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The impact of Credit Rating Announcements on Credit Default Swap Spreads

- An empirical study of the North American Credit Default Swap Market before, during and after the global financial crisis of 2008-2009

ABSTRACT. A Credit Default Swap spread is a reliable measure of credit risk as it is the compensation demanded by a party to bear this risk. Officially, credit risk is denoted as credit ratings announced by credit rating agencies. Since rating announcements contain information regarding credit risk, the market should incorporate this new information into the CDS spread. The aim of this study is to investigate if the CDS spread reacts differently to credit rating announcements during periods of global financial distress than under relative financial stability. The study covers a period between November 26, 2004 to November 13, 2014. By conducting an event study, 300 679 daily credit default swap spreads and 370 Moody´s credit rating events from 120 entities in the North American credit default swap market are analyzed over three time periods: (1) prior to the global Sub-prime crisis of 2008-2009, (2) during the crisis and (3) after the crisis. Specifically, the announcement types, upgrade, possible upgrade, downgrade and possible downgrade are examined. On the aggregated level, all announcement types show a significant impact on the spread at the actual event day, while only negative announcements show significant anticipation. Combining the before and after crisis period as the stable period, all event types except for downgrades show significance at the event day and no announcements display significant anticipation. During the crisis negative announcements show significant magnified anticipation and total reaction, while positive events lose its impact and significance. Lastly, after the crisis, Moody's rating announcements, both pooled positive and pooled negative, lose some of its impact magnitude compared to before the crisis. In sum, our findings propose that the impact of rating announcements depend on the underlying market conditions.

Key words: credit rating announcements, credit default swap spread, CDS spreads, event study, Moody's, credit rating agencies, financial crisis, recession

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1. Introduction

Credit risk is a financial risk present at the global credit market and concerned with the debt holder's capacity to meet its financial obligations. This risk is continuously monitored by market participants, such as hedge funds, banks and insurance companies and is primarily used for asset pricing, portfolio and risk management purposes. The latter can be managed with a Credit Default Swap (CDS), an insurance like credit derivative. The CDS market emerged in the 1990s and has during the last decade become the most dominant credit trading instrument. Particularly, the CDS markets outstanding notional amount rapidly grew from $13.9 to $58.2 trillion between 2005 and the beginning of the financial crisis of 2008-2009 (ISDA, 2013). One of the significant reasons for its popularity is the fact that the CDS allows investors to speculate and take positions purely on credit and the risk associated with it.

Similarly as an insurance contract, the CDS allows a party to transfer credit risk. Specifically, in order for the protection seller to be willing to keep the credit risk, a premium has to be paid annually by the counterparty, namely the CDS spread. As the spread is the compensation demanded of a part to bear this risk, the spread is a reliable measure of credit risk.

Officially, credit risk is measured by credit rating agencies, such as Moody´s and Standard & Poor´s, whose main duty is to increase the transparency and thereby fulfill an important function in order for the financial system to operate efficiently. In particular, such agencies assign a letter grade denoting the creditworthiness of the obligor. These grades rely upon public as well as non-public information that are further communicated to the market by credit rating announcements.

Since rating announcements contain information regarding credit risk, one would expect market participants to incorporate this new information into the CDS spread as it also is a measure of credit risk. This relationship and the informational content of rating announcements have been studied by numerous papers (Hull et al. 2004; Norden and Weber 2004; Micu et al. 2004; Micu et al 2006; Ismailescu and Kazemi 2010; Galil and Soffer 2011; Finnerty et al 2013).

By observing previous research, we find that this relationship has simply not been studied with regard to market conditions, as further discussed in Section *1.1 Overview of related studies and hypothesis motivation*. Explicitly, periods in global recession and the relative stable periods have not been investigated in separation. This is due to the relatively young research area in combination with the fact that parts of the "Dot-com crisis" of 2001-2002 and

the “Sub-prime crisis” of 2008-2009 often have been included in the samples without being specifically considered in the analysis.

During the Sub-prime crisis of 2008-2009, the demand for CDS contracts heavily increased. Additionally, the spread was substantially magnified and the number of negative rating announcements increased substantially due to the changed market conditions. Considering the new financial environment, one could speculate whether the relationship between CDS spreads and rating announcements changed for this period. If such results would be found, this would be favorable for market participants to be aware of. Therefore, the research and monitoring of this relationship during periods of financial distress is of great interest. The same arguments motivates the research for the stable periods before and after the crisis.

The purpose of this essay is to analyze the effect of credit rating announcements on CDS spreads during different market conditions. Specifically, we investigate if CDS spreads react differently to credit announcements during periods of global financial distress than under relative financial stability. We apply an event study to analyze the three time periods: (1) prior to the global Sub-prime crisis of 2008-2009, (2) during the crisis and (3) after the crisis. In addition, the total period as well as the combined periods before and after the crisis will be analyzed. The latter will be called “the stable period”. The study covers a period between November 26, 2004 to November 13, 2014 and the final sample consists of 120 entities from the CDX North America Investment Grade (CDX NA IG) corresponding to 300 679 CDS spread quotes as well as 370 rating announcements from Moody’s.

The remainder of this essay is composed as follows. Section 1.1 provides more detailed research findings within this field as well as a motivation for our hypotheses. Section 2 outlines the theoretical framework. Section 3 presents our data set and final sample. Section 4 explains the event study methodology that was applied as well as some discussion and critique regarding the methodology. Section 5 presents our results and discussion as well as the significance tests, and lastly, Section 6 outlines some concluding remarks and proposal to future research.

1.1 Overview of related studies and hypothesis motivation

There is an extensive amount of literature investigating the informational content of credit rating announcements. Most recent research has applied the standard event study methodology, where the concept is to investigate how CDS spreads react to credit rating announcements. Under the assumption of market efficiency, if an event contains new information to the market, abnormal spread changes should be observed at such events. In addition, market efficiency is tested by investigating the spread changes at periods before as well as after the actual event. Empirical research has investigated informational content by price changes on stock markets, bond markets and more recently, on the relatively new CDS market (CDS spreads). Numerous papers have investigated the CDS market, where Hull et al. (2004) was one of the earliest prominent papers.

Goh and Ederington (1993) point out that the potential reaction of rating events on stock prices depends on the underlying reason of the event, which is not the case for the CDS market in the same extent. For instance, a positive event will theoretically always have a negative direction of impact on the spread. Considering the stock market the same positive event will impact the spread in a direction depending on the reasons of the announcement, such as the change in the financial outlook or leverage. Hence, it is easier to investigate the CDS market because the underlying reason of the event does not have to be considered. (Micu et. al 2006) Additionally, Norden and Weber (2004) find that the CDS market is more efficient than the stock market, thereby suggesting that it is more accurate when investigating the informational content of rating announcements.

Regarding the relationship between the bond yield and the CDS spreads, Hull et. al (2004) explain the theoretical relationship and point out that the CDS spread is preferred to the bond market when investigating the informational content of credit ratings announcements. This is due to the fact that bond yields depend on both the risk free interest rate as well as credit risk, whereas the CDS spreads do not depend on the risk free interest rate. (Hull et. al (2004)

Because of these arguments mentioned above, the informational content of the credit rating announcements is investigated through the CDS market in this study. In Table 1 we shortly outline the summary of some significant previous results regarding the impact of credit rating announcements on CDS spreads.

Table 1
Literature overview. Recent research conserning the informational content of rating announcements on the CDS market.

Study, Data and Entities	Main Results
Hull et al. (2004)	
• 1998-2002, Moody's,	Anticipation for all negative events.
• rating changes, reviews, outlooks,	At the actual event day, only reviews for downgrade
• 59 positive events and 266 negative events,	showed a significant impact.
• adjusted CDS spread changes during [-90, 10]	(no conclusions for positive events due to small positive sample)
Entities: Corporations, sovereigns	
Norden and Weber (2004)	
• 2000-2002, Moddy's, S&P and Fitch,	Anticipation for all negative events, stronger for negative
• 231 rating changes and 116 watch listings,	reviews. At the announcement day, all negative events show
• adjusted CDS spread changes at [-90, 90]	significance.
Entities: Corporations	(no conclusions for positive events due to small positive sample)
Micu et al. (2004)	
• 2001-2003, Moody's and S&P,	Negative events contain valuable information,
• rating changes, reviews, outlooks,	where negative outlooks show least significance
• 325 positive events, 2010 negative events	Positive event were not significant.
• adjusted CDS spread changes at [-60, 20]	
Entities: Corporations	
Micu et al. (2006)	
• 2001-2005, Moddy's, S&P and Fitch,	Regarding percent spread changes: All types of rating
• rating changes, reviews and outlooks,	announcements - whether positive or negative, show significant
• 504 positive events, 1510 negative events	impact at event day, and only negative events are anticipated
• adjusted CDS spread changes and	Regarding absolute spread changes:
adjusted CDS spread percentage changes	only negative reviews display significance.
Entities: Corporations	
Ismailescu and Kazemi (2010)	
• 2001-2009, S&P,	Positive rating announcements have an immediate impact on
• rating changes, reviews, outlook,	sovereign CDS spreads, while negative events show no impact.
• adjusted CDS spread changes at [-60, 20]	Strong anticipation is founds for negative events.
adjusted CDS spread percentage changes	
Entities: Sovereigns (emerging markets)	
Galil and Soffer (2011)	
• 2002-2006, Moody's, S&P,	Significant abnormal change for all rating events is found on
• rating changes, reviews,	the announcement day. Negative events show larger impact on
• 1000 positive and 1866 negative events,	CDS spreads and are more anticipated than positive events.
• adjusted CDS spread changes for [-90, 90]	
Entities: Corporations and sovereigns	
Finnerty et al. (2013)	
• 2001-2008, S&P,	At announcement, all positive events show significance, while
• rating changes, reviews, outlook,	regarding negative events only reviews were significant,
• 1017 positive events, 3114 negativ events	Negative events were stronger anticipated then positive.
more positive events than previous research	During recession, spread changes were magnified for upgrades
• adjusted CDS spread changes for [-90, 90]	
Entities: Corporations	

In general, consistent with theory, the studies show that the spread decreases for positive rating announcements (review for possible upgrades and upgrades) while the spread for negative events (review for possible downgrades and downgrades) increases. Further in line with each other, negative events are typically better anticipated and show a stronger total impact on spreads than positive events. This asymmetry has been motivated with the argument that media highlights negative news more than positive news and as a consequence negative events show stronger anticipation than positive events. Specifically, possible downgrades have been consistently significant and show a stronger impact than the other announcement types. Regarding positive events, the results are relatively mixed. Earlier studies within this field, such as Hull et al. (2004), Norden and Weber (2004) and Micu et al. (2004) find that positive events do not convey any significant information, while on the other hand, later studies find contradicting results that positive information is significant. Similar disagreement is found for downgrades as Norden and Weber (2004), Micu el al. (2004), Micu et al. (2006), Ismailescu and Kazemi (2010) as well as Galil and Soffer (2011) find downgrades to reveal significant information while Hull et al. (2004) and Finnerty et al. (2013), do not.

It should be noted that the data set of these studies all cover periods with varying market conditions. Thus, some years in recession are covered, but never as an entire crisis period by its own nor an entire stable period characterized as a period with absence of global recession. This is due to the fact that the research is fairly young while the Dot-com crisis 2001-2002 and the Subprime crisis 2008-2009 has interfered with the results. Figure 1 clarifies this by illustrating the data sets used in related studies as well as the data set used in this study.

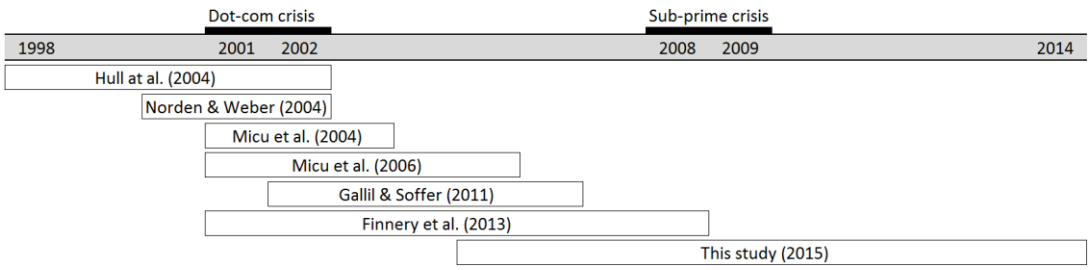

Fig. 1. *Data set analysis. Illustrates the data sets from the overviewed research and this study of 2015 in relation to the "Dot-com crisis" and the "Sub-prime crisis ".*

Moreover, the latest recognized results in this field of research were presented by Finnerty et al. (2013) whose data set only covers until the beginning of 2009, including the crisis 2001-2003 as well as the early beginning of the financial crisis 2008-2009. Further, Finnerty et al. (2013) are the only ones to our knowledge taking periods of financial distress into slight consideration in their analysis. Therefore, the research covering the financial crisis of 2008-2009 and its aftermath is limited.

This study contributes to the informational content research by observing the relationship between CDS spreads and credit rating announcements in consideration of different market conditions in the analysis. For this matter, we propose hypotheses in line with previous research that further are tested for the periods before, during and after the crisis as well as for the stable period aggregating the before and after periods.

H0 *(the announcement type does not contain new information)*:

This is the null hypothesis for each of the following alternative hypotheses for the different announcement types.

H1 *(**Upgrades/Downgrades** contain new valuable information to the market)*:

This hypothesis will be confirmed if a significant abnormal spread reaction is found for actual rating changes within the event window. To be clear, upgrades and downgrades are tested separately. Formally, H0 is rejected and H1 is not rejected if cumulative average abnormal returns for any of the window parts [-20,-2], [-1,1], [2,20] are significantly different from zero.

H2 *(**Possible upgrades/Possible downgrades** contain new information)*:

This hypothesis will be confirmed if a significant abnormal spread reaction is found for rating reviews within the event window. Precisely, possible upgrades and possible downgrades are tested separately. Formally, H0 is rejected and H1 is not rejected if cumulative average abnormal returns for any of the window parts [-20,-2], [-1,1], [2,20] are significantly different from zero.

H3 *(**Positive events** contain new information)*:

Confirmed if a significant abnormal spread reaction is found in connection to the pooled positive event. Possible upgrades and upgrades are combined. Formally, H0 is rejected and H1 is not rejected if cumulative average abnormal returns for any of the window parts [-20,-2], [-1,1], [2,20] are significantly different from zero.

H4 *(**Negative events** contain new information)*:

Confirmed if a significant abnormal spread reaction is found in connection to the pooled negative event. Precisely, possible downgrades and downgrades are aggregated. Formally, H0 is rejected and H1 is not rejected if cumulative average abnormal returns for any of the window parts [-20,-2], [-1,1], [2,20] are significantly different from zero.

1.2 Delimitations

This paper will only examine investment grade corporations in North America included in the CDX NA IG. Hence, all CDS contracts have corporations as their underlying asset. Only quotes from CDS contracts denoted in USD currency are included. This paper investigates the sample period between November 26, 2004 to November 13, 2014, and as a result the only crisis period that will be analyzed is the financial crisis of 2008-2009.

This study only considers credit rating announcements by Moody's. Therefore, the informational content of only this agency will be investigated and hence the contamination effects from other agencies will not be investigated, simply due to timing constraints. Since Moody´s is one of the most prominent credit rating agencies covering all the North American corporations included in the CDX NA IG, it is sufficient for this study. Moody's have seven types of rating announcements: downgrade, upgrade, possible downgrades, possible upgrade, stable outlook, negative outlook and positive outlook. In this study outlooks will be excluded as earlier studies have mainly focused on reviews and actual rating changes as outlooks.

2. Theoretical framework

In this section, the main concepts regarding credit rating agencies, the credit default swap as well as the efficiency market hypothesis are outlined.

2.1 Credit rating agencies

Credit rating agencies (CRAs) have been operating since the beginning of the last century. They emerged when the demand increased for specialized firms to assess the credit risk on issuer's debt instruments. At the time banks were primarily evaluating the credit quality, but their internal procedures were often lacking. (Crouhy, Galai & Mark, 2000)

The agency´s main duty is to mitigate the information asymmetry and thereby increasing the efficiency of the credit markets. This is achieved by the fact that the ratings are based on all information known to the CRAs, including publicly and non-public available information provided by the issuer. (Moody's, 2014-12-20) In fact, the agencies are exempt from fair disclosure laws, such as Regulation FD, and thereby entitled to access information not available to the rest of the market when formulating the ratings. (Saunders & Allen, 2010)

Today there are three global market leaders within the credit rating field; Moody's, Standard & Poor's Rating Services (S&P) and Fitch Ratings. Together they control about 95% of the global credit ratings market (de Haan & Amtenbrink, 2011).

2.1.1 Credit rating and rating scale

A credit rating does not address an investment recommendation for a given security. In the words of S&P (2014-12-20 a), ratings, "express relative opinions about the creditworthiness of an issuer or credit quality of an individual debt issue, from strongest to weakest, within a universe of credit risk." Since the ratings are merely relative opinions, not facts, they can neither be stated as accurate nor inaccurate. (Standard & Poor´s, 2014-12-20 a) Further, in the words of Fitch Ratings (2014-12-20), "ratings are inherently forward-looking and embody assumptions and predictions about future events that by their nature cannot be verified as facts." Therefore, ratings are not an exact measure of credit risk and can be affected by future events that cannot be foreseen. Thus, these opinions are considered in a long term perspective but are not static. (Fitch Ratings, 2014-12-20)

When an agency in the future changes its opinion, this is represented by a so called rating announcement or simply, a rating event.[1] Primarily, it consists of actual rating changes[2], rating reviews or outlooks. Outlooks are opinions about a ratings medium-term trend and represented mainly by positive, negative and stable announcements, where the stable outlook

[1] In this paper we will use the terms "rating event" and "rating announcement" interchangeably.
[2] In this paper we will use the announcement terms "rating change" and "actual rating change" interchangeably.

indicated that the rating probably will remain unchanged. Further, a rating is monitored continuously and analyzed when new information is available. If there is a reason for the CRA to believe that the analysis is likely to result in a rating change in the near future, a "watchlist/review" designation by Moody´s will be communicated in order to notify the market. A "possible upgrade (possible downgrade)" review indicates that a rating upgrade (downgrade) is distinctly possible. Reviews are more accurate indicators of future outcome than outlooks as these focus on the short term. However, CRAs can change a rating without a preceding review announcement. (Moody´s, 2015-03-12)

Ratings on long-term obligations are denominated as letter grades on an ordinal rating scale[3]. The grades are roughly divided into two categories depending on the issuer's level of default risk. Ratings above Ba1 are referred as "investment grade" and the remaining grades are referred as "speculative grade debt" or "junk bonds" as the latter is associated with considerably higher risk. (Moody´s, 2015-03-12)

2.1.2 Credit rating process and methodology

A credit rating process is illustrated in Figure 2. In order for the credit rating process to be initiated, a debt issuer has to deliver a formal request. Further, the credit rating agency designate a responsible team of analysts to assess current relevant information provided by the issuer, so called "Pre-evaluation". Afterwards, the analysts have an appointment with the management group of the entity reviewing and discussing the confidential information in order to get a clear picture of the current state. Following the meeting, a rating proposal is presented and reviewed by a rating committee specialized in the relevant sector or industry, which then votes on the proposal. A pre-publication including a conclusion and voting results are then communicated to the debt issuer who is entitled to examine the accuracy and reliability. The debt holder can further appeal the rating if new adequate information can be provided to support the case. Otherwise, the remaining step is to decide whether the rating should remain confidential or go public. (Moody´s, 2015-03-25)

[3] For a full credit rating scale illustration see Appendix 1.

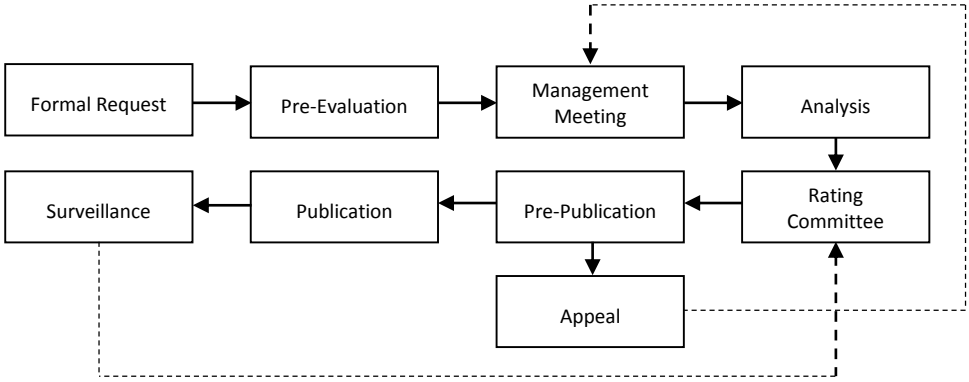

Fig. 2. *Credit Rating Process* **Source:** *Moody´s and Standard & Poor´s, 2014-12-20*

Communicated ratings to the public are published on the agencies´ websites and onwards continuously monitored in order to remain trustworthy to the credit market. If there is a reason for a credit rating agency to believe that new information is likely to result in a rating change, the "watchlist" warning will be communicated. The time frame for the whole rating process, from a request to issuer rating, differs from one to another but usually takes a couple of weeks. (Moody´s, 2015-03-25)

As shown by Cantor et al (1995), rating agencies´ opinions about the credit quality of the same entity often differ from each other. Since the evaluation methods used by the agencies are similar, but not exactly the same, this can give rise to different credit ratings. (Crouhy, Galai & Mark, 2000)

2.1.3 Credit rating agencies´ value creation through rating issues

Since CRAs are regarded as experts and unbiased evaluators of credit risk, their ratings are widely accepted by market participants and regulatory bodies. (Crouhy, Galai & Mark, 2000) Investors consider ratings as a crucial factor when pricing securities, but also when benchmarking different investment alternatives. There are three main values created to issuers by credit ratings together with the fact that investors depend on these ratings. Firstly, the issuer's offerings become attractive to a broader range of buyers as many institutions are prevented by regulation or charter to invest in non-investment grade debt issues. As expressed by Moody´s (2014-12-20), "A rating is effectively a *credit passport* that provide access to both domestic and international pools of debt capital". Further, this leads to reduced funding costs for the issuers and enables larger sales with longer maturities. Thirdly, the opinions expressed by the CRAs contribute to stabilize the market by supporting investors to keep their composure. This is evident during periods when the market is more volatile. Bad news for instance, could affect the price of a company's stock or outstanding bond even though it does not affect the firm's long term credit quality. (Moody´s, 2014-12-20)

2.1.4 A brief discussion – Criticism of the credit rating agencies

Following the financial crisis of 2008-2009 the credit rating agencies were criticized for not living up to their expectations. The criticism was based on the fact that the CRAs assigned too optimistic ratings on mortgage backed securities (MBS) and collateralized debt obligations (CDOs) products[4] in the US credit market. In late 2006, when mortgage loans began to default, Moody's and S&P started downgrading CDOs and MBSes. During the next two years the pair realized mass downgrades of these financial products. Specifically, approximately 90% of the top-rated securities created back in 2006-2007 were downgraded to a speculative status, thereby disrupting the market environment. (Levin & Coburn, 2011) Further, since the business model roughly builds upon the fact that the debt issuer pays the CRA in order to be assigned a rating, there is a financial incentive to act in the "customers" interest rather than the investors in theory. Therefore, there might be a reason to criticize the independence of CRAs. (Saunders & Allen, 2010) However, Micu et al. (2006) discuss that this incentive could be offset by the fact that the CRAs reputation is put at stake by realizing such action. In addition, Stolper (2009) shows that the existing approval scheme by regulators, such as Securities and Exchange Commission (SEC), could pressure the CRAs to assign correct ratings in theory but further clarifies that this is not as simple in reality.

2.2 Credit default swaps

A Credit Default Swap (CDS) is a popular over-the-counter (OTC) credit derivative. It is a formal agreement between two parties, usually between institutional investors and dealers such as investment banks, in order to transfer credit risk. It can be considered as an insurance contract except for the fact that there is no requirement to own the underlying debt in order to enter a CDS contract. In other words, the trading of CDS contracts is not limited by outstanding debt. (Saunders & Allen, 2010)

In a pure CDS, the party selling the credit risk (protection buyer) is contracted to annually pay the counterparty a fixed amount corresponding to a negotiated number of basis points (CDS spread) times the face value of the underlying debt (CDS notional principal).[5] These payments are characterized as periodic cash payments and are paid until maturity in exchange for a full

[4] Simply put, a large baskets of mortgage backed securities (MBSes).

[5] Hence, if the CDS spread is 200 basis points (bps) and the CDS notional principal is 10 million USD, the annual premium paid by the protection buyer is 200´000 USD.

compensation at settlement in case of a Credit Event.[6] Figure 3 illustrates the cash flow for a CDS contract in absence of a credit event. (Markit, 2014-11-03)

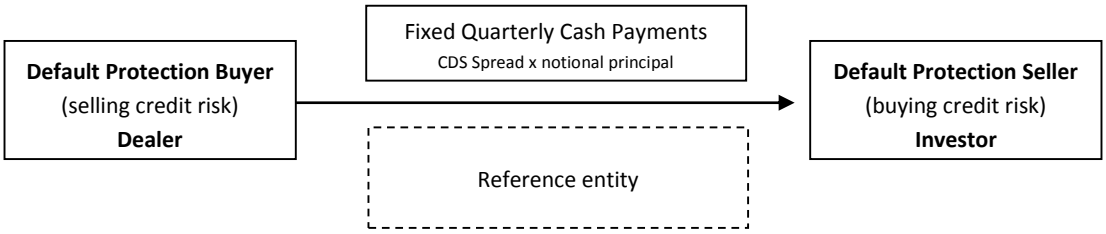

Fig. 3. *Cash-flow from initiation of trade to maturity with the absence of a credit event.* **Source:** *Markit, 2014-11-03*

Every specific contract builds up on a Reference Entity[7] and a Reference Obligation. The former represents the underlying entity which the insurance is issued upon, simply the capital borrower, whereas the latter is the type of debt being insured.[8] Further, the CDS contract does not need to have the same maturity as the underlying debt. (Markit, 2014-11-03)

In case of a credit event, the CDS settlement can both be executed in terms of a physical or cash transaction. If the reference obligation is a corporate bond, a physical settlement requires the insurance buyer to deliver a recover value of the defaulted asset.[9] Additionally, the accrued periodic payment for the present period has to be paid in order to receive a full compensation. The following cash-flows in Figure 4 illustrates the physical settlement of the CDS contract. (Markit, 2014-11-03)

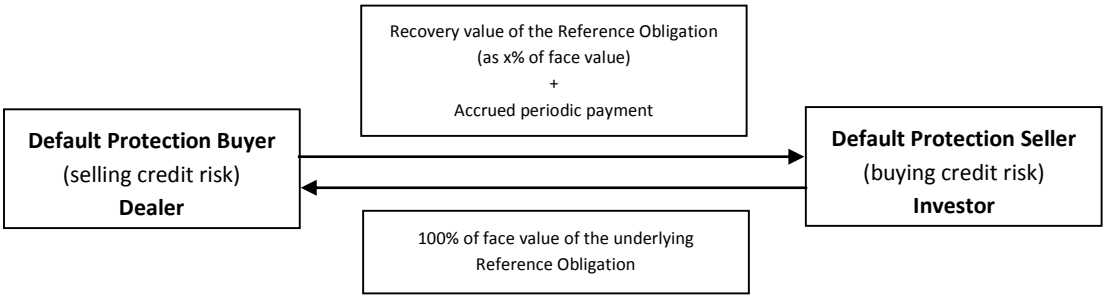

Fig. 4. *Cash-flow in case of a credit event.* **Source:** *Markit, 2014-11-03*

[6] A credit event triggers a settlement of the Credit Default Swap and is classified as one or more of the following six conditions: bankruptcy, payment default, debt restructuring, obligation default, obligation acceleration and repudiation/moratorium. It is worth noting that the three latter are less common events. In this paper we use the terms "default" and "credit event" interchangeably.

[7] Primarily, the reference entity of a CDS may be a corporation such as Transocean Inc., a sovereign such as Greece, or a quasi-sovereign such as the Federal Home Loan Mortgage Corporation.

[8] Specifically, the reference obligation denotes the minimum debt seniority accepted to be delivered to the protection seller during a settlement if the reference entity defaults as there is no requirement to own the underlying debt in order to enter a CDS contract. Thereby, a similar contract is accepted at settlement.

[9] Specifically, a physical bond with the corresponding seniority of the reference obligation in order to define the face value that the recovery value is derived from. At delivery the insured party thereby has the option to deliver the cheapest bond available with the acceptable seniority.

In case of default, the settlement process is handled by a Credit Auction Event[10] and further the cash settlement is the standard transaction in the CDS market today. It is very similar to the physical settlement except for the fact that only a net cash amount is paid to the protection buyer corresponding to the face value subtracted with the recover value set at the auction as well as the accrued periodic payment. However, the settlement amount can also be predetermined in the contract. (Daniels & Jensen, 2005)

By design, the credit default spread is negatively correlated with the creditworthiness of the reference entity. If the creditworthiness for an entity deteriorates the spread will widen while if the creditworthiness improves the spread will tighten. The spread increases at negative events simply as the market requires a higher compensation to the new announced larger default risk. The opposite analogy yields for positive events. (Hull et al, 2004) Further, as explained by Daniels and Jensen (2005), the CDS spread theoretically is the yield subtracted by the risk-free rate. Specifically, it is clarified that if one takes a position in a coupon-bond and meanwhile adding a CDS insurance on the same reference entity, this should be equivalent to a position in a risk-free coupon bond. This implies that the CDS spread should be close to the credit spread over the risk-free rate. (Daniels & Jensen, 2005) Hull et al. (2004), found this relationship to hold fairly well empirically.

The CDS market emerged in the 1990s and quickly became a popular market for hedging or investing purposes. Specifically, it enables investors or businesses, such as banks, with credit exposure to transfer credit risk. Thereby, freeing up capital as the investor does not have to set aside an amount in case of an obligor´s default. Further, the contract allows investors to speculate and take positions merely on credit and the credit risk associated with it. As the credit derivative has many benefits, the CDS has become the most dominant credit trading instrument as well as the main indicator of the credit quality of an entity. (Markit, 2014-11-03)

Debt Restructuring, one of the CDS credit events, is characterized as any delay or reduction in the notional amount or the interest paid. It is not easy to define at all times as it often may be characterized as a “soft” credit event where the loss of an investor is not exactly identifiable. In this case, opportunistic investors can take advantage of the possibility to

[10] As the CDS notional outstanding in the market became far larger than the debt outstanding last decade, the physical settlement was no longer an adequate method to use. The problem occurring was that when an extensive number of investors following a default struggled to find a debt instrument matching the reference entity, resulting in a trading activity increasing bond prices and thereby the anticipated recovery value. Therefore, the International Swaps and Derivatives Association (ISDA) in 2005 formalized a so called Credit Event Auction to handle the settlement process. By this auction, in a transparent way, a poll of dealers decide a market-wide fair value for the defaulted debt which further is used to settle in cash. However, investors owning the actual underlying debt can net their positions through a physical settlement.

deliver the cheapest bond at settlement to profit despite no significant change in the reference entities creditworthiness. For this reason, ISDA has progressively introduced different restructuring clauses, so called "Doc clauses", to CDS contracts in order to define the degree of protection at debt restructuring, also characterizing one of the main differences between traded contracts. (Packer & Zhu, 2005)

Specifically, four restructuring types were introduced: full restructuring (CR), modified restructuring (MR), modified-modified restructuring (MM) and no restructuring (XR). The former denotes that every possible restructure event classifies as a credit event, also any bond with a maturity up to 30 years is accepted to deliver. The MR clause was introduced with the aim to further limit the debt acceptable to have a maximum maturity of 30 months following the end of the CDS. Soon, the MM clause was introduced to nuance the maturity limitation to 60 months for restructured debt and 30 months for all the rest of the debt. The remaining type denotes that restructuring is not defined as a CDS credit event, thereby offset any opportunistic behavior. (Packer & Zhu, 2005)

Credit default swap contracts can be specified as single-name as well as multi-name contracts, primarily CDS indices, relating to the number of underlying reference entities. The market for single-name contracts has generally had a larger market share than the multi-name contracts. This ratio evened out during the financial crisis of 2008-2009. (Bank of International Settlements, 2015-03-20)

A CDS index is similar to a single-name CDS mainly apart from the facts that the CDS spread is an average of the different contracts included. The two main index families in the market are the CDX and iTraxx indicies of which the CDX North America Investment Grade (CDX NA IG) and the iTraxx Europe are the most central indicies. These, do each consist of a basket of the 125 most liquid contracts, equally weighted, that are updated semi-annually in order to maintain high level of liquidity and credit quality. Further, the indices include the five following sectors: industrials, consumers, energy, TMT (telecommunication, media & technology) and financials.[11] (Markit, 2015-03-23)

2.3 A brief discussion – Credit rating vs. CDS spread

The credit quality is an unobservable characteristic of a corporation. The CDS spread and the credit rating of a corporation are both driven by this attribute. CDS spreads generally change continuously since the most liquid contracts are traded daily. In contrast, credit ratings change discretely. As pointed out by Hull et al. (2004) the credit rating should be expected to lag the CDS spread changes with the assumption that they are driven by the same available

[11] The iTraxx further also includes the sector "autos".

information. However, as emphasized by Cantor and Mann (2003), credit rating agencies have stability as one of their targets, and therefore are keen to avoid a situation where a recent published actual rating change has to be revised. Therefore, this stability objective probably will result in actual rating changes lagging changes in the CDS spread. Despite this fact, credit rating agencies derive their opinions from several different sources of information including non-publicly accessible ones (Saunders & Allen, 2010). Under the assumption that the agencies are the only institutions or market participants having access to private information, there is a theoretical possibility of discrete rating changes leading continuous CDS spreads. Hence, this possibility cannot be excluded to occur in reality.

2.4 The efficient market hypothesis

The efficient market hypothesis states that all relevant information is fully incorporated in a security's market price at any time. This is a result of an efficient market that takes all relevant information into account at evaluation of a security. Further, the hypothesis comes in three degrees of efficiency; weak, semi-strong and strong efficiency. (Fama, 1970)

Weak efficiency states that all past information is incorporated in the security price. This implies that historical data or old news is not sufficient to forecast any future abnormal returns and that only recent news or insider information would be appropriate. (Zvi, Kane & Marcus, 2013)

Semi-strong efficiency is the next stage of efficiency as it incorporates past information as well as new information into the security price, and as a consequence only insider information is useful for the prediction of future abnormal returns. This implies that the price will quickly be incorporated directly following new information announcements that are relevant for the security. (Zvi, Kane & Marcus, 2013)

Strong efficiency is the strongest degree of efficiency and neither past, new nor insider information can be utilized for the prediction of the abnormal price performance. (Zvi, Kane & Marcus, 2013)

3. The data set and final sample

In this section the data set will be presented followed by a brief explanation of the approach used in order to receive a final sample. Additional descriptive statistics for the final sample is provided in Appendix 3.

3.1 The data set

The data set used in this paper consists of both daily CDS spreads and credit rating announcements for the 125 companies included in the CDX North America Investment Grade index (CDX NA IG) as of 22nd September 2014[12]. This index was obtained from Markit, a London-based provider covering the OTC derivative markets. The CDX NA IG was chosen in order to ensure that the sample contained the most liquid reference entities from the American market. Even though the crisis of 2008-2009 was a global crisis, the North American market was chosen as the crisis emerged from the US mortgage credit market and thereby is highly relevant for this study.

Credit rating announcements were obtained from Moody's, specifically four types of events were collected; upgrades, downgrades, possible upgrades and possible downgrades. Specifically, we gathered ratings for long term senior unsecured debt denominated in USD.[13] Senior unsecured debt rating was chosen as it reflects the issuer rating by definition as stressed by Hull et al. (2004) as well as it is the most used rating regarding prior research to our knowledge. A total of 419 rating events were obtained.

The CDS spread data was provided by Thomson Reuters Datastream covering the period from November 26, 2004 to November 13, 2014.[14] In total 313 532 spread mid-quotes for senior CDS contracts denoted in USD were gathered. More specifically contracts with a 5-year maturity with a MR clause were chosen. The mid-quote represents the midpoint price between the daily bid and ask quotes.

Further, in order to be consistent, CDS contracts exclusively with a MR clause are included, since there was a negligible difference in the quotes between contracts with different restructuring clauses. Only contracts with the maturity of five years are included because they are the most liquid and due to the fact that this is the benchmark maturity in the CDS market.

[12] Specifically, CDX NA IG Series 23 Version 1 was chosen.

[13] The seniority of a bond relates to the priority of repayment from the reference entities post-default recovery value. A senior bond has to be repaid a head of a subordinated (junior) bond. A debt being secured refers to a bond that is collateralized with an asset owned by the reference entity and an investors pledge in case of a default. Thereby, an investor holding an unsecured bond does not have any contractual rights to the assets and therefore is fully dependent on the credit quality of the reference entity.

[14] Two sources within the Thomson Reuters Datastream software were merged in order to receive a sample for the entire decade: Credit Market Analysis Ltd. (a McGrawHill company) from 2004 to 2007 and Thomson Reuters from 2007 to 2014.

3.2 Final sample

In order to compile a final sample we proceeded with the following approach. Firstly, we excluded the five outliers whose spread stood out from the rest of the sample in order to ensure that the sample would be representative[15]. The corporations were not representative for one of the two reasons: (1) the spreads were substantially wider than the remaining 120 firms[16], (2) their spreads where not following a stochastic process at all, as they instead were following straight horizontal lines for long time periods.

Secondly, we clear the sample for clustering of event windows in order to avoid contamination to affect the results. More specifically, overlapping event windows within the same security were processed with the following set of rules similar to Hull et al. (2004): (1) if two event windows overlapped with 20 days or less, only the later event was excluded, while (2) if the overlap was 21 days or more, both the events were excluded.

Lastly, all the remaining 120 companies and their corresponding spreads were included in our final sample. Even though they did not always have any rating events throughout the period, they still contributed to explaining the normal market behavior.

Our final sample consists of 120 reference entities corresponding to 300 679 individual daily spread mid-quotes and a total of 370 rating events.[17] The reference entities represent five sectors: consumer goods, energy, financials, industrials and telecommunications[18]. The most common sector in number of events included in the sample is consumer goods with 145 of the total 370 events, while the remaining sectors are similarly frequent. Table 2 presents a summary of the event distribution with respect to sector.

Table 2
Nr. of rating events included by sector and period.

	Before	Crisis	After	**Total period**
Consumer goods	54	31	60	**145**
Energy	24	11	21	**56**
Financials	20	17	12	**49**
Industrials	22	8	22	**52**
Telecommunications	26	13	29	**68**
Total nr. of events	**146**	**80**	**144**	**370**

[15] Particularly, American International Group Inc., Ford Motor Company, Assured Guaranty Municipal Corp., Genworth Holdings Inc. as well as General Electric Capital Corp. were excluded.
[16] As for an example Ford M. Company had a spread of 14000 compared to the average 88, max 1350 and min 1,5 for the remaining 120 firms.
[17] See Appendix 2 for a complete list of the final sample including the removed entities and their corresponding CDS quotes and rating events.
[18] Specifically, telecommunications, media and technology.

Further, as illustrated in Table 3 a number of 146 events were included before the crisis, 80 during the crisis and 144 after the crisis period.

Table 3
Nr. of rating events by announcement type and sample period.

	Before	Crisis	After	**Total period**
Upgrades	37	12	52	**101**
Possible Upgrades	36	5	18	**59**
Downgrades	29	35	27	**91**
Possible Downgrades	44	28	47	**119**
Total nr. of events	**146**	**80**	**144**	**370**

As the crisis period is the shortest of the three periods, this distribution is a natural consequence. Further, there are clearly fewer positive than negative announcements during the crisis period with 17 of 80 events, while this ratio during the stable periods is almost one to one.

4. Methodology

4.1 Applied Methodology – Event study

The event study methodology was primarily developed as a method to investigate the effect of economic events on stock prices. However, due to its general applicability and simplicity the methodology has become a well-used methodology within finance and especially within financial accounting (MacKinlay, 1997). With some modifications we follow MacKinlay (1997) who outlines the typical structure of an event study methodology. [19]

Firstly, we identify the period of investigation of the CDS spreads in connection to an event, also called the event window, as 20 days prior to the event, the event day and 20 days after the event, making the event window 41 days in total as illustrated in Figure 5. Further, to test our hypotheses, the window parts [-20,-2], [-1,1] and [2,20] are tested for significant abnormal spread reactions. It should be mentioned that there is no official rule regarding the length of an event window except for critique of statistical kind that will be discussed in *Section 4.2 Methodology assumptions and discussion*.

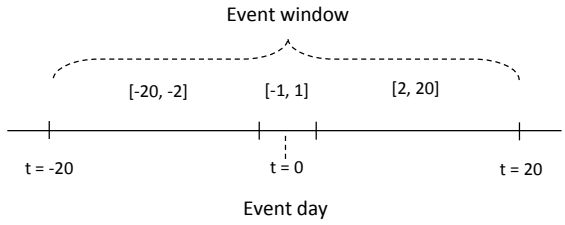

Fig. 5. *Event window including the sections [-20, -2], [-1, 1] and [2, 20] that are tested for significant abnormal spread reactions (cumulative average abnormal returns).*

Secondly, as the event study methodology was primarily developed to measure the significance of an event by observing stock price performance, it was natural to measure the impact in the context of returns. As CDS spreads are not actual price levels or returns but rather a price denoted as a percentage[20] of the notional amount, a proxy for returns has to be found. The overviewed research deals with this in two ways. One ways is simply to regard the spread level as a usual price level, and thereby use the percentage spread changes as a proxy for returns. The alternative way is to use absolute spread changes as a proxy. Both methods show similar popularity. In this study, the spread percentage change will be used as it measures the spread change relative to the spread level. This is especially important in this study as the crisis of 2008-2009 is investigated and for this period the spread levels and

[19] The applied methodology in this study was practically performed using the Python coding language.
[20] The CDS spread is denoted in basis points (bps), 1/100 of a percent.

thereby absolute spread changes strongly differ across securities and periods. Thus, to be able to compare a period of recession to stable periods and also not to risk that individual entities with magnified spreads will have a larger importance for the results than firms with smaller spreads, the spread levels have to be neutralized with its magnitude. Thereby percentage spread changes will be a proxy for returns in this study as seen in Equation 1, where the return $\boldsymbol{R_{i,t}}$ on day $\boldsymbol{t}$ for entity $\boldsymbol{i}$ is calculated, similar to Micu et al. (2004) and Ismailescu and Kazemi (2010).

$$R_{i,t} = \frac{Spread_{i,t} - Spread_{i,t-1}}{Spread_{i,t-1}} \tag{1}$$

Further, to determine whether there are any abnormal CDS spread changes caused by the event, *abnormal returns* (ARs) have to be calculated. Ideally, ARs are calculated as observed returns subtracted by normal returns, where a normal return refers to the expected return in absence of the event. However, normal performance is most likely impossible to determine in reality and thereby an appropriate proxy has to be found.

To simulate daily normal performance in this study, similarly as Micu et al. (2004)[21], four different indices are constructed, one for each rating category. The indices are created as follows: At a given day, the index corresponds to the median spread on that day, in particularly the median spread of the entities that on that day have a rating that belongs to the index. The following entity ratings belong to the corresponding indices:

AAA/AA index – containing the ratings AAA, AA+, AA, AA-

A index – containing the ratings A+, A, A-

Baa index – containing the ratings Baa+, Baa, Baa-

NIG index – containing all ratings lower than Baa-, also called non-investment grade (NIG) ratings

To give the reader a feeling for the indices created, Figure 6 shows the four indices for the entire period calculated as described. These indices as well as a couple of tests results were used to determine the crisis period. The final dates for the crisis period in this study were set from 2008-01-01 to 2009-12-31. As can be seen in Figure 6, the CDS spread was magnified between these dates due to the fact that the market required a higher compensation for bearing credit risk as could be expected during a period in recession. Further, one could also argue that the periods in connection to the crisis are evidently relatively stable compared to the

[21] Also, numerous previous studies have used a similar approach with the mean instead of median at index construction (Hull et al. 2004; Norden & Weber 2004; Ismailescu & Kazemi 2010; Finnerty at al. 2013)

chosen crisis period. The aggregated period consisting of the before crisis period and after crisis period will in this study be named the stable period.

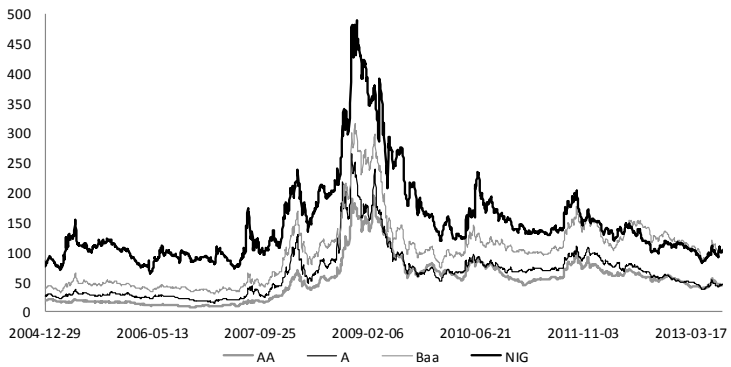

Fig. 6. *AA-, A-, Baa-, NIG index spreads (bps) for the total period.*

Further, in line with previous studies (Finnerty et al. 2014; Hull at al. 2004; Micu et al. 2006; Norden and Weber 2004) we use the index model to calculate abnormal returns (ARs). This model is simply the observed returns subtracted by the corresponding index. A company within a certain rating category for a specific day will have the index corresponding to that rating category as its normal performance measure. For instance, if a company is rated A+, A or A- at day 1 it will have the index named A as its normal performance measure on that day. Equation 2 summarizes the daily AR calculations where ***t*** is the day, ***i*** is a firm and ***ri*** corresponds to firm ***i***'s rating category. The index $I_{ri,t}$ is also denoted as daily percentage changes.

$$AR_{i,t} = R_{i,t} - I_{ri,t} \tag{2}$$

Further, we support Galil and Soffers (2011) discussion and critique regarding Norden and Webers (2004) approach, as Galil and Soffer (2011) state that any discontinuity within the event windows enables us to determine what actually caused the abnormality. Therefore, to avoid discontinuities of the AR calculations within the event windows, we keep the same index throughout the entire event window, even when a firm's rating category changes and thereby its corresponding index due to a downgrade or upgrade within the event window.

Lastly, in order to be able to draw general conclusions, the event windows to a specific event are aggregated into one single event window. Technically, this is done by calculating the daily average abnormal returns across the windows for each day within the event window as Equation 3. (MacKinlay, 1997)

$$\overline{AR}_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t} \tag{3}$$

To obtain a visual representation of the aggregated event window and to test specific window sections for significant abnormal performance, cumulative average abnormal returns (CAR)s are calculated for the different event types, as in Equation 4 (Mitchell & Netter, 1994). [22]

$$\overline{CAR}(t_{1,}\, t_2) = \prod_{t=t_1}^{t2} (1 + \overline{AR}_t) - 1 \qquad (4)$$

The results are presented graphically as CAR(-20, t) for t with the range -20 to 20. As daily average spread returns, or percentage spread changes are cumulated as in Equation 4, the graphs that will later be presented in Section 5. *Empirical results and discussion* and should be interpreted as average abnormal spread changes denoted in percent. The spread change starts at zero just before the window and the observed spread fluctuation should ideally only be due to the investigated event. However, this is most certainly not completely true as some amount of the spread fluctuation is due to other variables that were not neutralized by the benchmark indices. Further and deeper discussion regarding the robustness of our results will be discussed next.

4.2 Methodology assumptions and discussion

McWilliams and Siegel (1997) explain the theoretical and empirical issues concerning the event study methodology. They clarify that efficient markets, unanticipated events and no confounding events are the main assumptions that the event study methodology relies upon. In this section an explanation and discussion is outlined of how this study satisfies these assumption.

Efficient markets imply that the prices incorporate all relevant new information, and as the event study methodology indirectly measures the significance of an event by observing prices changes it relies on this assumption. For instance, if the market would appear inefficient in some degree, the effect of the announcement could possibly be expressed after the investigated event window. (McWilliams and Siegel, 1997) For this reason, the event window part [2, 20] is applied to check for inefficiency in some degree. Likewise, if the events are anticipated, the significance of the event at the actual event date would be underestimated. To check for anticipation in some degree the window part [-20, -2] is used. The event window

[22] Instead of Equation 4 one can also simply sum the average abnormal returns. However, as we use percentage changes together with the fact that we did not want to underestimate the asymmetry between positive and negative events, we used Equation 4. Our final results are still the same for the two methods.

[-1, 1] was chosen in order to check for a significant abnormal spread reaction at the actual event day consistent with Finnerty et al. (2013).[23]

Lastly, regarding the assumption of no confounding variables, which means that only the event effect is captured, we try to satisfy this in three ways as one can influence the degree of the assumption being satisfied which is not the case for the efficient market and non-anticipation assumptions.

Firstly, as events windows are aggregated as "average events windows", and the announcement is the *main* systematically aggregated variable within the event window, confounding variables should diminish with larger sample size.[24] Partly due to this (t-stats also require larger sample size, as it assumes normality), we try to keep the sample size higher by not dividing the investigated time into more than three periods; before, during, and after crisis as well as aggregating the before and after period as the stable period. However, it is important to note that, if the events cluster in time, across event windows, it does no longer have to be true that the event is the only systematically aggregated variable. Therefore an increased sample size would not weaken some confounding variables. As this study examines the relatively long period of 2600 trading days compared to the 370 investigated event days, cross-sectional event time clustering should not be of concern. Thereby, an increased sample size should contribute to the robustness of the results.

Secondly, a powerful measure of normal performance would also reduce the effects of other confounding variables. The benchmark index that we subtract from the spread, in some extent, isolates the investigated event from any fluctuations due to macroeconomic variables. Also as we change the index with respect to four different rating categories, the fact that entities with worse ratings have larger spread changes than those with better ratings, will be isolated in our study. Brown and Warner (1980) investigated the performance between different normal measures, such as the market adjusted return model (also called index adjusted return) as we use, the mean adjusted returns model, market model residuals method and a couple of other less used methods. They concluded that there was no clear winner and that the simplest models worked just as well as the more complicated models in certain conditions. This does not have to imply that the normal performance measure does not matter, as it could be an indication that none of the methods work well enough. An interesting idea would be to optimize an index to every investigated firm, by not aggregating every firm into the index, but only aggregating the firms with the strongest spread correlation to the investigated entity.

[23] Regarding the length of an event window Brown and Warner (1980) find that the power of a t-statistic decreases for longer event windows and therefore the window should be as short as possible and simultaneously long enough to still capture the investigated event.

[24] The announcement may not be the "only" systematically aggregated variable. For instance, industry specific variables could have also been aggregated accidently. For this mater the word "main" is more accurate.

As strong correlation should mean that the majority of the variables that determine the spread are the same, it should imply that an index with a strong correlation to the entity would take more variables into account and therefore isolates these variables from the investigated spreads more efficiently. For example variables as industry and even more company specific variables would be taken into account. However, pure company specific events such as credit rating announcements would still not be isolated which is important as this is the variable that is investigated in the first place. Certainly other pure company specific variables such as a change of the CEO would also not be isolated and such confounding variables would still have to be isolated by hand.

4.3 Alternative methodology

Concerning the overviewed research in this study, all studies apply the event study methodology, while Finnerty et al. (2013), Norden & Weber (2004) and Ismailescu & Kazemi (2010) also complement this methodology with a dummy variable regression. In particular, they use the dummy variable regression in attempt to explain the variation of the individual event windows. As we investigate how the varied market conditions influence the results, this model would be a strong candidate as an alternative methodology or even a complement to this study. Some complementary regressions can be found in Appendix 5.

Further, one could use pure alternatives to the event study methodology and simply compare the results between the crisis period and the stable period. Acharya (1993) presents three different pure event study alternatives and conducts simulation experiments to investigate the performance of these methods. A *latent variable model* suggested in Acharya (1986), a *standard event study model*, a *dummy variable model* and a *truncated regression models* were put to the test. Based on the results he concluded that the latent variable model had the best performance while the truncated regression had the worst. The standard model and the dummy variable model were close in performance to the latent variable model for high probability events, while for low probability events the two models tended to underestimate the significance of the abnormal returns. For more detailed results and conclusions, see Acharya (1993).

4.4 Statistical testing, assumptions and robustness

There are plenty of different inference tests developed for the event study methodology. In this study, the parametric *Cross-sectional t-test*[25] and as a robustness check the non-parametric *Wilcoxon sign-rank test*[26] are applied, mainly to be consistent regarding the fact that none of them require an estimation period. Shortly, the cross-sectional t-test is a

[25] Specifically, it is the two-tailed one sample Cross-sectional t-test that is applied.
[26] More accurately, it is the two-tailed one sample Wilcoxon sign-rank test that is utilized.

parametric-test, identical to the standard student's t-test, it tests whether the mean (average abnormal return) for a given day is different from zero, where the mean and variance of the mean is estimated across the event windows, and therefore it is robust against event-induced variance, shown by Brown and Warner (1980). To avoid any misunderstandings, we test CARs for the window parts [-20,-2], [-1,1] and [2,20] and not means (one day average abnormal returns). However, as CARs are only aggregated means and the CAR's standard deviation is the sum of the means standard deviations the argument regarding robustness against event-induced variance still applies for CARs, as well as the discussions in the following two paragraphs.

Beaver (1968) found that during events, regardless if any abnormal performance is present, the price variance tends to increase and thereby the name event induced-variance. If this phenomenon is not taken into account, the test may overestimate the significance of an observed abnormal return. Thereby, inferences drawn from the cross-sectional t-test will not overestimate the significance of events in this regard. However, to estimate the variance, the test assumes cross-sectional abnormal returns to be independently and identically distributed. As discussed before, independence is a reasonable assumption as the events do not cluster in time. Identically distributed abnormal returns are of much greater concern as this assumption is most certainly violated, also the direction and magnitude of this bias is uncertain in this study. Luckily, this problem can be solved in general by applying the powerful standardized cross-sectional t-test introduced by Boehmer, Musumeci and Poulsen (1991). It uses an estimation period before each event to take the individual distributions into account, making the inference robust against event-induced variance and non-identical distributions.

Lastly, due to the fact that the cross-sectional t-test is a parametric-test, it assumes the tested mean to be normally distributed. The central limit theorem states that the distribution of the mean will tend to a normal distribution as the sample size of the mean calculation increases. More importantly, the theorem states that the mean will tend to normality regardless of the underlying distribution of the sample. As seen in *Appendix 3* the abnormal returns are certainly not normally distributed. Therefore according to the central limit theorem, a sufficient sample size will be required when calculating average abnormal returns so that these will be normally distributed when tested. Generally a sample size of 25 or 30 observations is said to be sufficient, though one should ideally do as Finnerty et al. (2013) and apply Browns and Warners (1980) simulation experiment to analyze the rejection frequencies of the t-test be varying the sample size. However, as we do not do this due to a time constraint, we apply a robustness check with the non-parametric Wilcoxon sign-rank test instead (Ismailescu and Kazemi, 2010; Norden and Weber, 2004). This test is chosen as it is a non-parametric test and

its inference does not depend on the underlying distribution, hence it is a good complement to the parametric t-test. Lastly, it should be noted that the Wilcoxon test, in contrast to the t-test checks whether the median of a distribution is significantly different from zero and no longer the mean.

5. Empirical results and discussion

In this section, results and discussion will be intertwined and organized as follows. First, the aggregated positive and negative results will be presented graphically for all the investigated periods. Further, all the events are presented separately. These presentations are then followed by cross-sectional t-test results together with the Wilcoxon test as a robustness check.

The graphs will always be presented in pairs of cumulative mean (average) and median abnormal returns, however the mean will primarily be discussed while the median will only be used as a robustness check to avoid discussing results that do not show stability. As a remainder, cumulative average abnormal returns should be interpreted as average abnormal spread changes denoted in percent. Further, black lines will always represent negative events while gray lines go with positive events.

5.1 Positive and negative announcements

Positive events pool upgrades and possible upgrades while negative events combine downgrades and possible downgrades. Due to this aggregation of events, the discussions of these results will be slightly more careful and from another point of view. For example, if we find that the downgrades and possible downgrades do not behave in a similar way at a certain period, the aggregated negative graph will not make sense for all sort of conclusions and thereby any attempt to explain this aggregated phenomena could be misleading. Therefore, the results discussed in depth in this section are chosen with care. Lastly, it should be mentioned that all the graphs in this section have the same scale and size to avoid any visual illusions.

5.1.1 Total period - positive and negative announcements

By starting to observe the total period, Figure 7 shows that for both positive and negative events the spread reacts in the expected direction in line with theory. The spread increases at negative events as the market requires a higher compensation to the new announced larger default risk. The opposite analogy yields for positive events. Further, both events indicate to be anticipated as the spread is widening before the announcement day [-20,2]. For negative events the anticipation corresponds to a 7% spread widening and this is followed by a reaction of a 7% spread increase around the event day. Similar result yield for positive events but the overall magnitude is reduced by two to three times for all the event window periods. These results indicate that Moody's announcements contain price valuable information to the market, and this is especially true for negative announcements as it shows a stronger total reaction within the event window.

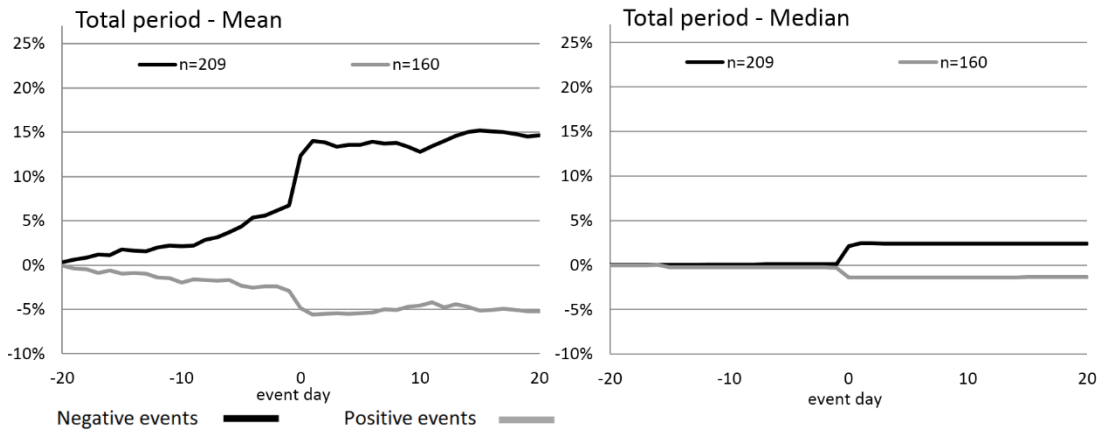

Fig. 7. *Cumulative mean and median abnormal returns for negative and positive events for the total period.*

This asymmetry between positive and negative events has also consistently been found by previous research[27]. In particular, it has been found that the negative events show stronger anticipation and overall magnitude than positive events. As mentioned in the literature overview, this phenomenon has been motivated with the argument that media highlights negative news more than positive news and as a result negative events show stronger anticipation than positive events that could possibly be the explanation for our results as well. However, regarding the larger overall spread impact for negative events, researchers do not seem to discuss any particular reason for this finding. A possible explanation for this will be discussed in *Section 5.1.3 During the crisis-positive and negative announcements.*

Lastly, after the announcement, the spread does not indicate any drift, or in other words, has a trend parallel to the x-axis, indicating that the market is efficient and incorporates all new information relatively fast after an announcement.

5.1.2 Before the crisis - positive and negative announcements

Regarding the results for the period before the crisis illustrated in Figure 8, we see a similar pattern as for the total period. Both events indicate to be slightly anticipated as the spread is widening before the announcement day [-20,2]. In contrast to the results for the total period and previous research, the anticipation is slightly stronger for positive events. Around the actual event day [-1,1] both event types show a greater reaction to the expected direction, where negative evens have a larger mean reaction than positive events. However, the overall mean spread reaction is very similar between the events and by observing the median event window, the positive events seem to have a larger reaction than negative events which show

[27] The term "previous research" will refer to Hull et al. (2004), Norden & Weber (2004), Micu el al. (2004), Micu et al. (2006), Galil & Soffer (2011) as well as Finnerty et al. (2013) in the entire *Section 5 – Empirical results and discussion* to enable a more fluent reading. Ismailescu & Kazemi (2010) are not referred to as they have not concluded nor contradicted the results regarding the fact that negative events have a stronger total impact than positive events. It should also be stressed that Ismailescu & Kazemi (2010) is the only study not including corporations as the underlying entity.

a downward jump some days later after the announcement. This is contrary to prior findings as the market seems not to view negative announcements as informative as previously found. This suggests that the market had an optimistic view for the days ahead as it perceived negative news less informative which is an interesting result just before the financial crisis. This could in other words be described as "riding the wave".

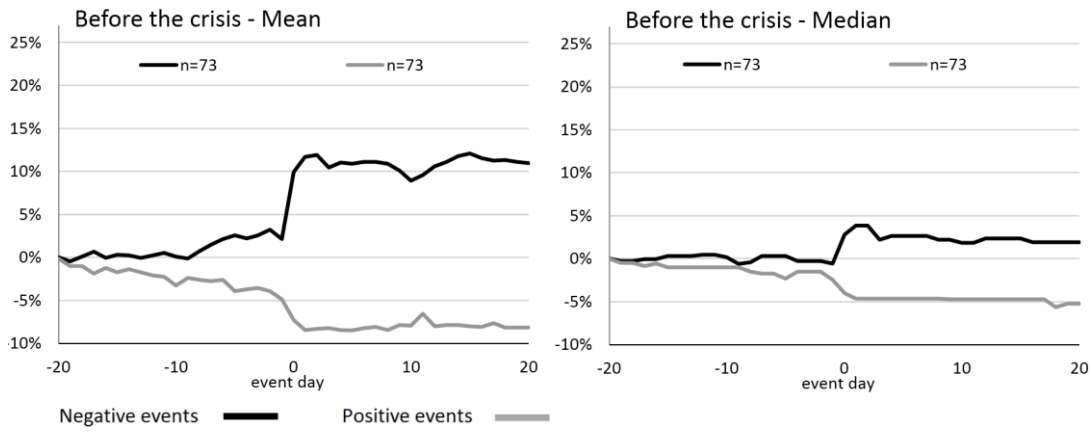

Fig. 8. *Cumulative mean and median abnormal returns for negative and positive events before the crisis.*

5.1.3 During the crisis - positive and negative announcements

During the crisis, as seen in Figure 9, negative event are strongly anticipated as the spread increases with roughly 13% at [-20,-2]. It is the largest spread increase for any [-20,-2] period. There are many possible explanations for this phenomenon. One explanation would be that the default fear increases during the crisis, and because of this, bad news and unstable companies get even more intensively monitored by the market, and thereby rating events get even more anticipated. Theoretically, this implies that when Moody's announces its events, it would not have any impact on the spread any longer as the market already strongly anticipated these actions. However, the impact around [-1,1] is just as for the pre-crisis period 9%, meaning that our explanation to this phenomena should not yield, unless, once again because of the fear factor the market takes the certainty before the uncertainty and "overreacts" to the already incorporated information and thereby making it appear that the informational content during the crisis has increased. This could also be a reason why positive events neither show anticipation nor any impact on the announcement day, as the mean and median spread for positive events seem to follow a random walk along the x-axis. It should be noted that since the sample size for positive events during the crisis only is n=17 compared to the other periods with samples ranging from n=63 to n=209, strong conclusions for positive events during the crisis cannot be made. Lastly, the spread has a slight upward drift for the negative events after the event, at [2,20]. This will be discussed in Section *5.2.3 During the crisis – all*

announcement types as the drift only is due to possible downgrades and not actual downgrades.

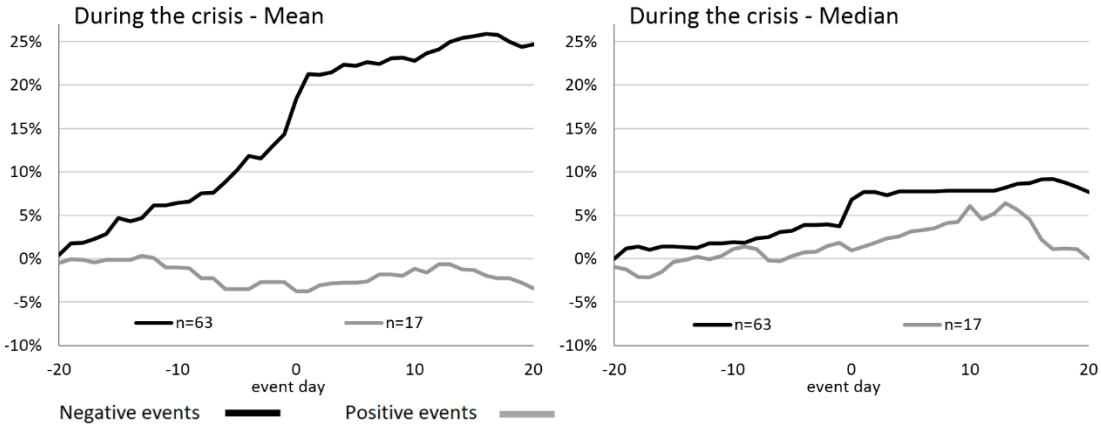

Fig. 9. *Cumulative mean and median abnormal returns for negative and positive events during the crisis.*

Regarding the sample size during the crisis, there were 63 negative events to the total 80 events, implying 79% negative events during this period. This, in relation to 50% negative events before crisis, and 51% after crisis, the chosen crisis period appears to be a convincing choice.[28]

5.1.4 After the crisis - positive and negative announcements

Comparing the crisis period with the period after the crisis in Figure 10, we observe that negative events are no longer as strongly anticipated and the fact that there is no after-drift. Positive events also seem to contribute with new relevant information to the market as before the crisis. The overall shape of the curves are similar to the before crisis period, indicating that the crisis has passed, if we assume that this characteristics indicate a stable market. The major difference is the reduced overall magnitude of the events. Positive events have dropped by approximately 4% while negative events only dropped by 2%. These results are also found for the median spread, indicating that the market no longer views Moody's rating announcements as relevant as before the crisis. One explained could simply be that credit rating agencies received a lot of critique during the crisis and as a consequence the market lost its faith for the rating announcements. Another possible explanation could be that this a characteristic post-crisis effect associated with the market psychology and has nothing to do with the previous explanation.

[28] The periods 2007-2008 and 2007-2010 were also tested and results were still very similar to these. Thereby, any discussion regarding the "right" crisis period should not compromise the robustness of our conclusions. At request, the results for 2007-2008 and for 2007-2010 can be provided.

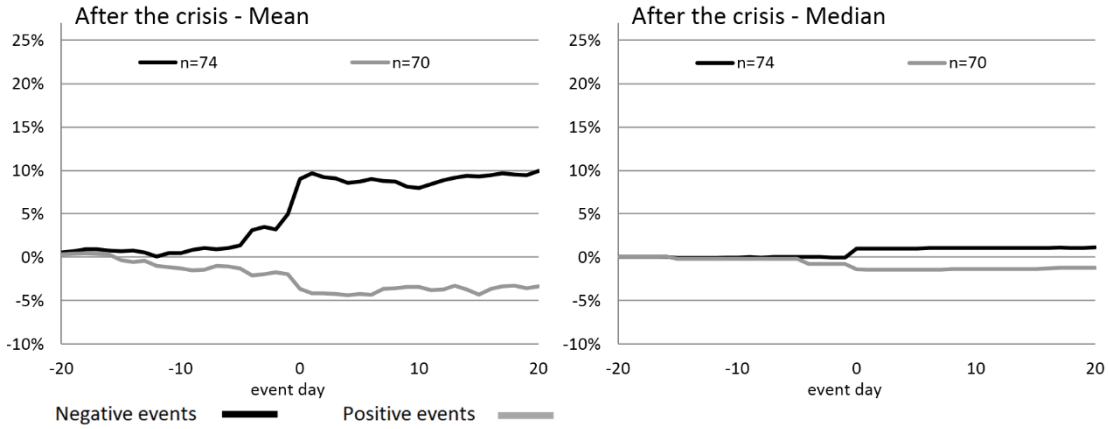

Fig. 10. *Cumulative mean and median abnormal returns for negative and positive events after the crisis.*

Lastly, due to the larger magnitude reduction for positive events relative negative events, the asymmetry between negative and positive events is even larger after the crisis. This would once again be consistent with previous research regarding this asymmetry in general market conditions. However, almost none of the asymmetry is found for the median spread. The asymmetry is also consistent with the descriptive statistics for the CDS spreads and abnormal returns, as the distributions are positively skewed.[29] This means that the probability is larger for outliers regarding a spread increase than a spread decrease, which would result in an asymmetry between the mean and median results as found.

5.1.5 Stable period - positive and negative announcements

By aggregating all the events from the before and after crisis periods we obtain the stable period as seen in Figure 11. Positive events seem to be slightly more anticipated in contrast to what was found for the total period. Also, the difference between the total reaction between positive and negative events seems to be reduced for the stable period. These two findings together with the result for the median spread, suggest that the asymmetry between negative and positive events reduce during periods of relative financial stability. The reaction at the event day is still magnified for negative events with an increase of 8% while positive events display half the effect with 4%. In addition, no drift is found after the event day.

[29] The descriptive statistics can be found in Appendix 3.

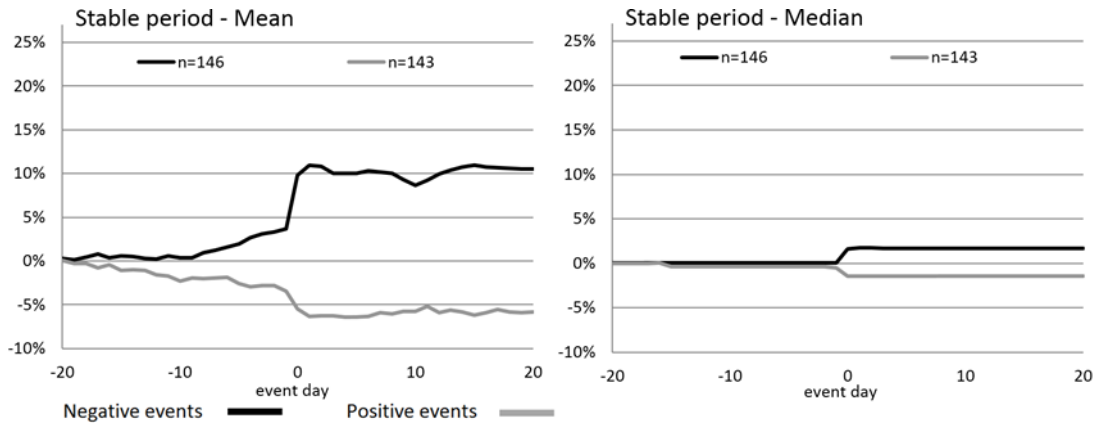

Fig. 11. *Cumulative mean and median abnormal returns for negative and positive events for the stable period.*

5.2 All announcement types

In this section all the event types (upgrades, downgrades, possible upgrades and possible downgrades) will be presented and discussed for the different periods. Consistent with the previous section, this section will also display graphs with the same scale to simplify the comparison between results from different periods.

5.2.1 Total period – all announcement types

Regarding all the event types for the total period as seen in Figure 12, all announcement types impact the spread in the expected direction in line with theory as was seen for the pooled positive and negative events. Further, there seems to be no difference between possible upgrades and actual upgrades, and comparing possible downgrades and actual downgrades only the stronger reaction for possible downgrades around [-1,1] seems to differ. The overall anticipation and the total impact is slightly stronger for negative events than for positive events, consistent with previous research. Further, no announcements show any strong drift after the announcement, once again indicating an efficient market as it incorporates the new information within one to two days. The result that stands out is that possible downgrades have the strongest overall impact which has also consistently been found among previous research.

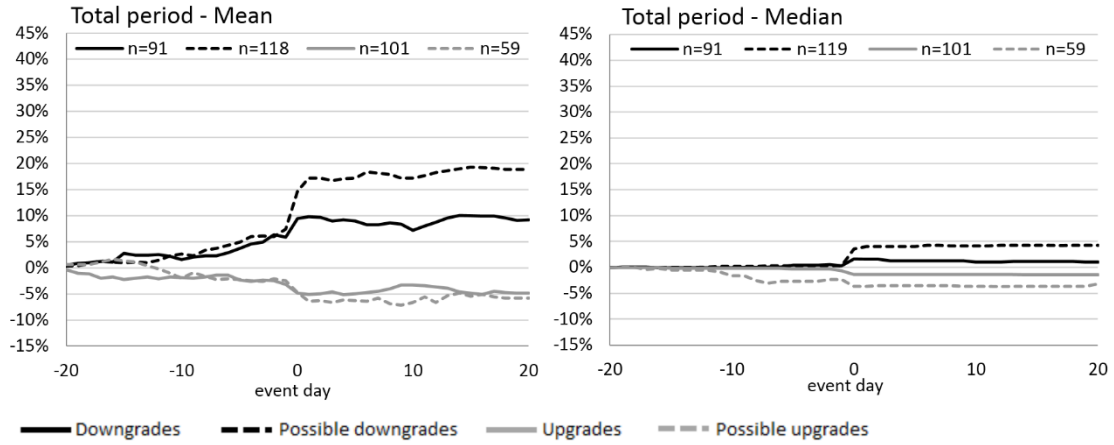

Fig. 12. *Cumulative mean and median abnormal returns for upgrades, downgrades, possible downgrades and possible upgrades for the total period.*

5.2.2 Before the crisis – all announcement types

As mentioned before, previous research has found that the overall magnitude and anticipation is stronger for negative events. Our results in Figure 13 contradict both these findings for the pre-crisis period. Upgrades are most anticipated, and the final mean spread level is around 10% for all event types except for possible upgrades, which fall slightly behind the 10% change mark. At [-1,1] possible downgrades have the greatest impact on the spread, raising it from approximately 2% to 14%. However, 8 days later the spread drops
close to the 10% level as mentioned.

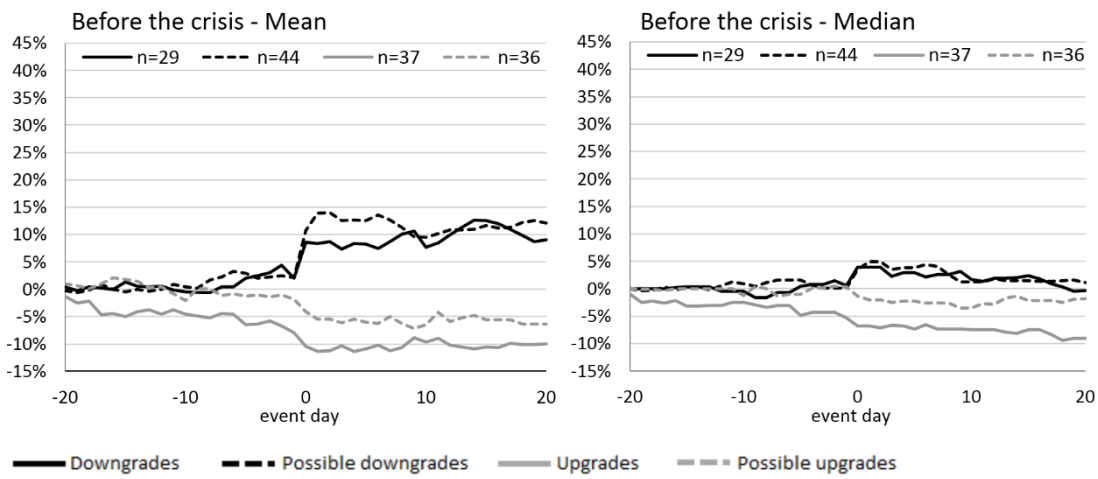

Fig. 13. *Cumulative mean and median abnormal returns for upgrades, downgrades, possible downgrades and possible upgrades before the crisis.*

Also, the median spread for negative events, does not follow the mean spread as good as it does for positive events, again indicating that positive events have a greater impact than previous research suggests. In addition, for both negative events, the median spread shows a reaction on the event day, but around 8 days later, at t=8, the spread level starts falling and ends up at, or close to 0%.

To summarize, these results show that the market is rather optimistic compared to prior research, as the market seems to react rather softly to negative events, and stronger for positive. These findings are interesting, as the market shows optimistic behavior just before the financial crisis, indicating that the market has no clue of what is coming. The sample size ranges from n=29 to n=44 which is on the edge of being too small in common statistical practice, as n=30 is supposed to be a good number, no matter of the underlying distribution.

5.2.3 During the crisis - all announcement types

During the crisis, results show that negative events have a greater role regarding informational content with a positive impact of 37% for possible downgrades and 15% for downgrades. Considering possible upgrades we see that for the first 10 days within the event window, the spread identically increases as for the entities that have a negative rating announcement ahead of them. This result has only 5 observations and could therefore be greatly biased. When we observed the individual 5 entities only one of them showed this behavior which is supported by the median in Figure 14. However, the downward impact at around 10 days before the announcement was true for all the 5 entities, suggesting that possible upgrades could be anticipated during crisis, but does not show any reaction on the announcement day. Moreover, by taking the median and mean into account when observing upgrades, it seems to follow a random walk along the x-axis, suggesting there is no informational value in upgrades. This could be due to the fear factor increase during the crisis as discussed earlier in Section *5.1.3 During crisis - positive and negative events*.

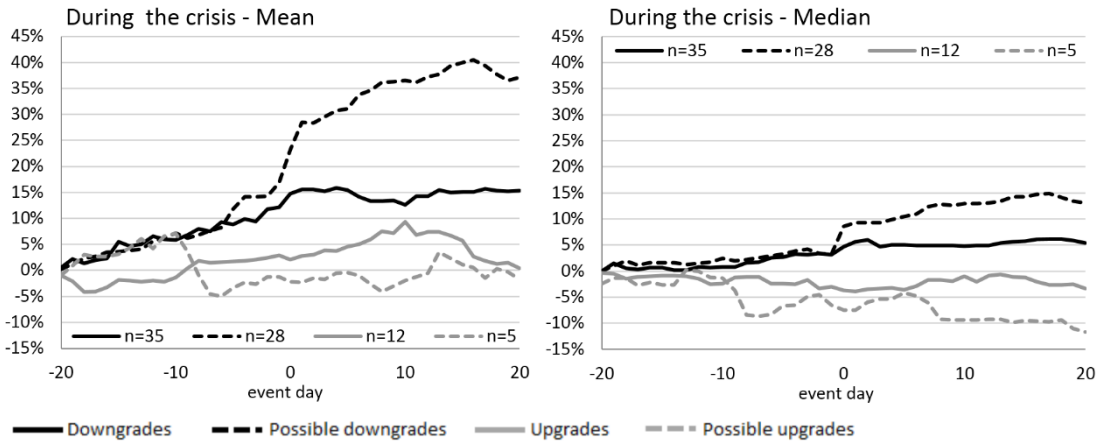

Fig. 14. *Cumulative mean and median abnormal returns for upgrades, downgrades, possible downgrades and possible upgrades during the crisis.*

Among possible and actual downgrades, anticipation is almost identical. Around the event day, reviews show a substantially greater impact than downgrades, with a spread increase of 15%, similar to what was found before the crisis. Nevertheless, negative reviews no longer have any downward drift around day t=8 as before the crisis, and rather shows a positive drift with a spread increase of 10% units at [2,20]. Downgrades do not show any such drift.

An explanation to why only possible downgrades show this drift and not downgrades could be the fact that rating reviews are often proceeded by actual rating changes, and because of this, the market starts to anticipate a rating change immediately after a rating review. The possible downgrade drift at [2,20] has the same slope as the anticipation drift at [-20,-2] for downgrades, slightly supporting our explanation. However, a further explanation why this only yields for the crisis period could be due to the mentioned fear factor, leading the market to take the certainty before the uncertainty and thereby starts to anticipate the next event as soon as there are signs. Another explanation could be that the probability of downgrades after rating reviews were probably much greater during the crisis, and anticipating downgrades directly after negative reviews would be a natural reaction.

Comparing the results found in this section with Finnerty et al. (2013), who are one of few researchers that have slightly considered market conditions in their analysis, we receive directly contradicting results. In particular, their study only observes upgrades and downgrades for this matter and finds that upgrades but not downgrades show a stronger impact on the spread, which is opposite to our findings. For the years 2001-2002 and 2008 they present to have a combined sample size of 20 upgrades as well as 65 downgrades which is similar to our positive and negative ratio, during the crisis period, 17/63. Further, they conduct a similar event study methodology. Indices are constructed with different rating categories and are subtracted from the spread to obtain abnormal returns identical to our approach in this regard. However, there are two different aspects that we believe to be of great importance regarding the different results. Firstly, they use absolute spread changes instead of percentage spread changes as a proxy for returns. As discussed in the methodology, this leads to the fact that companies with larger spread levels will most likely have a greater importance at aggregation, as for the creation of the indices. Secondly, as they calculate their indices as the mean and not the median spread, outliers will have a greater influence on the indices as well. These two factors, during financial distress, would imply that the indices would be biased towards the entities with higher spreads as there would naturally be more firms with higher spreads as well as outliers in this direction at such periods. Finally, these indices are subtracted from the spreads and as a consequence, during recession, it would have a tendency to neutralize negative announcements while exaggerating positive announcements under the assumption that spread levels are lower for firms receiving positive announcements during such periods. As this study uses percentage changes as a proxy for returns, median for index aggregation and removes heavy outliers with care, we believe our methodology is more suited for analysis during recessions and therefore we would argue that our results are more representative for such periods. However, Finnerty et al. (2013) mainly cover the Dot-com crisis and only the beginning of the Subprime-crisis. This, together with the fact that they

investigate S&P instead of Moody's as well as entities not only restricted to the North American market, could be an explanation of these split results.

5.2.4 After the crisis - all announcement types

Figure 15 certainly shows that the crisis has had an impact on how the market perceives Moody's announcements. Overall we see that actual rating changes, both negative and positive, no longer seem to have any substantial impact on the spread while rating reviews still show importance.

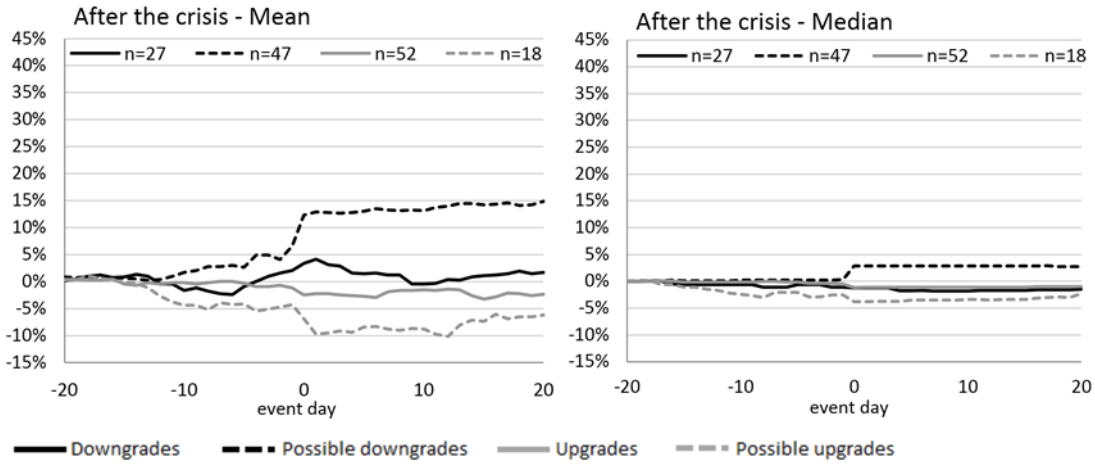

Fig. 15. *Cumulative mean and median abnormal returns for upgrades, downgrades, possible downgrades and possible upgrades after the crisis.*

More in detail, downgrades follow the 0% level throughout the window, except around the event day where the spread ends up at 4%, but falls down again around 10 days after the event. The median does the opposite to this, indicating that there is no robustness in these results, further implying that downgrades do not contain any new information to the market. Upgrades had a spread impact of around 11% before the crisis, and has now been reduced to a maximum impact of 2,5% in the expected direction.

Possible downgrades still have an overall impact of 15%, similar to what it had before the crisis, although the median indicates that it is less volatile now than before the crisis, meaning that the results are more consistent than before the crisis. Lastly, possible upgrades have doubled its informational content from 5% to 10%. However, on day 20 they seem to have the same spread level, although the median still slightly indicates that the informational content has increased for possible upgrades after the crisis.

As was found for pooled positive and negative events after the crisis, the market no longer perceived Moody´s rating announcements as relevant as before the crisis. In this analysis we can see that only actual rating changes has considerably lost its informational value. The

explanation for this could still be aligned with what was discussed for the results after the crisis concerning the pooled positive and negative events.

5.2.5 Stable period - all announcement types

Observing all the announcement types for the stable period in Figure 16 we see a similar overall pattern with the total period. In addition, the asymmetry between positive and negative events is reduced as downgrades show a mirrored image of the positive events while possible downgrades still show such distinct reaction especially at announcement. These findings suggest that during calm periods, the difference in magnitude, especially between downgrades and positive events, is not as great.

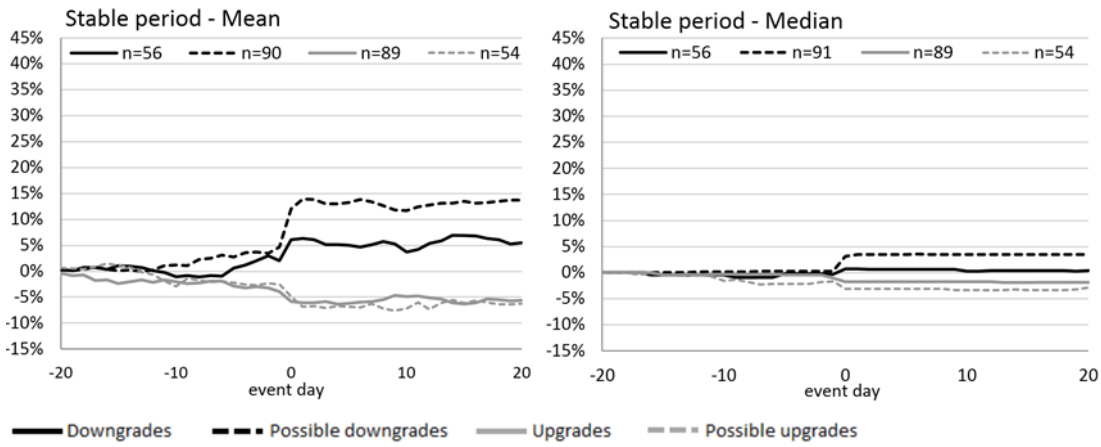

Fig. 16. *Cumulative mean and median abnormal returns for upgrades, downgrades, possible downgrades and possible upgrades for the stable period.*

5.3 Further results

Apart from reviews for downgrade during the crisis, no events show any convincing further drift after the announcement day. Especially after day 1, the spread typically loses its drift completely and follows a rather strictly horizontal path, denoting that the market exploits the price-worth information mostly within one day after an announcement. Additionally, the events that had an impact on the actual day were always more or less anticipated by the market. These two results together strongly suggest that the market is efficient regarding the utilization of the informational content found in Moody's announcements. This type of efficiency would theoretically be described as semi-strong due to the direct utilization of the information at the announcement, and a slight tendency toward strong efficiency regarding the fact that anticipation was more or less always observed.

These results are important as the event study's fundamental assumption is efficient markets, or specifically semi-strong efficiency as discussed earlier in Section *4.2 - Methology assumptions and discussion*. Without a semi-efficient market, there would be a risk that the spread would react before the event window (strong efficiency) or after the event window

(week efficiency), not allowing us to determine the informational content of Moody's announcements. However, it is important to stress that the existence of informational content and the proper degree of market efficiency reveal each other. Without one another, there would be no reaction within the event window and no conclusions could be made regarding which one of these do not exist. As our results clearly show significant reaction, we can discuss informational content and further state that the degree of market efficiency is in line with the methodology assumptions.

5.4 Testing statistical significance of results

In this section, the previous presented results are tested for significance with the two-sided cross-sectional t-test. These results will further be checked for robustness with the two-sided Wilcoxon sign-rank test and only commented when stronger contradicting significance is found for the two tests. Specifically, the Wilcoxon test will only be mentioned when it shows no significance of the event for any confidence level and contradicts the cross-sectional t-test. With this being said, the Wilcoxon test results are provided in Appendix – 4. Overall the results between the two methods are very similar.

5.4.1 Positive and negative announcements - significance test

Table 4, shows significance testing results for positive and negative events for all event window parts; [-20,-2], [-1,1] and [2,20]. These are tested in relation to the periods before, during, after the crisis as well as for the stable and total period.

Table 4
Results for the two tailed, Cross-sectional t-test, that test if the cumulative average abnormal returns are different from zero for pooled positive and negative events with respect to the eventwindow parts [-20,-2], [-1,1] and [2,20] and for the total period as well as before, during, after the crisis and stable period.

		Positive events			Negative events		
		CAR	n	P-value	CAR	n	P-value
Total	**[-20, -2]**	-2,52%	160	0,1140	6,13%	209	0,0000 ***
	[-1, 1]	-2,62%	160	0,0000 ***	7,41%	209	0,0000 ***
	[2, 20]	0,24%	160	0,8109	0,59%	209	0,6433
Before	**[-20, -2]**	-3,92%	73	0,1768	3,22%	73	0,2115
	[-1, 1]	-4,70%	73	0,0000 ***	8,19%	73	0,0028 ***
	[2, 20]	0,30%	73	0,9218	-0,62%	73	0,8081
During	**[-20, -2]**	1,44%	17	0,7454	12,94%	63	0,0001 ***
	[-1, 1]	-0,04%	17	0,9803	7,34%	63	0,0000 ***
	[2, 20]	-1,38%	17	0,7791	2,86%	63	0,2768
After	**[-20, -2]**	-1,71%	70	0,1926	3,19%	74	0,1040
	[-1, 1]	-2,53%	70	0,0151 **	6,27%	74	0,0001 ***
	[2, 20]	0,88%	70	0,5865	0,26%	74	0,8415
Stable	**[-20, -2]**	-2,83%	143	0,0782 *	3,30%	146	0,0421 **
	[-1, 1]	-3,64%	143	0,0000 ***	7,43%	146	0,0000 ***
	[2, 20]	0,60%	143	0,7348	-0,38%	146	0,7892

* Significance at 10%
** Significance at 5%
*** Significance at 1%

By observing negative events we find that these are significant at 1%-level for all the investigated periods on the announcement day. Positive events show similar results except for the crisis period were no significance is found. Further, regarding anticipation for negative events, 1%-significance is found for the total period and the crisis period, while the stable period shows a 5%-significance. Wilcoxon only contradicts the latter finding as no significance is found. Moreover, no significant anticipation is found for positive events except for the stable period. However, it is not supported by the robustness check. These results more or less confirm the main graphical findings. In particular, that the anticipation for negative events is significant during the crisis as well as for the total period. Regarding positive events, they show significance for all periods except for the crisis period. The latter result could suggest an explanation for the mixed previous research results concerning positive events. However, the sample size is only n=17 during the crisis for the positive events.

5.4.2 All announcements types – significance test

Table 5, shows significance testing results for all announcements types. Specifically, for all event window parts; [-20,-2], [-1,1] and [2,20] that are tested in relation to the periods before, during, after the crisis as well as for the stable and total period.

Table 5

Results for the two tailed, Cross-sectional t-test, that test if the cumulative average abnormal returns are different from zero for all the event types with respect to the eventwindow parts [-20,-2], [-1,1] and [2,20] and for the total period as well as before, during, after the crisis and stable periods.

		Upgrades			Possible upgrade			Downgrades			Possible downgrade		
		CAR	n	P-value	CAR	n	P-value	CAR	n	P-value	CAR	n	P-value
Total	**[-20, -2]**	-2,52%	101	0,1872	-2,17%	59	0,3757	6,35%	91	0,0032 ***	5,81%	119	0,0036 ***
	[-1, 1]	-2,62%	101	0,0001 ***	-4,35%	59	0,0034 ***	3,26%	91	0,0058 ***	10,44%	119	0,0000 ***
	[2, 20]	0,24%	101	0,9074	0,62%	59	0,8232	-0,51%	91	0,8026	1,68%	119	0,2987
Before	**[-20, -2]**	-6,71%	37	0,1472	-1,08%	36	0,7597	4,39%	29	0,2406	2,42%	44	0,4930
	[-1, 1]	-5,00%	37	0,0014 ***	-4,39%	36	0,0047 ***	3,77%	29	0,1756	11,18%	44	0,0082 ***
	[2, 20]	1,54%	37	0,7363	-1,05%	36	0,8017	0,68%	29	0,8720	-1,54%	44	0,6306
During	**[-20, -2]**	2,40%	12	0,6320	-1,25%	5	0,9131	11,81%	35	0,0064 ***	14,24%	28	0,0030 ***
	[-1, 1]	0,40%	12	0,8256	-1,07%	5	0,7899	3,32%	35	0,0333 **	12,52%	28	0,0001 ***
	[2, 20]	-2,29%	12	0,7250	0,63%	5	0,9381	-0,18%	35	0,9587	6,71%	28	0,0967 *
After	**[-20, -2]**	-0,63%	52	0,6595	-4,78%	18	0,1212	1,55%	27	0,5615	4,12%	47	0,1273
	[-1, 1]	-1,60%	52	0,0041 ***	-5,20%	18	0,1729	2,51%	27	0,1176	8,45%	47	0,0003 ***
	[2, 20]	-0,16%	52	0,9319	3,88%	18	0,2213	-2,30%	27	0,3461	1,75%	47	0,2612
Stable	**[-20, -2]**	-3,18%	89	0,1253	-2,30%	54	0,3660	3,03%	56	0,1881	3,32%	91	0,1308
	[-1, 1]	-3,02%	89	0,0000 ***	-4,65%	54	0,0037 ***	3,21%	56	0,0536 *	9,79%	91	0,0000 ***
	[2, 20]	0,57%	89	0,7953	0,60%	54	0,8395	-0,73%	56	0,7694	0,16%	91	0,9271

* Significance at 10%
** Significance at 5%
*** Significance at 1%

Considering upgrades, all periods except for the crisis period show significance at 1%. In addition, anticipation show no significance for any period. Similar results are found for possible upgrades except for the fact that significance is not found for the period after the crisis. These results are rather consistent with our graphical results except for the period after

the crisis, as upgrades are still significant but possible upgrades are not. This does not allow us to state that the weakened informational content of rating announcement is due to the decreased significance of actual rating changes. However, it should still be noted that possible upgrades have a rather small sample size of n=18 after the crisis that is of concern.

Further, downgrades during the event day show 1%-significance for the total period, 5%-significance during the crisis and 10%-significance during the stable period. However, the latter significant result is not confirmed by the robustness test. Additionally, anticipation is found to be significant at the 1%-level during the crisis and the total period. By these results, downgrades seem only to be significant for the total period as well as for the crisis period but not for any stable period. As previous research also obtained mixed results concerning downgrades, the different market conditions could be a possible explanation for this inconsistency. Lastly, possible downgrades show significance at 1%-level regardless of market conditions and anticipation is only found significant during the crisis and the total period. This finding is directly consistent with the graphical findings and also consistent with prior studies.

To summarize, these results propose that the informational value, specifically for positive announcements, downgrades and anticipation of the negative events, are dependent on the underlying market conditions. Therefore further research should take this variable into account for more accurate conclusions. With this being said, these results alone are not sufficient to state any strong guidelines but rather only propose suggestions. This study is lacking in several important aspects. Firstly, we believe that the sample for positive events during the crisis is not sufficient as it only contains n=17 observations. Secondly, we would argue that the main issue concerning this study is that we only cover one single global crisis period. As any other single observation, the crisis of 2008-2009 could have its own specific characteristics and therefore a data sample covering multiple global crises would be more representative. Lastly, a similar argument could criticize our restrictions to a specific credit rating agency and geographical market.

6. Conclusions

In this study we investigated the relationship between CDS spreads and credit rating announcements during different market conditions as these results would be of interest for market participants. An event study methodology was conducted to examine rating announcements by Moody's during the last decade, including the Subprime crisis of 2008-2009.

In line with previous research we find that possible downgrades show the strongest significant impact on CDS spreads, and in this study it was true regardless of market conditions as it showed significance impact for all periods. Regarding the mixed prior results concerning actual downgrades and positive events, we find that downgrades show a significant impact only during recession, while the positive events only showed informational significance during stable periods. Further, for the total period, all announcement types show a significant spread impact at the announcement day.

We find three new results. Firstly, we find that none of the announcement types show any significant anticipation during the stable period and that only negative events display significant anticipation during recession and the total period. Secondly, we contradict Finnerty et al. (2013) and discover that, during the crisis, positive events show no significant impact on the spread. In addition, both negative events show a significant enlarged impact, mostly due to magnified anticipation. Lastly, after the crisis, Moody's ratings announcements, both pooled positive and pooled negative announcements lose some of its impact magnitude compared to before the crisis. The latter finding suggests that the informational content of Moody's rating announcements has decreased after the crisis.

In sum, our findings propose that the informational content of positive announcements, downgrades and anticipation of the negative events are dependent on the underlying market conditions, and therefore suggest future research within this topic to take this variable into account for more accurate conclusions.

Further extensions to consider for future research could be to conduct similar studies, ideally covering other global crisis periods as well as larger data sets concerning positive announcements during the recession period.

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Appendix 1 – Credit rating table

Credit rating table
Long-term corporate credit ratings used by Moody's, Fitch and S&P

	Credit quality	Moody's	Fitch	S&P	Default rate [1]
Investment grade debt	Highest quality	Aaa	AAA	AAA	0.000
	Very strong payment capacity	Aa1 Aa2 Aa3	AA+ AA AA-	AA+ AA AA-	0.037
	Strong payment capacity	A1 A2 A3	A+ A A-	A+ A A-	0.042
	Adequate payment capacity	Baa1 Baa2 Baa3	BBB+ BBB BBB-	BBB+ BBB BBB-	0.210
Speculative grade debt	Payment capacity is vulnerable to adverse conditions	Ba1 Ba2 Ba3	BB+ BB BB-	BB+ BB BB-	1.069
	Payment capacity is likely to be impaired by adverse conditions	B1 B2 B3	B+ B B-	B+ B B-	6.185
	Payment capacity is dependent upon sustained favourable conditions	Caa1 Caa2 Caa3	CCC+ CCC CCC- CC C	CCC+ CCC CCC- CC	16.095
	In or near default	Ca C	DDD DD D	C D	32.493

[1] Moody's average annual Issuer-Weighted Corporate Default Rates by Alphanumeric Rating, 1983-2010

Sources: Company websites

Appendix 2 - Corporations included in this study

Final sample
Composition of the CDS data set by firm and period

No.	Corporation name	Sector	No. CDS spreads & Credit events					
			Before		During		After	
1	21st Century Fox America Inc.	TMT	807	2	523	2	1270	0
2	ACE Limited	FIN	807	0	251	0	0	0
3	Aetna Inc.	FIN	807	3	523	0	1270	4
4	Allstate Corp.	FIN	807	0	523	3	1270	0
5	Altria Group Inc.	CONS	807	2	523	0	1270	0
6	American Electrical Power Company Inc.	ENRG	807	1	523	3	1270	1
7	American Express Company	FIN	807	0	523	4	1270	0
8	American International Group Inc.	FIN	-	0	-	0	-	0
9	Amgen Inc.	CONS	807	0	523	2	1270	0
10	Anadarko Petroleum Corp.	ENRG	807	4	523	0	1270	2
11	Arrow Electronics Inc.	TMT	807	0	523	0	1270	0
12	Assured Guaranty Municipal Corp.	FIN	-	0	-	0	-	0
13	AT&T Inc.	TMT	807	2	523	0	1270	4
14	AutoZone Inc.	CONS	807	0	523	0	1270	1
15	Avnet Inc.	TMT	807	0	523	1	1270	0
16	Avon Products Inc.	CONS	807	0	523	0	1270	7
17	Barrick Gold Corp.	INDU	807	1	523	0	1270	2
18	Baxter International Inc.	CONS	807	1	523	0	1270	1
19	Beam Suntory Inc.	CONS	14	0	523	2	1270	1
20	Berkshire Hathaway Inc.	FIN	807	0	523	1	1270	0
21	Block Financial LLC	FIN	807	2	523	0	1270	2
22	Boeing Company	INDU	807	2	523	0	1270	0
23	Boston Scientific Corp.	CONS	807	4	523	1	1270	1
24	Bristol-Myers Squibb Company	CONS	807	3	523	0	1270	0
25	Campbell Soup Company	CONS	807	0	523	2	1270	3
26	Capital One Bank	FIN	807	4	523	1	1270	1
27	Cardinal Health Inc.	CONS	807	1	523	2	1270	2
28	Carnival Corp.	CONS	807	0	523	0	1270	1
29	Caterpillar Inc.	INDU	807	0	523	0	1270	0
30	CBS Corp.	INDU	512	0	523	0	1270	1
31	Chubb Corp.	FIN	807	0	523	0	1270	0
32	Comcast Corp.	TMT	807	1	523	2	1270	1
33	Computer Sciences Corp.	TMT	807	4	523	0	1270	2
34	ConAgra Food Inc.	CONS	807	2	523	0	1270	2
35	ConocoPhilips	ENRG	807	2	523	0	1270	1
36	Cox Communications Inc.	TMT	807	0	523	0	1270	1
37	CSX Corporation	INDU	807	1	523	0	1270	2
38	CVS Health Corp.	CONS	807	3	523	0	1270	1
39	Darden Restaurants Inc.	CONS	807	1	523	0	1270	4
40	Deere & Company	INDU	807	1	523	0	1270	0
41	Devon Energy Corp.	ENRG	807	3	523	0	1270	1
42	DIRECTV Holdings LLC	TMT	807	1	523	2	1270	4
43	Dominion Resources Inc.	ENRG	807	2	523	0	1270	1
44	Dow Chemical Company	INDU	807	0	523	2	1270	1
45	Duke Energy Carolinas LLC	ENRG	807	1	523	0	1270	4
46	E.I. du Pont de Nemours & Company	INDU	807	1	523	0	1270	1
47	Eastman Chemical Company	INDU	807	0	523	0	1270	0
48	ERP Operating Limited Partnership	FIN	130	0	523	0	195	0
49	Exelon Corp.	ENRG	806	1	523	1	1270	3
50	Expedia Inc.	CONS	353	2	523	1	1270	0

(continued on next page)

(continued)
Composition of the CDS data set by firm and period

No.	Corporation name	Sector	No. CDS spreads & Credit events					
			Before		During		After	
51	FirstEnergy Corp.	ENRG	807	0	523	0	1270	0
52	Ford Motor Company	CONS	-	0	-	0	-	0
53	Freeport-McMoRan Inc.	INDU	217	1	523	1	1270	2
54	Gap Inc.	CONS	807	2	249	0	941	0
55	General Electric Capital Corp.	FIN	-	0	-	0	-	0
56	General Mills Inc.	CONS	807	2	523	0	1270	2
57	Genworth Holdings Inc.	FIN	-	0	-	0	-	0
58	Halliburton Company	ENRG	807	4	523	0	1270	0
59	Hartford Financial Services Group Inc.	FIN	807	1	523	4	1270	0
60	Hewlett-Packard Company	TMT	807	2	523	0	1270	5
61	Home Depot Inc.	CONS	807	1	523	0	1270	2
62	Honeywell International Inc.	INDU	807	0	523	0	1270	0
63	Ingersoll-Rand Company	INDU	807	0	523	0	1270	1
64	International Business Machines Corp.	TMT	807	1	523	1	1270	2
65	International Paper Company	INDU	807	2	523	0	1270	1
66	Johnson Controls Inc.	CONS	807	3	523	2	1270	3
67	Kinder Morgan Energy Partners L.P.	ENRG	807	2	523	0	1270	1
68	Kohl´s Corp.	CONS	807	1	523	0	1270	0
69	Kroger Company	CONS	807	0	523	0	1270	0
70	Lockheed Martin Corporation	INDU	807	1	523	0	1270	0
71	Loews Corp.	FIN	807	3	523	0	1270	1
72	Lowe´s Companies Inc.	CONS	807	2	523	0	1270	1
73	M.D.C. Holdings Inc.	INDU	807	0	523	0	1270	1
74	Macy´s Inc.	CONS	807	2	523	4	1270	3
75	Marriot International Inc.	CONS	807	0	523	1	1270	1
76	Marsh & McLennan Companies Inc.	FIN	807	0	523	0	1270	1
77	McDonald´s Corp.	CONS	807	1	523	0	1270	2
78	McKesson Corp.	CONS	807	0	523	0	1270	3
79	Mead Westvaco Corp.	INDU	807	2	523	2	1270	1
80	MetLife Inc.	FIN	807	0	523	1	1270	0
81	Mondelez International Inc.	CONS	16	0	523	1	1270	1
82	Motorola Solutions Inc.	TMT	807	2	523	4	1270	3
83	Nabors Industries Inc.	ENRG	807	0	523	2	1270	1
84	National Rural Utilities Corp.	ENRG	807	0	523	0	1270	0
85	Newell Rubbermaid Inc.	CONS	807	0	523	2	1270	0
86	Newmont Mining Corp.	INDU	807	1	523	1	1270	3
87	Nordstrom Inc.	CONS	807	0	523	1	1270	2
88	Norfolk Southern Corp.	INDU	807	0	523	0	1270	0
89	Northrop Grumman Corp.	INDU	807	2	523	0	1270	0
90	Omnicom Group Inc.	TMT	807	0	523	0	1270	0
91	Pfizer Inc.	CONS	807	2	523	2	1270	0
92	Pitney Bowes Inc.	TMT	807	2	523	0	1270	4
93	Procter & Gamble Company	CONS	807	1	523	0	1270	0
94	Prudential Financial Inc.	FIN	807	1	523	2	1270	1
95	Quest Diagnostics Inc.	CONS	807	2	523	0	1270	1
96	Raytheon Company	INDU	807	4	523	0	1270	1
97	Reynolds American Inc.	CONS	0	0	400	0	1270	2
98	Ryder System Inc.	INDU	807	0	523	0	1270	0
99	Safeway Inc.	CONS	807	0	523	0	1270	3
100	Sempra Energy	ENRG	807	0	523	0	1270	0

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(continued)
Composition of the CDS data set by firm and period

No.	Corporation name	Sector	No. CDS spreads & Credit events					
			Before		During		After	
101	Sherwin-Williams Company	INDU	807	1	523	0	1270	1
102	Simon Property Group L.P.	FIN	807	4	523	0	1270	1
103	Southwest Airlines Company.	CONS	807	0	523	1	1270	1
104	Staples, Inc.	CONS	807	2	523	0	1270	0
105	Starwood Hotels & Resorts Inc.	CONS	807	2	523	2	1270	3
106	Target Corp.	CONS	807	3	523	0	1270	0
107	Teck Resources Limited	ENRG	3	0	177	1	1270	2
108	Time Warner Cable Inc.	TMT	176	0	523	0	1270	2
109	Time Warner Inc.	TMT	807	2	523	0	1270	0
110	Transocean Inc.	ENRG	807	3	523	0	1270	2
111	Tyson Foond Inc.	CONS	807	3	523	2	1270	3
112	Union Pacific Corp.	INDU	807	0	523	0	1270	2
113	United Health Group Inc.	FIN	807	2	523	1	1270	1
114	United Parcel Service Inc.	CONS	807	2	523	1	1270	1
115	Valero Energy Corp.	ENRG	807	1	523	2	1270	0
116	Viacom Inc.	TMT	807	0	523	0	1270	0
117	Verizon Communications Inc.	TMT	744	4	523	0	1270	0
118	Wal-Mart Stores Inc.	CONS	807	0	523	0	1270	1
119	Walt Disney Company	TMT	807	0	523	1	1270	1
120	Weatherford International Limited	ENRG	807	0	523	2	1270	2
121	Weyerhaeuser Company	INDU	807	2	523	2	1270	2
122	Whirlpool Corp.	CONS	807	2	523	0	1270	1
123	Xerox Corp.	TMT	807	3	523	0	1270	0
124	XLIT Ltd.	FIN	3	0	4	0	888	0
125	YUM! Brands Inc.	CONS	807	2	523	2	1270	0

FIN = financials
CONS = consumer goods
ENERG = energy
INDU = industrials
TMT = telecommunications, media & technology

Appendix 3 – Descriptive statistics

In this Appendix the descriptive statistics are provided with respect to period, sector and rating category for the spreads in its natural form as well as a graphical probability density function and descriptive statistics for the abnormal returns. All this data concerns the final sample of the 120 entities that were studied in this paper.

Table of Descriptive statistics

Panel A

Descriptive statistics concerning CDS spreads for the final sample with respect to period

Period	Number of mid-quotes	Standard Deviation	Mean	Median	Max	Min	Kurtosis	Skewness
Before	90117	29,35	38,64	31,20	378,30	1,50	12,45	2,83
Crisis	61218	131,52	141,47	96,80	1352,60	7,50	9,49	2,65
After	149344	67,76	96,13	77,27	911,91	10,21	9,42	2,32
Stable	**237384**	**62,34**	**74,02**	**53,92**	**911,91**	**1,50**	**10,80**	**2,48**
Total	**300679**	**86,06**	**88,13**	**61,70**	**1352,60**	**1,50**	**19,45**	**3,42**

Panel B

Descriptive statistics concerning CDS spreads for the final sample with respect to sector

Period	Number of mid-quotes	Standard Deviation	Mean	Median	Max	Min	Kurtosis	Skewness
CONS	113423	81,55	85,00	60,50	1053,50	1,50	18,02	3,33
ENERG	43043	72,83	87,37	61,10	737,58	6,00	9,10	2,31
FIN	39194	124,02	108,40	70,03	1352,60	6,50	13,70	3,18
INDU	61513	75,78	80,27	57,20	1165,00	5,80	27,60	3,84
TMT	46106	76,64	88,17	65,20	688,80	5,20	8,48	2,48

Panel C

Descriptive statistics concerning CDS spreads for the final sample with respect to rating category

Period	Number of mid-quotes	Standard Deviation	Mean	Median	Max	Min	Kurtosis	Skewness
Aaa/Aa	14297	50,13	44,53	33,76	525,00	1,50	17,23	3,48
A	85183	70,79	59,27	41,32	1352,60	5,20	47,85	5,61
Baa	186896	86,94	101,42	76,70	1151,88	3,60	15,73	3,08
NIG	14156	115,06	155,21	136,29	1165,00	10,00	12,48	2,77

CONS = Consumer goods, ERERG = Energy, FIN = Finacials, INDU = Indutrials, TMT = Telecom/Media/Tecnology

By observing Panel A in Table *of Descriptive statistics*, one can see that the crisis period has all the characteristics that are associated with a period of recession compared to the other periods. To be clear, specifically the standard deviation, mean, median, maximum and minimum spreads are magnified for this period. As the crisis period is shorter, it also conveys fewer CDS spread quotes as expected. One should also note that the after period is not as stable as the period before the crisis. Concerning Panel B, consumer goods have the largest

number of quotes while financials have the least and seem to have most of the recession characteristics. Lastly, Panel C shows a very consistent pattern where the higher rated firms show CDS spreads that have more stable characteristics, while the opposite is found for the lower rated firms, as one would expect. In addition, the AAA/AA rating category as well as the non-investment grade category show a substantially lower number of CDS spreads, while Baa is the most dominant in this regard. Overall, independently of the point of view we are observing the spread, it always shows a positively skewed distribution.

As illustrated in Figure *Distribution* the approximated probability density curve for the abnormal returns is not normally distributed as it shows a magnified kurtosis as well as a positively skewed distribution. The mean and median is zero and indicate that the benchmark index subtracted by the spread has neutralized these attributes.

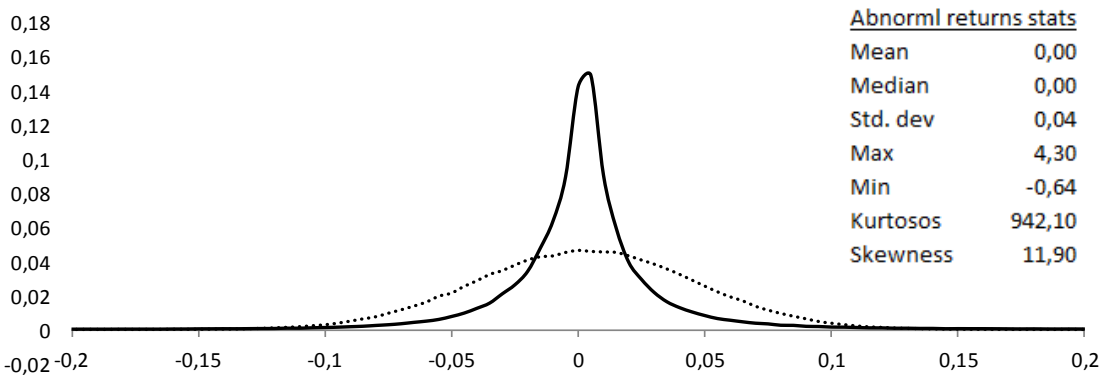

Fig. Distribution. *Approximated probability density function for the abnormal returns compared to the normal distribution with the same mean and standard deviation parameters as the abnormal returns.*

Appendix 4 – Robustness check

In this appendix, results for the two tailed Wilcoxon sign-rank test are provided for both negative/positive events as well as for all event types.

Pooled positive and negative announcements - Wilcoxon sign-rank test

Results for the two tailed, sign-rank Wilcoxon test, that test if the median of the distribution for the abnormal returns that are used for calculating the eventwindow parts [-20,-2], [-1,1] and [2,20] is different from zero in regard to the total period as well as before, during, after crissis and stable period.

		Positiv events			Negative events		
		CAR	n	P-value	CAR	n	P-value
Total	**[-20, -2]**	-0,22%	160	0,1746	0,14%	209	0,0049 ***
	[-1, 1]	-1,14%	160	0,0000 ***	2,31%	209	0,0000 ***
	[2, 20]	0,00%	160	0,2852	-0,04%	209	0,9429
Before	**[-20, -2]**	-1,50%	73	0,3666	-0,24%	73	0,3914
	[-1, 1]	-3,20%	73	0,0000 ***	4,07%	73	0,0113 **
	[2, 20]	-0,67%	73	0,5905	-1,86%	73	0,2626
During	**[-20, -2]**	-2,72%	17	0,7893	3,90%	63	0,0006 ***
	[-1, 1]	-1,05%	17	0,6741	3,55%	63	0,0001 ***
	[2, 20]	0,30%	17	0,5896	0,03%	63	0,1395
After	**[-20, -2]**	-0,77%	70	0,5028	-0,02%	74	0,6052
	[-1, 1]	-0,64%	70	0,0021 ***	1,02%	74	0,0008 ***
	[2, 20]	0,19%	70	0,6406	0,10%	74	0,8637
Stable	**[-20, -2]**	-0,35%	143	0,1814	0,06%	146	0,3054
	[-1, 1]	-1,14%	143	0,0000 ***	1,65%	146	0,0000 ***
	[2, 20]	0,03%	143	0,3531	-0,02%	146	0,2576

* Significance at 10%
** Significance at 5%
*** Significance at 1%

All announcements - Wilcoxon sign-rank test

Results for the two tailed, sign-rank Wilcoxon test, that test if the median of the distribution for the abnormal returns that are used for calculating the median CARs for the event window parts [-20,-2], [-1,1] and [2,20] is different from zero in regard to the total period as well as before, during, after crissis and stable periods.

		Upgrades			Possible upgrade			Downgrades			Possible downgrade		
		CAR	n	P-value	CAR	n	P-value	CAR	n	P-value	CAR	n	P-value
Total	**[-20, -2]**	-0,24%	101	0,3641	-0,37%	59	0,3021	0,56%	91	0,0360 **	0,33%	119	0,0608 *
	[-1, 1]	-1,12%	101	0,0000 ***	-1,33%	59	0,0029 ***	1,07%	91	0,0400 **	3,67%	119	0,0000 ***
	[2, 20]	-0,01%	101	0,1755	-0,14%	59	0,9125	-0,54%	91	0,6845	0,22%	119	0,6946
Before	**[-20, -2]**	-4,39%	37	0,2164	-0,37%	36	0,7486	1,47%	29	0,2345	0,11%	44	0,8312
	[-1, 1]	-2,56%	37	0,0009 ***	-1,33%	36	0,0056 ***	2,44%	29	0,4631	4,84%	44	0,0101 **
	[2, 20]	-2,45%	37	0,2280	-0,14%	36	0,5237	-4,15%	29	0,5143	-3,69%	44	0,3547
During	**[-20, -2]**	-3,32%	12	0,7512	-0,37%	5	0,9324	3,32%	35	0,0080 ***	3,39%	28	0,0311 **
	[-1, 1]	-0,51%	12	0,8233	-1,33%	5	0,6092	2,24%	35	0,0326 **	5,70%	28	0,0004 ***
	[2, 20]	0,59%	12	0,7084	-0,14%	5	0,6560	-0,29%	35	0,6321	3,43%	28	0,0926 *
After	**[-20, -2]**	-0,41%	52	0,8899	-0,37%	18	0,1423	-1,17%	27	0,2695	0,26%	47	0,1114
	[-1, 1]	-0,69%	52	0,0029 ***	-1,33%	18	0,2770	-0,07%	27	0,7860	2,55%	47	0,0001 ***
	[2, 20]	0,15%	52	0,7053	-0,14%	18	0,1075	-0,27%	27	0,7089	-0,05%	47	0,6065
Stable	**[-20, -2]**	-0,37%	89	0,4102	-0,37%	54	0,2905	-0,16%	56	0,6281	0,25%	91	0,3666
	[-1, 1]	-1,33%	89	0,0000 ***	-1,33%	54	0,0031 ***	0,84%	56	0,3616	3,26%	91	0,0000 ***
	[2, 20]	-0,14%	89	0,1918	-0,14%	54	0,9907	-0,28%	56	0,3584	0,00%	91	0,5905

* Significance at 10%
** Significance at 5%
*** Significance at 1%

Appendix 5 – Complementary regressions

In this Appendix, complementary regressions are provided for some of the main results. In particular, the results concerning the stronger anticipation for the negative events during crisis as well as the reduced informational importance of pooled positive events during recession is strengthened by these regressions.

Concerning possible downgrades, the anticipation window [-20,-2] is the dependent variable while the Crisis_Dummy is the explanatory dummy-variable. The Crisis_Dummy takes the value one if the anticipation window is observed during the crisis, and otherwise taking the value zero. One can see that the coefficient for the Crisis_Dummy variable is estimated to 10% and show significance at 5% level.

Table Dummy regression (possible downgrades)

Dummy variable regression estimating the additional impact at [-20,-2] for possible downgrades during crisis. The estimated model is;
CAR(-20,-2) = Intercept + (Additional_anticip) x Crisis_Dummy

	Estimated Coefficien	Std.error	p-value
Intercept	0,03	0,0220	0,1390
Crisis_Dummy	0,10	0,0454	0,0274 **
R^2/Adj. R^2	0,04/0,03		
Observations	n=119		

*** Significance at 10%, ** Significance at 5%, *** Significance at 1%**

Further, by observing the same regression for downgrades we see that the additional anticipation during crisis is estimated to 9% that is also found significant at the 5% level.

Table Dummy regression (downgrades)

Dummy variable regression estimating the additional impact at [-20,-2] for downgrades during crisis. The estimated model is;
CAR(-20,-2) = Intercept + (Additional_anticip) x Crisis_Dummy

	Estimated Coefficient	Std.error	p-value
Intercept	0,03	0,0258	0,2638
Crisis_Dummy	0,09	0,0435	0,0337 **
R^2/Adj. R^2	0,05/0,04		
Observations	n=91		

*** Significance at 10%, ** Significance at 5%, *** Significance at 1%**

Lastly, the regression for pooled positive events where [-1,1] is now the dependent variable, the intercept is significant at 1%, with the coefficient -4%. Further, as the Crisis_Dummy coefficient is estimated to 4% and as it is the additional reaction to the intercept, the total estimated reaction for positive events around the event day is zero percent during recession.

Table Dummy regression (pooled positive)

Dummy variable regression estimating the additional impact at [-1,1] for pooled positive events during crisis. The estimated model is;
CAR(-1,-1) = Intercept + (Additional_rection) x Crisis_Dummy

	Estimated Coefficient	Std.error	p-value
Intercept	-0,04	0,0061	0,0000 ***
Crisis_Dummy	0,04	0,0187	0,0524 *
R^2/Adj. R^2	0,02/0,02		
Observations	n=160		

*** Significance at 10%, ** Significance at 5%, *** Significance at 1%**