



MASTER THESIS

Do investors continue to trust credit rating agencies after crisis periods in the European market?

Author: Reem Allawy
Student number: 455251
Supervisor: Dr. Kan Ji

Finish date: March, 2018

Preface

NON-PLAGIARISM STATEMENT

By submitting this thesis the author declares to have written this thesis completely by himself/herself, and not to have used sources or resources other than the ones mentioned. All sources used, quotes and citations that were literally taken from publications, or that were in close accordance with the meaning of those publications, are indicated as such.

COPYRIGHT STATEMENT

The author has copyright of this thesis, but also acknowledges the intellectual copyright of contributions made by the thesis supervisor, which may include important research ideas and data. Author and thesis supervisor will have made clear agreements about issues such as confidentiality.

Electronic versions of the thesis are in principle available for inclusion in any EUR thesis database and repository, such as the Master Thesis Repository of the Erasmus University Rotterdam

Abstract

If capital markets are strongly efficient, prices reflect all available information. This thesis aims to investigate the informational content of credit rating changes by Standard & Poor's, Moody's and Fitch in the European markets. More specifically, abnormal stock price returns following upgrades and downgrades for 80 listed Western European firms are analyzed during the pre-crisis period from 2004 until 2006, as well as during the post-crisis period from 2014 until 2016. The abnormal returns during the two periods are then compared to examine whether European investors react differently to rating events after the global financial crisis and the sovereign debt crisis. I find significantly more pronounced negative stock price returns following downgrades during post-crisis periods. Less pronounced abnormal returns are observed following upgrades.

Table of contents

Preface	2
Abstract	3
Table of contents	4
List of tables and figures	6
1. Introduction	7
2. CRA Industry	9
2.1 Credit Rating Agencies	9
2.2 The Big Three	10
2.2.1 Standard & Poor's	10
2.2.2 Moody's	10
2.2.3 Fitch	11
2.3 Criticism on CRAs since the subprime mortgage crisis and the European sovereign debt crisis	11
3. Literature Review	13
3.1 Theoretical review	13
3.1.1 Efficient Market Hypothesis and Information Content Hypothesis	13
3.1.2 Issuer Type Hypothesis	13
3.1.3 Differential Information Hypothesis due to size of firm	14
3.1.4 Nationality Hypothesis	14
3.2 Empirical review	14
3.2.1 U.S. studies	15
3.2.2 Non-U.S. studies	15
3.2.3 Conclusions previous literature	17
3.2.4 Conceptual framework for measuring investors' trust	17
4. Hypotheses development	19
5. Dataset and Methodology	21
5.1 Period and dataset	21
5.2 Methodology	23
5.2.1 Univariate analysis	23
5.2.2 Multivariate regression analysis	27

6. Results	30
6.1 Descriptive statistics	30
6.2 Model assumptions and testing	31
6.3 Results univariate analysis	33
6.4 Results multivariate analysis	40
7. Conclusion and limitations	46
References	48
Appendix	51

List of tables and figures

Tables

I	Credit rating scales of S&P, Moody's and Fitch	22
II	Definition of variables	29
III	Number of rating changes by event type and period	30
IV	Summary statistics	31
V	Spearman Correlation Matrix	33
VI	Average abnormal returns downgrades Market Model	36
VII	Average abnormal returns upgrades Market Model	37
VIII	Results CAAR examination Market Model	39
IX	Mean return comparisons Downgrades sample before and after crisis periods	40
X	Multivariate Regression on Downgrades	41
XI	Multivariate Regression in Pre-Crisis and Post-Crisis periods	44
XII	Multivariate Regression on Upgrades	45
XIII	Country distribution	51

Figures

I	Relationship Credit Rating Changes to Abnormal Returns	17
II	Timeline of the tested periods	21
III	Timeline for calculating abnormal returns around the event	24
IV	Downgrade CAAR over the 100-day event window before and after crisis periods	34
V	Upgrade CAAR over the 100-day event window before and after crisis periods	35
VI	Residuals distribution	51

1. Introduction

Many investors and financial institutions have become highly dependent on credit rating agencies (CRAs). CRAs are assumed to provide independent assessments on credit risk of issuers. However, they have been under attack since the recent financial crises. According to some, CRAs underestimated the credit risk for several structured debt products. During the crisis, CRAs have been accused of not providing entirely independent assessments leading to the mispricing of financial instruments. Since 2007, even structured debt products with high ratings performed very poorly. The widely known mortgage-backed securities with AAA-rating fell by 70% between January 2007 and December 2008. This would indicate that the ratings of these products given by the CRAs understated the risk, leading to a mispricing of risk (Pagano & Volpin, 2010).

If the market is strongly efficient, prices should reflect all information available (Fama, 1970). However, a major number of studies have found significant stock price reactions following CRA actions, thus confirming the fact that investors value the informational content of their ratings. The focus area of these studies has been on the U.S. market. These studies have not yet analyzed the impact of CRA actions on corporate stock prices before and after, both the financial crisis starting in 2007, and the sovereign debt crisis in the European market. Therefore it is possible that the stock price reactions after a rating change will be less pronounced after these crisis-periods. Considering this gap, this study adds new evidence to the existing body of knowledge about the effects of ratings of CRAs in the European market. The main research question of this paper is as follows: '*Do investors continue to trust credit rating agencies after crisis periods in the European market?*'

A dataset of 80 firms from the Netherlands, Germany, France, Spain and Italy, listed on national indices is constructed from the Bloomberg database. Ratings of these firms allocated by credit rating agencies Standard & Poor's (S&P), Moody's and Fitch, who monopolize the rating industry, are also retrieved from Bloomberg. The ratings all occur during pre-crisis periods from 2004 until 2006 and during post-crisis periods from 2014 until 2016 for comparison. Crisis periods are not included in the sample. The economy is during such periods in an economic downturn and can trigger a lot of downgrades, which in turn can affect the sample. The final sample consists of 141 downgrades and 121 upgrades. The objective of the univariate analysis is to examine abnormal returns following the rating changes within event window [-10,10], as well as the cumulative average abnormal returns, to get the aggregate short-term effect over all the rating changes. Abnormal returns are calculated using the *Market model*. This is followed by a cross-sectional regression analysis, where the cumulative abnormal return over event window [-

1,0,1] is regressed against firm and rating characteristics, to help explain the variation in the abnormal returns. These regressions are run for both downgrades and upgrades samples.

Altogether, this research finds new evidence that investors in the European market do value the informational content of rating changes. In line with previous U.S. studies (e.g. Steiner and Heinke, 2001), significant stock price returns are found following downgrades and upgrades. Unexpectedly, stock price returns are more pronounced and with higher significance during post-crisis periods following downgrades, compared to pre-crisis periods. Thus, it can be concluded that investors still value the informational content of rating changes. During post-crisis periods, investors react more strongly to downgrades compared to upgrades. This supports the reasoning that investors react more strongly to bad news compared to good news and is in line with a major number of studies. Regarding the multivariate regression, a rating change greater than one notch, seems to have strong significant effect on abnormal returns for both the upgrades and downgrades sample. Furthermore, a higher B/M ratio of a firm can have stronger (weaker) effect on stock price returns following an upgrade (downgrades).

The rest of the paper is constructed as follows. The following section describes the CRA industry and the three major players. Section 3 explains theories on how rating changes can affect stock prices and how other factors can possibly contribute to stronger abnormal returns. Section 4 covers the data and methodology applied for the univariate and multivariate analysis. Section 5 reports the results of the analyses. Concluding remarks, as well as limitations to this study, are reported in Section 6.

2. CRA Industry

This section contains some background information on the topic. Specifically about the CRA industry in general, the three biggest players and the role they have played during crisis periods. The chapter concludes with shedding light on the criticism among investors on CRAs during crisis periods, which leads to the main research question of this paper.

2.1 Credit Rating Agencies

It all started in 1909 when John Moody kept a small rating book. Nowadays the current CRAs have turned the rating business into a multi-billion dollar industry. CRAs play an important part in the financial markets through providing information to market participants such as legislators, investors, issuers and regulators (Becker & Milbourn, 2010). The ratings of the CRAs provide information on credit risk of the issuers of the financial products. The market participants use this information provided to help them with making decisions on financial investments. For example: a main concern of a lender is often whether the borrower will actually be able to repay the loan. The higher the rating, the more likely the firm is able to repay the loan. Furthermore, sovereigns can use this information to attract foreign investors and financial institutions use this information to calculate their minimum capital requirements, since capital requirements depend on the ratings of the bonds in which the financial institution is investing.

CRAs provide this information through assigning the issuer a letter-based credit rating¹. In the article of the European Parliament and of the Council of credit rating agencies (2009), it is stated that a credit rating can be defined as ‘an opinion regarding the creditworthiness of an entity, a debt or financial obligation, debt security, preferred share or other financial instruments, or of an issuer of such a debt or financial obligation, debt security, preferred share or other financial instrument, issued using an established and defined ranking system of rating categories’. CRAs prefer their ratings to be defined as ‘opinions’, because CRAs enjoy the protection of the First Amendment of the U.S. Constitution if they are sued by market participants. According to Gonzalez et. al (2004), CRAs base their analyses not only on public information, but also private/confidential information, if the companies are willing to share it with CRAs. To predict the credit performance of a company, CRAs base their analyses on a range of financial and business factors, like a company’s financial statements, its competition within the industry, quality of its management, the value of the company, etc.

¹ Table I in section 5 *Dataset and Methodology* presents the letter-based scales of S&P, Moody’s and Fitch

2.2 The Big Three

John Moody kept a small rating book in 1909, where he publicly published bond ratings. Seven years later Poor's Publishing Company joined the rating market and six years later the Standard Statistics Company followed. The Fitch Publishing Company made an entry in the business in 1924. In 1941, Standard and Poor's merged. These rating companies kept their firms' bond ratings in books and sold them to investors, who were seeking information on whether borrowers were likely to repay their debt. Over the years, these three companies grew out to be the three biggest rating agencies in the world. The credit rating industry is extremely concentrated and making a new entry is almost impossible (Ferri et. al, 1999). In the 2016 annual report on Nationally Recognized Statistical Rating Organizations (NRSROs) by the U.S. Securities and Exchange Commission (SEC), it is stated that as of December 31, 2015, Standard & Poor's (S&P), Moody's and Fitch account for 96.5% of all the ratings outstanding reported by NRSROs. Currently there are ten credit rating agencies registered as NRSROs. S&P accounts for the highest percentage of ratings outstanding with 49.1% of the total outstanding ratings. Moody's is the second biggest rating agency, accounting for 34.4% of the total number of ratings, followed by Fitch, with 13.0% of the total. A short summary of each CRA is given in the following section.

2.2.1 Standard & Poor's²

S&P is the world's leading provider of credit ratings and is represented in 28 countries. The analysts, managers and economists of Standard & Poor's assess several finance and business factors that affect the creditworthiness of government, corporate, financial sector and structured finance entities and securities. S&P has approximately more than 1 million credit ratings outstanding and \$46.3 trillion in rated debt. Besides an actual credit rating change, Standard & Poor's uses the CreditWatch list when it believes that a rating action will occur within 90 days. The designation to an entity or sovereign can be positive or negative. Positive, which indicates a rating may be increased, or negative, which indicates a rating may be decreased. Thus, there is still a possibility that the actual change will not occur. These listings provide more timely information.

2.2.2 Moody's³

Moody's Corporation is the parent company of Moody's Investors Service and Moody's Analytics. Moody's Investors Service provides credit ratings, research and risk analysis, whereas Moody's Analytics offers unique tools for measuring and managing risk through expertise and

² More information can be found on www.standardandpoors.com

³ More information can be found on www.moodys.com

experience in credit analysis. Moody's is represented in 41 countries and provides ratings on 11,000 corporate issuers, 21,000 public finance issuers, 72,000 structured finance obligations and 135 sovereign nations. Similar to S&P, Moody's places an entity or sovereign on its Watchlist if it believes a positive or negative rating change might occur within 90 days.

2.2.3 Fitch⁴

Fitch Group is comprised of Fitch Rating, Fitch Learning, Fitch Solutions and BMI Research. Fitch Ratings is a global leader in credit ratings and research. Fitch Group has operations in more than 30 countries and is dual headquartered with offices in London and New York. Fitch has a similar list for possible upcoming credit rating changes and is called RatingAlert.

This paper uses the credit rating events by these three big CRAs. Steiner and Heinke (2001) mention in their paper on the price effects of credit ratings that there could be a moral hazard risk on behalf of the rating agency. Each CRA might be tempted to overrate the issuer, to gain more market share. This could result in a decline of the reliability of the CRA and stop price movements after an event. However, Holthausen and Leftwich (1986) found equal stock price reactions on rating changes from Standard & Poor's and Moody's. Thus, there is no reason to believe that there is a difference in the effect of ratings between The Big Three.

2.3 Criticism on CRAs since the subprime mortgage crisis and the European sovereign debt crisis

CRAs have been under attack since the subprime mortgage crisis in 2007. CRAs have been accused of not providing entirely independent assessments leading to the mispricing of financial instruments. According to some, CRAs underestimated the credit risk for several structured debt products. With a result that since 2007 even structured debt with high ratings performed very poorly. The widely known mortgage-backed securities with AAA-rating fell by 70% between January 2007 and December 2008. This would indicate that the ratings of these products given by the CRAs understated the risk, leading to a mispricing of risk (Pagano & Volpin, 2010). White (2009) gives several reasons in his paper for the excessively optimistic ratings by the three major agencies of the subprime mortgage-backed securities. It is a combination of their fee structure, insufficient historical data, the complexity of the priced securities and market pressures. CRAs have also been criticized for slowly adjusting their ratings when the problems in the sub-prime market became clear. De Haan & Amtenbrink (2011) mention in their paper that 'the day before

⁴ More information can be found on www.fitchratings.com

Lehman went bankrupt, The Big Three still gave the bank investment grade ratings⁵. The subprime mortgage crisis led eventually to the global financial crisis.

Furthermore, CRAs are criticized for their sovereign rating activities. Even before recent crisis periods in 1998, Ferri et. al (1999) also find evidence that CRAs have downgraded East Asian crisis countries more than their economic fundamentals would justify, and thereby exacerbated the East Asian crisis. Similarly, CRAs downgraded some sovereigns in Europe significantly, especially Greece by four notches in 2010. Some of these downgrades came as a surprise for the markets, which made Credit Default Swap (CDS) spreads widen significantly and as a result the fiscal problems exacerbated for some of these countries like Greece, Ireland, Italy, Portugal and Spain (IMF Global Financial Stability Report, 2010)⁵. De Santis (2012) also states in his ECB⁶ working paper that country-specific credit ratings have played a key role in the developments of the spreads for Greece, Ireland, Portugal and Spain. This criticism could possibly lead to a loss of trust of investors in CRAs after both crisis periods in the European market. How this loss of trust in CRAs of investors is measured in this paper, will be further explained in section 3.2.4 *Conceptual framework for measuring investors' trust*.

The roles the CRAs have played during both crisis periods in the European market are the main reason that lead to the increased criticism by investors. It is therefore interesting to research whether investors have lost their confidence in them over the years. Prior research has investigated this issue mainly in the United States and regarding other earlier crisis periods. There is no other study to my knowledge that researches the possible change in trust of the investors in the European market after the subprime mortgage crisis and the sovereign debt crisis. This thesis aims to fill this gap in literature. The next section will provide a review of the theories and literature related to the subject, as well as empirical findings of the authors.

⁵ A CDS is a contract, which provides insurance for the buyer against default by an entity or a sovereign (issuer).

⁶ ECB = European Central Bank

3. Literature Review

The focus of this study is to examine the price effects following rating changes. This section will provide more insights on the impact and theories of credit rating changes and will be divided into four parts. In the first part, different theories are discussed to explain the effect of ratings. The vast majority of the studies mentioned in this paper also apply these theories to their research. The second part covers the empirical findings of previous studies, based on these theories. The third part gives a conclusion of previous studies and the fourth part introduces the conceptual framework used for this research.

3.1 Theoretical review

3.1.1 Efficient Market Hypothesis and Information Content Hypothesis

The efficient market hypothesis states that at any given time and in a liquid market, existing stock prices always reflect all relevant information and thus reflect fundamental values. The efficient market hypothesis is built on several assumptions. In his paper, Fama (1970) explains this theory and the following underlying three conditions for capital market efficiency: (i) investors are rational and have homogeneous expectations, (ii) there are no transaction costs and (iii) there is no information asymmetry. It is however known that the previous assumptions often do not hold. There are three forms of market efficiency: weak, semi-strong and strong. The weak form states that stock prices reflect all historical information. The semi-strong form states that stock prices reflect all publicly available information and the strong form states that stock prices reflect both privately and publicly available information. If it is assumed that the corresponding markets are strongly efficient, then credit rating changes and announcements should not provide valuable information content to the market, and thus there should be no price effects observed following rating events. However, CRAs are known to having deeper knowledge of firms' fundamentals. CRAs examine inside information, which is not publicly available to investors. Thus, a credit rating change could be seen as new information on the financial performs of the firm. If the stock market is efficient in the semi-strong form, any new information on the credit risk of a particular stock should result in a stock price reaction around the event date of the credit rating change.

3.1.2 Issuer Type Hypothesis

Schweitzer et al. (1992) argue in their paper that some issuers are more closely monitored than others. Banks are under more supervision by regulatory institutions than other issuers and therefore, more information is available on credit risk. The issuer hypothesis states that financial firms react less after a rating action compared to non-financial firms, due to lower information

content. This means more significant stock price reactions are expected if the firm is non-financial. This null hypothesis is rejected after they empirically find that financial institutions react more pronounced after rating changes. More specifically, they find that downgrades lead to greater abnormal stock returns when involving banks. The theory behind this is that regulators tend to withhold information to the public to preserve the stability of the financial system. Groppe and Richards (2001) perform an event study of the effect of rating changes on equity price for European banks and find strong results. Thus, rating changes of financial firms convey new information for investors. Abad-Romero and Robles-Fernandez (2006) also find more significant abnormal returns around changes for financial firms.

3.1.3 Differential Information Hypothesis due to size of firm

Larger firms are usually better diversified, have more income and have more access to information compared to smaller firms. Thus, larger firms are less prone to default (Hundt. et al, 2017). It is therefore likely that larger firms react less negative (positive) to downgrades (upgrades). The research of Atiase (1985) focuses on whether there are differences in the security price reactions to earnings announcements of firms, which are associated with specific firm characteristics that lead to different amounts of disclosed information. In his study he uses capitalization of the firm to capture the ‘size’. He finds that the larger the firm (market capitalization), the smaller the amount of unexpected information is in a credit rating change, and thus the smaller the security price reaction, other things being equal.

3.1.4 Nationality Hypothesis

As discussed before, rating agencies have played a big role during recent crisis periods, especially for sovereigns in the Euro area during the sovereign debt crisis. As this study focuses on investors in European countries, it is interesting to examine whether issuers in countries that were heavily indebted during the sovereign debt crisis react stronger to rating changes compared to issuers in fiscally stable countries. Hundt et al. (2017) find significant influence on the prices in the convertible bonds⁷ market, if the issuer of the bond is headquartered in France.

3.2 Empirical review

Previous research has analyzed the effects credit rating events on different markets: stock, bond and CDS markets and more recently also on CB⁸ markets. This section will provide the main empirical findings of previous studies related to the subject. The first part summarizes the main

⁸ A convertible bond is a type of bond that the holder can convert into a number of shares.

findings of U.S. studies, while the second part covers the main findings of studies outside of the U.S.

3.2.1 U.S. studies

In 1986, Holthausen and Leftwich studied the effect of bond rating changes of firms listed on the New York or American Stock Exchange, by both Moody's and Standard and Poor's, on common stock prices. They use a time frame of 1977 until 1982 for the credit rating events. They find significant negative reactions after downgrades, but no significant reactions after upgrades. Hand et. al (1992) perform a similar analysis, but their analysis includes the reactions on both the stock and bond markets. They also find significant negative abnormal stock and bond returns for downgrades and less reliable effects for upgrades. Furthermore, they find that the average excess bond returns are stronger for bonds below investment grades, than for investment grade bonds. Hite and Warga (1997) base their analysis on the bond market in the U.S. They study the effect of bond-rating changes on bond price performance. Trader quotes are used from Lehman Brothers for March 1985 through March 1995. Credit rating changes for 1100 industrial firms in the U.S. are retrieved from S&P and Moody's. Downgraded firms show significant effects due to the rating announcement. This effect could already be seen in the period prior to the announcement. This could be explained by investors anticipating the announcement. The result is the strongest when the credit rating change results in the movement from an (below) investment grade to a non-investment grade. The effects of upgraded firms are again smaller and less significant. They are however, more positive when upgraded from a non-investment grade to an investment grade. Dichev and Piotroski (2001) studied the long-run stock returns following bond-rating changes by Moody's between 1970 and 1997. They find no reliable abnormal returns after upgrades, but they do find negative abnormal returns in the year following downgrades. Furthermore, the underperformance after downgrades is especially pronounced for small firms and firms with noninvestment grade debt.

3.2.2 Non-U.S. studies

The vast majority of the studies related to the subject base their analysis on the markets in the U.S. However, research on smaller markets outside the U.S. has been increasing. This section gives a summary of findings of similar studies outside the U.S. Steiner and Heinke (2001) introduce an international dimension by performing an event study on the effect of announcements of watchlistings and rating changes by Standard & Poor's and Moody's on international bond prices. They examine the effect of these events on daily excess German Eurobond returns. Similar to Hite and Warga (1997), they also use daily trader quotes, because

“traders have a strong incentive to provide accurate bid quotes”. They observe significant negative bond price reactions for announcements of downgrades and negative watchlistings, and that the reactions are stronger for downgrades into speculative grade. They also find evidence that the nationality of the issuer is a key factor for determining the magnitude of the price reactions after downgrades. Upgrades and positive watchlistings, on the other hand, do not show any significant effects. Hull et. al (2004) examine the relationship between CDS spreads and credit ratings, using worldwide CDS spreads of entities and sovereigns. The spread of a CDS contract is the rate of the payments per year the buyer has to pay to the issuer. In return, the buyer has the right to sell the bonds with a face value, in case the issuer defaults. They find evidence that the CDS markets anticipate negative credit events, and that the spreads widen significantly in advance and during the event. Similar to previous studies, they do not find any significance for positive events. Romero et. al (2007) intended to perform a similar research to a much smaller market than previous studies. They examine the relationship between rating changes made by international agencies to the debt of Spanish firms and the Spanish stock market. This market is significantly smaller and with lower liquidity. In contrast to the U.S. studies mentioned, they find that positive credit rating changes for Spanish firms also generate significant abnormal returns in the Spanish stock market. Positive excess stock returns have also been found earlier in a paper by Barron et. al (1997), where the effects of credit rating events on the UK capital market are researched. Excess stock returns are found after negative downgrades, as well as after positive CreditWatch announcements, made by Standard & Poor's. In the Australian market, Matolcsy and Lianto (1995) seem to find similar results to the U.S. studies, where the incremental information content is not significant for upgrades, but is significant for downgrades. Linciano (2004) examined the impact on Italian firms after credit announcements and found that overall, stock price reactions were quite moderate or statistically insignificant. The reason behind that, in her opinion, was that CRAs did not use any private information when assigning firms credit ratings.

Prior research has investigated the informational content of credit ratings for the stocks-bonds and CDS markets. A more recent study of Hundt et. al (2017) introduces a new financing instrument to perform a similar research on: the CB market in Europe. This study is specifically interesting, since its main objective is to examine the information content of rating changes in the European market, similar to this paper. The paper concludes that the announcement of negative rating changes causes significant decreases in the abnormal returns of CBs, which means that these announcement convey new information to investors.

3.2.3 Conclusions previous literature

A prominent conclusion can be drawn that credit rating changes do provide informational content to investors because the markets are in semi-strong form, which in return affects the prices. The results of previous literature, especially of the U.S. studies, are similar in that the price effects following a downgrade or a negative outlook are more significant than following an upgrade or a positive outlook. In other words: price reactions to credit rating events behave asymmetrical. Evidence on the effects of credit rating changes on abnormal returns in the European market is both scarce and rather ambiguous. Romero et. al (2007), find significant positive abnormal returns after positive rating changes in the smaller Spanish stock market, whereas Hundt et. al (2017) find significant decreases in abnormal returns following negative rating changes in the European markets. In Italy, on the other hand, Linciano (2004) finds moderate, insignificant stock price reactions after both positive and negative rating events.

Important for this research is to examine the price effects following rating changes in the European market and to examine how and if the recent crisis periods might have influenced investors' trust in CRAs ratings.

3.2.4 Conceptual framework for measuring investors' trust

Some of these aforementioned papers found a relationship between credit rating changes and abnormal returns. Brown and Warner (1985) examined in their paper how particular characteristics of daily stock return data affect event study methodologies. They find that 'the characteristics of daily data present few difficulties in the context of event study methodologies'. Therefore in this research daily stock prices will be used to calculate possible abnormal returns around the firm-specific rating change. The abnormal returns will represent the confidence of market participants in CRAs. A credit rating event by one of 'The Big Three' will be used as the firm-specific event. Therefore, this paper will be centered on answering the main research question using the relationship as displayed below, in the analyses.

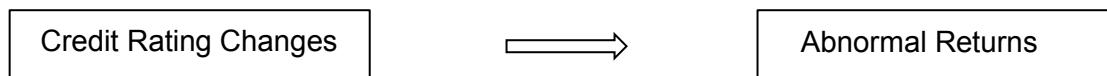


Figure I Relationship Credit Rating Changes to Abnormal Returns

Where credit rating changes are the independent variable in the relationship and abnormal returns the dependent variable. As stated before, CRAs stress that their ratings are just opinions based on

extensive analysis of the company and therefore the above-mentioned relationship is based on trust. The abnormal returns, which might appear after the credit rating events during the specific time periods, will represent the informational content of the credit rating changes and thus the trust of the investors. Observing abnormal stock returns after a credit rating change means that investors value the information content of the rating event of a certain company and therefore react to it by buying, selling or holding their shares of that specific company. Therefore this relationship will be researched empirically in section *5 Dataset & Methodology* as well as the relationship between other independent variables and the abnormal returns, to answer the main research question. The main research question is stated again in the next section, as well as three other hypotheses related to the subject.

4. Hypotheses development

The main research question of this study is: ‘‘*Do investors continue to trust credit rating agencies after crisis periods in the European market?*’’ As mentioned in the previous section, abnormal stock returns following a credit rating change represent the trust of investors in CRAs. Many prior studies have shown significant stock, bond and CDS price reactions after credit rating changes. Because investors value the informational content of the ratings of CRAs, they tend to sell (buy) a security after a downgrade (upgrade). Therefore, the first hypothesis is as follows:

H1: Abnormal stock price returns are negative (positive) following downgrades (upgrades) during 2004 until 2006 as well as during 2015 until 2017 in the European market.

Previous literature has not analyzed the price effects of rating changes during post-crisis periods. Most event-studies focus on a certain time period. It is therefore unclear how investors will react compared to pre-crisis periods. To further investigate the effects of credit rating changes on abnormal stock prices, this thesis tests the separate effects of crisis periods and non-crisis periods in the European market. Since many critics believe that CRAs played an important role in previous crisis periods, it is expected that investors have lost their trust in CRAs. Hence, the main objective of this research is to test whether abnormal stock price returns have decreased after crisis periods. Therefore, the second and main hypothesis of this research is:

HII: Abnormal stock price returns following both downgrades and upgrades are less pronounced during 2014 until 2016 after crisis periods.

Numerous studies seem to find evidence that the effects of upgraded firms are smaller and less significant than for downgraded firms (Hand et. al, 1992; Hite and Warga, 1997; Steiner and Heinke, 2001). Possible explanations for more pronounced negative abnormal returns following a downgrade could be due to information-processing, institutional or behavioral biases (Dichev and Piotroski, 2001). Holthausen and Leftwich (1986) explain that investors allocate more resources to retrieve information on negative credit risk compared to positive news. The reason is that investors perceive a rating that is too high to be worse than a rating that is too low. To test this asymmetrical response to credit rating changes by investors, the following hypothesis is constructed:

HIII: Abnormal stock price returns following downgrades are more pronounced, compared to upgrades both before and after crisis periods.

Finally, prior studies have found evidence that specific firm characteristics affect the rating change. In turn, the stock prices behave differently. As mentioned before, the *Differential Information Hypothesis* states that the larger the firm (market capitalization), the smaller the amount of unexpected information is in a credit rating change, and thus the smaller the security price reaction, other things being equal. According to the Fama-French three-factor model, another firm characteristic, which might affect stock prices is the Book-to-Market ratio (Fama & French, 1992). Additionally, according to the *Nationality Hypothesis*, the nationality of the issuer could also be a key factor for determining the magnitude of the price reactions. Furthermore, prior literature found more pronounced negative abnormal returns following downgrades for small firms. (Atiase, 1985; Dichev and Piotroski, 2001; Vassalou and King, 2005) and the *Issuer Type Hypothesis* states that the stock price reacts differently if the firm is a financial institution. Finally, previous studies find evidence that the intensity of the rating change can have profound effect on the abnormal stock price returns (Steiner and Heinke, 2001). Therefore the last constructed hypothesis is:

HIV: Specific firm and rating characteristics determine the magnitude of the abnormal stock price returns

5. Dataset and Methodology

This section is dedicated to specify the data and methodology used to research the outcomes of the testable hypotheses explained in section 4 of this paper. Previous studies are similar in that the authors first perform a univariate analysis to capture the price effects of rating changes and proceed with a cross-sectional multivariate analysis to explain the variation in abnormal returns (Steiner and Heinke, 2001; Hand et. al, 1992; Norden and Weber, 2004). This study will follow the same methodology. The construction of the dataset and the choice of period are explained in the first section. The second part will be dedicated to the methodologies used for the univariate and multivariate analysis.

5.1 Period and dataset

Recall that the aim of this paper was to test whether the trust of investors in the ratings of CRAs has decreased after the global financial crisis and the sovereign debt crisis in the European Union. The subprime crisis started in 2007 in the United States (National Bureau of Economic Research (NBER), leading to the global financial crisis, starting in 2008 and eventually partly spilled over to the European Union, triggering the sovereign debt crisis. Therefore, two periods will be compared to examine whether the trust of the investors has decreased over the years: The period before both crises, the beginning of 2004 until the beginning of 2006, compared to the period after the crises, the beginning of 2014 until the beginning of 2016. The crisis periods will not be included in the sample since during crisis periods the economy is in an economic downturn and can trigger a lot of downgrades, which in turn can affect the sample. Therefore the empirical tests might not be reliable. *Figure II* shows a graphical representation of the chosen time period.

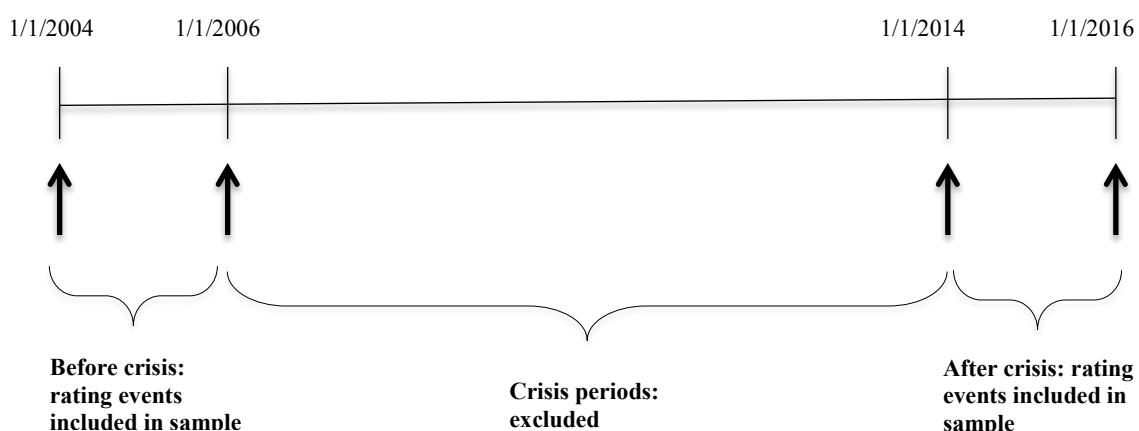


Figure II Timeline of the tested periods

To research the testable hypotheses mentioned in *section 4*, two types of data are needed: the credit rating events of the companies which have occurred during both these periods and the stock

prices of the companies around these event dates. How the abnormal returns are then calculated using the stock prices will be specified later on in section 5.2 *Methodology*. The specific events for each company are narrowed down to: downgrades, upgrades, positive and negative outlooks, i.e. watchlisting⁹. Micu et. al (2006) find in their studies that outlooks have significant impact on CDS spreads, therefore outlooks are included in this sample. As a result, a negative (positive) outlook will be considered as a downgrade (upgrade).

Table I presents the letter-based scales of the CRAs. The ratings between the CRAs show slightly different configurations. It is however widely accepted to treat the ratings across the agencies similar.

Table I
Credit rating scales of S&P, Moody's and Fitch

Agency	S&P	Moody's	Fitch
Investment grade	AAA	Aaa	AAA
	AA+, AA, AA-	Aa1, Aa2, Aa3	AA+, AA, AA-
	A+, A, A-	A1, A2, A3	A+, A, A-
Speculative grade	BBB+, BBB, BBB-	Baa1, Baa2, Baa3	BBB+, BBB, BBB-
	BB+, BB, BB-	Ba1, Ba2, Ba3	BB+, BB, BB-
	B+, B, B-	B1, B2, B3	B+, B, B-
Substantial risks	CCC+, CCC, CCC-	Caa1, Caa2, Caa3	CCC+, CCC, CCC-
	CC	Ca	CC
	C	C	C

Rating changes of firms located in the following five countries will represent the European market: The Netherlands, France, Germany, Spain and Italy. It is a good representation of the European market as a whole and it will allow comparing abnormal returns between these countries. This comparison might be interesting since Spain and Italy are PIIGS countries and thus suffered more during the sovereign debt crisis compared to the other three countries.¹⁰ The companies researched are all listed on the stock exchanges of each country during the entire

⁹ The definitions of such events for each CRA are mentioned in section 3.2 *The Big Three*

¹⁰ PIIGS countries: Troubled and heavily-indebted countries in Europe

period: AEX, CAC40, DAX, IBEX35 and FTSEMIB respectively. The companies can be retrieved through Bloomberg, by looking up the member constituents of each index. Since the member constituents of the FTSEMIB were not available on Bloomberg, the top 40 companies, ranked by market capitalization, on the Borsa Italiana are extracted from the Bloomberg database. This should give the same representation of companies. If a company is delisted during the selected period, the rating events of the company are excluded from the dataset. The total sample consists of 80 Western European companies.

The next step is to find the credit rating changes of the selected companies. These credit rating changes are retrieved from the Bloomberg-database at the Erasmus School of Economics by using the RATC command. It is possible that a company has several credit rating changes during the examined period. In that case, both or more events can be seen as separate observations. However, doubles are removed if a company receives a rating change from more than one agency on the same day. 10 double rating changes are removed from the sample in total. Furthermore, a rating change is excluded from the data sample if the company does not have well documented daily stock returns, as these are needed for the calculation of the abnormal returns. Fortunately, most stock prices are documented correctly, mainly because the selected firms are all members of big national indices. Of the whole sample, only five observations are dropped due to missing stock price returns. Bloomberg database, Center for Research in Security Prices (CRSP) and DataStream are all databases where the daily stock prices can be retrieved. I choose to retrieve the daily stock prices from DataStream for its simplicity. Daily stock prices are preferred over monthly stock prices to observe the direct short-term effect in abnormal returns surrounding the credit rating event. Brown and Warner (1985) examine the usage of daily stock returns in the case of event studies and find few difficulties. The total sample consists of 263 observations.

Finally, the following firm characteristics retrieved from the Datastream database since they are known to have considerable effects on abnormal returns (Fama & French, 1993): market capitalization (firm size) and the book-to-market ratio (B/M). For both characteristics, the number is extracted of the firm of the year in which the rating change occurred. The next section will explain further how this data is implemented in the analyses.

5.2 Methodology

5.2.1 Univariate analysis

The main objective of this paper is to study the information content of the credit rating changes in the European market. This information content can be observed, as applied by previous studies, by examining the following: CDS spreads, bond spreads, bond price returns and stock price

returns. This paper will focus only on the stock market, as Norden and Weber (2004) point out that prices of bonds reflect both aspects of issue risk, as well as issuer risk in contrast to stock prices. Furthermore, bond and CDS information is not readily available compared to stocks.

The traditional standard event study methodology originated by Fama et. al (1969) is applied for calculating abnormal returns around events. The examined events in this study are the credit rating changes applied by the three major CRAs. There are three widely known models for calculating abnormal returns around each specific event: The mean-adjusted return model, the market-adjusted return model and the market model. The univariate analysis will allow answering the first three aforementioned hypotheses.

Mean-adjusted returns model

The abnormal return is in fact the difference between the expected return and the actual return occurred of a particular stock.

$$AR_{jt} = R_{jt} - E(R_{it})$$

$E(R_{it})$ represents the expected return. According to the mean-adjusted returns model (Brown and Warner, 1980), the expected return of a stock is the average return. The average return on the examined day is then subtracted from the actual return. Thus, AR_{jt} is the difference between the mean return and the actual return of stock j , where t is the examined day in the ‘event window’ $[t1, t2]$. The event window is set at $[-90, 10]$, which means 90 days prior- and 10 days after the rating change. The average return of the stock is calculated over the stock returns during the ‘estimation window’ $[T1, T2]$ as shown in *Figure III*.

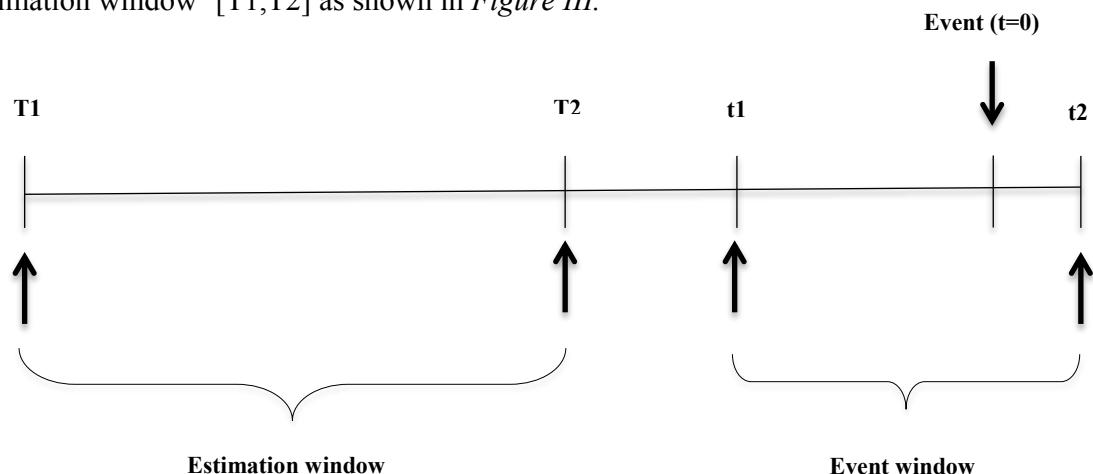


Figure III Timeline for calculating abnormal returns around the event

The estimation window is set at [-200,-100], which means 200 days until 100 days prior to the rating change. This is based on the study of Hundt et al. (2017). There is no common rule for setting an estimation window, but they find during their research that most event studies use an estimation window of 100 trading days. Furthermore, according to MacKinlay (1997), an event window is typically around 120 days.

There are however some disadvantages regarding the mean-adjusted returns model. This model assumes constant daily returns for each stock, and thus only differs across different stocks. Furthermore, the market risk is not incorporated and can therefore lead to substantial errors.

Market-adjusted return model

This method on the other hand, does incorporate the market risk by using the return on the market as a benchmark for calculating abnormal returns.

$$AR_{jt} = R_{jt} - E(R_{mt})$$

However, it assumes that the beta¹¹ of each security is equal to one, which is not the case. I will therefore apply an alternative and a more widely used method: *Market model*.

Market model

An alternative method is the market model. The market model calculates the expected return using the ordinary least squares (OLS) method. OLS estimates the alpha, beta and residual standard deviation of the particular data. This model is similar to the Capital Asset Pricing Model (CAPM)¹², except the risk-free rate is replaced by a constant. Similar to Hundt et. al (2017), instead of using just one benchmark index as the market return like Hand et. al (1992), the stock returns of the five national indices are extracted as benchmarks to increase the quality of the OLS regression: AEX, CAC40, DAX, IBEX35 and FTSEMIB. The stock returns of the particular firm, for each event, are matched to the stock returns of the index where the firm is listed during the same estimation window [-200,-100]. The intercept, slope and root mean squared error will represent the estimators $\hat{\alpha}$ and $\hat{\beta}$, and ε respectively.

$$E(R_{jt}) = \alpha_j + \beta_j R_{mt} + \varepsilon_{jt}$$

¹¹ Beta is a measure to determine the volatility of a security in relation to the market: $\beta_p = \frac{Cov(r_p, r_b)}{Var(r_b)}$

¹² CAPM calculates the required return of a security, taking the systematic risk into account

The estimators $\hat{\alpha}$ and $\hat{\beta}$ are calculated with the following formulas:

$$\hat{\alpha}_j = \hat{R}_j - \hat{\beta}_j \hat{R}_{mt}$$

$$\hat{\beta}_j = \frac{Cov(R_1, R_{mt})}{var(R_{mt})}$$

The abnormal return is then again calculated by subtracting the expected return from the actual return. There is no complete certainty that the market was not already informed prior to the rating event (McKinlay, 1997). To handle this event-date uncertainty, around each event the cumulative abnormal return (CAR) is calculated over the event windows, [-10,1], [-1,0,1] and [-1,10] to capture the short-term effect of the credit rating change. The CAR is calculated by simply adding the abnormal returns over the event window.

$$CAR_{j(t1,t2)} = \sum_{t=t1}^{t2} AR_{j,t}$$

Each AR or CAR can then be analyzed separately, however it is much more informative to average the information over all the events. The individual CARs will be more useful for the multivariate analysis to examine the impact of specific rating and firm characteristics. Aggregating the abnormal returns for each day for all events and dividing it by the number of observations, gives the average abnormal return at each time t . This eliminates idiosyncratic risks for some stocks.

$$AAR_t = \frac{1}{N} \sum_{j=1}^N AR_{j,t}$$

To observe the impact for the whole sample over a specific window, the AARs for each day of the event window are accumulated. This gives the aggregate effect of the abnormal returns during the event window over all the events

$$CAAR_t = \frac{1}{N} \sum_{j=1}^N CAR_{j,t}$$

or

$$CAAR_t = \sum_{t=1}^T AAR_t$$

Brown and Warner's (1980) cross-sectional, two-sided t-test will be conducted thereafter, to test the hypothesis whether the aggregate abnormal returns are significantly different from zero.

$$t_{CAAR} = \sqrt{N} \frac{CAAR}{S_{CAAR}}$$

Where S_{CAAR} is the standard deviation of the CARs across the event window and N the number of observations.

$$S_{CAAR}^2 = \frac{1}{N-1} \sum_{j=1}^N (CAR_j - CAAR)^2$$

Results of the calculations of the AARs and CAARs with the Market model are presented in section 6 *Results and discussion*.

5.2.2 Multivariate regression analysis

To answer the last hypothesis, the second part of the methodology involves a multivariate OLS regression analysis, where several independent explaining variables and control variables are regressed against the CAR for each stock. The multivariate regressions are run separately for Upgrades and Downgrades to try to explain cross-sectional variation in the cumulative abnormal returns. This analysis allows to solve for omitted variable bias. The regressions are estimated in the following form:

$$CAR_{[T_1, T_2]} = \beta_0 + \beta_1(Financial_i) + \beta_2(Notches_i) + \beta_3(Border_i) + \beta_4(Country_i) + \beta_5\left(\frac{B}{M_i}\right) + \beta_6(Pre - Post_i) + \beta_7(Firm size_i) + \varepsilon_i$$

Where $CAR_{[T_1, T_2]}$ denotes the cumulative abnormal return of stock i within the event window $[T_1, T_2]$ and β_n are the regression coefficients of variable n .

To test the *Issuer Type Hypothesis* as mentioned earlier, the dummy variable $Financial_i$ is added which takes the value of one if the firm provides financial services and zero otherwise. I

abstain from dividing the sample into other industries, as the sub-divided samples would become too small for significance testing. Similar to Abad-Romero and Robles-Fernandez (2006), I expect that the variable $Financial_i$ has a negative coefficient in the Downgrades regression and a positive coefficient in the Upgrades regression.

This analysis also controls for country fixed effects with the added dummy variable $Country_i$. The variable takes the value of one if the firm is headquartered in either Italy or Spain¹³ and zero otherwise. I again abstain from dividing the sample in separate countries, as the subdivided sample would become too small for significance testing¹⁴. The coefficient of this variable is expected to be negative for Downgrades and positive for Upgrades, as it is expected that investors in such severely indebted countries react stronger to rating changes.

To specify the price effects due to the intensity of the rating change, the dummy variables $Notches_i$ and $Border_i$ are added to the equation. $Notches_i$ takes the value of one if the rating change is greater than one notch (e.g. from A to AAA) and zero otherwise (e.g. from A to AA). $Border_i$ takes the value of one if the downgrade (upgrade) goes into speculative (investment) grade. For the Downgrades model, the coefficients of these variables are expected to be negative, since such intense rating changes imply that the default risk of the firm is increasing. For the Upgrades model, the coefficients are expected to be positive and the opposite holds.

$\frac{B}{M_i}$ and $Firm\ size_i$ are control variables and are defined as the book value per share divided by the market price per share and the market capitalization¹⁵ of the company. Since market capitalizations are often very high values, the distribution of this variable is expected to be heavily skewed. To normalize the data and to prevent it from affecting the results, it needs to be modified by taking the natural logarithm of the market capitalization. According to the theory, large firms are expected to experience smaller abnormal returns following rating changes compared to small firms, as smaller firms are considered to be riskier. Furthermore, firms with a high B/M ratio, also known as ‘value stocks’¹⁶, are also considered to be riskier, because they are trading at a lower value than its book value. Thus, investors investing in firms with a high B/M ratio might expect and anticipate a downgrade of the firm and not react as strongly. It is therefore expected that the sign of the coefficient will be positive following a downgrade. It is expected that the sign of the $\frac{B}{M_i}$ coefficient will also be positive following an upgrade, since this could be a sign that the firm is financially performing well. Investors are expected to react strongly to that, as they are not

¹³ PIIGS countries

¹⁴ The distribution of countries is summarized in *Table XIII* in the Appendix

¹⁵ Fama and French also measure firm size as the market capitalization (1992)

¹⁶ Value stocks are stocks that trade at a lower price compared to their fundamentals

expecting an upgrade. Additionally, the sign of the coefficient for the variable $Firm\ size_i$, is expected to be positive (negative) for the Downgrades (Upgrades) model.

Finally, to control for the two different periods, the dummy variable $Pre - Post_i$ is added. This variable takes the value of zero if the rating change occurred from 1/1/2014 until 1/1/2016. It takes the value of one if the rating change occurred from 1/1/2004 until 1/1/2006. As hypothesis III states, I expect this coefficient to be positive for Downgrades and negative for Upgrades.

Table II provides a concise overview of the definition of the independent variables included in the multivariate regression.

Table II
Definition of variables

Variable	Definition
Financial	Dummy with value 1 (0), if the firm is (non-)financial
Notches	Dummy with value 1 (0), if rating change greater (smaller or equal) than/to one notch
Border	Dummy with value 1 (0), if firm (not) downgraded or upgraded into speculative or investment grade
Country	Dummy with value 1 (0), if the firm is (not) headquartered in Spain or Italy
B/M	Book value per share divided by the market price per share of the firm in the year in which the rating change occurred
Pre-Post	Dummy with value 1 (0), if rating change occurred after (before) crisis periods.
Firm size	Natural logarithm of market capitalization of the firm of the year in which the rating change occurred

Robustness checks

Regarding the multivariate analysis, I include the regressions with the explaining variables against the CARs of the event windows [-10,1] and [-1,10] to account for the investors anticipating the rating change, as well as the possible lagged information processing in the European capital markets.

6. Results

This section gives an overview of the results of the univariate and multivariate analyses to answer the main hypothesis of this study: ‘‘*Do investors continue to trust credit rating agencies after crisis periods in the European market?*’’

First, descriptive statistics of the used sample are presented. The second part consists of model and assumption testing of the OLS regression as explained in the methodology section. Finally, the third and fourth parts of this section present the results of the univariate and multivariate analysis, respectively.

6.1 Descriptive statistics

Table III presents the number of rating changes, separated by the type of change, as well as the period in which the rating change occurred. Recall that the full sample consisted 80 European listed firms with a total of 263 observations. In the next section *6.2 Model assumptions and testing* I explain why I dropped another observation in the Upgrades sample.

The final sample consists of 262 observations, of which 141 downgrades and 121 upgrades. Contrary to prior studies (Hand et. al, 1992; Barron, 2003), the ratio *Downgrades/Upgrades* does not seem to be very high, meaning that the sample is almost equally distributed between downgrades and upgrades. This can be explained by the fact that the periods examined in this research are neither crisis periods, nor severe expansion periods. However, the number of rating changes during the post-crisis period is larger compared to the number of ratings during pre-crisis periods. This difference is especially more pronounced for downgrades.

Table III
Number of rating changes by event type and period

Frequencies correspond to the rating changes made by Fitch, Moody’s and S&P. *Pre-Crisis* refers to rating changes occurred between January 1st until 31st of December 2006. *Post-Crisis* refers to rating changes occurred between January 1st 2014 until 31st of December 2016. *Downgrades/Upgrades* to the ratio of downgrades versus upgrades.

Variable	Downgrades	Upgrades	Total	Downgrades/Upgrades
Pre-Crisis	57	54	111	1.06
Post-Crisis	84	67	151	1.25
Total	141	121	262	1.17

Table IV shows the summary statistics of the variables used in this research over the total sample period. The means of the CARs over the event windows [-10,1], [-1,0,1] and [-1,10] in both samples are stated in the first three rows. Notable is the fact that the means of the CARs, -

0.012, -0.006 and -0.006, in the Downgrades sample are negative and more pronounced compared to the positive means, 0.005, 0.007 and 0.002 in the Upgrades sample, which could be an indication of the asymmetrical response of investors following rating changes as stated in *Hypothesis III*. Furthermore, the means 0.064 and 0.049 for the dummy variable *Notches* are rather small for both samples. This means that a rating change greater than one notch did not occur often during the examined periods. This should be considered carefully when interpreting the results of this coefficient of the OLS regressions.

Table IV
Summary Statistics

This table provides summary statistics of the dependent variables CAR [-10,1], CAR [-1,0,1] and CAR [-1,10] and the independent variables *Financial*, *Notches*, *Speculative/Investment*, *Country*, *B/M*, *Pre-Post* and *Firm size*. *Financial*, *Notches*, *Speculative/Investment*, *Country* and *Pre-Post* represent dummy variables. The statistics show the mean, standard deviation (SD), minimum (Min) and maximum (Max) for each variable. The sample is comprised of 262 observations, of which 141 downgrades and 121 upgrades.

Variable	Downgrades (N= 141)				Upgrades (N=121)			
	Mean	SD	Min	Max	Mean	SD	Min	Max
CAR [-10,1]	-0.012	0.077	-0.440	0.238	0.005	0.054	-0.257	0.147
CAR [-1,0,1]	-0.006	0.039	-0.151	0.205	0.007	0.034	-0.105	0.267
CAR [-1,10]	-0.006	0.064	-0.265	0.182	0.002	0.054	-0.273	0.254
Financial	0.213	0.411	0	1	0.237	0.427	0	1
Notches	0.064	0.245	0	1	0.049	0.217	0	1
Speculative/ Investment	0.113	0.318	0	1	0.148	0.356	0	1
Country	0.234	0.424	0	1	0.303	0.462	0	1
B/M	0.941	0.642	0.094	2.667	0.694	0.472	0.157	2.247
Pre-Post	0.607	0.490	0	1	0.549	0.500	0	1
Firm size	16.890	1.028	14.302	18.870	16.804	0.815	14.90	18.384

6.2 Model assumptions and testing

OLS estimators are able to minimize the sum of the squared error terms. To make inference on OLS estimators, the model has to be tested, based on several assumptions.

Normality of residuals

First, the expected value of the error term should be zero. Since the *Jarque-Bera test* of normality is very sensitive to picking up departures from normality, especially since the dataset is not exceptionally large, I plot a graph of the residuals in Stata to graphically conclude whether it suggests non-normal residuals. The residuals for the downgrades model do not seem to depart

from normality. However, for the upgrades model, the residuals seem to be somewhat skewed to the right¹⁷. The means of both residuals are zero, thus this implies that I can assume that the expected value of the residuals are zero. This is enough to obtain unbiased OLS estimators.

Testing for heteroscedasticity

One of the important assumptions of the OLS regression is that the errors terms should be homoscedastic, which means that the variance of the residuals should remain constant. The homoscedasticity of the error terms is tested with the *White's general test* in Stata, because with this test the assumption of normally distributed errors has been relaxed. The test gives a low chi-squared value and thus the null hypothesis of homoscedasticity of the error terms is not rejected for all regression models. Thus, there is no need to account for possible heteroscedasticity with this dataset.

Multicollinearity

The problem of multicollinearity arises when two or more variables have a linear relationship (Farrar and Glauber, 1967). One of the methods to identify multicollinearity threats is to analyze the Spearman's correlation coefficients between the variables. *Table V* presents the correlation matrix of the variables in the model. All correlations seem to be below 0.5 or higher than -0.5, indicating that there are no strong positive or negative linear relationships between the variables.

Another method to further analyze the multicollinearity relationships is to perform a significance test in Stata, also known as the *Variance Inflation Factors (VIF)* test. For each variable the *VIF* value is calculated. If the standard errors of the estimated coefficients are inflated, multicollinearity exists. The *VIF* test quantifies how much variance is inflated for each variable. A *VIF* above 10 is by many practitioners regarded as a sign of severe correlation between that variable and another independent variable in the regression model (O'Brien, 2007). The results show that all *VIFs* are below 2.0, which indicate that no multicollinearity exists between the selected variables. Thus, there is no need to correct for this error.

¹⁷ Histograms of the distribution of the residuals of both models are included in the Appendix in *Figure VI*.

Table V
Spearman Correlation Matrix

This table presents the correlation between the variables used in the multivariate analysis. *CAR* is the dependent variable in the regression, which is the Cumulate Abnormal Returns calculated over the event window $[T_1, T_2]$. The next four variables are dummy variables. *Financial* equals one if the firm is a financial institution and zero otherwise. *Notches* equals one if the rating change is greater than one notch and zero otherwise. *Speculative/Investment* equals one if the rating change goes into speculative or investment grade. *Country* equals one if the country of the firm is located in either Spain or Italy and zero otherwise. *B/M* is calculated by dividing the market price per share by the book value per share. Period is also a dummy variable, which equals one if the rating change occurred after the financial crises and zero otherwise. Firm size is measured by the natural logarithm of the market capitalization of the firm.

	CAR	Financial	Notches	Border	Country	B/M	Pre-Post	Firm size
CAR	1							
Financial	-0.071	1						
Notches	-0.179	0.077	1					
Speculative/Investment	0.113	0.033	0.364	1				
Country	-0.141	0.122	0.061	0.014	1			
B/M	-0.015	0.417	0.091	0.081	-0.090	1		
Pre-Post	-0.161	0.216	0.097	0.204	-0.057	0.360	1	
Firm size	-0.056	-0.059	-0.122	0.061	-0.106	-0.053	0.362	1

Measurement errors

For the multivariate regression, I delete one observation of the total 122 observations in the Upgrades sample. As I initially summarize the statistics, the mean of abnormal returns of event window [-10,1] stands out. It appears that the returns of one particular observation are large enough to bias the results of the regression (0.506). Deleting this observation will allow the OLS estimators to follow the majority of the trend of the data. For the Downgrades sample I detect no peculiar abnormal returns and therefore I do not account for any outliers that might affect the results. Still some measurement errors can exist in the selected sample. The possibility of such measurement errors should always be considered carefully when interpreting the regression analyses, but in general, the noise of stock returns tend to cancel out when averaging them across a large number of observations (Scholtens & de Wit, 2004).

6.3 Results univariate analysis

This section presents the results of the univariate analysis. This analysis will allow to answer the first three hypotheses as stated in the section *Hypotheses development*, including the main research question of this study: “*Do investors continue to trust credit rating agencies after crisis periods in the European market?*” The analysis consists of graphs of the CAARs plotted over the 100-day event window [-90,10], an event study over event window [-10,10] to analyze each short-term AAR separately and finally an event study to examine the aggregate effects of the CAARs

over event windows $[-10,1]$, $[-1,0,1]$ and $[-1,10]$. For each analysis a distinction is made between upgrades, downgrades, pre-crisis and post-crisis periods.

First, the CAARs for both downgrades and upgrades over the total 100-day event window $[-90,10]$ are plotted in *Figures IV* and *V*. In the figures, a distinction is made between CAARs before and after crisis periods. In *Figure IV*, the market reaction seems to already be strongly negative 90 days preceding the downgrades, in both pre- and post-crisis periods. This can be explained by investors anticipating the downgrade before the rating change itself occurs. This result supports the first hypothesis that abnormal stock price returns are negative following downgrades and is in line with existing literature. However, there even seems to be stronger negative market reaction at $t=0$ (vertical line depicted in the graph), during the post-crisis period compared to the pre-crisis period. This indicates a contradiction to the second hypothesis, that abnormal stock price returns are less pronounced during post-crisis period following downgrades and upgrades.

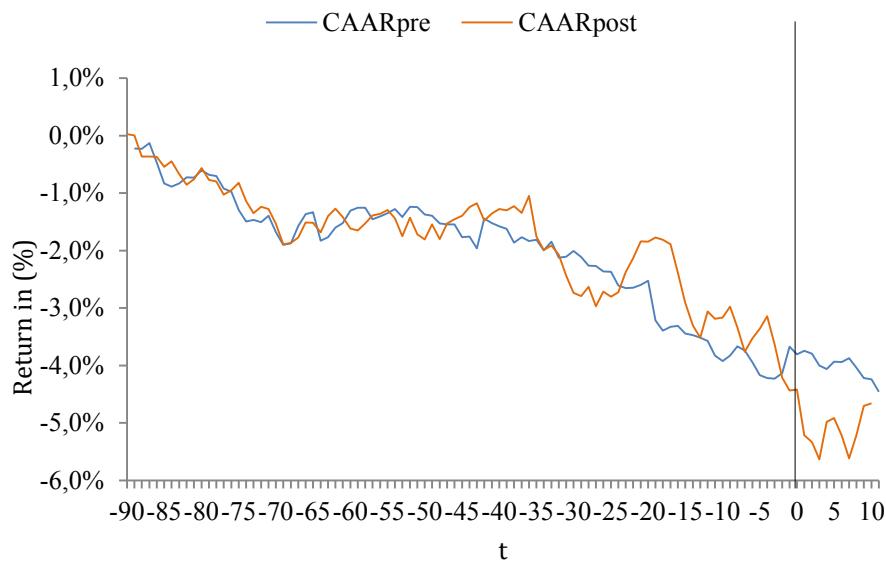


Figure IV. Downgrade Cumulative Average Abnormal Returns over the 100-day event window $[-90,10]$ before and after crisis periods. The vertical line at $t=0$ represents the day of the rating change.

As illustrated in *Figure V* for upgrades, the CAARs seem to be positive during post-crisis periods, as opposed to the CAARs during pre-crisis periods, which show some evidence of negative abnormal returns prior to the upgrade. At $t=0$, there seems to be a big difference between pre- and post-crisis periods for upgrades. During the pre-crisis period, the abnormal stock price returns are around -0.5% , but move quickly upward on the day of the rating event. This is partly in line with the second hypothesis, which states that abnormal stock price returns are less pronounced during post-crisis period following upgrades.

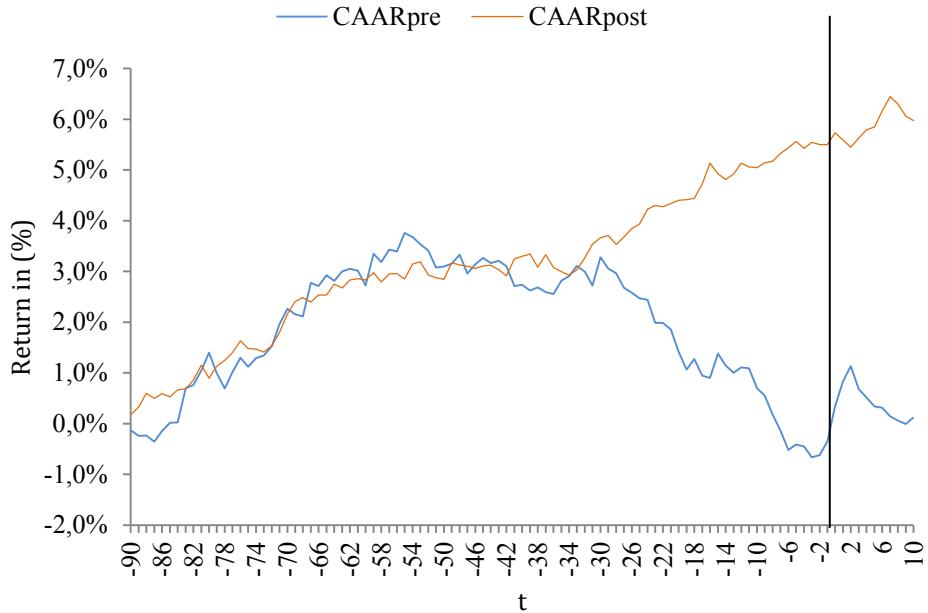


Figure V. Upgrade Cumulative Average Abnormal Returns over the 100-day event window $[-90, 10]$ before and after crisis periods. The vertical line at $t=0$ represents the day of the rating change.

Tables VI and VII present the AARs and their t-statistic over event window $[-10, 10]$ for both downgrades and upgrades, during pre-crisis periods and post-crisis periods. Contrary to what was expected but in line with previous figures, even though the AARs in Table VI overall for downgrades are negative during pre-crisis periods, they show very low significance. Whereas the abnormal returns for downgrades during post-crisis periods show high significance. Especially the day after the downgrade at $t=1$ the abnormal return of -0.797% is highly significant at the 1% level (t-statistic -4.114). These significant abnormal returns last until a few days following the downgrade. This is already not in line with the main hypothesis that the significances of abnormal returns are less pronounced during post-crisis periods. These results indicate the opposite: investors seem to react more strongly following downgrades during post-crisis periods. Interesting to see is the opposite reaction of investors on the 8th and 9th day during post-crisis periods, where abnormal returns become positive and significant at 0.407% and 0.506% (t-statistics 2.545 and 2.173 resp.). This can be explained by the behavior of investors, who might realize that they have overreacted to the downgrade and start buying shares again. This way, the financial market corrects itself. Overall, investors do seem to still value the informational content of the downgrades, which is in line with the first hypothesis.

Table VI
Average Abnormal Returns Downgrades Market Model

This table presents the Average Abnormal Returns (AAR) and t-statistics over the short-term event window [-10,10] for Downgrades made by Fitch, Moody's and S&P during pre-crisis periods from 2004 until 2006 and post-crisis periods from 2015 until 2017. Asterisks *, **, and *** denote levels of significance of 10%, 5% and 1%, respectively.

Pre-Crisis			Post-crisis		
t	AAR	t-statistic	t	AAR	t-statistic
-10	0.094%	0.438	-10	0.021%	0.086
-9	0.166%	1.080	-9	0.189%	1.212
-8	-0.076%	-0.538	-8	-0.362% **	-2.417
-7	-0.206%	-1.509	-7	-0.426% *	-1.662
-6	-0.223% *	-1.653	-6	0.237%	1.243
-5	-0.047%	-0.350	-5	0.168%	0.971
-4	-0.012%	-0.086	-4	0.214%	1.022
-3	0.095%	0.646	-3	-0.485%	-1.583
-2	0.463%	1.333	-2	-0.586%	-1.204
-1	-0.133%	-0.678	-1	-0.218%	-0.802
0 (event day)	0.057%	0.120	0 (event day)	0.014%	0.063
1	-0.046%	-0.259	1	-0.797% ***	-4.114
2	-0.206%	-1.361	2	-0.116%	-0.514
3	-0.063%	-0.465	3	-0.301% *	-1.706
4	0.128%	0.724	4	-0.651% ***	-2.636
5	-0.004%	-0.030	5	0.067%	0.256
6	0.062%	0.461	6	-0.304%	-1.434
7	-0.162%	-1.310	7	-0.398% **	-2.138
8	-0.181%	-1.406	8	0.407% **	2.545
9	-0.021%	-0.132	9	0.506% **	2.173
10	-0.220% **	-2.181	10	0.045%	0.203
N		57	N		84

The results for upgrades in *Table VII* show some significant values, but not as much and as pronounced compared to downgrades. Some AARs during pre-crisis periods unexpectedly have a negative sign, indicating that these abnormal returns probably do not exist due to the upgrades but other factors or events. During post-crisis periods the highest positive and significant abnormal return is 3.18% (t-statistic 1.84). These results do support the reasoning that investors react less strongly to upgrades compared to downgrades.

Table VII
Average Abnormal Returns Upgrades Market Model

This table presents the Average Abnormal Returns (AAR) and t-statistics over the short-term event window [-10,10] for Upgrades made by Fitch, Moody's and S&P during pre-crisis periods from 2004 until 2006 and post-crisis periods from 2015 until 2017. Asterisks *, **, and *** denote levels of significance of 10%, 5% and 1%, respectively.

Pre-Crisis			Post-crisis		
t	AAR	t-statistic	t	AAR	t-statistic
-10	-0.393% *	-1.827	-10	-0.015%	-0.087
-9	-0.149%	-0.888	-9	0.095%	0.584
-8	-0.374% **	-1.971	-8	0.030%	0.204
-7	-0.313% *	-1.939	-7	0.154%	0.678
-6	-0.381% *	-1.660	-6	0.111%	0.630
-5	0.109%	0.428	-5	0.131%	0.904
-4	-0.037%	-0.165	-4	-0.142%	-0.962
-3	-0.216%	-0.760	-3	0.119%	0.709
-2	0.042%	0.108	-2	-0.044%	-0.318
-1	0.272%	0.655	-1	-0.002%	-0.015
0 (event day)	0.696% *	1.813	0 (event day)	0.234% *	1.693
1	0.493%	1.550	1	-0.145%	-0.942
2	0.294%	1.691	2	-0.138%	-0.923
3	-0.456% **	-2.333	3	0.187%	1.411
4	-0.161%	-0.830	4	0.158%	1.310
5	-0.175%	-0.779	5	0.054%	0.446
6	-0.026%	-0.115	6	0.318% *	1.841
7	-0.174%	-0.686	7	0.279% **	2.193
8	-0.082%	-0.515	8	-0.142%	-1.207
9	-0.069%	-0.402	9	-0.243% *	-1.728
10	0.133%	0.713	10	-0.083%	-0.561
<i>N</i>	55		<i>N</i>	67	

As explained in the *Methodology* section, it is much more informative to aggregate and average the information over all the events and in separate event windows. Since I am interested in the short-term market reaction, I calculate the CAARs during the event windows [-10,1], [-1,0,1] and [-1,10]. Significance tests¹⁸ are performed to test whether they are indeed different from zero. *Table VIII* shows the CAARs for upgrades and downgrades for the total sample period, pre-crisis period and post-crisis period and their associated value of the cross-sectional t-test. As expected, the signs of the CAARs for all event windows for the downgrades sample are mostly negative and for the upgrades mostly positive, indicating that ratings do contain informational value to investors. These results support the first hypothesis. Over the total sample period, the CAARs for the downgrades sample are -1.156%, -0.646% and -0.584%, respectively. The CAARs over the event windows [-10,1] and [-1,0,1] are both significant at the 10% level (t-statistics -1.786 and -1.935 resp.). Over the total sample period, the CAARs for the upgrades are all positive, however only the CAAR for event window [-1,0,1] is significant at the 10% level (t-statistic 1.836).

¹⁸ Cross-sectional t-test

Overall, over the total sample period, the results give weak evidence that support *Hypothesis III*, which states that abnormal stock price returns are more pronounced following downgrades, compared to upgrades during all periods. The results only hold for the post-crisis period sample, which gives strong evidence that supports this hypothesis. The CAARs for the downgrades sample for the event windows [-10,1] and [-1,0,1] are -2.013% and -1.001% respectively and significant at the 5% level (t-statistics -2.039 and -2.425 resp.), whereas the CAARs for the upgrades in this sample are positive, but not significant. This asymmetric response of investors is in line with existing literature (Hand et. al, 1992; Hite and Warga, 1997; Steiner and Heinke, 2001). A possible explanation for this is that investors respond different to good and bad news. Bad news can have a larger impact on an individual compared to good news¹⁹. Surprisingly, but in line with the results of *Table VI*, the CAARs for downgrades for the post-crisis period sample seem to be more pronounced compared to CAARs during pre-crisis periods, thus again contradicting the second and main hypothesis. Even though they have the expected negative sign, it is not clear why the AARs and CAARs for downgrades during the pre-crisis period are mostly insignificant. It could be that the economy was in a boom and investors are in an euphoric state and thus are less inclined to react strongly to downgrades. Additionally, the number of downgrades during this period was significantly lower compared to post-crisis periods (57 vs. 84). Another explanation would be that other positive events or news in the same event window could affect abnormal returns and thus contaminate the sample.

¹⁹ Prospect theory: gains and losses are valued differently (Kahneman & Tversky, 1979)

Table VIII

Results CAAR examination *Market Model*

This table presents the Cumulative Average Abnormal Returns and t -statistics over the event windows $[-10,1]$, $[-1,0,1]$ and $[-1,10]$ for Upgrades and Downgrades made by Fitch, Moody's and S&P. First, the CAAR of the total sample period consisting of the years 2004 until 2006 and 2014 until 2016 is shown below in percentages. Furthermore, separate CAARs are calculated during the Pre-Crisis period from the 1st of January 2004 until 31st of December 2006 as well as the Post-Crisis period from 1st of January 2015 until 31st of December 2017 for comparison. The sample includes 262 observations on 80 companies. N stands for the total number of observations. The value of the t -test is shown in parentheses below the mean % return. Asterisks *, **, and *** denote levels of significance of 10%, 5% and 1%, respectively.

Period	Ratings	
Total sample period	Downgrades	Upgrades
CAAR [-10,1]	-1.156% *	0.597%
	(-1.786)	(1.157)
CAAR [-1,0,1]	-0.646% *	0.706% *
	(-1.935)	(1.836)
CAAR [-1,10]	-0.584%	0.175%
	(-1.078)	(0.273)
N	141	122
Pre-Crisis		
CAAR [-10,1]	0.133%	-0.253%
	(0.218)	(-0.206)
CAAR [-1,0,1]	-0.122%	1.460% *
	(-0.219)	(1.828)
CAAR [-1,10]	-0.790%	-0.744%
	(-1.219)	(0.736)
N	57	54
Post-Crisis		
CAAR [-10,1]	-2.013% **	0.526%
	(-2.039)	(0.896)
CAAR [-1,0,1]	-1.001% **	0.087%
	(-2.425)	(0.381)
CAAR [-1,10]	-0.445%	0.476%
	(-0.557)	(1.057)
N	84	67

To test whether the CAARs of the two periods of the Downgrades sample actually significantly differ from each other, differences of mean tests are performed for each event window. *Table IX* presents the results of the comparison between the CAARs of the Downgrades sample before and after crisis periods. The difference over the event window [-10,1] is significant at the 5% level (t-statistic 1.933). This result suggests reliable differences between the two samples. From this, I conclude that investors in the European market did not lose their trust in CRAs and thus rejecting the second and main hypothesis of this research, which states that abnormal returns should be less pronounced during post-crisis periods.

Table IX
Mean return comparisons Downgrades sample before and after crisis periods

This table presents the difference of mean tests of the CAARs and the t-statistic before and after crisis periods over event windows [-10,1], [-1,0,1] and [-1,10]. S.D. stands for Standard Deviation. Asterisks *, **, and *** denote levels of significance of 10%, 5% and 1%, respectively.

Variable	Mean	S.D.	t-statistic
CAAR [-10,1]	0.133%	0.006	1.933 **
	-2.013%	0.012	
CAAR [-1,0,1]	-0.122%	0.006	1.078
	-1.001%	0.005	
CAAR [-1,10]	-0.790%	0.007	0.125
	-0.445%	0.011	

It could be argued that investors in the European market value the informational content of downgrades even more after crisis periods. Regulators in Europe have tried to lower the power of credit rating agencies by implementing stringent regulation since the global financial crisis. Thus, it could be that investors are confident that credit rating agencies are not inclined to make the same mistakes again. However, concluding this seems far-fetched, as there is always the possibility that other factors or events could explain the existence of abnormal returns.

6.4 Results multivariate analysis

This section answers the fourth and last hypothesis whether different rating and firm characteristics explain the variation in the abnormal returns. *Table X* and *XI* present the regression results for the Downgrades and Upgrades sample.

In *Table X*, the first column shows the predicted sign of the coefficients. A negative (positive) sign indicates a stronger (weaker) reaction to abnormal returns. The next six columns represent six separate regressions, where the CARs with the three event windows denote the dependent variables regressed against the dummy variables *Notches* and against the other earlier mentioned explanatory control variables.

Table X
Multivariate Regression on Downgrades

Panel A: Regression Output of the Cross Sectional Analysis on Downgrades. Columns 1, 3 and 5 show the results of the regression of the CARs against the dummy variable *Notches*. Columns 2, 4 and 6 show the results of the regression of CARs against the dummy variable *Notches* and other control variables. Asterisks *, **, and *** denote levels of significance of 10%, 5% and 1%, respectively.

	Predicted Sign	CAR [-10,1]		CAR [-1,0,1]		CAR [-1,10]	
Constant		-0.010 (-1.52)	-0.041 (-0.34)	-0.005 (-1.41)	0.031 (0.51)	-0.005 (-0.95)	-0.104 (-1.04)
Financial	(-)		0.005 (0.30)		-0.001 (-0.11)		-0.015 (-1.00)
Notches	(-)	-0.022 (-0.84)	-0.028 (-0.97)	-0.026 ** (-1.96)	-0.032 ** (-2.21)	-0.008 (-0.34)	-0.002 (-0.07)
Speculative Grade	(-)		0.025 (1.12)		0.018 1.55		-0.011 (-0.57)
Country	(-)		-0.010 (-0.61)		-0.013 * (-1.68)		0.005 (0.40)
B/M	(+)		0.006 (0.48)		0.003 (0.52)		0.018 * (1.76)
Firm size	(+)		0.002 (0.35)		-0.002 (-0.53)		0.005 (0.87)
Pre-Post	(+)		-0.029 * (-1.86)		-0.0087 (-1.10)		-0.004 (-0.31)
<i>R</i> ²		0.005	0.039	0.026	0.074	0.001	0.030
N		141	141	141	141	141	141

The *Pre-Post* coefficient is important to support previous findings and give an answer the main research question. Recall that the dummy variable takes the value of one if the rating change occurred during the post-crisis period (i.e. from 1st of January 2014 until 31st of December 2016) and zero otherwise. When examining the first column of *Table X* for the Downgrades sample, the

coefficient -0.029 of the dummy variable *Pre-Post* is negative and significant at the 10% level (t-statistic -1.86). This means that if the rating change occurred during the post-crisis period, abnormal returns decrease with 2.9%. This is in contrast to what was expected, as the predicted sign is positive. This is however in line with the results of the univariate analysis in the previous section where the difference of mean tests between the two sample periods for event window [-10,1] shows significant differences. Thus, there is again weak evidence that investors react stronger to downgrades during post-crisis periods. Regarding the other regression models, the *Pre-Post* variable also has negative coefficients in columns 2 and 3 (-0.0087 and -0.004 respectively), but they are statistically insignificant.

As expected, the coefficients of the *Notches* dummy variable are negative for all regression models (-0.022, -0.028, -0.026, -0.032, -0.008 and -0.002 respectively). In columns 3 and 4, the coefficients for the model with event window [-1,0,1] are both significant at the 5% level (t-statistic -1.96 and -2.21 resp). This result can be interpreted as follows: if the downgrade is greater than one notch, abnormal returns decrease by 2.6% and 3.2%. This can be explained by the fact that investors consider the default risk of the firm to increase even more if the downgrade is of greater intensity. This is in line with numerous previous findings of studies such as Hand et. al, who find similar effects on excess bond returns (2001). Holthausen & Leftwich also find a highly significant marginal effect on abnormal stock returns of -3.69% for the downgrades regression (t-statistic -11.23). As mentioned earlier, this result should be interpreted with caution, as the number of observations in this study for this variable is low.

As for the *Country* dummy variable, the coefficients are expected to be negative, which holds for column 1 and 2, but not for 3. The coefficient in column 2 is significant at the 10% level (t-statistic -1.68). Thus, there is some weak evidence that if the downgrade belongs to a firm headquartered in Spain or Italy, the abnormal returns decrease with 1.3%. This result supports the *Nationality Hypothesis* that these countries tend to react stronger to downgrades due to their severe debt levels relative to the Netherlands, Germany and France.

The coefficients for the variable *B/M* are expected to be positive, as the sign indicates. This holds for all three models in the Downgrades sample. The coefficient in column 3 is significant at the 10% level (t-statistic 1.76), indicating that a 1% increase in the B/M ratio, results in a 1.8% increase in abnormal returns. This is in line with the reasoning that investors might expect and anticipate a downgrade for firms with a high B/M ratio, as these firms are trading at a lower market value per share than book value per share.

I do not find significant results for the remaining coefficients of the explanatory variables; therefore I cannot make any inference on them. Furthermore, R^2 suggests that the variables explain between 3.0% and 7.0% of the variation. Low or even negative R^2 values are also found

by previous researchers, who include four to six variables in their model (Steiner and Heinke, 2001; Hand et. al, 1992; Holthausen and Leftwich, 1986). For the Downgrades sample, the results support the fourth and last hypothesis, which states that specific firm and rating characteristics determine the magnitude of the abnormal stock price returns.

Since the *Pre-Post* dummy variable is significant, it would be interesting to examine how the coefficients of the explanatory variables would differ if the regressions are run separately for the Pre-Crisis periods and Post-Crisis periods. *Table XI* presents the results of the regressions again for three separate event windows during Pre-Crisis periods and Post-Crisis periods. This table clearly shows that the significance of the dummy variable *Notches* from the previous regression over the total sample period is attributable to the abnormal returns that occurred during Pre-Crisis periods. The coefficients of this variable in columns 1 and 2 are -0.113 and -0.094 and highly significant (t-statistic -3.02 and -2.68 resp). This significance seems to vanish during Post-Crisis periods. Furthermore, the *Nationality Hypothesis* holds during Post-Crisis periods for event window [-1,0,1]. This makes sense and is in line with the reasoning mentioned earlier. In column 6, the coefficients of the variables *Financial* and *B/M* have the expected sign and are -0.037 and 0.032 (t-statistics -1.69 and 2.14 resp).

Table XI
Multivariate Regression on Downgrades in Pre-Crisis and Post-Crisis Periods

Panel A: Regression Output of the Cross Sectional Analysis on Downgrades during Pre-Crisis Periods (Columns 1, 2 and 3) and Post-Crisis Periods (Columns 4, 5 and 6). Asterisks *, **, and *** denote levels of significance of 10%, 5% and 1%, respectively.

		Pre-Crisis Periods			Post-Crisis Periods		
	Predicted Sign	CAR[-10,1]	CAR[-1,0,1]	CAR[-1,10]	CAR[-10,1]	CAR[-1,0,1]	CAR[-1,10]
Constant		0.142	0.140	-0.030	-0.183	-0.021	-0.132
		(1.38)	(1.43)	(-0.25)	(-0.90)	(-0.26)	(-0.84)
Financial	(-)	-0.002	0.000	0.017	0.006	-0.004	-0.037 *
		(-0.09)	(0.01)	(0.77)	(0.23)	(-0.33)	(-1.69)
Notches	(-)	-0.113***	-0.094***	-0.032	-0.007	-0.018	0.003
		(-3.02)	(-2.68)	(-0.75)	(-0.17)	(-1.13)	(0.10)
Speculative Grade	(-)	0.038	0.042	0.053	0.023	0.013	-0.020
		(1.05)	(1.22)	(1.25)	(0.79)	(1.14)	(-0.90)
Country	(-)	-0.020	-0.005	-0.001	0.000	-0.019 *	0.003
		(-1.38)	(-0.35)	(-0.07)	(0.01)	(-1.87)	(0.16)
B/M	(+)	-0.005	0.001	0.005	0.008	0.006	0.032 **
		(0.41)	(0.07)	(0.35)	(0.42)	(0.72)	(2.14)
Firm size	(+)	-0.008	-0.008	0.001	0.009	0.001	0.006
		(-1.27)	(-1.45)	(0.15)	(0.75)	(0.12)	(0.68)
<i>R</i> ²		0.202	0.145	0.044	0.02	0.078	0.072
N		56	56	56	85	85	85

In *Table XII*, for the Upgrades sample, a positive (negative) sign indicates a stronger (weaker) reaction to abnormal returns. As expected, the coefficients for the dummy variable *B/M*, are positive for all three models. The coefficient in the second column for the regression with event window [-10,1], is significant at the 5% level (t-statistic 2.02). This implies that if the B/M ratio increases with 1%, abnormal returns increase with 2.8%. This supports the reasoning that investors react strongly to upgrades for firms with high B/M ratios, because investors perceive these firms as undervalued and therefore do not expect an upgrade.

The coefficients for the dummy variable *Notches* are positive for all six models, which is in line with what was expected. The coefficients for event window [-1,0,1] are highly significant at the 1% level (t-statistic 4.21 and 3.96 resp). This is strong evidence, which indicates that if an

upgrade is greater than one notch, abnormal returns increase with 5.65 and 5.5%. Adding the other control variables, does not seem to affect the coefficient by a great extent.

No other coefficients seem to be significant in the Upgrades sample. This can be explained by the asymmetrical response of investors, who react more strongly to downgrades, compared to upgrades. The *Pre-Post* dummy in this regression is also insignificant, which is in line with the findings of the univariate analysis where no obvious differences in abnormal returns were observed when comparing the two time periods. Furthermore, the Upgrades sample has 21 observations less. The R^2 of the Upgrades sample are higher compared to the Downgrades sample, explaining between 3.4% and 14.7% of the variation of abnormal returns.

Table XII
Multivariate Regression on Upgrades

Panel B: Regression Output of the Cross Sectional Analysis on Upgrades. Columns 1, 3 and 5 show the results of the regression of the CARs against the dummy variable *Notches*. Columns 2, 4 and 6 show the results of the regression of CARs against the dummy variable *Notches* and other control variables. Asterisks *, **, and *** denote levels of significance of 10%, 5% and 1%, respectively.

	Predicted Sign	CAR [-10,1]	CAR [-1,0,1]	CAR [-1,10]	
Constant		-0.003 (-0.52)	0.020 (0.19)	0.002 (0.66)	-0.013 (-0.21)
Financial	(+)		-0.000 (-0.03)		-0.008 (-0.90)
Notches	(+)	0.004 (0.20)	0.014 (0.60)	0.056 *** (4.21)	0.055 *** (3.96)
Investment Grade	(+)		-0.002 (-0.17)		-0.008 (-0.92)
Country	(+)		-0.002 (-0.14)		0.005 (0.77)
B/M	(+)		0.028 ** (2.02)		0.004 (0.46)
Firm size	(-)		-0.003 (-0.44)		0.001 (0.27)
Pre-Post	(-)		0.007 (0.64)		-0.005 (-0.75)
R^2		0.003	0.075	0.130	0.147
N		121	121	121	121
					0.012
					0.034
					-0.001
					(-0.09)
					121
					121

6. Conclusion and limitations

This research is designed to investigate and compare the informational content of credit ratings by Moody's, Fitch and S&P in the European market before and after crisis periods. More specifically, it aims to analyze the effect of downgrades and upgrades on stock price returns in the European market. The main research question of this paper is whether investors in the European market have lost their trust in these credit rating agencies after the global financial crisis and the sovereign debt crisis. If this is the case, investors should perceive the informational content of their credit ratings as less valuable, and diminishing effects on stock prices should be observed following rating changes. A dataset of 80 companies with 262 rating changes is constructed. The firms are all listed on the national stock indices of the country where they are headquartered. Data is collected for the years 2004 until 2006 and 2014 until 2016. Similar to previous work, this paper consists of a univariate and multivariate analysis. The aim of the univariate analysis is to examine abnormal returns following downgrades and upgrades during pre-crisis and post-crisis periods. The objective of the multivariate analysis is to detect whether and which specific firm and rating characteristics explain the variation of the abnormal returns.

Altogether, this research finds new evidence on the price effects of rating changes in the European market. The first hypothesis tests whether the informational content of the rating changes is valued by European investors and is not rejected. I find significant stock price returns following downgrades and upgrades, which is in line with the findings of U.S. studies. Testing the second and main hypothesis, I do not find less pronounced stock price returns during post-crisis periods. I rather find that the opposite is true. Especially regarding downgrades, I find significantly more pronounced negative stock price returns. The fact that the stock price returns are more pronounced regarding downgrades, supports the third hypothesis, which states that investors react more strongly to downgrades compared to upgrades. However this evidence is not strong, since this does not hold for the pre-crisis periods, where negative stock price returns following downgrades are mostly insignificant. Thus, the evidence is not sufficient to confirm this hypothesis. Finally, the analysis of the multivariate regression reveals that the variation in the abnormal returns can be explained by specific firm and rating characteristics. I find strong evidence that a downgrade greater than one notch (upgrade), has strong negative (positive) effects on abnormal returns. Regarding the downgrades regressions, this effect is mostly observed during pre-crisis periods. Furthermore, as expected, I find some evidence that a higher B/M ratio of a firm has both positive effects on abnormal returns following downgrades and upgrades. There is also some evidence that investors in Italy and Spain react more strongly to downgrades, compared to investors in the Netherlands, Germany and France. This effect is observed during post-crisis periods.

In conclusion, in theory it is very likely that since the sovereign debt crisis, investors in the European market doubt the trustworthiness of Moody's, Fitch and S&P. However, the results do not show any strong evidence that their ratings have lost their valuable informational content.

Limitations

There are several limitations to this study. First of all, the paper aims to examine reactions of investors to rating changes in the European market. Five countries have been examined in this paper. Consequently, these countries might not have been representative of the whole European market. Future research might include more countries to investigate the *Nationality Hypothesis* further. Moreover, investigations of the differences in CRA regulation between those countries and the U.S. could be interesting. As mentioned in the paper, since many European countries have been downgraded by The Big Three, it would also be interesting to extend the research to the yields of bonds or CDS spreads of sovereigns following rating changes.

Furthermore, enlarging the time periods will allow to retrieve a larger number of observations and more reliable results for the univariate analysis, as well as the cross-sectional regression analysis.

This paper does not control for other news or events concerning the firm during the event window that could possibly 'contaminate' the sample and in turn potentially introduce bias in the abnormal returns.

Only firms that are listed on national indices are included in this research, which tend to have large market capitalization. To investigate the *Differential Information Hypothesis due to size of firm* in the regression analysis better in the future, firms with a significantly lower market capitalization should be included in the sample to differentiate.

References

Atiase, R.K. (1985). Predisclosure Information, Firm Capitalization, and Security Price Behavior Around Earnings Announcements. *Journal of Accounting Research*, Vol. 23(1), pp. 21-36.

Annual Report on Nationally Recognized Statistical Rating Organizations of the staff of the U.S. Securities and Exchange Commission, December 2016.

Article 3(1) (a) Regulation (EC) 1060/2009 of the European Parliament and of the Council of credit rating agencies (O.J. 2009, L 302/1).

Bank for International Settlements (BIS) The National Bureau of Economic Research. www.nber.org

Barron, M.J., Clare, A.D. and Thomas, S.T. (1997). The Effect of Bond Rating Changes and New Ratings on UK Stock Returns. *Journal of Business Finance & Accounting*, Vol. 24(3) & (4), pp. 497 – 509.

Becker, B. & Milbourn, T. (2011). How did increased competition affect credit ratings? *Journal of Financial Economics*, Vol. 101(3), pp.493-514.

Brown, S.J. & Warner, J.B. (1980). Measuring Security Price Performance. *Journal of Financial Economics*, Vol. 8 (3), pp. 205-258.

Brown, S.J. & Warner, J.B. (1985). Using Daily Stock Returns: The Case of Event Studies. *Journal of Financial Economics*, Vol. 14 (1985), pp. 3-31.

Dichev, I.D. & Piotroski J.D. (2001). The Long-Run Stock Returns Following Bond Ratings Changes. *The Journal of Finance*. Vol 151(1), pp. 173-203.

Fama, E.F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*. Vol. 25 (2), pp. 383-417.

Fama, E.F., Fisher, L., Jensen, M.C. & Roll, R. (1969). The Adjustment of Stock Prices To New Information. *International Economic Review*. Vol 10(1), pp. 1-21.

Fama, E.F. & French. KR. (1992). Common risk factors in the returns on stocks and bonds*. *Journal of Financial Economics*. Vol.33 (1993), pp. 3-56

Farrar, D.E., & Glauber, R.R. (1967). Multicollinearity in regression analysis: the problem revisited. *The Review of Economic and Statistics*, 92-107.

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*, Vol. 39(1), pp. 101-112.

Gonzalez, F., Haas, F., Johannes, R., Persson, M., Toledo, L., Violi, R. and Wieland, M. (2004), Market dynamics associated with credit ratings: A literature review, *ECB Occasional Paper*, No 16.

Gropp, R., Richards, Anthony J. (2001). Rating agency actions and the pricing of debt and equity of European banks: What can we infer about private sector monitoring of bank soundness?, *ECB Working Paper*, No 76

De Haan, J. & Amtenbrink, F. (2011). Credit Rating Agencies. Unpublished working paper. De Nederlandsche Bank.

Ferri, G., Liu, L.-G. & Stiglitz J.E. (1999). The Procyclical Role of Rating Agencies: Evidence from the East Asian Crisis. *Economic Notes*, Vol. 28(3), pp. 335-355.

Han, S.H., Shin, Y.S., Reinhart, W., Moore, W.T. (2009). Market Segmentation Effects in Corporate Credit Rating Changes: The Case of Emerging Markets. *The Journal of Financial Services Research*, Vol. 35(2), pp. 141-166.

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*, Vol. 2, pp. 733- 752.

Hite, G. & Warga, A. (1997). The effect of Bond-Rating Changes on Bond Price Performance. *Financial Analysts Journal*, Vol. 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*, Vol. 17, 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*, Vol.28, pp. 2789- 2811.

IMF (2010), The uses and abuses of sovereign credit ratings, chapter 3 in the 2010 *IMF Global Financial Stability Report*.

Kahneman, D. & Tversky, A. (2013). Prospect Theory: An Analysis of Decision Under Risk. *World Scientific Handbook in Financial Economics Series*, Vol. 4, pp. 99-127.

Linciano, N. (2004). The Reaction of Stock Prices to Rating changes. Working Paper, Rome Available at SSRN: <http://ssrn.com/abstract=572365>.

Matolcsy, Z.P. & Lianto, T. (1995). The Incremental Information Content of Bond Rating Revisions: The Australian Evidence. *Journal of Banking & Finance*, Vol. 19, pp. 891-902

McKinlay, A.C. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature*, Vol. 35(1), pp. 13-39.

Micu, M., Remolona, E.M. & Wooldridge P.D. (2006). The Price Impact of Rating Announcements: Which Announcements Matter? Working Paper No. 207.

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

O'Brien, R.M. (2007). A Caution Regarding Rules of Thumb for Variance Inflation Factors. *Quality & Quantity*, Vol. 41, pp. 673-690.

Pagano, M. & Volpin, P. (2010). Credit ratings failures and policy options. *Economic Policy*, Vol. 25 (60), pp. 401- 431.

Romero, P.A. (2007). Bond rating changes and stock returns: evidence from the Spanish stock market. *Spanish Economic Review*, Vol. 9, pp. 70 – 103.

De Santis, R.A. (2012). The Euro Area Sovereign Debt Crisis: Safe Haven, Credit Rating Agencies and the Spread of the Fever from Greece, Ireland and Portugal, ECB Working Paper, No.1419.

Scholtens B. & de Wit R. (2004). Announcement effects of bank mergers in Europe and the US. *Research in International Business and Finance*, Vol. 18, pp. 217-228.

Steiner, M. & Heinke, V.G., (2001). Event study concerning international bond price effects of credit rating actions. *International Journal of Finance and Economics*, Vol. 6, pp. 139-57

White, L.J. (2009). The Credit Rating Agencies and the Subprime Debacle. *Critical Review*, Vol. 21(2-3), pp. 389-399.

White, L.J. (2010). The Credit Rating Agencies. *Journal of Economic Perspectives*, Vol. 24, pp. 211-226.

Appendix

Table XIII
Country distribution

This table shows the country distribution in number of ratings and percentages for the downgrades and upgrades sample.

Country	Downgrades		Upgrades	
	# Ratings	Percentage	# Ratings	Percentage
Netherlands	27	19.1%	25	20.5%
France	25	17.7%	28	23.0%
Germany	57	40.4%	32	26.2%
Italy	15	10.6%	10	7.1%
Spain	17	12.2%	27	22.1%
Total	141	100%	122	100%

Figure VI
Residuals distribution

These figures show the distribution of the residuals for the downgrades and upgrades regression model. In the upgrades model, the distribution deviates a little from the normal distribution and is somewhat skewed. In these models, the CAR serves as the dependent variable.

