(0.013)	(0.574)	(0.931)	(0.668)	(0.843)	(0.212)	(0.209)	(0.211)	(0.178)	(0.471)	(0.886)
After FC Competence Level	-11.367*	-11.760*	6.175	5.586	4.526	4.715	2.537	2.451	-0.533	-0.446	1.393*	1.408*
	(0.035)	(0.024)	(0.354)	(0.396)	(0.556)	(0.542)	(0.649)	(0.669)	(0.571)	(0.621)	(0.000)	(0.000)
N of notches		0.028*		0.030		-0.001		-0.007		0.002		0.000
		(0.032)		(0.292)		(0.965)		(0.763)		(0.312)		(0.823)
Standard & Poor's		-0.035*		-0.011		-5.637		-0.019		0.003		0.002
		(0.052)		(0.693)		(0.395)		(0.282)		(0.294)		(0.161)
IBEX Member		-0.046*		0.012		0.003		-0.032		0.008*		0.006*
		(0.011)		(0.698)		(0.931)		(0.277)		(0.011)		(0.001)
Prior Refinement		-0.030		0.084		5.586		0.022		-0.005		0.001
		(0.174)		(0.261)		(0.396)		(0.275)		(0.208)		(0.677)
Investment Grade		0.062		0.033		0.030		0.053		-0.006*		0.003
		(0.336)		(0.657)		(0.292)		(0.233)		(0.022)		(0.554)
R^2	0.101	0.137	0.032	0.080	0.030	0.043	0.027	0.041	0.020	0.040	0.385	0.434
F-statistic	5.587*	5.241*	0.605	1.042	1.524	1.478	0.511	0.514	1.032	1.378	11.513*	9.137*
	(0.000)	(0.000)	(0.808)	(0.414)	(0.127)	(0.109)	(0.881)	(0.931)	(0.415)	(0.153)	(0.000)	(0.000)

Note: In all cases, * indicates rejection of the H0 that no effect on the variable at least to a 10% significance level. Financial is a dummy variable taking value of one if the sector of the firm is "Financial & Insurance Activities", 0 elsewhere. Manufacturing is a dummy variable taking value of one if the firm is categorized on the Manufacturing sector. Utilities is a dummy variable taking the value of 1 if the NACE of the firm affected by the rating change is "Electricity, Gas, Steam and Air conditioning supply". Systematic refers to the Sector Beta. Idiosyncratic is the relative volatility: Sector Volatility / Global Index Volatility, i.e., the volatility of sector relative to the volatility of the index. Competence Level: Sector firms /Total number of firms is a measure of the competence on the sector. Economic importance: Average Capitalization Sector / Average Capitalization Market measure the weight of the firms on the sector against the market. After Financial Crisis (or After FC) is a dummy variable taking the value of one if the event has happened after the default of Lehman Brothers. N of Notches reflects the number of steps the rating changes. Standard and Poor's is a dummy variable that takes the value of one when the event has been accomplished by S&P. Prior Refinement reflects if it has been a prior refinement to the rating event and Investment Grade is a dummy that takes the value of one if the firm comes from investment grade to non-investment grade.

6.1. Determinants of returns responses

On the credit deteriorations, on the period prior to the Financial Crisis, the coefficients associated to the Financial and the Manufacturing Sector show positive and significative values; this indicates that the contagion effect found on the event study on stock returns is less intense on this sectors. This result could mean that the competence level is bigger in these industries than on other sectors on the market.

In terms of risk, we do not find significative differences associated to the sector systematic risk; meanwhile the sector idiosyncratic risk is relevant. Relative sector volatility ratio against the index has a negative effect on sector returns, pointing out that at the more volatile sectors the contagion effect gets increased under the announcement of credit a deterioration event.

Taking into account the Competence Level the bigger the number of firms on the sector the more intense the contagion effect found is. This result comes against our initial expectations, and may be caused because on bigger markets where there is less information on the performance on the firms, finding some evidence on one firm may be easily extrapolated to the other firms.

Considering the sector Economic Importance we find that the bigger sectors in terms of capitalization per firm the contagion effect found is lower, given that the coefficient is positive and significative. This also shocks our initial expectations and as the prior business, it may happen due to a less information on sector with smaller firms so the market assumes that the information obtained on a smaller firm sector spreads easier.

On the period after the Financial Crisis started, after Lehman Brothers default in 2008, the contagion effect is less intense as is indicated on the coefficient associated to the dummy that is significative and positive. In fact, we could be talking about a competition effect after downgrades on the period after crisis started.

Additionally, after the crisis started, the more volatile sectors have lower contagion effect, while the sectors with bigger Competence Levels the contagion is more intense. This result seems to point out that the market is more sensitive after the crisis started, increasing its response under deteriorations on credit quality.

The result on the model estimated for credit deteriorations are robust when the control variables are included only the financial sector quits being significative.

The model estimated for credit enhancements does not present significative coefficients (as seen on second column on table 28) neither on the basic model nor including the control variables. In this sense, we do not find that sector characteristics cause significative differences on how returns react under positive rating news affecting one of the members on the sector. This kind of asymmetry on the effects after rating changes on different sign is something usual on literature (see Abad and Robles 2014, Jorion and Zhang 2010, etc.) and point that the market is more sensitive to negative news.

6.2. Determinants of systematic risk responses

Third and fourth column on Table 28 show the model estimated to describe the behavior of the systematic risk around credit deteriorations and credit enhancements respectively. These models do not present significative coefficients in any sector specific characteristic. This result is robust to the control variables. It is reasonable that we do not find anything here because on the event study we did not find any evidence of spillover-effects.

6.3. Determinants of idiosyncratic risk responses

The last two columns on Table 28 present the models to study if there are any differential intensities on the effects on volatility given the specific characteristics of the industries of the firms who suffer the rating event. On the pre financial crisis period, we find a significative and negative impact on the sector idiosyncratic risk. We can conclude that under announcements of credit deterioration events, there is a bigger reduction on the uncertainty on the more volatile industries, and consequently, the reduction in volatility is more intense.

On sector Economic Importance we find that the bigger the capitalization per firm the effect on sector idiosyncratic risk is less intense, given that the coefficient is negative and significative. This could be because a downgrade on bigger companies reveals less information on the sector than downgrades on small companies.

When we study the Competence Level, the sector idiosyncratic risk is more intense when there are more firms on the sector. This makes sense considering that with a big number of firms on the sector the information contained in one of them will reduce less uncertainty on the market than if there are fewer firms. This result is robust to the control variables.

We do not find evidence of a different behavior on the idiosyncratic risk after the Financial Crisis period started.

On the credit enhancements scenarios (see last column of table 28), the coefficients associated to the Financial Sector show negative and significative values; this indicates that the effect found on the event study on idiosyncratic risk is more intense on this sector. This result could mean that enhancement scenarios of firms on the financial sector can enlighten uncertainty on the market.

In terms of risk we only find significative differences respect to the systematic risk. The announcement produces a greater reduction of the uncertainty on the sectors with more systematic risk. Given that there is a bigger non diversifiable risk on these industries, investors focus on good news about the risk on any firm on the same sector.

Since Lehman Brothers default, the effect is an increase on idiosyncratic risk under credit enhancements, as is indicated on the coefficient associated to the dummy that is significative and negative. This could be happening because the positive events in terms of credit risk on the crisis scenario, realizes more uncertainty on the markets (maybe it is more expected a downgrade on a crisis scenario, and having upgrade scenarios provides more information to the market).

The competence level of the sector during the crisis scenario considered is significative and positive, reducing the effect on enhancement scenarios. Considering the scenario of big uncertainty since the crisis started, good news on a firm that operates on a sector with a lot of companies, does not provide enough information to reduce the uncertainty on the sector.

The result on the model estimated for credit enhancements are robust when the control variables are included. The only variable that exits' being significative is the Financial sector.

7. CONCLUSIONS

The main purpose of this paper is to analyze the intra-industry information transfer hypothesis related to credit rating announcements in Spanish market. Under this hypothesis, relevant rating events affecting one firm will spill over its sector returns. This question has not been analyzed for the Spanish market yet. In addition, we extend the earlier literature by considering the spillover effect on the sectors systematic and idiosyncratic risks and analyzing what sector characteristics determine the intensity of spillover effect.

First, we conduct an event study in a dummy approach over a CAPM model with time-varying volatility. We find strong Spillover effects, specifically noting in returns. The effect can be categorized as contagion effect, given that positive (negative) new affect its own industry returns positively (negatively). It may prove the existence of close business ties among the Spanish industry firms. In general terms, it is not found a risk transmission in terms of credit risk provided that we do not find any clear response on beta. This could be meaning an absence of counterparty risk within the Spanish industries. Announcements on credit profiles changes on a firm by a Credit Rating Agency present relevant information to the sector, causing a volatility reduction independently of the kind of event (enhancements/deteriorations, effective rating changes or rating refinements). Considering the timing it is observed some degree of anticipation to the rating event on the sector and persistence of the effect for 5 weeks after the announcement date.

Second, we conduct a cross-section analysis to determine which sector characteristics are relevant to explain the intensity of the spillover effect. The sector characteristics are important only under downgrade scenarios on the returns. There are some differences on the intensity of the spillover effect on sector returns, volatility and competence level and their weight relative in the market. We also find differences related the start of the financial crisis after the Lehman Brothers default. After 2008 the market is more sensitive to sector characteristics. The intensity of volatility spillover effects has differential effects for enhancements and deteriorations. In the industries that present bigger levels of specific risk, the announcements are more informative. After the crisis started, the market is more sensitive to good news. In general terms, the results are robusts to the event characteristics such as size of the jump, if it changes from investment grade to speculative grade, which CRA announces it, etc.

The results on our study allow understanding better the linkages between credit risk of one firm and its peers/rivals behavior in the same sector. This evidence can be used to improve portfolio management that must take into account the existence of intra-industry transfer effects of rating events. The valuation and risk management of derivatives may also be improved as rating events are relevant for the industry instead of the rerated firm.

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Appendix 1.

Table A.1. Events grouping

Issues	
Agency	Rating Concept
FITCH	Preferred shares
FITCH	Mortgage related
FITCH	Covered bonds
MOODY'S	Covered bonds
MOODY'S	Preferred shares

Financial Strength	
Agency	Rating Concept
FITCH	Solvency
FITCH	Viability
MOODY'S	Bank Financial Strength
MOODY'S	Probability of default
MOODY'S	Solvency
STANDARD & POOR'S	Solvency

Short Term	
Agency	Rating Concept
DBRS	Short Term
FITCH	Short Term
FITCH	Issuer Short Term
MOODY'S	Short Term
MOODY'S	S. T. Debt Local crncy
MOODY'S	S. T. Debt Foreign crncy
STANDARD & POOR'S	Short Term
STANDARD & POOR'S	Issuer Short Term

Long term	
Agency	Rating Concept
DBRS	Senior Unsecured
FITCH	LT Bank Indiv
FITCH	LT Issuer
FITCH	Subordinated Debt
FITCH	Senior Secured
FITCH	Senior Unsecured
FITCH	Long Term
FITCH	Issuer Default FC LT
FITCH	Issuer Long Term
FITCH	Individual Rating
FITCH	Support Rating
MOODY'S	Issuer rating
MOODY'S	Long Term
MOODY'S	Corp rating Long Term
MOODY'S	Subordinated Debt
MOODY'S	Subordinated Debt
MOODY'S	Senior Secured
MOODY'S	Foreign LT Bank Deposits
MOODY'S	Long Term
MOODY'S	Local LT Bank Deposits
MOODY'S	Banc Deposits Long term
MOODY'S	Subordinated Debt
STANDARD & POOR'S	International Issuer LT
STANDARD & POOR'S	Local Issuer LT
STANDARD & POOR'S	Long Term

Appendix 2.

Table A.2. Number of firms and number of events

Sector	N.Firms	N.Event dates
Accommodation and food service activities	4	15
Administrative and support service activities	2	5
Agriculture, forestry and fishing	1	0
Arts, entertainment and recreation	2	0
Construction	25	43
Electricity, gas, steam and air conditioning supply	21	157
Financial and insurance activities	53	377
Human health and social work activities	3	0
Information and communication	21	25
Manufacturing	75	55
Mining and quarrying	8	26
Other services activities	2	0
Professional, scientific and technical activities	10	0
Real estate activities	25	0
Transporting and storage	4	0
Water supply; sewerage; waste managment and remediation activities	2	0
Wholesale and retail trade; repair of motor vehicles and motorcycles	14	1
Not classified	1	0

Appendix 3.

Table A.3.A. Sector and events by Firm considered

Sector / Firm	Number of event dates
Accommodation and food service activities	**15**
NH Hoteles SA	0
Tr Hotel Jardin del Mar	0
Melia Hotels International SA	15
Telepizza SAU	0
Administrative and support service activities	**5**
Altadis SA	5
Prosegur Cia de Seguridad SA	0
Agriculture, forestry and fishing	**0**
Agrofruse-Mediterranean Agricu	0
Arts, entertainment and recreation	**0**
Codere SA/Spain	0
Parque de Atracciones Madrid S	0
Construction	**43**
Abengoa SA	6
Abertis Infraestructuras SA	25
Acciona SA	0
Construcciones Lain SA	0
Duro Felguera SA	0
Fergo Aisa SA	0
Ferrovial SA	1
Grupo Dragados SA	0
Grupo Ezentis SA	0
HUARTE SA	0
Iberica de Autopistas SA	0
Informes y Proyectos SA	0
Inmobiliaria del Sur SA	0
Reyal Urbis SA	0
Sacyr SA	0
Sotogrande SA	0
Tecnicas Reunidas SA	0
Urbas Grupo Financiero SA	0
ACS Actividades de Construccio	0
Cleop-Cia Levantina EDF OP	0
Fomento de Construcciones y Co	0
Gines Navarro Construcciones S	0
Grupo Empresarial San Jose SA	0
Obrascon Huarte Lain SA	11
Parquesol Inmobiliaria y Proye	0
Electricity, gas, steam and air conditioning supply	**157**
Elec Reunidas DE Zaragoza	0
Enagas SA	12
Endesa SA	42
Fersa Energias Renovables SA	0
Gamesa Corp Tecnologica SA	0
Gas Natural SDG SA	21
Iberdrola Renovables SA	0
Iberdrola SA	31
Union Fenosa SA	14
Sociedad General de Aguas de B	8
Hidroelectrica del Cantabrico	12
Empresa Hidroelectrica del Rib	0
Elecnor SA	0
Fuerzas Electricas de Cataluna	0
Gas Y Electricidad SA	0
Saltos de Nansa	0
Red Electrica Corp SA	17
Cia Sevillana de Electricidad	0
Solaria Energia y Medio Ambien	0
Sociedad Nacional de Industria	0
Electra De Viesgo Distribucion	0

Table A.3.B. Sector and events by Firm considered

Sector / Firm	Number of event dates
Financial and insurance activities	**377**
AGF Union Fenix	0
Banca Civica SA	10
Banco Atlantico SA	3
Banco de Sabadell SA	11
Banco de Valencia SA	25
Banco de Vasconia SA	0
Banco Exterior de Espana	0
Banco Finantia Sofinloc SA	0
Banco Pastor SA	6
Banco Santander SA	41
Banco Simeon SA	0
Banco Vitalicio DE Espana	0
Banco Zaragozano SA	1
Bankia SA	25
Bankinter SA	24
Ecolumber S.A.	0
Grupo Catalana Occidente SA	0
Inverfiatc SA	0
Inverpyme SCR SA	0
Liberbank SA	20
Mapfre SA	15
Mobiliaria Monesa SA	0
Renta 4 Banco SA	9
Ronsa SA	0
Union Europea de Inversiones	0
Vilesa-Vidriera Leonesa SA	0
Corp Financiera Alba SA	0
Banco de Alicante SA	0
Banco de Andalucia SA	0
Argentaria Caja Postal y Banco	0
Banco Bilbao Vizcaya Argentari	28
Banco Central Hispanoamericano	0
Bolsas y Mercados Espanoles SA	0
Cia de Inversiones Mobiliarias	0
Banco Espanol de Credito SA	18
CaixaBank SA	33
Caja de Ahorros del Mediterran	21
Banco de Castilla SA	0
Banco de Credito Balear SA	0
General de Inversiones SICAV S	0
Dinamia Capital Privado Socied	0
Dimetal SA	0
Finanzas e Inversiones Valenci	0
Santander Consumer Finance SA	31
Fastibex SA	0
Banco de Galicia SA	0
General de Alquiler de Maquina	0
Banco Guipuzcoano SA	10
Banco Herrero SA	0
Corp Industrial Y Finan Banest	0
Mapfre Vida Seguros	2
Banco Popular Espanol SA	41
Barclays Bank SAU/Spain	3
Human health and social work activities	**0**
Clinica Baviera SA	0
EuroEspes SA	0
Corp Dermoestetica SA	0

Table A.3.C. Sector and events by Firm considered

Sector / Firm	Number of event dates
Information and communication	**25**
Altia Consultores SA	0
Bodaclick SA	0
Eurona Wireless Telecom SA	0
Grupo Anaya SA	0
Indra Sistemas SA	0
Jazztel PLC	0
Telefonica SA	25
Vocento SA	0
World Wide Web Ibercom SA	0
Atresmedia Corp de Medios de C	0
Amadeus IT Holding SA	0
Let's GOWEX SA	0
Promotora de Informaciones SA	0
Recoletos Grupo de Comunicacio	0
Secuoya Grupo de Comunicacion	0
Prisa Television SAU	0
Telecomunicaciones y Energia	0
Telefonica Moviles SA/Spain	0
Mediaset Espana Comunicacion S	0
Terra Networks SA	0
Vertice Trescientos Sesenta Gr	0

Table A.3.D. Sector and events by Firm considered

Sector / Firm	Number of event dates
Manufacturing	**55**
Aceralia SA	0
Acerinox SA	0
Airbus Group NV	18
Almirall SA	0
Amper SA	0
Arcelor SA	0
ArcelorMittal	0
Azkoyen SA	0
Azucarera de Espana	0
Baron de Ley	0
Bionaturis - Bioorganic Resear	0
Bodegas Bilbainas SA	0
Bodegas Riojanas SA	0
Bodegas y Bebidas SA	0
Campofrio Food Group SA	9
Carbures Europe SA	0
Cementos Molins SA	0
Cementos Portland Valderrivas	0
Cemex Espana SA	27
Cia Vinicola del Norte de Espa	0
Cie Automotive SA	0
Citroen Hispania SA	0
Construcciones y Auxiliar de F	0
Corp Uniland SA	0
Damm SA	0
Deoleo SA	0
Desarrollos especiales de sist	0
Dogi International Fabrics SA	0
Ebro Agricolas	0
Ebro Foods SA	0
Ence Energia y Celulosa S.A	1
Energia e Industrias Aragonesa	0
Ercros SA	0
European Paper & Packaging	0
Exide Technologies SAU	0
Faes Farma SA	0
Federico Paternina SA	0
Financiera Y Minera (SOC)	0
Finanzauto SA	0
Global Steel Wire SA	0
Grupo Tavex SA	0
Heineken Espana SA	0
Hornos Ibericos Alba SA	0
Iberpapel Gestion SA	0
Indo Internacional SA	0
Koipe SA	0
La Seda de Barcelona SA	0
Laboratorios Farmaceuticos Rov	0
Lingotes Especiales SA	0
Lumar Natural Seafood SA	0
Mecalux SA	0
Miquel y Costas & Miquel SA	0
Montebalito SA	0
Natra SA	0
Natraceutical SA	0
Nicolas Correa SA	0
Nueva Montana Quijano	0
Omsa Alimentacion SA	0
Papelera Espanola SA (LA)	0
Papeles y Cartones de Europa S	0
Pescanova SA	0
Portland Valderrivas SA	0
Prim SA	0
Puleva SA	0
Reno de Medici SpA	0
Sarrio SA	0
Service Point Solutions SA	0
Tableros de Fibras SA	0
Tubacex SA	0
Tubos Reunidos SA	0
Uralita SA	0
Urbar Ingenieros SA	0
Vidrala SA	0
Viscofan SA	0
Zardoya Otis SA	0

Table A.3.E. Sector and events by Firm considered

Sector / Firm	Number of event dates
Mining and quarrying	**26**
APERAM	0
Asturiana de Zinc SA	2
Espanola del Zinc SA	0
Hullera Vasco Leonesa SA	0
Repsol SA	24
Cia Espanola de Petroleos SAU	0
CLH SA	0
Minerales y Productos Derivado	0
Other services activities	**0**
Aldeasa SA	0
Funespana SA	0
Professional, scientific and technical activities	**0**
AB-Biotics SA	0
Biosearch SA	0
Catenon SA	0
Fluidra SA	0
Grifols SA	0
Neuron Biopharma SA	0
Suavitas	0
Zeltia SA	0
Grupo Nostrum RNL SA	0
Yell Publicidad SAU	0
Real estate activities	**0**
Ahorro Familiar SA	0
Alza Real Estate SA	0
AMCI Habitat SA	0
Ayco Grupo Inmobiliario SA	0
Cartera Industrial REA SA	0
Estacionamientos Subterraneo	0
Fadesa Inmobiliaria SA	0
Filo SA	0
Inmobiliaria Colonial SA	0
Inmobiliaria Urbis SA	0
Inmobiliaria Zabalburu SA	0
Inmolevante SA	0
Libertas Siete	0
Metrovacesa SA	0
Quabit Inmobiliaria SA	0
Realia Business SA	0
Renta Corp Real Estate SA	0
Riofisa SA	0
TESTA Inmuebles en Renta SA	0
Bami Inmobiliaria de Construcc	0
Cevasa - Cia Espanola de Vivie	0
Inmofiban SA	0
Martinsa-Fadesa SA	0
NYESA Valores Corp SA	0
Union Catalana de Valores SA	0
Transporting and storage	**0**
Vueling Airlines SA	0
Aurea Concesiones de Infraestr	0
Iberia	0
Transportes Azkar SA	0
Water supply; sewerage; waste managment and remediation activities	**0**
Befesa Medio Ambiente SA	0
Grino Ecologic SA	0

Table A.3.F. Sector and events by Firm considered

Sector / Firm	Number of event dates
Wholesale and retail trade; repair of motor vehicles and motorcycles	**1**
Adveo Group International SA	0
Commcenter SA	0
Cortefiel SA	0
Liwe Espanola SA	0
Medcom Tech SA	0
Superdiplo SA	0
Adolfo Dominguez SA	0
Centros Comerciales Carrefour	1
Continente SA	0
Distribuidora Internacional de	0
Enaco SA	0
Inditex SA	0
Cia de Distribucion Integral L	0
BP Oil Espana SAU	0
Not classified	**0**
Asland SA	0

Appendix 4.

INDEX BUILDING

On this section we will describe the process that we will follow to build the industry indexes and the Global Index. Our goal is to create the industry index excluding the firm affected directly by the rating change, with the aim of studying the spillover effect of the rating change. If we included the firm affected we would be contaminating the sample.

To create the sectorial indexes (as we have said, this index will exclude the return of the firm affected by the rating event) we have first taken logarithmic returns of each of the 274 firm names on our sample:

$$\dot{R}_{i,t} = \text{Return of asset i in t} = \ln\left(\frac{\text{Closign price of stock i at time t}}{\text{Closing price of stock i at time t}-1}\right) \qquad \text{(Equation A.4.1)}$$

Then, for each asset, we have taken into account on each date if in the last ten days it has at least seven returns that are different to 0 (we will only include this return on the index).

$$\widetilde{R_{i,t}} = \text{Return accountable at time t if } \sum_{n=t-9}^{t} I_{R_{i,n}=0} \leq 3 \qquad \text{(Equation A.4.2)}$$

Then, to build the index return $R_{i,t}$ that we will take into consideration on our analysis, we will take into consideration all firms that share the NACE Sector as Firm i (excluded the returns of stock i) that are accountable as seen on equation A.4.2:

$$R_{i,t} = \text{Stock i sector return index} = \frac{-\widetilde{\dot{R}_{i,t}} + \sum_{l=1}^{total\ Assets} \widetilde{R_{l,t}} * I_{l,t\ ,sector}}{-1 + \sum_{l=1}^{total\ Assets} I_{l,t\ ,sector}} \qquad \text{(Equation A.4.3)}$$

Being $I_{l,t\ ,sector}$ an indicator function equal to 1 if asset l belongs to the NACE sector of stock i and $R_{l,t}$ being a return accountable as seen on equation A.4.2, or 0 otherwise.

Then, we will build the Global Index in the same way we have proceeded for each of the sectorial Index, but taking into consideration all returns accountable at time t (included Firm i returns):

$$R_t = \text{Global return Index at time t} = \frac{\sum_{l=1}^{total\ Assets} \widetilde{R_{l,t}}}{\sum_{l=1}^{total\ Assets} I_{l,t}} \qquad \text{(Equation A.4.4)}$$