# Credit quality and CDS volatility: the key signal

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**Abstract**

This paper investigates the role of CDS volatility in providing information concerning the credit quality of a company.

In Castellano and D'Ecclesia (2011) a first analysis of how CDS quotes respond to rating announcements is provided and it is shown that market participants do not rely much on Rating Agencies, especially during periods characterized by very high volatility, i.e. during the financial crisis. Here, a more accurate analysis of the CDS's ability in providing timely information of the creditworthiness of reference entities is performed estimating the volatility of CDS quotes using Exponential GARCH(1,1) models. The event study methodology is then applied to a sample of CDS quotes for US and European markets, over the period 2004-2009. Results provide an accurate understanding of market behavior in presence of news released by Rating Agencies. Overall, market participants seem to provide timely reactions around the event date and we show that the key element of signaling is represented by the changing volatility in CDS quotes, before and after the rating event.

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## 1 Introduction

The effect of rating announcements on financial market dynamics has been largely investigated in literature. Earlier studies concentrated on the analysis of stock and bond price dynamics and investigated how effective rating changes

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could affect market behavior (Bremer et al., 2001, Steiner et al., 2001, Gropp et al., 2001, Kliger et al., 2000, only to cite a few). The introduction of Credit Default Swaps (CDSs) provides useful information regarding the creditworthiness of a company, so the analysis of how rating changes may affect CDS quote dynamics may reveal additional information regarding the investor's perception of the changing credit soundness of a company. When pronouncing on an issuer's creditworthiness, rating agencies face a trade-off between timeliness and volatility. Information to assess an issuer's creditworthiness arrives at a high frequency, and so credit ratings must be continually updated since they have to incorporate the latest information. Rating agencies attempt to balance these conflicting goals by making multiple announcements, some of which reflect the latest information and others provide a stable signal of credit quality.

In Castellano and D'Ecclesia (2011) the effects caused by rating announcements (rating changes and reviews) on CDS quotes have been analyzed using standard Event Study methodology. The results of the analysis were not always in line with expectations and, in some cases, were inconclusive. In some studies (Norden and Weber, 2004; Hull et al., 2004, only to cite the most relevant) evidences of abnormal changes in CDS quotes have been found, showing that markets anticipate rating announcements in case of "*bad news*". In addition, in most cases no post announcements effects were found. Some other studies (Micu et al. 2006) find that reviews, rating changes and outlooks affect market behavior and the market does not anticipate any rating agency's action.

In our opinion, the aforementioned studies have one major constraint as they assume constant volatility of market quotes, while heteroscedasticity often characterizes the real market. When news on creditworthiness reach the market, CDS quotes increase and, in line with the volatility clustering issue, also the volatility of CDS quotes increases. Hence, the assumption of constant volatility causes biases in the results.

In this paper, we introduce Exponential GARCH models to estimate the volatility of CDS quotes and then use the Event Study methodology to investigate market reactions.

Our work aims to extend Castellano and D'Ecclesia results (2011) by taking into account the role played by stochastic volatility. Following Yamaguchi (2008)

and Corhay et al. (1996), the volatility of CDS quotes is estimated using the Exponential GARCH models (Nelson 1991).

Event Study methodology is applied to a larger set of data than previous studies and the effects of rating announcements, reviews and effective changes, on CDS quotes are investigated. Data cover the period 2004 - 2009 for 60 international companies belonging to different credit grades.

The paper is organized as follows: in section 2, some relevant literature in rating announcements is reviewed; section 3 describes the methodology, showing the importance of introducing Exponential GARCH estimations to measure the conditional variance of abnormal spread changes; section 4 describes the data set, while section 5 provide a brief description of the results; finally, section 6 reports our conclusions.

## 2 Some recent literature

The main goal of credit rating is to facilitate the comparison of an issuer's underlying long-term creditworthiness by means of standardized categories, so rating decisions are typically not influenced by events whose impact on credit quality is expected to be temporary (Micu et al., 2006; Weinstein, 1977). For this reason, rating agencies provide various kinds of announcements. Outlooks and reviews were introduced in the 80's to meet investor demand for more timely indicators and forewarn investors of possible changes in creditworthiness. More precisely, outlooks reflect the likely direction of an issuer's credit quality over the medium term (usually two years). It is modified when a change in the issuer's risk profile is observed, but it is not regarded as permanent enough to review the credit rating. Reviews provide stronger signals than outlooks about future changes in rating, highlighting a high probability of upgrading or downgrading. Reviews are usually concluded in 90 days, after the receipt of additional information, clarifying the impact of a particular event on credit quality. Like credit ratings need not be on review to be changed, reviews or changes in outlook do not always imply changes in rating.

The variety of research papers related to our study is wide. The effects of rating announcements on market quotes have been investigated mainly using

stock (Best R.W., 1997; Akhigbe et al., 1997) and bond prices (Bremer et al., 2001; Gropp et al., 2001; Kliger et al., 2000). Bond markets are related to credit market, therefore results obtained for bond markets can be compared to results obtained for CDS markets.

Covitz et al. (2003) estimate that almost the 75 per cent of changes in bond prices occur six months before the rating downgrade. Only few studies find that rating announcements have different effects on equity markets compared to credit markets. Goh et al. (1993) find that the potential impact of rating announcements on equity prices is ambiguous and depends on the motivation of the announcement. When rating announcements are motivated by changes in the issuer's financial perspectives, they should have the same impact on equity and bond markets; negative (positive) rating announcements should cause a fall (rise) in equity prices. On the contrary, rating announcements caused by changes in leverage should have opposite effects in equity and bond markets; negative (positive) announcements motivated by an increase in leverage should result in a rise (fall) in equity prices. Kliger et al. (2000) find that rating announcements cause bond and equity prices to move in opposite directions.

As we focus on the effects that ratings announcements have on CDS quotes, we mainly refer to studies which have been applied to similar data sets, as well as Hull et al. (2004), Norden et al. (2004), Ammer et al. (2004), and Micu et al. (2006). Hull et al., 2004, and Norden et al., 2004, conclude that the reaction of CDS prices is most pronounced in the case of reviews for downgrades. Ammer et al. (2004) conclude for a significant negative reaction of asset-backed securities' prices to downgrades. Generally, with a few exceptions (Katz et al., 1974; Kliger et al., 2000; Micu et al., 2006), findings show that upgrades or reviews for upgrade do not have a significant impact on prices. Even while results show that negative announcements impact on prices, most of the price adjustments take place before announcements.

# 3 The Event Study methodology

Empirical tests of market efficiency examine price adjustments before, at and after a rating announcement. Basically, if credit ratings convey new informa-

tion, prices should react after a rating event causing CDS quotes to increase in presence of a deterioration in the creditworthiness of a company. Increases in CDS quotes cause changes in the volatility level in line with the argument of volatility clustering, this has to be taken into account when estimating abnormal CDS spread changes respect to a chosen benchmark.

The aim of this paper is to investigate the effects of rating announcements on CDS markets in presence of stochastic volatility. We expect significant positive changes in CDS quotes, together with an increase in volatility's level, at or after the negative rating events (the opposite holds for positive rating events). In some cases, credit markets may anticipate rating announcements and so abnormal performances may be detected also before the event.

The following hypothesis are made:

- Markets react after *review announcements* because they reveal new information. Reviews in most of the cases anticipate the actual rating changes, therefore markets should react, while no effective reactions are therefore expected around actual rating changes following the reviews.
- Markets react only after *rating change announcements* and do not show any abnormal reaction before it.

The results presented in Castellano and D'Ecclesia (2011) show that, in some cases, changes in CDS quotes may not have reflected announcements made by rating agencies. This has been particularly true in period of very volatile quotes as during the recent financial crisis. Standard Event Study methodology assumes constant volatility of abnormal returns and this may cause bias in the results. In financial time series it has been proved that volatility clustering occurs, so that in period of large changes, volatility reaches high levels. The methodology applied in this paper allows to take into account for stochastic volatility of abnormal price changes. In this context, Exponential GARCH models may represent the adequate tool to measure the abnormal spread volatility.

The main idea is to compare, for each reference entity $i$, the CDS daily changes, defined as $S_{i,t}$ :

$$S_{i,t} = CDS_{i,t} - CDS_{i,t-1}. \tag{1}$$

with some chosen benchmark (the mean of CDS daily changes, $E(S_{i,0})$), assuming that residuals can be measured by Exponential GARCH models.

The benchmark, for each reference entity $i$, is defined as the mean change, $E(S_{i,0})$, computed over a period of "normal behavior" identified by the Estimation Period (EP).

Following Armitage (1995), to capture the effects of any rating announcement on CDS quotes we define:

- the event date, $t^* = 0$, for a sample of CDS subject to rating announcements;
- the estimation period, $EP$, where the "normal behavior" or "benchmark" of CDS changes is measured;
- a test period, $TP$, or event window to analyze the abnormal reactions of CDS quotes to the announcements.

The $EP$ in this analysis is set equal to 100-business days, while $TP$ is set equal to 110 days divided in 6 subintervals:

1. $I_1 = [t_1, t_2 - 1]$ business days before the rating announcement;
2. $I_2 = [t_2, t_3 - 1]$ business days before the rating announcement;
3. $I_3 = [t_3, t_4 - 1]$ business days before the rating announcement;
4. $I_4 = [t_4, t_5 - 1]$ business days before the announcement;
5. $I_5 = [t_5, t_6]$ business days around the announcement;
6. $I_6 = [t_6 + 1, t_7]$ business days after the announcement.

An example of EP and TP is reported in the following scheme:

The effective abnormal spread changes are calculated within the TP (for further details see Norden and Weber, 2004) which starts 90 business days before the event's occurrence, $t^* = 0$, and ends 20 business days after the event.

We test the following hypothesis :

- If rating announcements are fully anticipated, then CDS quotes should adjust prior to the announcement in one of the four subintervals, $I_{1,}...,I_4$.
- If no anticipation occurs, announcements should have an effect on quotes only around the day of the event, i.e. subinterval $I_5$.

- In case of thin liquidity, the impact of rating announcements might be delayed to $I_6$. i.e. after the event occurrence.

## 3.1 Abnormal spread changes

In order to investigate the effects of an event it is necessary to evaluate the abnormal spread, $AS_{it}$, which measures the difference between the realized returns in the TP and the chosen benchmark:

$$AS_{it} = (S_{i,t} - E(S_{i,0}))\,. \tag{2}$$

$$CAS_i\,[I_j] = \sum_{t \in I_j} AS_{it}. \tag{3}$$

The cross-sectional average $CAS$ can be computed for each subperiods, $I_j$, and all the firms, $i$:

$$ACAS\,[I_j] = \sum_{i=1}^{N_s} \frac{CAS_i\,[I_j]}{N_s} \tag{4}$$

where $N_s$ is the number of firms subject to disclosure.

## 3.2 Volatility dynamics

We assume that abnormal spreads, $AS_{it}$, are conditional heteroschedastic:

$$AS_{it} = \varepsilon_{it} | \Psi_{i,t-1} \sim N(0, h_{it}) \tag{5}$$

According to Batchelor et al. (2010), three sources of heteroscedasticity may be recognized. The first two are well recognized in the Event Study literature, while the third is very familiar in empirical finance and relatively neglected in Event Study applications.

First, the model pools data from a number of different companies and time periods. The classical Event Study methodology means one necessarily constrains the effects of rating announcements on CDS abnormal spreads to be equal across companies. However, the variance of $AS_s$ may not be constant across companies subject to disclosure. As it is shown in figure 1 and 2, there are sizable differences in the behavior of variances of abnormal CDS spreads for the companies in the sample. This type of heteroscedasticity can be easily handled by normalizing the data – that is, by dividing all the observations on

each company or event by the standard deviation of observations across that company.

Second, there is no reason why the variance of abnormal spreads should be constant throughout each Test Period. Indeed, previous results by Castellano and D'Ecclesia (2010) were in some cases inconclusive mainly due to the changing variances in the test periods, particularly variable between pre- and post-event periods. This is an important hypothesis for investigation. In principle, this may be handled through data normalization – for instance, by dividing each observation not by the whole-event sample standard deviation, but by the standard deviation within the relevant inside-event window to which the observation belongs, as suggested by Boehmer et al. (1991). Heteroscedasticity of this kind is termed event related conditional heteroscedasticity.

Third, the GARCH model of Bollerslev (1986) has been found to provide a good description of the variance in daily stock returns (see, for instance: Akgiray, 1989; De Santis and Imrohoroglu, 1997). In GARCH models, any large shock to a share price which causes an exceptionally high or low abnormal return on a particular day, also causes the variance of returns to be high on the following day, and to decay slowly back to its long run average 'unconditional' value. So, if a dividend event causes a large mispricing on the ex-dividend day, say, prices are likely to be volatile for many days thereafter. Although there is much discussion of *event-induced variance* in the event study literature (e.g. Brown and Warner, 1985), few studies take the step of modelling the variance of returns trough a GARCH process, given the large computational problems that usually may arise.

Assuming that the $AS_{it}$, are conditionally heteroscedastic

$$\varepsilon_{it} = \sqrt{h_{it}} \cdot z_t \qquad z_t \sim N(0,1) \tag{6}$$

we find that the Exponential GARCH(1,1) specification proposed by Nelson (1991) adequately fits the volatility process of the sampled series:

$$\ln(h_{it}) = \alpha_i + \beta_{1i} \left| \frac{\varepsilon_{it-1}}{\sqrt{h_{it-1}}} \right| + \beta_{2i} \frac{\varepsilon_{it-1}}{\sqrt{h_{it-1}}} + \eta_i \ln(h_{it-1}). \tag{7}$$

The main feature of the Exponential GARCH models is that in [**??**] the log of the variances, $\ln(h_{it-1})$, will be positive regardless of whether the coefficients

on the right side are positive. The conditional variance (**??**) is constrained to be non-negative by the assumption that the logarithm of $h_{it}$ is a function of past innovations, $\varepsilon_{it}$. The second and third term in the RHS take into account the magnitude and the sign of $\varepsilon_{it}$. This enables $h_{it}$ to respond asymmetrically to positive and negative values of $\varepsilon_{it}$. This feature is very important to model the behavior of CDS's spread changes (i.e. positive changes of CDS show a worsening in the credit quality of a company).

After estimating the parameters in [**??**] , we can obtain the conditional variance, $h_{it}$, for each firm, $i$, and time $t$. Then, to apply Event Study methodology, the average variances over each subinterval, $I_j$, are estimated:

$$\overline{h}_i(I_j) = \frac{\sum_{t \in I_j} \exp(h_{it})}{N_{I_j}} \qquad j = 1, ..., 6 \tag{8}$$

where $N_{I_j}$ is the number of days in each corresponding time interval. Then, the cross sectional variance of the average $CAS$ is given by:

$$VAR\left[ACAS\left(I_j\right)\right] = \frac{1}{N_s} \sum_{i=1}^{N_s} \overline{h}_i(I_j).$$

A cross-sectional *J-test* aimed at verifying the null hypothesis, $H_0$, that the event does not affect the spread changes ($H_0 : AS_{it} = 0; \;\; H_1 : AS_{it} \lesseqgtr 0$) is defined by:

$$J = \frac{ACAS\left[I_j\right]}{\sqrt{\frac{1}{N_s - 1} VAR\left[ACAS(I_j)\right]}} \qquad J \sim N(0,1).$$

# 4 The data set

The data set consists of:

- CDS prices (5 years maturity) over the period 2004-2009;
- all information on credit rating data and events, considering effective rating changes and reviews, provided by the three major international rating agencies, Standard & Poors, Fitch and Moody's.

The total sample is composed of 78.554 CDS quotes referred to 60 firms, 32 from Europe and 28 from USA. The companies are classified by different

classes of rating in order to investigate possible different reactions to rating announcements. A description of the sample is reported in table 1.

Negative rating events clearly dominate given the occurrence of the financial crisis. The total number of events we considered is equal to 501 of which 187 events refer to reviews and 314 refer to rating changes. Out of 187 reviews, 155 were followed by an effective rate change (either downgrading or upgrading). The average number of days occurring between a review and an effective rate change has been 44 days. More than the 80% of events refers to a worsening in credit quality, i.e. reviews for downgrading or downgradings. Precisely:

- 167 negative reviews out of 187 (90%)
- 258 downgradings out of total 314 (82%) actual rating changes (positive + negative).

The largest part of negative events occurs during 2007-2009: 169 effective downgradings respect to the total of 258, as could be expected. S&P and Moody's are almost equivalent in terms of number of events for each class and both provide a larger set of announcements with respect to Fitch.

## 4.1 Dynamics of CDS changes

It is interesting to notice that, on average, daily CDS spreads increase with the reduction of credit quality. However, we should point out that when looking at speculative grades companies, the expected relationship between CDS quotes and credit quality is violated, highlighting the presence of cases of spread reversal. For instance, the average spread for *B rated* companies results lower than the average spread for *CCC rated* companies.

As regards the variance of abnormal spread changes evidences show that it is not constant over the analyzed period. This may be recognized simply looking at the dynamics of abnormal spreads for a particular company and event (some examples are shown in figures 1 and 2).

For the sample of analyzed companies and for each event the Exponential GARCH(1,1) models are estimated by maximum likelihood, using the 210 day windows (EP+TP). For each company, using the jointly estimated parameters

$\alpha, \beta_1, \beta_2, \eta$, the conditional variance in Equation (**??**) has been computed in the event window.

For each company and each window, the model performed well and almost all the Exponential GARCH(1,1) parameters result statistically significant. In table 3 the percentages of statistically significant results obtained for the estimated parameters and the percentages of positive parameters are reported, divided by class of rating and area. The tested Hypothesis is: $H_0 : \theta = [\alpha, \beta_1, \beta_2, \eta] = 0$.

As it is shown in table 3, the estimation of the conditional variance parameters performs well either in the case of downgrades or reviews. All the parameters, $\beta_1, \beta_2, \eta$ and $\alpha$ result statistically significant for more than 80% of the cases. Some differences may be found between *A rated* and *B rated* companies. In the former case, the percentage of significance is higher for the GARCH parameter, $\beta_1$, (100%); while in the latter it is higher for the leverage parameter, $\beta_2$, (90,2%).

In this context the Exponential GARCH(1,1) model for the variance of the abnormal spread changes, for each event, is defined by (**??**) where $\epsilon_{it}$ is the "abnormal change" in CDS quote on day $t$, and $h_{it}$ is its conditional variance. So the variance on day $t$ is conditional on the variance of the previous day ($h_{i,t-1}$), the size, $|\epsilon_{it-1}|$ and the sign, $\epsilon_{it-1}$, of the most recent abnormal spread changes ($AS_{it} = \epsilon_{it}$). In a steady state, assuming the $\epsilon_{it}$ is set equal to its expected value, $E(\epsilon_{it}) = 0$, and variance is constant over time so that $h_{i,t-1} = h_{it} = h_i$, the unconditional variance for each company, $i$, subject to disclosure is:

$$h_i = e^{\left(\frac{\alpha_i}{1-\eta_i}\right)}. \tag{9}$$

In the Exponential GARCH model, a large change in the abnormal spread will increase the variance of CDS quotes on the day following the shock, by an amount depending on the GARCH coefficient, $\beta_1$, and the asymmetry coefficient, $\beta_2$. Any big change in the abnormal spread will have a persistent effect on the CDS dynamics, raising abnormal spread changes for a number of days afterwards. The degree of persistence depends on the size of coefficient $\eta$. When $\eta$ is relatively large, then volatility takes a long time to die out following an announcement in the market.

We allow the variance to differ across companies and events, and also across days within each *test period,* taking into account the two sources of heteroscedas-

ticity mentioned above.

Looking at the various Exponential GARCH parameters (Table 4 and Table 5) across the various companies it is interesting to notice the main role played by the occurrence of shocks, or large changes in abnormal spreads. The estimates of the GARCH coefficient, $\beta_1$, and the asymmetry component, $\beta_2$, show the largest average values showing that Abnormal Spread's volatility is mainly affected by the occurrence of a change in the $AS_{t-1}$. For instance, in the case of *A rated* companies the mean value of the $\beta_1$ coefficients across companies results 0.902, and the mean value for $\beta_2$ is 0.532. The degree of persistence, measured by the coefficient $\eta$ results on average much lower. In the case of announcements regarding the downgrading $\eta = 0.266$, while in the case of reviews the average $\eta$ is equal to 0.09.

The class of rating does not influence changes in volatility, the main role is played, also in this case, by the occurrence of shocks at time $t-1$, which is going to affect the variance for a number of days afterwards.

# 5 Some results

We run the *J-test* for each of the 501 events in the sample. Test for subgroups of events is also run by class of rating and geographical area. The main idea is that European and US markets have different features in terms of liquidity and investors react differently according to the credit grade of each company.

The analysis aims to verify the assumption that market participants anticipate somehow rating announcements. Table 6 reports the results of the *J-test* for the entire sample.

For all the companies ($A$+$B$ *rated*) , the *J-test* results statistically significant in the case of reviews for downgrading and effective downgradings in subinterval $I_5$ and $I_6$, showing that CDS quotes show abnormal changes right around the event date and in the days following the event. However, some evidences show a different reaction of the market to reviews or downgrades. In case of reviews significant changes are also found in the intervals $I_1$ and $I_2$, no effects are detected in the intervals $I_3$ and $I_4$. Opposite results are found in the case of downgradings. We may say that market participants anticipate the occurrence

of reviews for downgrading 90 to 60 business days before the event and then heavily react, given the size of the average abnormal spread changes, around and after the event date. On the other hand, the effective downgrading is reflected in the change of CDS quotes up to 40 business days before the event and some effects are also found after that.

For companies belonging to different classes of rating (panels A and B in table 6) it is interesting to notice that for *A rated* companies no post-announcement effect is found, showing that the market timely react to official changes in the creditworthiness only around the event date: market behavior does not change after the event.

Tables 7 and 8 report the results of *J-test* by geographical area. Different evidences are detected for the US market where CDS quotes seem to timely react to rating announcements. In the case of *A rated* companies (panel A table 7) it is interesting to notice that reviews for downgrading are reflected on market quotes from one to three months ahead the event occurs, while no post-announcement effect is found. On the other hand (panel B, table 7), in the case of *B rated* companies, effective downgradings seem to affect the market's behavior only in the intervals around the event and no great anticipation occurs.

Results for European markets (table 8) show that participants anticipate reviews in the intervals $I_1, I_2, I_3$ and $I_5$, showing significant abnormal spread changes. Basically market participants cause an increase on CDS quotes 90 days before the occurrence of a review, anticipating official announcements.

### 5.0.1 Conditional Variance

The results of *J-test* have to be analyzed together with the behavior of conditional volatility which can provides very useful information. The conditional variance estimated for each abnormal CDS spread series accurately describes the volatility dynamics over the entire period (EP+TP) for each company. It succeeds in capturing the change in volatility occurring around the event date. In figures 3-5 some examples of how the conditional volatility behaves around the event date for three *B rated* companies are shown.

Using the Exponential GARCH parameters, we can calculate the long run unconditional variance, $h_i = e^{\left(\frac{\alpha_i}{1-\eta_i}\right)}$, and comparison between the conditional

and unconditional variance can be performed. In figure 3 this comparison for General Motors is reported. It is interesting to notice how the conditional variance is largely above the long run level starting 40 business days before the rating event, so basically 2 months before the events market's participants start to be very nervous about the company under review. Similar results are found for different companies, figure 4 and 5 provide an example of the volatility behavior for various US and European companies. The obtained results support our idea that the CDS quotes are exceptionally volatile when rating agency's eye is put on a specific company and abnormal spread change volatility should be observed more than the abnormal spread change in itself.

# 6 Conclusions

We show how using conditional variance modeling in the Event Study methodology more accurate results are provided. The volatility represents a key element in the assessment of abnormal spread changes.

Overall rating announcements have effect on CDS quotes mainly around the event date and, in the case of reviews, some anticipation effects, up to 5 months ahead, are found.

In general, European companies seem to be less sensitive to rating agencies news respect to US companies.

The crucial element is represented by the conditional variance and the Exponential GARCH model succeeds in tracking changes in variances around event dates. The conditional variance compared with the unconditional long run level, for each company, may provide effective signals of the feeling that prevail in the market.

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