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The Impact of Credit Rating Changes

An Empirical Study of the Stock Market Reaction to Credit Rating Change Announcements in the European Insurance Market

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Abstract

This thesis investigates the effect of credit rating change announcements on stock returns. Most of the previous literature on the topic studies the effect in the US market, as well as including a broad-based sample with regards to industries. This thesis adds to the existing literature by researching the stock effect on European insurance companies. The insurance industry was specifically chosen due to its presumed higher sensitivity to rating changes. The event study methodology, as described by MacKinlay (1997), was used to investigate the topic. Rating change announcements from S&P, Moody's, and Fitch are analysed from 2009 to 2021.

The general findings from the study are that rating downgrades lead to a significantly negative stock price reaction, while upgrades lead to a less significant positive reaction. The results also indicate that the impact of rating announcements varies somewhat, depending on the rating agency giving the rating. Rating downgrades from S&P seem to yield a significantly stronger reaction than the two other rating agencies. In addition to this, the results suggest that rating downgrades over multiple levels cause a stronger market reaction than rating changes over one level. Furthermore, rating upgrades moving a credit rating from speculative grade to investment grade show a significantly stronger market reaction.

Keywords – Credit Ratings, Credit Rating Agencies, Insurance Industry, Event Study

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1 Introduction

This thesis seeks to investigate the effect of credit rating changes on stock returns for insurance companies. The goal of the study is to add to the existing literature on whether rating changes provide new information to capital markets. The study is conducted through the event study methodology, investigating if significant abnormal returns around the announcement day of a rating change can be observed. Furthermore, a selection of relevant variables is examined through a cross-sectional regression, to see whether different characteristics affect the abnormal returns.

The data sample in this thesis consists of credit rating upgrade and downgrade announcements provided by the credit rating agencies: Standard and Poor (S&P), Moody's, and Fitch. The chosen credit rating category is long-term issuer ratings. The sample consists of 125 observations collected from 33 insurance companies in Europe over the period 2009-2021. Daily stock price data is used to capture the rating change effect as accurately as possible.

The thesis is structured as follows. Section 2 starts by providing the background for this study. Thereafter, a presentation of the theoretical framework and relevant previous literature is introduced in section 3. During this section, the hypotheses for the thesis are also presented. Section 4 presents the methodology used to perform the study, which is the event study methodology of MacKinlay (1997). Thereafter, the data sample is described in section 5, as well as illustrated with various tables and graphs. Then the results are presented and illustrated in section 6, and separately discussed in section 7. The reason for separating the analysis and the discussion is to compare the central findings of the study to previous literature as clearly as possible. Furthermore, section 8 includes a robustness analysis, to show how different research design choices impact the results. Finally, section 9 presents the conclusion.

2 Background

The following section presents a description of what a credit rating is, how the credit industry operates, as well as the history of the credit rating industry. In addition to this, the reasons for choosing the insurance industry as the sector in focus are explained.

2.1 Credit Rating Industry

The credit rating industry consists of multiple agencies, dominated by the three big agencies: Standard & Poor's (S&P), Moody's, and Fitch. The rating agencies are compensated by the issuer, meaning the entity that is seeking a credit rating for themselves (issuer rating) or one of its debt issues (issue-specific rating). An issuer is typically a corporation or a government. The debt issues can be bonds, notes, or other debt securities.

An issuer rating expresses a forward-looking opinion of the creditworthiness of an entity, meaning the entity's overall capacity to pay its long or short-term financial obligations. An issue-specific rating measures the credit quality of a specific debt issue, meaning an entity's capacity to pay interest and principal in a timely matter, in accordance with the contractual terms of the agreement. Credit ratings are not an absolute measure of default probability (Standard & Poor's, 2022a). Instead, a credit rating embodies multiple factors to compose an overall evaluation of the creditworthiness of an issuer or the credit quality of a specific debt issue. Each rating agency has its own formula for combining the factors and the relative importance of the different factors.

The primary factor for assessing credit ratings is the likelihood of default. Other important factors are the projected recovery rate in case of default, payment priority for issued debt, and credit stability related to the vulnerability of sudden deterioration of debt (Standard & Poor's, 2022a). When evaluating the factors above, a thorough process is conducted. The rating agencies perform an analysis, based on both public and non-public information regarding the firm's financial situation and future strategic plans. The rating agencies also have meetings with the management of the firm under review, to examine relevant information in greater detail. Before the rating is made public, the issuer has the chance to appeal. To succeed with the appeal, the issuer will have to provide the rating agency with new information (Standard & Poor's, 2022a; Fitch, 2022b; Moody's, 2022b).

The three rating agencies included in this thesis follow a similar rating format as they report their ratings by letters. The rating symbols are independent of the region, currencies, and various situations, intending to reflect the same level of creditworthiness or credit quality regardless of sector, industry, and at different times. Table 2.1 illustrate the structure of the rating tiers for Moody's, S&P, and Fitch:

Table 2.1: Rating Tiers for S&P, Fitch and Moody's

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

Note: Ratings are described in terms of S&P's classification scheme. The left column in the description describes the rating class, while the right column describes whether the rating classifies as investment grade or non-investment grade.

As the table illustrates, the ratings are divided into different grades with two main groups: investment grade and non-investment grade. Non-investment grade is also referred to as speculative grade. The threshold between investment grade and speculative grade has important implications as it works as a regulatory constraint for some investors. Some institutional investors can for instance not hold bonds rated below investment grade. This is because the risk associated with speculative bonds is considered significantly higher.

Furthermore, the rating agencies use CreditWatch and outlooks to indicate their view regarding the degree of likelihood of a rating change. In addition, the probable direction of the potential change is usually stated (Standard & Poor's, 2009).

2.2 The History of the Credit Rating Industry

The credit rating industry has developed from providing investing information for railroad investments in the US in the early 1900s, to having a central position in today's financial markets all over the world (White, 2010). Until the early 1970s, the rating agencies' business model was that investors paid the agencies to get ratings about entities they were interested in. However, this changed as the rating agencies converted to an "issuer pays" model, where the entity that issues bonds pay for the rating agency to rate the bonds. The reasons for this change have not been established definitely. However, some reasons have been proposed, like the problem of free riders, the willingness of bond issuers to assure bond investors that their bonds really are low risk, and the realisation of the rating agencies that bond issuers needed their bonds to be rated by one or more of the rating agencies to get the bonds into the portfolio of financial institutions (White, 2010). Finally, White (2010) argues that the credit rating business is like other information businesses, it involves a "two-sided market" where both sides are willing to pay for the information.

Regardless of the reason, this change of business model opened the door for a potential conflict of interest. A rating agency might shade its rating upward in an attempt to keep the issuer happy and prevent the issuer from taking its rating business to a different rating agency (White, 2010). The consequences of this did, however, reveal themselves during the financial crisis of 2008.

The housing boom in the US from the late 1990s through mid-2006 was fueled by subprime mortgage lending, among other factors. Subprime mortgage bonds were combined into mortgage-related securities. These securities were then further divided into securities using tranches of securities of various quality, resulting in collateralized debt obligations (CDOs) that financial institutions offered as investment vehicles. This securitization of subprime mortgages was in part able to succeed because of the favorable ratings of the more senior tranches bestowed by the rating agencies, that did so in order to keep their customers from moving to other rating agencies.

"As of June 30, 2009, 90 percent of the collateralized debt obligation tranches that were issued between 2005 and 2007 and that were originally rated AAA by Standard & Poor's had been downgraded, with 80 percent downgraded below investment grade" (White, 2010). This is a strong indicator of how wrong the ratings were, and how widespread the practice was.

Naturally, there had to be a regulatory response to the financial crisis and what it had exposed.[1][2][3] According to Rafailov (2020), the regulations were made with multiple purposes in mind. One purpose was to increase competition through clear rules for the registration of rating agencies. Another intent was to reduce the conflict of interest by prohibiting a person that has an interest in or receives compensation from the issuer, from assigning the rating opinion. Additional, rating agencies are "prohibited from providing additionally advisory services that directly affect the credit rating" (Rafailov, 2020). The regulations also sought to ensure transparency of rating agencies by requiring agencies to disclose detailed information on various aspects of their business and methods. The liability of rating agencies was addressed, by giving regulators the power to hold agencies accountable. This was done by giving them the power to impose various penalties. Furthermore, the regulations sought to limit the regulatory use of ratings, meaning that they wanted to reduce regulations on banks and other financial institutions that were dependent on ratings.

[1]The US implemented the Credit Rating Agency Reform Act of 2006 and Dodd-Frank Wall Street Reform and Consumer Protection Act from 2010

[2]EU implemented the Regulation (EC) No 1060/2009 of the European Parliament and of the Council of 16 September 2009 on credit rating agencies

[3]Other countries implemented similar regulations as the US and EU (Kruck, 2011; Darbellay, 2013)

2.3 Why the Insurance Industry

The chosen market sector in this thesis is the insurance sector in Europe. The reason for choosing the insurance industry is due to the insurance sector potentially being more sensitive to credit rating changes than other sectors, as its participants utilize the ratings provided for insurance companies for a variety of reasons. According to Berger, Cummins, and Tennyson (1992), consumers use ratings when choosing between insurance providers or when determining how much they are willing to pay for the insurance a particular company provides. Furthermore, corporate customers often use a minimum rating when purchasing commercial coverage from an insurer (Pottier & Sommer, 1999). Additionally, agents and brokers tend to recommend insurance companies that have ratings above some threshold and avoid insurers with ratings below such a threshold (Kosnett, 1999; Bradford, 2003; Parekh, 2006). Not to mention, investors use ratings as a tool for measuring investment risk (Sclafane, 2000). On the other hand, Doherty and Philips (2002) show that insurance companies themselves broadcast their credit rating as a marketing strategy to differentiate themselves from competitors.

Hence, the credit ratings of insurance companies seem to be relevant for where consumers, brokers, and investors choose to place their business. These ratings should therefore be relevant for how the stock price of a firm develops, through the ratings' impact on future cash flow and investment risk. The two major papers that have studied the effect of credit rating changes on the stock prices of insurance companies, conducted by Singh and Power (1992) and Halek and Eckles (2010), both focused on the US market. As there does not seem to exist a similar study for the insurance market in Europe, this thesis focuses on the European market.

3 Theory and Previous Literature

In the following section, the efficient market hypothesis is presented, as it will function as a backdrop for further discussion on the information value of credit ratings. Furthermore, earlier studies regarding the information content of credit rating announcements are presented. Throughout the review of the previous studies, the hypotheses for this thesis will be presented.

3.1 The Efficient Market Hypotheses

A basic assumption within the event study methodology is a rational market where prices reflect available information (MacKinlay, 1997). As a result, an important assumption within the event study methodology is the efficient market hypothesis, introduced by Fama (1970). According to Fama (1970), an efficient market is defined as "a market in which prices always fully reflect available information". Furthermore, he defines three variations of market efficiency: weak form, semi-strong form, and strong form. The different forms of efficiency define subsets of which available information is reflected in the stock prices. Weak form efficiency is a market where stock prices reflect the historical prices. Semi-strong form efficiency is a market where stock prices reflect all obvious publicly available information. Finally, strong form efficiency represents a market where stock prices reflect all information, both public and private.

It is generally accepted that the market is of a semi-strong nature (Fama, 1991). Under the assumption that the markets are semi-strong efficient, firm-specific and financially relevant news should be immediately reflected in a company's stock price as it is published. Hence, one expects that positive (negative) financial news should lead to an immediate increase (decrease) in a company's stock price.

As mentioned previously, the rating agencies do have access to both public and private information of the firm under review during a credit rating evaluation. This creates an information asymmetry between the rating agencies and the market. As a result, one would expect a rating change announcement to convey new information to the markets, implying that we should see movement in the firm's stock price in a semi-strong market. Contrary, if stock prices do not react it could suggest that the information represented by the rating change, both public and private, is already reflected in the market. As such, the research topic of this thesis does implicitly test if the markets are strong form efficient or not.

3.2 The Information Content of Rating Change Announcements

Over the years, numerous studies have been conducted on the effect of credit rating changes on stock prices. Most of the earlier studies originate from the US, due to its well-developed financial market and the fact that the leading rating agencies were established in the US (White, 2010). The consensus for the majority of the studies is a significant negative effect on stock prices from rating downgrades, while the effect from rating upgrades is none or insignificant. In the following subsection, some of the most renowned studies on the effect of credit rating announcements will be presented. The results from these studies form the foundation for the main hypothesis in this thesis:

H1: Stock returns of publicly traded insurance companies increase (decrease) in response to an upgrade (downgrade) in the corresponding insurance companies' rating.

Some of the first studies investigating the effect of rating changes on stock prices did not find any significant effect for either downgrades or upgrades (Weinstein, 1977, and Pinches & Singleton, 1978). Hence, they concluded that all information was already accounted for in the stock prices before the event. However, it must be mentioned that these papers used monthly data, as oppose to daily data when conducting their studies. According to Hand, Holthausen, and Leftwich (1992), daily data is favorable to isolate the effect of a rating announcement.

A more extensive and much-cited study by Holthausen and Leftwich (1986) was the first to make use of daily stock data when investigating the effect of rating changes. Their data sample consisted of 1014 rating changes by S&P and Moody's from 1977 till 1982. By controlling for CreditWatch-listings and excluding contaminated observations, they found evidence that rating downgrades had a significantly negative impact on stock prices (Holthausen & Leftwich, 1986). Another finding was that downgrades across rating classes had a greater effect than downgrades within rating classes (see table 2.1 for the definition of rating classes). In addition, their study was the first to examine the effects of "fallen angels", which represent rating downgrades that move a credit rating from investment grade to speculative grade. However, they did not find evidence that rating downgrades defined as fallen angels had any greater effect on stock returns. Based on the results regarding rating changes across and within classes, the following hypothesis has been formulated:

H2: A rating change that moves a rating across classes has a greater impact on stock returns than a rating change that moves within classes.

In a subsequent study, Hand et al. (1992) studied the effect of rating changes on daily stock returns, as well as the effect on bond returns. The results yielded similar results to that of Holthausen and Leftwich (1986), where they concluded that there were rating announcement effects on both stock and bond prices. The effects were significant for both the stock and bond prices when examining downgrades, but only significant for bond prices when investigating upgrades. In addition, their study investigated whether the magnitude of the rating change impacted the excess bond returns. Their results suggested that this was the case for both upgrades and downgrades, as rating changes over multiple levels yielded significantly stronger effects on excess bond returns, relative to changes over one level.

Another study that focused on bond returns, not stock returns, was conducted by Steiner and Heinke (2001). Their data sample consisted of daily data from non-US issuers. Their results suggest that downgrades have a significant negative impact on bond returns, while upgrades have no significant effect. They also tested whether a rating change over multiple levels had a greater impact than a rating change over one level. They did not find any evidence of this and argued that it is the rating change itself that carries the important information, rather than the size of the rating change.

Based on these contradicting findings with regards to the effect of the magnitude of a rating change, the following hypothesis has been developed:

H3: A rating change over multiple levels has a greater impact on stock returns than a rating change over one level.

The first study to find significant market reactions to rating changes by using monthly data was conducted by Hite and Warga (1997). They did primarily find evidence of a significant decrease in stock prices related to downgrades. Additionally, they found evidence of increased stock prices for upgrades, but only for “rising stars”. Rising stars are the opposite of fallen angels, meaning that it is a rating change that moves a bond from speculative grade to investment grade. One might note that Hite and Warga (1997) also studied the effect of fallen angels, in which they found a significantly stronger decrease in stock prices, relative to rating changes that did not move below the threshold. In addition, their study analyzed whether the rating agency that announced the rating change had any impact on the stock price reaction. They did not find any evidence to support this.

A study that did find significant stock price reactions for both downgrades and upgrades was conducted by May (2010). The effect seemed to be present when using daily data, as well as monthly. He also discovered evidence of falling angels increasing the effects of downgrades. In addition, he found significantly increased effects on stock prices of rating changes over multiple levels, relative to rating changes over one level. Finally, his results also implied that the old rating has a significant impact on the effect of the rating change, where a change in an already low rating had a significantly greater impact than a change in a higher rating. This seems logical, in relation to the findings of Hamilton and Cantor (2004), where they document three-year default rates of 0,0%, 0.0%, 0.4%, 1.5%, 4.4%, 17.7%, and 31% for AAA, AA, A, BBB, BB, B, and CCC bonds respectively. By looking at these default rates, one can conclude that a move from A to BBB, is substantially less consequential than a move from B to CCC.

Based on the results from Hite and Warga (1997) and May (2010), the following hypotheses have been constructed:

H4: The impact of credit rating changes on stock prices is indifferent to which credit rating agency announcing the credit rating change.

H5: A rating change from investment grade to speculative grade, or from speculative grade to investment grade, causes a stronger effect on stock returns than other rating changes.

H6: A rating change for an already low rating causes a stronger impact on stock returns than a rating change with a prior rating that is higher on the rating scale.

Another interesting study, by Hsueh and Liu (1992), had a hypothesis that the effect of a rating change is not homogeneous across firms. This means that different firms will see different effects of a rating change, based on certain characteristics of the firm. They primarily argued that the information available in the market on a firm had a significant impact on the effect of the rating change. It would for instance be easier to anticipate a rating change for a firm that gets a lot of coverage from the media, financial analysts, etc., than for a firm where the information available is rather limited. Hsueh and Liu (1992) found evidence of this, suggesting that the impact of a rating change is stronger for firms with less information available in the market. Based on their findings, the following hypothesis was formulated:

H7: A rating change on a firm with less media coverage has a greater impact on the stock returns than a rating change on a firm with a greater extent of media coverage.

All studies mentioned till now have had data samples consisting of a wide variety of industries. The first study that focused on the insurance industry exclusively, was performed by Singh and Power (1992). They found no significant impact of rating changes on the stock price of insurance companies. However, their data sample only included rating changes from A.M. Best.[4] In addition to this, criticism of their event study methods was made by Halek and Eckles (2010). To add to the existing literature on the effects of rating changes on insurance companies, Halek and Eckles (2010) conducted an event study on 2970 observations from the US, consisting of rating changes from A.M. Best, S&P and Moody's. They found that rating downgrades result in a significant decrease in stock prices, while upgrades lead to little or no significant response.

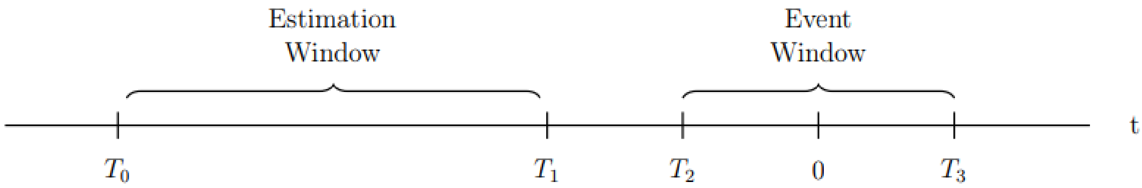
[4] A.M. Best is a rating agency that focuses solely on insurance companies.

4 Methodology

To be able to research the chosen topic, the event study methodology as described by MacKinlay (1997) has been used. The event study methodology is widely used for measuring the effect of a firm-specific event on the value of the corresponding firm. Hence, it makes a good fit for studying the effect of credit rating changes on stock prices. This is done by comparing the actual returns of the stock to the expected returns surrounding the predefined event. The following section will describe how this has been done in detail.

4.1 The Event Study Methodology

Figure 4.1: Timeline Event Study



The initial task when conducting an event study is to choose the events to analyse given the objective of the particular study (MacKinlay, 1997). Then, the specific event dates (t = 0) must be defined. In this thesis, the specific event dates are the announcement dates of credit rating changes by the rating agencies. However, some of the effects might be reflected in the stock price both before and after the event date. Hence, an event window of 11 days is defined in this thesis to increase the probability of capturing the rating change effect: [-5,5].

The next step is to define the estimation window. The estimation window's role is to map the normal performance of each firm's stock price before the event, such that the computation of a firm's expected return can be done in the event window. There is no right answer to the length of an estimation window. A meta-research by Holler (2012) reviewing 400 event studies found that estimation window lengths spread out between 30 and 750 days. According to Armitage (1995) and Park (2004), the results will not be sensitive to varying estimation window lengths as long as the estimation window exceeds 100 days. Thus, an estimation window of 200 days will be used in this study: [-206, -6].

After the estimation window is defined, the expected returns can be estimated, which in turn will be used to compute the abnormal stock returns in the event window. The abnormal return of a stock is defined as the expected return subtracted from the actual return. Equation 4.1 illustrates this sentence in mathematical terms.

$$AR_{i\tau} = R_{i\tau} - E\left(R_{i\tau} \mid X_{\tau}\right) \tag{4.1}$$

AR is the abnormal return of firm i at date τ, R is the actual return of firm i at date τ, and $E\left(R \mid X\right)$ is the expected return of firm i at date τ. There are multiple methods for computing the stock's expected performance. Some different methods, as well as the chosen method for this thesis, will be discussed in the next subsection.

4.2 Estimating Normal Performance

According to MacKinlay (1997), there are two loosely grouped categories regarding approaches to calculate the expected return of a given security: statistical and economic. The constant mean return model and the market model are examples of statistical models. These models follow from statistical assumptions regarding the behaviour of asset returns. Economic models on the other hand, such as the Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Theory (APT), rely on assumptions concerning investors' behaviour as well as statistical assumptions (MacKinlay 1997). These economic models can therefore be seen as restrictions on the statistical models, and thereby provide more constrained expected return models. However, there have been discovered deviations from the CAPM, and there are findings that support that the most important factor in the APT behaves like the market factor. Consequently, the validity of the restrictions imposed by economic models is questionable. Thus, the gains of using an economic model rather than a statistical model are rather small (MacKinlay 1997). For this reason, only statistical models are discussed in detail below.

4.2.1 The Constant Mean Return Model

The constant mean return model is based on the assumption that the mean return of an asset is constant over time (MacKinlay 1997). On that basis, the constant return parameter and a disturbance term are used to calculate the expected return of an asset.

Given these assumptions, The constant mean return model is given by equation 4.2:

$$\begin{gathered} R_{i\tau} = \mu_i + \varepsilon_{i\tau} \\ \hat{\mu}_i = \frac{1}{L_1} \sum_{\tau=T_0+1}^{T_1} R_{i\tau} \qquad E\left(\varepsilon_{i\tau} = 0\right) \qquad \operatorname{var}\left(\varepsilon_{i\tau}\right) = \sigma^2_{\varepsilon_i} \end{gathered} \tag{4.2}$$

In the equation above, $R_{i\tau}$ is the expected return on security i at time τ. $\hat{\mu}_i$ is the mean return of an asset over the chosen estimation window, and $\varepsilon_{i\tau}$ is the error term with an expected value of zero and a variance of $\sigma^2_{\varepsilon_i}$. Lastly, L_1 represents the number of observations in the chosen estimation window.

4.2.2 The Market Model

The market model assumes that there is a stable linear relationship between the return of an asset and the return of the market portfolio. This specification follows from the assumed joint normality of asset returns (MacKinlay 1997). For any security i, the market model is given by.

$$\begin{gathered} R_{i\tau} = \alpha_i + \beta_i R_{m\tau} + \varepsilon_{i\tau} \\ E\left(\varepsilon_{i\tau} = 0\right) \qquad \operatorname{var}\left(\varepsilon_{i\tau}\right) = \sigma^2_{\varepsilon_i} \end{gathered} \tag{4.3}$$

In equation 4.3, $R_{i\tau}$ and $R_{m\tau}$ are the expected return on the security i at time τ and the return on the market portfolio at time τ respectively. The disturbance term $\varepsilon_{i\tau}$ has an expected value of zero and a variance of $\sigma^2_{\varepsilon_i}$. α_i and β_i are parameters estimated by using ordinary least squares, based on the data in the specified estimation window. When applying this model, a broad-based stock index is typically used for the market portfolio (MacKinlay 1997).

According to MacKinlay (1997), the market model is representing a potential improvement over the constant mean return model. “By removing the portion of the return that is related to variation on the market return, the variance of the abnormal return is reduced” (MacKinlay 1997). As a consequence, this can lead to an increased ability to detect event effects. This paper will therefore use the market model as its model for estimating expected returns.

4.3 Abnormal Returns

As discussed in subsection 4.2, this thesis will be using the market model to compute the firms' expected stock performance. Hence, the equations which will be elaborated on in this subsection will be based on the market model.

The market model estimates two different parameters: α_i and β_i. These parameters are used to compute the expected return of a firm's stock price in the event window. Hence, the abnormal return based on the market model can be expressed as follow:

$$AR_{i\tau} = R_{i\tau} - \left(\hat{\alpha}_i + \hat{\beta}_i R_{m\tau}\right) \tag{4.4}$$

Under H_0 (AR = 0), MacKinlay (1997) states that the abnormal return will be jointly normally distributed with a zero conditional mean and conditional variance σ^2 equal to:

$$\sigma^2 \left(AR_{i\tau}\right) = \sigma^2_{\varepsilon i} + \frac{1}{L_1} \left[1 + \frac{\left(R_{m\tau} - \hat{\mu}_m\right)^2}{\hat{\sigma}^2_m}\right] \tag{4.5}$$

Equation 4.5 has two components. The first component is the disturbance variance $\sigma^2_{\varepsilon i}$, which is also found in equation 4.2. The second component is due to sampling error in α_i and β_i. However, as the equation indicates, when the length of the estimation window (L_1) becomes large, the sampling error becomes irrelevant (MacKinlay, 1997). As this thesis operates with an estimation window of 200 days, the second component can be overlooked, making the variance of $\sigma^2 \left(AR_{i\tau}\right)$ equal to $\sigma^2_{\varepsilon i}$.

4.3.1 Aggregating Abnormal Returns

In order to draw overall inferences for the events of interest, the abnormal returns must be aggregated. This can be done both through time and across securities (MacKinlay, 1997). Aggregation across securities is done by computing the average abnormal return (AAR). Given N events, the AAR and the variance of the AAR at a given time τ is derived in equation 4.6 and 4.7 respectively:

$$AAR_{\tau} = \frac{1}{N}\sum_{i=1}^{N} AR_{i\tau} \tag{4.6}$$

$$\operatorname{var}\left(AAR_{\tau}\right) = \frac{1}{N^2}\sum_{i=1}^{N} \sigma^2_{\varepsilon_i} \tag{4.7}$$

The AAR_{τ} can then be aggregated through time to calculate the cumulative average abnormal return (CAAR). The CAAR and the variance of CAAR from τ_1 to τ_2 is given by equation 4.8 and 4.9 respectively:

$$CAAR\left(\tau_1, \tau_2\right) = \sum_{\tau=\tau_1}^{\tau_2} AAR_{\tau} \tag{4.8}$$

$$\operatorname{var}\left[CAAR\left(\tau_1, \tau_2\right)\right] = \sum_{\tau=\tau_1}^{\tau_2} \operatorname{var}\left(AAR_{\tau}\right) \tag{4.9}$$

4.4 Cross-Sectional Test

To be able to examine if the rating announcement events influence the companies' stock price, a Student's t-test is used to investigate if the (cumulative) abnormal returns are significantly different from zero.

$$H0 : E(AR) = 0$$

$$H0 : E(CAR) = 0$$

The Student's t-test is valid when examining one event, but when grouping multiple events together there are complications that need to be addressed. Thus, a cross-sectional test is used to investigate if the (cumulative) average abnormal returns are significantly different from zero.

$$H0 : E(AAR) = 0$$

$$H0 : E(CAAR) = 0$$

With the first two null hypotheses, either a mean effect or a variance effect will represent a violation (MacKinlay, 1997). However, in some applications, the purpose could be to test if there is a mean effect like the latter two null hypothesises. This is where the cross-sectional approach uses the cross-section of cumulative abnormal returns to form an estimator of the variance, which makes it possible to test the two latter null hypotheses (MacKinlay, 1997). Formula 4.10 shows how the estimator is calculated.

$$\operatorname{var}\left(\mathrm{CAAR}\left(\tau_1, \tau_2\right)\right) = \frac{1}{N^2} \sum_{i=1}^{N} \left(CAR_i\left(\tau_1, \tau_2\right) - \mathrm{CAAR}\left(\tau_1, \tau_2\right)\right)^2 \tag{4.10}$$

Given the variance estimator shown above, the t-statistic for CAAR (AAR) can then be calculated by dividing the CAAR (AAR) by its corresponding standard error, as equation 4.11 indicate.

$$t_{\mathrm{CAAR}(\tau_1,\tau_2)} = \frac{CAAR\left(\tau_1, \tau_2\right)}{\operatorname{var}\left(CAAR\left(\tau_1, \tau_2\right)\right)^{\frac{1}{2}}} \sim N(0,1) \tag{4.11}$$

4.5 Cross-sectional Regression Analysis

To further examine the relationship between abnormal returns, a cross-sectional regression can be used to regress the abnormal returns on specified characteristics of interest (MacKinlay, 1997). By choosing characteristics specific to an event, or a multitude of events, this approach can be helpful when multiple hypotheses for the source of abnormal return exist.

Having a sample of N (cumulative) abnormal return observations and M characteristics, the regression model can be derived by the following equation:

$$\begin{gathered} CAR_j = \delta_0 + \delta_1 x_{1j} + \ldots + \delta_M x_{Mj} + \eta_j \\ E\left(\eta_j = 0\right) \qquad\qquad \operatorname{var}\left(\eta_j\right) = \sigma^2_{\eta_j} \end{gathered} \tag{4.12}$$

In this equation CAR is the cumulative abnormal return for the j^{th} event observation. x_{Mj} is an indicator for a specific characteristic M for the j^{th} observation, and η_j is the zero mean disturbance term, that is uncorrelated with the x's. The zero mean disturbance term has an expected value of zero, and a variance of $\sigma^2_{\eta_j}$. Running the regression model using ordinary least squares provides coefficients for how the chosen characteristics affect the (cumulative) abnormal returns.

5 Data

The data sample consists of credit rating change announcements by the three largest credit rating agencies in the industry: S&P, Moody's, and Fitch. Furthermore, as the thesis focuses on the insurance industry in Europe, the event data and stock price data are collected for 33 public companies in the insurance market in Europe.

5.1 Data Sources

In order to calculate the abnormal return, daily stock prices for the chosen companies are downloaded from Refinitiv DataStream. By using the adjusted closed price, the prices are adjusted for stock splits, dividends, and other corporate actions. (Datastream International, 2022)

As the Market Model (MacKinlay, 1997) requires a broad-based stock index to represent the market returns, the analysis uses an index for the insurance market in Europe called "Thomson Reuters Europe insurance Index". The corresponding price data is downloaded from Refinitiv DataStream. Equivalent to the examples in MacKinlay (1997), the index is value-weighted and should therefore periodically be adjusted throughout the included period. The reason for using a segment index is to collect as much of the variance caused by the targeted market. By doing so, the purpose is to exclude some part of the volatility that is not firm-specific.

For each company included in the study, all rating changes for the selected credit ratings in the period 2009-2021 are included. The purpose of starting in 2009 is to exclude the volatile period during the financial crisis where credit rating agencies played a role in exacerbating the crisis in America (The Financial Crisis Inquiry Commission, 2011). Additionally, as discussed in the Background-section, new regulations were implemented as a result of the financial crisis. This is yet another argument for choosing a data sample from 2009 and onward, as the new regulations were supposed to make the credit ratings more trustworthy.

Furthermore, as the purpose is to investigate how changes in credit ratings affect the stock price of companies, this thesis has chosen to focus on long-term issuer ratings as the credit rating of choice. For the different rating agencies, the S&P Long-term Issuer Rating

[SPI], Moody's Derived Long-term Issuer Rating [MDL], and Fitch Long-term Issuer Default Rating [FDL] are used. Investors use credit ratings to help assess credit risk and to compare different investment decisions. Businesses and financial institutions may use credit ratings to assess counterpart risk (Standard & Poor's, 2022b). The long-term issuer rating is the main rating assigned on the globally recognises rating scale at S&P (Standard & Poor's, 2022b), Moody's (Moody's, 2022a), and Fitch (Fitch, 2022a). Therefore, as these are the main rating categories for the issuers, the selected ratings should make a good choice when looking at the influence of rating changes on stock price development.

Data concerning credit rating announcements were also collected from Refinitiv DataStream. The total number of rating announcements before working with the data was 161, including both downgrades and upgrades.

5.2 Data Processing

This subsection describes how the data is processed in order to implement the event analysis with the correct input.

To make sure the sample is unbiased it is important to consider confounding effects in the data (MacKinlay, 1997). In the context of this study, confounding effects are effects that affect the stock development, not related to credit rating changes. Examples of such are mergers and acquisitions, public offerings, and surprise earning announcements. If events like these or other significant news occur during an event window, the corresponding credit announcement event is excluded from the data sample. This is a process that should be conducted watchfully. Accordingly, all events have been carefully examined by checking the event windows for company news and comparing the news to the corresponding abnormal returns. By using the databases Nexis Uni[5] and MarketLine[6] for news, 19 contaminated events have been excluded. These exclusions are shown in appendix 3.

Another issue with some of the events is the problem of inadequate data during the event window, as well as during the estimation window. The most significant issue is the lack of stock price data during the event window. To handle this problem, it was necessary to exclude events with lacking data in the event window. This resulted in the exclusion of

[5]Nexis Uni: A research tool for news, cases, law reviews, company information, country information
[6]MarketLine: A provider of company, industry, country, city and financial data.

17 events, as shown in appendix 3. Furthermore, regarding some events, there are a few missing data points in the 200-day estimation window. The adjustment to this concern has been to extend the estimation window to include 200 data points.

Furthermore, MacKinlay (1997) states that the covariance term needs to be zero to get the correct inference for estimations such as the (cumulative) average abnormal return. This is, however, hard to achieve in practice. One solution to accommodate the problem is to make sure the included securities do not overlap in calendar time. By avoiding overlapping event windows in the data sample, the problem of clustering could be reduced. However, by doing this a third of the observations in the sample are excluded, resulting in a significantly smaller data sample. The overlapping event windows are probably the cause of some amount of clustering. On the other hand, there will always be some noise in statistical analyses. Thus, the benefits of more observations are believed to outweigh the benefits of reducing clustering in this thesis. By this reasoning, no exclusions were made on the basis of overlapping event windows.

5.3 Descriptive Statistics

This subsection describes the sample in further detail. Table 5.1 illustrates the total number of rating change announcements for each calendar year, as well as the number of announcements from each rating agency.

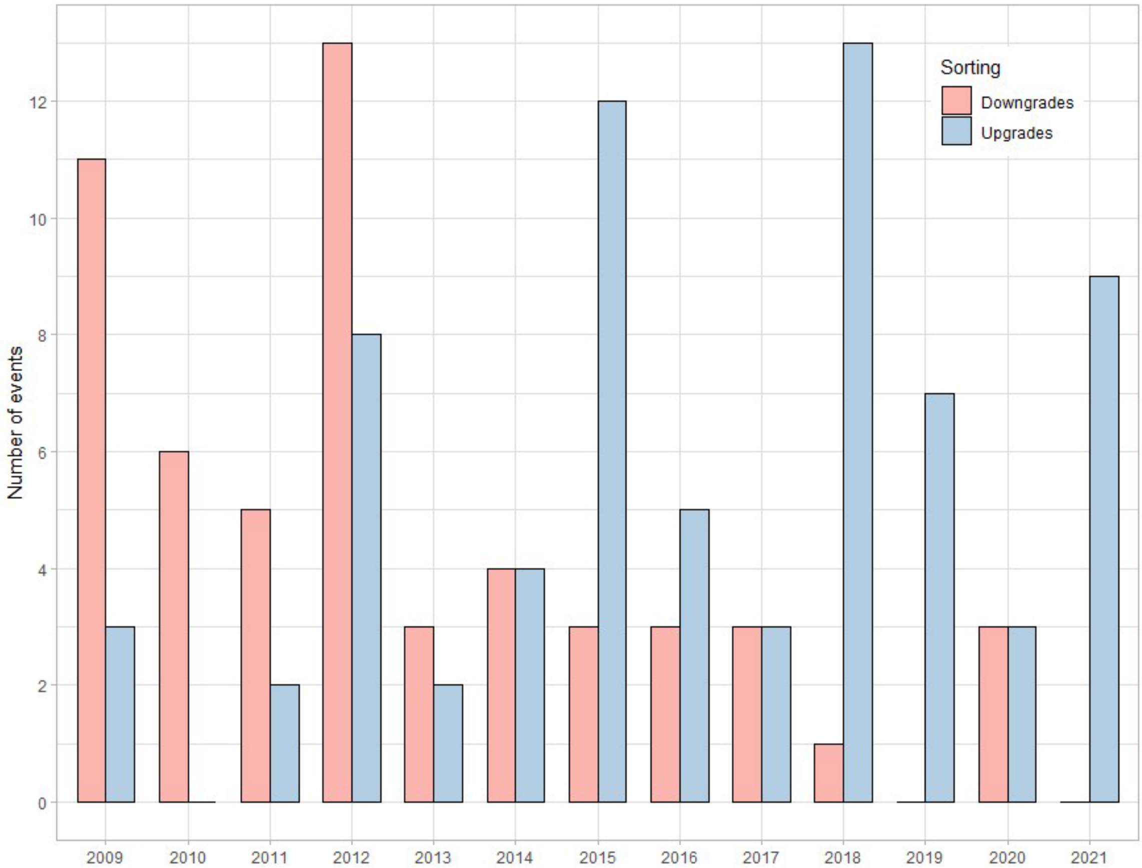
Table 5.1: Summary of Rating Change Announcements

Calendar year	Total	S&P	Moody's	Fitch
2009	13	5	2	6
2010	6	3	1	2
2011	7	5	0	2
2012	21	17	0	4
2013	5	5	0	0
2014	8	5	1	2
2015	15	7	0	8
2016	8	5	1	2
2017	6	4	0	2
2018	14	5	8	1
2019	7	6	1	0
2020	6	2	1	3
2021	9	2	1	6
Total	125	71	16	38

Note: The numbers include both upgrades and downgrades.

When analysing the total sample, a total number of 125 events have been used. The observations span over the three rating agencies, with S&P, Moody's, and Fitch having 71, 16, and 38 rating announcements respectively. The total number of 125 events consists of 54 downgrades and 71 upgrades. Figure 5.1 further illustrates how the downgrades and upgrades are spread out over the included time period.

Figure 5.1: Frequency of Total Upgrades and Downgrades by Year



A key observation from figure 5.1 is that the majority of downgrades are registered in the first part of the sample period, whilst the majority of upgrades are registered in the latter part of the period. The greater number of downgrades at the start of the data sample is likely due to the uncertainty that hit the insurance industry during the financial crisis. The new regulations for rating agencies, implemented as a result of the crisis, could also play a part in the high degree of downgrades during this period. However, as markets adjusted and improved, a noticeable shift from 2014 till the end of the sample period can be observed, with upgrades being the dominating rating change category recently.

Table 5.2: Rating Changes Within and Across Classes

Inital rating	Revised rating							Total	%
	AAA	AA	A	BBB	BB	B	CCC		
AAA	0							0	0%
AA		2	6					8	6.4%
A		2	40	9				51	40.8%
BBB			15	35	2			52	41.6%
BB				5	2	1		8	6.4%
B					3	3		6	4.8%
CCC							0	0	0%
Total	0	4	61	49	7	4	0	125	100%

Note: Ratings are described in terms of S&P's classification scheme. The underlined numbers represents rating changes within rating classes.

Table 5.2 is a transition matrix providing detailed information on the number of rating changes within and across classes. A rating change is defined as within classes if the change occurs within the three gradations of the rating level, e.g., from A+ to A or A-. Similarly, the rating change is defined as across classes if the change moves from one rating level to another, e.g., from A+ to AA-. From the table, one can observe that there are 82 rating changes within classes and 43 rating changes across classes. The rating changes in the sample vary from rating class AA to B, with 82% of the observations originating from rating class A or BBB.

5.4 Data Limitations

One of the main limitations concerning the data sample is the relatively small number of observations. The data sample consists of 125 observations, which is smaller than the samples of other renowned studies on the topic (Holthausen & Leftwich, 1986; Halek & Eckles, 2010). As equation 4.10 illustrates, the smaller sample affects the significance of the results, as the variance becomes higher when N becomes lower. This is especially true when looking at the announcement effects of each credit rating agency individually.

Another limitation is that a credit rating change can to some degree be anticipated by the market. As previously discussed, the three rating agencies use Creditwatch and rating outlooks to indicate their view regarding the likelihood of a rating change. Hence, if a firm's rating has been attached a negative outlook, it is likely that a rating downgrade is somewhat anticipated. This thesis does not control for Creditwatch placements or rating outlooks. Thus, while the study captures the effect of the rating changes, the rating changes might not capture the full effects of the change in the creditworthiness of a company, as some of the effect may have been captured by the market prior to the rating change.

As mentioned earlier, all firms included in the data sample are traded on public stock exchanges. Despite this, there were still a small number of observations with infrequent trading activity during the event window for some of the smaller firms. In those cases, the true effect of the rating change might not have been captured fully as a result of illiquid markets.

6 Analysis

The analysis in this section is based on the event study methodology described earlier, referring to MacKinlay (1997). The AAR and CAAR results are estimated through the market model, as equations 4.6 and 4.8 describe.

The plots included illustrate how rating upgrades and downgrades affect the stock price by showing the development in CAAR during the event window [-5, 5], where T=0 represents the event date. The y-axis of the different graphs is adjusted to fit the data output. Hence, when comparing the different graphs, the scale of the y-axis must be considered.

In addition to the plots, corresponding tables are presented. The tables include various estimations of CAARs to show the size and significance of the results for selected subperiods within the [-5, 5] event window. Supplementary to the CAARs, the AAR for day -1, 0, and 1 are provided in the tables to further demonstrate the rating change effect around the event date.

The analysis includes several parts. In the first part, the CAAR results for all upgrades and all downgrades are visualized in a plot, with a corresponding table displaying the results in further detail. Then, the analysis includes similar plots and tables for upgrades and downgrades for the different rating agencies. This is to investigate if there are differences between the three agencies. Finally, to complement the analysis further, the use of a cross-sectional regression analysis is included. The purpose is to investigate if and how different factors affect abnormal returns.

Be aware that this section will only present the results. The discussion of the results is separated from the analysis and will take place in the section: "Discussion".

6.1 The Stock Market's Reaction to Credit Rating Changes

Figure 6.1 illustrates the development of the CAAR for all downgrades and all upgrades during the event window [-5,5]. The figure shows that the CAAR development for downgrades seems to have a more noticeable development than the CAAR development for upgrades.

Figure 6.1: CAAR for Downgrades and Upgrades

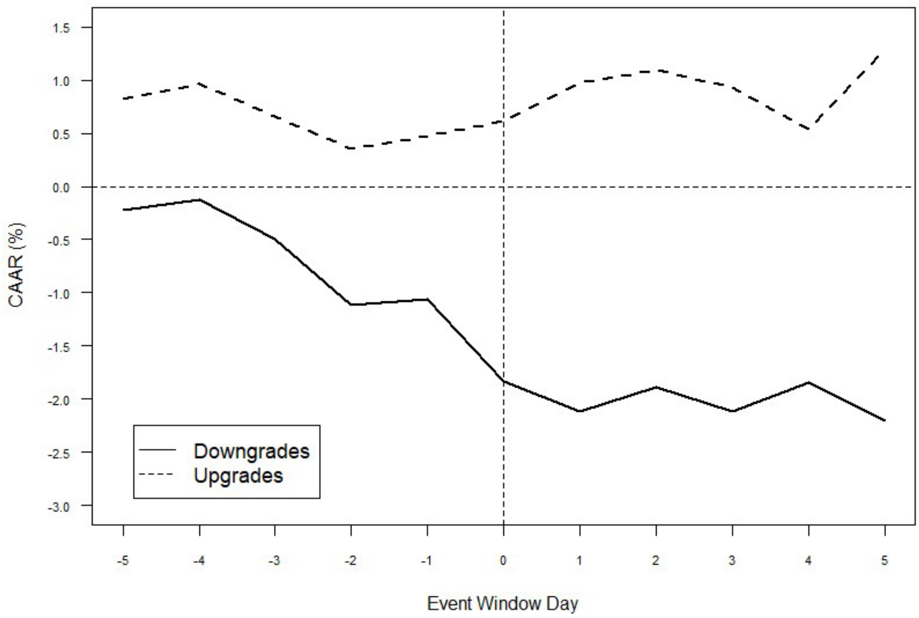


Table 6.1: CAAR and AAR Estimation for Downgrades and Upgrades

Timeline	CAAR Downgrades	CAAR Upgrades
[-5, 5]	-0.0210**	0.0047
	(-2.53)	(0.42)
[-2, 2]	-0.0139**	0.0038
	(-2.64)	(0.98)
[-1, 1]	-0.0085**	0.0068**
	(-2.33)	(2.62)
[-5, -1]	-0.0088	0.0044
	(-1.56)	(0.42)
[1, 5]	-0.0080	-0.0016
	(-1.11)	(-0.50)
Day	**AAR Downgrades**	**AAR Upgrades**
[-1]	0.0002	0.0019
	(0.10)	(1.25)
[0]	-0.0060**	0.0011
	(-2.46)	(0.74)
[1]	-0.0038	0.0029*
	(-1.43)	(1.97)
Observations	54	71

Note: T-statistics in parenthesis;
*p<0.1, **p<0.05, ***p<0.01

For the upgrades, the period prior to the event date does not seem to have a specific trend, as it fluctuates around 0.25%. This is supported by the small CAAR for [-5, -1] in table 6.1, with a correspondingly low t-statistic. For the downgrades there is a rather negative development in the CAAR before the event day. This could imply that there is some form of leakage of information related to rating downgrades. The effect from [-5, -1] is however not significant for the downgrade data sample, even though it is close.

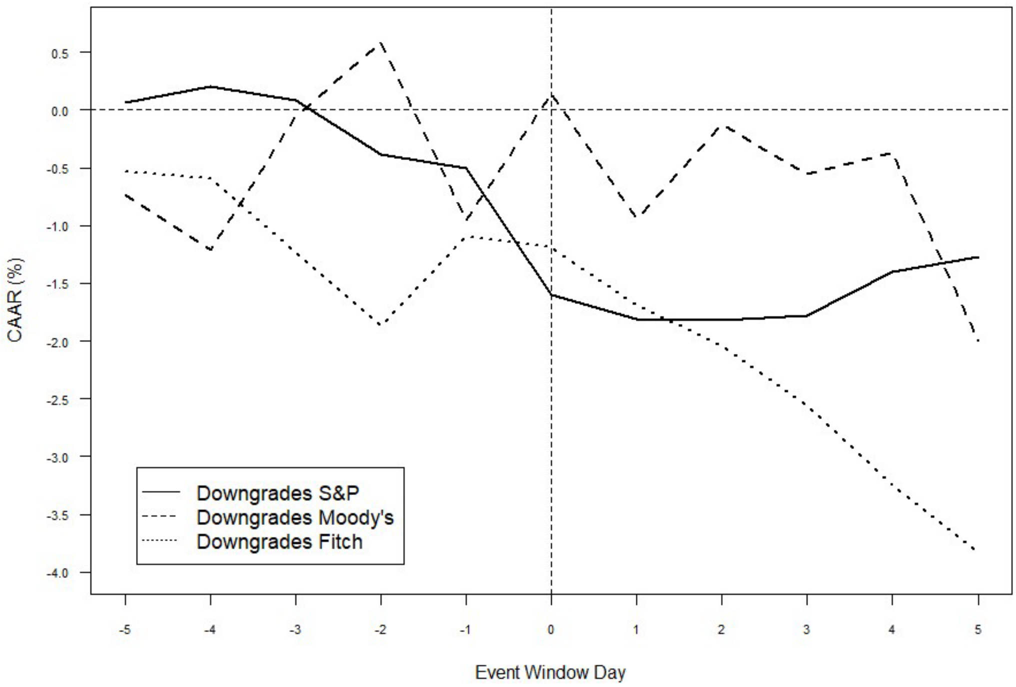
Focusing on the event day, the plot shows a positive development for the upgrades and a negative development for the downgrades. Nevertheless, from the table, one can observe that it is only the AAR at day 0 for downgrades that is significant. Table 6.1 further shows that the CAAR estimate for [-1, 1] is significant at the 5% significance level for both upgrades and downgrades. However, when expanding the time interval to [-2,2] and [-5,5], only downgrades show significant results.

From figure 6.1, the CAAR development after the event date has somewhat varying trends when comparing downgrades and upgrades. The development for downgrades seems to continue slightly downwards, while the development for upgrades seems to fluctuate somewhat more. However, neither downgrades nor upgrades yield significant results when looking at CAAR [1,5]. Although, it is worth noting that the AAR for upgrades on day 1 is significant at a 10% significance level, despite not being significant on the event day. Other than this observation, there are no statistically significant results in the period after the event date.

6.2 Downgrades

Figure 6.2 illustrates the development of CAAR for credit rating downgrades, sorted by each credit rating agency.

Figure 6.2: CAAR for Downgrades by S&P, Moody's and Fitch



From figure 6.2 it can be observed that the CAARs, sorted by rating agencies, are rather varying in their development over the event window. Especially the stock price development caused by rating changes from Moody's stands out, as it seems to fluctuate more than for the other two rating agencies. This is likely due to the smaller number of observations. However, a general trend is that all CAARs are negative when looking at the total event window [-5,5], with Fitch being the largest in size. On the event day (t=0) there are varying levels of AARs as well. Moody's has a positive AAR on the event day, Fitch has a slightly negative AAR, while S&P is the only agency with a significantly negative AAR. The CAAR development after the event day is also worth noting, as both Fitch and Moody's experience a decline, while S&P experiences an increase.

Table 6.2 further complements figure 6.2. It presents CAARs for multiple time intervals within the event window and AARs at the days surrounding the event day for each rating agency. Results for all downgrades are also included for comparison.

Table 6.2: CAAR and AAR Estimation for Downgrades

Timeline	CAAR All	CAAR S&P	CAAR Moody's	CAAR Fitch
[-5, 5]	-0.0210**	-0.0127	-0.0199	-0.0384*
	(-2.53)	(-1.40)	(-0.78)	(-1.98)
[-2, 2]	-0.0139**	-0.0188**	-0.0007	-0.0081
	(-2.64)	(-2.72)	(-0.09)	(-0.78)
[-1, 1]	-0.0085**	-0.0130**	-0.0152**	0.0027
	(-2.33)	(-2.67)	(-3.68)	(0.41)
[-5, -1]	-0.0088	-0.0073	-0.0094	-0.0133
	(-1.56)	(-0.34)	(-0.37)	(-1.52)
[1, 5]	-0.0080	0.0025	-0.0215	-0.0249**
	(-1.11)	(0.24)	(-1.14)	(-2.42)
Day	AAR All	AAR S&P	AAR Moody's	AAR Fitch
[-1]	0.0002	-0.0011	-0.0153	0.0078***
	(0.10)	(-0.48)	(-1.51)	(3.02)
[0]	-0.0060**	-0.0110***	0.0109	-0.001
	(-2.46)	(-3.92)	(1.93)	(-0.21)
[1]	-0.0038	-0.0021	-0.0108	-0.0050
	(-1.43)	(-0.55)	(-1.26)	(-1.46)
Observations	54	33	5	16

Note: T-statistics in parenthesis; *p<0.1, **p<0.05, ***p<0.01

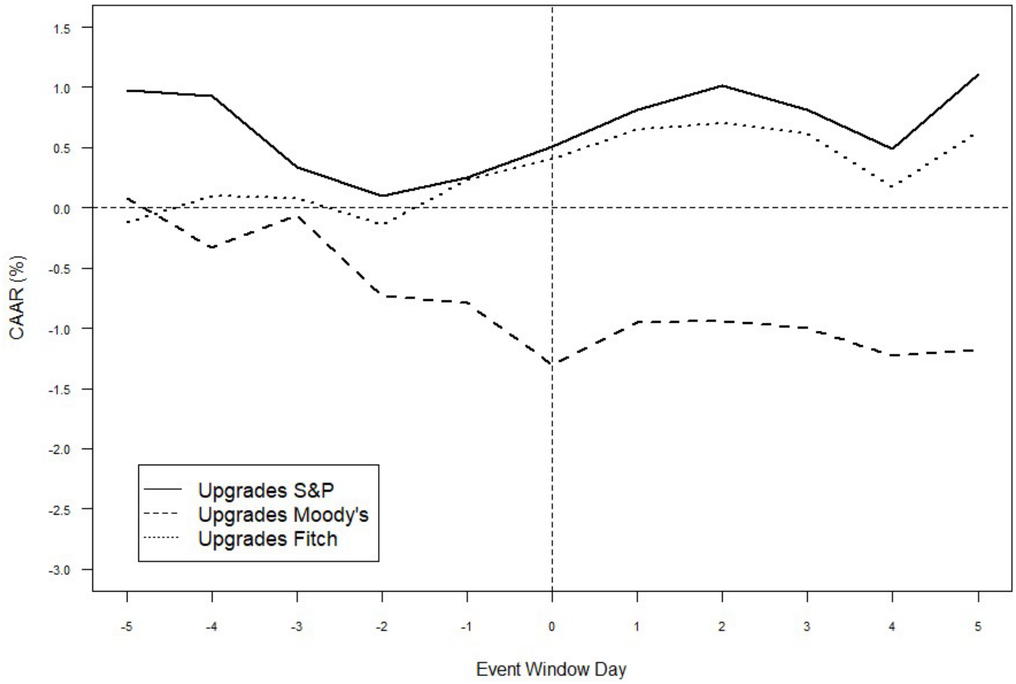
According to both figure 6.2 and table 6.2, all of the agencies yield a negative CAAR the days before the event day [-5,-1], but none of them are of significant size. Looking at [-5,5], only Fitch has a significant CAAR. However, when the timeline narrows, one can observe that rating downgrades from S&P result in a significant negative CAAR at the 5% level for both [-2,2] and [-1,1]. Rating downgrades from Moody's also result in a significant negative CAAR at the 5% level for [-1,1]. In the post-event period [1,5], there is a significant negative CAAR at the 5% level for Fitch.

As shown by the plot, the AAR at the event day differs for each rating agency, with S&P being the only rating agency observing a negative, significant AAR[0] of -1,1%. The positive AAR[-1] of 0,78% for Fitch downgrades is also worth mentioning, as it is significant at a 1% level.

6.3 Upgrades

Figure 6.3 illustrates the development of CAAR for credit rating upgrades, sorted by each rating agency.

Figure 6.3: CAAR for Upgrades by S&P, Moody's and Fitch



Compared to the downgrades, the volatility of the CAAR developments is lower for upgrades when sorting the sample by rating agency. Both the CAAR development for S&P and Fitch have a positive trend, while the CAAR development for Moody's has a negative trend. The CAAR development for S&P and Fitch experience a strong rise in CAAR from -2 to 2. The CAAR development for Moody's shows a strong decline from -3 to the event day. Furthermore, the plot shows some large AAR values for S&P at both the beginning as well as the end of the event window.

Table 6.3 further complements the plot by presenting various CAARs for different time intervals inside the event window, along with AAR around the event day. Results for all upgrades are also included for comparison.

Table 6.3: CAAR and AAR Estimation for Upgrades

Timeline	CAAR All	CAAR S&P	CAAR Moody's	CAAR Fitch
[-5, 5]	0.0047 (0.42)	0.0092 (0.43)	-0.0118 (-1.29)	0.0059 (0.72)
[-2, 2]	0.0038 (0.98)	0.0065 (1.08)	-0.0085 (-1.86)	0.0054 (0.79)
[-1, 1]	0.0068** (2.62)	0.0089** (2.21)	-0.0016 (-0.44)	0.0073* (1.73)
[-5, -1]	0.0044 (0.42)	0.0091 (0.46)	-0.007 (-0.69)	0.0026 (0.37)
[1, 5]	-0.0016 (-0.50)	-0.0035 (-0.65)	-0.0006 (0.14)	0.0003 (0.076)
Day	**AAR All**	**AAR S&P**	**AAR Moody's**	**AAR Fitch**
[-1]	0.0019 (1.25)	0.0015 (0.73)	-0.0006 (-0.20)	0.0037 (1.21)
[0]	0.0011 (0.74)	0.0026 (1.16)	-0.0051** (-2.60)	0.0017 (0.66)
[1]	0.0029* (1.97)	0.003 (1.48)	0.0035 (1.67)	0.0025 (0.81)
Observations	71	37	11	23

Note: T-statistics in parenthesis; *p<0.1, **p<0.05, ***p<0.01

Looking at table 6.3 relative to table 6.2, one can observe that there are less significant results for upgrades than downgrades. For the different subperiods within the event window, [-1, 1] is the only significant one. Both S&P and Fitch have positive CAARs for [-1, 1], which are significant at the 5% and 10% levels respectively. Focusing on the different AARs, day 0 shows a negative significant AAR for Moody's, which is opposite to the positive AAR[0] of S&P and Fitch. Furthermore, the AAR for day 1 is significant for the total data sample, but not significant when looking at the rating agencies individually.

6.4 Cross-Sectional Regression Results

Table 6.4 displays the results from a cross-sectional regression of the total data sample. The dependent variables are AR[0] and CAR[-1, 1]. The independent variable is the coefficient “Downgrade”, which is a dummy variable taking the value 1 if the rating change is a downgrade and 0 if the rating change is an upgrade.

Table 6.4: Cross-sectional Regression of the Total Sample

	Dependent variable	
	AR[0]	CAR[-1,1]
Downgrade	-0.0071**	-0.0153***
	(-2.60)	(-3.64)
Constant	0.0011	0.0068**
	(0.62)	(2.21)
Observations	125	125
R^2	0.05	0.10
Adjusted R^2	0.04	0.09
Note:	T-statistics in parenthesis; $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$	

In the regression above, the “Constant”-coefficient represents the effect of a rating upgrade on the dependent variables AR[0] and CAR[1-, 1]. As already observed in table 6.1, and again displayed in the table above, the effect of rating upgrades on abnormal returns is positive for both AR[0] and CAR[-1, 1], but it is only significant for the latter. From the downgrade-coefficient, one can observe that a rating downgrade reduces the AR[0] by 0,7% compared to an upgrade, and reduces the CAR[-1, 1] by 1,5% compared to an upgrade. Both estimates are significant at the 5% and 1% significance level respectively.

Tables 6.5 and 6.6 display the results from a cross-sectional regression for downgrades and upgrades respectively. The regressions are employed to investigate if certain characteristics can explain some of the variation in the observed abnormal returns, represented by CAR[-1,1]. The characteristics of interest are explained below.

- MULTIPLE_j is a dummy variable, taking on the value 1 if the rating change is over multiple levels (ie. from A+ to A-) and 0 if the rating change is over one level.
- FALLEN_ANGEL_j is a dummy variable, taking on the value 1 if the rating change moves the firm from "investment grade" to "speculative grade".
- RISING_STAR_j is a dummy variable, taking on the value 1 if the rating change moves the firm from "speculative grade" to "investment grade".
- ACROSS_j is a dummy variable, taking on the value 1 if the rating change moves the rating across rating levels, e.g., from A+ to AA-, and 0 if the rating change is within the same rating level (see table 5.2).
- LOW_PRIOR_j is a dummy variable, taking on the value 1 if the rating prior to the change was BBB+ or less, and 0 otherwise.
- NEWS_j is a dummy variable, taking on the value 1 if the firm being rated has less than 350 news articles registered on the Nexis Uni-database one year before the rating change, and 0 otherwise.
- $\text{S\&P}_j$ is a dummy variable, taking on the value 1 if the rating change is announced by S&P and 0 otherwise.

Based on the information above, the following regression models are derived for downgrades and upgrades respectively:

$$\begin{aligned} CAR_j^{[-1,1]} = \delta_0 + \delta_1 MULTIPLE_j + \delta_2 FALLEN\_ANGEL_j + \delta_3 ACROSS_j \\ + \delta_4 LOW\_PRIOR_j + \delta_5 NEWS_j + \delta_6 S\&P_j + \eta_j \end{aligned} \tag{6.1}$$

$$\begin{aligned} CAR_j^{[-1,1]} = \delta_0 + \delta_1 MULTIPLE_j + \delta_2 RISING\_STARj + \delta_3 ACROSS_j \\ + \delta_4 LOW\_PRIOR_j + \delta_5 NEWS_j + \delta_6 S\&P_j + \eta_j \end{aligned} \tag{6.2}$$

The regression output for the two regression models above will be presented in the two following tables.

Table 6.5: Cross-sectional Regression of Downgrades

	Dependent variable:
	CAR[-1, 1]
MULTIPLE	-0.021*
	(-1.99)
FALLEN_ANGEL	-0.001
	(-0.01)
ACROSS	0.001
	(0.10)
LOW_PRIOR	0.012
	(1.42)
NEWS	0.004
	(0.46)
S&P	-0.016**
	(-2.20)
Constant	-0.002
	(-0.30)
Observations	54
R^2	0.226
Adjusted R^2	0.128
Note:	T-statistics in parenthesis; *p<0.1; **p<0.05; ***p<0.01

As table 6.5 illustrates, the independent variables included in the regression analysis do account for some of the variation in CAR [-1, 1] for rating downgrades. The independent variable MULTIPLE has a coefficient of -0,021, which is significant at the 10% significance level. This indicates that a rating downgrade happening over multiple levels is related to a 2,1% decrease in CAR[-1, 1] relative to a rating downgrade over one level. The independent variable S&P is significant at the 5% level, with a coefficient of -0,016. This suggests that a rating downgrade from S&P is related to a decrease in CAR[-1, 1] of 1,6%, relative to a rating downgrade from the two other rating agencies.

Table 6.6: Cross-sectional Regression of Upgrades

	Dependent variable:
	CAR[-1, 1]
MULTIPLE	-0.009
	(-0.98)
RISING_STAR	0.024**
	(2.09)
ACROSS	0.001
	(0.22)
LOW_PRIOR	-0.003
	(-0.51)
NEWS	0.001
	(0.12)
S&P	0.006
	(1.09)
Constant	0.004
	(0.69)
Observations	71
R^2	0.079
Adjusted R^2	-0.008
Note:	T-statistics in parenthesis; *p<0.1; **p<0.05; ***p<0.01

From table 6.6 one can observe that the independent variables included in the regression do account for some of the variation in CAR[-1, 1] for upgrades as well. The variables are however of less explanatory power, according to the lower R^2 and adjusted R^2. The independent variable RISING_STAR is significant at the 5% level for upgrades, with a coefficient of 0.024. This suggests that a rating upgrade from a speculative grade rating to an investment grade rating is related to an increase in CAR[-1, 1] of 2,4% relative to a rating upgrade that does not move over the investment grade threshold.

7 Discussion

In the following section, the results presented in the analysis will be discussed and compared to previous literature on the topic of credit rating changes. First, the general findings of rating changes' effect on abnormal returns presented in tables 6.1, 6.2, and 6.3 will be discussed. Additionally, the insurance industry's reaction to rating changes vs. the reaction from a more broad-based study will be compared. Thereafter, a discussion of the results from the cross-sectional regressions will be presented. The hypothesis introduced in subsection 3.2 will also be considered throughout the discussion. Finally, a discussion of leakage of rating announcements will be discussed.

7.1 Asymmetry Between Upgrades and Downgrades

In summary, our study supports the notion that rating downgrade announcements for insurance companies on average are correlated with a significant negative response in stock price, while rating upgrades lead to a less significant response. These results are similar to the study of Halek and Eckles (2010) which focused on insurance companies in the US, and the more general studies of Holthausen and Leftwich (1986), Hand et al. (1992), and Goh and Ederington (1993). However, it is different from the study of Singh and Power (1992) which focused on the insurance industry, and the more general studies of Weinstein (1977) and Pinches and Singleton (1978). These papers show no stock price response to rating change announcements. However, it should be mentioned that the study of Singh and Power (1992) only examined rating changes from A.M. Best, while all the other papers included ratings from at least S&P and Moody's. Furthermore, Weinstein (1977) and Pinches and Singleton (1978) used monthly stock prices instead of daily to conduct their study.

This raises the question: what is the reason that this thesis, as well as the studies mentioned above, find that downgrades result in significant stock decreases, while upgrades result in less or no significant increases? Halek and Eckles (2010) suggest that a management's incentives to release information may not be symmetric. Meaning that an insurer's strategy may be to delay reports of "bad news" for as long as possible and reveal reports with "good news" as soon as possible. A study conducted by Chambers and Penman (1984) documented that on average this is the case for earnings reports. This could indicate that the information content related to a rating upgrade might already be captured in a firm's stock price at the day of the announcement, while a rating downgrade may provide information unknown to the markets. As a result, it can be argued that credit rating agencies play a significant role in reducing the information asymmetry between market participants (Halek & Eckles, 2010).

Another potential explanation for the asymmetric response to downgrades compared to upgrades is of behavioral nature. Hull, Predescu, and White (2004) discussed the asymmetric risk aversion of investors as a possible explanation, by suggesting that investors value bad news significantly more than they value good news. This might be especially true for insurance companies, as it would be very bad news for an insurance company to lose its creditworthiness, while increased creditworthiness - especially for an already creditworthy insurance company - would arguably not be as significant news. As a result, a greater reaction will happen in the case of a rating downgrade than an upgrade.

7.2 The Insurance Industry vs. Other Industries

The insurance industry was specifically chosen due to its assumed high sensitivity to credit rating changes. Halek and Eckles (2010) found very strong evidence of rating downgrades impacting the abnormal returns of insurance companies, with an AAR[0] of -2,17% (significant at the 1% level). The only other paper providing results for AAR[0] was Hand et al. (1992). They included all types of industries in their data sample and found an AAR[0] of -1,12% (significant at the 10% level). This is smaller and less significant than the AAR[0] found by Halek and Eckles (2010), which could suggest that the insurance industry is more sensitive to rating changes than other industries. Our thesis found an AAR[0] of -0,60% (significant at the 5% level), which is smaller than the AAR[0] from the two previously mentioned studies, but more significant than the results of Hand et al. (1992). This could suggest that the insurance industry is somewhat more sensitive to rating changes than other industries. Nevertheless, by only comparing AAR[0], as well as only three studies, the basis is not sufficient to make any conclusion on the topic. However, it is an interesting discussion, which is why it is included here.

7.3 Discussion of the Cross-sectional Regression Results

To test whether different variables affect the observed effects of credit rating downgrades and upgrades, a cross-sectional regression analysis was performed, resulting in the regression output presented in tables 6.5 and 6.6. These results will be discussed in detail during this subsection.

The MULTIPLE-coefficient, representing rating changes over multiple levels, is significant at a 10% significance level for rating downgrades, but not for upgrades. This result is somewhat consistent with the study of Hand et al. (1992), which found that the number of grades during a credit rating downgrade is in fact significantly related to a larger market reaction. However, in contrast to this thesis' result, Hand et al (1992) also found evidence of a greater market reaction to rating upgrades over multiple levels. The insignificant MULTIPLE-coefficient for upgrades is however in line with the findings of Steiner and Heinke (2001), in which they argue that the market seems to value the rating change itself and that the size of the rating change seems to carry no information. Hence, the results from the MULTIPLE-coefficient yield limited support for hypothesis 3, suggesting that rating changes over multiple levels result in greater stock returns, but only for downgrades.

When investigating whether rating downgrades and upgrades crossing the investment-grade threshold affects stock returns, the variables FALLEN_ANGEL and RISING_STAR are used respectively. The RISING_STAR-coefficient is significant, indicating that rating upgrades from speculative grade to investment grade result in a significantly stronger stock reaction compared to other rating upgrades. This is consistent with prior research like May (2010) and Hita and Warga (1997). Based on the studies of Steiner and Heinke (2001), Holthausen and Leftwich (1986), and Hita and Warga (1997), the effect was expected to be even more significant for rating downgrades. This expectation is also rational as a fall from investment grade can force selling decisions, while a rating upgrade does not necessarily have the same effect on buying decisions. However, the insignificant results from the FALLEN_ANGEL-coefficient do not indicate that this is the case. Although, a plausible explanation of this result is the small sample, as there were only two observations in which a rating fell from investment grade. Thus, the results are conflicting regarding hypothesis 5, in that a rating crossing the investment grade threshold should observe a greater stock effect, as it only yields support for upgrades.

It was further tested whether rating changes moving across classes affect stock returns through the variable ACROSS. The coefficients were not significant for downgrades or upgrades. This suggests that there is no support for hypothesis 2, that rating changes moving across classes have a greater impact on stock returns than rating changes moving within classes. Contrary to this result, Holthausen and Leftwich (1986) found that downgrades across classes caused significantly abnormal returns around the event day, while within-class downgrades were less significant.

To investigate whether the rating prior to a rating change has any impact on the effect of the rating change, a dummy was used to differentiate between lower prior ratings and higher prior ratings. The results presented in the regression output for LOW_PRIOR show no significant results for either rating downgrades or rating upgrades. Consequently, the results yield no support for hypothesis 6, in that a low prior rating causes a greater stock price effect. These results are contradicting the findings of May (2010), as he found evidence suggesting that rating changes with a low prior rating had a significantly stronger impact on the abnormal returns, compared to rating changes with higher prior ratings.

The variable NEWS was used to test if news coverage affects the stock price reaction to a rating change. The coefficients for NEWS in both regression outputs provide no significant findings. Hence, the results do not support hypothesis 7, in that firms with less news coverage experience a stronger effect on abnormal returns than firms with more coverage. On top of this, the coefficient found for downgrades is positive, suggesting that less covered firms observe a weaker effect in the event of a rating downgrade. This is not consistent with the results of Hsueh and Liu (1992), as they found significant evidence that the impact of a rating change is stronger for firms with less information available in the market.

From tables 6.2 and 6.3, one can observe that the effect of a rating change differs somewhat, depending on which rating agency announcing the change. From these tables, rating changes from S&P seem to have the greatest impact. To further test this, the variable S&P is included in the regression. The S&P-coefficient was significant for downgrades, but not for upgrades. This does not support hypothesis 4, that the impact of a rating change is indifferent to the rating agency announcing the rating change. It rather indicates that a rating downgrade from S&P has a greater effect on the stock price, compared to a rating downgrade from the two other rating agencies. This result is contradicting earlier studies (Hite & Warga, 1997; May, 2010), as these studies found no difference in effects between the rating agencies. The results are, however, somewhat in line with the studies of Norden and Weber (2004), and Alsakka and Gwilym (2012), which suggest that rating announcements from S&P and Moody's are more influential than announcements from Fitch. Looking at table 6.2, this seems to be the case for this study as well, as CAAR[-1, 1] for downgrades is significant for both S&P and Moody's, but not for Fitch.

7.4 Leakage of Rating Announcements

From figure 6.1 there appears to be a negative development of the CAAR for downgrades before the event day. This could indicate that the market either receives news of a downgrade or accurately anticipates a downgrade. However, when observing the results for CAAR [-5,-1] in table 6.1, the results are not significant, even though it is close. This is contradicting the study of Halek and Eckles (2010), as they found evidence of significant negative returns occurring in the days before downgrade announcements. Another study by Goh and Ederingtion (1993) also found significant negative returns in the days before a rating downgrade. They did, however, only find a significant effect for downgrades caused by specific news such as known bankruptcies, takeovers, and lawsuits. For rating downgrades caused by reduced financial prospects or increased leverage, the effect was not significant. This can suggest that it is not the leakage of the rating downgrade itself that causes the negative return prior to a rating announcement, but rather the already published news that causes the rating agencies to change the rating. Regarding credit rating upgrades, there is no indication of any leakage. This is in line with the results of previous studies (Halek & Eckles, 2010; Goh & Ederingtion, 1993).

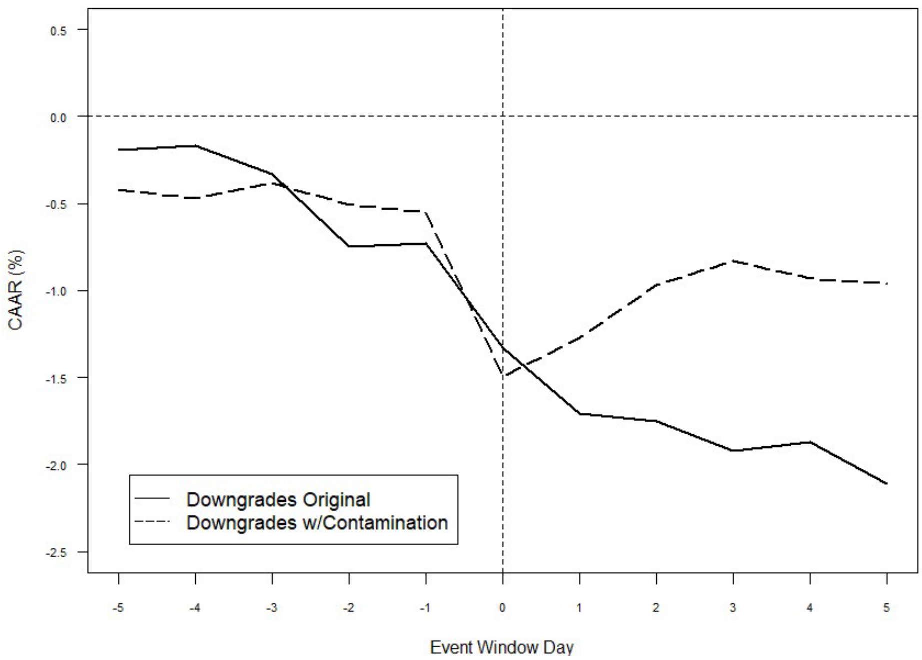
8 Robustness Analysis

This section includes a robustness analysis of the results presented in the Analysis-section. The goal is to test how different research design choices impact the results. First, the impact of including the contaminated events in the event analysis will be tested. Afterward the impact of excluding different independent variables in the cross-sectional regression will be investigated. Additionally, it will be tested how the choice of dependent variable affects the results, by running the regression on CAR [0, 1] instead of CAR[-1, 1]. Finally, the selection of test statistics and their impact on the results will be discussed.

8.1 Including Contaminated Events

As stated in the Data-section, the exclusion of contaminated events was one of the processing steps done with the data sample. These contaminated events, as specified in appendix 3, are events excluded due to confounding effects in the event window not related to the credit rating changes. 18 of the 19 contaminated events are rating downgrades. Hence, the difference when including contaminated events was naturally minimal for upgrades, with only one additional event. As a result, the robustness analysis of contaminated events will only focus on rating downgrades. In figure 8.1, the CAAR development for downgrades with and without the contaminated events is illustrated.

Figure 8.1: CAAR for Downgrades with and without Contaminated Events



The plot shows that the inclusion of the contaminated events affects the CAAR development for rating downgrades. The development of the CAAR is more stable before the event day, steeper on the event day, and shows a clear positive recovery after the event day. The positive recovery is in contrast to the CAAR development of the original sample, which shows a rather stable, negative trend following the event day. The positive development of the CAAR after day 0 suggests that the contaminated events excluded in the original sample, have a positive abnormal return the days following the event date.

The following table show the CAARs and AARs for the downgrade sample, including contaminated events. The CAARs and AARs from the original sample are also included for comparison.

Table 8.1: CAAR and AAR Results for Downgrades with and without Contaminated Events

Timeline	CAAR Original	CAAR w/Contamination
[-5, 5]	-0.0210**	-0.0097
	(-2.53)	(-0.67)
[-2, 2]	-0.0139**	-0.009
	(-2.64)	(-0.85)
[-1, 1]	-0.0085**	-0.0094
	(-2.33)	(-1.25)
[-5, -1]	-0.0088	-0.0069
	(-1.56)	(-0.73)
[1, 5]	-0.0080	0.0064
	(-1.11)	(0.75)
Day	**AAR Original**	**AAR w/Contamination**
[-1]	0.0002	-0.0023
	(0.10)	(-0.67)
[0]	-0.0060**	-0.0096
	(-2.46)	(-1.59)
[1]	-0.0038	0.0026
	(-1.43)	(0.66)
Observations	54	54
Note:	T-statistics in parenthesis; *p<0.1, **p<0.05, ***p<0.01	

Table 8.1 show that the contaminated events affect the CAAR results and the test statistic. The CAAR results of CAAR [-5, 5] and CAAR [-2, 2] are affected by the positive recovery after the event day, resulting in less negative CAARs. CAAR[-1, 1] and AAR[0] are of a larger magnitude with the contaminated events than without. However, the test statistics are smaller, resulting in less significant results. As both the sample size and effects measured by CAAR[-1, 1] and AAR[0] have increased when including the contaminated events, the reduced significance can be explained by increased volatility in the data sample.

8.2 Robustness Analysis of the Regression Results

As mentioned earlier, a robustness analysis of the results from the cross-sectional regression will be done on both the independent and dependent variables. Tables 8.2 and 8.3 show the new regression results for rating upgrades and downgrades respectively. Columns 1-4 are included to test how the exclusion of different independent variables affect the results. This is interesting to investigate, as some of the variables included in the original regression are mildly correlated (see appendix 4). As shown in appendix 4, the MULTIPLE- and ACROSS-variable have a correlation of 0,40 and 0,46 for downgrades and upgrades respectively, which is logical as a rating change moving multiple levels is likely to move across rating classes as well. This could suggest that by including both of these variables, the regression fails to measure the true effect of the variables. As a result, the most correlated variables are excluded one by one, to see if it affects the explanatory power of some of the independent variables.

Furthermore, column 5 in the tables is included to test how the choice of dependent variable affects the results. CAR[0, 1] is the new dependent variable. This time interval was chosen, as it is the most significant time interval for both downgrades and upgrades, second to CAR[-1, 1].

Table 8.2: Robustness Analysis of the Regression Output for Upgrades

	The dependent variables:				
	CAR[-1, 1]				CAR[0, 1]
	(1)	(2)	(3)	(4)	(5)
RISING_STAR	0.019*	0.025**	0.026**	0.026**	0.021**
	(1.95)	(2.26)	(2.28)	(2.22)	(2.27)
NEWS	0.001	-0.001	-0.000	-0.000	0.001
	(0.16)	(-0.13)	(-0.06)	(-0.05)	(0.17)
S&P	0.003	0.005	0.005	0.005	0.006
	(0.67)	(0.90)	(0.93)	(0.92)	(1.51)
MULTIPLE		-0.011	-0.010	-0.010	-0.009
		(-1.14)	(-1.03)	(-0.98)	(-1.01)
LOW_PRIOR			-0.003	-0.003	0.002
			(-0.45)	(-0.42)	(0.46)
ACROSS				-0.000	-0.002
				(-0.01)	(-0.42)
Constant	0.002	0.003	0.004	0.004	-0.001
	(0.48)	(0.65)	(0.78)	(0.76)	(-0.13)
Observations	71	71	71	71	71
R^2	0.060	0.078	0.081	0.081	0.107
Adjusted R^2	0.016	0.021	0.008	-0.008	0.021
Note:	T-statistics in parenthesis; *p<0.1, **p<0.05, ***p<0.01				

As shown in table 8.2, there is a very limited change in the regression results for upgrades, both when reducing the number of independent variables, as well as when changing the dependent variable to CAR[0, 1]. The RISING_STAR-coefficient is still the only significant coefficient. This further strengthens the conclusion that rating upgrades moving a rating above the investment-grade threshold observe a greater stock effect than other rating upgrades. Other than that, there are no changes in any other coefficient worthy of noting.

Table 8.3: Robustness Analysis of the Regression Output for Downgrades

	The dependent variables:				
	CAR[-1, 1]				CAR[0, 1]
	(1)	(2)	(3)	(4)	(5)
FALLEN_ANGEL	0.013	0.008	0.001	-0.0002	0.024
	(0.85)	(0.57)	(0.05)	(-0.01)	(1.44)
NEWS	0.009	0.007	0.004	0.004	0.003
	(1.27)	(0.93)	(0.50)	(0.46)	(0.49)
S&P	-0.015*	-0.017**	-0.016**	-0.016**	-0.010
	(-2.00)	(-2.32)	(-2.24)	(-2.20)	(-1.53)
MULTIPLE		-0.021**	-0.020**	-0.021*	-0.021**
		(-2.30)	(-2.23)	(-1.99)	(-2.16)
LOW_PRIOR			0.011	0.012	0.008
			(1.54)	(1.42)	(1.08)
ACROSS				0.001	-0.004
				(0.10)	(-0.49)
Constant	-0.005	0.001	-0.002	-0.002	-0.003
	(-0.81)	(0.20)	(-0.29)	(-0.30)	(-0.51)
Observations	54	54	54	54	54
R^2	0.100	0.188	0.226	0.226	0.288
Adjusted R^2	0.046	0.122	0.146	0.128	0.198
Note:	T-statistics in parenthesis; *p<0.1, **p<0.05, ***p<0.01				

As shown in table 8.3, there seem to be no major changes to the coefficients when running the regression on fewer independent variables. Both the MULTIPLE- and S&P-coefficient are still significant, while all of the other independent variables are insignificant. When using CAR[0, 1] as the dependent variable, the S&P-coefficient seems to lose its significance. This can suggest that rating changes from S&P are not as related to a greater decrease in CAR, as the original regression insinuated. The MULTIPLE-coefficient is still significant, which strengthens the conclusion that a rating downgrade over multiple levels is related to a greater decrease in abnormal returns than rating downgrades over one level.

8.3 Choice of Test Statistic

In this thesis, the cross-sectional test has been used to calculate the significance level of the results, as this test is the basic approach described in Mackinlay (1997). However, there exist several viable alternatives. MacKinlay (1997) mentions the Patell test (Patell, 1976) and the Brown and Warner approach (1980, 1985).

The Patell test is based on standardization, a common modification, where each abnormal return are standardized by the forecast-error-corrected standard deviation (Patell, 1976). This makes the statistic robust against the way that abnormal returns are distributed across the event window, but sensitive to cross-sectional correlation and volatility induced by the event. This test statistic was calculated to check if the Patell test statistic was very different from the cross-sectional test statistic. Some differences were found when comparing the two test statistics, but there were no drastic variations. Hence, it was decided to go with the basic approach described in MacKinlay (1997). Nevertheless, it is important to remember that different test statistics have different weaknesses and strengths, and results could be interpreted with some variation depending on the chosen approach.

9 Conclusion

This thesis has researched the effect of credit rating change announcements on stock returns. To analyse the effect, the event-study methodology was used. The study extends prior work by focusing on the European insurance market. To investigate the topic, a total number of 125 rating announcements from 2009 till 2021 by S&P, Moody's, and Fitch were used.

To test if rating upgrades and downgrades result in abnormal returns, different sub-periods within the event window [-5, 5] were analysed, as well as the AARs around the event day. Consistent with earlier research on credit ratings, the general findings are that credit rating downgrade and upgrade announcements are associated with asymmetrical reactions in the capital markets. Meaning that rating downgrades lead to a significant negative reaction in the corresponding companies' stock price, while rating upgrades lead to a less significant reaction in the companies' stock price. In addition, the findings indicate that the results are somewhat varying, depending on the credit rating agency making the announcements.

By comparing AAR[0], there were also indications of the downgrade effect being more significant for the insurance industry, than for studies including a more broad-based data sample. However, the basis for making a conclusion on this particular topic was too limited.

To further strengthen the analysis, a cross-sectional regression was conducted. The goal of running the regressions was to analyse if and how different characteristics affected the abnormal returns. The regression output indicates that rating downgrades from S&P seem to yield a more significant stock market reaction for downgrades than the other two rating agencies. In addition, the cross-sectional regression shows evidence of a significantly stronger effect for upgrades that moves a rating from speculative grade to investment grade. The results also suggest that rating downgrades over multiple levels cause a stronger market reaction than rating changes over one level.

9.1 Further research

While this study provides some interesting results on the information content of rating changes with regard to the insurance market, additional research could yield further interesting findings. As Halek and Eckles (2010) studied the US insurance market before the financial crisis and the new regulations that followed the crisis, it would be interesting to focus on the US insurance market with data after 2009. Another interesting approach could be to include multiple industries to test if the market reaction to rating changes is different, depending on the industry. Furthermore, the topic of whether rating changes are leading or lagging could be a potential research topic. This means investigating whether it is the market that reacts to the rating announcements, or whether it is the rating agencies that react to the market.

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Appendix

A1 List of Included Companies

Table A1.1: List of Included Companies

Ticker Symbol	Company Name	Country of Exchange
ADM	Admiral Group PLC	United Kingdom
AGN	Aegon NV	Netherlands
AGS	Ageas SA	Belgium
G	Assicurazioni Generali SpA	Italy
AV.	Aviva PLC	United Kingdom
CS	AXA SA	France
BALN	Baloise Holding AG	Switzerland
CNP	CNP Assurances SA	France
COFA	Coface SA	France
HNR1	Hannover Rueck SE	Germany
HSX	Hiscox Ltd	United Kingdom
LGEN	Legal & General Group PLC	United Kingdom
MAP	Mapfre SA	Spain
NN	NN Group NV	Netherlands
NBG6	NUeRNBERGER Beteiligungs AG	Germany
PHNX	Phoenix Group Holdings PLC	United Kingdom
PST	Poste Italiane SpA	Italy
PZU	Powszechny Zaklad Ubezpieczen SA	Poland
POSR	Pozavarovalnica Sava dd	Slovenia
PRU	Prudential PLC	United Kingdom
SAGA	Saga PLC	United Kingdom
SAMPO	Sampo plc	Finland
SCR	Scor SE	France
RGSS	SK Rosgosstrakh PAO	Russia
CASS	Societa Cattolica di Assicurazione SpA	Italy
STB	Storebrand ASA	Norway
SLHN	Swiss Life Holding AG	Switzerland
SREN	Swiss Re AG	Switzerland
TLX	Talanx AG	Germany
US	UnipolSai Assicurazioni SpA	Italy
UQA	Uniqa Insurance Group AG	Austria
WUW	Wuestenrot & Wuerttembergische AG	Germany
ZVTG	Zavarovalnica Triglav dd	Slovenia

A2 Summary of the Included Data Sample

Table A2.1: Summary of Included Events

Event	Date	Company	CRA	Rating	From	To
1	13.12.2021	UnipolSai Assicurazioni SpA	Fitch	Upgrade	BBB	BBB+
2	10.12.2021	Assicurazioni Generali SpA	Fitch	Upgrade	BBB+	A-
3	04.11.2021	CNP Assurances SA	S&P	Upgrade	A	A+
4	21.10.2021	SK Rosgosstrakh PAO	S&P	Upgrade	BB	BB+
5	02.07.2021	Phoenix Group Holdings PLC	Fitch	Upgrade	A	A+
6	25.06.2021	Ageas SA	Fitch	Upgrade	A	A+
7	10.06.2021	UnipolSai Assicurazioni SpA	Fitch	Upgrade	BBB-	BBB
8	19.04.2021	Ageas SA	Moody's	Upgrade	A2	A1
9	12.04.2021	NN Group NV	Fitch	Upgrade	A	A+
10	30.11.2020	Ageas SA	Moody's	Upgrade	A3	A2
11	16.11.2020	Ageas SA	S&P	Upgrade	A	A+
12	07.10.2020	SK Rosgosstrakh PAO	S&P	Upgrade	BB-	BB
13	07.05.2020	UnipolSai Assicurazioni SpA	Fitch	Downgrade	BBB	BBB-
14	05.05.2020	Assicurazioni Generali SpA	Fitch	Downgrade	A-	BBB+
15	24.04.2020	Swiss Re AG	Fitch	Downgrade	A	A-
16	18.11.2019	Mapfre SA	S&P	Upgrade	BBB+	A-
17	22.07.2019	Aviva PLC	S&P	Upgrade	A-	A
18	18.07.2019	Sampo plc	S&P	Upgrade	A-	A
19	06.05.2019	SK Rosgosstrakh PAO	S&P	Upgrade	B+	BB-
20	16.04.2019	Swiss Life Holding AG	S&P	Upgrade	BBB+	A-
21	29.01.2019	Ageas SA	Moody's	Upgrade	Baa2	A3
22	07.01.2019	Talanx AG	S&P	Upgrade	A-	A+
23	20.11.2018	Ageas SA	S&P	Upgrade	BBB	A
24	23.10.2018	Poste Italiane SpA	Moody's	Downgrade	Baa2	Baa3
25	28.09.2018	SK Rosgosstrakh PAO	S&P	Upgrade	B	B+
26	14.09.2018	Storebrand ASA	Moody's	Upgrade	Baa3	Baa2
27	30.07.2018	Pozavarovalnica Sava dd	S&P	Upgrade	A-	A
28	20.07.2018	Storebrand ASA	S&P	Upgrade	BBB-	BBB
29	27.06.2018	Baloise Holding AG	S&P	Upgrade	BBB+	A-
30	30.05.2018	Storebrand ASA	Moody's	Upgrade	Baa2	Baa1
31	30.05.2018	Legal & General Group PLC	Moody's	Upgrade	Ba1	Baa3
32	30.05.2018	Sampo plc	Moody's	Upgrade	Baa2	Baa1
33	30.05.2018	Coface SA	Moody's	Upgrade	A3	A2
34	30.05.2018	NN Group NV	Moody's	Upgrade	Baa1	A3
35	30.05.2018	Ageas SA	Moody's	Upgrade	Baa3	Baa2
36	08.05.2018	UnipolSai Assicurazioni SpA	Fitch	Upgrade	BBB-	BBB
37	31.10.2017	Poste Italiane SpA	S&P	Upgrade	BBB-	BBB
38	31.10.2017	Societa Cattolica di Assicurazione SpA	S&P	Upgrade	BBB-	BBB
39	13.06.2017	SK Rosgosstrakh PAO	S&P	Downgrade	B+	B
40	07.06.2017	Mapfre SA	Fitch	Upgrade	BBB+	A-
41	11.05.2017	NN Group NV	S&P	Downgrade	A-	BBB+
42	08.05.2017	Poste Italiane SpA	Fitch	Downgrade	BBB+	BBB
43	15.12.2016	Sampo plc	Moody's	Upgrade	Baa2	Baa1

44	27.10.2016	AXA SA	S&P	Upgrade	A-	A
45	23.08.2016	Aegon NV	Fitch	Downgrade	A	A-
46	04.07.2016	Zavarovalnica Triglav dd	S&P	Upgrade	A-	A
47	26.05.2016	Saga PLC	S&P	Upgrade	B+	BB+
48	20.04.2016	Sampo plc	S&P	Downgrade	A	A-
49	15.03.2016	Ageas SA	Fitch	Upgrade	A-	A
50	21.01.2016	Powszechny Zaklad Ubezpieczen SA	S&P	Downgrade	A	A-
51	11.12.2015	Aviva PLC	Fitch	Upgrade	A	A+
52	06.11.2015	Ageas SA	S&P	Upgrade	BBB-	BBB
53	07.09.2015	Scor SE	S&P	Upgrade	A+	AA-
54	28.08.2015	Legal & General Group PLC	Fitch	Upgrade	A	A+
55	26.08.2015	NUeRNBERGER Beteiligungs AG	Fitch	Upgrade	BBB+	A-
56	21.08.2015	Admiral Group PLC	Fitch	Upgrade	A-	A
57	29.07.2015	Pozavarovalnica Sava dd	S&P	Upgrade	BBB+	A-
58	20.07.2015	Hannover Rueck SE	Fitch	Downgrade	AA-	A+
59	17.07.2015	Coface SA	Fitch	Upgrade	A	A+
60	15.07.2015	Ageas SA	Fitch	Upgrade	BBB+	A-
61	10.07.2015	Storebrand ASA	S&P	Downgrade	BBB	BBB-
62	25.06.2015	NUeRNBERGER Beteiligungs AG	S&P	Downgrade	BBB+	BBB
63	20.05.2015	Swiss Life Holding AG	S&P	Upgrade	BBB	BBB+
64	19.05.2015	Mapfre SA	Fitch	Upgrade	BBB	BBB+
65	18.02.2015	NN Group NV	S&P	Upgrade	BBB+	A-
66	17.12.2014	Storebrand ASA	Moody's	Downgrade	Baa3	Ba1
67	12.12.2014	UnipolSai Assicurazioni SpA	S&P	Downgrade	BBB	BBB-
68	12.12.2014	Assicurazioni Generali SpA	S&P	Downgrade	A-	BBB+
69	12.12.2014	Societa Cattolica di Assicurazione SpA	S&P	Downgrade	BBB	BBB-
70	19.08.2014	Hannover Rueck SE	Fitch	Upgrade	A+	AA-
71	30.05.2014	Mapfre SA	S&P	Upgrade	BBB	BBB+
72	29.04.2014	Mapfre SA	Fitch	Upgrade	BBB-	BBB
73	20.02.2014	Mapfre SA	S&P	Upgrade	BBB-	BBB
74	12.11.2013	CNP Assurances SA	S&P	Downgrade	A+	A
75	17.10.2013	Uniqa Insurance Group AG	S&P	Upgrade	BBB+	A-
76	12.07.2013	Assicurazioni Generali SpA	S&P	Downgrade	A	A-
77	04.07.2013	Zavarovalnica Triglav dd	S&P	Upgrade	BBB+	A-
78	14.02.2013	Zavarovalnica Triglav dd	S&P	Downgrade	A-	BBB+
79	28.12.2012	Wuestenrot & Wuerttembergische AG	S&P	Upgrade	BBB	BBB+
80	18.12.2012	AXA SA	S&P	Downgrade	A	A-
81	14.12.2012	UnipolSai Assicurazioni SpA	S&P	Upgrade	BB	BBB
82	09.11.2012	UnipolSai Assicurazioni SpA	S&P	Upgrade	B+	BB
83	15.10.2012	Mapfre SA	S&P	Downgrade	BBB	BBB-
84	16.08.2012	Hiscox Ltd	Fitch	Upgrade	BBB+	A-
85	15.08.2012	Aviva PLC	S&P	Downgrade	A	A-
86	09.08.2012	UnipolSai Assicurazioni SpA	S&P	Upgrade	B	B+
87	07.08.2012	Zavarovalnica Triglav dd	S&P	Downgrade	A	A-
88	11.06.2012	Mapfre SA	Fitch	Downgrade	BBB+	BBB-
89	04.06.2012	Scor SE	S&P	Upgrade	A	A+
90	03.05.2012	Swiss Life Holding AG	S&P	Upgrade	BBB-	BBB
91	30.04.2012	Mapfre SA	S&P	Downgrade	BBB+	BBB
92	15.03.2012	Scor SE	Fitch	Upgrade	A	A+

93	31.01.2012	Mapfre SA	Fitch	Downgrade	A-	BBB+
94	27.01.2012	CNP Assurances SA	S&P	Downgrade	BBB+	BBB
95	27.01.2012	Societa Cattolica di Assicurazione SpA	S&P	Downgrade	AA-	A+
96	27.01.2012	Assicurazioni Generali SpA	S&P	Downgrade	A+	A
97	17.01.2012	Assicurazioni Generali SpA	S&P	Downgrade	A-	BBB+
98	17.01.2012	Societa Cattolica di Assicurazione SpA	S&P	Downgrade	AA-	A+
99	17.01.2012	Mapfre SA	S&P	Downgrade	A	BBB+
100	29.12.2011	UnipolSai Assicurazioni SpA	S&P	Downgrade	BB+	B
101	13.12.2011	Assicurazioni Generali SpA	Fitch	Downgrade	A+	BBB+
102	13.12.2011	Uniqa Insurance Group AG	S&P	Downgrade	A-	BBB+
103	15.11.2011	UnipolSai Assicurazioni SpA	S&P	Downgrade	BBB-	BB+
104	17.10.2011	Mapfre SA	S&P	Downgrade	A+	A
105	27.09.2011	Storebrand ASA	Fitch	Upgrade	BB+	BBB-
106	26.09.2011	Wuestenrot & Wuerttembergische AG	S&P	Upgrade	BBB-	BBB
107	01.10.2010	Prudential PLC	Fitch	Downgrade	AA-	A+
108	01.10.2010	UnipolSai Assicurazioni SpA	S&P	Downgrade	BBB+	BBB
109	26.07.2010	Aegon NV	Fitch	Downgrade	A+	A
110	18.05.2010	Legal & General Group PLC	Moody's	Downgrade	A2	A3
111	30.03.2010	AXA SA	S&P	Downgrade	A+	A
112	09.02.2010	Legal & General Group PLC	S&P	Downgrade	A+	A
113	29.09.2009	CNP Assurances SA	S&P	Downgrade	AA	AA-
114	03.08.2009	Ageas SA	S&P	Upgrade	BB	BBB-
115	23.07.2009	Swiss Life Holding AG	Fitch	Downgrade	BBB-	BB+
116	15.07.2009	Ageas SA	Moody's	Downgrade	Baa2	Baa3
117	09.07.2009	Ageas SA	Fitch	Upgrade	BB	BBB+
118	15.06.2009	Legal & General Group PLC	Fitch	Downgrade	A+	A
119	31.03.2009	Assicurazioni Generali SpA	S&P	Downgrade	AA	AA-
120	20.03.2009	AXA SA	Fitch	Downgrade	AA-	A
121	13.03.2009	Scor SE	S&P	Upgrade	A-	A
122	20.02.2009	Mapfre SA	Fitch	Downgrade	A+	A-
123	20.02.2009	Assicurazioni Generali SpA	Fitch	Downgrade	AA-	A+
124	12.02.2009	Sampo plc	Moody's	Downgrade	Baa1	Baa2
125	13.01.2009	NUeRNBERGER Beteiligungs AG	S&P	Downgrade	BBB+	BBB

A3 Summary of Removed Events

Table A3.1: Removed Events

Event	Date	Ticker	CRA	Rating	Reason for removal
1	13.02.2009	AGS	Fitch	Downgrade	Extremely volatile through the event window
2	17.02.2009	AGN	S&P	Downgrade	Extremely volatile through the event window
3	20.02.2009	AGS	S&P	Downgrade	Extremely volatile through the event window
4	25.02.2009	LGEN	Moody's	Downgrade	Disappointing Q3 report released at t = -3
5	06.03.2009	AGN	Moody's	Downgrade	Announcement of huge expect loss for Q4 at t = 0
6	13.03.2009	LGEN	S&P	Downgrade	Missing data in event window
7	19.03.2009	AV.	Fitch	Downgrade	Extremely volatile through the event window
8	26.03.2009	PZU	S&P	Downgrade	Missing data in event window
9	30.03.2009	LGEN	S&P	Downgrade	Disappointing annual report released at t = -3
10	31.03.2009	NN	Moody's	Downgrade	Disappointing Q1 report released at t = -1
11	31.03.2009	AV.	Fitch	Downgrade	Disappointing annual report released at t = 5
12	07.05.2009	STB	S&P	Downgrade	Announcement of disappointing results at t = 0
13	16.07.2009	PST	Fitch	Downgrade	Missing data in event window
14	03.09.2009	NN	S&P	Upgrade	Missing data in event window
15	26.10.2009	NN	S&P	Downgrade	Missing data in event window
16	26.03.2010	US	S&P	Downgrade	Sold significant subsidiary at t = -4
17	16.12.2010	ASRNL	Fitch	Downgrade	Disappointing Q4 report released at t = -1
18	09.03.2011	US	S&P	Upgrade	Merger with Generali at t = -3
19	05.10.2011	PST	S&P	Downgrade	Substantial capital raising at t = 0
20	07.12.2011	PST	Fitch	Downgrade	Missing data in event window
21	17.01.2012	PST	S&P	Downgrade	Announcement of substantial shareholder buys at t = 0
22	08.02.2012	PST	Moody's	Downgrade	Missing data in event window
23	16.02.2012	PST	S&P	Downgrade	Missing data in event window
24	16.07.2012	PST	S&P	Downgrade	Missing data in event window
25	12.03.2013	PST	Fitch	Downgrade	Missing data in event window
26	16.07.2013	PST	Moody's	Downgrade	Missing data in event window
27	02.12.2013	NN	S&P	Downgrade	Missing data in event window
28	02.06.2014	SAGA	S&P	Downgrade	Missing data in event window
29	12.12.2014	PST	Moody's	Downgrade	Missing data in event window
30	26.08.2015	KDHR	Fitch	Downgrade	Disappointing annual report released at t = -1
31	24.05.2016	RGSS	Fitch	Downgrade	Announcement of demerger at t = 0
32	14.03.2018	PRU	S&P	Downgrade	Missing data in event window
33	15.03.2018	PRU	S&P	Upgrade	Missing data in event window
34	04.04.2019	SAGA	S&P	Upgrade	Missing data in event window
35	20.03.2020	SAGA	S&P	Downgrade	Surprisingly good Q1 report released at t = -2
36	11.11.2021	CASS	S&P	Downgrade	Announcement of demerger at t = -1

Note: The event numbers from table A2.1 and this table are not the same events.

A4 Correlation Matrix of Independent variables

Table A4.1: Correlation Matrix of Independent Variables for Downgrades

	MULTIPLE	FALLEN_ANGEL	ACROSS	LOW_PRIOR	S&P	NEWS
MULTIPLE	1					
FALLEN_ANGEL	-0.108	1				
ACROSS	0.399	0.329	1			
LOW_PRIOR	-0.137	0.316	-0.244	1		
S&P	-0.153	-0.138	-0.128	-0.017	1	
NEWS	-0.200	-0.054	-0.035	0.240	0.331	1

Table A4.2: Correlation Matrix of Independent Variables for Upgrades

	MULTIPLE	RISING_STAR	ACROSS	LOW_PRIOR	S&P	NEWS
MULTIPLE	1					
RISING_STAR	0.462	1				
ACROSS	0.460	0.383	1			
LOW_PRIOR	0.238	0.198	0.387	1		
S&P	0.130	-0.068	0.029	0.123	1	
NEWS	-0.226	-0.044	-0.212	0.123	0.104	1