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The impact and the spillover effect of credit rating announcements on corporate CDS spreads

Industry-level evidence from S&P 500 firms

School of Accounting and Finance
Master's thesis in Finance
Master's Programme in Finance

Vaasa 2021

UNIVERSITY OF VAASA
School of Accounting and Finance
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Title of the Thesis: The impact and the spillover effect of credit rating announcements on corporate CDS spreads : Industry-level evidence from S&P 500 firms
Degree: Master of Science in Economics and Business Administration
Programme: Finance
Supervisor: Vanja Piljak
Year: 2021 **Pages:** 67

ABSTRACT:

This Master's Thesis investigates the effect of S&P 500 firms' credit rating events on the credit default swap (CDS) market. The impact is examined considering all industries together and at the industry level. Study period is 2010-2018. Contribute to the prior literature, this paper examines whether competitors experience spillover effects in their CDS spreads before and around an event firm's rating announcement.

Credit default swap (CDS) spread is a direct price of credit risk and hence is widely utilized to measure firms' creditworthiness. Generally, the higher a CDS spread, the more likely an entity will default. CDS contract protects the buyer if a reference entity, that is the issuer of a bond, defaults on a bond. The use of credit derivatives as a hedging instrument for credit risk has grown steadily during the 21st century.

Three major credit rating agencies (CRAs) are Standard & Poor's (S&P), Moody's, and Fitch. They analyze the creditworthiness of entities and the financial status of companies. The role has become more significant in recent years not only due to globalization but also due to the complexity of financial products and financial regulation.

The relationship between CDS spread and credit rating is inverse. The higher the rating, the lower is the expected CDS spread and vice versa. Currently, due to the high volatility of the CDS market and the significant reputation of CRAs, the relationship between the CDS market and rating events is a reasonable subject to study to reveal new information to portfolio hedging operations. Furthermore, investigating the effects of rating events on the CDS market reveals whether the CDS market is efficient based on the efficient market hypothesis (EMH).

In this thesis, rating data is collected from the FitchConnect database and after controlling consists of 110 downgrades and 144 upgrades. The CDS data is collected as time series from Thomson Reuters Datastream and consists of 323 886 daily CDS spread quotes. The effects of rating events on event firms' and non-event firms' CDS spreads are examined using the event study.

Overall, I find that the CDS market experience abnormal spread changes around upgrades but not around downgrades, and the CDS market anticipates upgrades but not downgrades. Also, the findings show that the spillover effects are observable among the S&P 500 firms since the CDS spreads of non-event firms react abnormally before and around downgrades and upgrades. However, the results show that the CDS market is segmented as the market reaction differs across the industries.

KEYWORDS: S&P 500, Derivatives, Credit rating, Spillover effect, Event study

VAASAN YLIOPISTO			
School of Accounting and Finance			
Tekijä:	Sakari Levo		
Tutkielman nimi:	The impact and the spillover effect of credit rating announcements on corporate CDS spreads : Industry-level evidence from S&P 500 firms		
Tutkinto:	Kauppatieteiden maisteri		
Oppiaine:	Rahoitus		
Työn ohjaaja:	Vanja Piljak		
Valmistumisvuosi:	2021	**Sivumäärä:**	67

TIIVISTELMÄ:

Tämän pro gradu -tutkielman tarkoituksena on tutkia, kuinka S&P 500-yritysten luottoluokitustapahtumat vaikuttavat luottoriskijohdannaisten markkinahintaan vuosina 2010-2018. Tätä vaikutusta tutkitaan ottamalla huomioon kaikki yritykset samanaikaisesti, mutta myös toimialakohtaisesti. Tutkimus tuo lisäarvoa aiempiin saman aihealueen tutkimuksiin tutkimalla toimialakohtaisesti, mikäli kilpailijoiden luottoriskijohdannaisten hinnat reagoivat merkittävästi ennen luottoluokitustapahtumaa ja sen aikana.

Luottoriskijohdannaisen hinta on suora luottoriskin mittari ja sitä käytetään laajalti yritysten luottokelpoisuuden mittaamiseen. Yleisesti ottaen, mitä korkeampi johdannaisen hinta on, sitä riskipitoisempi tämän vakuutuksen kohde-etuutena oleva laina on. Luottoriskijohdannaissopimus suojaa haltijaansa, mikäli sen kohteena oleva joukkovelkakirjan liikkeellelaskija laiminlyö velan takaisinmaksun. Sopimusten käyttö luottoriskin suojauskeinona on kasvanut tasaisesti 2000-luvulla. Kolme suurinta luottoluokituslaitosta ovat Standard & Poor's (S&P), Moody's ja Fitch. Näiden laitosten tehtävänä on analysoida yritysten luottokelpoisuutta ja taloudellista asemaa. Laitosten rooli on kasvattanut merkitystään viime vuosina sekä globalisaation että monimutkaisten rahoitusinstrumenttien ja rahoitusalan sääntelyn johdosta.

Luottoriskijohdannaisen hinnan ja luottoluokituksen välinen suhde on käänteinen. Mitä korkeampi luottoluokitus, sitä matalampi on johdannaisen odotettu hinta ja toisinpäin. Luottoriskijohdannaismarkkinan korkean volatiliteetin ja luottoluokituslaitosten merkittävän maineen johdosta luottoriskijohdannaisen hinnan ja luottoluokitustapahtumien välistä suhdetta on mielekästä tutkia, sillä tutkimuksen tarkoituksena on paljastaa ajankohtaista tietoa riskienhallinnan käyttöön. Tutkimalla luottoluokitustapahtumien vaikutusta luottoriskijohdannaismarkkinaan saadaan lisäksi vastauksia siihen, onko kyseinen markkina tehokas perustuen tehokkaiden markkinoiden hypoteesiin. Tässä tutkimuksessa luottoluokitusdata on kerätty FitchConnect -tietokannasta ja data koostuu 110:sta luottoluokituksen laskusta ja 144:sta luokituksen parantamisesta. Luottoriskijohdannaisdata on kerätty aikasarjana Thomson Reuters Datastream -tietokannasta ja koostuu 333 274:a päivittäisestä hintanoteerauksesta. Tutkimusmenetelmänä käytetään tapahtumatutkimusta.

Tutkimuksen tuloksina luottoriskijohdannaismarkkinan nähdään reagoivan merkittävästi luottoluokitusta parantaviin, mutta ei laskemiseen johtaviin tapahtumiin. Markkinan nähdään myös ennakoivan luottoluokista parantavia, mutta ei laskevia tapahtumia. Lisäksi tulokset osoittavat, että S&P 500-yritysten välillä kilpailijoiden luottoriskijohdannaisten hinnat vaihtelevat sekä ennen luokitustapahtumaa että sen aikana, niin luokitusta laskevien kuin parantavien tapahtumien kohdalla. Tulokset kuitenkin osoittavat, että luottoriskijohdannaismarkkina on segmentoitunut, sillä markkinareaktio vaihtelee merkittävästi eri S&P 500-toimialojen välillä.

AVAINSANAT: S&P 500, Derivatives, Credit rating, Spillover effect, Event study

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Abbreviations

ARCDS	abnormal CDS spread change
BIS	Bank for International settlements
CASC	cumulative abnormal CDS spread change
CBOT	Chicago board of trade
CDS	credit default swap
CME	Chicago mercantile exchange
CRA	credit rating agency
EMH	efficient market hypothesis
FV	face value
GICS	Global industry classification standard
ISDA	International swaps and derivatives association
MV	market value
OTC	over-the-counter
PV	present value
RICDS	CDS spread change of rating-class based index
S&P	Standard & Poor's
US	United States
YTM	yield to maturity
ZCB	zero-coupon bond

1 Introduction

Credit default swap (CDS) is an interesting instrument and subject in empirical research. According to Wengner et al. (2015), CDS is like an insurance contract that protects the buyer of the contract if a reference entity, that is the issuer of a bond, defaults on a bond. Hull et al. (2004) suggest that CDS spread is a direct price of a firm's credit risk. CDS spreads are already credit spreads without any adjustments and assumptions for suitable benchmark risk-free interest rates. In the case of bond yields, the assumption is required. Then, the CDS market provides a better measure for companies' creditworthiness than the bond market. Generally, the higher a CDS spread, the higher is the expectation that an entity will default.

Due to globalization and international trade funding, liquidity, and credit quality concerns have become more important than before. Hence, the use of credit derivatives as a hedging instrument for credit risk has grown steadily during the 21st century. According to the database of Bank for International Settlements, BIS (2021), the notional amount of CDS contracts was about $10 trillion at the end of 2004, $30 trillion at the end of 2006, and at the beginning of the financial crisis of 2007 the market has grown up to $60 trillion. During and after the financial crisis, the value of CDS contracts started to decrease and continued until the end of 2019. After that, the value of contracts has started to increase slightly again and is now approximately $10 trillion.

Three major credit rating agencies (CRAs) are Standard & Poor's (S&P), Moody's, and Fitch (White, 2009). According to Bannier and Hirsch (2010, p. 3037), CRAs provide statements and analysis on the creditworthiness and financial status of companies using quantitative models, such as financial statements, and qualitative models, such as management interviews, for surveying the credit risk of a company. These major CRAs have invested capital in front of billions of dollars, and they have a significant role in the financial markets. Bannier and Hirsch also state that the role of CRAs has become more significant in recent years not only due to globalization but also due to the complexity of financial products and financial regulation.

According to Rhee (2015, pp. 162-165), the reason for the existence of the CRAs is typically divided into two standard theories. First, CRAs exist because they make the information of creditworthiness symmetrical between investors and issuers. CRAs correct this so-called “lemon problem”, where high-quality borrowers will be driven out of the credit market (Akerlof, 1978), by providing independent information on the creditworthiness of issuers. The second theory, regulatory license theory, states that CRAs regulate investments by financial institutions, and the reason for their existence is based on the ability to reduce the costs of regulation by deducting the workload of investors and regulators that would analyze investments.

To criticize these theories, Rhee (2015) argues that there is always a degree of information asymmetry. Also, Rhee states that the CRAs do not exist merely based on the regulatory license theory. Hence, Rhee provides an alternative approach, and the paper concludes that CRAs have a public role in the credit market as they relieve the investment process and make the market more efficient and liquid.

Before 1934, the business model by these three major CRAs was originally the so-called “investor pays” model. In this model, an investor was buying information from CRAs. However, during the 1970s, the business model changed to an “issuer pays” model, where an issuer paid the CRA to rate its credit quality. (White, 2009, pp. 390-392.)

White (2009, p. 392) states that there are several reasons (or opinions) of why the model has changed. First, the CRAs thought that they will lose their income because if the investor paid for the rate, the other investor may have a free ride by replicating the rate without paying to CRA. Second, the bankruptcy in 1970 shocked the market and forced issuers to understand the importance of the bond rates, so they were ready to pay for the rates. Third, as CRAs noticed that issuers were ready to pay for the rates after the crisis, they changed the business model. Fourth and the final opinion is that because the bond rating business is a two-sided market, the payments can flow in from issuers, from investors, or some mix of these two.

Furthermore, according to White (2009), the change in the business model led to a situation in which issuers will choose a CRA that has the most optimistic estimate for creditworthiness. Thus, due to the fee structure of the CRAs, the complexity of the bonds, defective data, sloppiness, and pressure, the reputation of the CRAs suffered during the financial crisis that began in 2007. They played a central role as subprime mortgage-backed bonds were so highly rated and hence largely issued. As a result, the rating industry became more regulated. According to Rhee (2015, pp. 161-162), the Credit Rating Agency Reform Act of 2006, and the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 are the two major acts of the industry regulation. Rhee also argues that CRAs may be regulated even more in the future.

The relationship between CDS spread and credit rating is inverse. The higher the rating, the lower is the expected CDS spread and vice versa (Wengner et al., 2015, p. 82). Currently, due to the high volatility of the CDS market and the significant reputation of CRAs, studying the behavior of the CDS market around the ratings is a topical subject especially after the time of the financial crisis.

Furthermore, investigating the effects of rating events on the CDS market reveals whether the CDS market is efficient or not. The efficient market hypothesis (EMH) is based on an efficient market in which all available information is available to all market participants and in such a market the prices of instruments reflect all the information (Fama, 1970). Based on EMH, if CDS market prices and the rating decisions by agencies were grounded on the same information the market should anticipate the ratings. Prices react lastingly to the updated news, whereas ratings lag the CDS market. This means also that the CDS prices are more volatile indicators. However, Hull et al. (2004) state that CRAs use many different sources for their decisions meaning that they use not only public information but also unpublished sources. Then, if the ratings deliver useful and pricing relevant information to the market, the CDS market should price this information just after the announcement. This phenomenon is the so-called announcement day effect.

1.1 Purpose, hypotheses, and motivation of the study

The purpose of this thesis is to examine on an industry level whether the credit rating announcements impact S&P 500 firms' CDS spreads. Furthermore, the study examines whether the competitors profit or suffer from the event firm's rating announcements. Thus, this thesis follows Wengner et al. (2015).

First, according to Wengner et al. (2015, p. 81), firms use to hide negative news and release positive news. Based on EMH, this leads to the situation in which downgrades reveal new information to the CDS market as the information has not reached the market yet, whereas market prices already contain the information in the case of upgrades. Plenty of prior studies show that the CDS market reacts abnormally to rating announcements around the event day (Daniels & Jensen, 2005; Drago & Gallo, 2016; Finnerty et al., 2013; Galil & Soffer, 2011; Hull et al., 2004; Imbierowicz & Wahrenburg, 2009; Micu et al., 2006; Norden & Weber, 2004; Raimbourg & Salvadè, 2020). According to these studies analyzed in Section 2, it seems that the negative events draw a greater impact in the CDS market than the positive events. Hence, Hypothesis 1 (H1) is formulated as follows:

H1. The CDS spreads of S&P 500 firms increase significantly around downgrades, whereas a decrease in CDS spreads is insignificant around upgrades.

Second, according to Wengner et al. (2015), as the firms have the interest to reveal positive news as mentioned, the market already prices this information beforehand and hence anticipates upgrades. Hence, the Hypothesis 2 (H2) in my thesis will be as follows:

H2. The CDS market anticipates upgrades, but not downgrades.

Third, according to Daniels and Jensen (2005), the CDS market is segmented among industries. The findings by Wengner et al. (2015) support this statement. They find that there are heterogeneous market reactions to downgrades and upgrades across industries. Thus, it is important to study the effects of credit rating announcements on CDS spreads at the industry level also among S&P 500 firms. Hence, the Hypothesis 3 (H3) in my thesis will be as follows:

H3. CDS market reactions to credit rating events are heterogeneous across S&P 500 firm industries.

Finally, since we still assume that a firm's CDS spread and credit rating has an inverse relationship and we know about the prior studies that rating events contain new information, this means that competitors (non-event firms) may profit from event firm's downgrade in terms of decreasing CDS spreads. On the other hand, the competitors may suffer from event firm's upgrade in terms of increasing CDS spreads. There is just fractionally empirical evidence that the spillover effects are significant in the CDS market. Ismailescu and Kazemi (2010) find that this effect is significant for sovereign rating announcements. Wengner et al. (2015) find that the spillover effects are observable also for the global firms. This finding by Wengner et al. motivates to study whether the spillover effects are observable for S&P 500 firms as well. I assume that S&P 500 non-event firms in the same industry are competitors of the S&P 500 event firm. Now, according to findings by Wengner et al. discussed in Table 2, the Hypothesis 4 (H4) in my thesis will be as follows:

H4. Competitors profit (suffer) from downgrades (upgrades) of S&P 500 event firm in terms of decreasing (increasing) CDS spreads.

This thesis contributes to the prior literature in several ways. First, as the study period by Wengner et al. (2015) includes the time frame of financial imbalance due to the financial crisis of 2007-2009, it is important to study these effects outside the crisis period. Wengner et al. state that the spillover effect has even been more distinct since the financial crisis. Thus, this thesis includes the period between 2010-2018. Second, as the data set by Wengner et al. includes firms globally and do not focus on some specific market, this paper uses S&P 500 firms. These firms draw significant market share in the United States. Third, as Wengner et al. study the spillover effects only at the time of the announcement, my thesis also studies whether the information in CDS spreads spills over to the CDS spreads of competitors already 30 days before the announcement. Thus, to the best of my knowledge, this is the first paper to analyze the impact of S&P 500 firms' rating events on CDS spreads and spillover effects on competitors at the industry level before and at the time of announcement. The prior studies are introduced more carefully in the next section.

1.2 Structure of the study

In Section 2, this thesis analyzes the prior literature regarding the relationship between credit rating events and the CDS market. Section 3 discusses the theoretical background about bonds, the credit risks of bonds, and the credit rating process. The credit rating process part analyzes how do the CRAs make rating decisions, whereas in the Introduction part the reasons for the existence of CRAs and their history are handled. Section 4 presents a more specific analysis of CDS. The risk regarding CDS contracts, counterparty credit risk, is analyzed, and the CDS market, pricing, and CDS-bond basis as a definition are handled carefully. Section 5 presents data and methodologies used in this thesis. Section 6 is the empirical part, in which the results of this paper are presented and analyzed. Section 7 concludes.

2 Literature on the relationship between credit ratings and CDS market

This part of the paper analyzes the prior studies. First, the most prior studies (Daniels & Jensen, 2005; Finnerty et al., 2013; Galil & Soffer, 2011; Hull et al., 2004; Imbierowicz & Wahrenburg, 2009; Micu et al., 2006; Norden & Weber, 2004) study a corporate CDS market and its reactions to rating events. Second, the paper by Wengner et al. (2015) is the first study that also investigates the spillover effects in CDS spreads. Third, it is reasonable to analyze the papers by Drago and Gallo (2016), and Raimbourg and Salvadè (2020) since they investigate the spillover effect on the country level (sovereign ratings). Table 1 shows the basic information of the prior studies. It also presents the data and methodology used in these studies. At the end of this Section, Table 2 presents the main findings of the studies.

Table 1. Overview of the previous studies.

Year	Author(s)	Data	Methodology
2004	Hull, Predescu & White	Rating data: Moody's CDS maturity 5 years	Event study Event period 1998-2002
2004	Norden & Weber	Rating data: S&P and Moody's CDS maturity 5 years	Event study Event period 2000-2002
2005	Daniels & Jensen	Rating data: S&P CDS maturity 5 years	Event study Event period 2000-2002
2006	Micu, Remolona, & Wooldridge	Rating data: S&P, Moody's, and Fitch CDS maturity 5 years	Event study Event period 2001-2005
2009	Imbierowicz & Wahrenburg	Rating data: Moody's CDS maturity 5 years	Event study Event period 2001-2007
2011	Galil & Soffer	Rating data: S&P and Moody's CDS maturity 5 years	Event study Event period 2002-2006
2013	Finnerty, Miller, & Chen	Rating data: S&P CDS maturity 5 years	Event study Event period 2001-2009
2015	Wengner, Burghof & Schneider	Rating data: S&P CDS maturity 5 years	Event study Event period 2004-2011
2016	Drago & Gallo	Rating data: S&P CDS maturity 5 years	Event study Event period 2004-2015
2020	Raimbourg & Salvadè	Rating data: S&P, Moody's, and Fitch CDS maturity 5 years	Event study Event period 2008-2013

Hull et al. (2004) study the relationship between CDS markets, bond yields, and credit rating announcements. They first examine the relationship between CDS spreads and bond yields. Second, they examine whether the CDS market anticipates rating events and reacts abnormally to the events around them. They use firms from the United States (US) and rating data from Moody's. The event period is 1998-2002. As a methodology, they use event study analysis, or in particular, constant-mean-model to test the relationship between CDS spreads and rating events.

From the first part, they find that the CDS market leads the bond market. Hence, the prices are more sensitive to change in the CDS market than in the bond market. From the second part of the paper, they find that the CDS market anticipates all three types of negative events. The CDS spreads increase abnormally already 90 days before the event and the strength of an increase depends on the type of announcement. The spreads increase significantly 90-30 days before a downgrade and 30-1 days before a review or outlook. They also find that increase in CDS spreads is abnormal still around negative reviews. The announcement period starts one day before the event and ends one day after the event. However, this finding does not apply in the case of downgrade meaning that the CDS price conclude all the practical information already.

The results of positive events are less significant. Hull et al. (2004) show that CDS spreads change only slightly abnormally or the change is normal before, around, and after the positive rating events. There are at least two possible reasons for these results. First, CRAs focus more on negative than positive news. Second, the number of positive events is too small in this study to get significant results.

Norden and Weber (2004) study the stock market and CDS market reactions to the rating announcements. They use rating data from S&P and Moody's and the event period is 2000-2002. They use global firms in their sample and as a methodology, they use an event study method. With this method, they examine whether and how strongly the stock market and the CDS market react to rating events in terms of abnormal returns and adjusted CDS spread changes.

Similar to Hull et al. (2004), Norden and Weber (2004) find that CDS market anticipate the negative rating events. However, they find that the reaction of CDS spread changes is larger for reviews than for downgrades. They also show that the geographical origin of a firm partly explains the strength of the change in CDS spread before the events. European firms' CDS spreads anticipate the negative events stronger than the US firms. Norden and Weber also find that the level of old rating, as well as the number of previous rating events, significantly affect the strength of the reaction in CDS spread change before the event.

Similar to Hull et al. (2004), Norden and Weber (2004) also find that increase in CDS spreads is abnormal still around the negative events. However, likewise Hull et al., they find that CDS spreads react abnormally not only around a review but also around an actual downgrade. Hence, downgrade reveals new information to the CDS market. However, the changes in CDS spreads are insignificant before, around, and after the positive rating events. This finding is in line with the finding by Hull et al.

Daniels and Jensen (2005) study the relationship between bond credit spreads and CDS spreads, and how these spreads react to changes in credit ratings. More specifically, they study whether the strength of the announcement effect to CDS spreads depends on the volatility of the reference firm. They also study whether the size of the rating change (for example the change of one versus two rating classes) explains how strong the CDS market reaction is. The rating data is collected from S&P and the event period is 2000-2002. All the reference entities are companies from the US. They use the constant-mean-model to test whether a change in credit rating impacts credit spreads and CDS spreads.

Such as Hull et al. (2004), Daniels and Jensen (2005) find that the CDS market leads the bond market. Second, the findings by Daniels and Jensen are in line with Hull et al. and

Norden and Weber (2004) that the CDS spreads change abnormally well in advance before the downgrade. It is, however, noteworthy that Daniels and Jensen study only the actual downgrades excluding the other announcement types from their sample. They also find that the downgrades cause abnormal CDS spread changes still around the event day period. This finding is in line with the finding by Norden and Weber.

Daniels and Jensen (2005) also find that the impact in CDS spread changes is more significant for lower-rated event firms than for higher-rated event firms around the downgrade, so the effect of a downgrade on CDS spreads is larger for volatile, non-investment grade firms. The effect of downgrades on the CDS spreads of the BBB-rated firms is insignificant. They also find that a downgrade of two rating classes has a larger impact on CDS spread changes than a downgrade of only one credit rating. This is reasonable because the change of two classes instead of one class might be more surprising and hence the reaction of the market is more intensive. However, the changes in CDS spreads are insignificant before, around, and after the positive rating events. This finding is in line with the findings by Hull et al. (2004) and Norden and Weber (2004).

Micu et al. (2006) study the effects of rating events on CDS spreads by including all the announcement types – outlooks, reviews, and actual rating changes – in their paper. They also study the effects of split ratings on CDS spreads, that is, the relationship between firms with different ratings from different agencies. They use ratings from S&P, Moody's, and Fitch and event period 2001-2005. The reference entities are financial institutions and other corporations mostly from the US. As a methodology, they use event study.

According to findings by Micu et al. (2006), the results of the abnormal changes in CDS spreads before the negative events are in line with the abovementioned studies. They find that the CDS spreads change abnormally well in advance before the negative events and the reaction is larger for reviews than for the actual downgrades. Micu et al. also find that the change in CDS spreads around all types of negative events is abnormal. This finding of the announcement day effect implies that the corporate credit rating process might have improved since 2003, that is, since the end of the sample period in the studies by Hull et al. (2004), and Norden and Weber (2004) analyzed above. Finnerty et al. (2013) suggest that the CRAs react faster to the changes in creditworthiness, and before it is fully priced by the CDS market. Then, this finding by Micu et al. indicate that the CDS market value new information twice around the events, because all the event types contain useful information. First, the timely signal is priced during the review or outlook, and secondly, the stable signal is priced during the actual downgrade.

Micu et al. (2006) also find that the change in CDS spreads is the most significant for BBB-rated firms around the negative events. This is interesting finding as Daniels and Jensen (2005) find in turn that the effect of downgrades on CDS spreads for BBB-rated firms is insignificant. However, the finding by Micu et al. advocates that BBB-rated firms have a large pressure in their CDS prices since they are already so close to speculative, or non-investment grade, so the negative event is significant. On the other hand, the explanation for the finding by Daniels and Jensen that the changes in CDS spreads are not abnormal for BBB-rated firms might be that because the BBB-rated firms are already near to speculative grade, the expectations regarding to their creditworthiness are not as significant as the expectations for the firms in the higher rating classes. The final finding regarding to the negative events by Micu et al. is that the CDS spreads change abnormally also after the negative reviews and outlooks. The spreads increase during the 2–20 days afterwards.

Micu et al. (2006) is the first paper in this literature review that find the abnormal changes in CDS spreads before all types of positive events. One explanation of this finding compared with the prior studies might be that the dataset by Micu et al. contains a larger proportion of positive events. The changes in CDS spreads before the positive events are of the same magnitude as in the case of negative events, still depending on the event type.

Micu et al. (2006) find that the CDS spreads change abnormally still around the positive events. Micu et al. and Finnerty et al. (2013) also find that the CDS spreads around the upgrade change the most abnormally for the firms in lower rating classes, especially in BB rating class. These results are reasonable, because there are not as much expectations for the creditworthiness of the firms in lower rating classes than the expectations for the higher rated firms, and hence the lower rating is arduous for the companies to upgrade. Then, the upgrade cause abnormal changes in CDS spreads for these companies since it is surprising. The final finding regarding to the positive events by Micu et al. is that the CDS spreads change abnormally also after the positive reviews and outlooks. The spreads decrease during the 2–20 days afterwards.

Imbierowicz and Wahrenburg (2009) study the reasons for the rating events measuring which reason for the rating announcement causes abnormal changes in CDS spreads. The reasons are divided into five groups: operating performance, capital structure, financial metrics, event risk and new methodology. Imbierowicz and Wahrenburg use ratings from Moody's and event period 2001-2007. All the reference entities are firms mostly from North America and Europe. As a methodology, they use event study to find abnormal CDS spread changes.

The findings by Imbierowicz and Wahrenburg (2009) about the ability of the CDS market to anticipate the negative events are in line with the above-mentioned studies as they find that the CDS spreads change abnormally well in advance before the reviews and downgrades. They study the impact of reasons for the rating events by dividing them into the five groups based on the rating reports by Moody's where the reason is defined as a factor for a rating event. Imbierowicz and Wahrenburg find that the negative events resulting from the changes in firms' operating performance cause the most significant changes in CDS spreads already before the announcement day. This finding supports the theory of market efficiency since most of the firms are enforced to publish the changes in their operations immediately. Then, the result shows that this public information is priced in the CDS market already before the event.

Imbierowicz and Wahrenburg (2009) also widen the findings that in addition to the changes in the operating performance of firms, most of the other reasons for the event contain relevant information since the CDS market reacts to the events still around the event. Especially, the event risk and the capital structure are reasons for the reviews for downgrade and these reasons cause the event day effect in the CDS market. Hence, when these reasons cause the negative event, the CRAs may add useable information to the CDS market. Finally, hence the paper finds that CDS spread change abnormally not only before but also still around the negative event resulted from the changes in a firm's operating performance, this argues the importance of this reason for investors. The CDS market price the changes in operating performance already before the event due to information is public, but the event still causes significant reaction in the CDS market. However, Imbierowicz and Wahrenburg (2009) do not find abnormal effects in the CDS market around the upgrades or reviews for upgrade. This finding is noteworthy since the positive events cover more than 42% of all events in their dataset.

Galil and Soffer (2011) explore the research of the CDS market and rating events as they investigate whether the rating events can be clustered. They study how the sample of events followed by events by other CRAs differs from the sample of uncontaminated events. The uncontaminated events are independent as they are not followed by events by any CRA 90 days before and after the event. Galil and Soffer use ratings from S&P and Moody's, and event period 2002-2006. All the entities in the sample are international firms. As a methodology, they use event study analysis calculating the abnormal CDS spread changes and cumulative abnormal CDS spread changes.

Generally, the results are similar to the prior studies that the CDS market reacts more sensitively to bad news than good news. Moreover, they find that the CDS spreads increase still during the 2–10 days after negative reviews. These findings reflect the market underreaction on the negative reviews as the CDS spreads keep increasing still afterwards. Yet, Galil and Soffer find the market overreaction for actual downgrades as CDS spreads change into a downturn during the 10 days post-event period. This means that the CDS spread has increased over its expected value before or around the downgrade. They also find that the spreads decrease still during the 2–10 days after the upgrade and positive reviews. These findings reflect the market underreaction to positive events.

Contributing the prior studies, Galil and Soffer (2011) find that the negative rating announcements tend to cluster. This, for its part, explains the strength of the reaction of CDS market to the negative events. For example, increase in CDS spread around the downgrade is 2.57 bps averagely in the uncontaminated sample, whereas it is even 5.57 bps in the sample in which the events are clustered. Hence, the uncontaminated negative events are underestimated in the CDS market because the market reaction is stronger when the announcement has clustered. This finding also advocates for the market overreaction towards clustered events.

They find that the positive rating events tend to cluster as well. The sample of clustered events shows that the effects are even more significant compared to previous samples. For example, the average increase of CDS spread around the upgrade is –1.53 bps in the uncontaminated sample, while it is as much as –2.62 bps in the sample in which the events are clustered. Hence, again, it seems that the market reaction is stronger when a rating event is clustered.

Finnerty et al. (2013) incorporate clearly larger sample in their study compared to prior studies. The paper also expands the tests by Hull et al. (2004) by testing the probabilities of negative rating events predicted by the changes in CDS spreads for non-investment grade credits also. Hull et al. test the probabilities for investment grade credits. Finnerty et al. use rating data from S&P and event period 2001-2009. All the reference entities are global firms. They use an event study as a method to test abnormal changes in CDS spreads.

Finnerty et al. (2013) find that the CDS spreads change abnormally before the negative events. As mentioned, they test for non-investment grade credits whether the CDS spread changes predict the negative rating events and find that the changes in CDS spreads deliver useful information. Nevertheless, the rating change more often for the companies whose credit rating has changed during the short pass. This phenomenon is also called as ratings momentum (Hull et al., 2004).

Finnerty et al. (2013) find in their paper, that in addition of reviews for downgrade, also actual downgrades and negative outlooks cause abnormal changes in CDS spreads at the time of these events. These findings imply that the corporate credit rating process may have consolidated since 2003 – the end of the sample period in the studies by Hull et al. (2004) and Norden and Weber (2004) analyzed above – so CRAs may respond more quickly to credit changes before it is priced in the CDS market (Finnerty et al., 2013). This statement is reasonable because Hull et al. and Norden and Weber do not find that downgrades and outlooks have impact on CDS spreads around these events. According to findings by Micu et al. (2006), also these findings by Finnerty et al. indicate that an investor value new information twice in CDS spreads, because all the event types includes relevant data. First, the timely signal is priced during the review or outlook and second, the stable signal is priced around the actual downgrade.

Finnerty et al. (2013) find that the CDS market is being able to anticipate positive events as well as the CDS spreads change abnormally 30 days before the upgrades. They find the announcement day effect in the CDS market around all types of events, so this result is in line with Micu et al. (2006). Micu et al. and Finnerty et al. also find that the reaction in CDS spreads around the upgrade are the most significant for low rating groups.

Wengner et al. (2015) contribute the prior literature by incorporating the CDS spread spillover effects from event firm to non-event firm in their paper. They study whether the rating event cause abnormal changes not only in the CDS spread of the event firm, but also in spreads of the competitors operating in the same sector. This is the first paper studying the corporate spillover effects. They use rating data from S&P and event period 2004-2011. They investigate global firms around the world. The topic and methods they use will be closely followed in my Master's Thesis. They use an event study method to calculate the abnormal returns for CDS spreads of each firm. They use two different models for the event stud First, they run a rating-class based model, and second, they use an index model as a robustness check.

Wengner et al. (2015) find that the CDS market anticipates downgrades. They find that the CDS spreads change abnormally during the 2-day event period around the downgrades. This result is for the total sample. They also study the spillover effects from event firm to non-event competitor firms around the downgrade. The study finds that there is evidence for a positive competitive effect around the downgrades in all industries in the sample. This means that competitors' CDS spreads reduce around the downgrade of an event firm.

Wengner et al. (2015) do not find abnormal changes in CDS spreads before the upgrades. However, as around the downgrades, they find that the changes in CDS spreads are abnormal during the 2-day event period around the upgrades. This result is for the total sample. They also study the spillover effects from event firm to non-event competitor firms around the upgrade. The study finds that there is evidence for a negative competitive effect around the upgrades in all industries in the sample. This means that competitors' CDS spreads increase around the upgrade of an event firm.

Some papers also study the relationship between the rating events and sovereign CDS market and the spillover effects between the countries. Next, two studies about the relationship of the sovereign CDS market and rating events considering the spillover effects are handled shortly.

Drago and Gallo (2016) study the impact of a sovereign rating announcement on the euro area CDS market. They use rating data from S&P and the event period 2004-2015. As a methodology, they use an event study. They find that both, downgrades, and upgrades, affect the CDS market. However, according to their paper, it seems that the CDS spreads do not change abnormally around the outlook or review announcements. They also study the spillover effects from the event country to the CDS spreads of the other euro countries. They find that only downgrade event causes spillover effect and the size of this effect depends on the economic and financial conditions of the analyzed euro countries.

Raimbourg and Salvadè (2020) study the CDS spread and volatility changes around the European sovereign rating events. They find remarkable results for the CDS volatility. The rating events are well-anticipated by the CDS market in investment-grade countries. However, an event still affect the CDS market around the event day as it decreases the CDS volatility and helps to stabilize the market. However, the rating announcements are not anticipated by investors for speculative-grade countries and the event leads to an increase in CDS volatility meaning that the rating actions worsen the market stability in more stressful times. Raimbourg and Salvadè also find the spillover effect to German CDS spread and volatility around the rating event of another euro country.

Table 2. The main findings of the previous studies.

Year	Author(s)	The main findings
2004	Hull, Predescu & White	CDS market leads bond market. CDS market anticipates negative rating events.
2004	Norden & Weber	CDS spreads change abnormally before and around the negative rating event.
2005	Daniels & Jensen	CDS spreads change abnormally before and around the negative rating event.
2006	Micu, Remolona, & Wooldridge	CDS spreads change abnormally before, around, and after the negative and positive rating events.
2009	Imbierowicz & Wahrenburg	CDS spreads change abnormally before and around the negative rating event. Strength of the reaction depends on the reason for the event.
2011	Galil & Soffer	CDS spreads change abnormally before, around, and after the negative and positive rating events. Negative rating events are clustered.
2013	Finnerty, Miller, & Chen	CDS spreads change abnormally before and around the negative and positive rating events.
2015	Wengner, Burghof & Schneider	CDS spreads change abnormally around the negative and positive rating events. The market reaction spills over as the competitors profit (suffer) from the downgrade (upgrade) of the event firm.
2016	Drago & Gallo	CDS spreads change abnormally around the downgrades and upgrades. Downgrade causes spillover effect.
2020	Raimbourg & Salvadè	*Investment grade countries:* CDS spreads change abnormally before and around the rating events. *Speculative grade countries:* CDS market reacts at the time of announcement. German CDS spread reacts abnormally around the rating event for another Euro area country (spillover effect).

3 Bonds and credit rating

A bond is tradable security, where a bond issuer (or borrower) sells the bond to raise money from an investor (or lender) today and pays the money back in the future. The bond market includes treasury notes and bonds, corporate bonds, mortgage securities, federal agency debt, and municipal bonds. There are some unique characteristics for all bond varieties. (Berk et al., 2015, p. 184; Bodie et al., 2014, p. 34.)

The common features of a bond are performed on a table below.

Table 3. Bond features.

Bond certificate	Terms of a bond, dates and amounts of payments.
Face value	Also par value or principal, usually repaid on the maturity date.
Maturity	The end of the life of a bond.
Time value	As time passes, price of a bond increases.
Coupons	Interest payments which is a percentage of borrowed principal set by the issuer, usually semiannually payments.
Duration	Sensitivity of a bond price to a change in interest rates.
Convexity	How the duration of a bond changes as the interest rate changes.
Bond rating	Creditworthiness of a bond.

Calculating the price of a bond is based on its present value. The risk-free interest rate includes a risk-free rate of return and a premium above the real rate against expected inflation. Due to the time value of the money, a price *P* of a bond increases as time passes. Yield to maturity *YTM* sets a present value of a bond at the same level as its current market price. As time passes, price approaches the face value *FV* (Berk et al., 2015, pp. 186–187). Berk et al. determine the price of a zero-coupon bond (ZCB) as below:

$$P = \frac{FV}{(1+YTM_n)^n}. \tag{1}$$

Bodie et al. (2014, pp. 452-453) show that if there is one interest rate *r* that discounts cash flows of any maturity, and the coupons *C* paid are equal until the end of maturity *T*, the price of a bond can be written as follow:

$$P = C\ x\ \frac{1}{r}\left[1 - \frac{1}{(1+r)^T}\right] + FV\ x\ \frac{1}{(1+r)^T}\ , \tag{2}$$

where the first term $C\ x\ \frac{1}{r}\left[1 - \frac{1}{(1+r)^T}\right]$ on the right-hand side is annuity factor and the second term $FV\ x\ \frac{1}{(1+r)^T}$ is present value factor.

According to Bodie et al. (2014), an increase in interest rate leads to a decrease in the market price of the bond. The higher the interest rate is, the riskier is the bond. Hence, there is an inverse relationship between bond price and its yield. The sensitivity of a bond price to a change in interest rate is called duration. For example, if the duration of a bond is 5 and the interest rates increase by 1%, the bond's price will drop by about 5%. Likewise, if interest rates drop by 1%, the bond's price will increase by about 5%.

Convexity means how the duration of a bond changes as the interest rate changes. The form of the curve in Figure 1 reflects the convexity of the bond prices in different levels of interest rate. For instance, an increase from 1% to 2% in interest rate leads to a radical decrease in bond price but a decrease in bond price is much more moderate when the interest rate increase from 10% to 11%. (Bodie et al., 2014.)

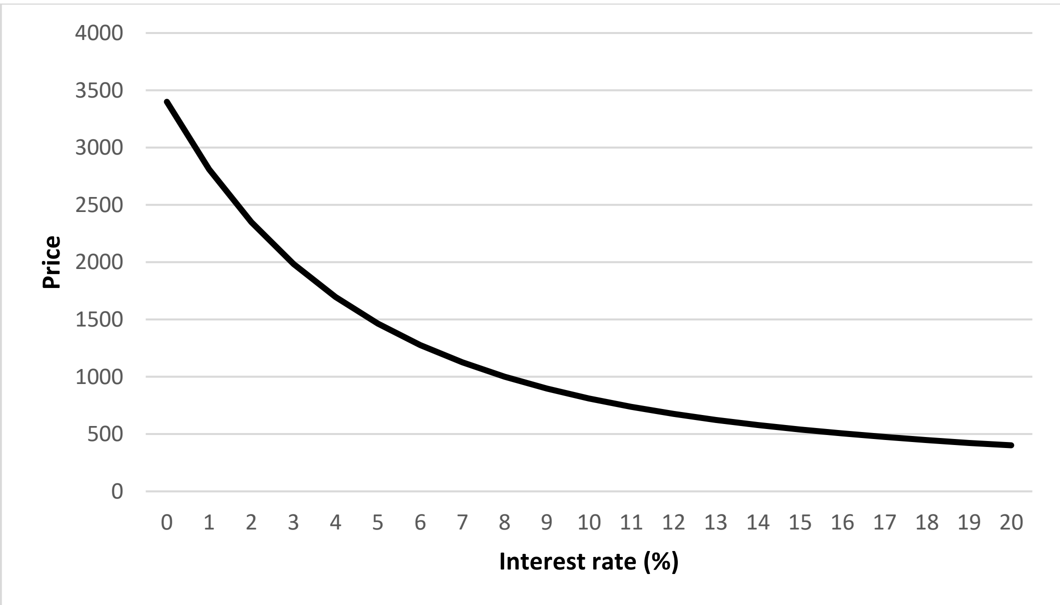

Figure 1. The inverse relationship between bond price and interest rate.

3.1 Credit risks

Once a lender has lent the money to a bond issuer, the loan is not riskless, and the level of risk is defined by different measures. Investigating the financial statements of a borrower and monitoring its solvency, those who lend money tend to seek the information of a bond issuer also from outside sources. The creditworthiness of bonds is measured by CRAs, and this paper will focus on the three major CRAs; Standard & Poor´s (S&P), Moody´s, and Fitch. According to White (2010), S&P and Moody’s are the biggest CRAs, and the rating operations of Fitch are slightly smaller. S&P and Moody’s rate more corporate bonds than Fitch.

Anson et al. (2004, pp. 5-6) suggest three types of credit risks for bonds. *Default risk* is the risk in which an issuer of a bond is not able to repay its debt according to the terms of an obligation. This risk is measured by the CRAs. According to Hull et al. (2005), the default risk can be divided into real-world default probability and risk-neutral default probability, depending on how the risk is defined. The formerly mentioned risk is calculated from the issuer’s historical data and the latter mentioned is calculated from bond prices. Generally, risk-neutral probabilities of default are larger than real-world default probabilities. *Downgrade risk* is the risk in which a CRA decreases its rating for a bond issuer as its risk of default has increased. In other words, the issuer’s credit quality has changed. The CRAs monitor the issuer continuously to react to the changes in the creditworthiness of the firm. *Credit spread risk* grows when the difference between a bond’s interest and risk-free interest increases. This is usually the reaction of financial markets to the rating actions by CRAs. (Anson et al., 2004, pp. 5-6.)

The credit risk of a bond can be hedged with different types of credit derivatives. The purpose of the credit derivatives is to share a risk of an underlying bond between the market participants. This paper focuses on the credit default swap (CDS) because it is a widely used derivative to protect against the default of a corporate bond. (Hull, 2015, pp. 571-574.)

The characteristics of CDS are analyzed in Chapter 4. Next, the paper will discuss about the credit rating process of CRAs.

3.2 Credit rating process

CRAs rates the sovereign and corporate bonds with signs that represent creditworthiness. This paper will focus on corporate bonds. All the rates assigned by S&P and Fitch are between AAA-D and all the ratings assigned by Moody’s are between Aaa-D. In addition, S&P and Fitch exact the ratings with the plus and minus signs (e.g. AA+, AA, AA-), and Moody´s exacts the ratings with numbers 1, 2, and 3 (e.g. Aa 1, Aa 2, Aa 3). (Hull et al., 2004, p. 2790.)

To illustrate the rating symbols and definitions, Figure 2 shows the characteristics of the ratings given by the three major CRAs.

Moody´s	S&P	Fitch	Brief definition
Aaa	AAA	AAA	Highest grade
Aa	AA	AA	Very high grade
A	A	A	Upper medium grade
Baa	BBB	BBB	Lower medium grade
Ba	BB	BB	Speculative
B	B	B	Highly speculative
Caa	CCC	CCC	Extremely speculative
Ca	CC	CC	Near or in default
C	C	C	Near or in default
D	D	D	Default

Investment grade

Non-investment grade (speculative)

Figure 2. Rating symbols and definitions.

Hull et al. (2004) state that usually rates can be viewed as the creditworthiness of an issuer instead of a bond itself since it is unusual to have different ratings between two bonds issued by the same entity. Hence, when CRA rates a bond, assumingly it is meant to reflect the creditworthiness of the entity instead of the bond.

According to Micu et al. (2006), the role of the CRAs is significant while a company is issuing a bond. CRA rates the bond before it is issued. To do rating decisions, CRAs seek information from the reports and other sources, and also through management discussions. In other words, CRAs use *quantitative* and *qualitative* factors to survey the credit risk of a company.

First, according to S&P (2021) credit rating process, the *quantitative* factors are structured based on the S&P credit rating criteria. In this part, the rating analysts review the financial information of the firm, analyze industry data, economic data, and signals of the financial plans of the firm. The analysts seek information from both, public and non-public sources. Furthermore, Fitch (2019) states in their credit rating process description that they use *information analysis* and *liquidity analysis* in their quantitative model to analyze the credit risk. The *information analysis* includes quantitative metrics that measure for instance cash flow, leverage, and coverage to estimate default risk. The *liquidity analysis* focuses on the ability to create a cash reserve from the operations.

Second, according to S&P's (2021) credit rating process, *qualitative* factors such as analyzing the financial strategy of the firm and the credibility of management are generally used during the rating process. The credibility of management is measured based on the meetings with the management and is intended to find key factors that may influence the credit rating. Usually, when CRA rates a firm, the firm´s management provides more information if it is not satisfied with the rating decision and believes the rating is too low (Hillier et al., 2011, p. 42). Moreover, Fitch (2019) uses variations of qualitative factors for different industries. Commonly used factors are competitive situation, competitiveness, and trends in the industry.

At the end of the rating process, CRA typically affirms the current rating, downgrades or upgrades the rating, or sets a new rating for the firm. CRA keeps monitoring the company after the rate has been decided. Hence, besides the actual rating change, there are also different types of rating events. Hull et al. (2004) state that where downgrades and upgrades are the actual rating changes, negative and positive reviews, and outlooks are signals for possible forthcoming rating change.

Reviews are ratings for a short-term horizon. Micu et al. (2006) state that review is a strong indicator for predicting future changes in rating. A review listed company indicates that a probability is substantial to this firm to be downgraded or upgraded. According to Bannier and Hirsch (2010), CRA set a firm to review list due to some significant event. The reason for review listing is usually e.g., a share buy-back, merger announcement, or a rapid change in a company's operations or financials. Bannier and Hirsch state that CRA collects additional information about the company under review. In practice, CRA usually interacts with rating analysts and company management. S&P (2021) states that it sets a review list at least annually. Meetings with the management are periodically fixed for the firms under review and in these meetings, analysts want to discuss the changes and new plans in the company's processes and want to mirror expectations to the management plans. The rating list is typically completed after 3-6 months and resolved by either rating change or affirming the initial rating.

Outlooks reflect a medium-term rating and are generally terminated after 12-18 months (Bannier & Hirsch, 2010, p. 3037). Hull et al. (2004) divide outlooks into three different types: positive, negative, and stable. A positive outlook reflects possible grade improvement in a firm's rating, a negative outlook reflects possible grade worsening in a firm's rating and a stable outlook indicates that a firm's creditworthiness is stable.

4 Credit default swap

Section 4.1 introduces a definition of a derivative and the principles of the OTC market. Sections 4.2–4.5 handle CDS contract, CDS market, pricing of the CDS, and the CDS-Bond basis.

4.1 Derivatives and OTC market in general

Derivatives can be roughly divided into *forward contracts, future contracts, and options*. A *forward contract* is an agreement in which the contract owner has right to buy or sell an asset at a certain future time for a certain price. Trading of a forward contract occurs in the over-the-counter (OTC) market. These contracts are used to hedge against foreign currency risk. A *future contract* is like a forward contract, except it is usually traded on an exchange. *Options* are divided into a call option and a put option. A call option gives the holder the right to buy the underlying asset by a certain date for a certain price, whereas a put option gives the holder the right to sell the underlying asset by a certain date for a certain price. Options can be traded in OTC market or on exchanges. (Hull, 2015, pp. 6-9.)

OTC market is a marketplace for derivatives. The participants in the OTC markets consist mostly of banks and other financial institutions. The difference between OTC markets and exchange-traded markets is that the OTC markets are not centralized for standard forms of contracts by an exchange. Instead of that, participants in OTC markets contact each other directly and make the agreements themselves. The largest exchange-traded markets for future contracts are Chicago Board of Trade (CBOT), and Chicago Mercantile Exchange (CME). (Hull, 2015, pp. 3-9.)

However, Hull (2015, p. 574) states that after the financial crisis of 2007-2008, OTC markets have intensified reducing the market risk. The OTC markets have steered to be more like the exchange-traded markets because the regulation of OTC markets has been tighter after the crisis. For example, all the deals between the participants must be reported to a registry and the transactions are more standardized and centralized.

4.2 CDS contracts and the structure of the CDS market

A swap contract is a simple instance of a forward contract. A swap is an OTC agreement between two counterparties to exchange cash flows in the future. CDS is the simplest type of a credit derivative. It is like an insurance contract that protects the buyer of the contract (insured) if a reference entity, that is the issuer of a bond, defaults on a bond. As mentioned in Chapter 3, this is hedged by CDS. Commonly the default occurs when an issuer fails to make a payment or goes bankrupt. CDS contract typically protects the buyer the same way as the insurance contract. However, the key difference is that the insurance contract requires that the insured owns the underlying asset, whereas the bond has not to be owned by insured in the case of CDS contract. (Hull, 2015, pp. 571-574.)

Longstaff et al. (2005, pp. 2216-2217) illustrate the plain example of a CDS contract. The buyer of protection wants to insure the loan against the default of the bond issuer. The seller receives a premium periodically from the buyer until the end of the maturity or when the issuer defaults. This premium is generally noticed in basis points (bp). 100 bps is 1%. This premium is called *CDS spread*. The seller of the protection agrees to buy back the issued bond from the buyer of the protection if the issuer defaults. This is called *payoff*. To illustrate, figure 5 below shows the basic characteristics of a CDS contract.

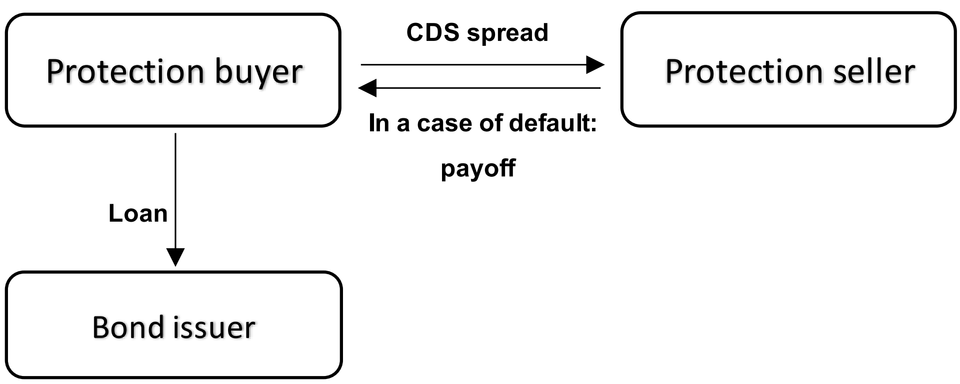

Figure 3. Basic structure of a CDS contract.

The biggest buyer party of the CDS contracts are banks and the biggest seller party of the contracts are insurance companies. CDS contracts with 5 years maturity are the most common contract type, but other maturities such as 1, 3, 7, or more are not however uncommon (Longstaff et al., 2005, pp. 2216-2217). According to BIS (2021), Figure 4 below illustrates the distribution of the CDS contracts by its maturity in USD trillions in 2010-2020.

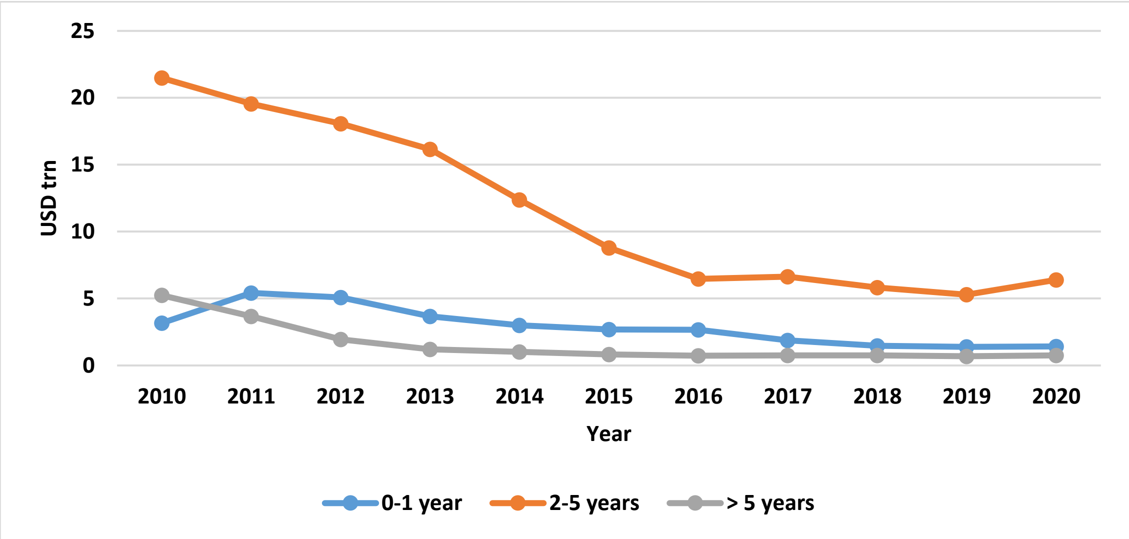

Figure 4. Distribution of the CDS contracts by its maturity in USD trillions.

Hull and White (2000, pp. 3-4) state that depending on the terms of the CDS contract, it includes *physical settlement* or *cash settlement*. If the deal requires a *physical settlement*, the buyer of protection is allowed to deliver the bond back at its face value (FV). For example, if the principal of the bond was $100 million and the issuer defaults at any time during the contract, the buyer has right to sell the bond for $100 million. In case the contract includes *cash settlement*, and the issuer defaults, the market value (MV) of the bond is considered in the payoff calculation. For example, if the MV of the bond is still $35 million out of $100 million, the payoff is $65 million. The payoff is then the FV minus MV. Also, the recovery rate is a percentage ratio between the MV and the FV, so in this case, the recovery rate is 0,35 or 35%.

Pan and Singleton (2008, pp. 2348-2350) introduce the principles of the sovereign CDS contract. The features of this type of contract are mainly the same as the contract issued by a company. The premium payments (CDS spreads) are similar to corporate CDS contracts, but usually, the contract issued by the sovereign includes only a physical settlement. It is noteworthy that a credit event or default in a sovereign contract does not mean bankruptcy, but rather reorganization of the government's cash reserve.

As mentioned at the beginning of this paper, the value of the CDS market grew radically until the financial crisis of 2007. The notional principal of CDS contracts was over $60 trillion after 2007. Since then, the value of CDS contracts has almost halved and was about $36 trillion after 2009. The steady decrease of the notional principals of global CDS contracts continued until the end of 2019. After that, the value of contracts has started to increase slightly. To illustrate, the figure below reflects the movement of the value of total CDS contracts in global OTC markets before, during, and after the financial crisis. (BIS 2021.)

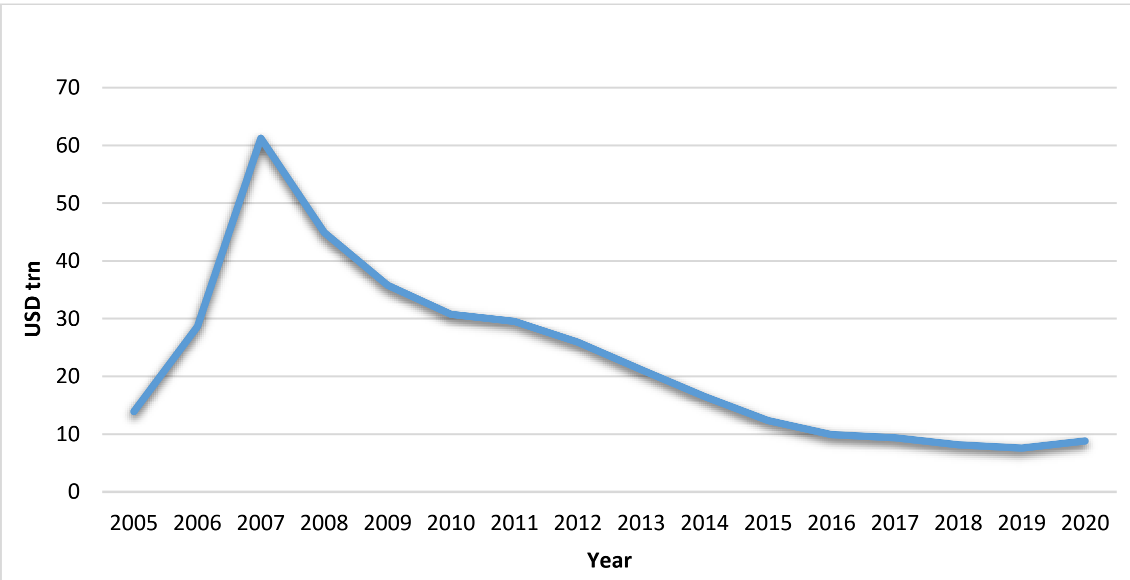

Figure 5. The notional principals of total CDS contracts in USD trillions.

4.3 Counterparty credit risk

Hull (2015, p. 555) states that derivative contracts include plenty of risks. In addition to credit risks of a bond, the derivative transactions between counterparties of the contract contain risks. The default event in transaction occurs when the counterparty fails to make a payment on a transaction or fails to deliver the collateral, which is required, or goes bankrupt.

Arora et al. (2011, p. 282) show that there are three ways how the counterparty risk may influence on a CDS contract. First, a case in which the seller counterparty drives into financial distress resulting from the bond issuer's default is possible. If the issuer defaulted on its debt, the seller of protection owes the buyer counterparty. Then, the seller may drive into financial distress and the buyer counterparty misses the receivables. Second, also a case where either counterparty of the CDS contract drives into financial distress without the default of a reference entity is possible. Then, the other counterparty experiences losses, because even the bond issuer does not default, the fair value of the CDS contract may differ from zero during the time as credit spreads develop.

Third, the counterparty may drive to significant losses through so-called collateral channel, if the other participant of the contract goes bankrupt. In a case where counterparty A delivers collaterals with counterparty B and in which counterparty B is the prime broker of counterparty A, the counterparty B may use the collaterals in the wrong way. The collaterals may intermingle with the general assets of counterparty B or this counterparty may rehypothecate the collaterals by transferring them to a third party. These were the common actors in Lehman's bankruptcy in the financial crisis.

Arora et al. (2011, pp. 282-283) suggest the ways how reducing the counterparty risk in CDS contract is possible. International Swaps and Derivatives Association (ISDA) provides frames to help the counterparties of a contract to avoid the possible losses in CDS contracts. For instance, the ISDA frameworks include standardized master agreements. Master agreement collects together all the information about the contracts between counterparties. The advantage is that the counterparties do not have to tie a new contract for each transaction, but once a master agreement is signed, all the transactions are part of it. In addition, the agreement allows to net all the contracts in the case of one or more counterparties default.

4.4 CDS pricing

The periodic premium paid to the seller for protection is called CDS spread. The magnitude of the spread depends on a default probability of a reference firm. The spread increases when the creditworthiness of a reference firm decreases (or the credit risk increases) and vice versa. Hull et al. (2004, pp. 2794-2795) suggest that a company's credit spread, that is, the yield over the risk-free rate, should equal the company's CDS spread. Hence, CDS contract usually modifies a risky corporate bond as a risk-free bond. Then, assuming no arbitrage opportunity exists in the markets, the CDS and bond markets price the credit risk equally, whereupon CDS spread (s) is a difference between the yield on a risky bond (y) and the yield on a riskless bond (r)

$$s = y - r \,. \tag{3}$$

Equation (Eq.) 5 above is the plainest formula for pricing CDS spreads. Houweling and Vorst (2005) suggest that the pricing of credit derivatives can be divided in two different models based on the prior literature. First, *the structural model* represents the idea that in case a firm defaults the value of the assets has reduced below a predesignated limit, so the model analyzes the capital structure of the firm. However, this model is complex, not merely due to problems of defining the limits but also due to changes in market value of the assets. Hence, during the volatility, it is hard to estimate the parameters. According to Meissner (2005), the structural model is based on the models by Black and Scholes (1973), and Merton (1974). Mathematically these models are identical besides the Merton's model estimates the probability of default by comparing the relation between firm's assets and liabilities. Plainly, the default occurs if the value of assets is below the firm's liabilities while the debt is due. Merton's model assumes the firm has issued only one bond, whereas the structural model considers the entirety as the firm can be viewed as defaulted when the value of assets reduce below a predesignated level.

The second model for pricing the credit derivatives suggested by Houweling and Vorst (2005) is called *the reduced-form model.* This model does not determine the default probabilities directly based on the capital structure of an entity. Instead, this model scrutinizes default occurrences with hazard rates and recovery rates. The hazard rate is measured by a stochastic or deterministic arrival intensity. The recovery rate is a percentage ratio between the market value and the face value of a bond. Hull and White (2000) price a CDS using the approach of a reduced-form model. This model is presented next.

Hull and White (2000) suggest that pricing so-called vanilla CDS consists of two stages. The first stage starts by defining the present value (PV) of the risk-neutral default probability at different times in the future. First, the PV of default costs can be calculated from the bond prices using Eq. 4 below. It assumes that a credit risk is the only explaining factor of the difference in bond prices.

$$PV\ of\ ZCB - PV\ of\ corp.bond = PV\ of\ default\ costs, \tag{4}$$

where *ZCB* is zero-coupon bond and *cor. bond* is corporate bond. To illustrate, there are two similar bonds with 5-year maturity; ZCB issued by a government and a corporate bond, with the face value of \$100. The ZCB yields 5% and the corporate bond yields 5,5%. Then, PV of the ZCB is $100e^{-0.05x5}$ = 77.8801 and PV of the corp. bond is $100e^{-0.055x5}$ = 75.9572. Finally, using the Eq. 5 above, the PV of default costs is

$$77.8801 - 75.9572 = 1.9229. \tag{5}$$

Second, calculating the PV of the risk-neutral probability of default *p* using the PV of default costs is possible. Assuming the recovery rate is zero, the expected loss 100*p* and the PV of default probability is

$$100pe - 0.05\,x\,5 \; = \; 1.9229, \tag{6}$$

where p equals 2.47% calculated from Eq. 6 above. Usually calculating these default probabilities are not as simple as in this example since the recovery rate is often non-zero and most of the bonds issued by companies are not ZCBs.

According to Hull and White (2000), the second stage of is to calculate the PV of the expected future payments and the PV of the expected future payoff. PV of the future payments is the value reflecting the expectations of the firm's business to be continued, whereas PV of the future payoff is the value measuring the expected possibility that a reference firm will default in the future.

The next parts assume that the defaults, recovery rates, and risk-free interest rates are reciprocally independent and that the FV of a reference bond is $1. Then, the risk-neutral probability of no default is one minus risk-neutral probability density of default at time t. The premiums are getting paid until the bankruptcy or the maturity date (T). Then, if bankruptcy occurred at the time t (t < T), the total PV of the payments includes the PV of the payments between time zero and t plus the PV of an accumulated payment at time t. Instead of that, if the payments last until the maturity date T, the total PV of the payments includes only the PV of payments per year between time zero and T. Hence, it is possible to calculate the PV of the expected future payments

$$w \int_0^T q(t)[u(t) + e(t)]\, dt + w\pi u(T), \tag{7}$$

where w = total payments per year, q(t) = risk-neutral probability of default, u(t) = PV of the payments per year between time zero and t, e(t) = PV of an accumulated payment at time t, π = risk-neutral probability of no default and T = maturity date.

The market value *MV* of a reference bond is the multiplication of its recovery rate *R*, face value *FV*, and accrued interest *A(t)*. Then, the payoff is the difference between FV and

MV as mentioned earlier in this chapter. Given that the FV of CDS is \$1, the expected payoff is calculated as follows

$$\int_0^T [1 - \hat{R} - A(t)\hat{R}]q(t)v(t)\,dt, \tag{8}$$

where $\hat{R}$ = estimated recovery rate and v(t) = PV of FV at the time t.

Finally, the CDS spread, s, can be calculated as a ratio between the PVs of expected payoff and expected payments

$$s = \frac{\int_0^T [1 - \hat{R} - A(t)\hat{R}]q(t)v(t)dt}{\int_0^T q(t)[u(t) + e(t)]\,dt + \pi u(T)}. \tag{9}$$

An idea of calculating the vanilla CDS spread with this equation is the ratio between the present values of payoff and payments at the time t. If the PV of payoff is larger than the PV of payment, the CDS spread is more than 1. Similarly, the CDS spread is less than 1 when the PV of payoff is smaller than the PV of payment. It argues that the better the creditworthiness, the smaller the CDS spread and vice versa.

4.5 CDS-Bond basis

CDS spread and bond yield spread should equal at least approximately as many studies have shown that these spreads measure the credit risk of the same company. However, arbitrages exist in the markets. The CDS-Bond basis means the difference between the CDS spread of a reference firm and the firm's corporate bond spread with a similar maturity. (Kim, Li, & Zhang, 2017, p. 842.)

If the yield on a risky bond over the risk-free rate was marked over the CDS spread, an investor has an arbitrage possibility by earning more than a risk-free rate by buying the risky bond, shorting the riskless bond, and buying the CDS protection. On the contrary, if the yield on the risky bond over the risk-free rate was marked under the CDS spread, an investor can exploit the arbitrage by shorting the risky bond, buying the riskless bond, and selling the CDS protection. The equation of the situation of this basis can be written as follow (Hull et al. 2004; Hull 2015: 575):

$$CDS\text{-}Bond\ basis\ =\ CDS\ spread - Bond\ yield\ spread\ . \tag{10}$$

Imbierowicz and Wahrenburg (2009) show that the CDS market measures the creditworthiness of a reference entity better than bond markets. Also, Blanco et al. (2005) find that CDS spreads are better indicators than bond spreads because the CDS market leads the bond market when measuring the credit risk. This means that when analyzing the prices, most of the changes happen in CDS markets instead of bond markets. This finding leads this paper appropriately to the next section in which the relationship of credit rating events and CDS spread is investigated.

5 Data and methodology

This section presents the data and methodologies used in this thesis. First, in chapter 5.1, rating data and CDS data are analyzed, respectively. Second, the methodologies are presented in chapter 5.2.

5.1 Data

The data set of this paper consists of two parts: rating data and CDS data. First, the rating data is collected from the FitchConnect database. This thesis uses only downgrades and upgrades for S&P 500 firms. These firms draw significant market share in the United States. The reviews for downgrades and upgrades and outlooks were omitted from the dataset due to data restriction issues. As this thesis studies the events at the industry level, it uses the Global Industry Classification Standard (GICS) sectors for these companies. This allows the construction of the S&P 500 industry portfolios for Communication Services (6 firms), Consumer Discretionary (13), Consumer Staples (14), Energy (13), Financials (25), Health Care (13), Industrials (27), Information Technology (7), and Utilities (20). Only the firms that have CDS data were included in this thesis. Also, only these GICS sectors were included since they have three or more events for the total period. A too low number of events would make the results unreliable for the corresponding sector. The S&P 500 companies per industry used in this thesis are listed in Appendix 1.

The raw dataset included 162 downgrades and 278 upgrades from Fitch, S&P, and Moody's. However, the dataset was controlled for contamination. Only the events that do not have other rating events from any CRA 90 days before and 30 days after the event were accepted. Also, only the events that have CDS data for the corresponding company were included. Ratings by S&P were omitted from this study as the number of ratings for the whole period was low (only 12). The description of the final rating data is observed in Tables 4 and 5 below. In Table 4, Panel A shows that Fitch has 57 downgrades and 64 upgrades, whereas Moody's has 53 downgrades and 80 upgrades. Hence, the total number of events for the period 2010-2018 is 110 downgrades and 144 upgrades. Panel B shows the number of downgrades per rater and industry from the total period. Likewise, Panel C shows the number of upgrades per rater and industry from the total period.

Table 4. Distribution of rating events per rater and industry.

Panel A: **Rating events per rater**	**Fitch**	**Moody's**	**Total**
Downgrade	57	53	110
Upgrade	64	80	144
Total	121	133	**254**

Panel B: **# of downgrades per rater and industry**	**Fitch**	**Moody's**	**Total**
Communication Services	3	3	6
Consumer Discretionary	1	2	3
Consumer Staples	11	3	14
Energy	6	6	12
Financials	9	14	23
Health Care	6	2	8
Industrials	9	11	20
Information Technology	6	6	12
Utilities	6	6	12
Total	57	53	**110**

Panel C: **# of upgrades per rater and industry**	**Fitch**	**Moody's**	**Total**
Communication Services	2	4	6
Consumer Discretionary	10	11	21
Consumer Staples	7	2	9
Energy	6	3	9
Financials	14	10	24
Health Care	5	2	7
Industrials	10	25	35
Information Technology	2	7	9
Utilities	8	16	24
Total	64	80	**144**

In Table 5, Panel A shows the annual number of downgrades and upgrades. Panel B shows the number of downgrades per year and industry. Likewise, Panel C shows the annual number of upgrades per industry.

Table 5. Distribution of rating events per year and industry.

Panel A: **Rating events per year**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**Total**
Downgrade	9	18	16	11	6	11	13	7	19	110
Upgrade	18	21	17	6	21	18	13	14	16	144
Total	27	39	33	17	27	29	26	21	35	**254**

Panel B: **# of downgrades per year and industry**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**Total**
Communication Services	0	1	0	3	0	0	1	1	0	6
Consumer Discretionary	0	1	0	0	0	0	1	1	0	3
Consumer Staples	2	2	2	1	0	0	2	0	5	14
Energy	0	1	1	1	2	2	5	0	0	12
Financials	2	7	5	4	0	1	1	1	2	23
Health Care	1	2	1	0	2	0	0	0	2	8
Industrials	1	2	4	1	1	3	1	3	4	20
Information Technology	0	1	2	1	1	4	0	1	2	12
Utilities	3	1	1	0	0	1	2	0	4	12
Total	9	18	16	11	6	11	13	7	19	**110**

Panel C: **# of upgrades per year and industry**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**Total**
Communication Services	2	1	0	0	0	1	0	0	2	6
Consumer Discretionary	3	7	4	0	2	2	1	1	1	21
Consumer Staples	0	1	3	1	0	1	2	1	0	9
Energy	1	1	1	0	1	0	1	3	1	9
Financials	3	2	2	2	1	5	2	1	6	24
Health Care	2	2	0	0	0	2	0	0	1	7
Industrials	3	3	5	1	7	6	5	4	1	35
Information Technology	2	3	0	0	1	0	0	1	2	9
Utilities	2	1	2	2	9	1	2	3	2	24
Total	18	21	17	6	21	18	13	14	16	**144**

As it can be noticed from Tables 4 and 5, the number of upgrades exceeds downgrades. It is exceptional to have more upgrades than downgrades in the dataset, as the number of downgrades in the prior studies (Daniels & Jensen, 2005; Drago & Gallo, 2016; Finnerty et al., 2013; Galil & Soffer, 2011; Hull et al., 2004; Imbierowicz & Wahrenburg, 2009; Micu et al., 2006; Norden & Weber, 2004; Raimbourg & Salvadè, 2020; Wengner et al., 2015) exceeds upgrades. This is reasonable as usually, CRAs focus on negative news and hence downgrade firms more sensitively. However, the study period 2010-2018 might be the reason why the dataset in this thesis includes more upgrades than downgrades for S&P 500 firms. As it can be noticed from Figure 6 below, S&P 500 index fluctuated between 1000-1500 during 2000-2008, decreased rapidly due to the financial crisis, and increased roughly during the period 2010-2018 (Yahoo Finance, 2021). Until the end of 2018, the value of the index was almost even 3000. This illustrates that the credit quality of the S&P 500 firms has improved from 2010 to 2018 and hence the number of upgrades exceeded downgrades.

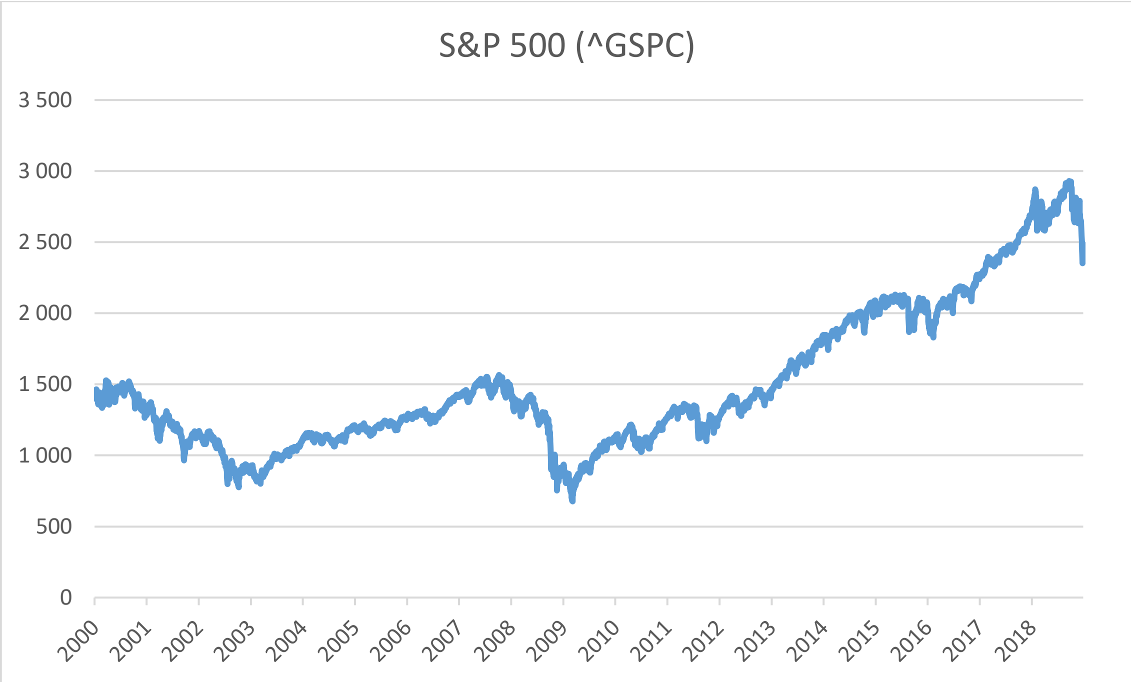

Figure 6. S&P 500 index (^GSPC) chart 2000-2018.

Second, the CDS data consists of 323 886 daily CDS spread quotes within the period from 1 January 2010 to 31 December 2018. This study uses CDS spreads with 5 years maturity as these are the most liquid. CDS data is collected as time series from Thomson Reuters Datastream. As mentioned at the beginning of this chapter, some of the S&P 500 firms that experienced rating events during the studied period do not have CDS data for the corresponding period. In this case, the event was omitted. Table 6 below illustrates the number of S&P 500 firms per industry and the number of CDS spreads changes per industry for the period 2010-2018. Every firm has an average of 2 347 observations in CDS spread changes for this period.

Table 6. Descriptive statistics of the # of firms and the # of observations per industry.

Industry	# of firms	# of obs.
Communication Services	6	14 082
Consumer Discretionary	13	30 511
Consumer Staples	14	32 858
Energy	13	30 511
Financials	25	58 675
Health Care	13	30 511
Industrials	27	63 369
Information Technology	7	16 429
Utilities	20	46 940
Total	**138**	**323 886**

5.2 Methodology

First, following Norden and Weber (2004), Galil and Soffer (2011), and Wengner et al. (2015), I use the rating-class model in which I calculate the abnormal CDS spread changes (ARCDS) for firm *i* at time *t* by subtracting the daily CDS spread change of rating-class-based index (RICDS) from the event firm's daily CDS spread change. RICDSs are calculated at the time before the rating change (*o*), and after the new rating around the announcement day (*n*) based on equally weighted CDS spread changes for the firms within the same rating class. The index consists of all firms when considering all industries, whereas the index consists of firms within the same industry when analyzing the reaction at the industry-level

$$ARCDS_{i,t} = \begin{cases} \left((CDS_{i,t} - CDS_{i,t-1}) - (RICDS_{i,o,t} - RICDS_{i,o,t-1})\right), t < date\ of\ the\ rating\ change \\ \left((CDS_{i,t} - CDS_{i,t-1}) - (RICDS_{i,n,t} - RICDS_{i,n,t-1})\right), t \geq date\ of\ the\ rating\ change \end{cases}. \tag{11}$$

After this, the cumulative abnormal CDS spread changes (CASC) are calculated for each firm *i* from time point t_1 to t_2 by adding the daily $ARCDS_{i,t}$ over a certain period. I use 30 days to 1 day before the event as a pre-announcement period to compute 30-day CASCs and to test whether the CDS market anticipates ratings. I also use days 0 and 1 day after as an announcement day period, where 0 is the event day

$$CASC_{i,t_1,t_2} = \sum_{t=t_1}^{t_2} ARCDS_{i,t} \ . \quad (12)$$

In Section 6, the results of the CASCs are presented as a median of CASCs of individual firms. When analyzing all industries together, all firms are considered and when analyzing the reactions at the industry level, firms in a corresponding industry are considered.

Following Norden and Weber (2004), and Galil and Soffer (2011), I use both, parametric t-test, and non-parametric Wilcoxon sign rank test to evaluate whether median CASCs are significantly different from zero. The results derived from the rating-class model are presented in Chapter 6.1.

Second, following Wengner et al. (2015), I use the index model to calculate the abnormal CDS spread changes by computing the equally weighted industry index (M) instead of the rating-class-based index. This index is constructed by considering CDS spread changes, regardless of rating class, of all firms when analyzing all industries together, whereas when analyzing the reactions at the industry level, the index consists of the CDS spread changes of all firms in the corresponding industry. This is the robustness check for the results from the rating-class model:

$$ARCDS_{i,t} = \left(CDS_{i,t} - CDS_{i,t-1}\right) - \left(CDS_{M,t} - CDS_{M,t-1}\right). \quad (13)$$

The results of robustness check derived from this index model are presented in Chapter 6.1.

Third, I study the spillover effects. The spillover effect as a definition in this paper means the effect of event firm's rating event at time t on competitors' CDS spreads. Competitors, or non-event (NE) firms, do not experience a rating event at time t. According to

Wengner et al. (2015, p. 86), rating events affect the competition for additional financing among the competitors. Hence, I assume that downgrades lead to a positive competitive effect of NE firms meaning that the CDS spreads of NE firms should decrease around the event day t. Similarly, I assume that upgrades lead to a negative competitive effect of NE firms when the CDS spreads of NE firms should increase around the event day t.

I use the rating-adjusted index model (Eq. 11) to compute 2-day CASCs to measure whether NE firms profit from downgrades and suffer from upgrades around the event day. I also use Eq. 11 to compute 30-day CASCs to measure whether CDS spreads of NE firms change abnormally already before the event. I use both, parametric t-test, and non-parametric Wilcoxon sign rank test to evaluate whether median CASCs are significantly different from zero. The results for spillover effects are presented in Chapter 6.2.

6 Empirical analysis

This part of the paper presents and analyzes the results of the effects of credit rating announcements on corporate CDS spreads. First, the relationship between rating events and CDS spread changes of event firms across the industries is analyzed in Chapter 6.1 and then, Chapter 6.2 analyzes the spillover effects and shows the results for industry-level CDS market reaction of NE firms.

6.1 CDS market reaction to rating events across industries

Tables 7 and 8 present the median CASCs for the total sample (All) and nine different industries at the industry level, and the corresponding p-values of t-test and non-parametric Wilcoxon sign-rank test. The CASCs are calculated based on rating-class adjusted indices using Eq. 11 mentioned in this paper. The observations consist of rating changes for the firms rated by Fitch and Moody's during the period 2010-2018. Panel A presents the CASCs for the 30-day event window before the event day [-30,-1], and Panel B presents the CASCs for the 2-day event window around the event day [0,1]. Zero is the event date. N is the number of observations.

Table 7. CDS market reaction before and around downgrades (Rating-Class Model).

	All	Comm. Serv.	Cons. Discr.	Cons. Staple	Energy	Financials	Health Care	Industrials	IT	Utilities
Panel A: CDS spread changes for event firms before downgrades [-30, -1]. Zero is the event day.										
N	110	6	3	14	12	23	8	20	12	12
CASC (median)	0,370	-1,170	-21,250	3,060	-0,865	-1,46	2,885	0,265	3,675	-0,255
p t-test	0,166	0,468	0,138	0,262	0,744	0,274	0,934	0,437	0,220	0,409
p sign rank test	0,752	0,600	0,109	0,331	0,433	0,274	0,889	0,709	0,209	0,953
Panel B: CDS spread changes for event firms around downgrades [0, 1]. Zero is the event day.										
N	110	6	3	14	12	23	8	20	12	12
CASC (median)	0,010	1,469	0,750	0,530	-0,060	1,000	0,010	0,020	0,022	0,010
p t-test	0,403	0,274	0,394	0,906	0,245	0,759	0,364	0,722	0,632	0,074*
p sign rank test	0,224	0,173	0,285	0,701	0,285	0,316	0,612	0,868	0,859	0,208

*** CASCs are significantly different from zero at 1% level,
** CASCs are significantly different from zero at 5% level, and
* CASCs are significantly different from zero at 10% level.

Table 7 presents the results for downgrades. Considering all industries, median CASCs are positive before (0,370 bps) and around (0,010 bps) downgrades, which means that the direction of spread changes is inverse with the rating change as assumed. Still, these

CASCs are not significantly different from zero, as can be noticed from Table 7 based on the corresponding p-values. We can conclude that considering all industries, the CDS market does not react abnormally before and around downgrades. This is a markable finding since according to the prior literature (Daniels & Jensen, 2005; Finnerty et al., 2013; Galil & Soffer, 2011; Hull et al., 2004; Imbierowicz & Wahrenburg, 2009; Micu et al., 2006; Norden & Weber, 2004; Wengner et al., 2015), all these studies find that downgrades cause abnormal changes in CDS spreads before and around the event. One explanation for the finding in this thesis can be that the thesis contains more upgrades than downgrades due to the increased credit quality of the S&P 500 firms. Another possible explanation for this contradictory result to the prior studies is that these studies contain firms globally, whereas this thesis consists of only S&P 500 firms and also the study period differs from the prior studies.

When analyzing the results before and around downgrades at the industry level, the number of observations for downgrades per industry varies abundantly and is codirectional with the number of firms per industry illustrated in Table 6. *N* is the highest for Financials and the lowest for Consumer Discretionary. For five of the nine industries, median CASCs before downgrades are negative and hence codirectional with the event. This is not as assumed since I assume an inverse relationship between CDS spreads and rating events. However, for the rest industries, the direction of CASCs before downgrades is as assumed. Furthermore, for all industries except the Energy sector, median CASCs around downgrades are positive and hence the direction is as assumed.

However, contrary to the prior studies analyzed in this thesis (Daniels & Jensen, 2005; Finnerty et al., 2013; Galil & Soffer, 2011; Hull et al., 2004; Imbierowicz & Wahrenburg, 2009; Micu et al., 2006; Norden & Weber, 2004; Wengner et al., 2015), I do not find the abnormal reaction in median CASCs before or around the downgrades in almost any industry. Exceptionally, the median CASC for the Utilities is abnormal (0,010 bps) around the downgrades. This result is statistically significant at the 10% level.

Table 8. CDS market reaction before and around upgrades (Rating-Class Model).

	All	Comm. Serv.	Cons. Discr.	Cons. Staple	Energy	Financials	Health Care	Industrials	IT	Utilities
Panel A: CDS spread changes for event firms before upgrades [-30, -1]. Zero is the event day.										
N	144	6	21	9	9	24	7	35	9	24
CASC (median)	-0,970	-21,073	-7,374	-0,560	3,284	-1,403	-2,980	-0,740	-0,020	2,970
p t-test	0,047**	0,044**	0,146	0,338	0,958	0,137	0,084*	0,088*	0,709	0,270
p sign rank test	0,000***	0,046**	0,050**	0,441	0,441	0,026**	0,116	0,030**	0,594	0,110
Panel B: CDS spread changes for event firms around upgrades [0, 1]. Zero is the event day.										
N	144	6	21	9	9	24	7	35	9	24
CASC (median)	-0,030	0,092	0,000	-0,240	0,030	-0,045	0,000	-0,120	-1,335	0,120
p t-test	0,000***	0,488	0,110	0,067*	0,268	0,036**	0,428	0,043**	0,165	0,477
p sign rank test	0,000***	0,917	0,156	0,018**	0,515	0,041**	0,600	0,017**	0,063*	0,681

*** CASCs are significantly different from zero at 1% level,
** CASCs are significantly different from zero at 5% level, and
* CASCs are significantly different from zero at 10% level.

Table 8 presents the results for upgrades. Considering all industries, median CASCs are negative before (-0,970 bps) and around (-0,030 bps) upgrades, which means that the direction of median CASCs is as assumed. The corresponding p-values for median CASCs before the upgrades are 0,047 for the t-test and 0,000 for the sign rank test and hence this result is statistically significant at the 5% level and 1% level, respectively. Furthermore, the corresponding p-value for median CASCs around the upgrades is 0,000 for both tests. Hence, this result is statistically significant at the 1% level. We can conclude that considering all industries, I find evidence of significant CASCs before and around the upgrades. This finding contradicts the most prior studies (Daniels & Jensen, 2005; Hull et al., 2004; Imbierowicz & Wahrenburg, 2009; Norden & Weber, 2004) but is in line with more recent papers (Finnerty et al., 2013; Galil & Soffer, 2011; Micu et al., 2006; Wengner et al., 2015).

A potential explanation why the CDS market reacts abnormally to S&P 500 firms upgrades especially around the event is that the credit quality has increased steadily during 2010-2018 as illustrated in Figure 6. Consequently, CRAs have started to focus on positive news as much as on negative signals and hence can provide new information to the market still around the event. According to Wengner et al. (2015), the abnormal market reaction before upgrades derives from the interest that firms have towards revealing the positive news, and hence the market already prices this information beforehand and anticipates upgrades.

When analyzing the results before and around upgrades at the industry level, similar to downgrades, the number of observations for upgrades per industry varies abundantly and is codirectional with the number of firms per industry illustrated in Table 6. *N* is the highest for Industrials and the lowest for Communication Services. For two of the nine industries, median CASCs before upgrades are positive and hence not as assumed. However, for the rest industries, the direction of CASCs before upgrades is as assumed. Furthermore, the direction of CASCs around upgrades is as assumed for only four of the nine industries.

As it can be noticed from Table 8, the market reactions before and around upgrades are heterogeneous across industries. For Energy and Utilities, median CASCs are not significant at any level in neither cases, before or around upgrades. For the Communication Services sector, median CASC is -21,073 bps before upgrades and the corresponding p-values are 0,044 and 0,046 for t-test and sign rank test, respectively. This result is statistically significant at a 5% level for both tests. However, the median CASC of 0,092 around upgrades is not statistically significant at any level. It means that the CDS market anticipates upgrades, but the actual event does not reveal useful information to the market anymore. The CDS market prices all the relevant information regarding upcoming upgrades beforehand and CRAs are not able to provide any new information to the market at the time of announcement.

For the Industrials sector, median CASC is -0,740 bps before upgrades and the corresponding p-values are 0,088 and 0,030 for t-test and sign rank test, respectively. This result is statistically significant at 1% and 5% level, respectively. Still, the CDS market reacts abnormally around the upgrades since median CASC -0,120 bps gives p-values of 0,043 and 0,017 for t-test and sign rank test, respectively. This result is statistically significant at a 5% level. It means that in the case of the Industrial sector, the CDS market anticipates upgrades 30-days before the actual event by pricing the relevant information but also the announcement reveal new information to the market. For other industries, median CASCs are statistically significant before, around, or before and around upgrades at 5-10% level.

One potential explanation why the CDS market anticipates upgrades in Communication Services, Consumer Discretionary, Financials, Health Care, and Industrial sectors is that the firms in these industries are eager to release positive news immediately and hence the market already prices this information beforehand. Also, the reason why the CDS market reacts abnormally still around the upgrades in Consumer Staple, Financial, Industrial, and IT sectors might be that CRAs have started to focus on positive news as much as on negative signals and hence can provide new information to the market still around the event.

To conclude Tables 7 and 8, considering all industries, the CDS market reacts abnormally to upgrades but not to downgrades around the event. Also, the CDS market anticipates upgrades but not downgrades. When analyzing an industry-level, since the direction of CASCs before and around downgrades and upgrades differ across industries and is not as assumed in all industries, it is a clear signal that the CDS market is segmented across industries. To support this signal, as it can be noticed from the results, the abnormal market reactions before and around the upgrades and downgrades are heterogeneous across the industries. Overall, the findings do not support Hypothesis 1, but support Hypothesis 2 and 3 in this thesis.

Tables 9 and 10 present median CASCs for the total sample and nine different industries at the industry-level, and the corresponding p-values of t-test and non-parametric Wilcoxon sign-rank test. The CASCs are calculated as a robustness check based on equally weighted industry indices using Eq. 13 mentioned in this paper. The observations consist of rating changes for the firms rated by Fitch and Moody's during the period 2010-2018. Panel A presents the CASCs for the 30-day event window before the event day [-30,-1], and Panel B presents the CASCs for the 2-day event window around the event day [0,1]. Zero is the event date. N is the number of observations.

Table 9. CDS market reaction before and around downgrades (Index Model).

	All	Comm. Serv.	Cons. Discr.	Cons. Staple	Energy	Financials	Health Care	Industrials	IT	Utilities
Panel A: CDS spread changes for event firms before downgrades [-30, -1]. Zero is the event day.										
N	110	6	3	14	12	23	8	20	12	12
CASC (median)	0,192	-17,210	-15,841	2,889	-1,235	-1,665	3,915	-0,995	4,202	0,000
p t-test	0,339	0,385	0,128	0,269	0,811	0,256	0,906	0,433	0,279	0,797
p sign rank test	0,492	0,345	0,109	0,331	0,583	0,248	1,000	0,332	0,209	0,638
Panel B: CDS spread changes for event firms around downgrades [0, 1]. Zero is the event day.										
N	110	6	3	14	12	23	8	20	12	12
CASC (median)	0,480	0,716	0,404	0,530	-0,130	0,530	-0,005	0,000	0,017	-0,275
p t-test	0,367	0,299	0,365	0,758	0,371	0,764	0,429	0,472	0,576	0,108
p sign rank test	0,405	0,463	0,180	0,807	0,386	0,412	1,000	0,562	0,814	0,102

*** CASCs are significantly different from zero at 1% level,
** CASCs are significantly different from zero at 5% level, and
* CASCs are significantly different from zero at 10% level.

As it can be noticed from Table 9, using the index model as a robustness check for examining the CDS market reaction before and around downgrades gives similar results. Still, the CDS market does not anticipate downgrades in any industry and the CASCs are not significantly different from zero around the actual events. Hence, we can state that the results are robust for downgrades.

Table 10. CDS market reaction before and around upgrades (Index Model).

	All	Comm. Serv.	Cons. Discr.	Cons. Staple	Energy	Financials	Health Care	Industrials	IT	Utilities
Panel A: CDS spread changes for event firms before upgrades [-30, -1]. Zero is the event day.										
N	144	6	21	9	9	24	7	35	9	24
CASC (median)	-1,868	-7,680	-5,440	-0,560	0,405	-0,750	-3,120	-0,850	-1,965	2,270
p t-test	0,056*	0,159	0,205	0,313	0,720	0,165	0,623	0,861	0,568	0,980
p sign rank test	0,000***	0,116	0,181	0,374	0,678	0,040**	0,310	0,512	0,767	0,493
Panel B: CDS spread changes for event firms around upgrades [0, 1]. Zero is the event day.										
N	144	6	21	9	9	24	7	35	9	24
CASC (median)	-0,130	-0,472	0,485	-0,240	-0,035	-0,108	0,004	-0,010	-0,040	0,000
p t-test	0,000***	0,208	0,125	0,067**	0,331	0,035**	0,631	0,169	0,290	0,452
p sign rank test	0,000***	0,075*	0,765	0,018**	0,314	0,050**	1,000	0,126	0,066*	0,940

*** CASCs are significantly different from zero at 1% level,
** CASCs are significantly different from zero at 5% level, and
* CASCs are significantly different from zero at 10% level.

As it can be noticed from Table 10, using the index model as a robustness check for examining the CDS market reaction before and around upgrades gives similar results. Considering all industries, median CASCs are -1,868 and -0,130 before and around upgrades, respectively. Both of these are statistically significant according to the t-test and sign rank test. Also, when analyzing the results at the industry level, again, the CDS market reaction before and around upgrades is segmented since the direction of median CASCs differs and the CDS market reactions before and around the upgrades are heterogeneous across the industries. Hence, the results are robust for upgrades.

6.2 Spillover effects

In this chapter, the effect of event firms' announcements on competitors CDS spreads is analyzed. The event firms are affected by a rating event at time t, whereas their competitors, or non-event (NE) firms, do not experience an event at the same time. Lang and Stulz (1992) find evidence that the intra-industrial competitors' stock returns profit from bankruptcy announcements. Furthermore, Wengner et al. (2015) assume the same competitive effect between CDS spreads and rating events. They find that NE firms profit from event firms' downgrades and suffer from upgrades, as assumed. Hence, I assume the same relationship for S&P 500 firms in this thesis. An idea of examining the reaction of NE firms' CDS spreads to events is the assumption that the competitors profit from downgrades and hence experience positive competitive effect, meaning that their CDS spreads should decrease around the event. Similarly, NE firms suffer from upgrades and are affected by negative competitive effect, meaning that their CDS spreads should increase around the event.

Tables 11 and 12 present median CASCs for NE firms within nine different industries at the industry-level, and the corresponding p-values of t-test and non-parametric Wilcoxon sign-rank test. The CASCs are calculated based on rating-class adjusted indices using Eq. 11 mentioned in this paper. The observations consist of NE firms rated by Fitch and Moody's during the period 2010-2018. Panel A presents the CASCs for the 30-day event window before the event day [-30,-1], and Panel B presents the CASCs for the 2-day event window around the event day [0,1]. Zero is the event date. N is the number of observations.

Table 11. CDS market reaction for NE firms across industries: Industry-level spillover effects before and around downgrades (Rating-Class Model).

	Comm. Serv.	Cons. Discr.	Cons. Staple	Energy	Financials	Health Care	Industrials	IT	Utilities
Panel A: CDS spread changes for NE firms before downgrades [-30, -1]. Zero is the event day.									
N	60	56	308	228	146	144	308	172	158
CASC (median)	-1,370	-4,581	-1,105	1,000	1,255	-0,455	-0,060	0,208	-0,020
p t-test	0,135	0,393	0,000***	0,227	0,027**	0,001***	0,000***	0,362	0,786
p sign rank test	0,006***	0,198	0,000***	0,035**	0,164	0,000***	0,000***	0,818	0,296
Panel B: CDS spread changes for NE firms around downgrades [0, 1]. Zero is the event day.									
N	60	56	308	228	146	144	308	172	158
CASC (median)	0,036	-0,240	-0,010	0,000	-0,005	-0,060	-0,001	-0,010	0,005
p t-test	0,593	0,005***	0,000***	0,002***	0,642	0,000***	0,023**	0,200	0,002***
p sign rank test	0,296	0,002***	0,000***	0,002***	0,049**	0,000***	0,000***	0,000***	0,004***

*** CASCs are significantly different from zero at 1% level,
** CASCs are significantly different from zero at 5% level, and
* CASCs are significantly different from zero at 10% level.

Table 11 presents the results for downgrades. When analyzing the results before and around downgrades at the industry level, the number of observations for downgrades per industry varies abundantly and is codirectional with the number of firms per industry illustrated in Table 6. *N* is the highest for Consumer Staples and Industrials and the lowest for Consumer Discretionary. It is clear that the direction of median CASCs (negative versus positive) and the strength of a positive competitive effect before and around the downgrades varies and hence, we can state that the CDS market is segmented across the industries.

For six of the nine industries, the direction of CASCs before downgrades (*Panel A*) is negative and as assumed. In four of these six industries, the firms experience a positive competitive effect already before the downgrades and the findings are statistically significant at the 1-5% level. However, for three of the nine industries, median CASCs before downgrades are positive for NE firms. This is not as assumed since I assume that the competitors profit from downgrades. Furthermore, from these three industries, the Energy and Financial sectors experience statistically significant negative competitive effect (median CASCs 1,000 and 1,255) at the 5% level before downgrades, which is markable since it means that the CDS market anticipates event firms' downgrades by increasing the competitors' CDS spreads.

In every industry, except Communication Services and Utilities sectors, NE firms' median CASCs around downgrades (*Panel B*) are negative and hence the direction is as assumed. Again, according to Table 11, the firms experience a positive competitive effect still around the downgrades in every industry except Communication Services and Utilities and the findings are statistically significant at a minimum 1% level. This finding is as assumed. Wengner et al. (2015) also find that the competitors experience negative median CASCs around the downgrades and the finding is statistically significant at the 1% level in every industry. However, according to Table 11, the Utilities experience statistically significant negative competitive effect (median CASC 0,005 bps) at the 1% level around downgrades, which is again markable and not as assumed since it means that the CDS market reacts abnormally still around event firms' downgrades by increasing the competitors' CDS spreads.

Table 12. CDS market reaction for NE firms across industries: Industry-level spillover effects before and around upgrades (Rating-Class Model).

	Comm. Serv.	Cons. Discr.	Cons. Staple	Energy	Financials	Health Care	Industrials	IT	Utilities
Panel A: CDS spread changes for NE firms before upgrades [-30, -1]. Zero is the event day.									
N	57	383	198	171	350	109	527	121	307
CASC (median)	1,145	0,673	1,270	0,020	-1,540	0,836	0,092	0,121	0,350
p t-test	0,485	0,094*	0,645	0,002***	0,000***	0,948	0,003***	0,517	0,907
p sign rank test	0,993	0,047**	0,955	0,003***	0,000***	0,911	0,009***	0,643	0,328
Panel B: CDS spread changes for NE firms around upgrades [0, 1]. Zero is the event day.									
N	57	383	198	171	350	109	527	121	307
CASC (median)	-0,045	0,001	0,001	0,001	0,010	0,020	0,010	0,005	0,000
p t-test	0,085*	0,000***	0,147	0,000***	0,000***	0,656	0,000***	0,404	0,000***
p sign rank test	0,013**	0,000***	0,000***	0,000***	0,000***	0,532	0,000***	0,009***	0,000***

*** CASCs are significantly different from zero at 1% level,
** CASCs are significantly different from zero at 5% level, and
* CASCs are significantly different from zero at 10% level.

Table 12 presents the results for upgrades. When analyzing the results before and around upgrades at the industry level, the number of observations for upgrades per industry varies abundantly and is codirectional with the number of firms per industry illustrated in Table 6. *N* is the highest for Industrials and the lowest for Communication Services. It is clear that the direction of median CASCs (negative versus positive) and the strength of a negative competitive effect before and around the upgrades varies and hence, we can state that the CDS market is segmented across the industries.

In every industry, except the Financial sector, the direction of CASCs before upgrades (*Panel A*) is positive and as assumed. In three of these eight industries, the firms experience a negative competitive effect already before the upgrades and the findings are statistically significant at a minimum 1% level. However, for the Financial sector, median CASC before downgrades is negative for NE firms. This is not as assumed since I assume that the competitors suffer from upgrades. Furthermore, the Financial sector experience a statistically significant positive competitive effect (median CASC -1,540) at the 1% level before upgrades, which is markable since it means that the CDS market anticipates event firms' upgrades by decreasing the competitors' CDS spreads.

In every industry, except Communication Services, NE firms' median CASCs around upgrades (*Panel B*) are positive and hence the direction is as assumed. In seven of these eight industries, the firms experience a negative competitive effect still around the upgrades and the findings are statistically significant at a minimum 1% level. This finding is as assumed. Also, Wengner et al. (2015) find that the competitors experience positive median CASCs around the upgrades and the finding is statistically significant at a minimum 1% level in every industry. However, for the Communication Services, median CASC is negative and not as assumed. The sector experiences statistically significant positive competitive effect (median CASC 0,005 bps) at the 5% level around upgrades, which is, again, markable and not as assumed since it means that the NE firms CDS spreads reacts abnormally still around event firms' upgrades by decreasing the competitors' CDS spreads.

To conclude Tables 11 and 12, it seems that a market reaction is segmented for both, downgrades, and upgrades. The event firms' rating information spillover is asymmetrical within industries and this finding supports the statement that the effect of rating announcements should not be generalized. Instead, the effects should be studied at an industry level. Overall, NE firms seem to profit from downgrades and suffer from upgrades. Hence, I find evidence to support Hypothesis 4 in this thesis.

7 Conclusions

In this thesis, I investigated whether downgrades and upgrades by Moody's and Fitch cause abnormal CDS spread changes to S&P 500 firms. I also studied whether these events cause spillover effects to competitors' CDS spreads in the same industry. The methodologies used in this thesis followed closely Wengner et al. (2015).

Hypothesis 1 (H1) is formulated based on the prior literature assuming that downgrades should cause significant positive CASCs at the time of downgrades of S&P 500 firms, whereas the decrease in CDS spreads at the time of upgrades should be insignificant. The results show that the CDS market reacts abnormally to upgrades but not to downgrades around the event and hence, I do not find evidence to support H1. A possible explanation for this contradictory result to the prior studies is that these studies contain firms globally, whereas this thesis consists of only S&P 500 firms and also the study period differs from the prior studies.

Hypothesis 2 (H2) assumes that according to prior literature analyzed in this paper, the firms prefer to reveal positive news and hide negative news, and hence the market should price these positive signals beforehand and anticipate the upgrades, whereas negative news are mostly published by CRAs and hence the market is not able to anticipate downgrades. I find evidence to support H2 since the results show that the CDS market anticipates upgrades but not downgrades of S&P 500 firms.

Hypothesis 3 (H3) is formulated to test whether the CDS market reaction to rating events is segmented across S&P 500 firms industries. The findings support the H3 as the results show that the abnormal CDS market reaction before and around upgrades and downgrades are heterogeneous across the industries.

Hypothesis 4 (H4) is formulated based on the findings by Wengner et al. (2015) that the spillover effects are observable in the CDS market for global firms. They find that the competitors profit (suffer) from downgrades (upgrades) in terms of decreasing (increasing) CDS spreads. Hence, I studied whether the spillover effects are observable for the S&P 500 firms as well. I find support to H4 since the results show that the S&P 500 NE firms seem to profit from event firms' downgrades and suffer from upgrades.

Overall, the results in this thesis suggest that the CDS market reaction to ratings should not be generalized but should rather be examined on an industry level for future research. Also, it would be reasonable to study more spillover effects for future research by investigating which variables explains the CASCs for S&P 500 NE firms before and around the event date, at the industry level. Following Wengner et al. (2015), this can be accomplished by computing a regression model and include variables related to bankruptcy risk, for example, financial leverage and market-to-book ratio, and variables that measure the rating level, for example, change in the credit rating.

The findings in this paper may be relevant at the economic level since the managers can estimate the spillover effects among S&P 500 firms. Thus, they can follow the CDS market movements before the rating events and utilize the market anticipation ability to portfolio hedging strategies.

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Appendices

Appendix 1. List of the companies per industry used in this thesis

Communication Services
CenturyLink, Inc.
Crown Castle International Corp.
DISH Network Corp.
Interpublic Group of Companies, Inc.
S&P Global Inc.
Verizon Communications Inc.
Consumer Discretionary
Best Buy Co., Inc.
BorgWarner, Inc.
Costco Wholesale Corporation
Dollar General Corporation
Ford Motor Company
General Motors Company
Home Depot, Inc. (The)
L Brands, Inc.
Marriott International, Inc.
MGM Resorts International
PVH Corp.
Target Corporation
Wynn Resorts, Limited
Consumer Staples
Altria Group, Inc.
Campbell Soup Company
Conagra Brands, Inc.
Darden restaurants
General Mills, Inc.
Kellogg Company
Kraft Heinz Foods Company
Molson Coors Beverage
Mondelez International, Inc.
Newell brands
PepsiCo, Inc.
Philip Morris International, Inc.
The Coca-Cola Company
Tyson Foods, Inc.
Energy
Apache Corporation
Chevron Corporation

ConocoPhillips
Devon Energy Corporation
Freeport-McMoRan Inc.
Hess Corporation
Loews Corporation
Marathon Oil Corporation
Newmont Mining Corp
NiSource
Occidental Petroleum Corp.
Packaging Corporation of America
Pioneer Natural Resources

Financials

American Express Company
American International Group, Inc. (AIG)
Assurant, Inc.
AvalonBay Communities, Inc.
Bank of America Corporation
Chubb Limited
Cigna Holding Company
Citigroup Inc.
Humana Inc.
JPMorgan Chase & Co.
Lincoln National Corporation
MARSH & MCLENNAN
Morgan Stanley
Prologis, Inc.
Prudential Financial, Inc.
Simon Property Group, Inc.
The Bank of New York Mellon Corporation
The Goldman Sachs Group, Inc.
The Hartford Financial Services Group, Inc.
UnitedHealth Group Incorporated
Unum Group
Ventas, Inc.
W. R. Berkley Corporation
Wells Fargo & Company
Welltower Inc.

Health Care

Agilent Technologies, Inc.
AmerisourceBergen Corp.
Amgen Inc.
Baxter International Inc.
Bristol-Myers Squibb Company
Cardinal Health, Inc.
CVS Health Corporation
Eli Lilly and Company

HCA Inc.
McKesson Corp.
PerkinElmer, Inc.
Pfizer Inc.
Quest Diagnostics Inc

Industrials

Automatic Data Processing Inc.
Caterpillar Inc.
CSX Corporation
D. R. Horton, Inc.
Delta Air Lines
Dover Corporation
General Electric Company
Iron Mountain Inc.
Johnson Controls International Public Limited Company
Lennar Corporation
Lockheed Martin Corporation
Martin Marietta Materials, Inc.
Masco Corporation
Mohawk Industries, Inc.
Northrop Grumman Corporation
NVR, Inc.
Parker-Hannifin Corp.
PPG Industries, Inc.
PulteGroup, Inc.
Sherwin-Williams Company (The)
Snap-on Incorporated
Stanley Black & Decker, Inc.
Textron Inc.
The Boeing Company
Union Pacific Corporation
United Airlines Holdings, Inc.
Whirlpool Corp.

Information Technology

Advanced Micro Devices, Inc.
eBay Inc.
HP Inc.
International Business Machines Corp. (IBM)
Micron Technology Inc.
Motorola Solutions, Inc.
Oracle Corporation

Utilities

Alliant Energy Corporation
Ameren Corporation
American Electric Power Company, Inc.
CenterPoint Energy, Inc.

CMS Energy Corporation
Consolidated Edison, Inc.
DTE Energy Company
Duke Energy Corporation
Edison International
Entergy Corporation
Eversource Energy
Exelon Corporation
NextEra Energy, Inc.
PPL Corporation
Republic Services, Inc.
Sempra Energy
The Southern Company
Waste Management, Inc.
WEC Energy Group, Inc.
Xcel Energy Inc.