MASTER THESIS FINANCIAL ECONOMICS

How credit rating change announcements affects corporate bond prices?

Evidence from the post and during crisis period.

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Date final version: 14.11.2019

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Abstract

Credit rating agencies have been severely questioned by market participants the last years and especially after the global financial crisis of 2007 - 2009. In this paper I investigate the impact of credit rating change announcements in the corporate bond market, to make inferences whether investors still making financial decisions based on credit rating agencies. Beside the abnormal returns prior to the rating change, indicating that CRAs tend to lag the market, my study finds significant cumulative abnormal returns around the day of the announcement for both downgrades and upgrades. This effect was stronger during the global financial crisis as investors were more pessimistic and overreacted to a rating change. The cross-sectional analysis documents that the magnitude of the effect of a rating change is determined by the size of the rating jump, the previous rating of the specific issuer and whether the rating change cross the investment grade boundary.

1. Introduction

Credit rating agencies provide assessments about the creditworthiness of bonds issued by corporations, governments, and packagers of asset-backed securities. Investors have been increasingly relying on credit rating agencies to assess the creditworthiness of a borrower. However, the role of credit rating agencies in the capital markets have been severely questioned and criticized by market participants.

When the credit ratings agencies first introduced, they were paid by investors who wanted information on the credit worthiness of securities issuers and their debt offerings. However, this concept change. Starting in the early 1970s, ratings agencies, such as S&P, Moody's, and Fitch, started receiving payment for their work by the securities issuers themselves, in order to rate their own company and their own securities. As a result, one may believe that a conflict of interest issue arises here. Can those credit ratings agencies always be impartial when issuing ratings for the securities issuers themselves? As Patrick Bolton, Xavier Freixas and Joel Shapiro (2012) mention, due to competition, securities issuers are "shopping" for the best ratings from the “Big Three” ratings agencies, until at least one of the agencies delivers favorable ratings and attract investors. A combination of trusting investors and with issuers that looking to benefit from the mispricing of their issues may lead to substantial ratings inflation with important systemic consequences. Those issues have been cited as one of the primary causes of the crisis, which began in 2007, when securities like mortgage-backed securities (MBSs) and collateralized debt obligations (CDOs) were rated so highly, that many institutional and individual investors were heavily investing in them. It the end, those securities rapidly and massively devalued, either due to defaults or high risk of default on some of their components, such as loans and credit cards account, resulting in one of the worst global financial crisis. Moreover, historically large defaults such as Enron 2001, Lehman Brothers 2008 and ford Motors 2009, has brought to the public (both investors and regulators) this potential source of conflict.

Under those thoughts, one can question the fact that investors still making investments decisions based on credit ratings. On the other hand, rating agencies claim that their ratings partially reflect private information, and hence there will be information content in a potential rating change. Anyhow, credit rating agencies have a strong influence on the bond market. As a result, the information content of a rating change is a topic that has received considerable attention in the academic literature.

There are numerous previous studies that have investigated the effect of credit rating changes in the corporate bond market, and the evidence are very mixed. Early Literature fail to find significant results like Katz (1974) Grier and Katz (1976) and Weinstein (1978), while numerous studies only manage to capture the information content of downgrades like Wansley et al. (1992), Hite and Warga (1997) and Steiner (2001). However later studies as in Hand et al. (1992) and May (2010), document the significant price movement under rating change for both upgrades and downgrades.

In this paper I investigate the impact of credit rating changes announcements, in corporate bond prices. I do so an event study, calculating cumulative abnormal returns on corporate bonds around the day off the announcement of a rating change (or a change credit “watch”). I use intraday data from TRACE and credit rating changes announcements as reported in the Mergent FISD Database. Abnormal returns are calculated as proposed by Bessembinder et al. (2009) Measuring Abnormal Bond Performance.

I am using intraday trades from the OTC market to calculate trade-weighted abnormal daily prices and calculating abnormal returns by finding the appropriate matching portfolio benchmark. Earlier studies have used monthly and weekly data, while other have used daily closing prices which might bias the results, the prices include transaction costs. To my knowledge only May (2010) used bond prices from TRACE to investigate the impact of credit rating change announcements so far and found significant market response to both upgrades and downgrades.

My Thesis contributes to the current Literature as it is the first to use a large data set form intraday daily prices, that were not available prior to 2005, representing 10 years of market movement post crisis, and 2 years of rating events during the global financial crisis period of 2007-2009. In this paper also, occurs the first attempt to explain why there is an asymmetric response to downgrades and upgrades and suggest further research on the investigation of this asymmetry. I am also including in my analysis how the market response to watchlisting announcements when they simultaneously announced with a credit rating change.

Considering the size of the bond market and the great influence of credit rating, it is a great deal of interest for market participants to be familiar with the impact of credit rating changes on corporate bond prices. To the extend a rating event influence bond prices could give better insight to individual investors that holds corporate bonds, that occasionally can be very illiquid, and when they are speculating possible abnormal bond returns, both positive and negative. As mention in Wakeman (1998), the credit rating industry largely determine the market's assessment of credit risk, and especially in corporate bonds the interest rate and issuer must pay.

Hence investors should be aware if a rating change carries new information to the market and how a review for a positive or negative outlook is perceived by market participants. It is also a great importance to see how non-US investors react to rating changes from US CRAs. My research also matters to institutional investors like pension funds that are highly investing in fixed income markets and where the latest low interest rate environment highly affected their reported earnings. Credit rating changes matter in financial regulation, as for example some institutional investors cannot hold securities below the investment grade level. Moreover, capital requirements under Regulations (Basel III, Solvency II) also take ratings into account when estimating risk weighted assets. Under this rationale, downgrades and especially "Fallen angels" can be highly affected by price pressure due to shorting decisions on their securities. In addition, it is useful to investigate how market participants react on rating changes under the Implementation of Dodd-Frank Wall Street Reform and Consumer Protection Act on July 2010 which significantly increases CRAs' liability for issuing inaccurate ratings[1].

My study also carries great importance for the issuers of the securities themselves. Depending on rating and credit quality, as imposed by a credit rating, a firm can see how much yield needs to pay to investors. To the extend a rating change affects bond prices should also be of interest of the firm's investment and capital structure decisions, as those can trigger a rating change. Obtaining a high credit rating, or maintain the same one, also represents a source of value for firms, as a downgrade reduces funding options, and trust to bondholders, so they have strong incentives to prevent a rating downgrade. Begley (2013) documented that, in the attempt to achieve a higher credit rating, firms reduce their investment in research and development and these types of adjustments might have negative effects on the overall economy, hence market participants should be aware of those effects.

Beside the abnormal returns prior to the rating change, indicating that CRAs tend to lag the market, my study finds significant cumulative abnormal returns around the day of the announcement for both downgrades and upgrades. This effect was stronger during the global

[1] See Valentin Dimitrov, Darius Palia, Leo Tang (2015)

financial crisis as investors were more pessimistic and overreacted to a rating change. The cross-sectional analysis documents that the magnitude of the effect of a rating change is determined by the size of the rating jump, the previous rating of the specific issuer and whether the rating change cross the investment grade boundary. This study is one of the few that do find information content in both upgrades and downgrades. My result also explains how investors made investment decisions during the global financial crisis and finds that the reliance to the credit rating agencies significantly decreased in the post crisis period.

The reminder of the paper is organized as follows. Section 2 describes the current literature on the reaction of credit rating announcements in the stock, CDS and bond market and the theory beyond the academic research. Section 3 analyze the hypothesis to be tested among the analysis. Section 4 and 5 describes the data to be tested and the methodology used to obtain my result respectively. Section 6 describes the findings of this paper and section 7 concludes.

2. Theory and Literature

2.1 The Credit Rating Industry

Before describing further my analysis and other relevant studies, it is useful to describe what a credit rating is, how the credit rating system looks like and how a credit rating is made. After that, I can discuss why one can expect to find information in a rating upgrade or downgrade. A credit rating is an assessment of the creditworthiness of a borrower, an evaluation of the credit risk of a debtor. Credit ratings are presented by a letter that reflects the ability of the borrower to pay back the debt and a forecast of the probability of the debtor defaulting. It is relevant with the credit score for the individuals but in this case, it is for a given entity (an individual, corporation, state or provincial authority, or sovereign government).

Credit assessment and evaluation for companies and governments is generally done by a credit rating agency (CRA) such as Standard & Poor's (S&P), Moody's, or Fitch.[2] The debt instruments rated by CRAs include government bonds, corporate bonds, CDS, municipal bonds, preferred stock, and collateralized securities, such as mortgage-backed securities and collateralized debt obligations. These rating agencies are paid by the entity[3] that is seeking a credit rating for itself or for one of its debt issues. However, in the past the paying customers of credit rating agencies were the buyers of the securities and not the issuers, something that now, raises a conflict of interest issue[4].

Credit Rating agencies uses a letter-rating system to indicate the creditworthiness of the issuers. Table 1 presents the Different rating tiers[5] for the Big Three CRAs.

Important distinction that arises from Table 1 is between Investment Grade and Speculative Grade Bonds. Investment Grade bonds, rating BBB-, Baa3 or higher, are the bonds that are judged by the rating agency as likely enough to meet payment obligations. Junk Bonds are the ones with rating BB+, Ba1 or lower. The risks associated with speculative-grade bonds are considered significantly higher than those associated with investment grade bonds. The

[2] S&P, Moody's and Fitch are the "Big Three" credit rating agencies controlling approximately 95% of the ratings business worldwide.
[3] At least 75% of the agencies income is obtained from these fees.
[4] See Sinclair, Timothy J. (2005).
[5] The tiers continue below CCC, Caa1 to D but in my analysis, I will only use the ones presented here.

threshold between investment-grade and speculative-grade ratings has important implications for market participants as I will explain later in this section.

Table 1

Rating Tiers from Moody's, S&P and Fitch

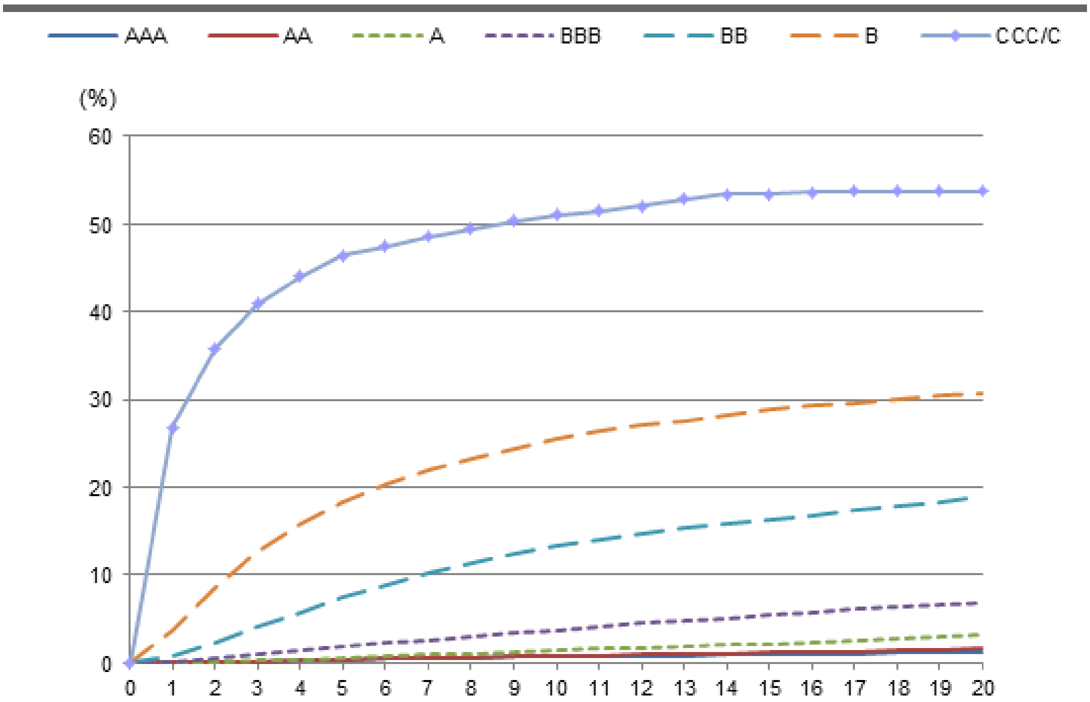
	Moody's	S&P	Fitch	Description	
1	Aaa	AAA	AAA	Prime	Investment-Grade
2	Aa1	AA+	AA+	High Grade	
3	Aa2	AA	AA		
4	Aa3	AA-	AA-		
5	A1	A+	A+	Upper Medium Grade	
6	A2	A	A		
7	A3	A-	A-		
8	Baa1	BBB+	BBB+	Lower Medium Grade	
9	Baa2	BBB	BBB		
10	Baa3	BBB-	BBB-		
11	Ba1	BB+	BB+	Non-Investment Grade Speculative	Non-Investment Grade, Speculative Grade, Junk Bonds
12	Ba2	BB	BB		
13	Ba3	BB-	BB-		
14	B1	B+	B+	Highly Speculative	
15	B2	B	B		
16	B3	B-	B-		
17	Caa1	CCC+	CCC	Substantial Risks	

To support the risk associated with a given credit rating, one can make inferences from the historical defaults rates by rating category. However, one should not assume that the historical defaults rates represents the probability of default of a bond issue in the given category. Moreover, default rates can vary significantly from one year to the other and market participants should be aware of that when making investment decisions. Chart 1 represents the

Historical Average Cumulative Default Rate of Corporate Bonds as presented by S&P Global Ratings.

Chart 1

S&P Global Ratings. Default, Transition, and Recovery: 2016 Annual Global Corporate Default Study and Rating Transitions. Global Corporate Average Cumulative Default Rates By rating (1981 – 2016).



To understand if a rating change carries important information for the market participants, I should consider the credit rating process followed by the credit rating agencies. In their rating process credit analyst review the company's ability to pay after considering a variety of factors at the business level. Their analysis includes an investigation of the risks that the company is facing (business risk, corporate governance risk, financial risk, operational risk), an analysis of the covenants and collaterals of the specific issues and their historical performance, prior earnings and capital structure.

CRAs claim that their ratings reflect publicly available but also private information that is gathered thought meetings with the issuer's management team. Beside the initial rating, the credit rating stays in contact with the issuers and if the agency believes that there is a change in their credit quality, a rating change can be made. Those include upgrades, downgrade watch-listings and outlooks. A Downgrade (Upgrade) specifies that the credit quality of the issuer has decreased (increased) and that their rating should be lower(higher) than the one they already have. On the other hand, a negative (positive) outlook indicates a potential downgrade (upgrade) within the next 2 years while a negative (positive) “watch” indicates a potential change the next 90 days. Under this rationale, I expect to find information content in any rating change announcement in my analysis, as those are perceived as a new information by the market participants and they will take investment decisions accordingly. The importance of using watch listing and credit outlooks in the credit rating process is documented in a the Bannier and Hirsch (2010) paper. They test two different periods in their research, one where Watch listings where not introduced and one where it was. The found that the information content of rating change significantly increases on the period where watch listing were introduced as the agencies were able to disclose different level and quality of risk-relevant information, given more detailed credit review to market participants.

Besides the fact that a rating change carries new information to the market, we should be able to understand why this may affect the bonds’ prices and what drives bonds’ yields in general. Bond prices are equal to the present value of expected cash flows (coupon + principal) when those are discounted with the appropriate required yield. As in stocks, and under an efficient market hypothesis[6], bonds prices should reflect the level of risk one undertakes when investing in them. Hence, in bonds, the required yield is equal to the risk-free rate plus a risk premium for the risks one bares by holding those type of securities. In such an analysis the risk-free rate is assumed to be the level of Treasury yields which determined by the level of the current spot curve. Therefore, yield levels of corporate bonds are subject to change if there is a movement in the level of yield curve, which can only be influenced by the central banks, or if there is a change in the level of risk of the individual bond issuers. As a result, the change of the credit rating of a firm, which is translated as a change in the credit quality, should be reflected on the risk premium and the yield level of the individual bond issues. Hence, I expect those rating changes, that are perceived as new information to the market, to impact the bond yields and as a result the bond prices.

Of course, to make inferences about the information content of rating changes I should first make assumptions about the bond market efficiency. Fama (1970) extended the theory and

[6] See Solnik (1991)

included three forms of market efficiency: weak, semi-strong, strong. The semi-strong form tests of Eugene F. Fama (1970) are supporting the efficient markets hypothesis. Semi strong form of market efficiency is a sufficient condition to support my hypothesis for information content in rating change announcement. Bond prices should reflect all publicly available information and under the assumption that a rating change also carries private information, bond prices around the day of the announcement should reflect this new information to the market.

2.2 The stock Market reaction

Although this study's focus is on how credit rating announcement affects bond prices it is useful to investigate what the current academic literature has to say on the stock market reaction. The reasoning on this, is that there is a positive stock-bond price correlation,[7] and by assuming a credit rating change is a new information to the market regarding the riskiness of a particular stock, bond or company, the effect should be visible across all different investment instruments. For the same reason I will also mention the current literature on how the CDS market perceives a credit rating announcement in the upcoming section.

There are numerous studies in the academic literature that have investigated the effect of credit rating announcements in the stock market. A handful of previous studies have failed to find significant price movements due to rating change announcements. This is mainly because they used monthly data instead of daily, something that might be problematic for controlling price movements due to other information releases during a month. Finding no effect, following a credit rating announcement is mostly mentioned in the early literature.

Starting in 1978 Pinches and Singleton (1978) used monthly returns on individual securities and find no significant residuals different than zero, even after controlling for other company specific event clustering, around the day of a rating change announcement. Their findings implies that all the information was already anticipated in the prices prior to the event (high abnormal returns since 15 months before the announcement),something that supports the view that credit rating agencies tend to lag the market and that a rating change is not perceive as new information by market participants. The stock markets lag substantially, especially if a credit

[7] See Hand et al. 1992

rating change is periodical and not caused by an unexpected event. They concluded that a substantial rating lag exists, especially where a specific event is lacking.

Those result were also consistent with other studies like Cook (1983) which was the first to examine the impact of a credit watch in a firm's stock price. By examining 111 firms which were under credit watch by Standard and Poor's he found little or low value information upon a listing announcement. However, he founds that the market reacts differently for firms that were under negative watch and eventually downgraded, and the firms that were negative watched, but their rating was eventually not changed.

Contrary to the previous ones, many studies in the academic literature found significant price reaction to credit rating change announcements, but only for downgrades such as Griffin and Sanvicente (1982). The main contribution of this paper was to question the methodology used to calculate abnormal stock performance in previous papers and was the first to mention that intraday data must be used for the estimation of abnormal returns. As I will discuss later, my research will be one of the first to use intraday data from TRACE database to calculate abnormal returns.

Later, a more extensive study by Holthausen and Leftwich (1986) brought new evidence in the market by using a different methodological approach. They examine abnormal returns of the common stock of companies experiencing bond rating changes, by being the first to use daily stock data. They included credit rating changes announcements and watch-listings from both Moody's and Standard and Poor's, and after controlling for contaminated [8]observations, they found significant negative abnormal bond returns associated with downgrades across rating classes[9]. This innovation for controlling for other public news (contaminated observations) was adopted in later studies[10] as well, which also found similar result for downgrades announcements. Moreover, they were the first to introduce the "fallen angels" concept, which implies that when a firm drop from investment grade to speculative, the rating change is more informative.

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[8] Contaminated observations are classified the rating change announcements which occurs under the same time of other company specific event announcement, like debt or equity financing, retirement of debt, merger, etc. At Holthausen and Leftwich (1986) study, if any other firm-specific information appears in the Wall Street Journal during the four trading days, day - 1 to day + 2, of the rating announcement then they are classified as contaminated.

[9] 1st class: AAA 2nd class: AA+, AA, AA- etc.

[10] Cornell et al.(1989), Hand et al. (1992), Wansley et al. (1992), Goh and Ederington (1993) and Followill and Martell (1997).

Similar results are presented by the study of Cornell, Landsman, and Shapiro (1989) who examines whether the price movements of stock prices, due to bond rating changes, are affected by the firm's intangible assets. In their cross-sectional variation, they found that a rating change effect is significant higher for companies that have more intangible [11]assets. In addition, they found no positive upgrade effect as their model has no explanatory power with low F statistic and with explanatory variables not significant different from zero.

Until now numerous studies have documented the negative reaction of stock prices. Goh and Ederington (1993) and Goh and Ederington (1999) also found significant reaction to downgrades. However, they were the first to test and examines what drives the downgrade decision from the credit rating agent. . Goh and Ederington (1993) used daily stock returns and credit rating change announcements from Moody's and they separate the rating announcements into groups based on the implications they have to equity holders and whether they seem to be in accordance with other recently released publicly available information. They found that downgrades that are due to a deterioration in the firm's financial prospects result in significant negative price movements and that downgrades that caused by any other reason have no effect. They concluded that rating downgrades should not be treated homogeneous. The Goh and Ederington (1999) extended the original research of the later one and found that the negative price movements effect is stronger to downgrades at the lower end of the rating scale. They also found stronger price movements if the preannouncement abnormal returns have already been negative and large.

The negative reaction of the stock market to downgrades was also documented in later papers. Dichev and Piotroski (2001) also examined Moody's data and present significant negative abnormal returns which were kept over a year following the day of the announcement and initiate the information processing bias which result in no effect for upgrades. Norden and Weber (2004) found significant abnormal returns starting around 2.5 months before the announcement, and in addition their cross-sectional analysis reveals that the magnitude of abnormal performance is influenced by the level of the old rating and as well as other previous rating events. A different approach followed on Li, Shin and Moore (2006), where they tested how the global rating agencies affect the Japanese stock market. Their finding present that credit rating downgrades are more influenced from the global rating agencies than the local one. They also confirm that the effect is only significant for downgrades, that there are not any

[11]To estimate Net intangible assets current cost data were used

significant differences between the two rating agencies they tested (Moody's and S&P) and that the result was similar for both the normal times and the recession of the Japanese economy.

Similar results are also presented in Kim and Nabar (2007), but by using a different methodological approach. They studied how the bankruptcy probabilities [12]change around the day of the credit rating change announcement. Consistent with the aforementioned studies they found that the default probabilities decrease prior but not after the announcement. On the other hand, default probabilities significantly increase both before and after a rating downgrade which implies that rating downgrades are timelier than upgrades.

Until now I have summarized the current literature that have found either no effect in equity prices due to a rating change or found effect only for downgrades. Contrary to those studies the first studies to find significant effect in both downgrades and upgrades was the Stickel (1986). The researcher examined the effect of credit rating change on preferred stock returns. By using daily stock return data and after controlling for contaminated observations they found significant price reaction to both upgrades and downgrades on event day +1.

The next paper that have also found significant price changes for both upgrades and downgrades is Hand et al. 1992. Their innovation was that they build an expectation model of rating change and separate the expected and unexpected observations. They also did the separation for contaminated observations like by Holthausen and Leftwich (1986).

Upon examining the observations in their sample, Hand et al. (1992) found that the impact of credit rating changes on the examined stock prices was significant but not economical significant. But the effect was much stronger and more significant with respect to unexpected observations as opposed by their expectation model, which can explain the differences with respect to earlier literature results. Of course, as expected the effect was much stronger for the downgrades and negative watch listings. On the other hand, after controlling for the contaminated observation the upgrade affect seems to disappear in the stock market.

In addition to the literature that have found significant price movements for both upgrades and downgrades is the line of studies by Jorion and Zhang. In their first paper, Jorion and Zhang

[12] Bankruptcy probabilities are assessed by using bankruptcy prediction models by using Chava and Jarrow monthly model that uses accounting and market information date, yields and industry effects.

(2005), study the effect of Regulation Fair Disclosure [13] implemented on October 2000. Since the effect of this act in U.S, credit analyst at rating agencies had access to non-publicly available information that equity analyst for example did not have. Under this rationale, this can increase the information content of credit rating changes as they have access to confidential information. By examining 2 periods, one before and one after the implementation of RFG, they found that the information content of the credit rating announcements, indeed increases in the period after RFG. But most importantly they were on of the first that found significant price movements for both upgrades and downgrades. This can explain the failure of the previous studies to find any price adjustment in case of upgrades, as at that point the credit rating agencies had an information advantage compare to the market.

A more recent study by Yang et al. (2017) by using a unique dataset of the Korean stock market were the first to also analyze the information asymmetry of a credit rating announcement between different investor groups around the day of the announcement. They found abnormal trading volume around the day of the announcement and that the trading behavior varies across different type of investors. It seems that institutional investors have information superiority compared to individual investors. In addition, there empirical results indicate that there is significant price movement around the day of the announcement for both downgrades and upgrades, although the effect was stronger for downgrades.

2.3 The CDS Market reaction

Later literature has studied the information content of the credit rating change announcements by examining the CDS market. Credit derivatives[14] became quite popular over the last 2 decades, and credit default swap (CDS) is the most common form of credit derivative and may involve municipal bonds, emerging market bonds, mortgage-backed securities or corporate bonds. So, what a CDS is and why do the previous researchers expect to find information content upon a rating change in the CDS market?

CDS is a contract between two parties and allows investors to transfer credit risk from investments. More specifically, the buyer of a CDS pay fixed annual payments to the seller, namely credit default swap spread, and the seller in case a predefined event occurs, for example

[13] The Regulation Fair disclosure prohibited U.S. public companies to make selective nonpublic disclosure in order to favor investment professionals. This was excluding the credit risk analyst from credit rating agencies.
[14] The first CDS contract was in introduced in 1998 and in 2018 the U.S. Comptroller of the Currency reported that the size of CDS is around $3.7 trillion.

a bankruptcy of a company, is obliged to pay the notional amount of the swap and receives in exchange the defaulted assets. The counterparties may agree on a cash settlement, where the seller must pay the loss amount occurred on the notional. Under this rational, the credit default spreads should reflect the riskiness of a particular asset or company. When a credit rating event occur, like a downgrade, the CDS spread should increase in order to reflect the new level of risk. For this reason, previous researcher studied the effect of credit rating change announcements on the CDS spreads.

Hull, Predescu and White (2004) examined cumulative abnormal CDS spread changes around the day of the announcement of credit rating changes, outlooks and watchlistings. They find significant positive adjusted CDS spread changes in case of downgrade or negative watch event. Their results also indicate that the largest CDS spread movement is occurring prior to the rating event [-30, 0], which implies that the credit downgrades are already anticipated by the market. In the post rating change event period, they find no significant movements, as CDS already incorporate different level of risk prior to the event. Consistent with prior research on the bond market, they fail to find significant CDS spread adjustments in case of upgrades or positive watchlisting announcements.

Similar methodology implemented by Norden and Weber (2004) and found that negative credit ratings and negative outlooks have a significant and string positive effect on CDS spreads. Their analysis across different credit rating agencies indicates that while S&P and Moody's, have a strong influence in the CDS market, Fitch rating announcements do not cause any effect. Their cross-section analysis also reveals that the level of the impact in CDS spread is associated and strongly depends on the level of the previous rating and the average rating level across all rating agencies prior to the event.

A later paper by Galil and Sofer (2011) brought new evidence in the market, for the information content of upgrades. They found that the CDS market response to credit rating announcement is significant for all type of rating events. Although, consistent with prior research, their findings indicate that the market reaction under downgrades and negative outlooks is much stronger than upgrades and positive outlooks. In addition, this study was the first to question the practice of using uncontaminated samples, claiming that this underestimates the market response to credit rating events. Their reasoning is that clustering of rating events reflects the significance of the information content on this ratings thus should not be excluded.

Finnerty et al. (2013) is another paper that manage to capture the effect of credit rating announcement in both upgrades and downgrades but, similar to prior research, their results show that downgrades are more anticipated by the CDS market. After controlling for credit rating events prior to the announcements they also found that Outlooks and Watchlistings significantly impacts the CDS spreads. They also mention that the effect of credit rating changes in the CDS market is magnified under the concept of Fallen angels and Rising Stars. Relevant for my study Finnerty et al. (2013) also mention that during recession period, the impact of upgrades is magnified. Explanation to this is that investors react and take investments decisions easier based in good news than in bad news during bad times.

Similar result also presented in Kiesel et al. (2016) who also studies the CDS spread response to rating changes and find significant spread movements during both upgrades and downgrades under normal market conditions. This study also compared the effect of rating changes during recession period to changes during normal times. His results confirm Finnerty et al. (2013) findings, that during recession, credit rating downgrades are not informative, but they did not find any information content in upgrades either. He claims that rating agencies merely follow markets in their decisions during the financial crisis.

2.4 The Bond Market reaction

Prior research was motivated in order to examine the degree at which bond ratings are related with the capital markets efficiency and whether credit rating agencies are capable, in terms of skills and information, to manipulate bond returns purposely. The results from previous studies that examined the effect of credit rating change announcements in the bond market are more controversial than the stock market and the CDS market. Early literature finds no significant results, later literature mostly supports that there is information content on credit rating changes but only for downgrades, while there are a few studies that find that both downgrades and upgrades lead to price movements.

More specifically, Katz (1974) paper investigates the efficiency in the bond market by examining the price adjustments prior and after a credit rating reclassification, and he was the first to question the information content of credit rating changes. By using monthly yields, the researcher examined 115 bond issues and associated credit rating changes from Standard and Poor's. He finds no unusual behavior on the yields during the month of the announcement. However, he supports that there is lag in the market that persists 6-10 weeks after a rating change. In addition, similar results obtained from the later study of Grier and Katz (1976). They also used monthly data and examined two different bond issuer groups, the industrial sector and the public utilities sector. Their results indicated, that the new information of a credit rating change is not instantaneously absorbed by the market but there is a gradual adjustment after the rating change which is also only significant for industrial bonds. Moreover, this paper correlated the time to maturity with the price sensitivity to credit rating announcements, proposing that short to mid-term industrial bonds may be profitable even in case of a downgrade. To my opinion the results presented by Katz (1974) and Grier and Katz (1976) are quite biased as the usage of monthly yields may not be able to capture any abnormal price movement around the day of the announcement.

The same might be true for the Weinstein (1978) paper. This paper contradicts the previous studies as it finds no significant reaction to credit rating change after the announcements. Monthly data was also used in this paper while the credit rating provider that was tested was only Moody’s. Previous studies also used one rating agency and I oppose that their results might be subject to sample selection bias, as the usage of one rating agency does not represent the whole credit rating industry. Nevertheless, Weinstein (1997) also fails to identify significant price movement before or after the rating change announcement and finds no abnormal performance 6 months prior to the rating event.

Contrary to the previous studies there are significant amount of prior research that manage to find significant price movement upon credit rating downgrades. I believe that the main reason that most recent studies succeed in finding significant price movements is the usage of different methodology and datasets that are more homogeneous.

Wansley, Glascock and Clauretie (1992), was the first study to use weekly data instead of monthly like the previous researchers. It was also one of the first papers, that beside the credit rating change announcements, also examined the impact of CreditWatch placement. They found no significant price reaction around the placement date on CreditWatch, for either positive or negative, which implies that there is no incremental information in the watchlisting placement. However, they do find bond price movements in case of a downgrade compared to upgrades and watchlistings. Their cross-sectional analysis indicates that the effect on bond prices is positive correlated to the number of grades the firm is downgraded and on the other hand the effect remains the same for issuer falling into non-investment grade. They also mention that by eliminating contaminated observations the effect on bond prices remains the same.

Hite and Warga (1997) is the first paper that uses monthly returns and find significant market reaction to downgrades at the month of the rating change announcement. They investigate industrial bonds in the event window [-12, +12] (months), and their results also indicates evidence of market reaction under upgrades, but only for Rising Stars[15]. The effect of price movements becomes stronger for Fallen Angels[16] and after eliminating contaminated observations. In their analysis they also present similar price movement when splitting the sample to the one by Moody's and the on by S&P.

A more extensive study by Steiner and Heinke (2001) brought new evidence to the academic research by studying Eurobond returns and investigating the impact of a US-credit rating agency to non-US issuers. They study daily bond abnormal returns 6 months prior and after the event day and find significant abnormal returns, starting 90 days before the announcement, for rating downgrades and negative Watch announcements. This abnormal market movements persist for up to 3 weeks after the day of the announcement indicating some market lag to adjust to this new credit information. They also fail to find any abnormal market movement in the event of upgrade or positive Watchlisting. In their cross-sectional analysis is indicated that the yield level, the issuer type and the issuer nationality are key determinants to the intensity of price reactions. As they also found stronger effect under Fallen Angels issues, they propose that this might be driven by price pressure do regulatory constraints[17] of some investors. They also mention that if there are other announcements before the day of a rating change or watchlisting, they do not affect the price movement.

Most of the aforementioned studies find significant market reaction in downgrade but, fail to capture the same effect in upgrades. The asymmetrical response to downgrades and upgrades is provided by many explanations. Holthausen and Leftwich (1986) state that rating agencies face asymmetric loss functions and that they allocate more resources on revealing negative credit information than on positive ones. Other explanation is the asymmetric risk aversion of bonds investors, as information with bad news are valued more. The price pressure under downgrades may also be a reason for more pronounced market reaction under upgrades. However, to my knowledge none of those potential explanations have been tested before.

[15] Upgrades from non-investment grade to investment grade.
[16] Downgrades from investment grade to non -investment grade.
[17] For example, institutional investors cannot hold non-investment grade bonds.

Contrary to the previous studies, there are a few example of studies in the academic literature that manage to capture the effect of a credit rating change in the bond market for both upgrades and downgrades.

As also mentioned earlier in the stock market section, Hand et al. (1992) also found significant effect for both downgrades and upgrades in the unexpected observation sample. Their results for the stock market where also similar to the bond market reaction. Credit rating changes and watch listing does have a significant effect on the corporate bond prices in their sample. However, compared to the stock market, the researchers found an inconsistency when controlling for the contaminated observations. While the upgrade effect disappear in the stock market and the downgrade effect persists, on the bond market they observed the exact opposite. Despite their inconsistencies though, the researchers do find significant prices movements in both upgrades and downgrades.

Additionally, an important findings of their study as far as downgrades are concerned, is that excess bond returns tend to be firmer for bonds evaluated below the investment grade than for bonds evaluated as investment grade bonds. This can be explained by the fact that the risk aversion of investors in not linear. When a bond that is already low rated, gets downgraded further it causes much stronger effect than if it was in the investment grade segment due to price pressure from shorting. I expect to find similar results when comparing different graded bonds and stronger effect for downgrades into junk bonds.

A later study by May (2010) also finds significant price movement for both downgrade and upgrades, although the bond market reaction to upgrades are economically small. This paper studies the 2 days event window [0, +1] and finds abnormality in all rating changes by using Bessembinder et al (2009) methodology and data from TRACE. In order to robust his results, and compare his finding with early literature studies, he also uses monthly data to calculate abnormal returns. His results indicate that using monthly returns also lead to significant price reaction, but the effect was overestimated compare to the two-day event window. The cross section supports the findings of earlier studies, Hite Warga (1997) and Steiner et al. (2001), on the Fallen angel effect and indicates that the price movement is stronger for lower rated companies and for surprising news[18].

[18] Under May (2010) surprising new are rating changes that during the event period [-15,0] do not present significant abnormal returns in the direction of the change.

2.5 Combined Studies

Many studies in the current academic literature have tested the effect of credit rating change announcements by calculating abnormal returns in more than one instrument. This can assist us understand how different those instruments may react and which market is more efficient to determine the information content of a credit rating event.

According to a Wansley and Clauretie (1985) paper, which examined firms' equity returns and bond prices fluctuation close to the dates of their listing on the Standard and Poor's Credit list, they found that the equity market reacts significantly in case of downgrades following the firms listing and no effect in upgrades and credit watch where the rating is not changed eventually. The Bond market findings indicate a large lagging to credit ratings changes, however firms getting listed in the Credit list before downgraded seems to decrease the lagging. Indicatively, the lag time in case a firm is not listed in the Credit list reaches four months. This justifies that a firm listing in the Credit list is expected to result in faster bonds' prices adjustments upon credit rating changes, mostly upon downgrades. Additionally, the researchers argued that bond market seems to be less efficient than stock markets, observing bond prices remaining stable even for a period of seven months from a change in the credit rating.

Moreover, according to Hand et al. (1992) paper, the stock and bond markets are correlated both with firms entering the Standard and Poor's Credit list and with credit rating changes, both actualized and announced by either Standard and Poor's or Moody's. Additionally, the inconsistencies found in their study as explain earlier suggest that that credit rating upgrades and downgrades affect the bond and stock markets differently.

This is also consistent with May (2010). His results indicate that although both market reacts negatively and significantly in downgrades, the effect is different for upgrades. According to this paper, the reason for this, beside the small information content on a credit rating upgrade, might be to some wealth transfer effects. This is related to the different implications that some rating may have for stockholders and bondholders. For example, a rating upgrade is perceived as a positive sign by bondholders, as it increases the credit quality of the obligors, while it can be perceived as a bad new from stockholders, if wealth is transferred from stockholders to bond holders, by increasing leverage. This is also consistent with Holthausen and Leftwich (1986), Goh and Ederington (1993).

2.6 Other Line of studies

An important line of studies in the current academic literature starts with Guttler and Wahrenburg (2007) that studied how credit rating announcements by different credit rating agencies interact with each other on the bond prices. They studied Moody's and Standards and Poor credit rating announcements for bonds issued by issuers close to default. More specifically, they examined whether there is lead or lag time and how this is related to different credit ratings (downgrades and upgrades. They concluded that one credit agency downgrade is followed by another agency higher level downgrade. Moreover, they found that it is more likely for a credit rating to cause a same sign credit rating by another agency, more often for downgrades rather than for upgrades. Therefore, this can justify the fact that the first downgrade in a series of downgrades can affect a bond price more than any consequent downgrade, which is also the case for upgrades, yet less often.

Following the later, another study by Alsakka and Gwilym (2012) analyzed how different credit rating agencies conclude in credit ratings independently. Their main results indicate that Moody's ratings are directed in order to maintain the maximum potential rating stability, Standard & Poor ratings are announced with an eye for the highest possible short-term accuracy, while Fitch tend to rate bond issuers upon the previous two agencies ratings. Those findings may explain potential differences on how the market participants interpret credit announcements from different credit rating agencies and explain potential deviations in the calculated abnormal returns by credit rating.

The last paper I would like to discuss is the one by Bessembinder, Kahle, Maxwell and Xu (2009) on the methodology for measuring abnormal bond performance by implementing different test of statistics on the different methodologies. They claim that using daily bond data instead of monthly, will significantly increases the power of the tests. This can explain why previous literature that used monthly data to find information content on a rating change failed to find significant results. Moreover, they indicate the importance of the TRACE database that gives access to intraday daily transactions and allows to use value-weighted intraday prices in an event study rather than the closing price. The intraday prices significantly increase their test. Finally, they propose that value weighted matching portfolio approach is a better specified and more powerful benchmark to use. Similar methodology on bond market event study was proposed in Ederington, Guan and Yang (2015). The Bessembinder et al. (2009) approach is also used for the purpose of my study as I will explain later in the Methodology section.

3. Hypothesis Development

In this section, I am describing the process followed for building the research hypotheses tested for the purposes of this study. By reviewing current literature and based on the data that were available, I develop 10 Hypothesis which will be tested for rejection or acceptance during the calculation of abnormal returns around the day of the announcement and during the cross-sectional analysis.

3.1 Information Hypothesis

After the global financial crisis credit rating agencies have been severely questioned by market participants. On the other hand, credit rating agencies claims that their ratings reflect explicit information that are not publicly available. This information content of credit rating changes has been tested in various previous research. The results in the bond market are controversial, as earlier literature find only significant results to downgrades, while there are some papers in the later literature that their results.

The main purpose of my study is to investigate if indeed a rating change carries new information in the market. Credit rating changes implies, a swift in the riskiness of an issuer, hence its specific bond issues. This can be translated as an additional risk premium bondholder require for holding riskier securities. Hence, I expect this new information of a swift in risk in a specific rating change, to have an impact on the corporate bond price. This effect should be stronger if the rating was assigned contemporaneously with the same direction credit watch.

As also mentioned in previous papers like Hite and Warga (1997) and Steiner and Heinke (2001), I expect that the price movement to be permanent since the new information should be fully anticipated by the market close to the day of the event. Moreover, previous researchers indicate that the credit rating agencies tend to lag the market. Hence, I expect to find significant price reaction 30 days prior to the event as the risk associated with the rating change may be already incorporated in the prices. The first hypothesis to be tested is the following:

> ***H1*:** There are abnormal bond returns in the event window [-1, +1] for both downgrades and upgrades. This effect should also hold true for rating changes that announced simultaneously with a watchlisting event.

The reason I am testing what happens 1 day prior to the event is to allow for information leakage effect. I am also including the day after the announcement to allow lag time adjustments in the market from non-US investors. Moreover, CRAs usually announce the rating change after the stock exchange closes for the day thus any investment decision based on this new information will occur the next day.

I am also testing for abnormal performance in the event windows [-30, -2] and [+2, 30] in order to find potential movements prior to event and lag by the market to fully incorporate the new risk associate with downgrades or upgrades respectively.

3.2 The Stronger Negative Effect

As mention in the Literature section, all prior studies in the academic literature finds that the stock, CDS and bond market reaction is significant stronger under credit rating downgrades and negative watch, compared to upgrades and positive watch. This asymmetric behavior can be explained by many reasons.

Holthausen and Leftwich (1986) states that CRAs allocate more resources on revealing negative credit rating changes than on positive ones. They concern about losing their reputation for keeping a rating falsely too high. Other explanation, mentioned in Hull et al. (2004) comes from behavioral economics, on asymmetric risk aversion of investors. Their decision is easier to get affected by bad news than good news.

> ***H2:*** The reaction of the bond market should be stronger for downgrades and negative watchlisting events compared to upgrades and positive watchlisting events.

I also propose another explanation, that companies themselves, are much more willing to provide positive information in the market than negative ones. Hence, the information content of upgrades will be also incorporated in the prices, as the management team of the firms would already communicate the good new to the public, and the bond prices will already reflect this information. To examine this hypothesis, I am testing whether the prior event window [-30, -2], provides stronger abnormal returns to upgrades than to downgrades.

Another explanation proposed in the current academic literature, is the price pressure from Fallen Angels and Rising stars. Downgrades trigger selling decisions while upgrades do not force buying ones. In this paper, I will examine if this explanation holds true by excluding from the original “normal times“ sample the Fallen Angels and Rising Stars. If the negative effect is still stronger after this exclusion, then the explanation of asymmetric behavior due to price pressure can be rejected.

3.3 Weaker reaction under recession

In this hypothesis I am testing weather the effect of credit rating change remains the same under recession times. Of course, the differences might be related to many other determinants. First the low interest rate environment after recession may cause firms to take more leverage, making their firms riskier in terms of long terms obligations. Moreover, as also mention in Jorion et al. (2005) downgrades are more frequent during recession times, and more expected by the market, hence less informative. Similarly, upgrades are very rare and might trigger overreaction on the buying side. The effect of upgrades during recession documented in Finnerty et al. (2013).

A counter argument of the above might be that investors are more pessimistic (optimistic) during down times and overreact (underreact) in case of downgrades(upgrades). However, I believe the firmer reasoning is more likely, hence my hypothesis is the following:

H3: Downgrades under recession times will be less informative, while the effect on upgrades will be significant stronger compared to normal times.

In order to test this hypothesis, I am splitting the sample in two sub periods as mention earlier. First the recession period which include the latest financial crisis in the US, December 2007 till June 2009, and the normal times sample to capture 10 years of market movements after the recession. Abnormal returns and Cumulative abnormal returns in the event window [-1, +1], for the 6 different rating change categories, will be presented for the two periods separately and compared to its main components.

3.4 Different Credit Rating Agencies Influence

Like Li et al. (2006) I expect, the magnitude and significance of a bod price movement due to a rating change, to remain the same across all rating agencies. I am testing credit rating changes and watchlistings announcement from the 3 major credit rating agencies, Moody's, S&P and Fitch.

Alsakka and Gwilym (2012) present that Moody's aims to rating stability, S&P to rating accuracy while Fitch tend to follow the rating from the other two rating agencies. S&P and Moody's are the biggest players in the credit rating industry that want to keep their reputation, while Fitch is the smaller one that aims to achieve higher market share. It might be the case that rating from Fitch are not perceived with the same importance as the ones from the other two CRAs. Thus, the content of a rating change by Fitch might be less informative. It would be interesting to see how the market actual values the information from the three different CAR. However, to my opinion the effect should remain the same, even if the above holds. Hence,

> ***H4:*** the difference of the impact on bond prices under a rating change from the 3 rating agencies, should not be statistical different from zero.

In order to test this Hypothesis, I am splitting the original "normal times" and "crisis" sample in 3 subsamples for the 3 different rating agencies and presenting abnormal returns and cumulative abnormal returns in the event window [-1, +1] to find potential significant differences. I am also including dummy variables in the cross-sectional analysis.

3.5 Fallen Angels and Rising stars

Under this hypothesis I am testing the concept of Fallen Angels and Rising stars. Fallen angel is a bond that used to be investment grade but due to a rating downgrade fall into speculative grade, below BBB- rating. Rising Star is a bond that was junk but due to a rating upgrade went above BBB- rating, to investment grade.

Financial institutions are subject to regulatory constrains regarding the riskiness of their investment portfolio. More specifically, they cannot hold big amounts of speculative bonds under the capital requirements constrains. Moreover, many fixed income investors use the speculative grade bonds as a border to their investments. All those conditions in the market, indicate that when a bond crosses this border, either with upgrade or downgrade, can cause significant price pressure due to the above investment constrains. This effect should be stronger than downgrades and upgrade within the same grade. Thus, I build below hypothesis:

H5: Fallen angels and Rising stars should have significant higher abnormal bond performance around the day of the announcement compared to rating change within speculative or investment grade.

I am testing this hypothesis in the cross-sectional variation. The coefficient for Fallen Angels (Rising Stars) should be negative (positive) and statistically significant in order to accept this hypothesis. A potential acceptance of this hypothesis will be consistent with previous studies like, Wansley et al. (1992) and Hite and Warga (1997), Steiner (2001) and May (2010) who investigate the impact of such movement. Earlier studies like Holthausen and Leftwich (1986) and Hand et al. (1992) fail to find significance abnormal price movement for rising stars and fallen angels compare to upgrades/downgrades within the same grade.

I also expect Fallen Angels to have stronger impact than Rising star. This is due to the reason that a bond falling in speculative grade, forces selling activities from institutions that cannot hold this type of investments, while an upgrade to investment grade do not necessarily cause buying activities.

3.6 Surprising news

In this hypothesis I am examining whether the effect of a rating change is stronger for surprising news. As opposed by Hand et al. unexpected events should trigger stronger price movement in the bond market that unexpected events.

In order to define a rating event as surprising I apply two conditions. First the specific bond issue should not have been subject a rating change over the last 24 months. Remaining in the same credit rating for a 2 years period, should increase the impact of a credit rating event, on the bond's returns. Secondly in the event window [-30, -2] the cumulative abnormal returns of the specific bond issue should be zero or positive for downgrades and zero or negative for upgrades. As there will be no same direction price movements over the month prior to the event, the market would not expect a rating change. Thus, I am building the following Hypothesis:

H6: The effect of a rating change under a surprising event should be stronger.

I am testing this hypothesis by characterizing specific bond issues as surprising or not if the agree with the above two conditions. Then in the cross-sectional variation I will examine if the coefficient of the surprising news is significant under both upgrades and upgrades.

3.7 Old Rating Class

Under this hypothesis I am examining if there is a significant different rating change effect under different rating classes. I firmly believe that the effect of a rating change will be stronger for lower rated firms, especially for downgrades. By examining the historical default rates of rating classes[19], I observe that default rates are increasing exponentially from high rated to

[19] See chart 1.

lower rated firms. Thus, a rating change for example from BB to CCC reflects higher risk increase than a downgrade from AA to BBB. Investors that are already investing in risky bonds, do react more pronounced in case their bonds become even more riskier, while higher grade bondholders may remain calm and not overreact for the same size of rating change in their investments. This Hypothesis is also consistent with the results of previous studies such as Steiner et al. (2001), Norden and Weber (2004) and May (2010).

> ***H7:*** The bond price reaction of a credit rating change should be higher for lower rated bond issues.

In order to test this hypothesis, I have built an attribute in my cross-sectional analysis. H7 is accepted in case the coefficient of the old rating in the cross-sectional analysis is negative for downgrades and positive for upgrades.

3.8 Size of the rating change

The final Hypothesis to be tested in this paper is with respect to the size of the rating change. Size reflect the rating jumps of a downgrade or an upgrade. For example, a downgrade from AA+ to BB is a rating change of size 4. I expect that the higher the size of the rating change is the more effect should be reflected in the bond prices, as it will be associated with higher risk differences. This hypothesis also tested in previous studies and found significant higher price movements when rating change was of a big size like May (2010) but contradicts the results from Steiner et al. (2001) who tested two different portfolios with size 1 movement and size >2 movements.

> ***H8:*** the price reaction should be stronger as the size of the rating jumps increases.

To test this hypothesis, I am calculating the size of the rating jumps based on the new and the previous rating. Then in cross sectional analysis I will test the SIZE coefficient for statistical significance. For upgrades, the coefficient should be positive and significant, and for downgrades the coefficient should be negative and significant.

4. Data And databases

The Following sections gives a good description of the Data used for the purpose of this paper. I describe the Database I sued to obtain daily prices, bond characteristics and bond rating announcement, the data selection process and some summary statistics tables.

4.1 TRACE Database

The Trade Reporting and Compliance Engine (TRACE[20]) is the FINRA[21]-developed database that facilitates the mandatory reporting of over-the-counter secondary market transactions in eligible fixed income securities. All broker-dealers who are FINRA member firms have an obligation to report all transactions in corporate bonds to TRACE under an SEC-approved set of rules. Originally TRACE was introduced in order to increase transparency in the OTC corporate bond market enhancing the reliability of the market and at the same time helps regulators to better monitor the market, pricing and execution quality.

Introduced in July 2002, TRACE consolidates transaction data for all eligible public and private corporate bonds (investment grade, high yield and convertible bonds), securitized products including asset-backed securities (ABS) as well as mortgage backed securities (MBS). Hence, individual investors and market professionals can access information on the over the counter (OTC) public and private bonds trading activity. Since its introduction many researchers have used TRACE to get access to intraday bond transactions.

Like in Bessembinder et al. (2009) and May 2010 I am also using TRACE to get intraday bond prices from each intraday transaction. In a coming section I will describe the filtering procedure I implement on my TRACE dataset and how I merge my data with the FISD database in order to get other bod characteristics, needed for my analysis.

4.2 Mergent FISD Database

As proposed in Bessembinder et al. (2009), I use Mergent FISD to obtain credit rating announcements and bond characteristics. Mergent Fixed Income Securities Database (FISD) is a comprehensive database of publicly offered U.S. bonds. Mergent FISD database gives access to issue details on over 140,000 corporate, corporate MTN, supranational, U.S. Agency, and U.S. Treasury debt offerings. It includes data on Bond Issues and Issuers, Bond Ratings, Bond Transaction and Redemptions with more than 550 data items.

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[20] https://www.finra.org/sites/default/files/TRACE_Overview.pdf
[21] Financial Industry Regulatory Agency

Besides the rating changes announcements data, I use Mergent FISD database to obtain bond characteristics such as yield, coupon, coupon frequency, maturity, offering date, industry, type and optionality characteristics for all publicly available bonds issues during the 2 sub periods of my analysis. Those data will be filtered as explained in the following section.

4.3 Data Selection

In the following section I present the data I obtained from the above databases and the filtering procedure I implement in order to get only the relevant data for my analysis. As a mention below, the data consist of corporate bond issues separated in two periods, intraday bond transactions from the OTC market, as reported in TRACE, and bond rating changes for specific bond issues from Mergent FISD database.

4.3.1 Periods

In order to test the recession hypothesis, I separate my ample into 2 sub periods. One during the economic crisis and one in normal times. For the recession period I will use the subprime mortgage crisis that led to the collapse of the United states housing bubble, the Great Recession. According to the national Bureau of Economic Research [22] the crisis began in December 2007 and ended in June 2009. Thus, the first period will be 01/12/2007 – 31/06/2009. To test my hypothesis under normal times I am taking the post-crisis period to cover 10 years of market movements. Thus, the second period of credit rating announcements will be the 01/07/2009 – 31/06/2019.

4.3.2 Bond Characteristics

As I am going to issue rating changes announcement on the firm level, there is a need for a homogeneity in my bond issues dataset. By Using the Mergent FISD database for specific bond issues, I implement the following procedure to filter the bond characteristics relevant for my study:

- As the specific Database, in Mergent FISD, also includes government bonds, I only keep the corporate [23] USD denominated bonds.
- I exclude bonds that are preferred, exchangeable, callable, puttable, asset-backed or convertible, as those have bond features that may not capture a price change in case of a credit rating announcement.

[22] See https://www-nber-org.eur.idm.oclc.org/cycles/sept2010.html
[23] By using the Industry group identifier, I exclude Government bonds (identifier = 4)

- Only include senior bonds with fixed rate coupon payments.
- I also exclude bonds that have credit enhancements as they have additional reassurance, compared to plain vanilla bonds, in case of defaults. I expect those bonds to act differently in case a rating change and I exclude them from the sample.
- Finally, I remove observations with missing values.

Similar bond characteristic was also used by Hand et al. (1992), Steiner et al. (2001) Bessembinder et al. (2009) and May (2010).

After the filtering procedure to the whole Bond issues sample downloaded from Mergent FISD database, from the 116.594 issues that were available at least one day during the crisis period, I am left with 17.713 unique bond issues from 2.835 issuers. Regarding the normal times period (01/07/2019), from the 299.330 debt issues that were available in the period 01/07/2009 – 31/06/2019 for at least one day, the final sample consists of 28.959 unique bond issues from 4.460 issuers

4.3.3 Rating Changes

For the bonds mentioned above, that fulfill the data characteristics needed for my analysis I download, from Mergent FISD database, credit rating change announcements from Moody's, Standard & Poor and Fitch. Those rating includes downgrades and upgrades, watch listing as well as initial rating assignments to new issues. As I will perform my analysis on the issuer level, the multiple rating changes for multiple bond issues an obligor may have will create duplicate values. As the specific bond issues, I have in my sample have same characteristics, in terms of security, seniority, optionality, coupon type and nationality of the issuer, I assume that the credit rating changes will be the same across all specific issues of a bond issuer. Even if this is not the case, I can assume that the credit rating change of different bonds under the same issuer will be positive correlated. Hence, I keep the rating changes on the issuer level.

As In previous studies, Steiner et al. (2001), Bessembinder et al. (2009) and May (2010) I exclude bond ratings changes that the new rating is below CCC+, as those may be contaminated observations that may be affected by other publicly available information such as a bankruptcies.

The Mergent FISD databases reports any different rating changes categories for the specific issues. For the purpose of my study I will only focus on downgrades and upgrades. In addition, the watch listing information is also available in this database, so I am separating the rating change announcement in the following 6 categories.

a) All available Upgrades (UPG)
b) All available Downgrades (DNG)

With the above I will test the different market reaction to downgrades and upgrades.

c) Upgrades with Positive Watch (UPGWPOS)
d) Downgrades with Negative Watch (DNGWNEG)

The above, will allow us to identify how the market reacts to Watch listing announcements at the same time with a downgrade/upgrade.

e) Upgrade with no watch (this include upgrades with negative watch) (UPGWNOT)
f) Downgrade with no watch (includes downgrades with positive watch) (DNGWNOT)

The last two categories will capture only the downgrade/upgrade effect. Table 2 presents credit rating announcement data statistics.

Table 2

Crisis Period							
	DNG		All DNG	UPG		All UPG	Total
Year	WNEG	WNOT		WPOS	WNOT		
2007	17	69	86		44	44	130
2008	394	867	1261	34	475	509	1770
2009	211	854	1065	5	118	123	1188
Total	622	1790	2412	39	637	676	3088

Normal Times Period							
	DNG		All DNG	UPG		All UPG	Total
Year	WNEG	WNOT		WPOS	WNOT		
2009	45	221	266	12	148	160	426
2010	74	437	511	44	540	584	1095
2011	120	498	618	41	588	629	1247
2012	77	586	663	44	545	589	1252
2013	68	461	529	47	603	650	1179
2014	48	383	431	26	730	756	1187
2015	73	618	691	17	515	532	1223
2016	26	592	618	16	517	533	1151
2017	16	328	344		382	382	726
2018	40	313	353	6	424	430	783
2019	14	140	154	2	233	235	389
Total	601	4577	5178	255	5225	5480	10658

The final sample consist of 3088 issuer level credit rating change announcement during the crisis period and 10658 rating changes across the normal times sample 01/07/2009 – 30/06/2019. I notice that during the crisis almost 80% of the rating changes are downgrades. This confirms Jorion et al. (2005) that downgrades are more expected during recessions, something that was expected, as upgrades during crisis period are very rare and that the market conditions cause a lot of downgrades. Fallen Angels are significant more during the crisis period compared to Rising stars. Moreover, 2008 and 2009 are by the far the years with the most credit rate changes. Downgrades and Upgrades are spread evenly across the normal times period sample. Something else worth mentioning, is that after the economic meltdown of 2007-2009 the credit rating changes are gradually decreasing every year. This may be related to the implementation of the Dodd Frank Act that increases the legal and regulatory penalties to the credit rating agencies for issuing inaccurate rating. Credit rating agencies may be more conservative for issuing false warnings and rating changes that can damage their reputation and incur some serious penalties.

Table 3

Crisis Times							
	DNG		DNG TOTAL	UPG		UPG TOTAL	TOTAL
Movement	WNEG	WNOT		WNOT	WPOS		
1	435	1289	1724	469	31	500	2224
2	125	355	480	107	6	113	593
3	34	95	129	16	2	18	147
4	9	24	33	15		15	48
5	11	9	20	17		17	37
6	2	7	9	2		2	11
7+	6	11	17	11		11	28
TOTAL	622	1790	2412	637	39	676	3088

In addition, in order to calculate the size of the rating change, as proposed by Steiner et al. (2001) I transform ratings into cardinal variables on a scale of 1 representing AAA, Aaa to 16 representing B-, B3[24]. This will also allow me to have uniform ratings across all 3 different credit rating agencies in my sample. I calculate the size of the credit rating movement by subtracting the previous rating variable from the new one. For example, a Downgrade from A+ to BBB is a size 4 movement. Table 3[25] and 4 represents the distribution of rating change by

[24] See Table 1
[25] Please refer to the Appendix for Table 3

the size of the movement across the 6 different credit rating change categories for both sub samples in my analysis. For both samples, most of the ratings are of 1 size movement and I also observe some extreme observations of above 10 movements, that represents less than 0.5% of the total credit rating changes.

Table 4

Normal Times							
	DNG		DNG TOTAL	UPG		UPG TOTAL	TOTAL
Movement	WNEG	WNOT		WNOT	WPOS		
1	472	3761	4233	4526	220	4746	8979
2	104	616	720	518	28	546	1266
3	9	101	110	90	4	94	204
4	13	56	69	39	3	42	111
5	3	21	24	17		17	41
6		13	13	14		14	27
7+		9	9	21		21	30
TOTAL	601	4577	5178	5225	255	5480	10658

Finally, I am reporting the table with the rating distribution by agency. The table indicates the market size of the 2 largest credit rating agencies Moody's and Standard and Poor's.

Table 5

Crisis Period							
	DNG		DNG ALL	UPG		UPG ALL	TOTAL
Agency	WNEG	WNOT		WNOT	WPOS		
FR	89	425	514	122	10	132	646
MR	350	629	979	176	4	180	1159
SPR	183	736	919	339	25	364	1283
Total	622	1790	2412	637	39	676	3088
Normal Period							
	DNG		DNG ALL	UPG		UPG ALL	TOTAL
Agency	WNEG	WNOT		WNOT	WPOS		
FR	89	1120	1209	1086	21	1107	2316
MR	290	1715	2005	2025	92	2117	4122
SPR	222	1742	1964	2114	142	2256	4220
Total	601	4577	5178	5225	255	5480	10658

4.3.4 Intraday Prices and data cleaning on TRACE

I obtain the intraday prices of each transaction for all bond issues that meet the characteristic discussed on a previous section from TRACE. Bessembinder et al. (2009) mention that using intraday data, increases the power of a test to detect abnormal performance. Those data will be used to calculate cumulative abnormal returns around the day of the announcement for each specific issuer and to build the matching portfolio, as I will describe in the methodology section, that will be the benchmark for identifying abnormal performance.

As also mentioned in Bessembinder et al. (2009) and Dick-Nielsen (2009) the TRACE database is mistakenly reporting some trades and creating duplicate values. By examining the reported data from TRACE, I found that the duplicate values of some trades are either corrections, cancellation or reversal[26] of some specific trades. In order not to consider those duplicates trades in my analysis, which might bias the daily price movements results I did the following cleaning procedure.

a. In case of a trade correction, I use the unique message sequence number to identify the duplicate trade and then I remove the first reported trade using the execution time, which will be the original trade, and keep the other trade. In case of multiple trades, I keep only the last observation.
b. In case of a cancellation, there will be 2 reported trades in my sample. The first observation is the original trade and the second will be the reported cancelation. Again, by using the message sequence number I remove both observations as they are not actual trades.
c. In case of a reversal, I use the same procedure as the one on a cancelation. The only difference is that a reversal is a cancellation that is not in the same day as the original.

Previous studies instead of keeping one observation of a duplicate value, have deleted both trades for cancellation, reversal or correction. That means that "correction" observations have been removed and not considered in the sample which might bias the results.

[26] Reversal is a cancellation of a trade report that was originally submitted into TRACE on a previous day.

My original sample was 64.468.045 observation. After the implementation of the aforementioned cleaning procedure in our data from Trace, the final sample consist of 62.379.036 observations[27].

As mentioned in Bessembinder et al. (2009) and May (2010), illiquid bonds may not capture the information content of a rating change around the day of the announcement. By using similar methodology as the above researchers, I apply a few trading restrictions. I require bonds to trade at least 10days over the last month of a rating change and at least one day in the event window [0, +1]. Those conditions are not that strict as in previous studies[28] to avoid potential sample selection bias. Some rating changes are more informative than others and may cause significant market reaction. Other rating changes may not be informative at all and cause no price movement or no transactions. I should not remove those type of rating from my sample as it can bias the results towards more informative price changes. Moreover, from the original sample of the bonds that are affected by a credit rating event, I exclude bonds that maturing less than a year after the day of the announcement, as their price movement is highly depended on the short time to maturity and may be not affected by the rating change of the issuer.

At this point, I would like to mention an important implication of previous research. Other studies that have use contaminated samples in the event study of abnormal returns. That means, that they excluded observation of rating changes if there were other firm specific events before the day of the announcement. However, studies like Wansley et al. (1992), May (2010) and Galil and Sofer (2011) found no different results even after controlling for contaminated observations. Keeping this in mind I will use contaminated samples. I also believe that even if there are other firm specific events it can still be the case that the credit rating change is driven from other private information. Hence removing such observations could bias the results.

[27] This is a 3.2% which in my opinion was important to be removed, for more unbiased results.

[28] Bessembinder et al. (2009) require bond to trade at least 10 days on [-20,-1] and on day -1 and day +1

5. Methodology

In this section I explain the methodology I use to examine the hypothesis described above.

5.1 Abnormal returns identification

I this event study I am using the Methodology proposed by Bessembinder et al. (2009). As proposed, I am using information from the over the counter market in order to calculate daily bond returns. After implementing the cleaning procedure on the data from TRACE database, as described on a previous section, in order to create continues times series date, I am calculating daily bond prices as the traded-weighted intraday price of all transaction of a bond within a day. Traded weighted price for each bond is calculated as follows:

$$P_t = \sum_i \left(P_{t,i} \times w_{t,i}\right) + AI_t \qquad (1)$$

where *t* is the time, $P_{t,i}$ is the intraday price of the trade *i*, $w_{t,i}$ is the relative weight [29]of this trade *i* and AI_t is the accrued interest since the last coupon payment which is calculated as follows.

$$AI_t = \frac{coupon \times n_{days}}{360} \qquad (2)$$

where n_{days} is the number of days elapsed since the last coupon payment.

Of course, to create continues time series I need each bond to trade each day. But this is not the case in the bond market as some bond issues tend to be very illiquid and not trade at all for a day even months. In order to overcome this issue, I set the missing price equal to the last observed traded-weighted price as calculated above.

In order to calculate bonds daily returns, I simply use the following equation which present the log raw return of a bond.

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \qquad (3)$$

where Pt is the trade-weighted price as calculated above.

Bessembinder et al. (2009) find that by using this method to compute daily returns increases the power of statistical test compared to usual closing prices. The problem when using closing prices is that TRACE reported prices include bid/ask fees. That means that in small trades the

[29] Volume of this trade divided by the total volume of all trades

portion of fees in the price is larger and will lead to biased results. The above method gives more weight to larger trades, so the effect of the fees almost disappears. Hence prices calculated as above, better reflect the actual prices.

As Bessembinder et al. (2009), value-weighted portfolio-matching approach appear to be the most powerful and appropriate benchmark to use in the calculation of abnormal returns. In my analysis I will also use the matching portfolio model. I will create the matching portfolios by using the two primarily risk factors that are most commonly controlled. First, the risk of default, translated by the credit rating of the specific issues, and secondly the time to maturity.

More specifically, regarding the credit rating I will split the bond issues in the sample based on the ranking grades as specified by the credit rating agencies. As I am removing from the sample rating below CC, I am left with 7 different ranking grades (see Table 1), AAA, AA, A, BBB, BB, B, CCC.

Regarding time to maturity, I am using Moody's specification and creates 3 different group of bonds.

- Long time to maturity for bonds maturing more than 10 years
- Medium time to maturity for bonds maturing in 5 to 10 years
- Short time to maturity for bond maturing in less than 5 years

At this point I sum up, three time to maturity groups and 7 ranking grades that produce 21 different matching portfolio combinations. I calculate the matching portfolio return on time *t* for N bonds that meet the same characteristics *i, j*, as:

$$PR_t^{i,j} = \frac{1}{N}\sum_n^N R_{t,n}^{i,j} \qquad (4)$$

Thus, based on those 2 characteristics, time to maturity and credit rating, I calculate abnormal returns by deducting the appropriate matching portfolio benchmark, comprised of all bonds of the same type, from the daily bond return. The equation is provided below.

$$AR_t^{i,j} = R_t^{i,j} - PR_t^{i,j} \qquad (5)$$

Where *i* is the rating grade cluster, j is the maturity cluster, *R* is the return of the bond affected by the rating change and PR is the matching portfolio for the specific issue.

For a specific bond to be included in the specific matching portfolio on a given day t, I require the matching bond to be traded on day t and day t-1. This will only include returns from actual trades, instead of having 0 return when a bond is not traded at all. Moreover, from the matching portfolio sample, I exclude the returns on [-30, +30] event window, for bond issues that were subject to a rating change on day 0.

Given that a firm may issue more than one bond, different issues from the same issuer may carry the same effect under a credit rating change. I need to avoid biasing the results, in favor of the effect from firms with more issues and aggregate bond returns at the issuer level. That will eliminate the problem of cross-correlation of bonds belonging in the same company and treat a specific event of a credit rating change of a firm as a single observation. I use Bessembinder et al. (2009) methodology, as in May (2010), and calculate weighted average abnormal bond return for a firm with multiple issues in a given day as:

$$AR_{k,t} = \sum_{i=0}^{J} AR_{i,k,t} \times w_{i,t} \qquad (6)$$

where J is the number of bonds outstanding from firm k and $w_{i,t}$ is the market weight of bond i relative to the total market value of bonds outstanding in that day.

Having this, I can calculate the cumulative abnormal return for every firm, in the event windows $[t_1, t_2]$ that I am testing as the sum of abnormal return in the window:

$$CAR_{t_1,t_2}^{k} = \sum_{t=t_1}^{t_2} (AR_t^k) \qquad (7)$$

Finally, I can compute the average cumulative abnormal return for the 6 rating change categories I am testing in my analysis as:

$$\overline{CAR_{t_1,t_2}^{c}} = \frac{1}{N} \sum CAR_{t_1,t_2}^{c} \qquad (8)$$

where c is the specific credit rating change category (UPG, DNG, UPGPOS, DNGNEG, UPGNOW, DNGNOW).

For the purposes of this study and the hypothesis builds so far, the windows to be tested and examine the cumulative abnormal returns are [-30, -1], [0, +1], [+2, +30].

Moreover, the t-statistic for the reported average abnormal returns and cumulative abnormal returns, that is presented in the results tables is calculated as described below. For average abnormal returns the t stat is:

$$tstat_{AR} = AR_t * \left(\frac{1}{\sqrt{n_t}}\right) / sd_t \qquad (9)$$

Where AR_t is the average abnormal return of window day t, n_t is the number of observations in the event window t and sd_t is the cross-sectional standard deviation of the abnormal returns in the event window.

The t statistic for cumulative average adjusted returns in the event window *t* is calculated as:

$$tstat_{CAR} = CAR_t * (\frac{1}{\sqrt{n_t}})/csd_t \quad (10)$$

where

$$csd_t = \sqrt{L * sd_t^2} \quad (11)$$

where *L* is the number of days within the event window.

5.2 Cross Section Analysis

In this section I am describing the cross-section analysis I implement on the cumulative abnormal returns over the event window [0, +1], in order to estimate the cross-sectional determinants that magnify the effect of a credit rating change. Under the results of this analysis I am testing the hypothesis *H4 – H8* built earlier.

The cross-sectional analysis of the abnormal returns associated with a credit rating change is done by estimating the following two regression models. I split my sample in downgrades and upgrades as I expect to have regression coefficient of a different sign.

For Downgrades the regressions model is the following:

$$Car_i^{[-1,1]} = a + b_1 * WNEG_i + b^T * Contr_i \quad (12)$$

where i is the ith firm the was subject to a rating downgrade, b are the regression coefficients and $Contr_i$ are the other control variables that I will explain below.

The Variables $WNEG_i$ is a variable that take the value of (1) if the rating downgrade was simultaneously announced with a negative watchlisting, and the value of (0) otherwise (off watch, no watch, positive watch). I expect the coefficient b_1 of $WNEG_i$ to be negative and significant. That means, that when a rating downgrade is announced together with a negative watch, the market reaction is stronger.

For Upgrades the regressions model is the following:

$$Car_i^{[-1,1]} = a + b_1 * WPOS_i + b^T * Contr_i \quad (13)$$

where i is the ith firm the was subject to a rating upgrade, b are the regression coefficients and $Contr_i$ are the other control variables that I will explain below.

The Variables $WPOS_i$ is a variable that take the value of (1) if the rating upgrade was simultaneously announced with a positive watchlisting, and the value of (0) otherwise (off watch, no watch, negative watch). I expect the coefficient b_1 of $WPOS_i$ to be positive and significant. That means, that when a rating change is announce together with a positive watch, the market reaction is stronger.

The Controls that will be used in the regression models are explained below. Those were chosen in accordance with the Hypothesis that need to be tested.

- MD_i a dummy variable that is equals to (1) if the rating announcement is done by Moody's and (0) otherwise.
- SP_i a dummy variable that is equals to (1) if the rating announcement is done by Standard and Poor's and (0) otherwise.
- FT_i a dummy variable that is equals to (1) if the rating announcement is done by Fitch and (0) otherwise.

Those coefficient will take different values depending on the influence on the bond market its rating agent have. However, as explained in *H4,* I expect those coefficients to be equal and not statistical different.

- $FALLEN_i$ is a dummy variable that is equals to one if the bond issuer is a Fallen Angel, downgrades from Investment grade to speculative, and (0) otherwise. This variable will only be tested in downgrades announcements, and as explained in H5, I expect the coefficient to be negative and significant.
- $RISING_i$ is a dummy variable that is equals to (1) if the bond issuer I a Rising star, upgrade from speculative to investment grade, and (0) otherwise. This variable will only be tested for upgrades. I expect to find positive and significant correlation.
- $SURPRISING_i$ is a dummy variable that is equal to (1) if the rating change is an unexpected new, as characterized in the hypothesis section, and (0) otherwise. Negative (positive) and significant coefficient for this variable, will indicate that the market reacts stronger, for downgrades (upgrades) announcements that seems to be surprising.

- OLD_i is a cardinal variable representing the old rating. For example, 1 for AAA, 4 for AA- and 16 for B-. As discuss previous in *H7,* I expect negative (positive) and significant coefficients under downgrades (upgrades), as downgrades in lower rating bonds are associated with higher risk differences.
- $SIZE_i$ is a variable representing the rating jumps under a rating upgrade or downgrade. For example, a rating downgrade from AAA to AA- is a rating jump of size 3. *H8* indicates that the coefficient of SIZE should be negative (positive) for downgrades(upgrades), as the market reaction should be magnified for extreme downgrade and upgrades.

The final regression models to be tested for the credit rating changes looks like below:

Downgrades

$$Car_i^{[-1,1]} = a + b_1 WNEG_i + b_2 MD_i + b_3 SP_i + b_4 FT_i + b_5 FALLEN_i + b_6 SUPRISING_i + b_7 OLD_i + b_8 SIZE_i \qquad (14)$$

Upgrades

$$Car_i^{[-1,1]} = a + b_1 POS_i + b_2 MD_i + b_3 SP_i + b_4 FT_i + b_5 RISING_i + b_6 SUPRISING_i + b_7 OLD_i + b_8 SIZE_i \qquad (15)$$

For robustness, I will also test other regression models that do not include all previously specified variables.

6. Results

This section describes the results obtained on cumulative abnormal returns, after applying the methodology proposed by Bessembinder et al.2009 and the cross-sectional determinant of cumulative abnormal returns under an OLS recession. In order to test my recession hypothesis *H3*, regarding the different market reaction to credit rating changes under "boom" times, I have separated the sample in two subsamples and apply the methodology separately to each. That will allow me to test both sample without the one period biasing the results of the other. As mentioned earlier, the two samples are the crisis times, "01/12/2007 – 30/06/2009" and the normal times "01/07/2009 – 30/06/2019.

6.1 Cumulative Abnormal Returns

The abnormal returns are calculated by matching the unique bond issues with the appropriate benchmark. That is the matching portfolio that belongs to the same maturity and credit rating group as the specific bond issue that was subject to rating change.

In addition, as described earlier, in order to tackle the liquidity that arises in bond market, as there are some bonds that do not trade at all during the [-30, +30] event window, I apply some trading restrictions. This eliminates a significant amount of observation. For the normal times period sample, from the 14,047 specific bond issues from 1,526 issuers, I remove 9,925 ussies due to illiquidity, leaving me with 4,122 unique bond issuer from 1,000 obligors. For the crisis period from 8,216 unique bond issues I remove 6,922 bonds, leaving me with a sample of 1,597 issues from 421 unique firms. After eliminating those illiquid bonds, the final sample of rating changes on issuer level includes 2,572 rating changes during the normal times period and 859 rating changes during crisis period.

Table 6 represents the average cumulative abnormal returns (in percentages) for the 6 different categories of rating change, downgrades with negative watch (WNEG), downgrade off watch (WNOT), upgrades with positive watch (WPOS), upgrade off watch (WNOT), all downgrades and all upgrades together. Together with the mean CAR I also report the t statistic that the average abnormal returns are significantly different from zero and the number of rating changes by each category.

Table 6

Normal Period (Jul.2009 - Jun.2019)								
		Downgrades			Upgrades		
Event Window	Rating Status	WNOT N=1248	WNEG N=156	ALL N=1404	WNOT N=1117	WPOS N=51	ALL N=1168
[-30, -2]	CAR(%)	-0.81 ***	-2.42 ***	-0.99 ***	0.28 **	0.45	0.29 ***
	t-stat	(-4.51)	(-3.65)	(-5.68)	(2.37)	(0.58)	(2.47)
[-1, +1]	CAR(%)	-0.54 ***	-0.75 *	-0.57 ***	0.12 **	0.14	0.12 **
	t-stat	(-3.82)	(-1.72)	(-5.01)	(2.48)	(1.06)	(2.9)
[+2, +30]	CAR(%)	0.05	-0.93	-0.06	0.07	-0.1	0.07
	t-stat	(0.22)	(-0.85)	(-0.22)	(0.62)	(-0.16)	(0.64)
[0, +1]	CAR(%)	-0.43 **	-0.15	-0.4 **	0.12 **	-0.01	0.11 **
	t-stat	(-3.84)	(-1.87)	(-3.68)	(6.95)	(-0.55)	(6.53)
[-5, +5]	CAR(%)	-0.92 ***	-1.5 *	-0.99 ***	0.29 ***	0.7 *	0.31 ***
	t-stat	(-3.54)	(-1.53)	(-3.54)	(3.77)	(1.33)	(4.8)
[+15, +30]	CAR(%)	0.36 **	-0.3	0.28 **	0.01	-0.28	0
	t-stat	(2.26)	(-0.61)	(1.97)	(0.14)	(-0.93)	(-0.02)

6.1.1 The information Content

As expected, for the full sample of 1,404 downgrade announcements, during the normal times period, the average cumulative abnormal return during the event window [0, +1] is -0.4% and statistically significant. The effect is stronger if I also include in the event window the day prior to the announcement, to allow for one day information leakage. The mean CAR for downgrades for the window [-1, +1] is -0.57% and statistically significant at 99% confidence level. This findings are in line with previous studies that find significant price movement under downgrades announcements like Hand et al. (1992), Hite and Warga (1997) and Steiner et al. (2001) and contradicts results from earlier literature like Katz (1974) and Weinstein (1978). However as describe in a previous section and as mention in Bessembinder et al. (2009) their results are biased due to the use of monthly abnormal returns instead of daily.

Table 6 also reports the mean CAR in case a downgrade is announced at the same time with a negative watch or not. For the normal times sample, I observe 156 negative watch listing announcements. During the event window [-1, +1] the effect is stronger, with an average CAR of -0.75%, in case a downgrade is simultaneously announced with a negative watchlisting while the effect of a downgrade in off watch status is -0,54%. That indicates that there is information content in watchlisting announcements as well, as the market reacts stronger under watchlisting announcements. This effect is significant at 90% confidence level as opposed by the t-statistic. For robustness, I run a t-test [30] that the average abnormal return for downgrades with negative watch is significantly higher than downgrades with "off watch" and found it significant at 95% confidence level. This is in line with Steiner et al. (2001) that study the effect of credit watch placement, in credit rating change announcement. Similar Results on the effect of credit watch in the CDS market are presented in Hull, Predescu and White (2004), Norden and Weber (2004) and Galil and Sofer (2011).

Contrary to previous studies, that fail to find significant results during upgrades, the full sample of 1,168 upgrades during the event window [0, +1] in "normal times", indicates a mean average cumulative abnormal returns of 0.11%, which is significant at 95% confidence interval. This results also hold true for the [-1, +1] window with a mean CAR of 0.12%. Although the mean CAR for upgrades is economically small, it is line with the hypothesis that the information content of rating changes should be visible in both downgrades and upgrades, as both announcement are related with a change in the level of risk of specific issues, and that should be reflected in the bond prices. Those results are consistent with Hand et al. (1992) and May (2010) that manage to capture the effect of both upgrades and downgrades. My paper applies similar methodology and data as May (2010), as proposed by Bessembinder et (2009), which suggest more robust results, when using intraday price from TRACE.

However, I fail to find significant price movement for upgrades that are simultaneously announced with a positive watch placement. The effect is still positive, 0.14% during the event window [-1, +1], but not statistically significant. The fail of significance may be related to the small sample of upgrades with positive watch, only 4% of the total upgrades, while the negative watch placement is 11% of the total downgrades. That may be related to the reputation hypothesis first stated by Holthausen and Leftwich (1986). Under this hypothesis the credit rating agencies may issue more negative watch announcement, as they afraid to lose their reputation in case a bond was falsely too high. That is not the case when a bond is falsely too low. Thus, positive watchlisting may not carry important information.

Given the findings indicated above, my *H1* Hypothesis, that the credit rating changes carries important new information to the market, is accepted. The effect holds true for both upgrades and downgrades and for downgrades that simultaneously announced with a negative watch

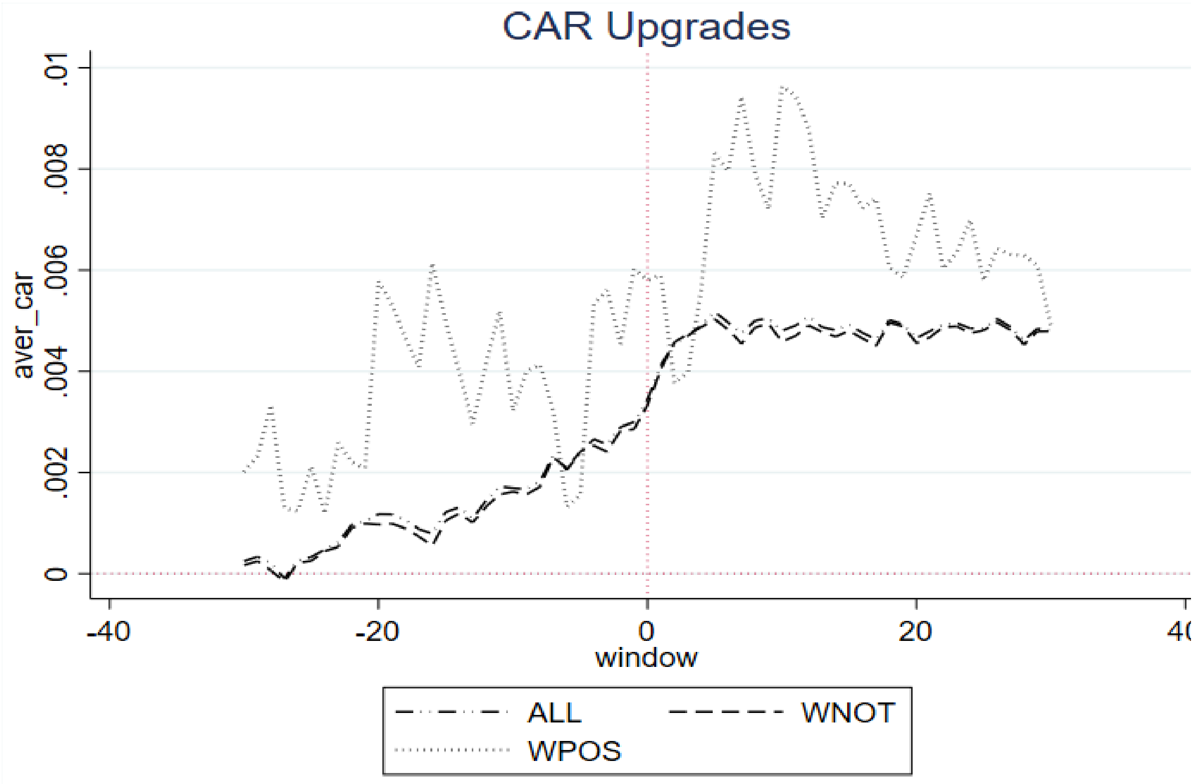
[30] See Table 7, Appendix

placement, as those are perceived as a swift in risk of specific bond issues and issuers from the market. However, I believe that the economical significance of this effect is rather small, less than 1%, for the whole rating changes sample. Previous studies like Steiner et al. (2001) and May (2010) find significant price movement even 3 months prior to the rating change event. Thus, it is useful to investigate how the bond prices fluctuates prior to the event.

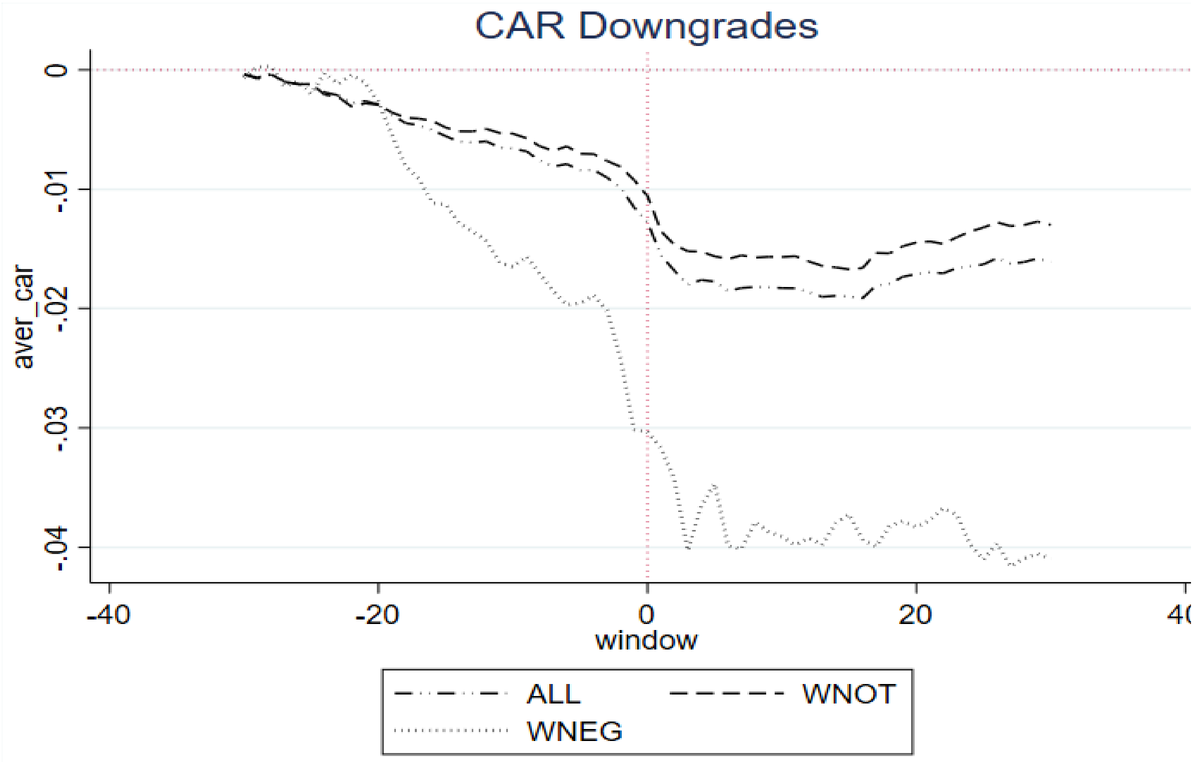
Table 6 also presents the average cumulative abnormal bond returns during the event window [-30, -2]. The mean CAR for the whole sample of downgrades is -0.99% and statistically significant. The price movement for the rating downgrades that simultaneously announced with a negative watch is much stronger with a mean CAR of -2.42%. For the whole sample of upgrades, the mean CAR stands at 0.45%, but again I fail to find any significance for the positive watchlisting upgrades. Those results indicate that there are significant price movements prior to the rating change event, meaning that the shift in risk as opposed by a rating change, is already partially reflected in the bond price before the rating agency decide to adjust the rating. Hence, I can safely assume that credit rating agencies tend to partially lag the market before the rating change and then lead the market for a short time after the rating change announcement. Under those findings, credit ratings do reflect private information, but they also partially follow the bonds market movements before their rating change.

In addition to safely say that a credit rating change is indeed associated with private information and that they do reflect a swift in risk of specific bond issues, I must examine how the market reacts after the days of the announcements. Table 6 also reports the average cumulative abnormal bond returns during the event window [+2, +30]. The results indicate that there are no significant cumulative abnormal returns during this period for either upgrades or downgrades, as the p-values of t-stat do not reject the H0 that CAR=0. Thus, the price movement of a rating change is permanent following the days after the announcement. This can be seen more clearly in the Charts 1 and 2, that represents the average cumulative abnormal returns over the window [-30, +30]. The charts indicate, that for both upgrades and downgrades, the cumulative average abnormal returns seem to stabilize after the event day +5, indicating that there are no further movements after the day of the announcements.

Graph 1



Graph 2



However, mean CAR for downgrades seems to follow an upward trend after the day +15. For this reason, table 6 also reports mean CAR for event window [+15, +30]. I observe a positive mean CAR of 0.28% which is significant at 95% confidence level. This is consistent with the overreaction Hypothesis as stated in De Bondt and Thaler (1985). The bond market seems to overreact in case of downgrades in the event window [0,+15], leading the prices lower than the expected, and then over the event window [+15,30], there is a price correction that stabilizes the abnormal bond returns to the expected level.

Moreover, in order to capture the overall market reaction around the credit rating change announcements, Table 6 reports the average cumulative abnormal returns during the event window [-5, +5]. The mean CAR is 0.99% for the whole sample of 1,404 downgrades and 0.31% for the 1168 upgrades. Both CARs are statistically significant at 99% confidence level. Moreover, during this event window, upgrades with positive watch seem to have significant mean CAR of 0.7% contrary to the previous tested event windows. However, under the t-test [31]reported in the appendix I fail to find significant stronger reaction for Upgrades that are announced simultaneously with positive watch. Downgrades with negative watch report a significant CAR of -1.5 % at 90% confidence level indicating again the significant reaction to negative watch listing.

Finally, to further support above findings I am including in the Appendix, Graph 3 and 4 that represents the average abnormal returns during the event window [-30, +30]. It can be clearly seen, the abnormal returns spikes for both upgrades and downgrades, on the event day +1, which stand at -0.3% for downgrades and at 0.06% for upgrades. The overreaction of the bond market during downgrades is also very clear as well as the correction occurring after 15 trading days.

6.1.2 The stronger reaction under Downgrades

All prior research that have studied the effect of credit rating change in the bond market, either the stock or CDS market, finds that the price movement to downgrades is significantly stronger than the price reaction to upgrades. Of course, most previous studies fail to find any significant price move to upgrades, like Wansley et al. (1992), Hite and Warga (1997), Steiner et al.

[31] See Table 8, Appendix

(2001),Hull et al. (2004) but the stronger reaction to downgrades is documented in any paper that find significant reaction to both upgrades and downgrades like Hand et al. (1992), Jorion et al.(2005), May (2010),Yang et al.(2017). However, to my knowledge no explanation of this asymmetry has been tested.

Table 9

Two Sample t-test with unequal variances, that the Average Abnormal Return of Upgrades is significantly higher (in absolute terms) than Upgrades over the event window [-5, +5]. The result accepts the Ha Hypothesis.

```
    diff = mean(DNG) - mean(UPG)                                  t =   2.7876
Ho: diff = 0                     Satterthwaite's degrees of freedom =  10.9611

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9911         Pr(|T| > |t|) = 0.0177          Pr(T > t) = 0.0089
```

The findings of my research in table 6, also indicates the stronger reaction to downgrades in every event window tested. Namely, in the event window [-5, +5], that gives a good overview of the overall market reaction to rating changes announcement, the mean CAR for the whole sample of downgrades and upgrades is -0.99% and 0.31% respectively, and both significant at 99% confidence level. For robustness, Table 9 also reports the t statistics for the *Ha* Hypothesis, that the average abnormal return of downgrades is significantly higher than the average abnormal returns to upgrades. With p-value of 0.0089 the *Ha* hypothesis is accepted. Hence, as expected from the finding of previous research, I also accept my *H2* stronger negative effect Hypothesis.

A possible explanation to this asymmetry, as I also mention in the Hypothesis section could be that bond issuers themselves are more willingly to allocate good news to the market than bad news. Hence ratings upgrades will carry information that might be already available to the public. Contrary, bond issuers are not going to deliver bad new on their own and they will wait for the credit rating to do it for them. Hence, credit ratings downgrades may carry information that is not already available to the public. I am testing this Hypothesis by examining how the bond market performs prior to the credit rating event, and I assume that if important good information is already publicly available then the event window [-30, -2] will indicate stronger abnormal returns for upgrades. However, Table 6 indicates significantly stronger mean CAR for downgrades in the event window [-30, -2], hence my results cannot support this hypothesis.

Another potential explanation for this asymmetry is price pressure. Fallen Angels may trigger selling decisions driving the bond prices very low in case the bond issuer falls below investment grade. On the other hand, Rising Stars will not strictly force buying decisions. This may be a potential explanation to the asymmetric response to upgrades and downgrades. For this reason, I recalculate cumulative abnormal returns, first only for the Fallen Angels and Rising Stars and then by removing them from the original sample. Table 11 represents the mean CAR for the event window [-1, +1] after applying those adjustments.

Table 11

Full Sample							
Event Window	Rating Group	Downgrades			Upgrades		
		WNOT	WNEG	ALL	WNOT	WPOS	ALL
[-1, +1]	CAR(%)	-0.54 ***	-0.75 *	-0.57 ***	0.12 **	0.14	0.12 **
	t-stat	(-3.82)	(-1.72)	(-5.01)	(2.48)	(1.06)	(2.9)
Only Fallen Angels and Rising Stars							
Event Window	Rating Group	Downgrades			Upgrades		
		WNOT	WNEG	ALL	WNOT	WPOS	ALL
[-1, +1]	CAR(%)	-1.41 ***	-5.85 *	-1.74 ***	0.57 **	0.26	0.55 **
	t-stat	(-3.56}	(-1.75}	(-3.62}	(2.02}	(0.31}	(2.01}
Full Sample excluding Fallen Angels and Rising Stars							
Event Window	Rating Group	Downgrades			Upgrades		
		WNOT	WNEG	ALL	WNOT	WPOS	ALL
[-1, +1]	CAR(%)	-0.42 ***	-0.32	-0.41 ***	0.07 **	0.11	0.07 **
	t-stat	(-3.88}	(-0.89}	(-6.32}	(2.84}	(0.45}	(2.84}

The results in Table 11 indicates that indeed after removing the fallen angels and rising stars from the original sample the mean CAR decreases for both upgrades and downgrades. Indicatively the average cumulative return during the [-1, +1] window stand at -0.41% for the sample of downgrades after removing the fallen angels and at 0,07% for the sample for upgrades after removing the rising stars. However, I still observe that even after controlling for the price pressure hypothesis, the effect of downgrades is still significantly stronger than the one of upgrades. Thus, the asymmetric response of downgrades to upgrades cannot be fully explained by the price pressure hypothesis, that were assumed in previous studies.

After testing those 2 potentials explanation for the asymmetric response of downgrades and upgrades, I can only assume and suggest behavioral explanations. As mention in Hull et al. (2004) investors face an asymmetric risk aversion. That means that put significantly more weight on bad news than on good news. Hence, they will react more in case of a downgrade than in an upgrade, resulting in stronger cumulative abnormal returns in negative credit rating events. Another explanation was proposed by Holthausen and Leftwich (1986), that credit rating agencies also face asymmetric loss function. Credit ratings agencies are concerned about their reputation as they may issue a high rating to a bond issuer and that issuer may eventually default. Hence, they allocate put more resources and effort to find potential rating downgrades that upgrades, making downgrades more informative. Those 2 other explanation have never been tested before and comes to the limitations of this paper.

6.1.3 Recession times

On of the main purpose of this study is to examine how the influence of the credit rating agencies in corporate bond market vary over time. Many market participants after the financial crisis of 2007-2009 have questioned the reliability and added value to the overall economy by the presence of credit rating agencies. Hence, it is useful to investigate how investors responded to credit rating agencies during and after the financial crisis. *Table 12* reports the mean CAR (%) for both upgrades and downgrades for different event windows.

Table 12

Crisis Period (Dec.2007 - Jun.2009)							
		Downgrades			Upgrades		
Event Window	Rating Status	WNOT N=492	WNEG N=168	ALL N=690	WNOT N=161	WPOS N=8	ALL N=169
[-30, -2]	CAR(%)	-3.05 ***	-3.33 **	-3.12 ***	1.23	-0.66	1.14
	t-stat	(-2.69)	(-1.95)	(-3.25)	(1.07)	(-0.28)	(1.07)
[-1, +1]	CAR(%)	-1.59 ***	-5.88 **	-2.69 ***	0.84 ***	0.81 ***	0.84 ***
	t-stat	(-8.62)	(-2.91)	(-5.07)	(6.66)	(6.16)	(7.15)
[+2, +30]	CAR(%)	1.01	-4.58 *	-0.42	0.48	1.94	0.55
	t-stat	(0.84)	(-1.64)	(-0.38)	(0.72)	(0.67)	(0.83)
[0, +1]	CAR(%)	-1.11 **	-5.47 ***	-2.23 ***	0.58 **	0.62 ***	0.58 **
	t-stat	(-6.33)	(-7.78)	(-44.89)	(4.76)	(7)	(5.2)
[-5, +5]	CAR(%)	-1.26	-6.52 **	-2.61 **	0.74	3.48 *	0.87
	t-stat	(-1.21)	(-1.83)	(-1.73)	(0.74)	(1.58)	(0.97)

As shown in table 12, consistent with the normal times period the average cumulative abnormal returns for the 690 downgrades, during the event window [0, +1] stands at -2.23% and is statistically significant at 99% confidence level. This effect is significantly stronger when the downgrade announcement includes a negative watch placement, with mean CAR of -5.47%. That indicates, that during the crisis period the market significantly respond to watchlisting announcement, causing overreaction on the selling side. In addition, as well as during normal times, during the crisis period the credit rating agencies tend to lag the market before the rating change announcement. Indicatively, a -3.12% mean CAR during the event window [-30, -2] for the sample of downgrades, means that the bond prices already partially reflect the swift in risk prior to the event. I also find no significance price movement after the event indicating that the price remains stable reflecting the new level of risk. Though, this does not hold true for downgrades which simultaneously announced with negative watchlisting announcement, as the prices continues to fall further even after the rating event[32].

Similar results are presented in table 12 for upgrades. Proving again the stronger reaction under downgrades, the mean CAR for the full sample of upgrades is 0.84% and significant during the event window [-1, +1]. However, I fail to find any significant price movement prior to the event. That indicates that during recession, upgrades are not expected by the investors and they do not make investments decisions based on their expectation of credit risk change. This is also the case given that the credit rating upgrade represents less than 20% of the total rating changes. In addition, the market response to positive watch listings is significant. Yet, I cannot make inferences based on that information, as the sample of positive watchlist announcements is relatively small, only 8 across all period representing 5% of the whole sample of upgrades.

Table 12

Donwgrades				
Event Window		Normal N=1404	Crisis N=690	t-stat Pr(T < t)
[-1, +1]	CAR(%)	-0.57 ***	-2.69 ***	0.0382 **
	t-stat	(-5.01)	(-5.07)	
[-5, +5]	CAR(%)	-0.99 ***	-2.61 **	0.1676
	t-stat	(-3.54)	(-44.89)	
Upgrades				
Event Window		Normal N=1168	Crisis N=169	t-stat Pr(T < t)
[-1, +1]	CAR(%)	0.12 **	0.84 ***	0.0135 **
	t-stat	(2.9)	(7.15)	
[-5, +5]	CAR(%)	0.31 ***	0.87	0.2847
	t-stat	(4.8)	(5.2)	

The main question of our research though is presented on table 12 where I compare how the credit rating change announcement differently perceived by the market during crisis and during normal times. I calculate the t-stat for the Ha hypothesis that the market response to downgrades is statistically and significantly stronger during the recession period compared to the normal times. This Hypothesis is accepted for the event window [-1, +1] for both upgrades and downgrades. The stronger reaction to downgrades was expected, as also described in my Hypothesis, as the upgrades during down times are fairly rare the market overreact on the buying side and pushing the corporate bond prices. Those findings are consistent with Finnerty

[32] See Graph in Appendix

et al. (2013) who documented the effect of upgrades during recession. The stronger effect of upgrades during a crisis period compare to normal times, might also be attributed to the fact that credit rating agencies will not issue an upgrade unless they are absolute sure that it is a correct one. Issuing inaccurate upgrades during recession will highly damage their reputation, as those actions will be accused for trying to manipulate and drive the market to favored prices, for them and their clients. This stronger market reaction for upgrades and the crisis period was expected as also describe in my *H3* Hypothesis.

However, I cannot accept my recession Hypothesis as I was expecting smaller effect to credit rating downgrades under the crisis period. As it can been seen in Table 12, the market reaction to downgrades is significant larger, as reported by the p values of the t-test, during the crisis period. That indicates that pessimistic investors who are aware of the negative market conditions overreact during a rating downgrade and start shorting their assets as they afraid that the prices might drop even further. That causes a significant price movement to corporate bond issues in the event window [-1, +1]. Those finding contradicts prior research like Li et al. (2006), Jorion et al. (2005) and Kiesel et al. (2016). My results indicate that during the financial crisis of 2007 – 2009 investors were still making financial decisions based on the announcement of the credit rating agencies, although the later were severely accused for inaccurate ratings. May also this be the reason, that investors reaction during credit rating change announcements severely decreased. This result may document the investors loss of faith to the credit rating industry.

6.2 Cross Section Analysis

In this section I perform a cross sectional analysis on the cumulative abnormal returns in order to estimate the cross-sectional determinants that magnify the effect of a credit rating change and to test whether above described results on credit watchlisting announcements are significant. I estimate all regressions using OLS with dependent variable the cumulative abnormal return of each specific bond issuer in my normal times sample for the even window [0, +1]. The results will be split to those of downgrades and upgrades and I will use the specific controls described in the methodology section and test my original hypothesis.

Table 13

Downgrades					Upgrades				
	(1)	(2)	(3)	(4)		(1)	(2)	(3)	(4)
watch	-0.264	-0.286	-0.277	-0.291	watch	-0.00947	-0.0296	-0.0238	-0.0182
	(-1.06)	(-1.15)	(-1.11)	(-1.16)		(-0.06)	(-0.18)	(-0.14)	(-0.11)
FALLEN	-1.339***	-1.301***	-1.126***	-1.121***	RISING	0.482***	0.477***	0.464***	0.471***
	(-5.47)	(-5.30)	(-4.35)	(-4.32)		-4.46	-4.41	-4.17	-4.25
OLD		-0.0439*	-0.045*	-0.0471*	OLD		0.0124	0.0115	0.0156
		(-1.79)	(-1.84)	(-1.91)			-1.17	-1.08	-1.45
SIZE			-0.208*	-0.209*	SIZE			0.0215	0.0234
			(-2.09)	(-2.08)				-0.49	-0.54
SURPRISING				-0.0948	SURPRISING				0.219**
				(-0.59)					-3.07
MD				-0.167	MD				0.0892
				(-0.90)					-1.03
SP				0	SP				0.0932
				(.)					-1.05
FT				-0.173	FT				0
				(-0.86)					(.)
INTERCEPT	-0.382***	0.00175	0.265	0.454	INTERCEPT	0.0702	-0.0666	-0.083	-0.343*
	(-4.33)	-0.01	-1.01	-1.45		-1.93	(-0.54)	(-0.65)	(-2.26)
N	1404	1404	1404	1404	N	1168	1168	1168	1168
R-sq	0.021	0.024	0.027	0.028	R-sq	0.017	0.018	0.018	0.028

Table 13 reports the multivariate results of the robust OLS regression for the whole sample of downgrades and upgrades during the event window [-1, +1]. Starting with the control variables MD, SP and FT, which indicates whether the rating change was from Moody's and Standard and Poor's or Fitch respectively, I observe that the dummy coefficients are insignificant in both upgrades and downgrades, something also holds true for any different model that I tested, and not presenting here. Thus, I can conclude that the magnitude and significance of a bond price movement due to a rating change remains the same across all rating agencies. This is consistent with Li et al. (2006) and May (2010) that also tested the different effect of the three different rating agencies. Thus, I can accept the *H4* Hypothesis that the price movement should be irrelevant of who was the agent announcing the credit rating change.

The regression model reports also the coefficients of falling stars, in case of downgrades from investment to speculative grade, and rising stars in case of upgrades from speculative to investment grade. As, it was expected the FALLEN coefficient is negative and significant at 99% confidence interval. That means that market respond stronger to downgrades that cross the investment grade level. This is also consistent with table 11 described above that represent higher average cumulative abnormal returns for fallen angels. This was expected given the fact that when a bond fells into speculative grade can cause selling transactions as there are financial institutions that are subject to regulatory constraints for the risky assets they can hold. This finding is consistent with prior research that examined the effect of the investment grade boundary like Holthausen and Leftwich (1986), Hite and Warga (1997), Steiner et al. (2001), May (2010) and Finnerty et al. (2013).

Same results are presented in table 13 for the rising star issuers. The RISING coefficient is positive and significant indicating that upgrades from speculative to investment grade result in a significant stronger price movement compare to other upgrades, consistent with prior research like Hite and Warga (1997) and Finnerty et al. (2013). Moreover, as it was expected from the results in table 11, the coefficient of FALLEN is significant stronger that RISING. That is, because fallen angels forces selling decision, while rising not necessarily. Having said that, I can safely accept my H5 hypothesis.

In contrast, I cannot accept the *H6* hypothesis of surprising news. That is, credit rating change announcements that either had their rating stable for 2 years or that prior to the event had opposite direction significant abnormal returns. The effect of surprising new is positive and significant for upgrade but, I fail to find any significance of the surprising downgrades although the coefficient is negative. This contradicts previous studies like Hand et al. (1992) and May (2010). However, those studies used quite different expectation models to test this Hypothesis.

Finally, in case of downgrades, the SIZE and OLD coefficient are negative and significant. That indicates that the more rating notches the rating change is referring to, the stronger the price movement. This was also expected as more rating jumps reflect a higher decrease in credit quality of the issuer. This finding supports the results from May (2001), but it is not consistent with Steiner et al. (2001). The OLD negative coefficient also indicates stronger price movement in case of downgrades between lower grades regardless of the size or the investment grade boundary. The level of risk, associated with a downgrade is increasing exponentially as moving from higher to lower rating bonds, given the increased default probabilities[33]. However, both SIZE and OLD coefficient are not significant on case of upgrades, but with the correct sign. This was expected given the lower significance indicated in the first analysis of the cumulative abnormal returns.

[33] See Graph 1

7. Conclusion

This study examines the impact of credit rating changes announcements on corporate bond prices. At the same time, I also test the reaction of downgrades and upgrades when they simultaneously announced with a credit watch placement. I use intraday daily data from the OTC market and calculate cumulative abnormal returns using as a benchmark the matching portfolios as proposed from Bessembinder et al. (2009). From the 1.404 unique issuers downgrades that issue bond securities with specific characteristics, I find a significant cumulative abnormal return of -0.57% during the event window [-1, +1]. Contrary to the previous studies that fail to find any significant bond performance around the day of the announcements for upgrades, I find significant market reaction with abnormal returns of 0.12%.

By examining how the market fluctuates for the specific bond issues that were subject to a credit rating event I found that the rating change was anticipated by the market and that trading 30 days prior to the event, and that the swift in risk was already partially reflected by the corporate bond prices. I fail to find significant price movement after the event indicating that the price changes are permanent and do reflect the different level of risks a credit rating change carries. However, for downgrade there is some price movement to the opposite direction in the event window [+15, +30], indicating that the market overreacts in case of a downgrade and after some days there is some correction that brings the price to the normal levels.

The statistical tests that the downgrades come with the stronger market movement compared to upgrades, were significant. That indicates that indeed the market reaction is stronger. However, I fail to explain this asymmetric response to rating changes, as it cannot be adhered to fallen angels and rising stars, neither to the fact that bond issuers release “good news” information to the market on their own. The only explanation for this asymmetry can be behavioral, as the asymmetric risk aversion of investors. However, the examination of this hypothesis comes to the limitations of this paper, but it would be a useful suggestion for next researcher.

Moreover, I also examine the impact of credit rating changes during the financial crisis of 2008. My results indicate that during the crisis, investors heavily rely their investment decisions on the credit rating agencies. Contrary to previous studies I found significantly stronger price reaction to both upgrades and downgrades for my recession sample. However, I believe that to make inferences on how market reacts to rating changes, one has to look both a post-crisis period and a pre-crisis one. My study is limited to the post crisis period and for more robust results, I suggest to further research to include samples before crisis.

Finally, in my cross-section analysis I find that the cumulative abnormal returns are magnified when the specific issuer cross the investment/speculative boundary. The regression coefficient of fallen angels (rising stars) where negative(positive) and significant. Moreover, I found significant stronger price movements when the rating downgrade is more than one rating notch, thus larger rating jump produce higher cumulative abnormal returns. The previous rating of the issuer that were subject to rating change is also an important determinant of the magnitude of the market reaction. Contrary to previous studies, I fail to find significant results for the surprising news. However, my paper is limited to the "surprising model" that I used. Further research should incorporate many different attributes in order to determine the surprising news, such as the specific issuer abnormal returns prior to the event, the time that the issuer spend on the same rating, whether the issuer was in the same sign credit watch prior to the event and other non-credit risk-related information.

Another potential suggestion for further research is to build a model that will measure the effect of credit rating agencies by simultaneously examining 3 different market, the equity, the CDS and the bond market. Prior research indicates that those market react differently in case of a credit rating change announcement. I believe that this holds true, but it also might be the case the one market may capture a specific rating change information content and one other not. None of the previous research have studied all market at the same time, by also controlling for the interaction of them. For example, the presence of CDS market, might be a potential reason that downgrades fail to capture some price movements, as some investors that hold the securities might be covered by a CDS. Thus, a shift to a riskier investment will actually be in favor of them and will not force any selling actions.

References

Alsakka, R. & ap Gwilym, O., 2012. Rating agencies' credit signals: An analysis of sovereign watch and outlook. *International Review of Financial Analysis*, 21, pp.45–55.

Bannier, C.E. & Hirsch, C.W., 2010. The economic function of credit rating agencies–What does the watchlist tell us? *Journal of Banking & Finance*, 34(12), pp.3037–3049.

Bereskin, F.L., Kim, B. & Oh, F.D., 2015. Do credit rating concerns lead to better corporate governance? Evidence from Korea. *Pacific-Basin Finance Journal*, 35, pp.592–608.

Bessembinder, H. et al., 2008. Measuring abnormal bond performance. *The Review of Financial Studies*, 22(10), pp.4219–4258.

Bessembinder, W. et al., 2009. New methodology for event studies in bonds. *Review of Financial Studies*, 22, p.42194258.

Bolton, P., Freixas, X. & Shapiro, J., 2012. The credit ratings game. *The Journal of Finance*, 67(1), pp.85–111.

De Bondt, W.F.M. & Thaler, R., 1985. Does the stock market overreact? *The Journal of finance*, 40(3), pp.793–805.

Cook, T., 1983. Common Stock Returns and Potential Bond Rating Changes: An Analysis of Standard and Poor's CreditWatch. In *meetings of the Financial Management Association*.

Cornell, B., Landsman, W. & Shapiro, A.C., 1989. Cross-sectional regularities in the response of stock prices to bond rating changes. *Journal of Accounting, Auditing & Finance*, 4(4), pp.460–479.

Ederington, L., Guan, W. & Yang, L.Z., 2015. Bond market event study methods. *Journal of Banking & Finance*, 58, pp.281–293.

Fama, E.F., 1970. Efficient market hypothesis: A review of theory and empirical work. *Journal of Finance*, 25(2), pp.28–30.

Finnerty, J.D., Miller, C.D. & Chen, R.-R., 2013. The impact of credit rating announcements on credit default swap spreads. *Journal of Banking & Finance*, 37(6), pp.2011–2030.

Galil, K. & Soffer, G., 2011. Good news, bad news and rating announcements: An empirical investigation. *Journal of Banking & Finance*, 35(11), pp.3101–3119.

Goh, J.C. & Ederington, L.H., 1999. Cross-sectional variation in the stock market reaction to bond rating changes. *The Quarterly Review of Economics and Finance*, 39(1), pp.101–112.

Goh, J.C. & Ederington, L.H., 1993. Is a bond rating downgrade bad news, good news, or no news for stockholders? *The journal of finance*, 48(5), pp.2001–2008.

Grier, P. & Katz, S., 1976. The differential effects of bond rating changes among industrial and public utility bonds by maturity. *The Journal of Business*, 49(2), pp.226–239.

Güttler, A. & Wahrenburg, M., 2007. The adjustment of credit ratings in advance of defaults. *Journal of Banking & Finance*, 31(3), pp.751–767.

Hand, J.R.M., Holthausen, R.W. & LEFTWICH*, R.W., 1992. The effect of bond rating agency announcements on bond and stock prices. *The journal of finance*, 47(2), pp.733–752.

Hite, G. & Warga, A., 1997. The effect of bond-rating changes on bond price performance. *Financial Analysts Journal*, 53(3), pp.35–51.

Holthausen, R.W. & Leftwich, R.W., 1986. The effect of bond rating changes on common stock prices. *Journal of Financial Economics*, 17(1), pp.57–89.

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

Jorion, P., Shi, C. & Zhang, S., 2005. Tightening credit standards: Fact or fiction. *Job Paper. Irvine: University of California*.

Katz, S., 1974. The price and adjustment process of bonds to rating reclassifications: a test of bond market efficiency. *The Journal of Finance*, 29(2), pp.551–559.

Kiesel, F., 2016. Do investors still rely on credit rating agencies? Evidence from the financial crisis. *The Journal of Fixed Income*, 25(4), pp.20–31.

Kim, Y. & Nabar, S., 2007. Bankruptcy probability changes and the differential informativeness of bond upgrades and downgrades. *Journal of Banking & Finance*, 31(12), pp.3843–3861.

Malkiel, B.G. & Fama, E.F., 1970. Efficient capital markets: A review of theory and empirical work. *The journal of Finance*, 25(2), pp.383–417.

May, A.D., 2010. The impact of bond rating changes on corporate bond prices: New evidence from the over-the-counter market. *Journal of Banking & Finance*, 34(11), pp.2822–2836.

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

Pinches, G.E. & Singleton, J.C., 1978. The adjustment of stock prices to bond rating changes. *The Journal of Finance*, 33(1), pp.29–44.

Steiner, M. & Heinke, V.G., 2001. Event study concerning international bond price effects of credit rating actions. *International Journal of Finance & Economics*, 6(2), pp.139–157.

Stickel, S.E., 1986. The effect of preferred stock rating changes on preferred and common stock prices. *Journal of Accounting and Economics*, 8(3), pp.197–215.

Wakeman, L., 1998. Bond rating agencies and the capital markets.

Wansley, J.W. & Clauretie, T.M., 1985. The impact of creditwatch placement on equity returns and bond prices. *Journal of Financial Research*, 8(1), pp.31–42.

Weinstein, M.I., 1978. The seasoning process of new corporate bond issues. *The Journal of Finance*, 33(5), pp.1343–1354.

Yang, H. et al., 2017. Information asymmetry and investor trading behavior around bond rating change announcements. *Emerging Markets Review*, 32, pp.38–51.

Appendix

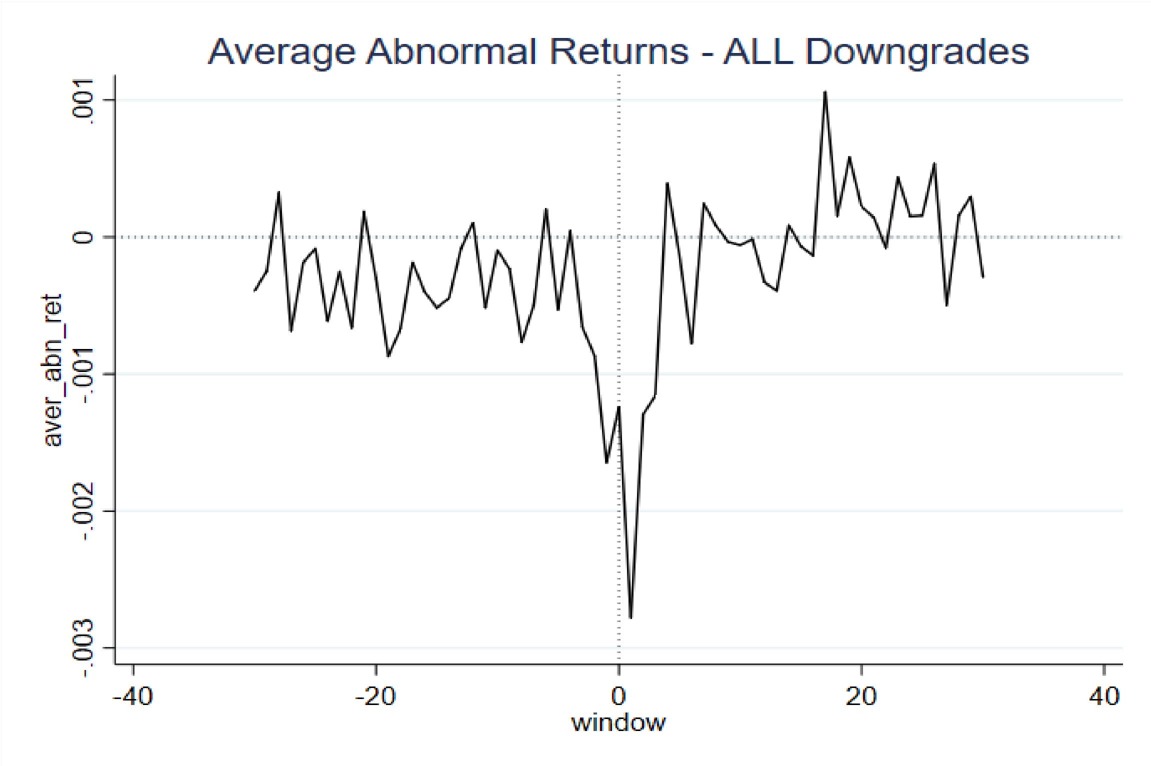
Heteroskedasticity Test:

After running the OLS regressions described in the results section, I plotted the residuals an find some evidence of heteroskedasticity. Thus, I performed a Breusch-Pagan test to test for heteroskedasticity in the residuals. The Null Hypothesis of constant variance, meaning that the is homoskedasticity in data, is rejected as the p-values are below 0.05. So, in my regression I am controlling for the heteroskedasticity in my dataset, otherwise regression will produce p-values that are smaller than they should be.

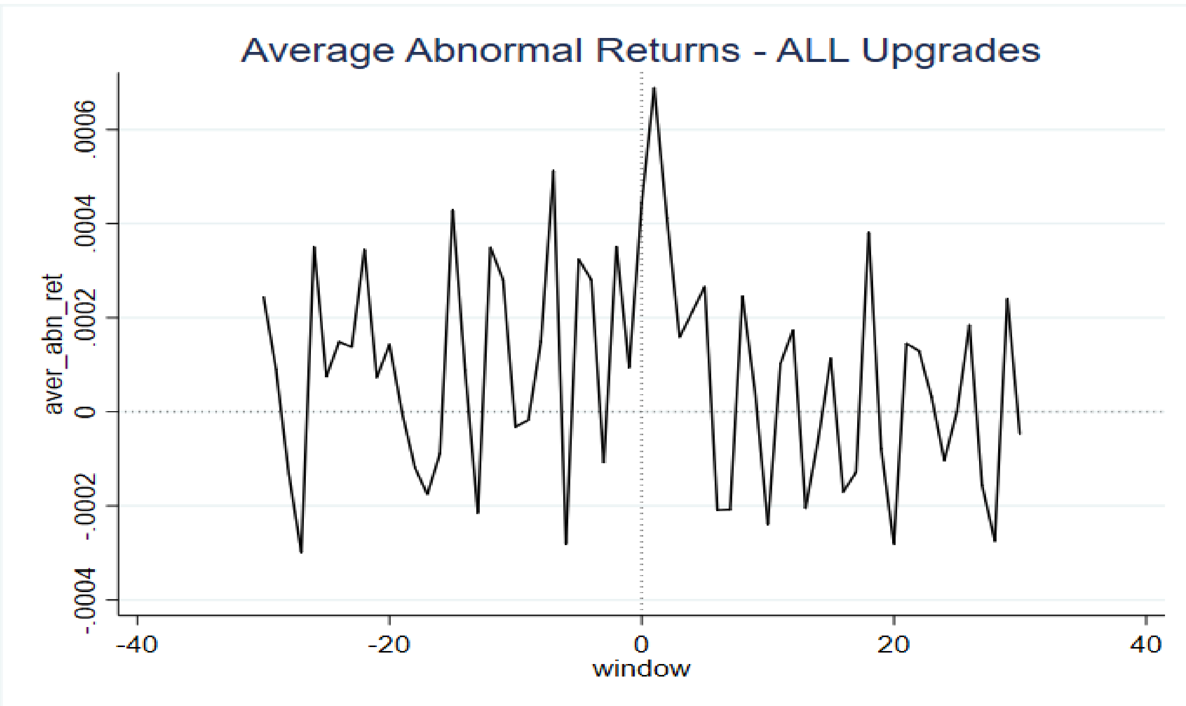
Multicollinearity Test:

Multicollinearity occurs when independent variables in a regression model are correlated. This correlation is a problem because independent variables should be independent. I did perform a Multicollinearity using the variance inflation factor. 1/VIIF was smaller than 0.1 thus there are no signs of multicollinearity in my data set.

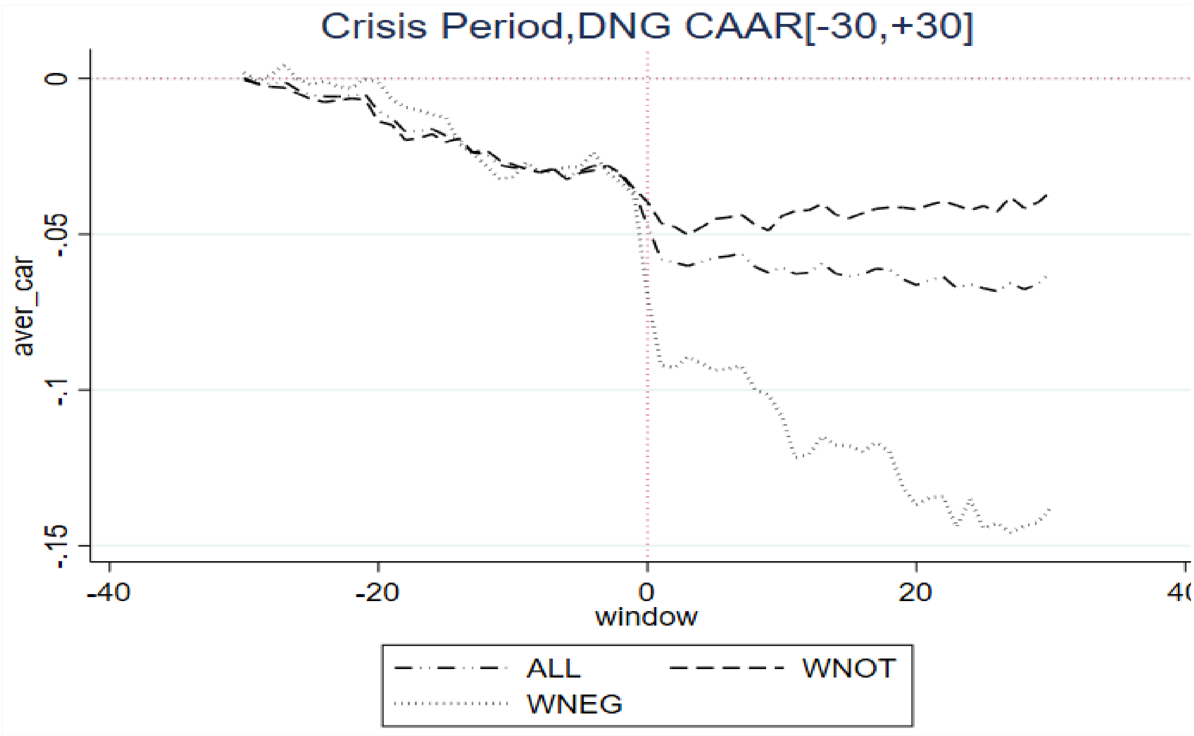
Graph 3



Graph 4



Graph 5



Graph 6

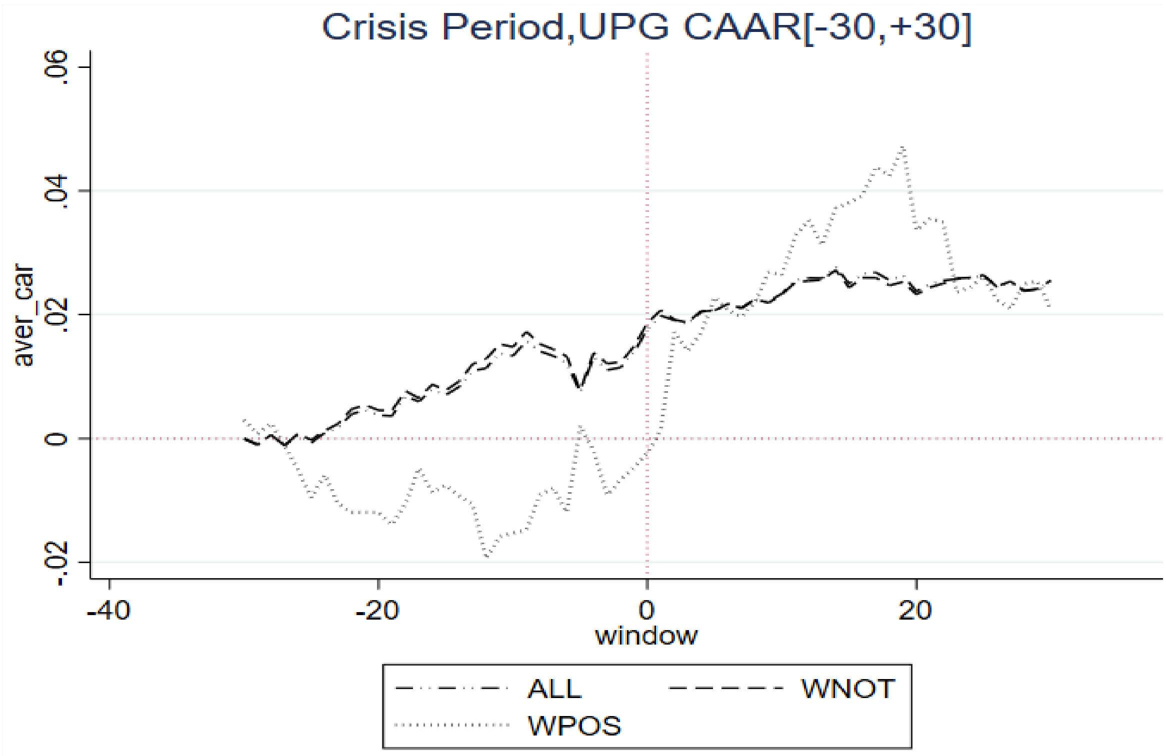


Table 7

Two Sample t-test with unequal variances, that the Average Abnormal Return of downgrades that simultaneously announced with negative credit watchlisting is significantly higher (in absolute terms) than downgrades that announced with off watch status. The results accept the Ha Hypothesis.

```
    diff = mean(WNEG) - mean(WNOT)                                  t =  -1.8827
Ho: diff = 0                     Satterthwaite's degrees of freedom =  72.1726

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.0319         Pr(|T| > |t|) = 0.0638          Pr(T > t) = 0.9681
```

Table 8

Two Sample t-test with unequal variances, that the Average Abnormal Return of Upgrades that simultaneously announced with Positive credit watchlisting is significantly higher (in absolute terms) than Upgrades that announced with off watch status. The result accepts the Ho Hypothesis.

```
    diff = mean(WNOT) - mean(WPOS)                                  t =  -0.7249
Ho: diff = 0                     Satterthwaite's degrees of freedom =  10.4388

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.2422         Pr(|T| > |t|) = 0.4844          Pr(T > t) = 0.7578
```

Table 10

Two Sample t-test with unequal variances, that the Average Abnormal Return of Upgrades is significantly higher (in absolute terms) than Upgrades over the event window [-1, +1]. The result accepts the Ha Hypothesis.

```
    diff = mean(DNG) - mean(UPG)                                    t =   3.0013
Ho: diff = 0                     Satterthwaite's degrees of freedom =  2.54642

    Ha: diff < 0                 Ha: diff != 0                 Ha: diff > 0
 Pr(T < t) = 0.9646         Pr(|T| > |t|) = 0.0709          Pr(T > t) = 0.0354
```