THE EFFECT OF LONG-TERM BOND RATING CHANGES ON COMMON STOCK PRICES IN EUROPE

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Abstract

This paper uses daily common stock return data, surrounding credit rating changes by Moody's Investors Service, in order to examine whether the absolute cumulative abnormal common stock return as a result of a credit rating downgrade is higher than the absolute cumulative abnormal common stock return after a credit rating upgrade. Put differently, it examines whether Moody's conveys relatively more private information about a firm through a rating downgrade compared with a rating upgrade. An event study methodology is followed to measure the impact of a rating change on the value of the firm in the two-day window beginning the day of the press release by the rating agency. All rating changes by Moody's related to Senior Unsecured Debt of firms of which the common stocks are listed on either the FTSE 100, AEX 25, BEL 20, DAX 30, IBEX 35 or CAC 40 index, during the examination period from 2007-2013, are included in the analysis. The rating change is classified as contaminated in the case that the firm released firm-specific data around the rating change. The result supports the reasoning that Moody's conveys relatively more private information about a firm through a rating downgrade compared with a rating upgrade. In addition, multivariate cross-section regression analyses are performed to analyze the nature of the variance within the dependent variable, Abnormal Return. For each dataset related to either downgrades or upgrades the balanced panel data concerning two time series observations are analyzed. The most innovative explanatory variables included, are the Crisis dummy variable that controls for the financial crisis, and; the Investment dummy variable that controls for the old credit rating. For the regression analysis related to the uncontaminated downgrades dataset, the Crisis variable showed more pronounced negative price reactions during the financial crisis. In addition, the Investment variable showed that lower prior ratings are associated with larger negative Abnormal Returns.

Table of Contents

Chapter 1: Introduction

This paper uses daily common stock return data, surrounding credit rating changes by Moody's Investors Service (Moody's) related to Senior Unsecured Debt, in order to examine whether the absolute Cumulative Abnormal common stock Return (CAR) as a result of a credit rating downgrade is higher than the absolute CAR after a credit rating upgrade. Put differently, it examines whether the evidence for the information provision hypothesis is stronger for rating downgrades than for rating upgrades. Meaning, whether Moody's conveys relatively more private information about a firm through a rating downgrade compared with a rating upgrade. Empirical evidence shows that downgrades have a statistically significant and economically large effect on daily stock prices. Upgrades, however, have a much more muted effect, which is 'puzzling'. (Jorion & Zhang, 2007) Besides the information provision hypothesis another cause of CARs can be the effect implied by the cost imposition hypothesis. Meaning, that there is a stock price reaction because a downgrade[1] imposes an increase in future borrowing costs on a firm. (Kim & Nabar, 2003) It is important to clarify that, similar to Holthausen and Leftwich (1986), no distinction is made between the substantiation of the CARs as a result of the effect implied by the information provision hypothesis and/or the cost imposition hypothesis. However, it is assumed that the effect implied by the cost imposition hypothesis is equal for both rating downgrades and upgrades. As a result, any observed difference in the absolute CARs is deemed to be a consequence of the effect implied by the information provision hypothesis.

This research only examines credit rating changes by Moody's because of data availability considerations as well as because of Moody's' established international reputation. Furthermore, this research strictly analyzes the abnormal common stock returns during the two-day announcement period starting on the day of the rating change. Contaminated rating changes are removed from the complete datasets related to downgrades and upgrades in cases where the firm released firm-specific data within the time frame from three days before until three days after the specific rating

[1] Whereas an upgrade would reduce the future borrowing costs of a firm.

change event date.[2] Lastly, it focuses on rating changes related to Senior Unsecured Debt of firms of which the common stocks are listed on either the FTSE 100, AEX 25, BEL 20, DAX 30, IBEX 35 or CAC 40 index during the examination period from 2007-2013.

Information provision hypothesis and Social relevance

The information provision hypothesis touches upon the social relevance of this research because it is related to the Efficient Market Hypothesis (EMH) by investigating how valuable credit rating changes are to the investors active at major European equity markets. According to the EMH by Eugene Fama and Paul Samuelson "a market in which prices always 'fully reflect' available information is called efficient" (Fama, 1970, p. 383). There are three basic forms of the EMH; weak, semi-strong and strong. This research assumes that the semi-strong EMH holds which means that all publicly available information is reflected in the market prices. According to Holthausen and Leftwich (1986) there are two important alternative views of how rating agencies obtain information about default risk. One view is that rating agencies only have access to publicly available information and that on top of that they generally lag the market in processing that information. Under this view, when assuming that markets are efficient in the semi-strong form, announcements of bond rating changes should not affect security prices. The second view is that rating agencies are information specialists that often even have access to not publicly available (private) information for the rating review process. Kliger and Sarig (2000) mention that even though bonds of larger firms are rated whether the issuer pays for the rating or not, about 98 percent of the issuers choose to pay for the rating. Why would corporations pay for ratings when they do not have to? Kliger and Sarig (2000) provide two possible explanations: (1) to gain better ratings, which they believe is unlikely because the raters' income is crucially dependent on its reputation, and; (2) paying for ratings may allow firms to incorporate inside information into the assigned ratings without fully revealing it. Under this second view it is to be expected that rating changes affect security prices (Holthausen & Leftwich, 1986).

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[2] The exact distinction between the all downgrades and the uncontaminated downgrades dataset as well as between the all upgrades and uncontaminated upgrades dataset will be elaborated upon in the data description and source section.

Cost imposition hypothesis

The cost imposition hypothesis is based on the fact that potential lenders and other contractors often use bond ratings to determine the amount of risk premium they must charge firms. In addition, when debt of a firm has a low credit rating, implying a low creditworthiness, it may also face restrictions in its access to sources of capital. As a result, bond downgrades lead to an increase in expected borrowing (and other contracting) costs for affected firms and as a result their stock prices decline to reflect the decrease in their expected future free cash flows.[3] (Kim & Nabar, 2003)

Common stock returns

This research is able to use common stock returns to measure the market reaction as a result of a rating change related to long-term debt because it follows the classical approach to a firm's capital structure that is described by the Merton (1974) model. Under this model, equity is viewed as being similar to a call option on the assets of a firm, with an exercise price equal to the face value of its debt outstanding. This model abstracts from redistribution of wealth between firm claimants (e.g. as a result of sudden changes in leverage or risk) and predicts that bond and stock prices for the same firm will move in the same direction (Jorion & Zhang, 2007). Hand, Holthausen and Leftwich (1992) indeed find that for downgrades the negative average effects on the prices of debt and equity are similar, thereby providing support for the Merton (1974) model. The main advantage when relying on common stock returns is that these data are easily accessible. On the contrary, bond data are more difficult to obtain and in addition few bond issues trade regularly, this would restrict the sample of firms with usable observations (Holthausen & Leftwich, 1986).

Scientific relevance

As mentioned this research examines whether there is non-linearity in the effect of a credit rating change on common stock returns. Meaning, whether the absolute CAR as a result of a credit rating downgrade is higher than the absolute CAR after a rating upgrade. The scientific relevance of this research is mainly related to its focus on firms listed on some of the most important European equity indices (either FTSE 100,

[3] Whereas, bond upgrades lead to a decrease in expected borrowing (and other contracting) costs for affected firms resulting in an increase in their stock prices.

AEX 25, BEL 20, DAX 30, IBEX 35 or CAC 40) as well as its recent examination period from 2007-2013. This is because the already existing research on CARs as a result of credit rating changes does not cover this recent time period and, so far, has always been focusing on firms listed on American indices. In addition to testing the non-linearity, multivariate cross-section regression analyses are performed to analyze the nature of the variance within the dependent variable, Abnormal Return. For each dataset related to either downgrades or upgrades the balanced panel data concerning two time series observations are analyzed. The two time series observations are for each firm (1) the Abnormal Return realized on the day of rating change, and; (2) the Abnormal Return on the day after the rating change. The most innovative explanatory variables that are included in the regression analysis are the Crisis dummy variable that controls for the financial crisis, which occurred during 2008 and 2009, and; the Investment dummy variable that controls for the rating category to which the old credit rating belonged.

In order to examine the non-linearity in the effect of a credit rating change on CARs the following research question was constructed:

Are the cumulative abnormal returns of European common stocks after a negative bond credit rating change significantly higher in comparison with the cumulative abnormal returns after a positive bond credit rating change?

As mentioned before this research can be separated into two parts. First, the existence of CARs of firms experiencing a bond rating change is examined. In this part, it is also closely examined whether the CARs (when present) are of equal magnitude for both rating upgrades and rating downgrades. Meaning, whether there is linearity in the effect of a credit rating change on CARs.

Second, in addition to the linearity analysis a multivariate cross-section regression analysis is performed to analyze and partially explain the variance of the dependent variable, being the Abnormal Return, by using explanatory variables.

In order to incorporate these two dimensions of the analysis, the aforementioned research question is separated into five sub-questions of which sub-questions 1.1 and 2.1 are related to the observations related to both all downgrades (285 observations) and uncontaminated downgrades (221 observations) and similarly sub-questions 1.2

and 2.2 are related to both all upgrades (90 observations) and uncontaminated upgrades (74 observations). Sub-question 1.3 is focusing on examining in detail whether the CARs (examined as part of sub-questions 1.1 and 1.2) are of equal magnitude for both rating upgrades and rating downgrades.[4]

Sub-questions

Part 1: Cumulative Abnormal Returns after rating changes

Sub-question 1.1 (related to downgrades): are there significantly negative cumulative abnormal common stock returns associated with rating downgrades by Moody's related to Senior Unsecured Debt?

This sub-question will be tested by using a one sample t-test in order to determine the combined effect of both the information provision hypothesis and the cost imposition hypothesis.

Sub-question 1.2 (upgrades): are there significantly positive cumulative abnormal common stock returns associated with rating upgrades by Moody's related to Senior Unsecured Debt?

This sub-question will again be tested by using a one sample t-test in order to determine the combined effect of both hypotheses.

Sub-question 1.3 (downgrades and upgrades): are the absolute cumulative abnormal common stock returns significantly larger after a rating downgrade compared with a rating upgrade?

The results of sub-questions 1.1 and 1.2 are compared and carefully analyzed. Plausible explanations are provided and tested for the observed results under sub-questions 1.1 and 1.2.

Part 2: Explanatory variables for Abnormal Returns

Sub-question 2.1 (downgrades): which of the explanatory variables included in the multivariate cross-section regression analysis significantly explain part of the variance in the Abnormal Return?

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[4] It is important to note that the CARs of the all upgrades and all downgrades datasets and the CARs of the uncontaminated upgrades and uncontaminated downgrades datasets are compared separately.

The explanatory variables that are included in the multivariate cross-section regression analysis will be defined in the theoretical framework section and an expectation of the sign of their coefficients, based on previous empirical findings and theory, will be substantiated in the related literature section.

Sub-question 2.2 (upgrades): which of the explanatory variables included in the multivariate cross-section regression analysis significantly explain part of the variance in the Abnormal Return?

Similar to the analysis related to downgrades an expectation of the sign of the coefficients of the explanatory variables will be substantiated in the related literature section after they have been defined in the theoretical framework section.

Overview of results

For the first part of the analysis the empirical evidence suggests for the datasets related to downgrades (both ‘all downgrades’ and ‘uncontaminated downgrades’) that downgrades by Moody’s related to Senior Unsecured Debt result in significantly negative CARs during the two-day event window. For the two datasets related to upgrades (‘all upgrades’ and ‘uncontaminated upgrades’) there is no evidence for significantly positive CARs. Prior research has predominantly shown that US equity markets react negatively to rating downgrades of debt by several rating agencies. Conversely, the reactions of US equity markets related to upgrades tend to be positive, although the significance and consistency of such findings for upgrades is considerably less strong than for downgrades. (Goh & Ederington, 1993)

The result of the independent samples t-test provides evidence for a significant absolute difference in the size of the capital market reactions related to the uncontaminated downgrades and upgrades datasets. This result supports the reasoning that Moody’s conveys relatively more private information about a firm through a rating downgrade compared with a rating upgrade.

For the second part of the analyses, the best fit multivariate cross-section regression model related to the uncontaminated downgrades dataset showed that the LossInvGra, Investment and Crisis control variables significantly explain part of the variance in the dependent variable, Abnormal Return. The LossInvGra variable provides evidence for the notion that markets pay more attention to rating changes around the investment-grade boundary. The significance of the result for the LossInvGra variable is consistent with the empirical findings of both Jorion, Liu, and Shi (2005), and; Holthausen and Leftwich (1986). The Investment variable shows that lower prior ratings are significantly associated with larger negative Abnormal Returns for downgrades. This result is consistent with the empirical findings of Jorion and Zhang (2007). Lastly, the Crisis variable shows that the negative price reactions to downgrades were more pronounced during the financial crisis when compared with the negative Abnormal Returns during the other years included in the sample. The negative coefficient of the crisis variable is consistent with the empirical evidence by Miao, Ramchander and Wang (2014).

In addition, the best fit multivariate cross-section regression model related to the uncontaminated upgrades dataset showed that the Leverage variable significantly explains part of the variance in the Abnormal Return. This result indicates that the Abnormal Return as a result of an upgrade is more positive for firms with less financial leverage, which is not consistent with the formulated expectation.

Structure of the Research

First, in the theoretical framework and related literature section the key concepts are conceptualized and thereafter the sub-questions that were previously formulated are combined with empirical findings of related literature in order to formulate testable hypotheses for sub-questions 1.1, 1.2 and 1.3. Second, in the data description and source section, the data gathering process is explained. Third, in the research methodology section the event study methodology is explained and the use of the one sample t-test, independent samples t-test and multivariate cross-section regression analysis are introduced. Fourth, in the results section the three hypotheses that were formulated in the theoretical framework and related literature section are tested. The hypotheses are tested along with the discussion of the results of the one sample t-tests, independent samples t-tests and multivariate cross-section regression analyses. Fifth, in the conclusion section the sub-questions that were formulated in the introduction section are answered along with the main research question. Finally, in the recommendations for further research section some recommendations for further research are provided.

Chapter 2: Theoretical Framework and Related Literature

2.1 Theoretical Framework

An important concept for this research is that of a 'credit rating of a bond'. According to Holthausen and Leftwich (1986) "Bond ratings attempt to measure the probability of default, a continuous variable that changes as new information arrives," (Holthausen & Leftwich, 1986, p. 59). As presented in Table 5, in the data description and source section, this research uses the rating classification scheme of Moody's.

This research examines rating changes related to Senior Unsecured Debt of firms. If debt is senior unsecured instead of junior unsecured (i.e. subordinated) it means that when the creditors make claims against the company's assets, in case of a default, senior unsecured debt has to be repaid before the junior unsecured debt. In addition, when debt is secured, it means that an asset, pledged as collateral for the loan, secures the loan of the creditor. This research uses rating changes related to Senior Unsecured Debt because of both previous research (e.g. Jorion and Zhang (2007) also restricted their sample to Senior Unsecured Debt ratings) and data availability considerations. Rating changes related to Senior Unsecured Debt namely occurred most often and it was preferred to only include rating changes related to one specific type of debt.

Definition regression variables

The dependent variable, Abnormal Return, is the Abnormal Return realized on the day of rating change (day 0), and; the Abnormal Return on the day after the rating change (day 1). It is important to clarify that for the one sample t-test analyses, the CAR is used, which adds up the Abnormal Return of day 0 and day 1 for each observation. In the Event Study paragraph of the research methodology section it is elaborated upon how these Abnormal Return and CAR variables are substantiated.

The explanatory variables included in the regression analyses, are the following: Leverage, Numberdowngrades (Numberupgrades), LossInvGra (GainInvGra), Investment, Crisis, and the index dummies. The Leverage variable represents a measure of a firms' long-term debt relative to its shareholders equity. The Numberdowngrades (Numberupgrades) variable represents the number of grades that the rating is reduced (increased), where ratings are measured from 1 (Aaa) to 21 (C), following the Moody's classification scheme as presented in Table 5. Because the values of both the Numberdowngrades and Numberupgrades variables are calculated by subtracting the new rating value from the old rating value, it should be noted that the Numberdowngrades variable will have negative values. For the datasets related to downgrades the LossInvGra variable, 'Loss of Investment Grade', is a dummy variable that takes the value 1 for downgrades from investment grade (Baa3 or better) to speculative grade (Ba1 or worse), and is coded 0 otherwise. For the datasets related to upgrades the GainInvGra variable, 'Gain of Investment Grade', is a dummy variable that takes the value 1 for upgrades from speculative grade to investment grade, and is coded 0 otherwise. The Investment variable is a dummy variable that controls for the rating category to which the old credit rating belonged. It takes the value 1 for a previous credit rating that was qualified as being investment grade, and is coded 0 when it was qualified as being speculative grade. The Crisis variable is a dummy variable that controls for the financial crisis, which occurred during 2008 and 2009(Guillen, 2012). It takes the value 1 for credit rating changes by Moody's that occurred during either 2008 or 2009, and is coded 0 otherwise. The index variables are dummy variables that control for the index on which the common stocks of the firm, that receives a credit rating change, are listed.

2.2 Related Literature

In this section, empirical evidence of previous research puts the five sub-questions into perspective. In addition, for sub-questions 1.1, 1.2, and 1.3 a testable hypothesis is formulated that will either be accepted or rejected in the results section of this research. Lastly, previous research is used to substantiate expectations for the signs of the explanatory variables included in the multivariate cross-section regression analysis.

Sub-question 1.1: are there significantly negative cumulative abnormal common stock returns associated with rating downgrades by Moody's related to Senior Unsecured Debt?

Empirical evidence from prior studies mainly indicates that firms report significantly negative CARs as a result of announcements of downgrades related to their bonds. For example, Holthausen and Leftwich (1986) find evidence that suggests that downgrades by both Standard and Poor's and Moody's are associated with negative

CARs in the two-day window beginning the day of the rating change by the rating agency (Holthausen & Leftwich, 1986). Later studies (e.g. Hand, Holthausen and Leftwich (1992); Griffin and Sanvicente (1982), and; Nayar and Rozeff (1994)) confirm these findings. As mentioned in the introduction, Hand, Holthausen and Leftwich (1992) examine both the bond and equity price effects of downgrades. They observed that although "the negative average effects on the debt and equity are similar, the effects on equity are somewhat more negative than the effects on debt," (Hand, Holthausen, & Leftwich, 1992, p. 734). Their findings confirm the methodology of this research to use CAR as a measure of the market reaction as a result of a rating change. The research by Hand, Holthausen and Leftwich (1992) has one additional novel aspect; it namely utilizes an expectations model of rating changes. With this model they compare the Yield-To-Maturity (YTM) of a specific bond estimated from the price available just prior to the rating agency announcement, with the YTM of a benchmark. This methodology is outside of the scope of this research. Goh and Ederington (1993) find that not all downgrades create a significant negative CAR. They make an important distinction between downgrades due to changes in a firm's leverage that do not create a significant negative CAR because they transfer wealth from bondholders to stockholders and downgrades associated with deteriorating financial prospects that do convey new negative information. This research did not make a distinction based on the underlying reason of Moody's for the downgrade because this specification was not available. On the contrary, both Lal and Mitra (2011) who examined the Indian market (while using daily stock returns) and older studies from the 1970s (e.g. Pinches and Singleton (1978), and; Wakeman (1978)) that were using monthly instead of daily stock returns did not find significant negative CARs.

The following alternative hypothesis will be tested in order to answer question 1.1: H_1: The cumulative abnormal common stock returns as a result of downgrades by Moody's related to Senior Unsecured Debt are unequal to zero.

Based on the empirical evidence from prior studies the expectation is that this alternative hypothesis will be accepted.

Sub-question 1.2: are there significantly positive cumulative abnormal common stock returns associated with rating upgrades by Moody's related to Senior Unsecured Debt?

Empirical evidence from prior studies mainly indicates that firms do not report significantly positive CARs as a result of announcements of upgrades related to their bonds. For example, Holthausen and Leftwich (1986) find little evidence of abnormal performance on announcements of an upgrade. Later studies (e.g. Griffin and Sanvicente (1982); Nayar and Rozeff (1994), and; Lal and Mitra (2011)) confirm these findings. However, empirical evidence from Hand, Holthausen and Leftwich, (1992) does show significantly positive bond price returns.

The following alternative hypothesis will be tested in order to answer question 1.2:
H_2: The cumulative abnormal common stock returns as a result of upgrades by Moody's related to Senior Unsecured Debt are unequal to zero.

Based on the empirical evidence from prior studies the expectation is that this alternative hypothesis will not be accepted.

Sub-question 1.3 (downgrades and upgrades): are the absolute cumulative abnormal common stock returns significantly larger after a rating downgrade compared with a rating upgrade?

As aforementioned the prior findings have shown that US equity markets react on average more to rating downgrades of debt by several rating agencies than to rating upgrades. Jorion and Zhang (2007) specifically performed an independent samples t-test of which the results strongly rejected the null hypothesis, which stated that the magnitude of stock price reactions to downgrades and upgrades is identical; their downgrade effect was 14 times larger than their upgrade effect.
In the literature there are multiple theories that can provide an (partial) explanation for this observed non-linearity in the effect of a credit rating change on common stock returns. First of all there are two explanations that imply that rating upgrades in essence have less information content than rating downgrades. The first explanation is that there exists a bias towards negative information content for credit rating changes.

This could happen because companies are less reluctant to release good news to the market than to release unfavourable information. (Goh & Ederington, 1998) Second, the high reputational cost related to failing to detect looming credit problems for credit rating agencies could provide them with an incentive to expend more resources in detecting deterioration in credit quality rather than improvements. (Jorion & Zhang, 2007) However, it does not have to be the case that the information content of upgrades is lower. Another plausible explanation for the difference is an unequal composition of the rating change data. Within this explanation there are two scenarios that can explain the observed non-linearity. For the first scenario the prior value of the rating is of great importance. Objectively, a downgrade from Aaa to Aa1 should have much less information content than a downgrade from B3 to Caa1. In the former case, the change in the estimated probability of default is relatively small compared to the latter case that represents a much larger increase in the default probability. This larger increase in the default probability can be expected to result in larger changes in bond yield spreads and should thus also have a larger impact on stock prices. Accordingly, if upgrades less often start from lower ratings than downgrades, it is not surprising to observe an, on average, stronger CAR for downgrades. Empirically Jorion and Zhang (2007) found that the distribution of prior credit ratings is not identical. For the second scenario the size of the credit rating change is of great importance. When downgrades often involve a much bigger change in credit rating than upgrades, it can be expected that the CARs related to downgrades are substantially larger than those related to upgrades.

The following alternative hypothesis will be tested in order to answer question 1.3: H_3: the absolute cumulative abnormal common stock returns as a result of credit rating downgrades are larger than the absolute cumulative abnormal common stock returns as a result of upgrades.

Based on the empirical evidence from prior studies the expectation is that this alternative hypothesis will be accepted.

Sub-question 2.1 (downgrades): which of the explanatory variables included in the multivariate cross-section regression analysis significantly explain part of the variance in the Abnormal Return?

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Sub-question 2.2 (upgrades): which of the explanatory variables included in multivariate cross-section regression analysis significantly explain part of the variance in the Abnormal Return?

Below, the expectation for the signs of the explanatory variables Leverage, Numberdowngrades (Numberupgrades), LossInvGra (GainInvGra), Investment, and Crisis are formulated and defended for both the multivariate cross-section regression analysis related to downgrades (sub-question 2.1) and upgrades (sub-question 2.2). For the index dummies that control for the indices no expectation is provided. This is because there is no existing research that focuses on European indices and it is hard to predict the signs because they are relative to the base scenario, which is the AEX index.

Empirical evidence from research by Kim and Nabar (2003) on the validity of the cost imposition hypothesis indicates that for downgrades the firms' CARs are negatively related with their leverage (debt-to-equity) ratios. Within their regression analysis the correlation between the leverage variable and the dependent variable, CARs (measured over day 0 and day 1) is significantly negative. This indicates that the magnitude of the negative CARs as a result of bond downgrades is greater for firms with more financial leverage and that downgrades significantly impact firms' borrowing costs. Based on the empirical findings of Kim and Nabar (2003) the expected sign of the leverage variable for downgrades is negative.

Even though Kim and Nabar (2003) only examined a dataset related to downgrades and therefore have no findings related to upgrades, their reasoning can be used to form an expectation for the sign of the Leverage variable related to upgrades in this research. Given the nature of the cost imposition hypothesis it can be expected that the opposite relationship compared to downgrades is present for upgrades. Meaning that an upgrade lowers restrictions that firms have in their access to sources of capital and that bond upgrades can be expected to lead to a decrease in expected borrowing costs. The stock prices of firms can thus be expected to increase, to reflect the increase in their expected future free cash flows. As a result, the expected sign of the leverage variable for upgrades is positive.

For the datasets related to downgrades and upgrades the expectation is that the coefficients of the Numberdowngrades and Numberupgrades variables will both have a positive sign. The intuition behind this expectation is that, the bigger the rating change, the higher the informational content and/or cost of such a change is likely to be for investors. Empirical evidence by Holthausen and Leftwich (1986) confirms this intuition, for their contaminated dataset related to downgrades the coefficient is negative and it suggests that the marginal effect on abnormal performance of a change in rating of one grade is -3.69% (t-statistic of -11.23). The difference in sign is explained by the different method followed to classify downgrades. As aforementioned this research namely used negative categories (0, -1 step, -2 steps, -3 steps, and -4 steps) while Holthausen and Leftwich (1986) used positive categories for their downgrades datasets. For their uncontaminated downgrades dataset as well as their datasets related to upgrades the coefficients have the predicted negative and positive signs, respectively. However, the coefficients are not significantly different from zero.

The expectation is that the coefficient of the LossInvGra (GainInvGra) variable will have a negative (positive) sign for the datasets related to downgrades (upgrades). The intuition behind these expectations is based on previous research by Kisgen and Strahan (2010) that examined whether regulations based on credit ratings affect a firm's cost of capital. In the case of the United States, they specify that the Securities and Exchange Commission (SEC) designates certain rating agencies as Nationally Recognized Statistical Rating Organizations (NRSROs), thereby certifying these agencies as qualified for implementation of various kinds of regulations. Numerous institutions and regulatory bodies thus rely on ratings from NRSROs for bond investment rules and regulations. Moody's, of which the rating changes are under examination in this study, is designated by the SEC as one of the few NRSROs. Kisgen and Strahan (2010) find that the effect of a rating change, by one of the NRSROs, on yields, is stronger around the investment-grade boundary, where regulations based on ratings are most prevalent and significant. For example, many institutions have rules that prohibit them from owning non-investment-grade debt

(Kisgen & Strahan, 2010). The opposite reasoning also holds, given that more investors can hold investment-grade debt, it can be expected that an upgrade from non-investment-grade to investment-grade has a relatively large downwards pressure on the yield of such debt. Empirical evidence by both Jorion, Liu, and Shi (2005) and Holthausen and Leftwich (1986) confirms this intuition. For their uncontaminated dataset related to downgrades the coefficients are negative and they suggest that the marginal effects on abnormal performance of a revision from investment grade to speculative grade are -0.25% (t-statistic of -1.78, significant at the 5% level in a two-tailed test) and -1.35% (t-statistic of -1.76, significant at the 5% level in a one-tailed test), respectively. For both, the coefficient is insignificant for their dataset related to upgrades. These empirical findings for downgrades are thus consistent with the notion that markets pay more attention to rating changes around the investment-grade boundary.

The expectation is that the coefficient of the Investment variable will have a positive (negative) sign for the datasets related to downgrades (upgrades). The intuition behind this expectation is based on previous research by Jorion and Zhang (2007) that demonstrates that the CARs as a result of rating changes depend on the value of the ratings prior to the announcement. Their empirical results show that holding constant the magnitude of the rating change, the rating prior to the announcement is the single most important variable included in cross-section analysis of stock returns. Their findings show that lower prior ratings are significantly associated with larger price effects, both for downgrades and upgrades.

The expectation is that the coefficient of the Crisis variable will have a negative (positive) sign for the datasets related to downgrades (upgrades). Similar to Miao, Ramchander and Wang (2014) this expectation is based on the occurrence of heightened market uncertainty that is likely to elevate the informational relevance of rating changes (both downgrades and upgrades) by credit rating agencies. Their empirical findings indeed indicate that the negative price reactions to downgrades, which occurred during the financial crisis period between 2008 and 2009, are more pronounced when compared with the overall sample. There are no empirical findings related to upgrades because there were no upgrades observed during the financial crisis period for their target firms (insurers).

A summary of the expectations related to the sign of the coefficients of the explanatory variables included in the multivariate cross-section regression analysis is presented below in Table 1 and Table 2 for the datasets related to downgrades and upgrades, respectively.

Table 1: Summary expected signs of explanatory variables related to sub-question 2.1

Explanatory Variable	**Predicted Sign**
Leverage	-
Numberdowngrades	+
LossInvGra	-
Investment	+
Crisis	-
FTSE_100	+/-
BEL_20	+/-
DAX_30	+/-
IBEX_35	+/-
CAC_40	+/-

Table 2: Summary expected signs of explanatory variables related to sub-question 2.2

Explanatory Variable	**Predicted Sign**
Leverage	+
Numberupgrades	+
GainInvGra	+
Investment	-
Crisis	+
FTSE_100	+/-
BEL_20	+/-
DAX_30	+/-
IBEX_35	+/-
CAC_40	+/-

Chapter 3: Data Description and Source

It is part of the scientific relevance of this research that it focuses on some of the most important European equity indices. Due to the easy availability of data this research focuses on six equity indices namely the: FTSE 100 (England), AEX 25 (The Netherlands), BEL 20 (Belgium), DAX 30 (Germany), IBEX 35 (Spain), and CAC 40 (France). The first step in the data gathering process was to determine the index constituents for these aforementioned indices from 2007-2013. CompuStat Global, accessed through Wharton Research Data Services, was used to extract the names of the companies as well as their International Securities Identification Number (ISIN) (Wharton Research Data Services, 2014). The 'GVKEYX' (Ticker code) of each index was used to request the index constituents.

The second step was to use the Rating Changes (RATC) function of Bloomberg to determine the relevant Rating Changes for the index constituents (Bloomberg, 2014). In order to do so, first, the Creating & Updating Portfolios (PRTU) function of Bloomberg was used. This function provided an efficient way to extract all the relevant Rating Changes at once for each index. It should be noted that the choice was made to only select long-term credit rating changes. Long-term credit rating changes are generally assigned to those obligations considered long-term in the relevant market. In Europe that means obligations with an original maturity of more than 365 days. This methodology is similar to the one followed by Lal and Mitra (2011). Rating changes by Moody's related to Senior Unsecured Debt were used because those observations occurred most frequently of all debt types. The problem with the Rating Changes output however was that there was no option to include the companies ISIN. Therefore, once all the relevant Rating Changes were extracted it was needed to match each company's name with its ISIN by again using the output of the index constituents. Having both the ISIN and the date of the rating change was important because those two variables were used as the input for the Event Study Tool[5] (EST). It is important to mention that the EST also required a distinction of the rating changes per index because, as will be mentioned in the research methodology section, the market index used to calculate the abnormal returns with, was equal to the

[5] This Event Study Tool will be elaborated upon in the research methodology section.

index upon which the common stock was listed (e.g. the abnormal returns of Dutch stocks were calculated by using the Dutch AEX index as the market index).

The third step was to manually check for contaminated rating changes. As aforementioned, data points are contaminated and thus removed from the complete dataset when the firm released firm-specific data within the time frame from three days before until three days after the specific rating change event date. This was done by using the Bloomberg terminal of the Erasmus University Rotterdam and by following the methodology listed below: (1) look for the security in Bloomberg by using the company's ISIN; (2) go to Company Overview → Company Fillings (CF); (3) search for important press releases around the credit rating change event window, and; (4) mark the rating change as 'Contaminated' in the case that the firm released firm-specific data within the time frame from three days before until three days after the specific rating change event date. For example, the 65th data point related to ISIN: GB0033986497 (Company Name: ITV PLC) and a rating change on 03-05-2009 (MM-DD-YYYY) was excluded because of a FY 2008 Earnings Call released on 03-04-2009 (MM-DD-YYYY). This contamination check eventually resulted in 64 contaminated rating downgrades and 16 contaminated rating upgrades. (Bloomberg, 2014) As presented in Table 3, of the 285 rating downgrades, 221 downgrades are classified as being uncontaminated. Similarly, as presented in Table 4, of the 90 rating upgrades, 74 are classified as being uncontaminated. Table 3 and Table 4, display in detail the underlying cause for each contamination of a rating change.

Table 3: Cause contaminated rating downgrade observations

	Number of downgrades
All Downgrades	285
Contaminated observations:	
- Earnings call	-19
- Business update call	-9
- Tender offer/Acquisition	-8
- Issuance of debt	-6
- Annual report released	-6
- Sales & Revenue call	-3
- Half year results released	-3
- Merger call	-2
- Preliminary year results released	-2
- 'Other'[6]	-6
Total contaminated:	-64
Uncontaminated Downgrades	221

Table 4: Cause contaminated rating upgrade observations

	Number of upgrades
All Upgrades	90
Contaminated observations:	
- Earnings call	-4
- Sales & Revenue call	-2
- Half year results released	-2
- Quarterly financial report released	-2
- Business update call	-1
- Tender offer/Acquisition	-1
- Merger call	-1
- 'Other'	-3
Total contaminated:	-16
Uncontaminated Upgrades	74

The fourth step was to calculate the leverage ratio for each firm in the sample by using data from Thomson One Banker. By using the ISIN list that was used as input for the EST, firm specific information concerning 'Total Liabilities and Shareholders Equity', 'Total Long-Term Debt' and, 'Total Liabilities' was extracted for each year from 2007-2013. For each of those three variables the average over 2007-2013 was calculated before making the final long-term debt-to-equity ratio calculation. The ratio was calculated by dividing 'Total Long-Term Debt' by 'Total Liabilities and Shareholders Equity' minus 'Total Liabilities', effectively the 'Total Long-Term

[6] E.g. removal from listing and divestment call.

Debt' was thus divided by the 'Shareholders Equity' as presented in the following formula:

$$Leverage\ Ratio = \frac{Long - Term\ Debt}{Shareholders\ Equity} \quad (1)$$

The calculation of this Leverage Ratio resulted in the exclusion of 1 data point for both the all downgrades and uncontaminated downgrades datasets and the exclusion of 2 data points for both the all upgrades and uncontaminated upgrades datasets. This is because the Thomson One Banker Database did not provide information on Getronics NV (ISIN: NL0000853091). (Thomson One Banker Database, 2014)

The fifth step in the data process was to classify and categorize the rating changes. This step was required to substantiate the Numberdowngrades (Numberupgrades), LossInvGra (GainInvGra) and Investment explanatory variables for the multivariate cross-section regression analyses performed with the downgrades (upgrades) datasets. By using the 'VLOOKUP' function in Excel the Old and the New Ratings by Moody's were given a certain number that was taken from Table 5, which is presented below.

Table 5: Classification of the Credit Ratings

Aaa	1		
Aa1	2		
Aa2	3		
Aa3	4	Upper	
A1	5		Investment
A2	6		
A3	7		
Baa1	8		
Baa2	9		
Baa3	10		
Ba1	11	Middle	
Ba2	12		
Ba3	13		
B1	14		
B2	15		
B3	16		Speculative
Caa1	17		
Caa2	18	Lower	
Caa3	19		
Ca	20		
C	21		
WR	NA		
NR	NA		

The difference between both numbers, calculated by subtracting the value of the new rating from the value of the old rating, was used as the value for the Number of downgrades (upgrades) explanatory variable. For example, an old Baa3 rating would be classified as a '10', if Moody's then upgraded this Senior Unsecured Debt to a Baa2 rating, this would be classified as a '9'. The Number of upgrades explanatory variable would, for this rating change, have a value of '1', because the debt was upgraded by one notch. The aforementioned rating change can also be called an across class rating change. It is important to note that there are also rating outlook changes 'within classes' (e.g. from A2 to A2+), such a rating change would be classified as a '0' for the Number of upgrades explanatory variable. Lastly, it should be noted that the number of downgrades explanatory variable thus uses negative categories (-1, -2, -3, and -4) for across class rating downgrades. Table 6 and Table 7 display the break down of the four samples by the size of rating changes. In Table 6 the break down of the all downgrades and all upgrades samples are compared and in Table 7 the uncontaminated samples are compared.

Table 6: Distribution by absolute magnitude of rating changes for the full datasets

Absolute magnitude of rating categories changed	All Downgrades Number	All Downgrades %	All Upgrades Number	All Upgrades %
0	121	42.5	36	40.0
1	122	42.8	47	52.2
2	32	11.2	5	5.6
3	9	3.2	2	2.2
4	1	0.4		
Total	285	100	90	100
Mean	0.76		0.70	
Median	1		1	

Table 7: Distribution by absolute magnitude of rating changes for the uncontaminated datasets

Absolute magnitude of rating categories changed	Uncontaminated Downgrades		Uncontaminated Upgrades	
	Number	%	Number	%
0	85	38.5	26	35.1
1	102	46.2	42	56.8
2	24	10.9	5	6.8
3	9	4.1	1	1.4
4	1	0.5		
Total	221	100	74	100
Mean	0.82		0.74	
Median	1		1	

These break downs presented above are especially relevant for sub-question 1.3 because as aforementioned in the related literature section, when comparing CARs, the size of the credit rating change is of great importance. It can be observed that of the full samples the average downgrade is 0.76 notches, versus 0.70 notches for upgrades. In addition, for the uncontaminated samples the average downgrade is 0.82 notches, versus 0.74 notches for upgrades.

Lastly, it is important to note that when either the old or the new rating was classified as either Withdrawn Rating (WR) or Not Rated (NR) the rating change was excluded from the analysis. In Table 8 it can be observed that for the rating upgrades dataset these criteria meant a loss of 4 observations and for the rating downgrades dataset a loss of 10 observations (of which 1 was contaminated meaning that the uncontaminated downgrades dataset lost 9 observations).

Table 8: Overview of lost observations as a result of either a Withdrawn Rating or an observation that is Not Rated per dataset

	All Downgrades	Uncontaminated Downgrades	All Upgrades	Uncontaminated Upgrades
Number of lost observations	10	1	4	0

The Loss of Investment Grade (Gain of Investment Grade) is a dummy variable which is coded '1' when there is a rating change from 'Investment Grade' to 'Speculative

Grade', and '0' otherwise for the datasets related to downgrades. For the datasets related to upgrades it is coded '1' when there is a rating change from 'Speculative Grade' to 'Investment Grade', and '0' otherwise. From Table 5 it can be observed that ratings between Aaa and Baa3 are classified as investment grade and ratings between Ba1 and C as speculative grade.

The Investment variable is a dummy variable that is coded equally for the analyses related to both the downgrades and upgrades datasets. It is coded '1' when the Senior Unsecured Debt had an investment grade rating before the rating change, and '0' when it had an speculative grade rating.

The sixth step in the data process was to substantiate the Upper, Middle and Lower dummy variables that are, similarly to the Investment variable, dependent on the old credit rating. These three dummy variables are created in order to examine the importance of the prior value of the rating and to be able to analyze and compare the distributions of the old ratings. The Upper dummy variable is coded '1' when the old rating is between Aaa and A3, and '0' otherwise. The Middle dummy variable is coded '1' when the old rating is between Baa1 and B1, and '0' otherwise. Lastly, the Lower dummy variable is coded '1' when the old rating is between B2 and C, and '0' otherwise. It should be noted that because of the limited amount of observations in the Lower (old rating) category it has been decided to use the aforementioned Investment dummy variable with only two categories in the regression analysis, namely Upper and Middle. Table 9 and Table 10 display the break down of the four samples by the classification of the old credit rating. In Table 9 the break down of the all downgrades and all upgrades samples are compared and in Table 10 the uncontaminated samples are compared.

Table 9: Distribution by classification of the old credit rating for the full datasets

Original Rating Class	All Downgrades			All Upgrades		
	Old rating between	Number	%	Old rating between	Number	%
Upper	Aaa – A3	188	65.96	Aaa – A3	32	35.56
Middle	Baa1 – B1	90	31.58	Baa1 – B1	55	61.11
Lower	B2 – C	7	2.46	B2 – C	3	3.33
Total		285	100		90	100

Table 10: Distribution by classification of the old credit rating for the uncontaminated datasets

Original Rating Class	Contaminated Downgrades Old rating between	Number	%	Contaminated Upgrades Old rating between	Number	%
Upper	Aaa – A3	145	65.61	Aaa – A3	25	33.78
Middle	Baa1 – B1	70	31.67	Baa1 – B1	46	62.16
Lower	B2 – C	6	2.71	B2 – C	3	4.05
Total		221	100		74	100

These break downs presented above are especially relevant for sub-question 1.3 because as aforementioned in the related literature section, when comparing CARs, the classification of the old credit rating is of great importance. For the both the full and uncontaminated samples, it can be observed that the distributions of prior ratings are not identical. This will be elaborated on in the results section.

The seventh step in the data process was to substantiate the Crisis variable. For all datasets, the Crisis variable is coded '1' when the rating change occurred during either 2008 or 2009, and '0' otherwise. It is important to realize that the occurrence of the financial crisis and thereafter the European Debt crisis is the main explanation for the fact that the samples related to downgrades have substantially more observations than the samples related to upgrades. This asymmetry causes the power of tests based on upgrade data to be relatively low compared to the power of tests based on downgrades data.

Table 11 below shows the transition matrix of all the rating changes related to Senior Unsecured Debt by Moody's, in the period 2007-2013, that were used during the data analysis. The total sample of both downgrades and upgrades contains 375[7] rating changes of which 285 are related to rating downgrades and 90 are related to rating upgrades.

[7] The entire sample covers a total of 138 issuers, with 81 issuers with downgrades and 57 issuers with upgrades. On average, an issuer was downgraded 3.52 times during this period, and was upgraded about 1.58 times. When the contaminated observations are left out, the sample covers a total of 128 issuers, with 77 issuers with downgrades and 51 issuers with upgrades. On average, an issuer was downgraded 2.87 times during this period, and was upgraded about 1.45 times.

Table 11: Transition Matrix of Rating Changes

		Revised Rating[a]																						
		Aaa	Aa1	Aa2	Aa3	A1	A2	A3	Baa1	Baa2	Baa3	Ba1	Ba2	Ba3	B1	B2	B3	Caa1	Caa2	Caa3	Ca	C	**Total**	% Down within class[b]
Prior Rating[a]	Aaa	**0**																					0	0
	Aa1		**11**	6	4	1																	22	90,9
	Aa2		5	**16**	12	4																	37	81,3
	Aa3		1	2	**14**	8	9	2															36	100,0
	A1		1	1	2	**24**	13	5															46	75,0
	A2				2	1	**13**	15	2	2													35	100,0
	A3						3	**20**	16	1	3	1											44	80,0
	Baa1							6	**18**	13		1											38	61,1
	Baa2								6	**14**	9	3											32	71,4
	Baa3									9	**14**	8	1										32	57,1
	Ba1										5	**6**	3	2									16	50,0
	Ba2											2	**2**	5									9	50,0
	Ba3										1		2	**2**	6								11	50,0
	B1													2	**1**	3	1						7	100,0
	B2															**0**	2						2	0
	B3														1		**2**	2					5	100,0
	Caa1																1	**0**	1				2	0
	Caa2																	1	**0**				1	0
	Caa3																			**0**			0	0
	Ca																				**0**		0	0
	C																					**0**	0	0
	Total	0	18	25	34	38	38	48	42	39	32	21	8	11	8	3	6	3	1	0	0	0	**375**	

[a] Ratings are described in terms of Moody's classification scheme as presented in Table 1.

[b] The main diagonal represents all of the 157 within-class (outlook) rating changes. The '% down within class' column indicates the percentage of within-class changes that are downgrades.

The diagonal just above the main diagonal reports the distribution of the 122 across-class downgrades of one class. The observations above that diagonal indicate that there are 42 downgrades of more than one class. The rating changes above the main diagonal that are presented in 'Red' are the observations that receive value '1' for the explanatory variable Loss of Investment Grade in the datasets related to downgrades. The diagonal just below the main diagonal reports the distribution of the 47 across-class upgrades of one class. The observations below that diagonal indicate that there are 7 upgrades of more than one class. The rating changes below the main diagonal that are presented in 'Green' are the observations that receive value '1' for the explanatory variable Gain of Investment Grade in the datasets related to upgrades.

Lastly, for the index dummies that are included in the linear regression analysis for both downgrades and upgrades it is useful to use the index separation that was used for the EST. This index separation was used to create a dummy for each index in order to be able to include those dummies in the linear regression analysis.

Chapter 4: Research Methodology

First, an event study methodology is presented that is used to calculate the CARs. Second, the one sample t-tests are introduced as well as the nonparametric binomial tests. Both the one sample t-tests and the nonparametric binomial tests are performed in order to answer sub-questions 1.1 and 1.2.

Third, the independent samples t-tests are introduced as well as the further analysis that is performed to investigate whether the CAR depends on the prior rating and the absolute magnitude of the rating change. Both the independent samples t-tests as well as this detailed analysis is performed in order to answer sub-question 1.3.

Fourth, the multivariate cross-section regression analysis is introduced that is used to test the relationship between the dependent variable, Abnormal Return, and multiple explanatory variables. The regression analysis is performed to answer sub-questions 2.1 and 2.2.

4.1 Event Study

The main research method that is used for this research is an event study. The results of this event study are used as input for the one sample t-tests, independent samples t-tests and multivariate cross-section regression analyses. As mentioned by MacKinlay (1997) "the usefulness of such a study comes from the fact that, given rationality in the marketplace, the effects of an event will be reflected immediately in security prices," (MacKinlay, 1997, p. 13). In other words, an event study measures the impact of a specific event on the value of the firm (Lal & Mitra, 2011). As aforementioned this research examines the effects of an event by looking at common stock returns because such data is relatively well available and accessible.

The initial task when performing an event study is to define the event of interest. For this research the event of interest is either a negative or a positive credit rating change by Moody's related to Senior Unsecured Debt. Given this definition both an estimation period and an event window are required. The estimation period is used to estimate the market model parameters that will be used to calculate the realized Abnormal Returns of a certain security during the event window right after the respective rating change has occurred. For this research, the market model parameters, for each rating change observation, are estimated using a 150 trading days long estimation period before the respective rating change occurred, from trading day -180 to -30. It is standard practice to use an estimation period prior to the event window (MacKinlay, 1997). The event window itself includes the day of the announcement of the rating change by Moody's as well as the day after the announcement. This two-day event window is needed because the dates of the rating changes by Moody's do not provide an indication whether the announcement occurred before or after the end of the trading day. As mentioned by MacKinlay (1997) this allows capturing the common stock price effects of announcements even when the respective rating change announcement is made after the stock market closes.

Given that an event is classified as either a negative or a positive rating change by Moody's related to Senior Unsecured Debt, it is important to determine the selection criteria of such events. As aforementioned, this research includes all observations related to rating changes by Moody's of firms of which the common stocks were listed on any of the major European equity indices (FTSE 100, AEX 25, BEL 20, DAX 30, IBEX 35 and CAC 40), between 2007 and 2013. The specific steps followed to extract the data and information on disregarded data points is provided in the data description and source section of this research.

Given the selection of the included events, this research used the Event Study Tool by Oord (2013) in order to calculate the common stock returns during the estimation period (-180, -30) as well as the common stock returns during the event window (-1, +1). The common stock returns during both periods are required when calculating the Abnormal Returns while using the market model that can be defined as a statistical model, which relates the return of any given security to the return of the market portfolio. First, the Event Study Tool calculated the daily returns for each sample company for both the estimation window and the event window as follows:

$$R_{it} = (P_{it} - P_{it-1})/P_{it-1} \qquad (2)$$

Where, P_{it} and P_{it-1} are the respective daily prices for company 'i' at time 't' and 't-1'.

Second, in order to calculate the parameters of the market model the Event Study Tool also calculated the actual daily returns for the market. This research used the index on which the particular common stocks of a specific sample firm were listed. For example, when the daily returns of the Dutch firm Corio NV are calculated those are matched with the daily returns of the AEX index on which Corio NV is listed. This is in line with the practice to use a broad based stock index for the market portfolio (MacKinlay, 1997). The Event Study Tool calculated the actual daily returns of the respective market index as follows:

$$R_{mt} = (I_t - I_{t-1})/I_{t-1} \qquad (3)$$

Where, I_t and I_{t-1} are the respective daily index values at time 't' and 't-1'.

Third, as aforementioned, given R_{it} and R_{mt} the market model statistically relates both returns in order to estimate the parameters α_i and β_i. The Event Study Tool did this by estimating the following equation:

$$R_{it} = \alpha_i + \beta_i R_{mt} + AR_{it} \qquad (4)$$

Where,
R_{it} is the observed daily return for the share of a company 'i' at time 't',
R_{mt} is the observed daily return for the market index at time 't',
α_i is the estimate of the intercept for the company 'i',
β_i is the estimate for the market beta for the shares of company 'i', and
AR_{it} is the abnormal return of company 'i' at time 't' (i.e. the error term).

Fourth, after the estimation of the parameters α_i and β_i of the market model, for each firm, the Abnormal Return (AR), realized on the announcement day as well as on the day after the announcement day were calculated. As defined by MacKinlay (1997) an abnormal return is "the actual ex post return of the security over the event window minus the normal return of the firm over the event window," (MacKinlay, 1997, p. 15). The actual ex post return of the security is calculated by using formula (2). Furthermore, the normal return is equal to the return estimated by using the market model equation. Meaning, given the values of the parameters α_i and β_i, the return of the overall stock market, during either the announcement day or the day after the announcement day, was used to calculate the normal return on that respective day. This normal return can be interpreted as the return that would have been realized when the credit rating change would not have occurred. The Event Study Tool calculated the Abnormal Return realized on the common stocks of a certain firm for both days included in the event window separately by using the following formula:

$$AR_{it} = R_{it} - (\alpha_i + \beta_i R_{mt}) \qquad (5)$$

Finally, the Cumulative Abnormal Return (CAR), used to answer sub-questions 1.1, 1.2 and 1.3, is computed for each firm by accumulating the Abnormal Return on the announcement day (day 0) and the Abnormal Return on the day after the announcement day (day 1). Thus, the CAR is the total Abnormal Return during the event window (-1, +1). The CAR was calculated by using the following formula:

$$CAR_i = \sum_{t=-1}^{+1}\left[R_{it} - \left(\alpha_i + \beta_i R_{mt}\right)\right] \quad (6)$$

4.2 One Sample T-test

In order to answer sub-questions 1.1 and 1.2 related to downgrades and upgrades respectively, one sample t-tests are performed in order to determine the combined effect of both the information provision hypothesis and the cost imposition hypothesis in Europe. Such one sample t-tests are thus performed for all four datasets. These one sample t-tests are used to examine whether the CAR of the sample is significantly different from zero. In addition, a nonparametric binomial test will be performed for each of the four datasets. These binomial tests are performed to test the null hypothesis of an even distribution. This test proportion of 0.5 means, that when there is an even distribution, half of the CAR observations are expected to be negative (therefore receiving the value 1) and the other half positive (therefore receiving the value 0). Thus, with regard to the tested variable for downgrades, an observation has the value 1 when its CAR from day -1 to 1 is smaller than zero and the value 0 when its CAR is larger than zero. Conversely, for upgrades, an observation has the value 1 when its CAR from day -1 to 1 is larger than zero, and 0 otherwise.

4.3 Independent Samples T-test

In order to answer sub-question 1.3, whether the absolute CARs are higher after a rating downgrade compared with a rating upgrade, independent samples t-tests are performed that compare the CAR of the downgrades samples with the CAR of the upgrades samples. In addition, because of prior empirical findings, further analysis is performed to investigate whether the CAR depends on the prior rating and the absolute magnitude of the rating change. For this further analysis, numerous CARs of subsamples, that partially control for prior rating and the absolute magnitude of the rating change are calculated for both downgrades and upgrades.

4.4 Multivariate Cross-section Regression Analysis

As mentioned before, this research performs multivariate cross-section regression analyses to test the relationship between a firm's Abnormal Return, the dependent variable, and multiple explanatory variables. It should be noted that for the regression analyses, the Abnormal Returns on day 0 and day 1 are kept as separate Abnormal Return values and are thus not accumulated. The explanatory variables included in the regression analyses for downgrades (upgrades) are Leverage, Numberdowngrades (Numberupgrades), LossInvGra (GainInvGra), Investment, Crisis and the Index dummies. More specifically, the Akaike Information Criterion will be consistently examined, to establish a best fit model for each dataset. The correlation table of all the independent and control variables will be examined for an indication of multicollinearity. A partial autocorrelation test on the dependent variable, Abnormal Return, will be performed to check for autoregressive behavior and it will be examined whether the assumptions of the Gauss-Markov Theorem are satisfied.

Chapter 5: Results and Discussion

First, in paragraph 5.1, hypothesis one is tested by providing the results related to the performed one sample t-tests for the two datasets related to downgrades as well as the results related to the performed nonparametric binomial tests. Second, in paragraph 5.2, hypothesis two is tested by providing the results related to the performed one sample t-tests for the two datasets related to upgrades as well as the results related to the performed nonparametric binomial tests. Third, in paragraph 5.3, hypothesis three is tested by providing the results of the independent samples t-tests. In addition, the results of the further analysis are presented, that is performed to investigate whether the CAR depends on the prior rating and the absolute magnitude of the rating change.
Fourth, in paragraph 5.4, multivariate cross-section regression analyses are used to analyze the balanced panel data for both datasets related to downgrades. For each rating downgrade two time series observations are examined namely, the Abnormal Returns on the day of the rating change (day 0) as well as on the day after the rating change (day 1). Fifth, in paragraph 5.5, multivariate cross-section regression analyses are used to analyze the balanced panel data for both datasets related to upgrades. For

each rating upgrade again two time series observations are examined namely, the Abnormal Returns on day 0 and day 1.

5.1 CAR as a Result of a Downgrade

5.1.1 All Downgrades

The one sample t-test performed for the 'all downgrades' dataset, concerning 285 observations, showed negative CARs as a result of rating downgrades by Moody's related to Senior Unsecured Debt. From Table 12 it can be observed that the mean two-day CAR is -0.67 percent.

Table 12: One Sample T-test All Downgrades

Event Window	All Downgrades	t-value
0 to 1	-0.6711	-2.667 (**)
Sample size	285	

Note: (**) Significant at 1% level.

In addition, a nonparametric binomial test, of which the outcome is presented in Table 13, showed that 59 percent of the sample firms experienced negative CARs. The 'Test or Hypothesized Proportion' specifies the expected proportion of records as "Successes", meaning that the CAR is smaller than zero. The default of 0.5 means that when there is an even distribution, half of the CARs are expected to be negative (therefore receiving the value 1) and the other half positive (therefore receiving the value 0). This is because; when there is no stock price reaction as a result of a rating change and thus no bias in the data, the error term (AR_{it}) of equation (4) is expected to have a mean of 0[8]. With regard to the tested variable, an observation has the value 1 when its CAR from day -1 to 1 is smaller than zero (i.e. negative) and the value 0 when its CAR is larger than zero (i.e. positive).

[8] This is the case for both day 0 and day 1 after the rating change and thus also from day -1 to 1. This is important because in this part the sign of the Cumulative Abnormal Return from day -1 to 1 is analyzed.

Table 13: Nonparametric Binomial test All Downgrades

	Category	N	Observed Proportion	Test Proportion
Group 1	1.00	167	0.59 (**)	0.50
Group 2	0.00	118	0.41	
Total		285	1.00	

Note: (**) Significant at 1% level.

These results indicate that the combined effect of both the information provision hypothesis and the cost imposition hypothesis for downgrades in Europe is significantly negative. Therefore, these results, which are in line with the previously formulated expectation and empirical evidence, allow to accept the following alternative hypothesis:

H_1: The cumulative abnormal common stock returns as a result of downgrades by Moody's related to Senior Unsecured Debt are unequal to zero.

5.1.2 Uncontaminated Downgrades

The one sample t-test performed for the 'uncontaminated downgrades' dataset, concerning 221 observations, also showed negative CARs as a result of rating downgrades by Moody's related to Senior Unsecured Debt. From Table 14 it can be observed that the mean two-day CAR is -0.67 percent.

Table 14: One Sample T-test Uncontaminated Downgrades

Event Window	All Downgrades	t-value
0 to 1	-0.6669	-2.688 (**)
Sample size	221	

Note: (**) Significant at 1% level.

In addition, a nonparametric binomial test, of which the outcome is presented in Table 15, showed that 60 percent of the sample firms experienced negative CARs and that the null hypothesis of an even distribution was rejected at the 1 percent level.

Table 15: Nonparametric Binomial test Uncontaminated Downgrades

	Category	N	Observed Proportion	Test Proportion
Group 1	1.00	132	0.60 (**)	0.50
Group 2	0.00	89	0.40	
Total		221	1.00	

Note: (**) Significant at 1% level.

These results indicate that also for the uncontaminated downgrades dataset the combined effect of both the information provision hypothesis and the cost imposition hypothesis for downgrades in Europe is significantly negative. Compared to the tests performed for the 'all downgrades' dataset the results for the uncontaminated downgrades dataset are slightly more significant. Therefore, these results, which are in line with the previously formulated expectation and empirical evidence, again allow to accept the following alternative hypothesis:

H_1: The cumulative abnormal common stock returns as a result of downgrades by Moody's related to Senior Unsecured Debt are unequal to zero.

5.2 CAR as a Result of an Upgrade

5.2.1 All Upgrades

The one sample t-test performed for the 'all upgrades' dataset, concerning 90 observations, showed no significantly positive CARs as a result of rating upgrades by Moody's related to Senior Unsecured Debt. From Table 16 it can be observed that the mean two-day CAR is 0.11 percent (Sig. 2-tailed p-value > 0.05).

Table 16: One Sample T-test All Upgrades

Event Window	All Upgrades	t-value
0 to 1	0.1100	0.441
Sample size	90	

In addition, a nonparametric binomial test, of which the outcome is presented in Table 17, showed that 57 percent of the sample firms experienced positive CARs and that the null hypothesis of even distribution was not rejected at the 5 percent level (Sig. 2-tailed). With regard to the tested variable for upgrades an observation has the value 1 when its CAR from day -1 to 1 is larger than zero and the value 0 when its CAR is smaller than zero.

Table 17: Nonparametric Binomial test All Upgrades

	Category	N	Observed Proportion	Test Proportion
Group 1	1.00	51	0.57	0.50
Group 2	0.00	39	0.43	
Total		90	1.00	

These results indicate that for the all upgrades dataset the combined effect of both the information provision hypothesis and the cost imposition hypothesis for upgrades in Europe is insignificantly positive. Therefore, these results, which are in line with the previously formulated expectation and empirical evidence, do not allow to accept the following alternative hypothesis:

H_2: The cumulative abnormal common stock returns as a result of upgrades by Moody's related to Senior Unsecured Debt are unequal to zero.

5.2.2 Uncontaminated Upgrades

The one sample t-test performed for the 'uncontaminated upgrades' dataset, concerning 74 observations, showed no significantly positive CARs as a result of rating upgrades by Moody's related to Senior Unsecured Debt. From Table 18 it can be observed that the mean two-day CAR is -0.04 percent (Sig. 2-tailed p-value > 0.05) and thus even negative.

Table 18: One Sample T-test Uncontaminated Upgrades

Event Window	Uncontaminated Upgrades	t-value
0 to 1	-0.0351	-0.133
Sample size	74	

In addition, a nonparametric binomial test, of which the outcome is presented in Table 19, showed that 54 percent of the sample firms experienced positive CARs and that the null hypothesis of even distribution was not rejected at the 5 percent level (Sig. 2-tailed).

Table 19: Nonparametric Binomial test Uncontaminated Upgrades

	Category	N	Observed Proportion	Test Proportion
Group 1	1.00	40	0.54	0.50
Group 2	0.00	34	0.46	
Total		74	1.00	

These results indicate that also for the uncontaminated upgrades dataset the combined effect of both the information provision hypothesis and the cost imposition hypothesis for upgrades in Europe is insignificantly positive. Compared with the tests performed for the 'all upgrades' dataset, the results for the uncontaminated upgrades dataset are less strong and even more insignificant. Therefore, these results, which are in line with the previously formulated expectation and empirical evidence, still do not allow to accept the following alternative hypothesis:

H_2: The cumulative abnormal common stock returns as a result of upgrades by Moody's related to Senior Unsecured Debt are unequal to zero.

5.3 Comparison Absolute CARs after a downgrade and an upgrade

The result of the independent samples t-test related to the full datasets that is presented in Table 20 provides no evidence for the claim, that the absolute CAR as a result of rating downgrades is larger than the CAR as a result of rating upgrades (Sig. (1-tailed) p-value = 0.057). However, when having a closer look at the two means, it can be observed that the all downgrades sample is associated with a highly significant CAR of -0.671%, while the all upgrades sample is associated with an insignificant CAR of only 0.110%. Although the absolute CAR as a result of downgrades is insignificantly higher than the CAR as a result of upgrades, its absolute effect is approximately six times larger than the upgrade effect.

Table 20: All Rating Changes related to the full downgrades and upgrades datasets

All Downgrades			All Upgrades			T-test for Difference	
N.	CAR	T-stat	N.	CAR	T-stat	Absolute Difference	T-stat
285	-0.671	-2.667 (**)	90	0.110	0.441	| 0.561 |	-1.584

Note: ** denotes statistical significance at the 1% level.

However, the result of the independent samples t-test related to the uncontaminated datasets that is presented in Table 21 provides evidence for the aforementioned claim (Sig. (1-tailed) p-value = 0.042). When having a closer look at the differences between the two means, it can be observed that the all downgrades sample is associated with a highly significant CAR of -0.667%, while the all upgrades sample is associated with an insignificant and even negative CAR of -0.035%.

Table 21: All Rating Changes related to the uncontaminated downgrades and upgrades datasets

Uncontaminated Downgrades			Uncontaminated Upgrades			T-test for Difference	
N.	CAR	T-stat	N.	CAR	T-stat	Absolute Difference	T-stat
221	-0.667	-2.688 (**)	74	-0.035	-0.133	| 0.632 |	-1.742 (*)

Note: **, * denote statistical significance at the 1% and 5% levels, respectively.

Although the results of the independent samples t-tests are inconsistent, the fact that the result of the second, more important t-test related to the uncontaminated dataset is significant, together with the strong empirical evidence by Jorion and Zhang (2007), allows to accept the following alternative hypothesis:

H_3: the absolute cumulative abnormal common stock returns as a result of credit rating downgrades are larger than the absolute cumulative abnormal common stock returns as a result of upgrades.

Given that the alternative hypothesis is accepted, further analysis is performed to examine whether the difference in the absolute magnitude of the CAR related to downgrades and upgrades can be (partially) explained by the distribution of both the prior ratings and the absolute magnitude of the rating changes. In other words, as aforementioned in the related literate section, it is examined whether the composition of the rating change data is an explanation for the difference in absolute magnitude. First, Table 6 and Table 7, displayed in the data description and source section, are referred to, because the information in both tables is needed to be able to conclude whether the distributions of the size of the credit rating changes are equal. As aforementioned, of the full samples the average downgrade is 0.76 notches, versus 0.70 notches for upgrades. In addition, for the uncontaminated samples the average downgrade is 0.82 notches, versus 0.74 notches for upgrades. Furthermore, it can be observed that of the full samples 14.8 percent of the ratings is downgraded two or more notches, while only 7.8 percent of the ratings is upgraded two or more notches. For the uncontaminated samples these percentages are 15.5 and 8.2, respectively. The difference in the absolute magnitude of the rating changes thus provides a partial explanation for the difference in the absolute magnitude of the CAR related to downgrades and upgrades. This is because when ratings are on average downgraded more notches than upgrades, it can be expected that the CARs related to downgrades are substantially larger than those related to upgrades. Second, Table 9 and Table 10, also displayed in the data description and source section, are referred to, because the information in both tables is needed to be able to conclude whether the distributions of the prior ratings are equal. As aforementioned, for the full samples, it can be observed that the distributions of prior ratings are not identical. The full upgrade sample has larger proportions of observations with a Lower and Middle original rating class and the full downgrades sample thus has a higher proportion of observations with an Upper original rating class. For the uncontaminated samples the same pattern is present and thus again the upgrade sample is more skewed towards a greater proportion of firms with a relatively low prior credit rating. This is not consistent with the distributions of the sample data by Jorion and Zhang (2007). For them, the downgrade sample was more skewed towards a greater proportion of firms with a relatively low prior rating. The unequal distributions of the prior value of the ratings by itself do not provide an explanation for the observed differences in the absolute magnitude of the CAR related to downgrades and upgrades. This is because, as explained in the related literature section, a downgrade from Aaa to Aa1 should have less information content than a downgrade from B3 to Caa1.

Given that the distributions of both prior ratings and the absolute magnitude of the rating changes are unequal for the datasets related to downgrades and upgrades, a final analysis is performed that controls for these distributional differences.

The results of this further analysis are provided in Table 22 and Table 23. Numerous CARs were calculated while controlling for the classification of the prior rating and when only including rating changes of one notch for both downgrades and upgrades.

Table 22: Absolute value Numberdowngrades/Numberupgardes variable = 1

Moody's Class	All Downgrades			All Upgrades		
	N	CAR	T-stat	N	CAR	T-stat
Upper	70	-0.792	-1.742	13	0.262	0.414
Middle	47	-1.316**	-2.187	32	-0.128	0.244
Lower	5	0.534	0.325	2	-3.050	-2.440

Note: ** denotes statistical significance at the 1% level.

Table 23: Absolute value uncontaminated Numberdowngrades/Numberupgardes variable = 1

Moody's Class	Uncontaminated Downgrades			Uncontaminated Upgrades		
	N	CAR	T-stat	N	CAR	T-stat
Upper	56	-0.547	-1.217	10	0.000	0.000
Middle	41	-0.851**	-2.099	30	-0.373	-1.313
Lower[9]	5	0.534	0.325	2	-3.050	-2.440

Note: ** denotes statistical significance at the 1% level.

When properly accounting for the prior rating as well as for the size of the rating change, the separate CAR calculations for upgrades reveal a remarkable pattern. For both samples related to upgrades, it is the case that the higher the prior rating, the more positive the CARs are. For both samples related to downgrades it is the case that the CARs are only significantly negative when the prior rating belongs to the Middle category. A plausible explanation for this is the fact that, as aforementioned in the related literature section, the effect of a rating change is typically stronger around the investment-grade boundary that lies within the Middle category. This explanation is supported by the estimation results of the multivariate cross-section regression analyses for both datasets related to downgrades, which show significantly negative coefficients on the LossInvGra variable. The overall tendency of the CARs presented

[9] For all four samples, the number of observations in the Lower, prior rating, category are limited.

in Table 22 and Table 23 is inconsistent with the empirical evidence by Jorion and Zhang (2007). Their findings namely show that the absence of an announcement effect for upgrades can be in large part explained by the non-linear dependence on the prior rating when controlled for the size of the rating change. Meaning, their findings show that, the lower the prior ratings, the more significant and the more negative (positive) the CARs are for downgrades (upgrades). Given the inconsistency between the results of this final analysis and the empirical evidence by Jorion and Zhang (2007), the results presented in Table 22 and Table 23 do not contribute in explaining the observed absolute differences in the CARs.

5.4 Multivariate Cross-section Regression Analyses Downgrades

5.4.1 All Downgrades

5.4.1.1 Descriptive Statistics

The descriptive statistics for the dependent variable and explanatory variables are reported in Table 25. The mean Abnormal Return on day 0 and day 1 is -0.336 percent. This mean Abnormal Return is equal to half of the mean CAR as reported in section 5.1.1. This is because, for the analysis in that section, the Abnormal Returns on day 0 and day 1 are first accumulated for each firm, then accumulated across all firms and finally divided by 285 (the number of observations). For the multivariate cross-section regression analyses however, the Abnormal Returns on day 0 and day 1 are kept separate, then accumulated in total and finally divided by 570 (number of observations*the two time series observations per data point). The mean of the Leverage variable is 1.71; this indicates that on average a firm has long-term debt outstanding equal to 1.71 times the value of its equity. The mean of Numberdowngrades is -0.76; this indicates that on average the Senior Unsecured Debt is downgraded 0.76 notches. This is because negative outlook changes (i.e. within-class rating changes) are classified as ‘0’ and occur relatively often. The mean of LossInvGra is 0.049; this indicates that almost one-twentieth (4.9 percent) of the sample is downgraded from investment grade to speculative grade. The mean of the control variable Investment is 0.884; this indicates that 88.4 percent of the sample is downgraded from a previous investment grade credit rating and that 11.6 percent is downgraded from a previous speculative grade credit rating. The mean of the Crisis control variable is 0.344; this indicates that approximately one-third (34.4 percent) of the sample is downgraded during either 2008 or 2009. The mean of each index control variables reported in Table 25 are important because they indirectly reveal the relative importance of each index included in the analysis. This is only indirectly the case because the coded values ranging from 0 to 5 were used to control for the respective index of an observation. As a result, the means of the index control variables add up to more than 1, which makes it difficult to understand the relative importance of each index. Table 24 displays the information required for the calculation of the relative importance of each index. The relative importance was calculated by using the coded value (0, 1, 2, 3, 4 or 5) of the control variables as well as their mean, which is reported in Table 25.

Table 24: Coding and proportion of the Index control variables

Index	Coded Value	Mean reported in Table 25	Proportion[a] in %
AEX	0		5.66[b]
FTSE	1	0.270	27.00
BEL	2	0.091	4.55
DAX	3	0.568	18.93
IBEX	4	0.800	20.00
CAC	5	1.193	23.86

[a] Calculated by (mean reported/coded value)*100.

[b] Calculated by using that the 'Proportion in %' column adds up to 100%.

For example, it can be concluded that of this sample of 570 observations 27.0 percent is related to firms of which the common stocks are traded at the British FTSE index.

Table 25: Descriptive Statistics All Downgrades		
Dependent Variable	**Mean**	**Standard Deviation**
Abnormal Return	-0.336	3.179
Explanatory Variable		
Leverage	1.707	1.601
Numberdowngrades	-0.761	0.799
LossInvGra	0.049	0.216
Investment	0.884	0.320
Crisis	0.344	0.475
FTSE_100	0.270	0.444
BEL_20	0.091	0.418
DAX_30	0.568	1.177
IBEX_35	0.800	1.601
CAC_40	1.193	2.133
The sample consists of 570 observations.		

5.4.1.2 Multivariate Cross-section Regression Analysis

The estimation results for the full model as well as for the model with the lowest Akaike Information Criterion (AIC) value, for the all downgrades dataset are presented in Table 26. The adjusted R^2s are 8.5 and 8.06 percent and the AIC values are 5.074 and 5.056, respectively. Both the full model and the model with the best fit are significant at the 1 percent level. The correlation table of all the independent and control variables does not provide an indication for multicollinearity between the explanatory variables. The leverage variable and the IBEX index variable show the highest correlation of 0.417. Therefore all explanatory variables can be used in the same regression without causing a spurious regression. The partial autocorrelation test on the Abnormal Return (dependent) variable shows no clear indication that it is autoregressive with a p-value of 0.193 (Q-Statistic). However, when including the 1-day lagged Abnormal Return variable, thereby creating a first order auto-regressive model, it is interesting to observe that the AbnormalReturn(-1) variable is almost significant at the 5 percent level in both estimated models. The p-values are 0.077 and 0.060, respectively. Finally, the AbnormalReturn(-1) variable is included because it substantially lowers the AIC values of both models. The interpretation of the coefficient is that a one percent negative Abnormal Return on day 0 will result in a 0.10 percent and 0.105 percent positive Abnormal Return on day 1 as estimated by the full and best fit model, respectively. The coefficient can thus be seen as the correlation coefficient between the Abnormal Returns of day 0 and day 1. Even given the insignificance of the coefficients, interpreting this negative correlation as a correction on the Abnormal Returns realized on day 0 as a result of the downgrade, should be done while keeping in mind that there is no certainty that the downgrade was announced before the end of the trading day on day 0. Therefore, the Abnormal Return on day 1 can as well be the first response of investors to the respective downgrade.

By including the 1-day lagged Abnormal Return variable in both models there is no autocorrelation in the error-terms. However, it is important to mention that the errors are also uncorrelated when the 1-day lagged Abnormal Return variable would not have been included. Furthermore, a scatterplot of the residuals of both models indicates that the residuals are homoskedastic. Lastly, both the full model and the best fit model have an error term of which the mean is close to zero with values of

1.26e-16 and -6.22e-16 respectively. Together with the assumption that both models estimate a correct and linear model, it can be concluded that the assumptions of the Gauss-Markov Theorem are satisfied and that therefore the Ordinary Least Squares (OLS) estimation method is the Best Linear Unbiased Estimator (BLUE).

The estimation results of the full model provide an indication that the Abnormal Return is positively related to the long-term debt-to-equity ratio. The insignificant coefficient at the 5 percent level on the Leverage variable is 0.179 (p-value 0.15). This indicates that the magnitude of the negative stock price response to Senior Unsecured Debt downgrades is greater for firms with less financial leverage. This research thus provides no empirical evidence that the more leveraged a firm is, the more its expected borrowing costs will increase due to the downgrade by Moody's. The sign of the coefficient as well as its insignificance are not consistent with the previously formulated expectation and empirical evidence by Kim and Nabar (2003).

The positive coefficient of the Numberdowngrades variable is consistent with the expectation that was substantiated in the related literature section. In the full model the coefficient is far from being significant at the 5 percent level (p-value = 0.55). The insignificance of the result for the Numberdowngrades variable is inconsistent with the empirical findings of Holthausen and Leftwich (1986). Their empirical results related to their contaminated downgrades dataset showed a strong marginal effect on abnormal performance per downgrade of one notch of -3.69 percent (t-statistic of -11.23). The difference in sign is explained by the different method followed to classify downgrades. This research namely used negative categories (0, -1 step, -2 steps, -3 steps, and -4 steps) while Holthausen and Leftwich (1986) used positive categories. The negative coefficient of the LossInvGra variable is also consistent with the expectation that was substantiated in the related literature section. In the full model the coefficient of -2.54 is significant at the 1 percent level (p-value = 0.004). When included in the best fit model the coefficient is even more negative namely, -2.83 and also significant at the 1 percent level (p-value = 0.001). Meaning that the marginal effects on abnormal performance as a result of a revision from investment grade to speculative grade are -2.54 percent and -2.83 percent respectively. Both the sign of the coefficient and its significance are consistent with the empirical findings of Jorion, Liu, and Shi (2005). However, the marginal effects as estimated by this

research are substantially larger than the marginal effect of -0.48 percent (t-statistic of -3.32, significant at the 1 percent level in a two-tailed test) as found by Jorion, Liu, and Shi (2005). These empirical findings for the all downgrades dataset are thus consistent with the notion that markets pay more attention to rating changes around the investment-grade boundary.
The positive coefficient on the Investment variable shows that the marginal effect on abnormal performance is less negative for Senior Unsecured Debt that had an investment grade rating before the downgrade compared with Senior Unsecured Debt that had a speculative grade rating. In the full model the coefficient of 1.89 is significant at the 1 percent level (p-value = 0.001). When included in the best fit model the coefficient is more positive, namely 2.04 and also significant at the 1 percent level (p-value = 0.000). It can thus be concluded that the Senior Unsecured Debt that previously had a speculative grade rating experienced significantly more negative (-1.89 and -2.04 percent) Abnormal Returns. These findings are consistent with the empirical findings of Jorion and Zhang (2007) that show that lower prior ratings are significantly associated with larger negative Abnormal Returns for downgrades.

The negative coefficient of the crisis variable is consistent with the empirical evidence by Miao, Ramchander and Wang (2014) and with the expectation that was substantiated in the related literature section. In the full model the coefficient is not far from being significant at the 5 percent level (p-value = 0.14). Additionally, in the best fit model the coefficient is also not far from being significant at the 5 percent level (p-value = 0.15). Despite its insignificance the crisis variable is included in the best fit model because it lowered the value of the AIC.

The results of the variables that control for the indices are insignificant, except for the FTSE variable with a coefficient of 1.70 that is significant at the 5 percent level (p-value = 0.04). Meaning that when the Senior Unsecured Debt of a firm of which the common stocks are listed on the FTSE index is downgraded, the return is 1.70 percent more positive (or less negative) relative to the base scenario. Furthermore, all the coefficients of the index control variables are positive meaning that relative to the base scenario, which is that the common stocks are listed on the Dutch AEX index, the Abnormal Returns are less negative.

Table 26: Factors associated with the stock price response to bond rating downgrades			
Model 1 (all independent and control variables): Abnormal $Return_{it} = \beta_1 + \beta_2 AbnormalReturn(-1)_{2it} + \beta_3 Leverage_{3it} + \beta_4 Numberdowngrades_{4it} + \beta_5 LossInvGra_{5it} + \beta_6 Investment_{6it} + \beta_7 Crisis_{7it} + \beta_8 FTSE_{8it} + \beta_9 BEL_{9it} + \beta_{10} DAX_{10it} + \beta_{11} IBEX_{11it} + \beta_{12} CAC_{12it} + e_{it}$			
Model 2 (lowest value Aikaike Information Criterion): Abnormal $Return_{it} = \beta_1 + \beta_2 AbnormalReturn(-1)_{2it} + \beta_3 LossInvGra_{3it} + \beta_4 Investment_{4it} + \beta_5 Crisis_{5it} + e_{it}$			
		Full model	**Best fit model**
Variable	**Predicted Sign**	**Coefficient (T-statistic)**	**Coefficient (T-statistic)**
Intercept	+/-	-2.729** (-2.805)	-1.641** (-3.050)
AbnormalReturn(-1)	+/-	-0.100 (-1.773)	-0.105 (-1.886)
Leverage	-	0.179 (1.427)	
Numberdowngrades	+	0.1413 (0.603)	
LossInvGra	-	-2.543** (-2.941)	-2.828** (-3.419)
Investment	+	1.888** (3.277)	2.042** (3.658)
Crisis	-	-0.570 (-1.494)	-0.538 (-1.430)
FTSE_100	+/-	1.703* (2.062)	
BEL_20	+/-	0.509 (0.909)	
DAX_30	+/-	0.247 (0.855)	
IBEX_35	+/-	0.135 (0.614)	
CAC_40	+/-	0.227 (1.350)	

The signs '**' and '*' indicate significance at the 0.01 and 0.05 level (two-tailed) respectively.
Model 1: The sample consists of 285 observations, because the 285 observations related to day 0 are used to estimate the 1-day lagged Abnormal Return variable. The adjusted R^2 of the regression is 8.5 percent. The ANOVA F-statistic is 3.405, which means that the tested regression is significant at the 1% level. The dependent variable is the day 0 and day 1 Abnormal Return. The value of the Akaike Information Criterion is 5.074.
Model 2: The sample again consists of 285 observations. The adjusted R^2 of the regression is 8.06 percent. The ANOVA F-statistic is 7.223, which means that the tested regression is significant at the 1% level. The dependent variable is the day 0 and day 1 Abnormal Return. The value of the Akaike Information Criterion is 5.056.

5.4.2 Uncontaminated Downgrades

5.4.2.1 Descriptive Statistics

The descriptive statistics for the dependent variable and independent variables are reported in Table 27. The mean Abnormal Return on day 0 and day 1 is -0.334 percent. This mean is equal to half of the mean CAR of the uncontaminated downgrades dataset. The mean of the Leverage variable is 1.77. The mean of the Numberdowngrades variable is 0.82. The mean of the LossInvGra variable is 0.054, which indicates that 5.4 percent of the sample is downgraded from investment grade to speculative grade. The means for the control variables Investment and Crisis are 0.882 and 0.348, respectively. Similar, as for the all downgrades dataset the mean of each index control variable, reported in Table 27, indirectly reveals the relative importance of each index included in the analysis.

Table 27: Descriptive Statistics Uncontaminated Downgrades		
Dependent Variable	**Mean**	**Standard Deviation**
Abnormal Return	-0.334	2.650
Explanatory Variable		
Leverage	1.771	1.641
Numberdowngrades	-0.819	0.816
LossInvGra	0.054	0.227
Investment	0.882	0.322
Crisis	0.348	0.477
FTSE_100	0.262	0.440
BEL_20	0.010	0.435
DAX_30	0.597	1.199
IBEX_35	0.889	1.663
CAC_40	1.041	2.032
The sample consists of 442 observations.		

5.4.2.2 Multivariate Cross-section Regression Analysis

The estimation results for the full model as well as for the model with the lowest Akaike Information Criterion (AIC) value, for the uncontaminated downgrades dataset are presented in Table 28. The adjusted R^2s are 3.8 and 4.2 percent and the AIC values are 4.773 and 4.756, respectively. Both the full model and the model with the best fit are significant at the 1 percent level. The correlation table of all the independent and control variables does not provide an indication for multicollinearity between the explanatory variables. The Leverage variable and the IBEX index variable show the highest correlation of 0.406. Therefore all explanatory variables can be used in the same regression without causing a spurious regression. The partial autocorrelation test on the Abnormal Return (dependent) variable shows no indication that it is autoregressive with a p-value of 0.719 (Q-Statistic).

The Durbin-Watson statistic provides no evidence for autocorrelation in the error-terms with a value of 2.19 and 2.17 for the full and best fit model, respectively.[10] Furthermore, a scatterplot of the residuals of both models indicates that the residuals are homoskedastic. Lastly, both the full model and the best fit model have an error term of which the mean is close to zero with values of 1.10e-16 and 3.66e-16, respectively. Together with the assumption that both models estimate a correct and linear model, it can be concluded that the assumptions of the Gauss-Markov Theorem are satisfied and that therefore the Ordinary Least Squares (OLS) estimation method is the Best Linear Unbiased Estimator (BLUE).

The estimation results of the full multivariate cross-section regression analysis show that the Abnormal Return is significantly positive related to the long-term debt-to-equity ratio. The coefficient on the Leverage variable is 0.188 (p-value = 0.026). This indicates that the Abnormal Returns as a result of a downgrade are more negative for firms with less financial leverage. The estimation results of the best-fit model show a comparable outcome. The coefficient on the Leverage variable of the best fit model is 0.149, however, it is just insignificant at the 5 percent level (p-value = 0.051). This sample of uncontaminated downgrades thus also provides no empirical evidence for a negative correlation between a firm's leverage and the expected increase in borrowing costs due to a downgrade by Moody's. The results for both models are not consistent with the previously formulated expectation and empirical evidence by Kim and Nabar (2003).

The positive coefficient of the Numberdowngrades variable is consistent with the expectation that was substantiated in the related literature section. Furthermore, the insignificance of the result for the Numberdowngrades variable is consistent with the empirical findings of Holthausen and Leftwich (1986). The negative coefficient of the LossInvGra variable is also consistent with the expectation that was substantiated in the related literature section. In the full model the coefficient of -1.173 is significant at the 5 percent level (p-value = 0.043). When included in the best fit model the coefficient is more negative namely, -1.440 and significant at the 1 percent level (p-

[10] As a rule of thumb, when the Durbin-Watson statistic is larger than 2, there is no evidence for autocorrelation in the error-terms.

value = 0.009). The coefficient on the LossInvGra variable in both the full and the best fit model indicates the marginal effects on abnormal performance of a revision from investment grade to speculative grade. Furthermore, the significance of the result for the LossInvGra variable is consistent with the empirical findings of both Jorion, Liu, and Shi (2005), and; Holthausen and Leftwich (1986).

The positive coefficient on the Investment variable shows that the marginal effect on abnormal performance is less negative for Senior Unsecured Debt that had an investment grade rating before the downgrade compared with Senior Unsecured Debt that had a speculative grade rating. In the full model the coefficient of 0.931 is significant at the 5 percent level (p-value = 0.021). When included in the best fit model the coefficient is more positive namely, 0.990 and also significant at the 5 percent level (p-value = 0.011). It can thus be concluded that Senior Unsecured Debt that previously had a speculative grade rating experienced significantly more negative (-0.93 and -0.99 percent) Abnormal Returns. These findings are again consistent with the empirical findings of Jorion and Zhang (2007) that show that lower prior ratings are significantly associated with larger negative Abnormal Returns for downgrades.

The negative coefficient of the crisis variable is again consistent with the empirical evidence by Miao, Ramchander and Wang (2014) and with the expectation that was substantiated in the related literature section. As aforementioned their findings indicate that the negative price reactions to downgrades are more pronounced during the financial crisis when compared with their overall sample. In the full model the coefficient of -0.714 is significant at the 1 percent level (p-value = 0.007). Furthermore, in the best fit model the coefficient of -0.661 is significant at the 5 percent level (p-value = 0.011). These results indicate that the Abnormal Return as a result of a downgrade that occurred during either 2008 or 2009 is approximately 0.7 percent more negative compared with Abnormal Returns during the other years included in the sample.

The results for the variables that control for the indices are insignificant. Furthermore, all the coefficients of the index control variables, except the coefficient of the Spanish IBEX index, are positive meaning that relative to the base scenario (Dutch AEX index), the Abnormal Returns are less negative.

Table 28: Factors associated with the stock price response to bond rating downgrades			
Model 1 (all independent and control variables): Abnormal $Return_{it} = \beta_1 + \beta_2 Leverage_{2it} + \beta_3 Numberdowngrades_{3it} + \beta_4 LossInvGra_{4it} + \beta_5 Investment_{5it} + \beta_6 Crisis_{6it} + \beta_7 FTSE_{7it} + \beta_8 BEL_{8it} + \beta_9 DAX_{9it} + \beta_{10} IBEX_{10it} + \beta_{11} CAC_{11it} + e_{it}$			
Model 2 (lowest value Aikaike Information Criterion): Abnormal $Return_{it} = \beta_1 + \beta_2 Leverage_{2it} + \beta_3 LossInvGra_{3it} + \beta_4 Investment_{4it} + \beta_5 Crisis_{5it} + e_{it}$			
		Full model	**Best fit model**
Variable	**Predicted Sign**	**Coefficient (T-statistic)**	**Coefficient (T-statistic)**
Intercept	+/-	-1.185 (-1.766)	-1.163** (-3.073)
Leverage	-	0.188* (2.242)	0.149 (1.959)
Numberdowngrades	+	0.211 (1.325)	
LossInvGra	-	-1.173* (-2.030)	-1.440** (-2.630)
Investment	+	0.931* (2.309)	0.990* (2.550)
Crisis	-	-0.714** (-2.697)	-0.661* (-2.552)
FTSE_100	+/-	0.405 (0.717)	
BEL_20	+/-	0.081 (0.214)	
DAX_30	+/-	0.106 (0.535)	
IBEX_35	+/-	-0.022 (-0.147)	
CAC_40	+/-	0.022 (0.190)	

The signs '**' and '*' indicate significance at the 0.01 and 0.05 level (two-tailed) respectively.
Model 1: The sample consists of 442 observations. The adjusted R^2 for the regression is 3.8 percent. The ANOVA F-statistic is 2.727, which means that the tested regression is significant at the 1% level. The dependent variable is the day 0 and day 1 Abnormal Return. The value of the Akaike Information Criterion is 4.773.
Model 2: The sample consists of 442 observations. The adjusted R^2 for the regression is 4.2 percent. The ANOVA F-statistic is 5.807, which means that the tested regression is significant at the 1% level. The dependent variable is the day 0 and day 1 Abnormal Return. The value of the Akaike Information Criterion is 4.756.

5.5 Multivariate Cross-section Regression Analyses Upgrades

5.5.1 All Upgrades

5.5.1.1 Descriptive Statistics

The descriptive statistics for the dependent variable and explanatory variables are reported in Table 29. The mean Abnormal Return on day 0 and day 1 is 0.055 percent. This mean is equal to half of the mean CAR of the all upgrades dataset. The mean of the variable Leverage ratio is 1.55. The mean of the Numberupgrades variable is 0.70, which indicates that on average the Senior Unsecured Debt is upgraded 0.70 notches.

This is possible because positive outlook changes (i.e. within-class rating changes) are classified as ‘0’. The mean of the GainInvGra variable is 0.07, which indicates that 7 percent of the sample is upgraded from speculative grade to investment grade. The means of the control variables Investment and Crisis are 0.778 and 0.156, respectively. The mean of each index control variable, reported in Table 29, again indirectly reveals the relative importance of each index included in the analysis.

Table 29: Descriptive Statistics All Upgrades		
Dependent Variable	**Mean**	**Standard Deviation**
Abnormal Return	0.055	1.749
Explanatory Variable		
Leverage	1.547	1.474
Numberupgrades	0.700	0.676
GainInvGra	0.067	0.250
Investment	0.778	0.417
Crisis	0.156	0.363
FTSE_100	0.311	0.464
BEL_20	0.067	0.360
DAX_30	0.700	1.272
IBEX_35	0.711	1.534
CAC_40	0.722	1.763
The sample consists of 180 observations.		

5.5.1.2 Multivariate Cross-section Regression Analysis

The estimation results for the full model as well as for the model with the lowest Akaike Information Criterion (AIC) value, for the all upgrades dataset are presented in Table 30. The adjusted R^2s are 2.8 and 5.3 percent and the AIC values are 3.976 and 3.917 respectively. It should be noted that the full model is not significant at the 5 percent level (p-value = 0.116) as a result, only the significant coefficients are interpreted. The best fit model is significant at the 1 percent level (p-value = 0.003). The correlation table of all the independent and control variables does provide an indication for multicollinearity between some of the explanatory variables. The Investment variable and the GainInvGra variable show the highest correlation of -0.500. In relation to the correlation between the Investment and GainInvGra variables, Jorion and Zhang (2007) show that accounting for the prior rating crucial. In addition, the Leverage variable and the IBEX index variable show a correlation of 0.496. Therefore, the Investment and the GainInvGra variables as well as the Leverage and IBEX index variables cannot be used in the same regression without possibly causing a spurious regression. Separate regressions are estimated in order to determine which explanatory variables are excluded from the analysis. The explanatory variable included in the regression with the highest adjusted R^2 is used as one of the explanatory variables in the final model. First, separate regressions with either the Investment or GainInvGra variable are estimated. The separate regression, in which the Investment variable is included, has the highest adjusted R^2 of the two and thus the GainInvGra variable is excluded. Second, separate regressions with either the Leverage or IBEX variable are estimated. The separate regression, in which the Leverage variable is included, has the highest adjusted R^2 of the two and thus the IBEX variable is excluded. The partial autocorrelation test on the Abnormal Return (dependent) variable shows no indication that it is autoregressive with a p-value of 0.536 (Q-Statistic).

The Durbin-Watson statistic provides no evidence for autocorrelation in the error-terms with a value of 2.32 and 2.31 for the full and best fit model, respectively. Furthermore, a scatterplot of the residuals of both models indicates that the residuals are homoskedastic. Lastly, both the full model and the best fit model have an error term of which the mean is close to zero with values of 1.31e-16 and 5.64e-17, respectively. Together with the assumption that both models estimate a correct and linear model, it can be concluded that the assumptions of the Gauss-Markov Theorem are satisfied and that therefore the Ordinary Least Squares (OLS) estimation method is the Best Linear Unbiased Estimator (BLUE).

The estimation results of the full multivariate cross-section regression show that the Abnormal Return is significantly negative related to the long-term debt-to-equity ratio. The coefficient on the Leverage variable is -0.280 (p-value = 0.005). The estimation results of the best fit model show a similar outcome with a coefficient on the Leverage variable of -0.259 (p-value = 0.003). This indicates that the Abnormal Returns as a result of an upgrade are more positive for firms with less financial leverage. As a result, there is no empirical evidence that the more leveraged a firm is, the more its expected borrowing costs will decrease due to an upgrade by Moody's. These results for both models are not consistent with the previously formulated expectation.

The positive coefficient on the Investment variable shows that the marginal effect on abnormal performance is more positive for Senior Unsecured Debt that had an investment grade rating before the upgrade compared with Senior Unsecured Debt that had a speculative grade rating. In the full model the coefficient of 0.669 is significant at the 5 percent level (p-value = 0.042). When included in the best fit model the coefficient is more positive namely, 0.628 and also significant at the 5 percent level (p-value = 0.042). It can thus be concluded that Senior Unsecured Debt that previously had a speculative grade rating experienced significantly less positive (-0.669 and -0.628 percent) Abnormal Returns. These findings are inconsistent with the empirical findings by Jorion and Zhang (2007) that show that lower prior ratings are significantly associated with larger positive Abnormal Returns for upgrades. As a result, the findings thus contradict the reasoning that a relatively large decrease in the estimated probability of default is expected to result in a relatively large positive Abnormal Return.

The Numberupgrades and Crisis variables are not significant when included in the insignificant full model and therefore not interpreted.

The coefficients of the index dummies included in the full model are also insignificant. However, it should be noted that, as a result of the exclusion of the IBEX index dummy, the base scenario now consists of both the Dutch and Spanish observations, instead of only the Dutch observations.

Table 30: Factors associated with the stock price response to bond rating upgrades **Model 1 (all independent and control variables except GainInvGra and IBEX):** Abnormal Return$_{it}$ = $\beta_1 + \beta_2$Leverage$_{2it}$ + β_3Numberupgrades$_{3it}$ + β_4Investment$_{4it}$ + β_5Crisis$_{5it}$ + β_6FTSE$_{6it}$ + β_7BEL$_{7it}$ + β_8DAX$_{8it}$ + β_9CAC$_{9it}$ + e_{it} **Model 2 (lowest value Aikaike Information Criterion):** Abnormal Return$_{it}$ = $\beta_1 + \beta_2$Leverage$_{2it}$ + β_3Investment$_{3it}$ + e_{it}			
		Full model	**Best fit model**
Variable	**Predicted Sign**	**Coefficient (T-statistic)**	**Coefficient (T-statistic)**
Intercept	+/-	-0.040 (-0.097)	-0.034 (-0.116)
Leverage	+	-0.280** (-2.835)	-0.259** (-2.988)
Numberupgrades	+	0.097 (0.426)	
Investment	-	0.669* (2.054)	0.628* (2.053)
Crisis	+	0.032 (0.087)	
FTSE_100	+/-	-0.031 (-0.081)	
BEL_20	+/-	0.066 (0.160)	
DAX_30	+/-	-0.006 (-0.045)	
CAC_40	+/-	-0.077 (-0.817)	
The signs '**' and '*' indicate significance at the 0.01 and 0.05 level (two-tailed) respectively. Model 1: The sample consists of 180 observations. The adjusted R^2 for the regression is 2.8 percent. The ANOVA F-statistic is 1.643, which means that the tested regression is insignificant at the 5% level. The dependent variable is the day 0 and day 1 Abnormal Return. The value of the Akaike Information Criterion is 3.976. Model 2: The sample consists of 180 observations. The adjusted R^2 for the regression is 5.3 percent. The ANOVA F-statistic is 6.104, which means that the tested regression is significant at the 1% level. The dependent variable is the day 0 and day 1 Abnormal Return. The value of the Akaike Information Criterion is 3.917.			

5.5.2 Uncontaminated Upgrades

5.5.2.1 Descriptive Statistics

The descriptive statistics for the dependent variable and explanatory variables are reported in Table 31. The mean Abnormal Return on day 0 and day 1 is -0.017 percent. This mean is equal to half of the mean CAR of the uncontaminated upgrades dataset. The mean of the Leverage variable ratio is 1.59. The mean of the Numberupgrades variable is 0.74. The mean of the GainInvGra variable is 0.08. The means of the control variables Investment and Crisis are 0.757 and 0.162, respectively. The mean of each index control variable, reported in Table 31, again indirectly reveals the relative importance of each index included in the analysis.

Table 31: Descriptive Statistics Uncontaminated Upgrades		
Dependent Variable	**Mean**	**Standard Deviation**
Abnormal Return	-0.017	1.748
Explanatory Variable		
Leverage	1.586	1.535
Numberupgrades	0.743	0.640
GainInvGra	0.081	0.274
Investment	0.757	0.430
Crisis	0.162	0.369
FTSE_100	0.297	0.459
BEL_20	0.054	0.325
DAX_30	0.770	1.315
IBEX_35	0.703	1.527
CAC_40	0.676	1.715
The sample consists of 148 observations.		

5.5.2.2 Multivariate Cross-section Regression Analysis

The estimation results for the full model as well as for the model with the lowest Akaike Information Criterion (AIC) value, for the uncontaminated upgrades dataset are presented in Table 32. The adjusted R^2s are 0.2 and 3.3 percent and the AIC values are 4.018 and 3.942 respectively. It should be noted that the full model is not significant at the 5 percent level (p-value = 0.422) as a result, only the significant coefficients are interpreted. The best fit model is significant at the 5 percent level (p-value = 0.033). The correlation table of all the independent and control variables does provide an indication for multicollinearity between two of the explanatory variables. The Investment variable and the GainInvGra variable show a correlation of -0.524. Therefore, the Investment and the GainInvGra variables cannot be used in the same regression without possibly causing a spurious regression. Again separate regressions are estimated with either the Investment or GainInvGra variable in order to determine which explanatory variable is excluded from the analysis. The separate regression, in which the Investment variable is included, has the highest adjusted R^2 of the two and thus the GainInvGra variable is excluded. The partial autocorrelation test on the Abnormal Return (dependent) variable shows no indication that it is autoregressive with a p-value of 0.333 (Q-Statistic).

The Durbin-Watson statistic provides no evidence for autocorrelation in the error-terms with a value of 2.44 and 2.39 for the full and best fit model, respectively. Furthermore, a scatterplot of the residuals of both models indicates that the residuals are homoskedastic. Lastly, both the full model and the best fit model have an error term of which the mean is close to zero with values of -4.61e-17 and -7.39e-17, respectively. Together with the assumption that both models estimate a correct and linear model, it can be concluded that the assumptions of the Gauss-Markov Theorem are satisfied and that therefore the Ordinary Least Squares (OLS) estimation method is the Best Linear Unbiased Estimator (BLUE).

The estimation results of the full multivariate cross-section regression show that the Abnormal Return is significantly negative related to the long-term debt-to-equity ratio. The coefficient on the Leverage variable is -0.262 (p-value = 0.021). The estimation results of the best fit model show a similar outcome with a coefficient on the Leverage variable of -0.216 (p-value = 0.022). As a result, there is no empirical evidence that the more leveraged a firm is, the more its expected borrowing costs will decrease due to the upgrade by Moody's. This is not consistent with the previously formulated expectation.

The positive coefficient of the Investment variable provides an indication that the marginal effect on abnormal performance is more positive for Senior Unsecured Debt that had an investment grade rating before the upgrade compared with Senior Unsecured Debt that had a speculative grade rating. However, the coefficient on the Investment variable is insignificant at the 5 percent level in both the full model (p-value = 0.134) and the best fit model (p-value = 0.125). The positive coefficient is inconsistent with the empirical findings by Jorion and Zhang (2007) that show that lower prior ratings are significantly associated with larger positive Abnormal Returns for upgrades. As a result, this finding thus contradicts the reasoning that a relatively large decrease in the estimated probability of default is expected to result in a relatively large positive Abnormal Return.

The Numberupgrades, Crisis and Index dummy variables are not significant when included in the insignificant full model and therefore not interpreted.

Table 32: Factors associated with the stock price response to bond rating upgrades **Model 1 (all independent and control variables except GainInvGra):** Abnormal $Return_{it} = \beta_1 + \beta_2 Leverage_{2it} + \beta_3 Numberupgrades_{3it} + \beta_4 Investment_{4it} + \beta_5 Crisis_{5it} + \beta_6 FTSE_{6it} + \beta_7 BEL_{7it} + \beta_8 DAX_{8it} + \beta_9 IBEX_{9it} + \beta_{10} CAC_{10it} + e_{it}$ **Model 2 (lowest value Aikaike Information Criterion):** Abnormal $Return_{it} = \beta_1 + \beta_2 Leverage_{2it} + \beta_3 Investment_{3it} + e_{it}$			
		Full model	**Best fit model**
Variable	**Predicted Sign**	**Coefficient (T-statistic)**	**Coefficient (T-statistic)**
Intercept	+/-	0.043 (0.081)	-0.063 (-0.204)
Leverage	+	-0.262* (-2.344)	-0.216* (-2.317)
Numberupgrades	+	-0.021 (-0.079)	
Investment	-	0.538 (1.509)	0.513 (1.544)
Crisis	+	-0.033 (-0.079)	
FTSE_100	+/-	0.005 (0.010)	
BEL_20	+/-	-0.034 (-0.068)	
DAX_30	+/-	0.011 (0.060)	
IBEX_35	+/-	0.056 (0.373)	
CAC_40	+/-	-0.117 (-0.964)	

The signs '**' and '*' indicate significance at the 0.01 and 0.05 level (two-tailed) respectively.
Model 1: The sample consists of 148 observations. The adjusted R^2 for the regression is 0.2 percent. The ANOVA F-statistic is 1.027, which means that the tested regression is insignificant at the 5% level. The dependent variable is the day 0 and day 1 Abnormal Return. The value of the Akaike Information Criterion is 4.018.
Model 2: The sample consists of 148 observations. The adjusted R^2 for the regression is 3.3 percent. The ANOVA F-statistic is 3.487, which means that the tested regression is significant at the 5% level. The dependent variable is the day 0 and day 1 Abnormal Return. The value of the Akaike Information Criterion is 3.942.

Chapter 6: Conclusion

The empirical findings provide evidence for significantly negative two-day CARs associated with rating downgrades by Moody's related to Senior Unsecured Debt. The findings thus allow to conclude, with respect to sub-question 1.1, that there are significantly negative cumulative abnormal common stock returns associated with rating downgrades by Moody's related to Senior Unsecured Debt. The mean CARs of the all downgrades and uncontaminated downgrades datasets are -0.671 and -0.667

percent, respectively. Both CARs are significantly different from zero at the 1 percent level. Meaning that on average when Moody's announces a downgrade related to Senior Unsecured Debt the expected CAR is -0.67 percent. The findings related to downgrades provide evidence for the view that rating agencies are information specialists that often have access to private information for the rating review process.

However, the empirical findings on the other hand do not provide evidence for significantly positive two-day CARs associated with rating upgrades by Moody's. As a result, it is concluded, with respect to sub-question 1.2, that there are no significantly positive cumulative abnormal common stock returns associated with rating upgrades by Moody's related to Senior Unsecured Debt. The mean CARs of the all upgrades and uncontaminated upgrades datasets are 0.110 and -0.035 percent, respectively. Both CARs are insignificantly different from zero at the 5 percent level.

The independent samples t-test performed provides evidence of a significant absolute difference in the size of the capital market reactions related to the uncontaminated downgrades and upgrades datasets, at the 5 percent level. With respect to sub-question 1.3, it is concluded that the absolute cumulative abnormal common stock returns are significantly larger after a rating downgrade compared with a rating upgrade.

The multivariate cross-section regression analyses performed for the full and uncontaminated downgrades datasets reveal several explanatory variables that significantly explain part of the variance in the dependent variable, Abnormal Return. With respect to sub-question 2.1 it is concluded, for the best fit model of the full downgrades dataset, that the LossInvGra, Investment and FTSE index control variables significantly explain part of the variance in the Abnormal Return. The significant LossInvGra variable provides evidence for the notion that markets pay more attention to rating changes around the investment-grade boundary. As a result, those downgrades are associated with larger negative Abnormal Returns. The significant Investment variable shows that lower prior ratings are significantly associated with larger negative Abnormal Returns for downgrades. The significant FTSE variable implies that when the Senior Unsecured Debt of a firm of which the common stocks are listed on the FTSE index is downgraded, the Abnormal Return is less negative compared with the scenario in which the common stocks are listed on the AEX index.

In addition, for the best fit model of the uncontaminated downgrades dataset it is concluded that the LossInvGra, Investment and Crisis control variables significantly explain part of the variance in the Abnormal Return. Thus, compared with the best fit model of the full downgrades dataset, evidence is provided for the significance of the coefficient on the Crisis control variable. This significant Crisis variable shows that the negative price reactions to downgrades were more pronounced during the financial crisis when compared with the negative Abnormal Returns during the other years included in the sample.
The multivariate cross-section regression analyses performed for the full and uncontaminated upgrades datasets also reveal several explanatory variables that significantly explain part of the variance in the dependent variable, Abnormal Return. With respect to sub-question 2.1 it is concluded, for the best fit model of the full upgrades dataset, that the Leverage and Investment variables significantly explain part of the variance in the Abnormal Return. The significant Leverage variable indicates that the Abnormal Return as a result of an upgrade is more positive for firms with less financial leverage. As a result, there is no empirical evidence for the inference that the more leveraged a firm is, the more its expected borrowing costs will decrease due to an upgrade by Moody's. The significant Investment variable provides evidence for the claim that the Abnormal Return is more positive for upgrades related to Senior Unsecured Debt that previously had an investment grade rating. This finding contradicts the reasoning that a relatively large decrease in the estimated probability of default results in a relatively large positive Abnormal Return. It should be noted that for the datasets related to downgrades, evidence was found that supports the reasoning that a relatively large increase in the estimated probability of default results in a relatively large negative Abnormal Return. In addition, for the best fit model of the uncontaminated upgrades dataset it is concluded that only the Leverage variable significantly explains part of the variance in the Abnormal Return. The significant Leverage variable again indicates that the Abnormal Return as a result of an upgrade is more positive for firms with less financial leverage.

Having answered all five sub-questions, the only question that remains to be answered is the research question: are the cumulative abnormal returns of European common stocks after a negative bond credit rating change significantly higher in comparison with the cumulative abnormal returns after a positive bond credit rating change?

As aforementioned, the independent samples t-test performed to answer sub-question 1.3 provides evidence of a significant absolute difference of 0.632 percent in the size of the CARs between the uncontaminated downgrades and upgrades datasets at the 5 percent level (Sig. (1-tailed) p-value = 0.042). This result supports the reasoning that Moody's conveys relatively more private information about a firm through a rating downgrade compared with a rating upgrade. Three partial explanations for the observed absolute differences in the CARs are provided. First, the absolute difference in the magnitude of the CARs can be a result of the fact that ratings are on average downgraded more notches than upgrades. Second, the existence of a bias towards negative information content for credit rating changes can cause the absolute difference in the magnitude of the CARs. A last partial explanation is the fact that the high reputational cost related to failing to detect looming credit problems for credit rating agencies could provide them with an incentive to expend more resources in detecting deterioration in credit quality rather than improvements. On the contrary, the inconsistent results of the multivariate cross-section regression analyses related to the Investment control variable are highly relevant for the non-linearity analysis. Recall that the Investment control variable is included in all four best fit models. The coefficient on the Investment variable is significantly positive in the full downgrades, uncontaminated downgrades and full upgrades best fit models and its coefficient is insignificantly positive in the uncontaminated upgrades best fit model. For the samples related to upgrades, the positive coefficients on the Investment variables together with the knowledge that the prior ratings of the observations included in the samples are more skewed towards a greater proportion of firms with a relatively low prior credit rating, imply a relatively weak prior rating effect on the Abnormal Returns. For the samples related to downgrades, the positive coefficients on the Investment variables together with the knowledge that the prior ratings of the observations included in the samples are more skewed towards a greater proportion of firms with a relatively high prior credit rating, also imply a relatively weak prior rating effect on the Abnormal Returns. As a result, it can be concluded that the inconsistent effect of the prior rating on the Abnormal Returns together with the distribution of the prior ratings, provides an implausible explanation for the fact that the absolute CARs are significantly larger after a rating downgrade compared with a rating upgrade.

The main finding of this research is that the absolute cumulative abnormal returns of European common stocks after a negative bond credit rating change are 0.632 percent larger than the absolute cumulative abnormal returns after a positive bond credit rating change. Given that this study has focused on rating changes related to Senior Unsecured Debt of firms of which the common stocks are listed on either the FTSE 100, AEX 25, BEL 20, DAX 30, IBEX 35 or CAC 40 index during the examination period from 2007-2013 it can be concluded that this main finding is generalizable across Europe. In relation to the generalizability of this result it should also be noted that the results are in line with empirical evidence of studies that focused on the US equity markets.

The added value of this research lies mainly within its focus on credit rating changes related to firms listed on some of the most important European equity indices as well as its recent examination period from 2007-2013. It is novel that such an elaborate analysis is performed on the non-linearity in the effect of a credit rating change on common stock returns for European data. In addition, some innovative explanatory variables were included in the multivariate cross-section regression analyses performed to analyze the nature of the variance of the dependent variable, Abnormal Return. These innovative explanatory variables are the Crisis dummy variable that controls for the financial crisis, which occurred during 2008 and 2009, and; the Investment dummy variable that controls for the rating category to which the old credit rating belonged. The innovative explanatory variables provided interesting results when included in the regression analysis related to the uncontaminated downgrades dataset. The significant Crisis variable showed that the negative price reactions to downgrades were more pronounced (-0.66 percent) during the financial crisis when compared with the negative Abnormal Returns during the other years included in the sample. In addition, the significant Investment variable showed that lower prior ratings are significantly associated with larger negative Abnormal Returns (-0.99 percent) for downgrades. However, when both variables were included in the regression analysis related to the uncontaminated upgrades dataset, the coefficients were insignificant.

Chapter 7: Recommendations for Further Research

Further research concerning rating changes related to debt of firms of which the common stocks are listed on European indices is needed in two directions. First, similar to the method followed by Hand, Holthausen and Leftwich (1992) an expectations model for bond rating agency announcements should be developed and tested. For example, the expectation of a bond rating change can be measured by comparing the yield-to-maturity on a bond of interest, estimated just prior to the rating change, with the yield-to-maturity of a benchmark (the yield-to-maturity of other bonds with the same rating). Second, it should be examined whether a distinction exists in the CARs as a result of downgrades due to changes in a firm's leverage and as a result of downgrades associated with deteriorating financial prospects. While a downgrade is clearly bad news for bondholders it is not necessarily bad news for stockholders. For example, if a bond is downgraded because of a foreseen increase in leverage this will transfer wealth from bondholders to stockholders. As a result, bond prices should fall but equity prices should rise. However, as aforementioned, this study follows the classical approach to a firm's capital structure that is described by the Merton (1974) model that assumes that bond returns and common stock returns will move in the same direction. Meaning that it abstracts from redistribution of wealth between firm claimants, which might not be a robust assumption. Instead, when measuring and comparing the informational content as a result of the different causes for the credit rating changes it seems intuitive to use bond returns instead of common stock returns as the appropriate measurement tool.

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