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The Effect of Credit Rating Announcements on Credit Default Swap Spreads

- An empirical study of the European, American and Asian-Pacific Credit Default Swap Markets

ABSTRACT. Credit default swap spreads and credit ratings are two indicators and measures of credit risk. A credit default swap is a type of financial derivative that protects the holder from any losses incurred by the reference entity in the case of a negative credit event, in return for an annual premium, the spread. The main question asked in this essay is whether credit rating announcements have any significant impact on credit default swap spreads. Since ratings are a source of information, spreads should behave in accordance with the type of information being distributed. Positive rating announcements should affect spreads negatively, and negative announcements in the opposite direction. By means of an event study, 216 448 daily credit default swap spreads and 336 Moody's credit rating events from 152 entities in the European, American and Asian-Pacific credit default swap markets are analysed in terms of abnormal returns to investigate this relationship. It is found that, on an aggregated level, the rating categories *possible downgrade* and *possible upgrade* as well as pooled *positive events* and *negative events* are statistically significant, i.e. display abnormal returns that are different from zero. On a market specific level, *possible downgrades* and *positive events* are significant on the US market. On the EU market, *possible upgrades* and *possible downgrades* are significant, and finally on the Asian-Pacific market *downgrades*, *possible downgrades* and *negative events* have a statistically significant impact on CDS spread changes on at least a 10 % level. Consistent with previous research, and with theory, the results confirm a significant effect of credit rating announcements on credit default swap spreads, however positive events are less significant than negative and "possible"- events are more prevalent than actual rating changes.

Key words: credit rating, credit default swap spread, credit risk, event study, Moody's

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1 Introduction

Over the past twenty years, the market for credit derivatives has grown substantially over the whole world. It has developed into being a mainstream market with participants ranging from banks, hedge funds, insurance companies and other non-financial firms as its main players. The purpose of credit derivatives is to fully, or at least partly, hedge and transfer credit risk. It is a private contract between two parties. The Credit Default Swap (CDS) is an example of the most popular credit derivative. It is very similar to an insurance contract that provides protection to the buyer of the contract against a default or another negative credit event. In order to maintain the contract, the buyer has to pay an annual fee; the CDS spread, which reflects the cost of protection against default risk, or credit risk. Credit risk is the risk concerned with credit. It emerges from the uncertainty of the obligor's ability to meet its financial obligations and it is one of the most basic and common types of risks in society.

A credit rating is one way of measuring credit risk. An entity is assigned a grade according to a grading scale consisting of 21 ratings depending on the likelihood of default. Due to credit rating agencies holding a significant role in society by being providers of credit risk information, credit ratings serve as one of the cornerstones of the functioning of the financial market, even though the ratings merely are opinions. The recent financial crisis put much pressure on the rating agencies that were held responsible for rating too pleasingly and hence distorting the view of credit risk on the financial markets. The CDS spread is another way of measuring credit risk. The spread represents a "rate of protection" of a negative credit event of a specific entity, and hence, a high spread implies that credit risk is also relatively high whereas a low spread indicates a relatively low credit risk.

A rating will intuitively have an effect on the CDS spread since the two reflect the same thing, namely credit risk. At the same time, credit rating agencies are being investigated and questioned about the reliability and robustness of their ratings. Hence, if CDS spreads are directed by credit ratings, and credit ratings are assumed to be less reliable, then an interesting question one can ask is whether CDS spreads really reflect a fair and accurate picture of credit risk in the market? The relationship

between CDS spreads and credit ratings is therefore very interesting and not least important to analyse and monitor.

The aim of this essay is to analyse the relationship between credit ratings and credit default swap spreads and in particular examine if credit ratings have a significant impact on spreads. 152 entities listed on the iTraxx Europe, iTraxx Asia (excl Japan), iTraxx Australia and CDX North America Investment Grade are included in the essay and guarantee the most liquid CDS contracts being used in the study. The essay begins with describing a theoretical framework concerning credit risk, credit default swaps and credit ratings. Next, the methodology and data are presented, followed by a section that presents the results. The essay concludes with a summary of the results and some concluding remarks.

1.1 Problem formulation and hypothesis

The purpose of this essay is to investigate the relationship between CDS spreads and credit rating events. Specifically, do credit rating announcements have any impact on CDS spreads? The question will be investigated in the US, European and Asian-Pacific CDS markets as well as on an aggregated level including the three different markets. What is to be tested more specifically is if CDS spreads increase/decrease significantly when a negative/positive rating announcement is published. If this is the case, the conclusion can be drawn that credit rating announcements most likely have an impact on CDS spreads and hence, spreads are indicators of a firm's default risk. Statistical tests will be carried out for each of the three mentioned markets.

Formally, the issue being studied is if the mean and median of the daily average abnormal returns for a period of time consisting of 8 days prior to the rating announcement and 8 days after the announcement day, is statistically different from zero. The null hypothesis states that the average mean and median of the average abnormal returns for the event window should be equal to zero, in words; credit rating announcements do not have any statistically significant impact on CDS spreads. The alternative hypothesis states that the mean and median of the average abnormal returns over the event window is not equal to zero, and hence credit rating announcements do have a statistically significant effect on CDS spreads.

$$\begin{array}{ll}
 H_0: \mu_{AR} = 0 & H_0: M_{AR} = 0 \\
 H_1: \mu_{AR} \neq 0 & H_1: M_{AR} \neq 0
 \end{array}$$

An average abnormal return mean and median equalling zero means that there are, on average, no abnormal returns that can be connected to the chosen credit event on, and around, the particular day of the event. Hence, “returns” (spreads) are not affected by the event. Similarly, an average abnormal return mean and median not equalling zero indicates that the credit event does have an impact on spreads.

1.2 Delimitations

This essay will only consider investment grade firms in the US, European and Asian-Pacific markets listed on the CDX and iTraxx indices. Further, all firms included in the indices will not be covered due to either lack of continuous CDS data or credit rating history for the period of interest. A requirement for a company to be included is that it both has CDS spread data covering the period 2008-01-01 to 2013-06-14 as well as at least one credit rating announcement during the same period. Credit ratings will only be obtained from one rating agency, Moody’s. The reason for this is that the ratings are easily available from Moody’s website. Moody’s rating services further offer six events characterised as rating announcements. These are *Upgrade*, *Downgrade*, *Possible Upgrade*, *Possible Downgrade*, *Negative Outlook*, *Positive Outlook* and *Stable Outlook*. Here, only the first four, as well as aggregated *positive* and *negative events*, consisting of *upgrade/possible upgrade* and *downgrade/possible downgrade*, will be examined, simply due to a timing constraint.

The transaction currencies for the CDS contracts will be in USD (US, Asia-Pacific) and EUR (EU). The restructuring documentation clauses of CDS contracts are *modified restructuring (MR)* for US and Australia, *full restructuring/cumulative restructuring (CR)* for Asia and *modified-modified restructuring (MM)* for Europe. There exist five restructuring types in total, however due to them being similar in the quoted CDS spread, it is less important which one is selected. MR, MM and CR were simply chosen because they were, in my opinion, most frequently occurring.

Days consisting of two rating announcements during the same day, will be excluded due to the fact that the effect on spread changes cannot be distinguished. If there is more than one rating announcement occurring during the same event window or overlapping parts of an event window, only the first (the earliest) will be considered. This is acted in order to mitigate possible contamination effects of ratings. However, the time between two rating announcements must be at least 8 days prior to the previous event in order to be included. Finally, the spreads, spread changes, abnormal returns and cumulative abnormal returns will all be expressed in absolute terms, i.e. always in basis points.

Last, it cannot be ignored that the period used in this essay covers parts of the financial crisis. However the crisis and its connection to CDS contracts will not be included or discussed in this essay. The one possible thing that might be worth mentioning is the fact that CDS spreads did increase heavily during the crisis; however, studying the index, there was also a reversion afterwards, hence it was not a permanent increase. Therefore, not including the financial crisis in the analysis does not reduce the value of this essay.

2 Literature review and previous research

Most empirical research concerning the CDS market focuses on one (or more) of the following topics; (1) the determinants of CDS spreads, (2) the efficiency of the CDS market, (3) the relationship between the CDS market and other financial markets and (4) the effects of rating announcements on CDS spreads. This essay will focus on the latter; the effect of rating announcements on CDS spreads. Hull, Predescu and White (2004), Norden and Weber (2004), Micu, Remolona and Wooldridge (2004), Galil and Soffer (2011) and Finnerty, Miller and Chen (2013) are only a few examples of a growing literature in this field. This essay was mainly inspired by the work of Finnerty et al (2013) and Hull et al (2004), however to get a more full-bodied overview of research and empirics of this topic, the work of all previously mentioned authors will be reviewed next.

2.1 Hull, Predescu and White (2004)

“The relationship between credit default swap spreads, bond yields and credit rating announcements”

In this paper, the authors both investigate the relationship between bond yields and CDS spreads as well as rating announcements and CDS spreads. For the latter, the main research question is “to which extent credit rating announcements by Moody’s are anticipated by participants in the credit default swap market”. The CDS data set consists of daily 5 year CDS quotes during the period 1998-01-01 to 2002-05-24. 6 events are investigated: *upgrades, downgrades, review for upgrade (downgrade) and positive (negative) outlook*. The authors carry out two tests. First, by means of an event study, spread changes are conditioned on rating events. The issue considered is whether the mean adjusted spread change for a rating event differs from zero; greater than zero in the case of negative rating events, and less than zero in the case of positive rating events. Further, it is also investigated whether CDS spreads are useful in estimating the probability of a rating event. This is performed by means of a logistic model, which takes the following form

$$P = \frac{1}{1 + e^{-a-bx}}$$

In the model, P represents the probability of a rating event occurring at the end of a 30 day interval and x illustrates the adjusted spread change in this interval. *a* and *b* are constants and estimated from a maximum likelihood analysis. The authors

conclude that, for negative events, the CDS market anticipates all three negative events however no significance was found for positive events. The results for positive rating events were also much less significant. The second result shows that neither credit spread changes nor credit spread levels help in estimating the probability of a negative credit event.

2.2 Finnerty, Miller and Chen (2013)

“The impact of credit rating announcements on credit default swap spreads”

The issue addressed in this paper is, like the title suggests, how credit default swap spreads react to credit rating events and if there is a systematic difference between each market sector’s reaction to downgrade and upgrade announcements. This paper is an extension of Hull et al (2004) and the impact of rating changes, credit watches and outlook events are investigated as well as the ability of CDS spreads to predict positive or negative credit rating events.

The methodology in this paper is an event study and a logistic and regression analysis. The dataset consists of 5-year CDS spreads covering the period from 2001-01-02 to 2009-05-31 and credit rating event information obtained from Standard & Poor’s. Specifically, 1371 firms are included with corresponding 1951 rating change actions. In the event study, the authors test the cumulative abnormal returns around the rating change event in order to analyse if a rating change has any impact on CDS spreads. The abnormal returns and cumulative abnormal returns are calculated as follows:

$$AR_{it} = \Delta Spread_{it} - \Delta Index_t$$
$$CAR_{it} = \sum_{s=0}^t AR_{is}$$

Following Hull et al (2004), a logistic analysis is implemented in order to address the question whether CDS spreads contain any useful information to estimate the probability of a rating event. A “Probability Sensitivity Measure” is calculated as the derivative of the logistic model and provides an intuitive measure of the impact of the spread change on the probability of a rating event. A regression model is also set up in order to further examine the relationship between CDS spread changes and rating events but at the same time also control for macroeconomic factors that might

affect spread changes. Further elaboration on the logistic and regression analyses performed in this study can be found in Finnerty et al (2013).

Four new results are obtained, extending Hull et al (2004). Contradictory to previous studies, and for example Hull, the authors find that positive credit events have a statistically significant impact on CDS spreads. Second, Standard & Poor's CreditWatch (CW) and Outlook (OL) credit warnings are also found to be affecting the cumulative abnormal returns at the time of the announcements for both positive and negative events. This also contradicts previous findings about the CDS market anticipating these types of events. Third, Hull et al. (2004) findings are extended regarding the findings that changes in CDS spreads are useful for predicting the probability of negative credit rating events for both investment grade and non-investment grade firms. Fourth, the CDS spread impact of upgrades, but not downgrades, is found to be magnified during times of recession. To summarise, rating change downgrades impact CDS spreads much more than upgrades and the CDS market also better anticipates them.

2.3 Norden and Weber (2004)

“Informational efficiency of credit default swap and stock markets: The impact of credit rating announcements”

The authors analyse the response of the stock and CDS markets to rating announcements during the years 2000-2002 by means of an event study analysis. More than 1000 reference entities are included; corporate, financial and sovereign. Rating announcements, consisting of actual rating changes and reviews for rating changes, are used from the three major rating agencies Moody's, Fitch and Standard & Poor's.

Their hypotheses relate to the following issues; (1) the informational content of rating changes and rating reviews and (2) asymmetric price adjustment. The first one relates to markets not anticipating the rating change news until they are actually published, i.e. spreads start to change when the new information is released to the market. The second one relates to the fact that upgrades do not express any significant abnormal reaction, whereas there are significant negative abnormal

returns surrounding downgrades. Mean and median abnormal returns are tested for significance by means of a t-test and Wilcoxon signed rank test, with the null hypotheses being $AR_{\mu} = 0$ and $AR_M = 0$ respectively.

The authors find that both the stock and CDS markets anticipate *downgrades* approximately 90-60 days before the rating announcement day. *Reviews for downgrade*, announced by S&P and Moody's but not by Fitch, are associated with significant abnormal performance in both markets. A cross-sectional analysis further reveals that the old rating, as well as previous rating events, have a significant influence on the extent to which abnormal returns behave, also both on the stock and CDS markets.

2.4 Micu, Remolona and Wooldridge (2004)

“The price impact of rating announcements: evidence from the credit default swap market”

Micu, Remolona & Wooldridge (2004) examine the effect of rating changes, outlooks and reviews on CDS spread changes. A smaller sample of 694 reference entities is used with corresponding 5 year maturity CDS spread data and 2335 rating events covering the period 2001-2003. A traditional event study methodology is employed where the event window consists of four time intervals: -60 to -21 days before the event, -20 to -2 days prior to the event, one day before and one day after the event and 2 to 20 days after the event. It is hypothesized that if rating events are fully anticipated by the market, then CDS spreads should adjust prior to the event in either the first or the second time interval. If price-relevant information is included in a rating announcement, then these events should have a noticeable influence on CDS spreads on the day of the event or within a day after the event, i.e. an effect should be visible in the third time interval.

The authors find that *downgrades* and *negative reviews* have a highly significant impact on CDS spreads, and participants react as strongly to reviews as they do to actual downgrades. *Rating outlooks* show the least significant results with the possible explanation that they only serve as indicators of long term trends in credit quality and it is uncertain if they will or will not lead to an actual rating change in the

future. The authors also conclude that the impact of a rating events is most pronounced for A and BBB rated issuers.

2.5 Galil and Soffer (2011)

“Good news, bad news and rating announcements: An empirical investigation”

This study involves the examination of how the CDS market reacts to rating announcements after controlling for already present private and public information. The time period is 2002 to 2006 and 2152 entities and being analysed with their corresponding 5 year CDS and rating history data from Moody’s and Standard & Poor’s. A standard event study methodology following Hull et al (2004) and Norden and Weber (2004) is applied on 2866 rating announcements. 12 daily CDS indices are constructed to represent normal market behaviour for each of the 12 existing rating grades in order to estimate the abnormal returns related to a rating event. Abnormal returns are here named adjusted spread changes (ASC) and take the following form:

$$ASC = (S_{it} - S_{it-1}) - (I_{rt} - I_{rt-1})$$

S_{it} is the CDS spread for firm I on day t , and I_{rt} is the CDS spread index for rating class r on day t . The authors further separate between two samples; an unconditional and a conditional one. The unconditional sample includes all rating events and allows for rating contamination, i.e rating events occurring less than 90 days before and after the event in question are allowed in the sample. The conditional sample excludes all events preceded or followed by other rating actions within 90 days from the event in question, hence this sample controls for informational contamination. This division is made in order to further demonstrate that CDS spread changes are affected by credit rating changes in the first place, and not by other public and private information flowing in the market. Adjusted spread changes and cumulative adjusted spread changes are consequently tested by means of a t-test and Wilcoxon signed rank test in order to determine significance. However, conclusions are based exclusively on the non-parametric test results due to the abnormal distribution of CDS spread changes.

The authors find that the market responds to all types of rating announcements; *upgrades*, *downgrades*, *positive reviews* and *negative reviews*. However, negative announcement types (*downgrades* and *reviews for downgrade*) are more prevalent than positive announcements; in absolute terms, CDS spread changes are greater when it comes to negative events than when it comes to positive events. This is explained by the fact that the market is assumed to be more sensitive to negative news leading to rating agencies and information providers giving more attention to such news. However, the results of Galil & Soffer (2011) confirm previous research in showing that spreads do change abnormally after rating announcements and rating reviews.

To sum up, previous research indicates that *negative events* are typically better anticipated than *positive events* and events of the “review” or “possible” type also have a more distinct effect on spread changes. Existing research and empirics seem to agree upon the fact that CDS spreads are indicative of credit risk; spreads tend to rise (fall) in the case of a negative (positive) credit event. CDS spreads are hence interpreted as a reflection of the default risk of a firm (Finnerty et al. 2013). Previous research also suggests that the event study methodology is well used and serves as the main tool in the investigation of the relationship between CDS spreads and credit rating announcements.

3 Theoretical framework

3.1 Credit risk

Credit risk is the risk concerned with credit. It refers to the risk that a borrower will default, that is, fail to meet its obligations by not making payments on time. Unlike other types of risk, credit risk is a non-systematic risk generally restricted only to one asset and apart from systematic risk, it can be diversified away. Market risk, on the other hand, is risk linked to market fluctuations and subsequent changes in market prices and market values.

Credit risk is measured by ratings that are being published by credit rating agencies. The task of rating agencies is to impartially rate according to both public and private information and making the ratings publically available to the market (Moody's, 2013-06-09). To hedge credit risk, a credit derivative can be purchased; for example a CDS. The annual cost of maintaining this CDS is called the spread and it is also an indirect measure of credit risk. A high spread indicates that it is costly to protect oneself from a certain credit or default event due to the fact that this event occurring is highly probable. Hence, when spreads increase, this is a sign of increased credit risk. Overall, credit risk is a basic risk in society and it is important to manage and hedge it properly.

3.2 Credit rating agencies

Credit ratings are opinions about credit risk and creditworthiness made available by credit ratings agencies (CRAs). CRAs emerged in the early 1900s with the purpose of enabling investors to make better investment decisions, and pressure obligors to respect their obligations by the publishing of financial reports, statistics and information (Standard & Poor's, 2013-06-09). Today, a highly concentrated oligopoly market best describes the CRA arena with Standard & Poor's, Moody's and Fitch as the main global operators.

The CRA business is upheld essentially by two provided services. Firstly, independent assessment is offered, which finishes in evaluations being published to the market in the form of credit ratings. Secondly, "monitoring services" are offered in order to influence issuers to take remedial actions when a downgrade is anticipated

(de Haan, Amtenbrink 2011). However, the central purpose of CRAs is to provide information about credit risk and hence reduce information asymmetry in the financial market (Standard & Poor's, 2013-06-09).

Ratings are ranked on a letter scale consisting of 21 discrete grades (see appendix 2). A distinction is made between ratings at/above or below Baa3, where ratings at or above Bbb3 are called "investment grade" and ratings below this grade are called "speculative ratings" or simply "junk status". The boundary separates entities that are moderate to very low in risk, from those that hold substantial to very high risk, implying that default is considered likely (Moody's, 2013-06-09).

Ratings can change over time. This is characterised by so called credit events consisting mainly of upgrades, downgrades, possible upgrades and possible downgrades. Possible upgrades and possible downgrades are not rating changes per se, but instead rating announcements implying that an upgrade or downgrade is likely to occur in the near future. A "possible"-event will sooner or later be confirmed by an actual rating change or a confirmation of a previously held rating.

3.2.1 A brief discussion of the criticism of CRAs

Lately, and especially since the financial crisis in 2008, CRAs have been put under pressure regarding the reliability of their credit ratings. The main criticism concerns the financial products, for example CDOs, which were rated too positively and regarded as safe investments until a majority was downgraded during a short period of time creating chaos in the markets. For example, in 2006, Moody's downgraded 83 % of mortgage securities rated Aaa. This corresponded to a value of approximately \$869 billions (Levin & Coburn 2011). At the same time, rating agencies are selective in pointing out that ratings are merely opinions and not direct advice in investment management. Credit ratings cannot be seen as exact measures of default probability or credit risk. A rating has to be interpreted in relation to, for example, other rated entities and not least, other firm specific and macroeconomic factors (Standard & Poor's, 2013-06-09).

Another issue is whether there exists a conflict of interest between a rating agency and the issuer. Due to an issuer-pays model utilised in the CRA business today, it is

not impossible that problems of moral hazard type shows. Opportunistic behaviour has not been proven, but theoretically, incentives exist. Hence, one might criticise the independence of the rating agencies (Saunders & Allen, 2010).

3.2.2 A brief overview of the rating process

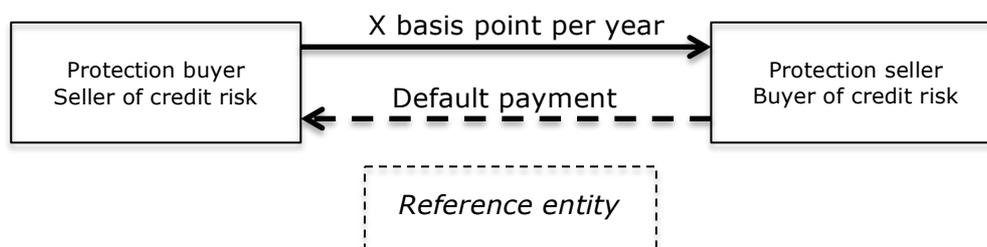
The rating process consists of an analysis of an entity’s finances, history and legal information, both in a qualitative and quantitative way. General macroeconomic factors such as politics and financial systems are also examined. According to Moody’s, their rating methodology is based on two questions; *what is the risk to the debt holder of not receiving timely payment of principal and interest on this specific debt security?* and *How does the level of risk compare with that of all other debt securities?* Fundamentally, the emphasis lies on stability and the predictability of future cash flow. A rating is also considered in a long term taking the future economic environment, regulatory developments or any changes in management strategy of the specific issuer into consideration. However, the exact way of carrying out a rating analysis is not revealed to the public (Moody’s, 2013-06-09).

3.3 Credit default swaps

Credit default swaps (CDSs) developed in the early 1990s and are among the most popular credit derivatives. Basically, a CDS is a private over-the-counter contract between two parties that provides insurance against a party (the reference entity) defaulting. The buyer of the insurance pays the seller a fee (CDS spread) and in exchange receives a payoff if there is a default. The relationship is best illustrated with a figure:

Figure 1 **The credit default swap relationship**

Source: ISDA



The reference entity is usually a company. In that case, a CDS holder has the right to sell bonds issued by this company for their face value and the CDS seller is on the

other hand obliged to buy these bonds for their face value if a failure of payment or any other negative credit event occurs (Hull, 2011). Thus the contract is tied to an underlying debt instrument, such as a corporate bond or a government bond.

The fee, or spread, of a CDS is the premium that has to be paid in order to maintain the contract. The spread is often expressed in basis points (1/100 of a per cent) and has to be paid annually. Theoretically, the spread is equivalent to the difference between the yield of a bond and the risk free interest rate (Hull, Predescu, White, 2004). The spread is dependent on a number of factors, the most important one being the probability of default or payment failure on bonds or loans of the reference entity during a particular period of time. If the riskiness of the reference entity, the probability of default, increases, the spread tends to increase as well, making it more expensive to insure against the reference entity (Jacobs, Karagozoglu, 2011). A regular investor can also buy and sell CDS without being part of the debt that is being protected. These types of CDS are traded with the purpose of speculating in the debt and creditworthiness of an issuer (Regulation C 33 E/298, 2011).

Depending on the underlying reference entity, CDS contracts can come in several formats. There can be single-name and multi-name contracts, where the latter separates from the former by having multiple underlying reference entities, such as an CDS index, instead of just one. CDS contracts can also be of sovereign type, meaning that the reference entity is a government of a country. Apart from pure CDS contracts, there are also so called Credit Swaptions and CDS forwards which are options and forwards written on CDS contracts. However, the majority of all trading in CDS contracts is accounted for by single-name CDSs (Weistroffer, 2009). Further, traded CDS contracts have to have a transaction currency and a restructuring documentation clause. The most actively traded contracts are typically denominated in USD, EUR, JPY, or AUD with USD and EUR holding the majority of contracts. Further, there exist five different types of restructuring forms depending on how a credit event is characterised - *full restructuring (CR)*, *modified restructuring (MR)*, *modified-modified restructuring (MM)* and *no restructuring (XR)*. The first one suggests that a credit event is characterised by any restructuring event and it was the standard contract term in the late 1990s. This contract type is valid on any bond type

with maturity up to 30 years. The second one was introduced by ISDA (International Securities and Derivatives Association) in 2001 in order to limit opportunistic behaviour by sellers in the case of a restructuring event that did not cause any losses but still was characterised as a credit event. The MM was further introduced in 2003 as an adjustment of the MR. The last one excludes all restructuring events from being so called “trigger events”. Even “soft” credit events, that do not incur any true losses, are being ruled out due to the fact that these might still encourage opportunistic behaviour by the protection buyers. Typically, the restructuring type is chosen depending on regional preference (Thomson Reuters, 2013-06-09).

The CDS contract terminates either at the time of default by the reference entity or at maturity. When terminated, the contract can be settled in two ways; cash settlement or physical settlement. In the case of a cash settlement, the CDS holder keeps the underlying asset but is compensated for the loss incurred by the default. If the contract is settled physically, the underlying asset is exchanged for the face value of the asset (Daniels & Jensen, 2005).

The main motives for using CDS contracts include credit risk management and trading. Especially banks utilise CDS contracts in order to avoid concentration risk and pass on the credit risk to another party. However, banks themselves also offer CDS protection. CDS contracts are also attractive in trading purposes. The CDS buyer does not necessarily have to be exposed to the underlying reference entity in order to enter a CDS contract written on that entity (Weistroffer, 2009).

3.3.1 Credit default swap indices

Apart from single-name CDSs, there are also CDS indices, pooling together the most liquid CDS contracts in a single portfolio. Two existing index families are the CDX and iTraxx indices. Within these indices there are two important portfolios consisting of the most actively traded reference entities; the CDX North America Investment Grade (CDX NA IG) and the iTraxx Europe indices. These two include 125 investment grade companies each in North America and Europe where each company is equally weighted in the portfolio. The index spread is therefore, roughly, the average of all CDS spreads in the portfolio. Protection can be bought and sold on all 125 companies in the index and the index bid price quotes the price to be paid for

every single company. Six different sectors are represented in the indices; *consumers*, *financials*, *TMT* (telecom/media/technology), *energy*, *autos* and *industrials*. The indices are further reviewed and adjusted two times a year, 20th of September and 20th of March where firms are either being added or removed from the index depending on, for example, what rating they have at the moment, or if they have defaulted (Markit, 2013-06-09). The index CDS enables taking on a market wide exposure. It is also priced and traded more efficiently than single-name CDSs and hence forms a more liquid CDS market (Mengle, 2007).

4 Methodology

4.1 The event study

The event study methodology is a well-known and widely used method within finance. Its main purpose is to analyse the impact of an economic event, such as a merger, acquisition, earnings announcement or rating announcement, on the value of a firm (MacKinlay, 1997). Event studies date back to at least the 1930s where Dolley (1933) conducted a study that examined price effects of stock splits. However the first recognised event study, and the event study as we know it today, was performed by Fama, Fisher, Jensen and Roll in 1969. The event study practice will be the main approach used in this essay.

MacKinlay (1997) gives a brief outline of the structure of an event study. First, the event itself has to be identified and also the time period of interest around the date of the event, the event window. In order to investigate whether an event has an impact on the value of a firm's returns, in this case *spreads*, abnormal returns (ARs) must be calculated and statistically tested. Abnormal returns consist of the actual change in return on a certain day minus a "normal" return for that specific day. Or in other words, an abnormal return is what is systematically different from predicted. Formally, abnormal returns can be calculated as:

$$AR_{it} = \Delta Spread_{it} - \Delta Index_t$$

Here, the $Spread_{it}$ is the firm specific CDS spread and the $Index_t$ is representing the "normal market behaviour". The point with subtracting the index spread change from the actual company specific spread change, is to control for changes that are a result of other events than the particular event chosen in the event study. The index is calculated as the average CDS spread for all firms in the index over the period of interest, consistent with Greatrex (2009) and Jenkins (2011).

After having calculated ARs for all companies during their respective event windows connected to the particular event, an aggregated abnormal return measure is constructed in order to obtain average aggregated abnormal returns for each day of

the event window for the particular event. It is the mean and median of these distributions that are being tested for significance.

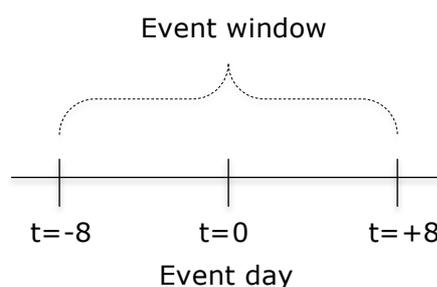
To get an illustration of how the spreads change during the event window, cumulative abnormal returns (CARs) are calculated by subsequently adding the daily ARs together. Formally, CAR is calculated as:

$$CAR_{it} = \sum_{s=0}^t AR_{is}$$

As noticed, event studies are usually conducted including stock market data; hence *returns* are natural to speak of. In the case of CDSs, there are no actual returns but instead there are spreads, and spread changes, that represent the yield that compensates for bearing credit risk. However, CDS spread changes can be used as a proxy for returns in the calculations included in an event study and hence the event study method serves as a reliable method to use even when dealing with non-stock data (Finnerty et al. 2013).

In this essay, the event is characterised by a rating change which here involves either an upgrade, downgrade, possible upgrade or possible downgrade and the complete time of interest is a five year period, 2008-01-01 to 2013-06-14. There are no guidelines regarding the length of an event window, but here an event window that equals 8 days prior to the event and 8 days after the event will be applied. Hence, the total event window comprises out of 17 days, including the day of the event denoted $t=0$. Due to the fact that no assumptions are made regarding the degree of efficiency in the CDS market, days both before and after the event day are included. The time frame of the event study is illustrated below:

Figure 2 Time frame of the event study



4.2 Methodology choice discussion and critique

4.2.1 Motivation

The event study methodology was chosen because it is an easy method to grasp as well as being versatile and extensively used within research in finance and economics (and other areas such as political science and biomedicine). The method does not require any difficult calculations, which makes it easy even for a layman to understand and implement.

4.2.2 Alternative methods

Alternatives to the event study in this case would be various econometric techniques such as a regression analysis. For example Acharya (1993) presents an econometric model as an alternative to the regular event study methodology and claims that this kind of model can decrease the inconsistency and selectivity bias that might occur in standard event studies. This model also performs at least as well as other standard event study techniques. Acharya presents three models that can be used as alternatives to the standard event study method; a *dummy variable model*, a *latent variable model* and a *truncated regression model*. Following, the dummy variable model will briefly be discussed as it seems as most comparable to the standard event study. For information on the two other methods, consult the paper by Acharya (1993).

Performing a *dummy variable model*, the following function has to be estimated for a sample of firms:

$$R_{it} = \beta_i' W_{it} + \delta_e I_{eit} + \delta_n I_{nut} + \eta_{it}$$

In this model, I_{eit} is a dummy variable taking the value 1 when $t \in \{event\}$ and value 0 when $t \in \{nonevent\}$ for firm i , and $I_{nut} = 1 - I_{eit}$. δ_e measures the expected return conditional on the event and δ_n measures the expected return conditional on the non-event. Instead of calculating abnormal returns from actual spread changes and index spread changes (like in Finnerty et al. 2013), abnormal returns are instead estimated using a regression model where the dummy variables represent the abnormal returns. The dummy variable event study is thereafter carried out as the standard event study (Acharya, 1993).

Another way to measure the relationship between credit ratings and CDS spreads, without introducing abnormal returns, is simply to calculate a correlation coefficient, such as the *Spearman rank coefficient* as in for example Greatrex (2008) or Hull, Nelken and White (2003). The Spearman correlation coefficient is a non-parametric method measuring the strength of a monotonic relationship between two variables. The calculation results in a coefficient taking values between -1 and 1 with 0 indicating an absent relationship, -1 a perfectly negative and +1 a perfectly positive relationship. The calculation of the coefficient does not require normally distributed variables. Spearman's rank coefficient can be calculated in the following way; CDS spread changes (variable x) and credit ratings (variable y) are transformed into numbers according to a numerical scale starting with 1 and then sorted in ascending order. That is, the lowest value is assigned the number 1 etc. The coefficient is then calculated in the following way (if ties are present, i.e. if two, or more, values have the same ranking):

$$r_s = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2 \sum_i (y_i - \bar{y})^2}}$$

If ties are absent, the formula can take the following simpler form:

$$r_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)}, \quad d_i = x_i - y_i \text{ for each observation.}$$

Last, the coefficient is statistically tested to determine significance where the null hypothesis states that there is no monotonic relationship. The Spearman calculation is appropriate both for discrete and continuous variables. Therefore, it is a relevant candidate for analysing the issue of this essay due to credit ratings being discrete and CDS spreads being practically continuous variables.

4.2.3 Methodology critique

Most problems relating to event studies are of econometric or statistical kind. For example, in order to perform statistical inference on the average abnormal returns one has to assume that average abnormal returns are independent and identically distributed which they most definitely are not. For example, abnormal returns are often correlated and different for different firms (Binder, 1998). Another problem is

what Beaver (1968) calls event-induced heteroscedasticity. Homoscedastic data implies that all variables included have a finite variance, whereas in this case, CDS spread change variance might be different. For example, the variance will most likely be larger during the event, thereof the name event-induced heteroscedasticity. Inference based on violated assumptions and heteroscedastic data might therefore bias the results in a negative way.

Several ways of estimating “normal market behaviour”, or the “index”, in order to calculate abnormal returns, exist. The method applied in this essay is consistent with Jenkins (2011) and Greatrex (2009). This method involves constructing an index as an average of all CDS spreads of all companies included in a CDS index, for each day. This method does not consider the fact that different companies have, for example, different credit ratings, are in different industries and the magnitude of rating changes, which all affect the volatility of spread changes. As an alternative, and consistent with Finnerty et al (2013) and Hull et al (2004), a different index is calculated for different credit ratings; i.e. companies with the rating Aaa have an assumed “normal market behaviour” that is different from the “normal market behaviour” of companies rated e.g. Baa2. In this way, the previously described flaw is amended. Another way to construct an index is applying the market model. This method obtains abnormal returns by first assuming that the principles of the capital asset pricing model (CAPM) holds, and then calculating excessive return by the CAPM model (MacKinlay, 1997). This is typical when dealing with stock data. It is possible that the choice of index-calculation affects the results to some extent.

Problems with event studies can be linked to all steps involved in such a study. The choice of how long an event window should be is one of them. In this essay, an event window of 17 days, 8 days prior to and 8 days after the event, has been chosen. This choice is arbitrary and not based on any previous study. A period of 8 days around the event day seemed, in my opinion, as an interesting period relating to the anticipation of a rating announcement and the behaviour of spreads after the announcement has been published. The choice of an event window including several days before and after the event day is also interesting to look at from a market efficiency point of view. The risk of choosing an event window that is too short is based on the fact that markets are not entirely efficient or inefficient; hence spreads

might not react directly but after a day or so. The risk of choosing an event window that is too long goes with the same argument. For example, the time of the event is not when the event itself actually occurred, but rather when the market gains knowledge of it. For example, Moody's headquarters is located in the US. Assume they publish a rating at 3:00pm; the US market incorporates it, but the market participants in Asia are probably sleeping and the markets are closed. There is a time lag, and choosing an event window that is too short will most likely lag CDS spread changes and not be visible in the analysis. However, the more days included in the event window, the lower the power of the study (Henderson, 1990).

As with most methods and models, there are advantages as well as disadvantages when implementing them, and there is, as always, a trade-off between theoretical functionality and practical applicability.

4.3 Statistical tests

4.3.1 t-test and Wilcoxon signed rank test

In order to examine whether the mean average abnormal return is significantly different from zero during the event window, a two sided one sample t-test and Wilcoxon signed rank test are used. The t-test is a parametric hypothesis test assuming the variable to be normally distributed. Here, the mean is used as the test statistic and a resulting p-value is compared to a significance level. The Wilcoxon signed rank test is a non-parametrical equivalent to the t-test. It does not require the data to be normally distributed. Unlike the t-test, the test statistic is the median. CDS spread changes, or any other financial data, are typically not normally distributed, therefore the Wilcoxon signed rank test is also performed as a complement to the t-test. The Wilcoxon test does not assume any particular underlying distribution of the CDS spread changes and therefore makes a good candidate for testing significance in this case.

5 Data

5.1 CDS data and credit rating data

The data was collected primarily from two sources. The CDS data was collected in Thomson Reuters Datastream and credit ratings were obtained from Moody's website. This data was obtained for (almost) all reference entities included in the iTraxx Europe, iTraxx Asia (excl Japan), iTraxx Australia and CDX North America Investment Grade indices. The index membership lists (as of 20th march 2013 and 20th September 2012) were obtained from Markit. The period covered in this essay is 2008-01-01 to 2013-06-14, a five-year period.

The **CDS data** includes 5 year mid-spread quotes expressed in basis points from 152 reference entities and contains 216 448 individual daily quotes. A 5 year maturity was chosen because it is the most common and liquid maturity. The mid-spread characterises an average between the quoted bid and ask prices. Further, 65 companies are from the US market, 25 from the Asian-Pacific and 62 from the European market, denominated in USD and EUR. Five different sectors are represented; industrials, consumers, energy, financials and TMT (television, media, telecommunications). Below is a summary by sector division.

Table 1 Companies included in the essay, by sector and market during 2008-2013

2008-2013	US	Europe	Asia-Pacific
Industrials	10	18	3
Consumers	29	12	2
Energy	4	8	3
Financials	12	19	14
TMT	10	5	3
Total	65	62	25

In order to be included in the sample data, a company must have both CDS data covering the whole period, as well as at least one credit rating event during the same period. Companies listed in the iTraxx and CDS indices were chosen due to the fact that these indices comprise the most liquid entities in the CDS market. See Appendix 1 for a list of these 152 companies.

In order to calculate abnormal returns, a benchmark index representing the market factor, had to be obtained. The daily average of all company CDS spreads was calculated throughout the period, and this will represent the market proxy i.e “normal” returns/index data consistent with Greatrex (2008) and Jenkins (2011).

Concerning the **credit rating data**, 336 rating events are included. In total, 74 were *upgrades*, 105 *downgrades*, 23 *possible upgrades* and 134 *possible downgrades*. Below is a table illustrating the number and types of rating events. Rating events consisting of two events on the same day (*upgrade/downgrade*, *possible upgrade/upgrade* or *possible downgrade/downgrade*) as well as rating events with overlapping event windows were excluded from the data. Further, Moody’s long-term ratings are used.

Table 2 Amount of ratings published, by rating category and market during 2008-2013

2008-2013	Total	US	Europe	Asia-Pacific
<i>Upgrade</i>	74	41	15	18
<i>Downgrade</i>	105	17	76	12
<i>Possible upgrade</i>	23	13	4	6
<i>Possible downgrade</i>	134	53	61	20
Total	336	124	156	56

5.2 Data processing

As we want to measure *changes* in CDS spreads due to changes in ratings, the daily CDS data had to be expressed in an absolute “change” measure. The spread data and the index data was altered in the following way:

$$\Delta Spread = Spread_{t+1} - Spread_t$$

$$\Delta Index = Index_{t+1} - Index_t$$

The rating data from Moody’s was later incorporated into the CDS data by marking out the parts concerned with the event window and the particular event. This data was then used to estimate average abnormal returns for the event window (consisting of an average of all companies abnormal returns during each day of the event

window, see Appendix 3 for this data). To get an overview of how the spreads behave during the whole event window, cumulative abnormal returns were calculated. The calculations of abnormal returns and cumulative abnormal returns were performed as described in the methodology part of the essay and can be found in the next section of the essay. Statistical tests of significance of the mean and median in the average abnormal return samples were then performed.

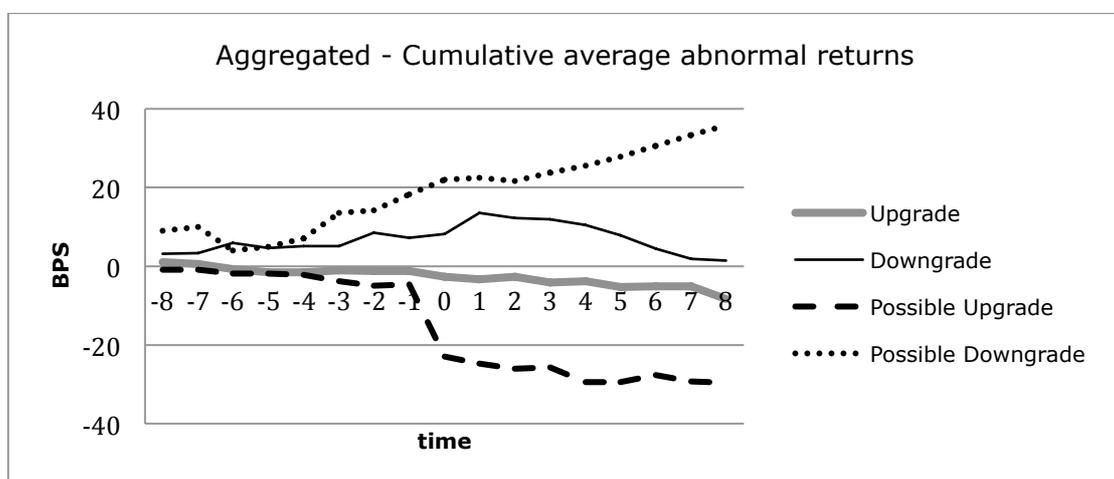
6 Empirical results and discussion

This section will be organised as follows; first, the aggregated results consisting of all three markets (US, EU, APAC) together will be presented. Average abnormal returns and cumulative average abnormal returns for *upgrades*, *downgrades*, *possible upgrades*, *possible downgrades*, *positive events* and *negative events* will be demonstrated in figures in order to illustrate graphically how spread changes behave. An equivalent approach will be taken to present the results of the different markets; US, European and Asian-Pacific. Last, the results of the t-tests and Wilcoxon tests will be presented in tables. In order to get a more coherent presentation of the results and avoid repetition, the discussion part of the essay will be intertwined in the results part. Last, the *empirical* distributions, graphical and numerical, of abnormal returns can be found in Appendix 3 and 4.

6.1 Abnormal returns in the aggregated CDS market

To get an overview of the results, cumulative abnormal returns representing the aggregated 152 firms are charted below for the four different rating announcements; *upgrades*, *downgrades*, *possible upgrades* and *possible downgrades*. Cumulative return is an interesting measure as it depicts the total average abnormal returns incurred by a rating announcement over the time period of interest. It also is an indication of market efficiency in a way that when the rating is announced, the market fully incorporates the information and should stabilise at a new level, taking the new information into account. There should consequently be no further drift in spreads after the announcement day.

Figure 3 Aggregated cumulative average abnormal returns during 2008-2013 for rating categories upgrade, downgrade, possible upgrade and possible downgrade with an event window of 17 days

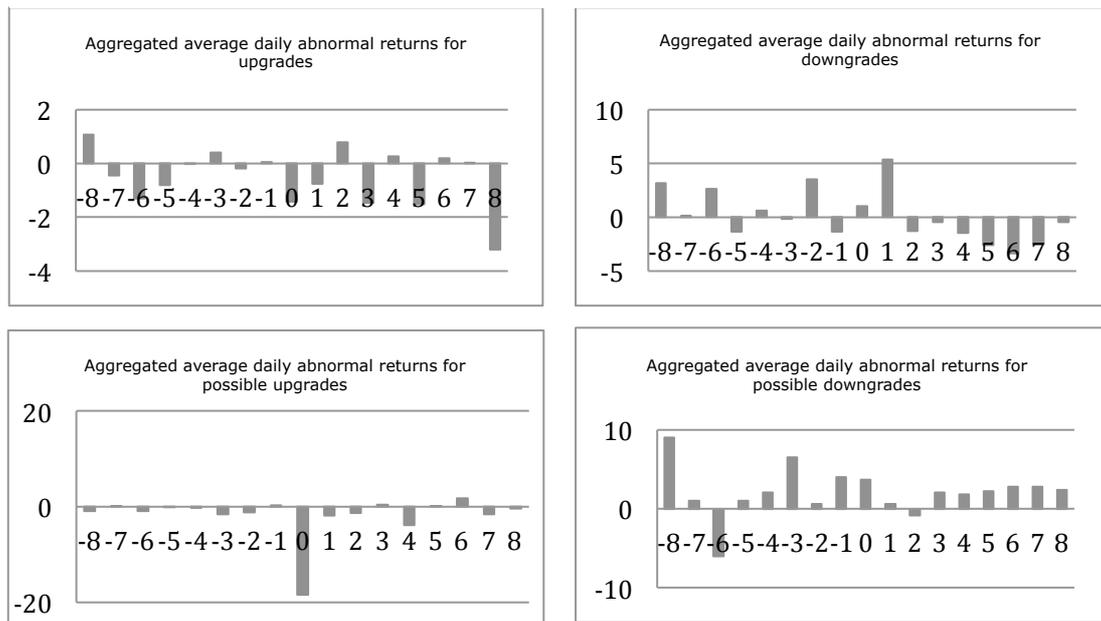


As can be seen from the chart, *possible upgrades* and *possible downgrades* represent the rating announcements that have incurred the greatest total spread changes over the time period $t=-8$ to $t=8$.

Possible downgrades and *possible upgrades* show a reaction which is consistent with theory; spread changes react negatively to positive rating announcements and positively to negative rating announcements. For *upgrades* and *downgrades*, the reaction is vague. It is understood that cumulative abnormal returns continue to rise (fall), even after the announcement day, indicating that the market has not yet fully incorporated the announcement information in the spread. This is most visible for *possible downgrades* where the spread continues to rise throughout the event window. Comparing to *possible upgrades*, the development is slightly different. The spread falls sharply between the day prior to the event and the event day, indicating that the positive news is incorporated in the market directly. This behaviour is, as previously mentioned, not very clear for either *downgrades* or *upgrades* respectively. One explanation might be that a “possible”-event already takes into account the information that is to come with the actual rating change announcement. Since “possible”-events are generally followed by an actual rating change (and the market recognises this), these events might have a stronger impact on spreads than the actual rating change events. Hence, the actual rating change announcement can be said to already be anticipated when the rating agency publishes the “possible”-event. Another explanation could be that there is more, or other, information flowing into the market affecting spreads that is not captured by the rating announcement. Or simply that the market is inefficient. This cannot be further analysed due to a too short event window.

To get a more specific illustration of each rating announcement category, next are tables of daily average abnormal returns during each day of the event window. This illustration enables a snapshot of how quick, or slow, a rating announcement is incorporated in CDS spreads and how spreads behave before, on and after the announcement day.

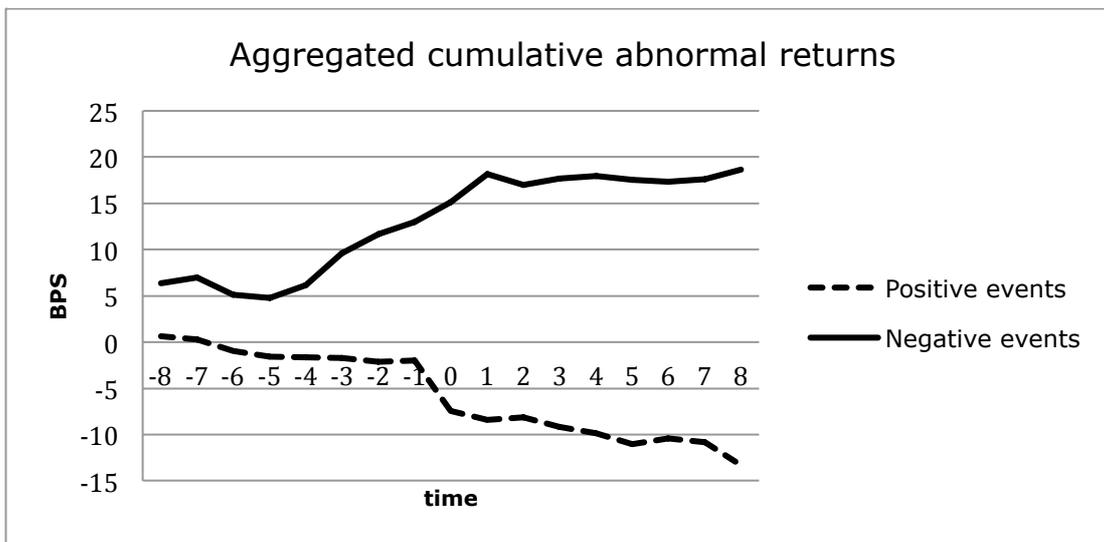
Figure 4 Aggregated average daily abnormal returns for the rating categories upgrade, downgrade, possible upgrade and possible downgrade during 2008-2013 and an event window consisting of 17 days



Looking at day 0, the announcement day, all rating categories behave in the expected direction. Only looking at *upgrades* and *possible upgrades*, *upgrades* are a milder version of *possible upgrades*, looking at day 0 and day 1. However, for *downgrades* and *possible downgrades*, the effect on day 0 is larger for *possible downgrades* than for *downgrades*, but smaller for *possible downgrades* than for *downgrades* on day 1.

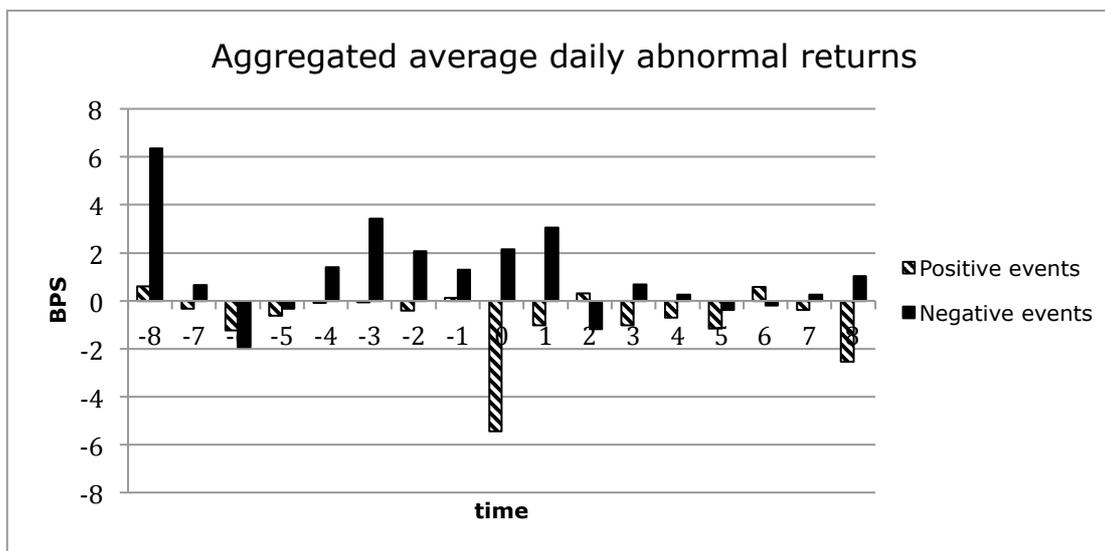
Due to small sample sizes and a possibility of unusual spread changes having a too strong effect on the data as a whole, below is also a representation of announcements separated in positive and negative events. By pooling together *upgrades* and *possible upgrades*, a category called *positive events* is formed. *Negative events* are formed in the same manner. This is also performed in order to get a more clear view on how different types of information (positive or negative) affect spreads.

Figure 5 Aggregated cumulative abnormal returns (CARs) for positive and negative events during 2008-2013 consisting of an event window of 17 days



In this figure (figure 5), it is more clearly visible how the spread stabilises as a new level that takes into account the published information. Between day 0 and day 1 for *negative events*, and day -1 and 0 for *positive events*, there is a sharp incline and drop respectively, for the two types of information.

Figure 6 Aggregated average daily abnormal returns for positive and negative events during 2008-2013 consisting of an event window of 17 days



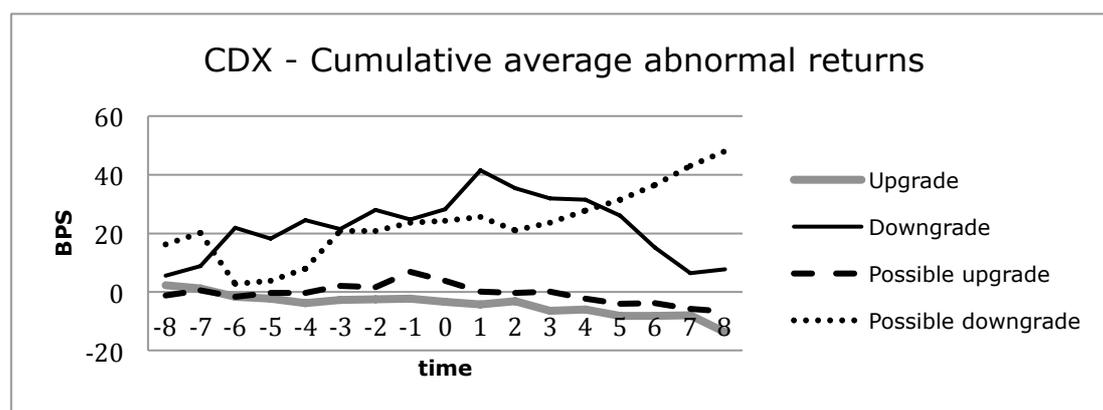
Looking at aggregated average daily abnormal returns, is it visible that *positive event* spread changes and *negative event* spread changes are not symmetrical. *Negative events* tend to educe spread changes in the first part of the event window, i.e. before

the event day. *Positive events* on the other hand, incur spread changes that are, first, smaller in magnitude and second, rather dispersed over the whole event window but being more perceivable in the second part of the event window, i.e. after the event day. This behaviour can be explained by *negative events* being anticipated in a greater extent than *positive events* and that media most often focuses on *negative events* rather than positive. The market is assumed to be more sensitive to negative news publishing.

6.2 Abnormal returns in the US CDS market

In this section, the results for the US market are presented and briefly discussed.

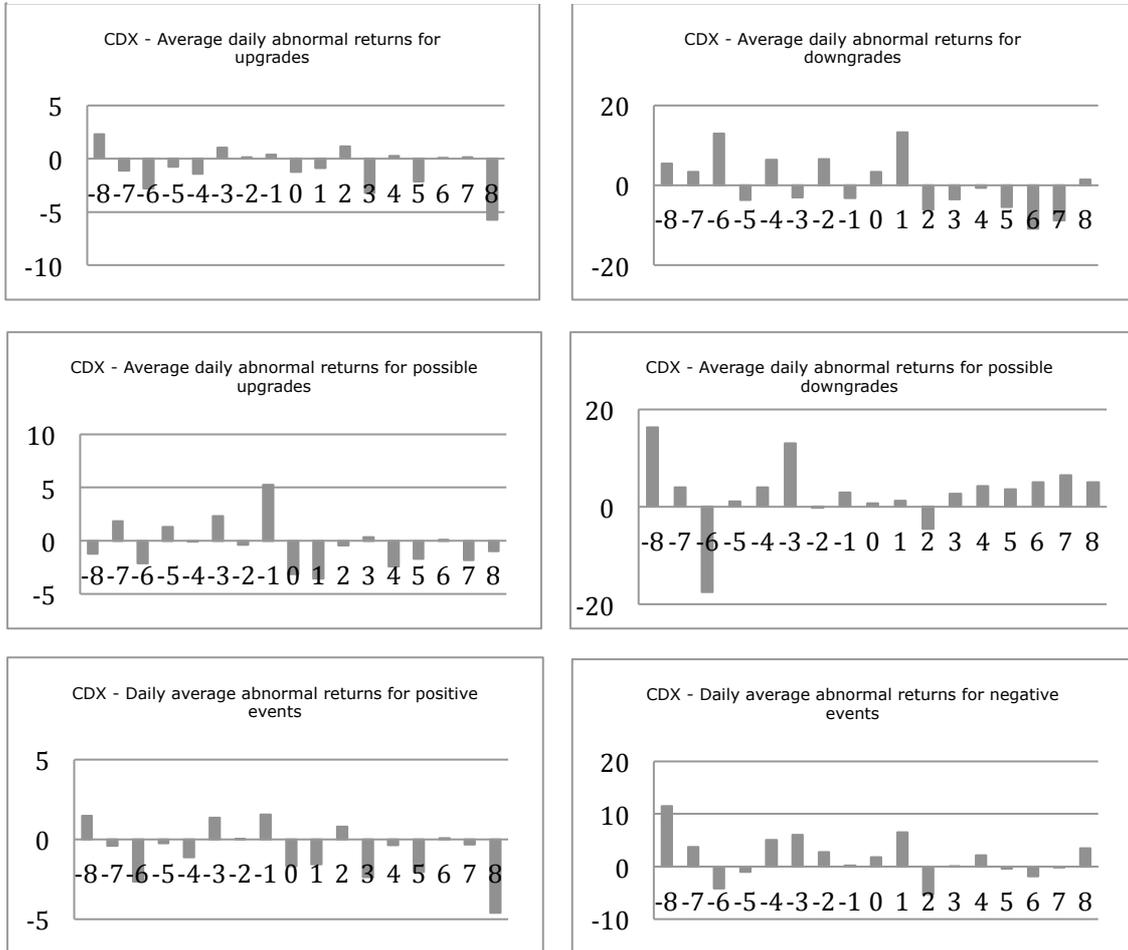
Figure 7 Cumulative average abnormal returns on the US market during 2008-2013 consisting of an event window of 17 days



As can be seen from the figure above, for negative events, *possible downgrade* is the rating announcement category that brings the largest accumulated spread change and also reacts the most in terms of having the largest accumulated spread change during the event window. *Possible downgrade* is also the only category that shows a monotonic trend upwards. As regards to the *downgrade* announcement, spread changes tend to first increase the spread and subsequently decrease it after the event day. Positive events in the form of *upgrade* and *possible upgrade* show a constant uniform behaviour in relation to negative events and do not exhibit any clear trend up or down. As previously mentioned, this result might be due to the fact that the majority of attention is put on negative news rather than positive.

Below is a representation of average daily abnormal returns for all four rating categories and well as for *positive events* and *negative events*.

Figure 8 Average daily abnormal returns on the US market for the rating categories upgrade, downgrade, possible upgrade and possible downgrade during 2008-2013 and an event window consisting of 17 days

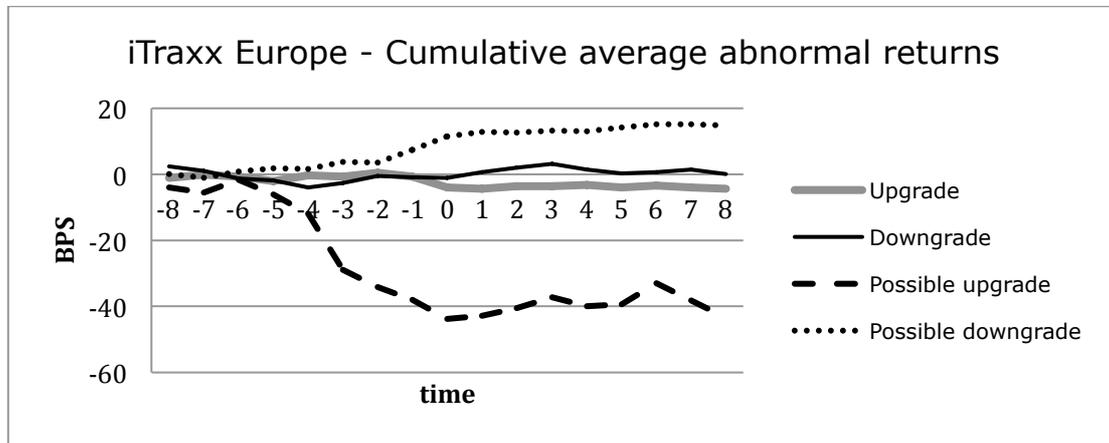


All event types display a reaction in the expected direction on the day of the event and the day after the event, day 0 and day 1. *Positive events* show 10 days out of 17 where spread changes are in the expected direction, whereas the equivalent number of days for *negative events* is 11. What differs the two categories from each other is that positive information (*upgrade, possible upgrade*) has the majority of negative spread change days after the event day, whereas for negative information the opposite holds; the majority of spread changes occur before the event day, on average. This is consistent with the notion that negative information is typically better anticipated than positive information.

6.3 Abnormal returns in the European CDS market

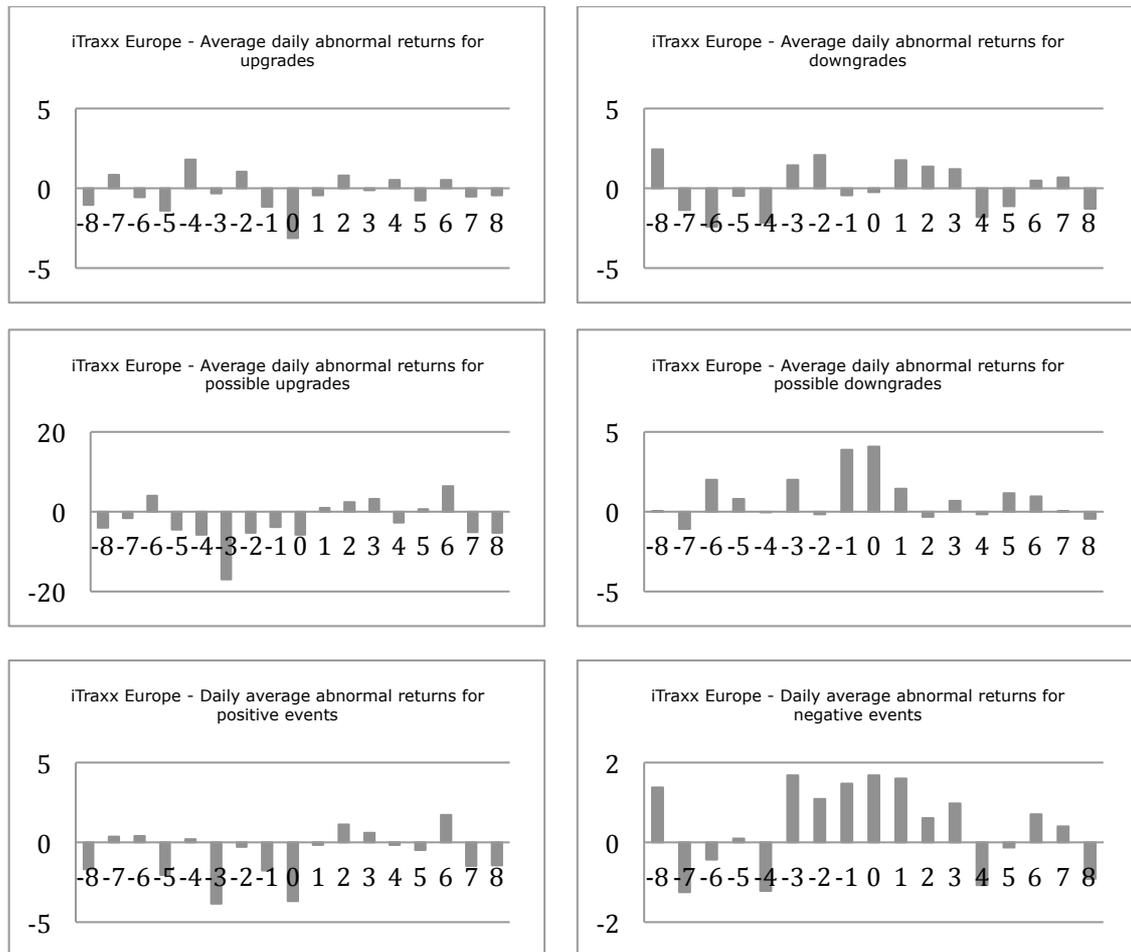
In this section, the results of the European market are presented and discussed.

Figure 9 Cumulative average abnormal returns on the European market during 2008-2013 consisting of an event window of 17 days



In figure 9, it is, as opposed to the US market, *possible upgrade* that has the largest accumulated spread change in absolute terms during the event window. This contradicts the finding that negative information is typically more attentive than positive information. However, it is clear from the figure that both *possible upgrade* and *possible downgrade* tend to reach a new fairly stabilised spread level after the event day, $t=0$, which is consistent with theory. For the pure rating changes, *upgrade* and *downgrade*, the spread changes are clustered around 0. This result again confirms possible-events having a stronger effect on spreads, leaving the actual changes relatively poor as regards to their informational content.

Figure 10 Average daily abnormal returns on the European market for the rating categories upgrade, downgrade, possible upgrade and possible downgrade during 2008-2013 and an event window consisting of 17 days

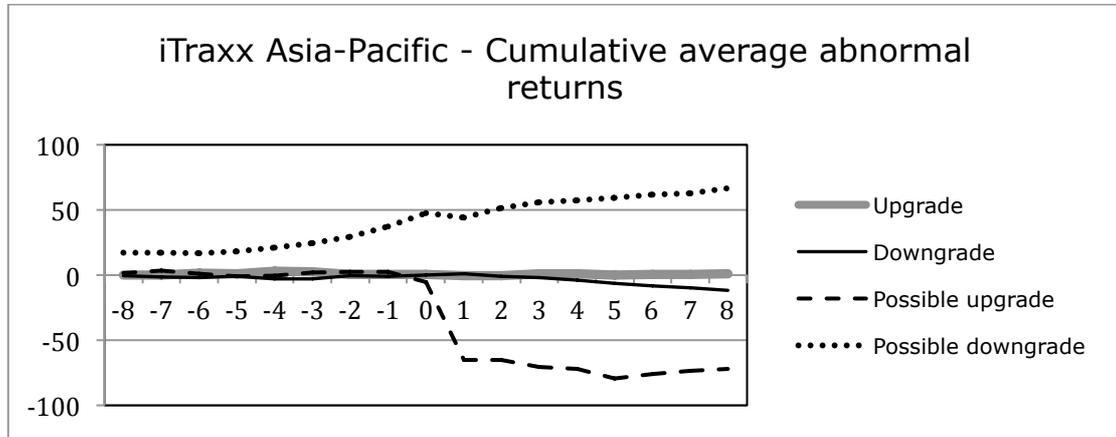


Taking a look at daily average abnormal returns for the European market, all rating categories, apart from *downgrades*, react in the expected direction during the day of the event and the day prior to the event, $t=0$ and $t=-1$. The magnitude of spread changes is, on average, greater during the 8 days after the event for *negative events*, and 8 day prior to the event for *positive events*, which is the opposite of what was the case on the US market, indicating that, on this market, *positive events* may be better anticipated than *negative events*.

6.4 Abnormal returns in the Asian-Pacific CDS market

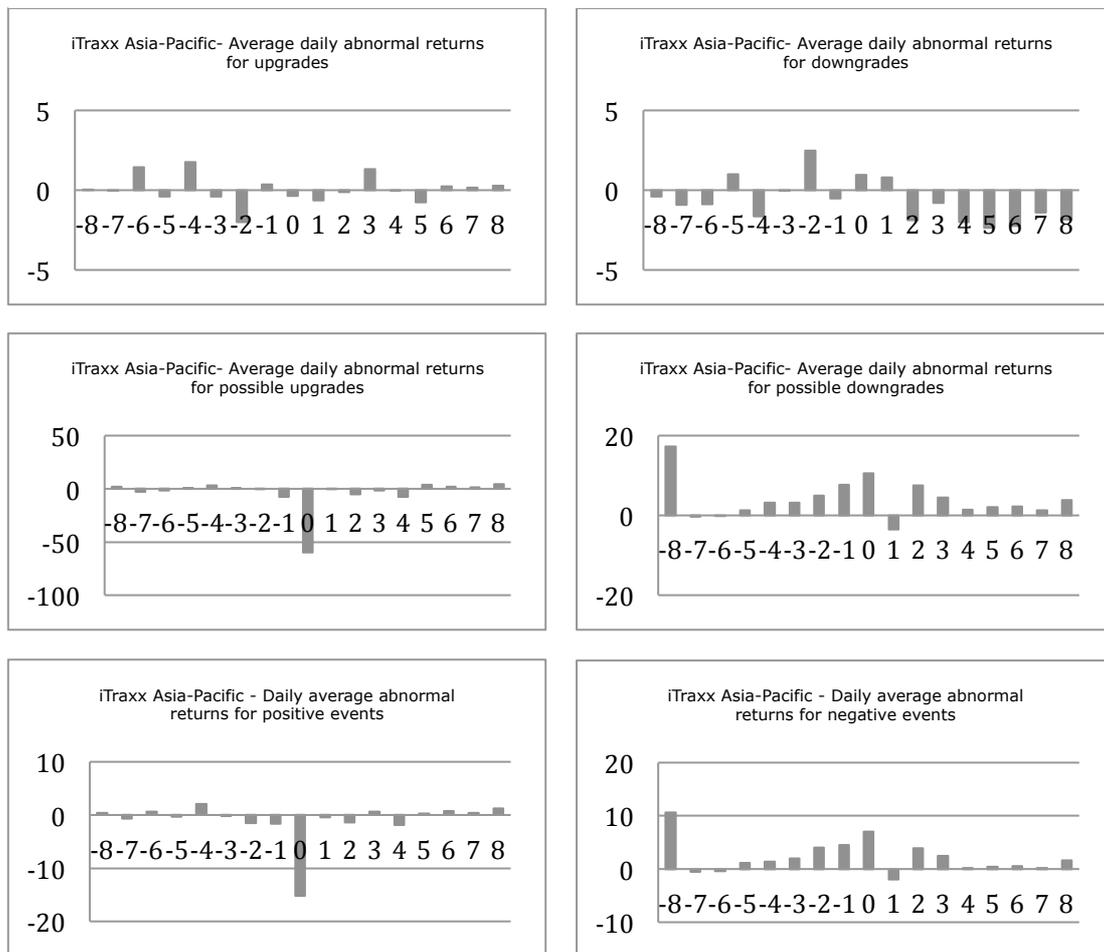
In this section, the results for the Asian-Pacific market are presented.

Figure 11 Cumulative average abnormal returns on the European market during 2008-2013 consisting of an event window of 17 days



Observing the cumulative abnormal returns for the Asian Pacific market it is yet again clear that *possible downgrade* and *possible upgrade* are the two rating categories inducing the largest total spread changes in absolute terms. The *possible upgrade* graph is further a very good visual example on how the CDS spread adapts to a new stabilised level after the publishing of the rating announcement. The results of the Asian-Pacific markets also confirm possible-events being more prevalent than actual rating change events.

Figure 12 Average daily abnormal returns on the Asian-Pacific market for the rating categories upgrade, downgrade, possible upgrade and possible downgrade during 2008-2013 and an event window consisting of 17 days



All four rating categories show average abnormal returns in the expected direction on the day of the event. However, taking into account that the Asian-Pacific is relatively small, the results should be interpreted with care. A discussion on sample size will follow at the end of this section.

To get an illustration of how the different CDS index spreads behave relative to each other, next is a graphical representation of cumulative average abnormal returns for *positive events* and *negative events* for the three different CDS market and the aggregated market.

Figure 13 Cumulative average abnormal returns for positive events, a comparison of the US, European and Asian-Pacific market relative to the aggregated market consisting of an event window of 17 days

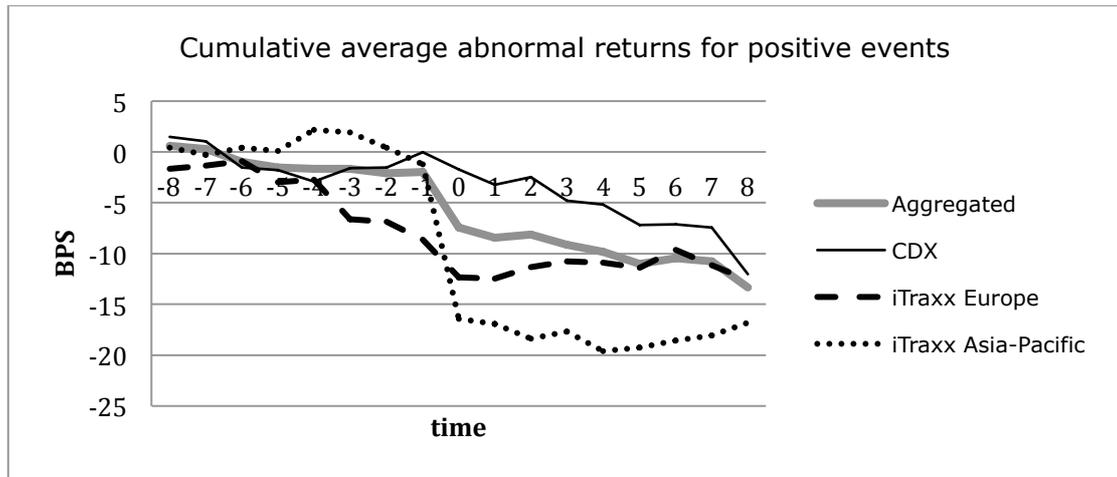
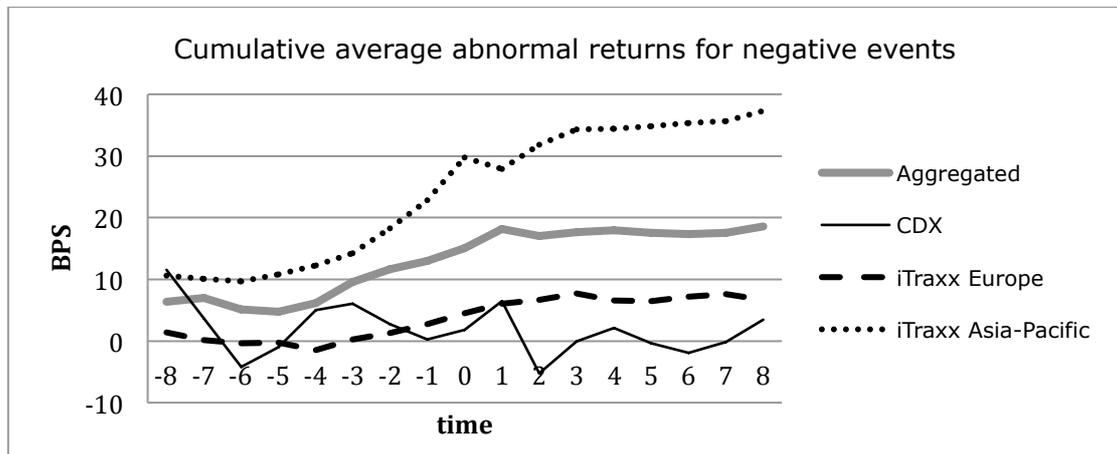


Figure 14 Cumulative average abnormal returns for positive events, a comparison of the US, European and Asian-Pacific market relative to the aggregated market during 2008-2013 consisting of an event window of 17 days



The results of the cumulative abnormal returns for the US, European and Asian-Pacific markets in relation to each other are varying. In both figure 13 and 14, the Asian-Pacific market seems to behave most extremely in the sense that its accumulated abnormal return graph is above/below the remaining graphs during the majority of the event window period. This is most likely due to the fact that the number of firms included in the data from iTraxx Asia and iTraxx Australia is small, maybe too small. More extreme events, or outliers, are not diluted in the sample and appear sizeable due to the small sample size.

Cumulative abnormal returns for *positive events* are most perceptible for the Asian-Pacific market and least perceptible for the US market. This is also true for *negative events*, except for the US market where the graph does not display any clear trend

over the event window. Here one would like to discuss possible regional differences; as previously mentioned, the different markets can differ in terms of efficiency, liquidity and age which are factors that will most likely have an impact on the behaviour of CDS spread changes before and after the publication of a rating announcement.

6.5 Testing statistical significance of abnormal returns

In this section, the previously presented data is tested for statistic significance, i.e. if abnormal returns are significantly different from zero. The results of the tests will have the same form and structure as the presentation of the empirical results. Two tests were performed; a two sided one sample t-test assuming that spread changes are normally distributed, and a two sided one sample Wilcoxon signed rank test, not assuming any particular underlying distribution of spread changes. Histograms of the distribution of the aggregated average abnormal returns during the event window for six rating categories are presented in appendix 4 as well as the numerical average abnormal returns for all event categories and all markets. For a recap of the hypotheses, see page 3.

6.5.1 Aggregated market

Table 3 *t*-test and Wilcoxon test results for the aggregated market during an event window of 17 days

(-8,8)	<i>Upgrade</i>	<i>Downgrade</i>	<i>Possible Up</i>	<i>Possible Down</i>	<i>Positive events</i>	<i>Negative events</i>
<i>N</i>	74	105	23	134	97	239
<i>Mean</i>	-0,488	0,086	-1,738	2,101	-0,784	1,096
<i>t-statistic</i>	-3,04	0,42	-1,93	8,01	-5,6	9,25
<i>p-value</i>	0,004***	0,674	0,067*	0***	0***	0***
<i>Median</i>	-0,3923	-0,1468	-0,7553	2,08	-0,5325	0,8849
<i>W-statistic</i>	44	73	31	135	24	122
<i>p-value</i>	0,13	0,887	0,033**	0,006***	0,014**	0,033**

*: $p < 10\%$, **: $p < 5\%$, ***: $p < 1\%$

Starting with an aggregated analysis, both *positive events* and *negative events* appear statistically significant after performing both a t-test and a Wilcoxon test. Consequently positive as well as negative information in the form of a positive or negative credit rating announcement have an impact on CDS spread changes that is different from zero and consistent with theory. If looking at each of the four rating announcements, *possible upgrades* and *possible downgrades* indicate significance at least at the 10% level, whereas pure *upgrades* and *downgrades* are taken not to

appear significant. These results are consistent with the graphical analysis in the previous section.

6.5.2 US, European and Asian-Pacific markets

Presented below are the results for each of the US, European and Asian-Pacific markets. A brief discussion will follow thereafter.

Table 4 t-test and Wilcoxon test results for the **US market** during an event window of 17 days

(-8,8)	<i>Upgrade</i>	<i>Downgrade</i>	<i>Possible Up</i>	<i>Possible Down</i>	<i>Positive events</i>	<i>Negative events</i>
<i>N</i>	41	17	13	53	54	70
<i>Mean</i>	-0,808	0,46	-0,396	2,828	-0,709	1,794
<i>t-statistic</i>	-2,78	0,27	-0,67	3	-3,27	4,33
<i>p-value</i>	0,008***	0,791	0,515	0,004***	0,002***	0,094*
<i>Median</i>	-0,5764	0,1711	-0,5684	3,158	-0,5793	1,66
<i>W-statistic</i>	47	81	52	124	40	109
<i>p-value</i>	0,17	0,85	0,256	0,026**	0,08*	0,13

*: $p < 10\%$, **: $p < 5\%$, ***: $p < 1\%$

Table 5 t-test and Wilcoxon test results for the **European market** during an event window of 17 days

(-8,8)	<i>Upgrade</i>	<i>Downgrade</i>	<i>Possible Up</i>	<i>Possible Down</i>	<i>Positive events</i>	<i>Negative events</i>
<i>N</i>	15	76	4	61	19	137
<i>Mean</i>	-0,259	0,008	-2,55	0,871	-0,741	0,3921
<i>t-statistic</i>	-0,9	0,05	-0,98	4,85	-2,14	4,45
<i>p-value</i>	0,382	0,963	0,4	0***	0,046**	0***
<i>Median</i>	-0,2614	0,02476	-2,244	0,6989	-0,6606	0,3802
<i>W-statistic</i>	61	79	37	119	44	108
<i>p-value</i>	0,478	0,925	0,065*	0,047**	0,13	0,142

*: $p < 10\%$, **: $p < 5\%$, ***: $p < 1\%$

Table 6 t-test and Wilcoxon test results for the **Asian-Pacific market** during an event window of 17 days

(-8,8)	<i>Upgrade</i>	<i>Downgrade</i>	<i>Possible Up</i>	<i>Possible Down</i>	<i>Positive events</i>	<i>Negative events</i>
<i>N</i>	18	12	6	20	24	32
<i>Mean</i>	0,697	-3,181	-33,35	40,53	-0,989	2,195
<i>t-statistic</i>	3,41	-8,31	-5,69	38,96	-1,3	4,13
<i>p-value</i>	0,003***	0***	0,002***	0***	0,205	0***
<i>Median</i>	-0,0212	-0,7287	-0,6839	3,234	-0,256	1,743
<i>W-statistic</i>	73	38	65	140	64	134
<i>p-value</i>	0,887	0,072*	0,603	0,003***	0,57	0,007***

*: $p < 10\%$, **: $p < 5\%$, ***: $p < 1\%$

The visual analysis in the previous section is more or less confirmed by the results of the statistical tests. All three markets show a statistically significant result for *possible downgrades*. To start with, only looking at the t-test results, all three markets are significant concerning *possible downgrade* and *negative events*. This confirms theory as well as previous research. When looking at the results from the Wilcoxon tests, this conclusion slightly changes and only the Asian-Pacific market shows significant results concerning *negative events*. Taking the categories in turn,

upgrades are only significant for the US and European markets after performing a t-test, whereas the Wilcoxon test shows no significance on any market. *Downgrades* only appear significant on the Asian-Pacific market whereas the results are far from significant for the US and European markets after performing both tests. The rating category *possible upgrade* gives a varied impression. It is not significant for the US market, significant only when performing a Wilcoxon test on the European market, and last, significant for the Asian-Pacific market only when assuming normality and applying a t-test.

As can be understood from the discussion in this and the previous sections, a market specific analysis is varying and not the least distinct from the aggregated market analysis. In my opinion, this variation is based on varying and relatively small sample sizes. A sample size of 30 is considered as “good” according to statistical principles, and only very few rating categories within each market achieve this requirement of having an underlying sample size larger than 30. The accuracy of the market specific results can therefore be questioned and interpretation must be carried out carefully taking the sample size into account. This is particularly important for the Asian-Pacific sample that in this case only consists of 24 positive events and 32 negative events. The number of events can be lacking in terms of being representative of how positive and negative events typically impact CDS spreads and instead, sample specific features will control the results. This reasoning is also consistent with the law of large numbers and the central limit theorem. A small sample size will therefore most likely not be representative of the population, which we want to reproduce, and the statistical inference will be more or less biased. Therefore, the importance of sample size cannot be overlooked.

The assumption of normally distributed CDS spread changes is further a typical schoolbook assumption; financial data is generally not considered normally distributed in the real world. Nevertheless, a t-test might still be valid for larger samples even though their distribution is non-normal. The other way around is however not true; if the sample size is small, a t-test will often be worthless if the sample population is distributed non-normally. When pooling *upgrades* and *possible upgrades* into *positive events*, and *downgrades* and *possible downgrades* into *negative events*, the sample size is larger for both the aggregated market and the three

specific markets. It is therefore justified to apply the t-test. However, in order to compensate for any possible resulting errors, the Wilcoxon signed rank test is also performed, which, as previously described, does not require any specific underlying distribution of CDS spread changes. With this in mind, the Wilcoxon test results seem more representative of the results and will therefore be interpreted as the “true” results from which the conclusions are drawn.

7 Conclusions

The aim of this essay was to investigate the relationship between credit default swap spreads and credit rating announcements and consequently answer the question whether rating announcements have any significant impact on CDS spreads. The US, European and Asian-Pacific markets were included in the analysis that consisted of an examination both on market specific level as well as on an aggregated level, putting all three mentioned CDS markets together. The method involved calculating so called *abnormal returns* (ARs) that basically are the actual return minus the expected “normal” market return - in the case of a CDS; a firm specific CDS spread change minus a market specific CDS index spread change representing the abnormal “return” of the CDS market. The mean and median of the abnormal returns were tested for significance, with the hypotheses being $H_0: AR_{\mu/M}=0$ and $H_1: AR_{\mu/M}\neq 0$ during an investigation period, event window, of 17 days, 8 days prior to the event and 8 days after the event. If the null hypothesis is rejected, abnormal returns are assumed to be significantly greater than zero and CDS spread changes are hence affected by credit rating announcements.

First, performing market specific analyses, the US market shows ARs that are significantly different from zero on the 5 % level concerning the rating category *possible downgrade*. *Positive events*, including *possible upgrade* and *upgrade* together, show significance at the 10 % level. Regarding the European market, neither *positive events* nor *negative events* indicate significance; only the rating announcement *possible upgrade* and *possible downgrade* show statistical significance at the 10 % and 5 % level respectively. For the Asian-Pacific market, the rating categories *downgrade* and *possible downgrade* display statistical significance at the 10% and 1% level respectively resulting in *negative events* also being significant. The only rating category that is jointly significant for all three markets is the rating category *possible downgrade*, this is true after performing both the t-test and the Wilcoxon test. However, due to insufficient sample sizes and non-normally distributed CDS spread changes, the market specific results should be interpreted with caution and the results of the aggregated CDS market, that follows next, will serve the foundation for the conclusions in this essay.

On the aggregated CDS market, rating announcements seem to have an effect that is statistically different from zero on CDS spread changes. Both *positive events* and *negative events* show statistically significant ARs during the event window indicating that both *positive events* and *negative events* have an impact on CDS spreads. Categorically, however, only *possible upgrades* and *possible downgrades* show a statistically significant result implying that “possible”-events most likely already anticipate the information held in the pure rating change events. This is probably why the *upgrade* and *downgrade* events do not show any significance.

To sum up in short, credit rating announcements, in particular *possible upgrades* and *possible downgrades*, do have a statistically significant impact on CDS spread changes. “Possible”-events are more significant than actual rating changes. This is most likely due to the fact that in a possible event, the information that an actual rating change is to take place in the near future is already anticipated and integrated in the publishing of the possible-announcement. Hence, a great deal of information in an actual rating change is already accounted for in the publishing of the “possible”-event. Overall, when testing for positive and negative information respectively, the null hypothesis is rejected and both pooled *positive events* and *negative events* are assumed to have a statistically significant impact on CDS spread changes. These results are consistent with previous findings and support the fact that spreads are inversely related with credit rating announcements.

References

Journals

- Acharya, S (2012), "Value of latent information: Alternative event study methods", *Journal of Finance*, 48(1), pp. 363-385
- Beaver, W.H (1968), "The information content of annual earnings announcements", *Journal of Accounting Research*, 6, pp. 67-92
- Binder, J (1998), "The event study methodology since 1969", *Review of Quantitative Finance and Accounting*, 11, pp. 111-137
- Daniels, K & Jensen, S (2005), "The effect of credit ratings on credit default swap spreads and credit spreads", *Journal of Fixed Incomes*, 15(3), pp. 16-33
- Dolley, J (1933), "Characteristics and procedure of common stock split-ups", *Harvard Business Review*, 11, pp.316-326
- Fama, E (1991), "Efficient capital markets: II", *Journal of Finance*, 46(6), pp. 1575-1617
- Fama, E, Fisher, L, Jensen, M & Roll, R (1969), "The adjustment of stock prices to new information", *International Economic Review*, vol 10(1), pp. 1-21
- Finnerty, J, Miller, C & Chen, RR (2013), "The impact of credit rating announcements on credit default swap spreads", *Journal of Banking & Finance*, 37(6), pp. 2011-2030
- Galil, K & Soffer, G (2011), "Good news, bad news and rating announcements: An empirical investigation", *Journal of Banking & Finance*, 35(11), pp. 3101-3119
- Henderson, G (1990), "Problems and solutions in conducting event studies", *Journal of Risk and Insurance*, 27(2), pp.282-306
- Hull, J, Nelken, I & White, A (2004), "Merton's model, credit risk and volatility skews", *Journal of Credit Risk*, 1(1)

Hull, J, Predescu, M & White, A (2004), “The relationship between credit default swap spreads, bond yields, and credit rating announcements”, *Journal of Banking & Finance*, 28(11) pp.2789-2811

Jorion, P& Zhang, G (2007), “Good and bad credit contagion: Evidence from credit default swaps” , *Journal of Financial Economics*, 84(3). pp- 860-883

MacKinlay, AC (1997), “Event studies in economics and finance”, *Journal of economic literature*, 35(1), pp-13-39

Micu, M, Remolona, E & Wooldridge, P (2004), “The price impact of rating announcements: evidence from the credit default swap market”, *Bank of International Settlements (BIS) Quarterly Review*, June 2004

Norden, L & Weber, M (2004), “Informational efficiency of credit default swap and stock markets: The impact of credit rating announcements”, *Journal of Banking & Finance*, 28(11), pp. 2813-2843

Electronic sources

ISDA, International Securities and Derivatives Associations, “How Credit Default Swaps work”, available online http://www.isdacdsmarketplace.com/-about_cds_market/how_cds_work , retrieved 2013.06.09

Markit, Markit Credit and Loan Indices, Index Documents, available online www.markit.com, Retrieved 2013.06.09

Moody’s, “How to get rated”, available online www.moodys.com/ratings-process, retrieved 2013.06.09

Standard & Poor’s (2011), “Guide to credit rating essentials: what are credit ratings and how do they work?” available online <http://jpn.c2com.up.pt/documento-s/pdf/rating.pdf>, retrieved 2013.06.09

Thomson Reuters, “Thomson Reuters CDS FAQ”, available online <http://extranet.datastream.com/data/CDS/Documents/Thomson%20Reuters%20CDS%20-%20FAQ.doc>, retrieved 2013.06.09

Weistroffer, C (2009), "Credit default swaps: heading towards a more stable system", Deutsche Bank Research, available online www.dbresearch.com, retrieved 2013.06.09

Printed sources

Hull, J (2011), "Options, futures and other derivatives", 8th edition, Pearson

Saunders, A, Allen, L (2010), "Credit risk management in and out of the financial crisis: new approaches to value at risk and other paradigms", 3rd edition, Wiley

Other

De Haan, J & Amtenbrink, F (2011), "Credit rating agencies", *DNB Working paper*, No 278

Greatrex, CA (2008), "The credit default swap market's determinants, efficiency and relationship to the stock market", *ETD Collection for Fordham University Paper AAI3301438*.

Greatrex, CA (2008), "The credit default swap market's reaction to earnings announcements", *Fordham University Department of Economics Discussion paper no. 2008-06*

Imbierowicz, B & Cserna, B (2008), "How efficient are credit default swap markets? An empirical study of capital structure arbitrage based on structural pricing models", *21st Australasian Finance and Banking Conference 2008 Paper*, Working paper

Jacobs, M & Karagozoglou, A (2011), "Measuring credit risk: CDS spreads vs. Credit Ratings", *Working paper*, available online <http://ssrn.com/abstract=1551406>

Jenkins, N, Kimbrough, MD & Juan, NT (2011), "The extent of informational efficiency in the credit default swap market: Evidence from post-earnings announcement returns", available online <http://ssrn.com/abstract=1785734>

Levin, C & Coburn, T (2011), “Wall Street and the financial crisis: Anatomy of a financial collapse: Inflated Credit Ratings – Case Study of Moody’s and Standard & Poor”, Permanent Subcommittee on Investigations, United States Senate

Mengle, D (2007), “ Credit derivatives: an overview”, *Federal Reserve Bank of Atlanta Economic Review*, 4th quarter 2007

Official Journal of the European union, (2011), , *Regulation of the European Parliament and of the Council on Short Selling and certain aspects of Credit Default Swaps*, C 33 E/298

Appendix 1

List of companies included in the essay

CDX NA IG – MR

1. AETNA INC (FIN)
2. AMERICAN EXPRESS CO (FIN)
3. AMERICAN INTL GROUP INC (FIN)
4. AT&T INC (TMT)
5. AVNET UNC (CONS)
6. BARRICK GOLD CORP (INDU)
7. BAXTER INTL INC (CONS)
8. BEAM INC (CONS)
9. BERKSHIRE HATHAWAY (FIN)
10. BLOCK FINANCIAL LLC (FIN)
11. BOSTON SCIENTIFIC CORP (CONS)
12. CAMPBELL SOUP CO (CONS)
13. CAPITAL ONE FINANCIAL CORP (FIN)
14. CARDINAL HEALTH INC (CONS)
15. CARNIVAL GROUP (CONS)
16. CBS CORPORATION (TMT)
17. COMCAST CORPORATION (TMT)
18. CONAGRA FOODS INC (CONS)
19. CONOCOPHILLIPS (ENERG)
20. COX COMMS INC (TMT)
21. E.I. DU PONT DE NMS & CO (INDU)
22. EXELON CORP (ENERG)
23. EXPEDIA INC (CONS)
24. FORD MOTOR COMPANY (CONS)
25. FREEPORT MCMORD CORP & GD (INDU)
26. GENERAL ELECTRIC CAPITAL CORP (FIN)
27. GENERAL MILLS INC (CONS)
28. GOODRICH CORP (INDU)
29. H.J. HEINZ COMPANY (CONS)
30. HEWLETT PACKARD CO (TMT)
31. INGERSOLL RAND CO (INDU)
32. INTL BUS MACHINES (TMT)
33. JOHNSON CONTROLS INC (CONS)
34. LOEWS CORPORATION (FIN)
35. LOWES COMPANIES (CONS)
36. MACY'S INC (CONS)
37. MARRIOTT INTERNATIONAL (CONS)
38. MCDONALD'S CORP (CONS)
39. MCKESSON CORP (CONS)
40. MEADWESTVACO CORP (INDU)
41. NEWELL RUBMD INC (CONS)
42. NEWS AMERICA INC (TMT)
43. NORDSTROM INC (CONS)
44. PITNEY BOWES INC (TMT)
45. RAYTHEON COMPANY (INDU)
46. REYNOLDS AMER INC (CONS)
47. SAFEWAY INC (CONS)
48. SLM CORPORATION (FIN)
49. SOUTHWEST AIRL CO (CONS)
50. STARWOOD H&R WWD INC (CONS)
51. THE ALL STATE CORP (FIN)
52. THE DOW CHEMICAL CO (INDU)
53. THE HARTFORD FIN SVS GP (FIN)
54. THE HILLSHIRE BNS CO (CONS)
55. THE HOME DEPOT INC (CONS)
56. SHERWIN-WILLIAMS CO (INDU)

57. TRANSOCEAN INC (ENERG)
58. TYSON FOODS INC (CONS)
59. UNION PACIFIC (INDU)
60. UNITED PARCEL SVS (CONS)
61. UNITED HEALTH GP (FIN)
62. VALERO ENERGY (ENERG)
63. VERIZON COMMS INC (TMT)
64. VIACOM INC (TMT)
65. WHIRLPOOL CORP (CONS)

iTraxx Europe – MM

66. AEGON N.V (FIN)
67. AKTIEBOLAGET VOLVO (INDU)
68. AKZO NOBEL N.V (INDU)
69. ALSTOM (INDU)
70. ANGLO AMERICAN PLC (INDU)
71. ASSICURAZIONI GENERALI S.P.A(FIN)
72. ATLANTIA S.P.A (INDU)
73. AVIVA PLC (FIN)
74. BARCLAYS BANK PLC (FIN)
75. BASP SE (INDU)
76. BAYTER MOTOREN WERKE AG (INDU)
77. BERTELSMANN AG (TMT)
78. BNP PARIBAS (FIN)
79. BRITISH AMERICAN TOBACCO PLC (CONS)
80. CARREFOUR (CONS)
81. CIE DE SAINT-GOBAIN (INDU)
82. COMMERZBANK AG (FIN)
83. COMPAGNIE FINC MICH (INDU)
84. CRDIT SUISSE GROUP (FIN)
85. CREDIT AGRICOLE SA (FIN)
86. DEUTSCHE BANK AG (FIN)
87. DEUTSCHE TELEKOM AG (TMT)
88. E.ON SE (ENERG)
89. ELECTRICITE DE FRANCE (ENERG)
90. ENBW ENGE BA-WUERTT (ENERG)
91. ENEL S.P.A (ENERG)
92. ENI S.P.A (ENERG)
93. EUROPEAN AEROC DEFE (INDU)
94. GAS NATURAL SDG S.A (ENERG)
95. GDF SUEZ SA (ENERG)
96. GLENCORE INTL AG (INDU)
97. HANNOVER RUCK AG (FIN)
98. HOLCIM LTD (INDU)
99. HSBC BANK PLC (FIN)
100. JTI (UK) FINANCE PLC (CONS)
101. KINGFISHER PLC (CONS)
102. LLOYDS TSB BANK (FIN)
103. MARKS & SPENCER PLC (CONS)
104. METRO AG (CONS)
105. NESTLE S.A (CONS)
106. PERNOD RICARD (CONS)
107. POSTNL N.V (INDU)
108. RBOS PLC (FIN)
109. RWE AG (ENERG)
110. SAFEWAY LIMITED (CONS)
111. SANOFI-AVENTIS (INDU)

- 112. SIEMENS AG (INDU)
- 113. SOCIETE GENERALE (FIN)
- 114. SOLVAY (INDU)
- 115. STD CHARTERED BANK (FIN)
- 116. SUEDZUCKER AG (CONS)
- 117. SWISS REINSURANCE CO (FIN)
- 118. TATE & LYLE PUBL LTD (CONS)
- 119. TELEFONICA S.A (TMT)
- 120. TELEKOM AUSTRIA AG (TMT)
- 121. TELENOR ASA (TMT)
- 122. TESCO PLC (CONS)
- 123. UBS AG (FIN)
- 124. UNICREDIT BANK OE AG (FIN)
- 125. VOLKSWAGEN AG (INDU)
- 126. XSTRATA PLC (INDU)
- 127. ZURICH INSURANCE CO (FIN)

iTraxx Asia (excl Japan) – CR

- 128. BANK OF CHINA (FIN)
- 129. CNOOC BANK (FIN)
- 130. DBS BANK (FIN)
- 131. GS CALTEX CORP (ENERG)
- 132. HANA BANK (FIN)
- 133. HUTCHISON WHAMPOA (FIN)
- 134. HYUNDAI MOTOR COMPANY (INDU)
- 135. ICICI BANK (FIN)
- 136. KOERA ELECTRIC POWER CORP (ENERG)
- 137. KOOMIN BANK (FIN)
- 138. KT CORP (TMT)
- 139. POSCO (INDU)
- 140. SK TELEKOM (TMT)
- 141. TELEKOM MALAYSIA (TMT)
- 142. THE KOREA DEVELOPMENT BANK (FIN)
- 143. WOORI BANK (FIN)

iTraxx Australia – MR

- 144. AUSTRALIA & NZ BANKING GP (FIN)
- 145. FOSTER'S GP (CONS)
- 146. GPT RE (FIN)
- 147. JEMENA LIMITED (ENERG)
- 148. NATIONAL AUSTRALIAN BANK (FIN)
- 149. QANTAS AIRWAYS (INDU)
- 150. QBE INSURANCE GP (FIN)
- 151. WESFARMERS LIMITED (CONS)
- 152. WESTPAC BANKING CORP (FIN)

FIN = financial

CONS = consumer

ENERG = energy

INDU = industrial

TMT = telecom/media/technology

Appendix 2

Credit rating table

Moody's	S&P	Fitch	Meaning	
Aaa	AAA	AAA	Prime	
Aa1	AA+	AA+		
Aa2	AA	AA	High grade	
Aa3	AA-	AA-		
A1	A+	A+		Investment grade
A2	A	A	Upper medium grade	
A3	A-	A-		
Baa1	BBB+	BBB+		
Baa2	BBB	BBB	Lower medium grade	
Baa3	BBB-	BBB-		
Ba1	BB+	BB+		
Ba2	BB	BB	Non investment grade speculative	
Ba3	BB-	BB-		
B1	B+	B+		
B2	B	B	Highly speculative	
B3	B-	B-		
Caa1	CCC+	CCC+	Substantial risks	Non investment grade / junk
Caa2	CCC	CCC	Extremely speculative	
Caa3	CCC-	CCC-		
Ca	CC	CC+	In default w/ little prospect for recovery	
	C	CC		
		CC-	In default	
D	D	DDD		

Appendix 3

Numerical average abnormal returns in absolute terms for aggregated (US+EU+APAC), US, EU and APAC markets.

Aggregated

	<i>Upgrade</i>	<i>Downgrade</i>	<i>Possible Up</i>	<i>Possible Down</i>	<i>Positive events</i>	<i>Negative events</i>
-8	1,080	3,146	-0,934	9,026	0,603	6,351
-7	-0,452	0,176	0,053	1,032	-0,332	0,660
-6	-1,302	2,629	-0,946	-6,038	-1,218	-1,913
-5	-0,794	-1,358	-0,006	1,008	-0,607	-0,327
-4	-0,011	0,605	-0,301	2,040	-0,080	1,408
-3	0,420	-0,128	-1,585	6,538	-0,056	3,421
-2	-0,192	3,524	-1,143	0,599	-0,417	2,069
-1	0,050	-1,319	0,325	4,038	0,115	1,301
0	-1,409	1,020	-18,366	3,702	-5,430	2,145
1	-0,753	5,347	-1,835	0,621	-1,009	3,053
2	0,790	-1,300	-1,267	-0,842	0,302	-1,167
3	-1,468	-0,472	0,405	2,041	-1,024	0,673
4	0,268	-1,434	-3,827	1,799	-0,703	0,253
5	-1,525	-2,609	0,081	2,241	-1,145	-0,376
6	0,202	-3,359	1,739	2,758	0,567	-0,202
7	0,009	-2,537	-1,578	2,787	-0,367	0,247
8	-3,210	-0,470	-0,359	2,361	-2,534	1,037

US

	<i>Upgrade</i>	<i>Downgrade</i>	<i>Possible up</i>	<i>Possible down</i>	<i>Positive events</i>	<i>Negative events</i>
-8	2,322	5,470	-1,212	16,259	1,471	11,553
-7	-1,102	3,381	1,811	3,960	-0,401	3,707
-6	-2,784	12,944	-2,142	-17,474	-2,630	-4,206
-5	-0,743	-3,656	1,300	1,135	-0,251	-0,955
-4	-1,448	6,421	-0,108	3,962	-1,125	5,035
-3	1,041	-3,039	2,342	13,043	1,354	6,028
-2	0,158	6,479	-0,374	-0,166	0,030	2,732
-1	0,368	-3,178	5,242	2,877	1,541	0,236
0	-1,232	3,345	-3,117	0,682	-1,685	1,843
1	-0,909	13,349	-3,540	1,260	-1,543	6,533
2	1,179	-6,056	-0,430	-4,571	0,792	-5,219
3	-3,193	-3,484	0,329	2,713	-2,345	0,010
4	0,289	-0,601	-2,437	4,183	-0,368	2,096
5	-2,140	-5,409	-1,675	3,581	-2,028	-0,340
6	0,079	-10,818	0,093	5,040	0,082	-1,877
7	0,140	-8,823	-1,848	6,535	-0,339	-0,164
8	-5,757	1,451	-0,970	5,057	-4,605	3,484

EUROPEAN

	<i>Upgrade</i>	<i>Downgrade</i>	<i>Possible up</i>	<i>Possible down</i>	<i>Positive events</i>	<i>Negative events</i>
-8	-1,034	2,450	-4,039	0,041	-1,666	1,378
-7	0,849	-1,381	-1,543	-1,082	0,345	-1,248
-6	-0,546	-2,382	3,947	1,984	0,400	-0,438
-5	-1,387	-0,489	-4,457	0,810	-2,033	0,090
-4	1,780	-2,177	-5,727	-0,035	0,200	-1,223
-3	-0,316	1,428	-17,044	1,986	-3,838	1,677
-2	1,042	2,093	-5,302	-0,150	-0,294	1,094
-1	-1,171	-0,440	-3,907	3,868	-1,747	1,478
0	-3,137	-0,228	-5,713	4,066	-3,680	1,684
1	-0,445	1,746	0,969	1,433	-0,147	1,606
2	0,805	1,360	2,338	-0,316	1,128	0,614
3	-0,122	1,208	3,255	0,674	0,589	0,970
4	0,537	-1,792	-2,738	-0,170	-0,153	-1,070
5	-0,778	-1,136	0,560	1,144	-0,496	-0,121
6	0,511	0,489	6,335	0,953	1,737	0,696
7	-0,537	0,678	-5,048	0,044	-1,487	0,395
8	-0,447	-1,291	-5,234	-0,450	-1,455	-0,916

ASIAN-PACIFIC

	<i>Upgrade</i>	<i>Downgrade</i>	<i>Possible up</i>	<i>Possible down</i>	<i>Positive events</i>	<i>Negative events</i>
-8	0,013	-0,384	1,739	17,264	0,445	10,646
-7	-0,056	-0,910	-2,690	-0,283	-0,714	-0,518
-6	1,444	-0,880	-1,617	-0,200	0,679	-0,455
-5	-0,416	0,995	0,132	1,278	-0,279	1,171
-4	1,770	-1,651	2,896	3,274	2,052	1,427
-3	-0,382	-0,043	0,214	3,185	-0,233	1,975
-2	-2,016	2,494	-0,036	4,910	-1,521	4,004
-1	0,344	-0,532	-7,510	7,631	-1,619	4,570
0	-0,373	0,977	-59,843	10,598	-15,241	6,990
1	-0,652	0,817	-0,010	-3,547	-0,492	-1,910
2	-0,111	-1,896	-5,483	7,438	-1,454	3,938
3	1,338	-0,821	-1,332	4,428	0,671	2,460
4	-0,001	-2,016	-7,566	1,486	-1,892	0,173
5	-0,749	-2,374	3,564	2,039	0,330	0,384
6	0,228	-2,252	2,240	2,216	0,731	0,541
7	0,168	-1,414	1,321	1,226	0,456	0,236
8	0,291	-1,834	4,214	3,791	1,271	1,681

Appendix 4

Empirical distribution of **aggregated** (US+EU+APAC) average abnormal returns during the event window (17 days) for *upgrade*, *downgrade*, *possible upgrade*, *possible downgrade*, *possible events* and *negative events*.

