Credit Ratings and Credit Default Swaps during the European Sovereign Debt Crisis

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Abstract

We investigate the relationship between credit rating events and credit default swap spreads for EU countries around the Subprime and European Debt Crises. Using event studies and OLS regressions we analyse the behavior of CDS spreads before, around and after credit rating events. Our results indicate that CDS spreads anticipate positive rating events as early as 2-3 months before the event however the anticipation for negative events is only 1-2 months prior; in addition we also observe announcement and post announcement effects in some instances. We also find that the behavior of CDS spreads and credit rating events has undergone a significant change after the crisis period. On similar lines, using logit and multinomial logit regressions we find that a change in CDS spreads are effective in predicting forthcoming credit rating events.

Keywords: Credit ratings, CDS spreads, rating changes
JEL Codes: G12, G24

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1 Introduction

The European Sovereign Debt Crisis of 2008-2011 saw the threat of default mainly by Greece, but to a lesser extent also by Ireland, Italy, Portugal, and Spain - the so-called PIIGS. During this time period prominent attention was given to credit ratings issued by the well-established rating agencies. Rating changes, most notably downgrades, were often criticised by politicians and their judgements questioned. However, credit ratings are not the only way to obtain information on the credit risk associated with government debt; the development of credit default swaps (CDS) provides a more market-based assessment of the credit-worthiness of debt issuers, including governments. CDS spreads are commonly regarded as providing a better measure of credit risk than credit ratings as has been pointed out, for example, in Daniels and Jensen (2005) and Liu and Morley (2013).

This paper seeks to assess whether the publication of changes to credit ratings provided any additional information to market participants, i. e. whether it affected the CDS spreads. We also investigate whether changes to CDS spreads makes changes to credit ratings more likely, thus whether CDS spreads anticipate rating changes. Such knowledge is important for governments to assess the value of commissioning credit ratings and for investors to determine how much attention to pay to credit ratings compared to CDS spreads in the risk assessment of government bonds.

The coming section briefly reviews the main results in the literature on the relationship between credit ratings and CDS spreads, section 3 describes the data we used and how we analyzed these while section 4 seeks to determine how CDS spreads are affected by rating events. Section 5 then explores whether CDS spreads can be used to predict rating changes before section 6 concludes our findings.

2 Literature Review

Credit ratings are issued by credit rating agencies, most prominently by Moody's, Standard & Poor, and Fitch. These ratings are mostly requested, and paid for by the issuers of debt instruments and are supposed to provide an independent assessment of the credit risk of the issuer. Ratings may be changed at any time by the rating agency and in addition to such changes they may also indicate the possibility of future changes by issuing a (positive or negative) credit watch for potential changes within the next 60-90 days or a credit outlook for possible changes within 1-2 years.

Such rating changes have been shown to affect bond yields as established in Griffin and Sanvicente (1982), Hand et al. (1992), Nordon and Weber (2004), and Gande and Parsley (2005), amongst others. They find strong evidence that downgrades affect yields significantly while upgrades have a much less pronounced effects or show no effect at all. Similarly Chung et al. (2012) investigate the informational contents of credit watch events and conclude that they are informative and in a corporate setting enable companies to take remedial actions to avoid a downgrade. Hull et al. (2004) point out that bond yields are affected by many other changes that may occur concurrently to a ratings change, such as tax treatments, bond liquidity, or risk-free rates, and thus complicate any analysis; none of these issues are likely to affect CDS markets. Furthermore, Blanco et al. (2005) and Packer and Habin (2005) point out that CDS markets are much more dominated than bond markets by well informed traders, most notably investment banks and hedge funds, and therefore prices should reflect available information better. Along similar lines argue Zhu (2004), Forte and Pena (2009) and Flannery et al. (2010) that CDS markets react faster to any new information than ratings and should thus allow for a more accurate assessment of credit risk. Lee et al. (2017) also find that CDS spreads lead stock returns, suggesting that their informational value is significant.

Investigating the impact of changes to credit ratings on CDS spreads, a number of investigations such as Hull et al. (2004), Nordon and Weber (2004), Micu et al. (2004), Daniels and Jensen (2005), Lehnert and Neske (2006), Ismailescu and Kazemi (2010), Afonso et al. (2012) and Finnerty et al. (2013) show a consistent effect for downgrades only while for upgrades the effects are much smaller or absent, similar to the investigations for bond yields. Only Wang et al. (2014) finds a significant effect also for upgrades. The early investigations are mainly based on data around the year 2000, when CDS markets were much less mature and overshadowed by the burst of the dotcom bubble. Later investigations were mainly based around the year 2008 prior to the Subprime and European Sovereign Debt crisis. Both sample periods suffered from a lack of upgrades, making any sound conclusions from these events difficult.

Our paper will look at a longer time period, including the Subprime and European Sovereign Debt crises and have a sufficient number of both upgrades and downgrades on a limited number of debt instruments that are sufficiently similar to aggregate and derive meaningful conclusions. These results can be used to evaluate the value added by ratings over and above the information provided by CDS spreads.

3 Data and Methodology

We obtained daily CDS data for all EU countries from Thomson Reuters Datastream for the time period 2003-2015, although not all data series start at the earliest point. We do not have sufficient data on 6 countries to include them in our analysis, namely Croatia, Finland, Luxemburg, Malta, the Netherlands, and Slovakia. For the remaining 22 countries we collected any rating changes, credit watches, and credit outlooks for the same time period from the webpages of Moody's, Standard & Poor, and Fitch.

The CDS data from Thomson Reuters datastream experienced a change of definition of the spread reported. The early data were provided by the Competition and Market Authority until 30 September 2010 and from December 2007 onwards data from Thomson Reuters themself were available. We tested for a structural break in the time series and found that such a break cannot be rejected at the 5% level. We thus decided to make the change in data provision on 1 October 2010 and in any analysis of the full dataset we use a dummy variable to be able to distinguish between these two datasets; using a different date for the switchover does not alter the results reported here.

Table 1 provides a summary of the resulting statstics of the CDS spreads we use and table 2 shows the distribution of rating events across time, different event types, and rating agencies.

[Table 1 about here.]

Following Hull et al. (2004), Nordon and Weber (2004), Finnerty et al. (2013), and Wang et al. (2014), amongst others, we employ an event study methodology to assess the impact a rating has on the CDS spread. A rating change, credit outlook or credit watch are all classified as an event and we assess the impact these events have in an event window. In line with the literature we choose a post-announcement window $[1; 30]$ trading days after the event, the announcement window $[-1; 1]$ trading days, and four pre-announcement windows to capture any anticipations of the rating event: $[-30; -1]$, $[-60; -31]$, $[-60; -1]$, and $[-90; -61]$ trading days. To prevent bias and spurious results, we need to control for contamination in the event window. If there is more than one event on the same entity in the event window, the second/third event might also affect the observed outcome and it becomes very difficult to draw any robust conclusions about the effect of the first event.

Contamination can be of two types; intra-agency window contamination and inter-agency window contamination as discussed in Nordon and Weber (2004) and Finnerty et al. (2013). Intra-agency window contamination is defined as multiple events in the window on the same entity by the same rating agency. Similarly, inter-agency window contamination is defined as multiple events in the window on the same entity by different rating agencies. Finnerty et al. (2013) show that controlling for window contamination does not change parameter estimates, it only reduces t-statistics, and avoids spurious statistical significance. Since our study includes events from all three rating agencies, we need to remove both types of window contaminations. We do this by dropping all the windows with more than one event. As a result, every event window will only have a single event.

We also have a structural break in our sample as discussed above. This means that those event windows that cross the structural break date may generate biased results. Thus an event window that lies across the structural break will also generate biased predictions. To remove the effect of structural breaks we drop all those events whose event or estimation window crosses the structural break date. Given the number of event windows that need elimination through these procedures, our sample size reduces significantly and the number of credit watch events reduces so far that the sample size is too small to include them into the analysis as a separate category in our event study and we therefore combine them with credit outlooks.

[Table 2 about here.]

The majority of upgrades and downgrades in our sample were not preceded by appropriate watch and outlook events as we can see from table 3. This observation suggests that rating agencies give investors relative little warning of any impending rating changes and thus announcements of rating changes should come as a surprise to investors, which should be reflected in larger movements of the CDS spread in reaction to any such announcements.

[Table 3 about here.]

The absence of a well defined benchmark return to determine abnormal returns relative to those markets that have not seen a rating event, such as the market return in the CAPM, lead us to construct our own market CDS spread, $s_{M,t}$, as the unweighed average of the CDS spreads of the 22 countries used in our analysis. We show the evolution of this market spread in figure 1 where we can clearly identify the subprime crisis in 2008 and the sovereign debt crisis from 2009 onwards.

[Figure 1 about here.]

In line with Finnerty et al. (2013) we determine a benchmark change of CDS spread as follows

$$\Delta s_{i,t} = \alpha_i + \beta_i \Delta s_{M,t} + u_{i,t}, \tag{1}$$

where $u_{i,t}$ denotes an error term. We estimate these parameters, $\widehat{\alpha}_i$ and $\widehat{\beta}_i$, using a 550 day window prior to the start of the event window, such that

$$\Delta\widehat{s}_{i,t} = \widehat{\alpha}_i + \widehat{\beta}_i \Delta s_{M,t}. \tag{2}$$

The abnormal returns are then easily defined as $AR_{i,t} = \Delta s_{i,t} - \Delta\widehat{s}_{i,t}$ and the cumulative abnormal returns with τ days into the event window of length T are thus defined as

$$CAR^{\tau}_{i,t} = \sum_{j=1}^{\tau} AR_{i,t-T+j}. \tag{3}$$

These CARs are now analysed in the coming sections to assess the relationship between credit ratings and CDS spreads.

4 The effect of rating events on CDS spreads

In this section we will analyse the CARs firstly in the form of a classic event study by establishing the statistical significance of the CAR in various event windows and selecting events with a range of characteristics. After that we will continue with a regression analysis of CARs on these characteristics to ensure that the results obtained are robust.

4.1 Analysis of event windows

Analyzing the cumulative abnormal returns around rating events as outlined in the previous section for the various event windows, we observe from table 4 that CDS spreads change not only around the event date, but anticipate this event by a considerable amount of time. For positive outlooks the window of anticipation is 31-90 trading days and for negative outlooks and downgrades it is 31 to 60 trading days. Interestingly, we observe that actual upgrades show no reaction in the CDS spreads within any of the investigated event windows. In addition we find that downgrades are accompanied by a contemporaneous increase in the CDS spread, thus presenting the market with a negative surprise, while there is no comparable reaction for upgrades. There is, however, an adjustment in CDS spreads observed after a positive event.

Thus we find that overall positive rating events are anticipated earlier than negative rating events. An explanation for this observation could be that governments have an incentive to leak good news after promising discussions with rating agencies, see Gande and Parsley (2005). Additionally, a better credit rating would reduce the borrowing costs, providing additional incentives to governments to leak any such information. Similarly they would seek not to disclose any bad news, accounting for the later reaction of CDS spreads for negative events, including announcement day effects. Nevertheless these results suggest that the market anticipates most of the rating changes well in advance. The reaction of CDS spreads after a positive event might be explained by the reluctance of investors to accept the improved rating instantly without additional scrutiny of the reasoning, fearing a positive bias towards the issuer.

[Table 4 about here.]

These rather general results can now be explored further by investigating various characteristics, such as the issuer of a rating, the timing of the rating event relative to the crisis, the size of the rating event, or the countries affected.

[Table 5 about here.]

When splitting the rating events according to the issuing rating agency, we see from table 5 that the results overall are consistent with those discussed above, although some significant differences between rating agencies exist. Most notably Fitch and Moody's show statistically significant announcement effects for positive rating events and only Moody's shows statistically significant reactions to positive events 61 to 90 trading days prior to the event. The number of statistically significant observations is highest for Moody's, which is consistent with results reported in Nordon and Weber (2004) for an earlier time period. Overall, we observe that there are no big differences between rating agencies, though. This suggests that the market views their ratings as of approximately similar quality.

[Table 6 about here.]

Distinguishing between rating events prior to the Subprime and European Debt Crisis in table 6 we clearly observe that while positive rating events were anticipated after the onset of the crisis as outlined above, no such anticipation was observed prior to it. The debt crisis we have defined as commencing on 1 January 2008 with the subprime crisis becoming more widespread and implications for government finances becoming apparent, but our results are robust to the exact date being used. Actually using the break in our data series of 1 October 2010 as the defining point in our regression analysis below, we observe results that are highly consistent with those reported here. The anticipation of negative rating events has become less early since the onset of the crisis and announcement effects can now be found. This suggests that negative rating events are less well anticipated after the crisis while this is more so the case for positive rating events. The incentive structure and credibility of rating agencies was heavily criticized in the immediate aftermath of the debt crisis, this may have led to an improvement in both the timeliness of ratings and the information they contain, especially for negative rating events, thus causing this change. Leakage of positive information would have become more important after the onset of the crisis. Additionally the post-crisis results corroborate our results that positive events are anticipated 2-3 months prior to the actual event and then negative events with 1-2 months; thus adding emphasis to the possibility of information leakage.

[Table 7 about here.]

Rating events that encompass multi-notch rating changes, i. e. changes of more than one grade, are more significant on the announcement day than single-notch events. Table 7 shows that multi-notch events have significantly higher announcement effects for negative events, who are also well anticipated over 60 trading days earlier. This suggests that while such events are anticipated, them actually happening is still eliciting a reaction by traders. No reactions are observed for equivalent positive rating events. An explanation for such a different reaction to these events might be that multi-notch negative events can cause a debt to cross over from investment grade to non-investment grade. Such a crossover would deem the debt unfit to hold for many institutional investors like pension funds that are only allowed to invest in investment grade or have even stricter constraints on the holding of high quality instruments, see Finnerty et al. (2013). This importance will result not only in a stronger market reaction, but due to its impact also an earlier reaction by wary investors seeking to rebalance their portfolios.

[Table 8 about here.]

If we divide our events by those countries that were most affected by the debt crisis, the PIIGS countries, we can observe some distinct differences in table 8. We clearly see that positive events for PIIGS countries are not anticipated at all, nor are there any noticeable reactions to these. This might be explained by a general scepticism about the future prospects of these countries as well as the ability of the rating agencies to assess these appropriately as outlined above. On the other hand, negative events are well anticipated and also show an announcement effect, indicating that the actual event contains some new information to the market. For non-PIIGS countries we observe the previously mentioned early anticipation of the events and find the post-announcement returns for positive events, but no announcement returns for either positive or negative events. Hence we can conclude that the post-announcement returns for positive events are originating in non-PIIGS countries while the announcement returns for negative events are from PIIGS countries. This latter finding might be explained with the fact that bail-out programmes are often announced with such rating changes and many of these programmes were found to be less generous than the market had anticipated, see Aizenman et al. (2013).

[Figure 2 about here.]

The event windows analyzed above show that many events are well anticipated by the market and the announcement effects seem to be limited to negative events in PIIGS countries. While the event windows used show in which period any market reactions can be observed, it would be of interest to see if there are any other clear patterns in the CARs. To this effect we plotted the CARs for positive events in figure 2 starting 90 trading days prior to the event and see that overall the CARs accumulate steadily over the entire sample period. We might only infer that for single-notch upgrades by Fitch in PIIGS countries a clear demarcation emerges at around 40 days prior to the event itself. For negative events in figure 3 we observe a very similar pattern in that CARs accumulate steadily. In addition we find that around the event date a clear upturn of the CARs can be observed for most groups of events.

Hence our observations suggest that rating events are well anticipated, but the information is accumulated slowly over time and it is uncommon to have clear timings for any market reactions. This strongly suggests a slow accumulation of information across time, which is duly reflected in the CDS spread prior to the rating event.

[Figure 3 about here.]

Analysing the results from the event windows so far clearly suggests that events are well anticipated by the market through adjusting CDS spreads accordingly 3-4 months prior with only limited announcement effects for negative rating events and post-announcement effects for positive events. Given the complex interactions the different characteristics we have investigated individually might have, we will continue our analysis of the CAR by engaging in a regression analysis. This will allow us to consider more characteristics simultaneously and inform any discussion on determinants of CARs.

4.2 Regression analysis of CARs

Our above analysis of the event studies has shown that while the overall picture emerging is highly consistent across events with different characteristics, there are nevertheless specific differences. These differences, as pointed out, affect events with certain characteristics only. It is, however, impossible to assess all feasible combinations of characteristics as the sample size would reduce too much. To this effect we conducted a range of OLS regressions seeking to explain the CARs as the dependent variable and the characteristics used before as the explanatory variables. We deliberately did not include other explanatory variables into our regressions, such as macroeconomic variables, as we do not seek to explain the evolution of credit spreads based on fundamental factors. Instead we restrict ourselves to assess CARs in relation to credit rating events, which should be driven by the same fundamental factors and how these are affected by these different characteristics.

The results of these regressions for the different event windows are shown in table 9. We employ regressions using all rating events and subsequently split them for positive and negative rating events.

[Table 9 about here.]

[Table 10 about here.]

Our results broadly confirm the results derived from the event study analysis above. However, we can derive a few more detailed results from these regressions. Firstly we note in Panel A of table 9 that negative rating events have a significantly positive effect on the CDS spread as expected, but only for 31 to 60 days prior to the event, in addition to the announcement effect. Interestingly, looking at only the negative events in Panel C, we note that announcement effects are not statistically significant, except for ratings issued by Fitch that show a much lower reaction. Statistically significant CARs can be found overall in the time period of 31 to 60 trading days prior to the event, but we observe no variation across event types. However, we observe that even earlier anticipation of rating events 61 to 90 days prior to the rating event can be observed for multi-notch events and PIIGS countries. After the crisis this effect is reduced, however. For positive rating events in Panel B we find that overall announcement effects are statistically significant only for rating events issued by S&P. We see that rating events after the crisis are more anticipated than before in the time period of 31 to 90 trading days prior to the event.

Interestingly, for neither positive nor negative rating events does it matter whether the rating event is an actual change in the rating or a change in the outlook or watch.

[Table 11 about here.]

[Table 12 about here.]

As a further check on the stability of our results we have investigated alternative specifications in table 10 using interactive terms on the type of event to account for negative events in panel A and positive events in panel B. As can easily be verified the results obtained are very much consistent with those described above.

The results of our analysis thus far clearly suggest that rating events are well anticipated by the market by over 3 months and CDS spreads adjust slowly over time with announcement effects limited to negative events in PIIGS countries after the onset of the crisis. Although some of the anticipation can probably be explained with the leaking of (positive) information by governments and other sources, there is also significant anticipation for negative rating events. This suggests that most of the information contained in rating changes would already be available to the market, making the value of ratings themselves seem diminished as the low announcement returns suggest.

Now that we have established that CDS spreads anticipate rating changes by a significant margin, we seek to explore in the coming section whether the CDS spreads can be used to predict the rating events themselves.

5 CDS spreads as determinants of rating event

We seek to estimate the likelihood of a rating event using the CARs as explanatory variables. Firstly we will use a standard logit model in which to estimate the likelihood of a rating event and then continue to distinguish the different types of events in a multinomial logit regression. We determine in blocks of a single month's length whether a rating event has occurred and use the CARs of the previous month as an explanatory variable. If two consecutive months show a rating event, the later one is dropped to avoid undue overlap of rating events as in Ismailescu and Kazemi (2010).

Since our study includes a structural break due to the change in the data source as discussed above, we include a dummy variable, which is 0 before 1st October 2010 and 1 afterwards. As our break date is near the European Debt Crisis, we might well interpret these results as being prior to and after the outbreak of the crisis, thus not making this distinction explicit. Results reported here proved to be stable when including a crisis dummy additionally into our regressions or moving the break date.

[Table 13 about here.]

We clearly see from table 11, showing the coefficient estimates of our logit regressions, that CARs affect the likelihood of observing a rating event in non-PIIGS countries for negative events prior to the crisis, both for a downgrade and a negative outlook or watch. Combining the different rating events in a multinomial logistic regression by distinguishing between rating changes and watch/outlook changes in table 12 gives us results virtually identical to those obtained from the logit regressions. It is clear that in line with Finnerty et al. (2013) we have evidence that the markets react much more sensitive to negative news, i. e. downgrades.

[Table 14 about here.]

If we furthermore distinguish between outlook and watch events in table 13, we observe a very similar pattern. However, we note that negative watch and outlook events after the onset of the crisis can be predicted using this specification as well. The same is true of for positive outlooks. Thus all different specifications we used show results that are highly consistent with each other and we have also conducted regressions using two-month windows rather than one month time period, giving very similar results. Finally, our results are highly robust to varying specifications of the regressions conducted.

The distinction between PIIGS and non-PIIGS countries shows that for PIIGS countries only downgrades and negative watches seem to be predictable using CDS spreads. After the crisis the predictive power of CDS spreads has been limited to outlook and watch events. There can be two reasons for this. Firstly, after the crisis CDS market efficiency decreased due to lower volumes and general skepticism about CDSs; secondly, rating agencies became more careful and the general quality of ratings improved. This is also verified by the event study results where we see that after the crisis a rating event showed an announcement return of CDS spreads, suggesting that the rating event conveyed new information not anticipated in the CDS market. However, the sample size is relatively small and thus the results for other events might be based on too few observations in this more detailed view to show statistically significant results.

[Table 15 about here.]

Our regressions show, consistent with the analysis of our event studies, that CDS spreads in certain circumstances can anticipate rating changes well, namely negative rating events in non-PIIGS countries prior to the debt crisis. These results confirm the conclusions derived above that CDS spreads lead rating changes and information on credit risk is conveyed in CDS spreads effectively.

6 Conclusions

We conducted a comprehensive investigation into the relationship of rating changes and CDS spreads of EU countries prior to and during the Subprime and European Debt Crisis. Our results suggest that in many instances rating changes are well anticipated by the market as evidenced through CDS spreads. This is particularly true for negative events of non-PIIGS countries prior to the crisis, but positive events are also anticipated. Announcement effects are limited to negative events in PIIGS countries. These results suggest that a significant proportion of the information contained in rating changes are already known to the market. Our analysis cannot establish whether this is due to ratings containing very little information that is not known by market participants or leakage of any such information generated by rating agencies. As downgrades are also affected by this observation and the same incentives to leak information is not present, it is a strong suggestion that such leakage might not play a pivotal role overall; it might merely affect the timing of such information to become known.

Based on our analysis we have some evidence that the value of ratings obtained by government seems to have diminished with the arrival of credit derivatives markets. CDS spreads provide a source of information to the market on the credit risk of a government bond that previously was only available through ratings. As CDS spreads are determined continuously while ratings are only updated periodically, it seems that CDS spreads are leading the published assessments of rating agencies, making them potentially redundant.

Future research might seek to explore in more detail the potential for leakage of information prior to rating events and thereby establish more firmly whether the information content of rating changes is widely known in the market prior to their release from other sources as well. This would then allow more comprehensively to assess the question whether ratings have significant value for investors or have become redundant in light of the existence of CDS markets.

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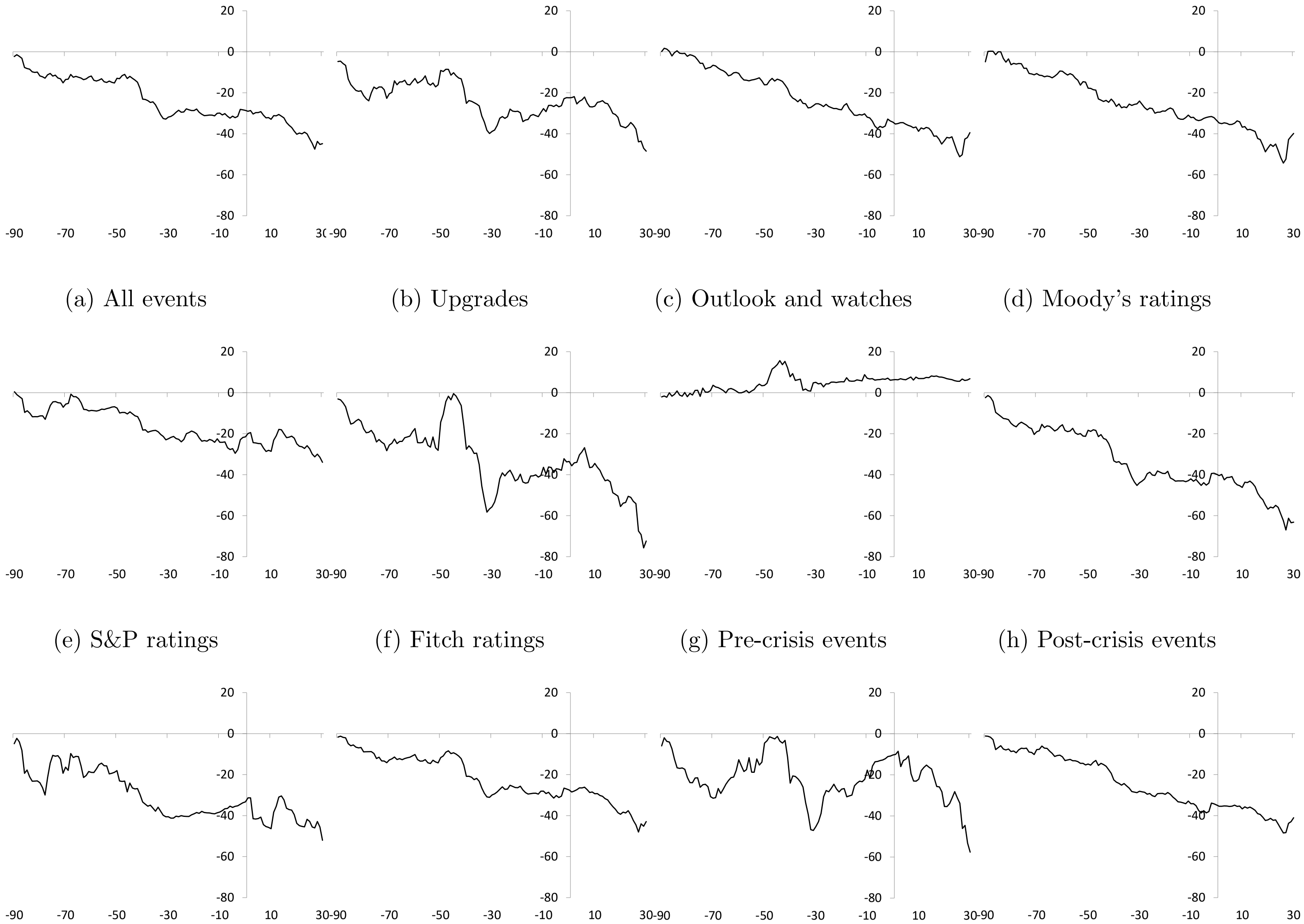
Figure 1: Evolution of the equally-weighted CDS spread average

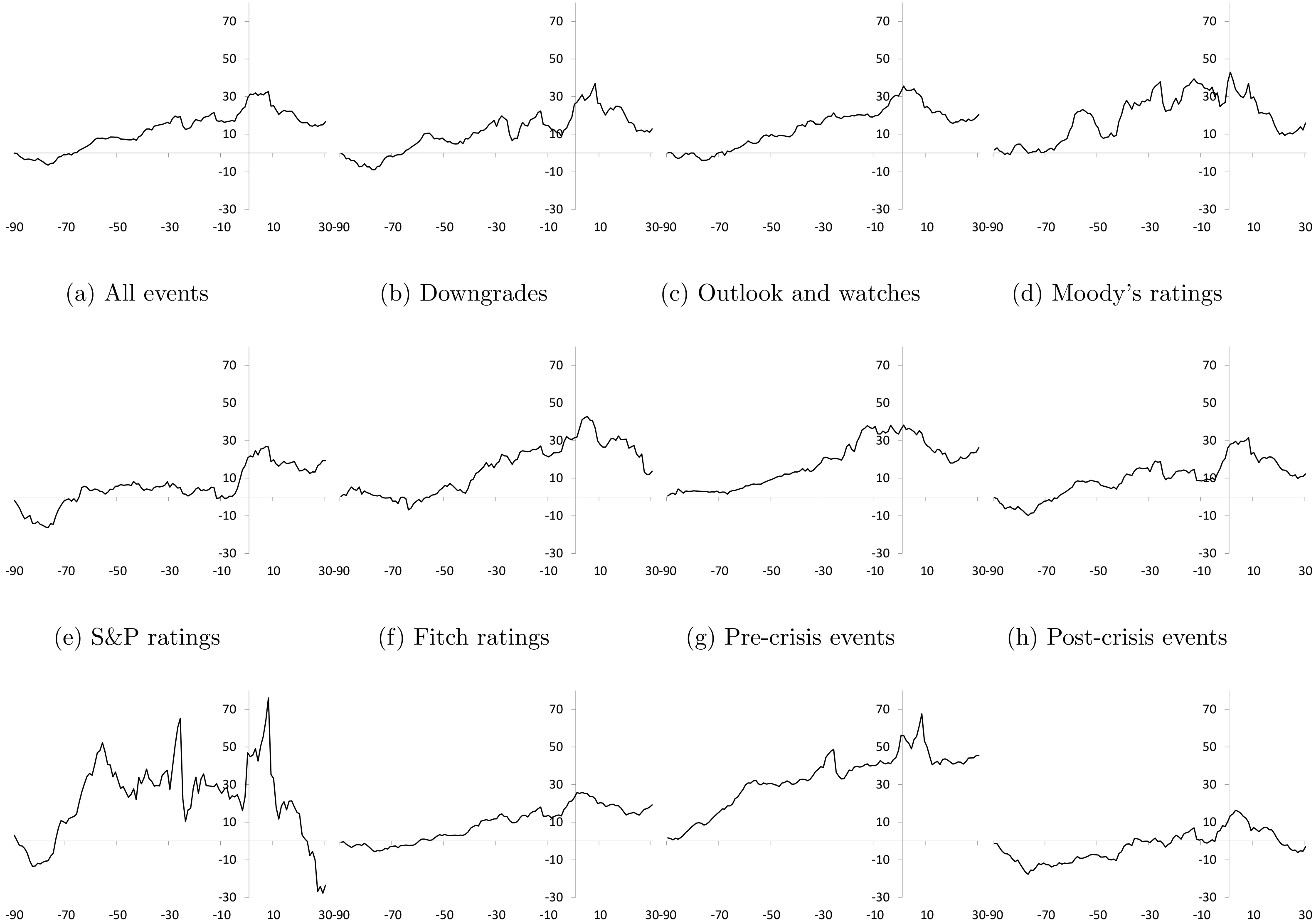


(a) All events (b) Upgrades (c) Outlook and watches (d) Moody's ratings

(e) S&P ratings (f) Fitch ratings (g) Pre-crisis events (h) Post-crisis events

(i) Multi-notch events (j) Single-notch events (k) PIIGS countries (l) Non-PIIGS countries

Figure 2: Graphical representation of the CAR for positive rating events across the event horizon



(a) All events (b) Downgrades (c) Outlook and watches (d) Moody's ratings

(e) S&P ratings (f) Fitch ratings (g) Pre-crisis events (h) Post-crisis events

(i) Multi-notch events (j) Single-notch events (k) PIIGS countries (l) Non-PIIGS countries

Figure 3: Graphical representation of the CAR for negative rating events across the event horizon

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This table shows the basic statistic of the CDS spreads in basis points (bp) for all the countries included in our sample, together with the starting date of the data.

Country	Data start	Mean	Median	Volatility	Maximum	Minimum
Austria	06/01/2004	37.33	17.07	44.91	273.00	0.50
Belgium	05/01/2004	51.85	32.58	62.71	341.98	1.00
Bulgaria	01/01/2004	156.34	119.68	126.08	698.16	13.00
Cyprus	01/01/2003	292.73	42.70	417.02	1674.22	1.00
Czech Republic	06/01/2004	57.04	51.50	52.08	350.00	4.30
Denmark	08/09/2003	29.35	15.16	34.19	200.56	1.60
Estonia	08/02/2006	116.00	75.38	133.58	736.80	1.00
France	16/08/2005	40.30	33.08	36.44	171.56	0.50
Germany	08/01/2004	18.29	12.14	18.02	91.85	0.60
Greece	09/01/2004	4734.59	232.10	6614.06	14911.74	4.40
Hungary	01/01/2004	191.10	172.90	156.91	661.24	9.20
Ireland	23/10/2006	211.56	128.86	228.65	1191.16	1.50
Italy	20/01/2004	111.350	89.40	113.53	498.66	5.30
Latvia	13/01/2006	228.53	164.40	226.23	1193.23	1.05
Lithuania	06/06/2005	168.75	114.91	157.75	849.90	1.00
Poland	01/01/2004	85.36	64.65	74.41	417.58	6.80
Portugal	26/01/2004	228.73	95.76	313.53	1521.45	1.90
Romania	01/01/2004	189.06	171.45	143.75	780.78	17.20
Slovenia	01/01/2003	100.70	60.45	108.96	448.67	3.80
Spain	23/10/2006	139.32	103.04	111.71	492.07	2.40
Sweden	11/08/2003	25.19	13.49	26.46	160.84	1.00
United Kingdom	13/11/2007	48.86	46.34	29.65	175.00	4.50
Average		300.81	138.64	340.51	1028.54	7.11

Table 1: Summary statistics of CDS spread data used in our analysis (all in bp)

This table shows the number of rating events split by years and divided by rating agencies and rating events. Negative events are defined as negative watches, negative outlooks, and downgrades while positive events are positive watches, positive outlooks, and upgrades.

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	Total
	Panel A: Different rating agencies													
Fitch	8	7	6	6	8	16	12	15	33	15	11	11	10	158
Moody's	5	2	2	16	6	10	20	18	26	19	4	9	12	149
S&P	11	12	12	11	9	13	27	20	13	26	16	15	16	198
	Panel B: Different rating events													
Rating Downgrade	2	6	4	5	3	17	25	20	38	40	14	4	10	187
Outlook Negative	5	3	3	6	9	15	18	4	9	11	3	4	3	92
Watch Negative	0	1	0	2	1	3	13	11	13	2	2	1	2	51
Watch Positive	2	1	1	3	1	0	0	1	1	0	0	0	0	10
Outlook Positive	3	2	6	9	6	1	3	14	7	2	5	4	10	71
Rating Upgrade	12	8	6	8	3	3	0	3	4	5	7	22	13	94
Negative Events	7	10	7	13	13	35	56	35	60	53	19	9	15	330
Positive Events	17	11	13	19	10	4	3	18	12	7	12	26	23	175
Total	24	21	20	31	23	38	59	53	72	60	31	35	38	505

Table 2: Distribution of the number of rating events used in our analysis across years and split by rating agency and event type

The table entries show the number of watch (W) and outlook (O) events as well as the number of outlook followed by watch (O&W) events that preceded a rating event, plus the number of rating events for comparison, for each of the event windows considered in our analysis. We also included the number of cases where the watch and outlook event were from the same rating agency that effected the rating event.

	Negative Events							Positive Events						
	Any agencies			Same agencies				Any agencies			Same agencies			
	W	O	O&W	W	O	O&W	Down-grades	W	O	O&W	W	O	O&W	Up-grades
$[1, 30]$	8	14	1	6	5	0	42	2	9	1	2	2	1	47
$[-1, 1]$	17	14	6	11	4	0	73	3	13	2	2	4	1	46
$[-30, -1]$	8	10	2	4	4	0	45	4	9	3	2	4	1	34
$[-60, -1]$	3	9	1	1	6	0	29	0	7	0	0	3	0	24
$[-60, -31]$	10	14	2	6	7	0	61	0	11	0	0	3	0	34
$[-90, -61]$	17	16	5	11	10	0	72	1	12	1	1	6	0	29

Table 3: Number of rating events preceded by watch and outlook events in our sample

This table shows the cumulative abnormal returns (in basis points) for the different event windows and rating events. Outlook events include credit watches as their small number did not make the creation of their own category viable. Positive events include positive outlooks and upgrades while negative events encompass negative outlooks and downgrades. The first number indicates the cumulative abnormal returns, the square brackets indicate the t-value and the number in italics the observations. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Event window	All positive	Upgrades	Positive outlook	All negative	Downgrades	Negative outlook
$[1, 30]$	-15.9867*	-25.8667	-4.9092	-11.0399	-12.2163	-10.0316
	[1.70]	[1.50]	[1.09]	[1.32]	[0.82]	[1.12]
	70	*37*	*33*	*91*	*42*	*49*
$[-1, 1]$	-1.2048	0.2956	-2.7385	7.2361***	10.5825**	3.4192
	[0.93]	[0.15]	[1.63]	[2.68]	[2.44]	[1.17]
	91	*46*	*45*	*137*	*73*	*64*
$[-30, -1]$	4.6553	17.6412	-7.2777	7.5191	0.6430	14.7149*
	[0.59]	[1.20]	[1.09]	[1.04]	[0.05]	[1.91]
	71	34	*37*	*99*	*45*	*43*
$[-60, -1]$	-14.6443	-4.9764	-22.9311	24.9170***	19.5114**	29.6674***
	[1.45]	[0.42]	[1.46]	[4.37]	[2.24]	[3.94]
	52	*24*	*28*	*62*	*29*	*33*
$[-60, -31]$	-20.5487**	-25.3502	-16.2525**	11.8041***	12.4243*	11.1629**
	[2.34]	[1.48]	[2.36]	[2.84]	[1.88]	[2.22]
	72	*34*	*38*	*120*	*61*	*59*
$[-90, -61]$	-12.2994**	-14.5293	-10.0695**	4.4745	4.8929	4.0316
	[2.41]	[1.55]	[2.42]	[0.82]	[0.56]	[0.61]
	78	*39*	*39*	*140*	*72*	*68*

Table 4: Cumulative abnormal returns split by the type of rating event

This table shows the cumulative abnormal returns (in basis points) for the different event windows and rating agencies split by positive and negative rating events. Positive events include positive watches, positive outlooks and upgrades while negative events encompass negative watches, negative outlooks and downgrades. The first number indicates the cumulative abnormal returns, the square brackets indicate the t-value and the number in italics the observations. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

	Moody's		S&P		Fitch	
Event window	All positive	All negative	All positive	All Negative	All positive	All negative
$[1, 30]$	-6.5018	-18.8926	-12.0955	-1.9335	-38.5588	-15.2632
	[1.38]	[1.31]	[1.06]	[0.19]	[1.08]	[0.71]
	27	*30*	*27*	*37*	*16*	*24*
$[-1, 1]$	-3.1679*	14.5632**	2.8422	7.9165*	-3.9252*	-0.0976
	[1.91]	[2.17]	[1.09]	[1.89]	[1.86]	[0.04]
	32	*33*	*33*	*65*	*26*	*39*
$[-30, -1]$	-6.5834	-2.1740	1.1014	7.9185	23.3237	14.3628
	[0.86]	[0.18]	[0.16]	[0.60]	[0.93]	[1.34]
	25	*22*	*26*	*37*	*20*	*29*
$[-60, -1]$	-13.7855	33.8080***	-2.3954	27.2080**	-41.2364*	16.0443**
	[0.56]	[2.98]	[0.23]	[2.66]	[1.89]	[2.15]
	15	*15*	*25*	*27*	*12*	*21*
$[-60, -31]$	-16.0123*	16.6876*	-14.1109*	4.5861	-37.6437	17.9235**
	[1.78]	[1.74]	[1.80]	[0.78]	[1.23]	[2.71]
	21	*33*	*33*	*52*	*18*	*35*
$[-90, -61]$	-9.3871**	11.7726	-8.8762	3.5405	-19.0661	-2.3939
	[2.33]	[1.41]	[1.24]	[0.50]	[1.45]	[0.17]
	24	*44*	*29*	*57*	*25*	*39*

Table 5: Cumulative abnormal returns split by rating agency and event type

This table shows the cumulative abnormal returns (in basis points) for the different event windows and pre/post-crisis split by positive and negative rating events. The starting point for the crisis is defined as 1 January 2008. Positive events include positive watches, positive outlooks and upgrades while negative events encompass negative watches, negative outlooks and downgrades. The first number indicates the cumulative abnormal returns, the square brackets indicate the t-value and the number in italics the observations. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

	Pre-crisis		Post-crisis	
Event window	All negative	All positive	All negative	All positive
$[1, 30]$	-7.1904	0.7411	-12.5797	-23.1557*
	[0.63]	[0.36]	[1.16]	[1.74]
	26	*21*	*65*	*49*
$[-1, 1]$	0.7756	1.5162	9.2861***	-1.0734
	[0.18]	[1.14]	[2.85]	[0.61]
	33	*27*	*104*	*64*
$[-30, -1]$	16.8306**	2.0838	3.6143	5.8099
	[2.14]	[0.80]	[0.37]	[0.51]
	26	*22*	*62*	*49*
$[-60, -1]$	36.7921***	1.0735	17.9138***	-21.0164
	[3.43]	[0.31]	[2.82]	[1.50]
	23	*15*	*39*	*37*
$[-60, -31]$	13.2087***	3.9853	11.1278*	-28.7267**
	[3.70]	[0.66]	[1.88]	[2.53]
	39	*18*	*81*	*54*
$[-90, -61]$	4.7554**	0.8286	4.3736	-16.5271**
	[2.32]	[0.28]	[0.59]	[2.53]
	37	*19*	*103*	*59*

Table 6: Cumulative abnormal returns pre- and post-European Sovereign Debt crisis (1 January 2008)

This table shows the cumulative abnormal returns (in basis points) for the different event windows split single/multi-notch rating events. A multi-notch rating event is defined as a downgrade, credit outlook, or credit watch by at least 2 ratings, e.g. from AAA to A. The first number indicates the cumulative abnormal returns, the square brackets indicate the t-value and the number in italics the observations. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Event window	Multi-notch rating event		Single notch rating event	
	All negative	All positive	All negative	All positive
$[1, 30]$	-69.6819	-18.5414	-2.1323	-15.2899
	[1.64]	[0.92]	[0.31]	[1.43]
	12	*15*	*79*	*55*
$[-1, 1]$	19.6603**	2.8656	3.6254*	-2.1399*
	[2.14]	[0.67]	[1.76]	[1.72]
	19	*17*	*118*	*74*
$[-30, -1]$	-18.4855	6.9693*	9.4218	4.2311
	[1.09]	[1.91]	[1.24]	[0.45]
	6	*11*	*82*	*60*
$[-60, -1]$	n/a	21.8624	25.4388***	-20.3231*
		[1.87]	[4.40]	[1.80]
	0	*7*	*61*	*45*
$[-60, -31]$	1.6848	-22.0595	13.1406***	-20.2465**
	[0.09]	[1.14]	[3.30]	[2.05]
	14	*12*	*106*	*60*
$[-90, -61]$	35.9436**	-18.4807	-1.3926	-10.8277*
	[2.47]	[1.51]	[0.24]	[1.92]
	22	*15*	*118*	*63*

Table 7: Cumulative abnormal returns of single and multi-notch rating events

This table shows the cumulative abnormal returns (in basis points) for the different event windows and PIIGS/non-PIIGS countries split by positive and negative rating events. PIIGS countries are Portugal, Italy, Ireland, Greece, and Spain. Positive events include positive watches, positive outlooks and upgrades while negative events encompass negative watches, negative outlooks and downgrades. The first number indicates the cumulative abnormal returns, the square brackets indicate the t-value and the number in italics the observations. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

	Non PIIGS countries		PIIGS countries	
Event window	All negative	All positive	All negative	All positive
$[1, 30]$	-12.0146	-6.0651*	-8.9561	-46.9186
	[1.04]	[1.81]	[0.98]	[1.27]
	62	*53*	*29*	*17*
$[-1, 1]$	3.7983	-1.8959	12.3616***	0.9629
	[1.15]	[1.52]	[2.73]	[0.26]
	82	*69*	*55*	*22*
$[-30, -1]$	8.4723	-5.2010	5.5797	35.9635
	[0.87]	[1.02]	[0.57]	[1.28]
	59	*54*	*29*	*17*
$[-60, -1]$	28.5880***	-16.0166	16.6090**	-9.5295
	[3.75]	[1.40]	[2.41]	[0.43]
	43	*41*	*19*	*11*
$[-60, -31]$	11.5338**	-18.2789***	12.2390*	-29.1929
	[2.27]	[2.94]	[1.70]	[0.81]
	74	*57*	*46*	*15*
$[-90, -61]$	-11.6760	-10.5016**	27.3080***	-17.8820
	[1.64]	[2.43]	[3.55]	[1.09]
	82	*59*	*58*	*19*

Table 8: Cumulative abnormal returns for PIIGS and non-PIIGS countries

This table shows the OLS estimates of a regression of the absolute Cumulative Abnormal Returns for the different event windows on a range of explanatory variables. All variables are dummy variables taking the value of 1 if the condition is met and zero otherwise. Change denotes a change in ratings (the alternative is a change in outlook or watch), S&P denotes the rating agency S&P, Fitch the rating agency Fitch, Crisis denotes an event after the debt crisis, Multi-notch a multi-notch change, and PIIGS a country belong to the PIIGS. The first number indicates the cumulative abnormal returns and the square brackets indicate the t-value, while *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

	[1,30]	[-1,1]	[-30,-1]	[-60,-1]	[-60,-31]	[-90,-61]
	Panel A: All rating events					
Constant	0.9286	-4.1749	-2.9804	-2.6389	-6.0853	-3.2012
	[0.09]	[1.29]	[0.32]	[0.16]	[0.74]	[0.40]
Change	-0.1930	1.3389	4.3336	-0.6136	-0.2272	-6.6955
	[0.02]	[0.52]	[0.37]	[0.05]	[0.03]	[0.86]
S&P	5.1337	0.2174	8.7586	13.2436	-6.0477	0.5718
	[0.43]	[0.05]	[0.76]	[0.74]	[0.69]	[0.08]
Fitch	-16.2125	-7.0443*	19.9397	-14.7730	-7.2679	-8.8392
	[0.77]	[1.71]	[1.54]	[0.88]	[0.60]	[0.85]
Crisis	-8.9331	0.6764	-7.8343	-28.3843**	-12.0343*	-18.7089**
	[0.85]	[0.19]	[0.78]	[2.27]	[1.90]	[2.56]
Multi-notch	-31.0286	14.0291*	-11.4089	43.7127**	-6.7722	20.3161*
	[1.13]	[1.71]	[0.64]	[2.16]	[0.43]	[1.74]
PIIGS	-8.9993	4.6765	16.3326	-1.7400	1.8581	29.2076***
	[0.51]	[1.18]	[1.11]	[0.17]	[0.16]	[2.97]
Negative	3.6495	8.2632**	-1.0551	44.7621***	30.9463***	11.8202
	[0.25]	[2.55]	[0.08]	[3.73]	[2.64]	[1.41]
R^2	0.04	0.1	0.10	0.19	0.08	0.09
Observations	161	228	159	114	192	218
	Panel B: Positive rating events					
Constant	18.4089	-3.8754*	-19.3444	-15.2416	7.1708	3.7527
	[1.06]	[1.77]	[1.40]	[0.59]	[0.41]	[0.38]
Change	-20.0255	1.2818	23.0547	4.3513	-9.0799	-2.2345
	[1.00]	[0.58]	[1.31]	[0.20]	[0.42]	[0.19]
S&P	2.3112	7.0367*	9.0224	39.8016	10.2463	4.0798
	[0.15]	[1.96]	[0.66]	[1.03]	[0.61]	[0.42]
Fitch	-17.8073	0.1578	26.1425	3.8523	-13.5247	-7.5091
	[0.74]	[0.05]	[1.30]	[0.09]	[0.47]	[0.66]
Crisis	-24.1758	-2.7836	-5.4558	-43.7975	-34.2272**	-17.2644**
	[1.38]	[1.03]	[0.37]	[1.52]	[2.43]	[2.02]
Multi-notch	24.6268	4.6998	-18.1700	62.5201*	11.9404	-1.3500
	[0.67]	[1.02]	[0.59]	[1.71]	[0.33]	[0.06]
PIIGS	-37.0010	2.0911	37.0525	6.2026	-5.1189	-2.982
	[1.05]	[0.64]	[1.42]	[0.30]	[0.15]	[0.18]
R^2	0.10	0.10	0.12	0.14	0.06	0.04
Observations	70	91	71	52	72	78

Table 9: OLS regressions to explain CARs for different event windows

	[1,30]	[-1,1]	[-30,-1]	[-60,-1]	[-60,-31]	[-90,-61]
			Panel C: Negative rating events			
Constant	-3.7645	4.2319	12.8920	51.1130***	17.7074*	3.0134
	[0.20]	[0.65]	[0.80]	[3.91]	[1.90]	[0.36]
Change	5.1111	1.9965	-11.2348	-6.9802	3.7716	-5.6036
	[0.32]	[0.49]	[0.73]	[0.55]	[0.45]	[0.56]
S&P	4.3211	-4.3631	5.4521	-4.4750	-13.7973	-1.2176
	[0.24]	[0.57]	[0.28]	[0.27]	[1.23]	[0.12]
Fitch	-4.4452	-12.7460*	13.5092	-20.5029	0.4461	-8.4116
	[0.16]	[1.82]	[0.78]	[1.45]	[0.04]	[0.57]
Crisis	-3.4982	2.4100	-7.7713	-20.9510	-0.7071	-23.6827**
	[0.24]	[0.41]	[0.54]	[1.48]	[0.08]	[2.02]
Multi-notch	-67.2143	23.1750	-17.4698	-7.1669	-14.6716	36.7325**
	[1.56]	[1.64]	[0.82]	[0.61]	[0.78]	[2.52]
PIIGS	3.5874	6.4647	0.8929	-2.4255	0.5665	45.4602***
	[0.21]	[1.12]	[0.06]	[0.20]	[0.06]	[3.55]
R^2	0.09	0.12	0.03	0.09	0.03	0.15
Observations	91	137	88	62	120	140

Table 9 (ctd.)

This table shows the OLS estimates of a regression of the Cumulative Abnormal Returns for the different event windows on a range of explanatory variables. All variables are dummy variables taking the value of 1 if the condition is met and zero otherwise. Negative means the rating event is negative, Positive that it is positive, Change denotes a change in ratings (the alternative is a change in outlook or watch), S&P denotes the rating agency S&P, Fitch the rating agency Fitch, Crisis denotes an event after the debt crisis, Multi-notch a multi-notch change, and PIIGS a country belong to the PIIGS. The first number indicates the cumulative abnormal returns and the square brackets indicate the t-value, while *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

	[1,30]	[-1,1]	[-30,-1]	[-60,-1]	[-60,-31]	[-90,-61]
	Panel A					
Constant	18.4089	-3.8754*	-19.3444	-15.2416	7.1708	3.7527
	[1.07]	[1.79]	[1.41]	[0.59]	[0.42]	[0.39]
Change	-20.0255	-1.2819	23.0547	4.3513	-9.0799	-2.2345
	[1.01]	[0580]	[1.32]	[0.20]	[0.42]	[0.20]
Negative	-22.1734	8.1073	32.2364	66.3546**	10.5366	-0.7395
	[0.87]	[1.18]	[1.52]	[2.30]	[0.54]	[0.06]
Change*Negative	25.1366	0.7147	-34.2895	-11.3314	12.8515	-3.3691
	[0.98]	[0.15]	[1.47]	[0.45]	[0.56]	[0.22]
S&P	2.3112	7.0367**	9.0224	39.8016	10.2463	4.0798
	[0.15]	[1.98]	[0.66]	[1.03]	[0.62]	[0.43]
S&P*Negative	2.0099	-11.3997**	-3.5703	-44.2766	-24.0436	-5.2974
	[0.08]	[1.98]	[0.15]	[1.06]	[1.20]	[0.38]
Fitch	-17.8073	0.1578	26.1425	3.8523	-13.5247	-7.5091
	[0.74]	[0.05]	[1.31]	[0.09]	[0.48]	[0.66]
Fitch*Negative	13.3621	-12.9038*	-12.6333	-24.3552	13.9709	-0.9025
	[0.37]	[1.69]	[0.48]	[0.54]	[0.45]	[0.05]
Crisis	-24.1758	-2.7836	-5.4558	-43.7975	-34.2272**	-17.2644**
	[1.39]	[1.04]	[0.37]	[1.53]	[2.46]	[2.04]
Crisis*Negative	20.6776	5.1937	-2.3155	22.8465	33.5201**	-6.4183
	[0.90]	[0.81]	[0.11]	[0.72]	[2.04]	[0.44]
Multi-notch	24.6268	4.6998	-18.1700	62.5201*	11.9404	-1.3500
	[0.68]	[1.03]	[0.60]	[1.72]	[0.33]	[0.07]
Multi-notch*Negative	-91.8411	18.4752	0.7002	-69.6870*	-26.6119	38.0825
	[1.62]	[1.24]	[0.02]	[1.82]	[0.65]	[1.50]
PIIGS	-37.0010	2.0911	37.05250	6.2026	-5.1189	-2.9820
	[1.06]	[0.65]	[1.42]	[0.30]	[0.15]	[0.18]
PIIGS*Negative	40.5884	4.3736	-36.1596	-8.6281	5.6854	48.4422*
	[1.05]	[0.66]	[1.20]	[0.36]	[0.16]	[2.31]
R^2	0.09	0.14	0.07	0.21	0.11	0.14
Observations	161	228	159	114	192	218

Table 10: OLS regression to explain CARs for different event windows using interactive terms

	[1,30]	[-1,1]	[-30,-1]	[-60,-1]	[-60,-31]	[-90,-61]
				Panel B		
Constant	-3.7645	4.2319	12.8920	51.1130***	17.7074*	3.0133
	[0.20]	[0.65]	[0.80]	[3.89]	[1.89]	[0.36]
Change	5.1111	1.9965	-11.2348	-6.9802	3.7716	-5.6036
	[0.32]	[0.49]	[0.72]	[0.54]	[0.45]	[0.56]
1-Negative	22.1734	-8.1073	-32.2364	-66.3546**	-10.5366	0.7395
	[0.87]	[1.18]	[1.52]	[2.30]	[0.54]	[0.06]
Change*Positive	-25.1366	-0.7147	34.2895	11.3314	-12.8515	3.3691
	[0.98]	[0.15]	[1.47]	[0.45]	[0.56]	[0.22]
S&P	4.3211	-4.3631	5.4521	-4.4751	-13.7973	-1.2176
	[0.23]	[0.57]	[0.28]	[0.27]	[1.22]	[0.12]
S&P*Positive	-2.0099	11.3997	3.5703	44.2766	24.0436	5.2974
	[0.08]	[1.35]	[0.15]	[1.06]	[1.20]	[0.38]
Fitch	-4.4452	-12.7460*	13.5092	-20.5029	0.4461	-8.4116
	[0.16]	[1.81]	[0.78]	[1.45]	[0.04]	[0.56]
Fitch*Positive	-13.3621	12.9038*	12.6333	24.3552	-13.9709	0.9025
	[0.37]	[1.69]	[0.48]	[0.54]	[0.45]	[0.05]
Crisis	-3.4982	-2.4100	-7.7713	-20.9510	-0.7071	-23.6827**
	[0.23]	[0.41]	[0.54]	[1.47]	[0.08]	[2.01]
Crisis*Positive	-20.6776	-5.1937	2.3155	-22.8465	-33.5201**	6.4183
	[0.90]	[0.81]	[0.11]	[0.72]	[2.04]	[0.44]
Multi-notch	-67.2143	23.1750	-17.4698	-7.1669	-14.6716	36.7325**
	[1.55]	[1.63]	[0.82]	[0.60]	[0.77]	[2.50]
Multi-notch*Positive	91.8411	-18.4752	-0.7002	69.6870*	26.6119	-38.0825
	[1.62]	[1.24]	[0.02]	[1.82]	[0.65]	[1.50]
PIIGS	3.5874	6.4647	0.8929	-2.4255	0.5665	45.4602***
	[0.21]	[1.11]	[0.06]	[0.20]	[0.06]	[3.53]
PIIGS*Positive	-40.5884	-4.3736	36.1596	8.6281	-5.6854	-48.4422**
	[1.05]	[0.66]	[1.20]	[0.36]	[0.16]	[2.31]
R^2	0.09	0.14	0.07	0.21	0.11	0.14
Observations	161	228	159	114	192	218

Table 10 (ctd.)

This table shows the Logit estimates of a regression of the rating event on the Cumulative Abnormal Returns before and after the crisis. The first number indicates the parameter estimate, the square brackets indicate the t-value and the third number in italics the Propensity score matching, while *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level. The Pseudo R^2 is McFaddens's R^2.

	All negative	Negative rating	Negative outlook/watch	All positive	Positive rating	Positive outlook/watch
	Panel A: All countries (excluding Baltic states)					
Constant	0.6284***	1.0728***	0.2507	0.2941	0.7977***	-0.2214
	[3.55]	[4.07]	[1.09]	[1.36]	[2.63]	[0.71]
Before break	0.0120***	0.0165***	0.0088*	-0.0050	-0.0022	-0.0073
	[2.86]	[2.81]	[1.70]	[1.13]	[0.30]	[1.33]
	0.0005	*0.0002*	*0.0003*	*-0.0001*	*-0.0000*	*-0.0001*
After break	-0.0002	-0.0004	0.0001	-0.0009	0.0004	-0.0022
	[0.40]	[0.55]	[0.07]	[0.68]	[0.39]	[1.23]
	-0.0000	*-0.0000*	*0.0000*	*-0.0000*	*-0.0000*	*-0.0000*
Pseudo R^2	0.0469	0.0586	0.01363	0.0668	0.0517	0.0217
Observations	2351	2266	2278	2293	2244	2242
	Panel B: PIIGS countries					
Constant	0.5803**	0.7014*	0.4421	2.2145***	19.6140	0.4832
	[2.10]	[1.90]	[1.14]	[3.43]	[0.01]	[0.58]
Before break	0.0068	0.0102	0.0015	-0.0030	0.0000	-0.0039
	[1.13]	[1.46]	[0.16]	[0.16]	[0.00]	[0.18]
	0.0007	*0.0006*	*0.0001*	*-0.0000*	*0.0000*	*-0.0000*
After break	-0.0004	-0.0006	-0.0001	-0.0062	-0.0005	-0.0012
	[0.56]	[0.64]	[0.14]	[0.67]	[0.54]	[0.47]
	-0.0001	*-0.0001*	*-0.0000*	*-0.0001*	*-0.0000*	*-0.0000*
Pseudo R^2	0.0000	0.0000	0.0000	0.0120	0.0067	0.00000
Observations	474	445	440	430	424	417
	Panel C: Non-PIIGS countries (excluding Baltic states)					
Constant	0.6845***	1.5291***	0.1683	-0.1589	0.1820	-0.4971
	[2.97]	[3.89]	[0.58]	[0.63]	[0.53]	[1.38]
Before break	0.0174***	0.0303***	0.0135**	-0.0046	-0.0014	-0.0073
	[2.97]	[3.08]	[2.00]	[1.00]	[0.20]	[1.28]
	0.0005	*0.0001*	*0.0003*	*-0.0001*	*-0.0000*	*-0.0002*
After break	0.0047	0.0034	0.0109	0.0056	0.0056	-0.0142**
	[1.39]	[0.88]	[1.55]	[1.01]	[0.64]	[2.20]
	0.0002	*0.0001*	*0.0003*	*-0.0001*	*0.0001*	*-0.0002*
Pseudo R^2	0.0482	0.0814	0.0168	0.0823	0.0724	0.0223
Observations	1877	1821	1838	1863	1820	1825

Table 11: Logit regression results on the effect of rating events on CDS spread changes

This table shows the Multinomial logit estimates of a regression of the rating event on the Cumulative Abnormal Returns before and after the crisis. We use the outcome of no rating event as our base case. The first number indicates the relative log odds and the square brackets indicate the t-value, while *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level. The Pseudo R^2 is McFaddens's R^2.

		All countries	PIIGS	non-PIIGS
Rating Downgrade	Constant	0.8705***	0.6706*	1.1581***
		[3.42]	[1.82]	[3.15]
	Before Crisis	0.0169***	0.0104	0.0216**
		[3.06]	[1.48]	[2.46]
	After Crisis	-0.0008	-0.0007	0.0044
		[0.55]	[0.69]	[0.75]
Watch/Outlook Negative	Constant	0.2206	0.4103	0.1672
		[0.98]	[1.06]	[0.59]
	Before Crisis	0.0107**	0.0016	0.0155**
		[1.98]	[0.16]	[2.29]
	After Crisis	0.0002	-0.0001	0.0065
		[0.27]	[0.13]	[1.27]
Watch/Outlook Positive	Constant	-0.1972	0.4537	-0.3853
		[0.65]	[0.55]	[1.14]
	Before Crisis	-0.0095*	-0.0040	-0.0097
		[1.66]	[0.19]	[1.63]
	After Crisis	-0.0018	-0.0011	-0.0101**
		[1.24]	[0.50]	[2.36]
Rating Upgrade	Constant	0.8640***	15.5450	0.3171
		[2.95]	[0.03]	[0.97]
	Before Crisis	-0.0033	0.0007	-0.0026
		[0.37]	[0.00]	[0.29]
	After Crisis	-0.0005	-0.0005	0.0016
		[0.29]	[0.44]	[0.22]
Observations		2471	498	1973
Pseudo R^2		0.0145	0.04634	0.0169

Table 12: Multinomial logit regression results on the effect of rating events on CDS spread changes

This table shows the Multinomial logit estimates of a regression of the rating event on the Cumulative Abnormal Returns before and after the crisis. We use the outcome of no rating event as our base case. The first number indicates the relative log odds and the square brackets indicate the t-value, while *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level. The Pseudo R^2 is McFaddens's R^2.

		All	PIIGS	non-PIIGS
Rating Downgrade	Constant	0.8731***	0.6742*	1.1592***
		[3.43]	[1.82]	[3.16]
	Before Crisis	0.0173***	0.0109	0.0217**
		[3.09]	[1.51]	[2.46]
	After Crisis	-0.00079	-0.00072	0.00535
		[0.55]	[0.69]	[0.82]
Watch Negative	Constant	1.4321***	1.4684**	1.3951*
		[2.85]	[2.24]	[1.69]
	Before Crisis	0.0245***	0.01631	0.0328**
		[3.01]	[1.58]	[2.40]
	After Crisis	-0.0001	-0.0001	-0.0130**
		[0.03]	[0.07]	[2.51]
Negative Outlook	Constant	-0.1742	-0.3130	-0.1452
		[0.65]	[0.57]	[0.46]
	Before Crisis	0.0058	-0.0088	0.0123
		[0.89]	[0.81]	[1.62]
	After Crisis	0.0003	-0.0002	0.0132***
		[0.38]	[0.12]	[2.62]
Positive Outlook	Constant	-0.0686	0.4532	-0.2441
		[0.21]	[0.55]	[0.68]
	Before Crisis	-0.0108*	-0.0042	-0.0112*
		[1.84]	[0.19]	[1.83]
	After Crisis	-0.0018	-0.0011	-0.0106**
		[1.17]	[0.50]	[2.24]
Watch Positive	Constant	-1.3022	—	-1.5249
		[1.17]		[1.27]
	Before Crisis	0.0004	—	0.0013
		[0.02]		[0.07]
	After Crisis	-0.0023	—	-0.0146
		[0.53]		[1.38]
Rating Upgrade	Constant	0.8640***	16.9263	0.3177
		[2.95]	[0.02]	[0.97]
	Before Crisis	-0.0034	0.0008	-0.0027
		[0.38]	[0.00]	[0.29]
	After Crisis	-0.0005	-0.0005	0.0020
		[0.29]	[0.44]	[0.24]
Observations		2471	498	1973
Pseudo R^2		0.0185	0.0532	0.0247

Table 13: Multinomial logit regression results on the effect of rating events on CDS spread changes using more detailed event definitions