The Effect of Credit Rating Announcements on Stock Returns

An Empirical Assesement of the Scandinavian Stock Market

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Abstract

This master thesis aims to explain the association between changes in credit ratings and stock returns. In efficient markets, all pricing relevant information is discounted in the stock price. Hence, stock prices will not react to credit rating announcements unless the announcement conveys new information. I assess the information content of credit ratings by measuring the abnormal stock returns associated with credit rating announcements. Abnormal returns are calculated relative to two expected returns models, (i) the market adjusted return model and (ii) the market model.

I found that both upgrades and downgrades yield significant cumulative abnormal returns. Downgrades are significant on the announcement day and the pre/post-event day, in the pre-event window and the post-event window. Upgrades are significant on the announcement day and the pre/post-event day. Hence, it is evident that credit ratings do indeed convey new information to the capital markets. The results were not altered by choice of expectation model. Firms with a high current ratio experience less negative abnormal returns in case of downgrades on the event day. In the case of upgrades I found that firms with a higher debt-to-asset ratio experience less positive abnormal returns on the announcement day.

Changes in credit rating yields more negative abnormal returns for firms which are downgraded to non-investment grade, compared to firms which are not reclassified. This is especially evident in the post-event window. Reclassification did not yield any significant results for upgrades. Furthermore, this study shows that non-investment grade firms experience significantly more negative abnormal returns in case of downgrades, compared to investment-grade firms. The results are highly significant for all event windows except the post-event window.

In order to explain abnormal returns, I used a multiple regression model based on the aforementioned variables (leverage, reclassification, (non)-investment grade) and a control variable to account for market anticipation. By controlling for all the explanatory variables, I found that the current ratio had a significant effect on downgrades on the announcement day. Moreover, credit rating announcements which were not anticipated yielded cumulative abnormal returns on the pre/post-event day. In general, the multiple regressions model seems to perform poorly when it comes to upgrades.

Preface

Credit rating agencies (CRAs) have obtained massive media coverage since the onset of the financial crisis. The CRAs received considerable criticism in the years following the crisis and investors, regulators and the business community have questioned the role of rating agencies in the market turmoil. One example that underpins the critique is that the CRAs were responsible for contributing to the housing bubble in the US by awarding AAA rating to complex, unsafe asset backed securities and other derivatives. This is clearly a subject of public interest, as credit ratings (or the lack of appropriate ratings) could cause a tremendous impact on the economy. This triggered my interest for the CRAs and the credit rating process. As I have gained more knowledge of the credit rating process, I have been increasingly motivated to learn more about the information content of credit rating announcements and whether or not they affect stock returns. This paper is motivated by the question;

Do credit rating agencies provide new information to the capital markets?

This thesis is a sole authorship however, I would like to express my gratitude towards those who have supported me during the work and made valuable contributions to this master thesis. First and foremost I would like to thank professor Tore Leite for his guidance and insightful thoughts on credit ratings and event study methodology. Second, I thank Eirik Nerheim and Skjalg Y. Thomassen for being such good friends and for their feedback and advice regarding this thesis. Special thanks also go to my family whom I love very much.

Contents

1. Introduction

Credit ratings reflect the likelihood of default on a continuous basis. Rating categories, on the other hand, are discrete. They do not change on a timely basis like stock prices because they are supposed to reflect the long term creditworthiness of the issuer. Credit ratings should not react to any change in market conditions unless the change will affect the firm's ability to repay its debt and interests. On the contrary, in efficient markets stock prices will immediately reflect all new information. Hence, the interesting question is whether all pricing relevant information is already incorporated in the stock price at the time of a credit rating announcement. This is important because it has implications for market efficiency, security valuation and public policies. In that sense, this paper is a test of the efficient market hypothesis. This master thesis applies event study methodology in order to assess the effect of credit rating announcements on stock returns. The event study methodology is favourable in this context because it can be used to evaluate the impact of company policies on firm value. To my knowledge, no research has been done on the combined Scandinavian stock market (only individual countries). Hence this study contributes to the empirical research on credit ratings and stock returns.

The credit rating agencies use publically available information when they conduct the credit rating process. There is one source of information, however, that is not always publically available, namely data from meetings or conversations with the debt issuer. This means that when a credit rating agency announces a change in credit rating, this may contain information not previously known to the public. According to the efficient market hypothesis (Fama, 1970), one would not expect stock prices to react to a change in credit rating unless the announcement conveys new information. The literature on this topic is ambiguous, and the empirical results are contradictory. However, the general perception is that credit rating announcements do convey new information to the market (Hand, Holthausen, & Leftwich, 1992). Furthermore, the direction of the effect is disputable. Theories have been set forth (Merton 1974) suggesting a transfer of wealth between bond- and stockholders as risk is revised up (downgrade) or down (upgrade). Contradictory theories with respect to the stock price effect of upgrades and downgrades make this an interesting topic for further study. However, the majority of studies find that credit rating downgrades are associated with negative abnormal return.

I measure abnormal returns relative to two models, (i) the adjusted return model and (ii) the market model. I specify three event windows, $[t_{-5}; t_0]$, $[t_{-1}; t_1]$ and $[t_0;\ t_5]$, in addition to the announcement day, t_0. Different event windows are used to gauge the efficiency of the markets. The t-statistics is used to test whether the cumulative abnormal returns over the event window is significantly different from zero.

The most influential paper on capital structure and firms value (Modigliani & Miller, 1958) states that the firm value is independent of the capital structure, that is, in perfect capital markets. Leverage is one of the most important determinants for credit rating and previous research suggests that highly leveraged firms experience a more significant stock price reaction to credit rating downgrades than do less leveraged firms. Theory and empiricism do, once again, contradict each other. I assess whether it is a relationship between capital structure and abnormal returns. That is, contingent on the firm being upgraded or downgraded, does capital structure explain the magnitude of abnormal returns? I operationalize this by constructing a variable for net debt-to-assets and for the current ratio. Then I run regressions of cumulative abnormal returns on the independent variables. Stock prices are inherently forward looking, in that they reflect the present value of future cash flows. Failing to control for anticipation would influence the results. Consequently, the information content of credit rating is contingent on the availability of information. I use a dummy variable to account for warnings of possible rating changes via additions to the S&P CreditWatch List. I do a separate examination of credit rating preceded by positive, neutral or negative outlooks.

Government regulators and corporate policies rely heavily on credit ratings. Many market participants and institutional investors are prohibited from investing in the securities of non-investment grade firms. Moreover, the rating affects the conditions and costs under which firms access debt markets; hence the credit rating is closely linked to the debt cost of capital. Consequently, the divide between investment grade and non-investment grade is of special interest. I investigate whether there are any differences between downgrades or upgrades, contingent on the firm being classified as either investment grade or non-investments grade. By using two-sample t-tests I assess differences between the two groups. Moreover, I test whether the reclassification from investments grade to non-investment grade, or vice versa, yields abnormal returns.

1.1 Outline

The remainder of the paper is organized as follows. In section 2, I outline the history of credit rating agencies and their present role in the financial markets. I describe the credit rating process, the methods used, and the information contained in credit ratings. Section 3 presents the theoretical framework which helps contextualise the research on the effect of credit ratings on stock returns. These theories evolve around the information content of credit ratings, the wealth redistribution theory and the association between capital structure and the effect of credit rating announcements. Section 4 provides a description of the empirical research methodology, the design of the study and the data sample. Furthermore, it describes how the data has been processed and which statistical tests have been used. Section 5 provides the results from the tests and includes a discussion of the results and their implications. Section 6 concludes the paper.

2. The Credit Rating Agencies

2.1 The History of Credit Rating Agencies

The credit rating agencies (henceforth CRAs) have a long history in the financial markets with traces all the way back to the latter part of the 19th century. The first CRAs emerged in the US as a response to the increased interest for investing in railroads. Railroad construction and development swiftly became the most capital-intensive industry in the US, and the need for investors to support the rapid expansion fostered growth in the capital markets. However, "railroad information" to the investors was very limited, thus creating a new business opportunity of gathering, processing and distributing information. Henry Varnum Poor was the first one to capitalize on this new business model in 1860, and it started out as a "user-pay" revenue model in that investors paid to receive the information (Sylla, 2001).

Soon after other providers of railroad information entered the market. One of them was Luther Lee Blake who established Standard Statistical Bureau in 1906. In 1941 Poor merged with Standard and are today known as Standard & Poor's Corporation. Another pioneer, John Moody, joined the party in 1909 and was the first to assign letter grades to companies and their securities in a declining order of credit quality. John Knowles Fitch was yet another player who established Fitch Publishing Company in 1913. Fitch introduced the now familiar AAA through D ratings scale that ultimately became the benchmark for credit rating agencies (Moody's Investors Service, 2002).

The CRAs have evolved tremendously since their inception and are now considered one of the most important financial institutions. The decisive moment for the CRAs was the stock market crash in 1929. The crash and the following economic consequences led to requests for more regulations of the financial markets and an urge for "safety". Regulators began placing heavy emphasis on CRAs' credit ratings, e.g. the Federal Reserve, individual states and fund managers. Consequently, the CRAs became elevated from information brokers to unofficial gatekeepers to the financial markets, and their "approval" became the ticket to the capital markets. The CRA industry benefited from both selling information and the rating of securities. In the 1970s the industry had transformed completely from a "user-pay" system to an "issuer-pay" system. The creation of "National Recognized Statistical Rating Organizations" (NRSRO) by the Securities and Exchange Commission (SEC) helped to further manifest the CRAs' position. In addition, the SEC has refused to qualify most agencies that have applied for NRSRO status, which in turn has enhanced the position of the "big three" rating agencies. As of today, Moody's, Standard & Poor and Fitch dominate 95% - 98% of securities rating, and the remaining is shared between seven minor players. However, the market is mainly dominated by the two first agencies, and Fitch's share of the market is significantly less than that of its two main rivals (Sylla, 2001).

2.2 The Credit Rating Industry as of Today

The CRAs have specialized in analysing and evaluating the future relative creditworthiness of sovereign and corporate issuers of debt securities. Their opinion is derived by fundamental credit analysis and expressed by the familiar AAA–C symbol system. The rating symbols strive to reflect an objective, consistent and simple measure of instruments and securities. The objective is to report the likelihood that debt will be repaid in a timely manner, thereby contributing to transparency and integrated financial markets (Moody`s Investors Service, 2002). Ratings constitute opinions, not buy and sell recommendations, or whether the investment is suitable for an investor. The credit rating does not provide guidance on other aspects essential for investment decisions, and bonds with the same rating may have very different market prices. The fact that CRAs do not provide investment recommendations has shielded them from investor legislation and, until recently, prevented direct regulation of their operations. The U.S. regulators have relied heavily on the CRAs as a basis for setting regulatory policies. By incorporating credit ratings into their policy making, the CRAs have received significant market recognition and credit ratings are now essential for all who wishes to enter the capital markets (The World Bank, 2009).

Credit ratings are used in the market for a variety of applications. For example, they are crucial for banks in determining their capital requirements under Basel II, in that the ratings may be used to assign the risk weights for minimum capital charges for different categories of borrowers. Furthermore, ratings are regularly used in security selection and portfolio composition by pension funds, mutual funds, insurance companies, and brokers by restricting or prohibiting the purchase of bonds with a low credit rating (SEC, 2003). Credit ratings are also used in portfolio governance, in performance attribution, in the regulation of financial markets and institutions, and in financial contracts and covenants (Moody's Investor Service, 2003).

Consequently, rating changes can have substantial economic consequences for a variety of debt issuers and investors. A change in credit rating from investments grade to non-investment grade may have significant consequences, as investors who are committed to mandates could be forced to rebalance their portfolios, thus resulting in downward pressure on bond prices. Moreover, the rating affects the conditions and costs under which firms access debt markets; hence, the credit rating is closely linked to the debt cost of capital. The CRAs help to mitigate the asymmetric information between lenders (investors) and borrowers (issuers) by assessing the creditworthiness of the latter. Hence they contribute to solving the principal-agent problems. In addition, it reduces investor’s cost of gauging the creditworthiness of a security or issuer, thereby increasing overall market efficiency (Moody's Investors Service, 2002).

2.3 The Credit Rating Process, Definitions and Methods

Credit ratings express forward looking opinions regarding the creditworthiness of issuers and issues. The term creditworthiness refers to the likelihood of an issuer to make timely payments of interest and principal, in accordance with its contractual terms, but it is not an absolute measure of default probability (S&P Global Credit Portal, 2009). A credit rating embodies multiple factors that compose the overall assessment of creditworthiness. Besides the likelihood of default, it also encompasses payment priority, recovery and credit stability. The CRAs do not have a “formula” for combining various factors, and the relative importance of the factors may vary between types of securities, firms and industries, between regions, currencies and different situations. Hence, the CRAs must use a great deal of subjective judgement during the credit rating process. Furthermore, the rating symbols are intended to reflect the same general level of creditworthiness for issuers and issues regardless of different sectors, industries, and at different times (S&P Global Credit Portal, 2009).

The primary factor for assessing creditworthiness is the likelihood of default. The two major agencies define default as, “missed or delayed disbursement of interest and/or principal” (Moody‘s) and “first occurrence of a payment default on any financial obligation” (S&P). The CRAs do not attach specific probabilities of default to each rating category. On the contrary, they form views about the likelihood of plausible scenarios and outcomes in order to make qualified estimates of creditworthiness. In general, issuers or issues with a higher credit rating should default less frequently than issuers or issues with lower ratings.

The CRAs assess multiple secondary credit factors during the credit rating process. One such factor is the projected recovery rate in case of default (loss given default). This is obviously of interest to creditors and differs greatly between industries. Another secondary factor is payment priority for firms that issue both senior/subordinate and secured/unsecured debt. A third factor is credit stability, which is a measure of how vulnerable the issuer is to sudden deterioration or default. While most firms display a period of gradual decay before they default, others may not give any warning at all. Other secondary factors which are associated with default and recovery rate are leverage, coverage, liquidity or profitability (Moody`s Investor Service, 2006). Besides hard facts and numbers, the CRAs also evaluate the management and its corporate governance. The management could be of significant importance with respect to credit rating, as default could result not only from a firm's lack of repayment capacity but also from willingness to honour its obligations. Furthermore, high probability of default may tempt the management to sub-optimize, thereby exploiting debt holders. The CRAs are important financial market participants by acting as vehicles for greater transparency and disclosure. Hence, it is vital to understand how the CRAs arrive at the ratings, what they entail, and why they are changed. Investors want ratings to reflect the issuer's relative fundamental credit risk, i.e. measure intrinsic financial strength. Moreover, they desire stability in credit ratings, and they believe that changes in ratings increase volatility (Moody's Investors Service, 2002). Because credit ratings affect both investor's and issuer's behaviour and thinking, stable ratings are highly valued by the market participants.

The fact that about 98 percent of all large corporate bond issues are rated by at least one rating agency (these ratings are costly) underpins the importance of credit ratings. The emphasis on credit ratings obliges the CRAs to promote transparency and to minimize any misunderstandings about what they do. Moody's is aware that their ratings can become self-fulfilling prophesies. According to Moody's Investor Service (2006, p.4) upgrades can mean "*greater capital market access and interest cost savings for issuers, and improved security prices for investors*". Moreover, downgrades can mean "*higher capital costs for issuers, and portfolio turnover and losses for investors*".

S&P and Moody's follow a very similar format and the assessed creditworthiness is reported by assigning one of the letters, AAA through D:

Moody‘s: Aaa, Aa, A, Baa, Ba, B, Caa, Ca, C and D

S&P: AAA, AA, A, BBB, BB, B, CCC, CC, C and D

AAA (Aaa) is the highest rating, representing minimum credit risk, and there is an inverse relationship between credit rating and likelihood of default. Ratings from AAA (Aaa) to BBB (Baa) are classified as investment grade. An obligor rated AAA–AA has a very strong capacity to meet their financial commitments. A–BBB issuers have strong/adequate capacity to meet its financial obligations, but are somewhat more susceptible to adverse changes in the economy, which may deteriorate their financial capacity. An obligor rated BB (Ba)-CC (Ca) is classified as non-investment grade (or speculative grade/junk-bonds/high-yield bonds). BB is regarded as having the least degree of speculation and CC has the most significant speculative aspects. While non-investment grade credit ratings may have some quality and protective characteristics, these might be outweighed by high uncertainty and/or major exposure to adverse conditions. C is the lowest rated class and is typically in default, with little prospect of recovery of principal or interests. D rating is assigned when a default is believed to be a general default and the issuer will fail to pay all or substantial parts of its obligations (S&P Global Credit Portal, 2009). For more refined ratings, Moody’s uses 1, 2 and 3, while S&P uses + and – signs. Moreover, S&P capitalizes all the letters, while Moody’s uses lowercase after the main rating letter. For example, S&P rating BBB+ is equivalent to Moody’s Baa1, and S&P BB- is equivalent to Moody’s Ba3.

Credit ratings are at their core forward-looking, and the CRAs constantly monitor their ratings. Hence, they should not react to any change in market conditions, unless they perceive that the change will affect the firm’s ability to repay its debt and interest. Many financial participants rely on the CRAs credit ratings. Thus, a challenge for the CRAs is to increase the information content of ratings without adding unnecessarily to market volatility. Besides the credit rating announcements itself, the CRAs also have other non-rating signals to convey information to the market such as outlooks and reviews. Outlooks give an opinion regarding the likely direction of any rating actions over the medium-term and are expressed as positive, stable or negative. If changing market conditions challenge the current rating, the CRAs can place the rating under review. S&P, Moody’s and Fitch each have their own review of credit ratings, named CreditWatch, Watchlist and Rating Watch, respectively. Ratings that are placed under watch are assigned into one of the following categories, positive, negative or developing/uncertain/evolving, until the CRA has determined whether the risk is still consistent with the assigned rating. Historically, 66%-76% of all ratings have been changed in the same direction as indicated by the review and rarely in the opposite direction (Moody's Investors Service, 2002).

The rating process is initiated by the CRAs forming a committee. The committee consists of a managing director, a lead analyst and a sufficient number of other members needed to perform the rating. The size of the committee may depend on the size of the issuer, the complexity of the securities, etc. All discussions and exchange of information between the committee and the management is strictly confidential (Moody`s Investor Service, 2006). The analysts utilize all relevant sources of information in order to derive the appropriate rating. Sources of information may include public available data (e.g. annual reports, prospectuses, offering memoranda), market data (e.g. stock price, volume, bond spreads etc), economic data from industry groups, associations, bodies or agencies and discussions with expert sources in the industry, government or academia (Moody`s Investor Service, 2006). The CRAs are also provided with detailed inside information during the rating process, e.g. five-year forecasts, pro-forma statements, and internal reports (Kliger & Sarig, 2000).

The CRAs strive to disclose the results of credit rating analysis, first to the issuer and banker, and second, to the market. They endeavour to explain the rationale for ratings as clearly as possible, subject to the confidentiality of non-public information disclosed to the CRAs by the issuer. The CRAs' primary objective is to produce ratings that are accurate and stable measures of creditworthiness. Accuracy may be measured in terms of cumulative accuracy profiles and accuracy ratios. It could also be measured as default rates and the average rating of defaulting issuers prior to their default. Rating stability is best measured in terms of (i) frequency of rating changes, (ii) frequency of large rating changes and (iii) frequency of rating reversals. It could be a trade-off between accuracy and stability. For example, by reacting more aggressively to new information, one could increase the short-term correlation between ratings and defaults. On the other hand, ratings will become more volatile to new information, thus reducing stability (Moody`s Investor Service, 2003, April).

The CRAs attempt to counter the problem that the current rating may not always reflect potential changes in the issuer's credit rating, by providing the market non-rating signals in the form of rating outlooks and reviews. By doing so, they can keep investors informed regarding the issuer's current financial stability and outlooks, without adding unnecessarily to market volatility.

3. Theoretical Framework and Hypothesis

3.1 The Information Content of Rating Change Announcements

Eugene Fama (1970) defined an efficient market as "a market in which prices always fully reflect available information". He put forth the efficient market hypothesis, which states that security prices could adjust in accordance with three information subsets, namely weak, semi-strong-, and strong form of market efficiency. Fama shows that markets are at least weak form efficient, in that one could not expect to earn excess returns based on historical prices. He also finds support of semi-strong market efficiency, which means that prices are assumed to fully reflect all obviously publicly available information. Strong-form of market efficiency assumes that all available information, even private information, is reflected in security prices. This is, according to Fama (1970), a very strict assumption, and the strong-form efficient markets model is best viewed as a benchmark against which deviations from market efficiency can be judged.

The CRAs have, through the credit rating process, access to non-public private information. This information is, in addition to all other available sources of information, utilized by the CRAs in order to form an opinion regarding the issuer's creditworthiness. The fact that CRAs have access to insider's information creates asymmetry between CRAs and the market. If stock prices react to credit rating announcements, it implies that the CRAs convey new information. On the other hand, if stock prices do not react to changes in credit rating, it means that the stock market has already absorbed this information and it is discounted into the stock price. This motivates the investigation of the information content of credit ratings. Systematically nonzero abnormal stock returns following a change in credit rating are inconsistent with market efficiency. The research on the effect of credit rating announcements on stock returns could thus be thought of as a test on strong-form market efficiency.

Extensive research has been done on the information content of credit rating announcements. According to Holthausen and Leftwich (1986), early papers by Pinches and Singleton (1978) and Weinstein (1977) find no significant effect of credit rating announcements on stock returns. Successive research by Griffin and Sanvicente (1982) and Wansley and Clauretie (1985) however, provide evidence of abnormal stock price behaviour after credit rating announcements. The absence of significant results in prior research could be due to the fact that they base the research on monthly and/or weekly data. The use of daily data is favourable to isolate the effect of the announcement on stock prices (Hand, Holthausen, & Leftwich, 1992).

Holthausen and Leftwich (1986) find evidence that downgrades by both Moody's and Standard and Poor's are associated with negative abnormal stock returns. This supports the argument that the rating agencies provide information to the capital markets through a downgrade or that downgrades impose higher costs to the firms, effectively increasing its marginal cost of debt. They find little evidence in support of abnormal returns related to upgrades. Hand, Holthausen, and Leftwich (1992) find evidence that there are both bond and stock price effects associated with announcements of rating changes by Moody's and Standard and Poor's. They find a significant negative relationship between rating downgrade announcements and stock returns. However, the results are not significant with respect to rating upgrade announcements.

Hsueh and Liu (1992) suggest that the conflicting empirical results in previous studies are due to failure to controll for anticipation. In other words, the content of credit ratings should not be treated as homogenous regardless of firm and time. Rather, one must take into account the availability of information in the market prior to the rating announcement. Firm-specific information is more readily available for some firms than for others due to differing coverage by the press, financial analysts etc., and investors are more likely to anticipate the rating change on firms they have more information about. Consequently, the information content of credit ratings is more significant for firms in which information is relatively limited. In other words, the stock price reaction to credit rating announcements is contingent on the market's anticipation. Hsueh and Liu (1992) also show that the effect of a rating change is more pronounced during periods of high market uncertainty.

A study by Kliger and Sarig (2000 p.2899) claims that there is a generaly accepted rationale for why rating information is valuable, namely because "*issuers disclose inside information to raters, who assign ratings that reflect this information without fully disclosing the specific underlying details to the public at large*".

Subsequently, the relevant question to ask is whether this information is pricing relevant and useful. This question has been subject to research, without any uniform answer. Kliger and Sarig (2000) found a method to isolate the price reactions to rating changes that exclusively reflected rating information. Prior to 1982 Moody's had a broader rating classification without numerical modifiers, which on April 26 was changed into a finer rating partition. This allowed for an examination of the information that Moody’s ratings sends investors regarding creditworthiness because the fine ratings assigned that day were based on the same information that underlies the preceding ratings. The refinement is therefore perfectly suited to isolate the information content of credit ratings, as it simply provides information in a striktly finer partition than before (Kliger & Sarig, 2000). Their conclusion is that rating information is indeed valuable and that both bond prices and stock prices adjusted to the new information.

3.2 The Wealth Redistribution Hypothesis

Although the majority of studies find a negative relationship between bond rating downgrades and stock prices, Holthausen and Leftwich (1986) argue that downgrades are not necessary bad for stockholders. More specifically, if a downgrade occurs because the firm is taking on more debt, it may in fact transfer wealth from bondholders to stockholders, also known as asset substitution or the wealth redistribution hypothesis (Berk & DeMarzo, 2007).

Robert Merton (1974) has proposed a method for pricing the firm’s equity using option pricing theory. He consider the firm’s equity (E) as a European call option on the firm’s assets (V) with a strike price equal to the face value of debt (D) and maturity date (T) equal to the maturity of the debt. In other words,$E_T = \max(V_T - D, 0)$, which looks like a call option. It can be shown from the Black-Merton-Scholes option pricing formula that the value of a call option increases with the volatility of the firm‘s assets. Consequently, a firm which takes on more debt incurs greater volatility in its cash flows and increases the value of the call option. Greater volatility raises the likelihood of an extremely good outcome for equity holders without increasing the downside, as the value of their shares cannot drop below zero. Bondholders, on the other hand, can be thought of as “owners” of the firm’s assets, having written a call option on them to the equity holders. They have a fixed claim on the firm and do not benefit as the firm takes on more risk. This theory could be used to argue why downgrades are not necessary bad for stockholders and why one could actually expect a positive stock price reaction from a credit rating downgrade.

Holthausen and Letwich (1986) and Goh and Ederington (1993) observed significant returns prior to announcements, indicating some anticipation. As the credit rating agencies publish a short explanation for their credit rating announcement, Goh and Ederington (1993) hypothesize that the market reaction will be contingent on this reason. They argue that one could not expect to find a significant negative stock reaction for all downgrades, because an anticipated transfer of wealth from bondholders to stockholders should be good news for stockholders. Consequently, a credit rating downgrade could call for a positive stock price reaction.

As mentioned, most studies find a significant negative relationship between rating downgrade announcements and stock returns. However, the results are not significant with respect to rating upgrade announcements. This is a puzzling result, as there is no a priori rationale why only downgrades should have an impact on stock prices (Hsueh & Liu, 1992). The implication of Mertons' theory is of theoretical and practical interest. It illustrates that the rationale behind a change in credit rating is of both statistical and economic interest, and it provides an explanation for why downgrades are not necessarily bad for stockholders. Furthermore, it might help explain why previous studies find no significant equity reaction to upgrades. Goh and Ederington (1993) investigates whether the rationale behind a change in credit rating is relevant for the stock price reaction i.e. whether the change is related to firm-sepecific news (e.g. leverage, earnings, margins) or whether it relates to general market conditions (e.g. contraction, deteriorating market conditions).

They put forth the conjecture that previous studies may have failed to find a significant association between credit rating upgrades and stock returns because they fail to recognize the rationale behind the change in credit rating. More specifically, they argue that firm-specific news must be decomposed into upgrades (downgrades) that are due to (i) an improvement (deterioration) in the firm's financial prospects and (ii) a decrease (increase) in leverage (Goh & Ederington, 1993). The former reason will have a positive impact on the stock price, while the latter one could have the opposite effect. These two underlying reasons have, offseting effects, which might explain the non-significant equity reaction to upgrades.

They find that, as expected from previous studies, the market reacts negatively to downgrade announcements. Furthermore, they find that these downgrades are generally based on projections of the firm's future financial prospects and therefore are likely to entail significant information. On the contrary, announcements of downgrades related to increased levels of debt (e.g. due to leveraged buyouts, debt-financed expansion etc) are small and insignificant, suggesting that these downgrades are either anticipated by the market or have less interest to stockholders (Goh & Ederington, 1993). They do not find any significant association between upgrades and stock returns after a decomposition based on the underlying reason, i.e. financial prospects or leverage. The important insight, however, is that rating changes cannot be treated as homogeneous, and the rationale behind the change in credit rating must be considered.

Kliger and Sarig (2000), on the other hand, provide evidence in support of the asset-substitution theory. They find that shareholders lose when risk is revised downward i.e. a credit rating upgrade, while bondholders benefit from reduced risk assesments. Moreover, implied volatility derived from the prices of options on the stock decline following announcements of better than expected ratings. Kliger and Sarig (2000) find that rating information is relevant for the valuation of debt and equity respectively but do not find that it impacts the combined value of the firm. This implies that a change in credit rating only transfers wealth between stock- and bondholders. Hsueh and Liu (1992) also find significant stock price reactions to rating upgrades after controlling for anticipation. Firms that investors have less information about prior the the announcement exert a positive stock price reaction from rating upgrades.

The redistribution hypothesis is of interest with regard to credit rating announcements because it challanges the more intuitive explanations about the association between credit rating downgrades and negative stock returns. It provides a theoretical, sound explanation for why downgrades could in fact provoke a positive stock price reaction. However, despite its theoretical justification, most empirical research seems to agree that the market reacts negatively to downgrade announcements (Holthausen and Leftwich (1986), Hand, Holthausen, and Leftwich (1992), Goh & Ederington (1993)). Credit rating upgrades, on the other hand, are more disputable. Kliger and Sarig (2000) find evidence in support of the wealth redistribution theory that shareholders lose when risk is revised downward. On the contrary, Hsueh and Liu (1992) find that upgrades are associated with a positive stock price reaction. Based on previous research, I would assume similar results in my data sample, i.e. a negative stock price reaction to downgrades (credit ratings convey new information to the market/ no redistribution of wealth) but no significant reaction to upgrades.

$Hypothesis_1$*: Credit rating downgrades have a negative effect on stock returns.*

$Hypothesis_2$*: Credit rating upgrades have no effect on stock returns.*

3.3 Capital Structure and Credit Rating

Modigliani and Miller (1958) showed with their propositions (I and II) how the market value of any firm is independent of its capital structure. This holds in perfect capital markets because of the law of one price and the fact that investors can replicate any firm's capital structure by borrowing or lending to his or her own portfolio and thus produce cash flows identical to unlevered equity. Hence the management's choice of capital structure is irrelevant for the firm value, as investors could easily alter the leverage choice of the firm themselves. The assumption of perfect capital markets is of course unrealistic, but it serves as a basis for explaining why and when capital structure does in fact matter. Capital structure matters due to market imperfection, like taxes, financial distress and agency costs/benefits of debt. The interest tax shield provides an incentive to add debt to the capital structure in order to reduce tax payments. However, firms do not add unlimited amounts of debt to their capital structure, and the difference between net debt-to-enterprise values varies greatly in and between industries. Balancing the advantages and disadvantages of debt is formally referred to as the trade-off theory. By acknowledging that capital structure is relevant for the valuation of the firm, it becomes interesting to examine whether the stock price effect of a credit rating announcement is related to the firm's capital structure, i.e. the level of leverage.

Kliger and Sarig (2000) find that the effect of rating information on bond prices is monotonic in firm leverage, i.e. the more leveraged the firm has, the stronger the reaction to new rating information. The fact that firms near a credit rating upgrade or downgrade issue less debt relative to equity than firms not near a change in rating underpins the important inverse relationship between leverage and credit rating (Kisgen, 2006). It is tempting to expect that leveraged firms face more financial problems when they are downgraded than less leveraged firms due to the relative increase in interest expenses. However, it does not always need to be the case as the firm might have a large and stable cash flow. Moreover, a change in credit rating affects the marginal cost of debt and usually not the interest on already outstanding debt. Another relevant aspect which complicates the research is that firms have different sources of financing, i.e. the bond market and bank financing. The Scandinavian bond market is underdeveloped compared to the US or UK. There are also differences between the Scandinavian countries and the Danish bond market is, for example, much more developed than the Norwegian. The terms on which firms can fund themself through banks is not neccessarily affected in the same way as the the cost of issuing new bonds, which distortes the association between credit rating changes and stock returns.

It is a common view in corporate finance that firms are underleveraged given the potential large tax benefits of debt (Molina, 2005). Molina (2005) argues that this capital structure puzzle could be partially explained by misspecifications in previous research. He claimes that previous estimates on the financial distress costs (indirect costs of bankruptcy) of leverage are biased downward because they fail to recognize an endogeneity problem in the estimation of credit rating as a function of leverage. More specifically, the endogeneity occurs because leverage and ratings are jointly determined. By using and instrumental approach, he shows that the true ex ante cost of financial distress is in fact up to three times larger than previously suggested. The significant impact of leverage on financial distress costs implies that firms may not be as underleveraged as previously suggested. Moreover, it translates into a strong relationship between an increase in debt and a rating downgrade due to the increase in default probabilities.

Graham and Harvey (2001) find that credit ratings are the second most important concern to CFOs when determining the capital structure. This is consistent with the view that leverage and ratings are jointly determined. They report that credit rating is considered more important than many factors suggested by traditional capital structure theories, such as the tax advantage of debt. The most important debt policy factor, however, is financial flexibility. If the market perceives that a firm does not hold an optimal capital structure, increasing the level of debt could make the stock price go up, even though increased levels of debt results in a credit rating downgrade. Hence, there is a trade-off between the cost of capital, shareholder value and credit rating. Two examples of this is refered to in a publication by Zanders Treasury & Finance Solutions (Tijdhof). In one case, Nestlé decided not to reduce its leverage, even though they explicitly announced that a reduction in leverage would reduce its WACC. The main reason for this was that they wanted to maintain maximum financial flexibility for potential acquisitions. In another case, KPN Telecom increased its leverage despite warnings from the CRAs of a possible downgrade. They did this due to a potential hostile takeover by a group of private equity firms, which felt KPN Telecom was too conservatively leveraged. The additional debt was used to repurchase shares and for future acquisitions. Consequently, the firms was downgraded. The stockmarket, however, rewarded the stock by sending it up by 6.4 percent.

The Modigliani and Miller world assumes perfect capital markets. These examples illustrate the complexity of capital structure desicion making and that the finance markets do not always act according to theory. Firms might take on more debt even though it results in a downgrade because they perceive that it is beneficial for some other reason than credit rating. This distorts the relationship between capital structure and credit rating. However, in general, managers find that credit ratings directly affect capital structure decisions (Graham & Harvey, 2001) and vice versa (Molina (2005), Kisgen (2006)). Hence, it seems likely that, unless there are compelling reasons to do otherwise, firms will adhere to maintain or improve its credit rating. As leverage is one of the most important determinants for credit rating, both intuition and previous research (Kliger & Sarig, 2000), suggest that highly leveraged firms experience a more significant stock price reaction to credit rating downgrades than do less leveraged firms. On that insight I arrive at my third hypothesis:

$Hypothesis_3$: Highly leveraged firms experience more significant stock price reactions to credit rating announcements than do less leveraged firms.

Many institutional investors (e.g. pension funds, mutual funds, insurance companies and brokers) are restricted or prohibited from purchase of bonds with a low credit rating. This implies discrete costs/benefits associated with a change in credit rating and similarly a discontinuous relationship between leverage and the firm value. Consequently, one would expect that changes in credit rating that leads to a reclassification, from investment grade to non-investment grade or vice versa, would have the most profound effect on the company's stock price. Kisgen (2006) finds that managers are concerned with rating-triggered costs and the effects of regulations of bond investors. Specifically, managers are concerned about credit rating levels that affect the access to commercial papers and bond liquidity issues most severely. He also shows that a change from investment grade to non-investment grade is incrementally significant. Hand, Holthausen, and Leftwich (1992) find that below investment grade firms experiense more negative excess stock returns associated with rating downgrade announcements compared to investment grade firms. The same applies to rating upgrades (positive excess returns) however, the results are not significant. I would like to test whether it is a significantly larger stock price reaction when firms are downgraded from investment grade to non-investment grade, or vice versa, compared to downgrades that do not result in such a reclassification. It seems likely that there is a significant difference, according to the aforementioned research and discussion.

$Hypothesis_4$: Credit ratings that result in a reclassification from investment grade to non-investment grade, or vice versa, have a greater effect on stock prices than credit rating announcements that do not invoke such a reclassification.

As a natural extension of this hypothesis, I will also assess whether there are scale effects. That is, whether firms with low credit rating experience a more significant stock price reaction associated with credit rating announcements than firms with higher credit rating.

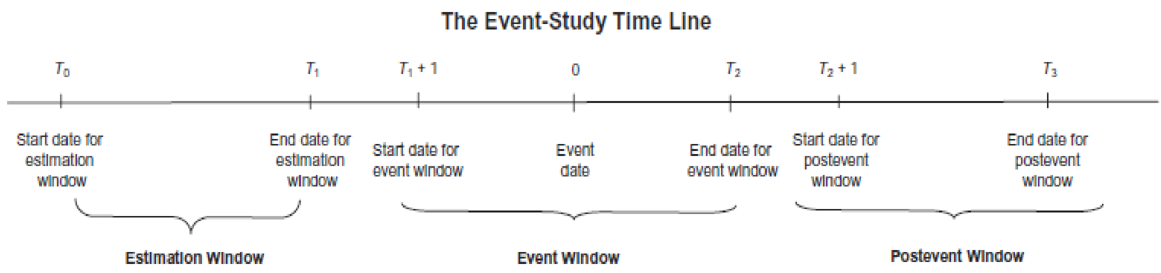
> $Hypothesis_5$: *Changes in credit rating have a more significant effect on stock prices for firms with low a credit rating, compared to firms with a high credit rating.*

4. Methodology and Data Sample

4.1 Event Study

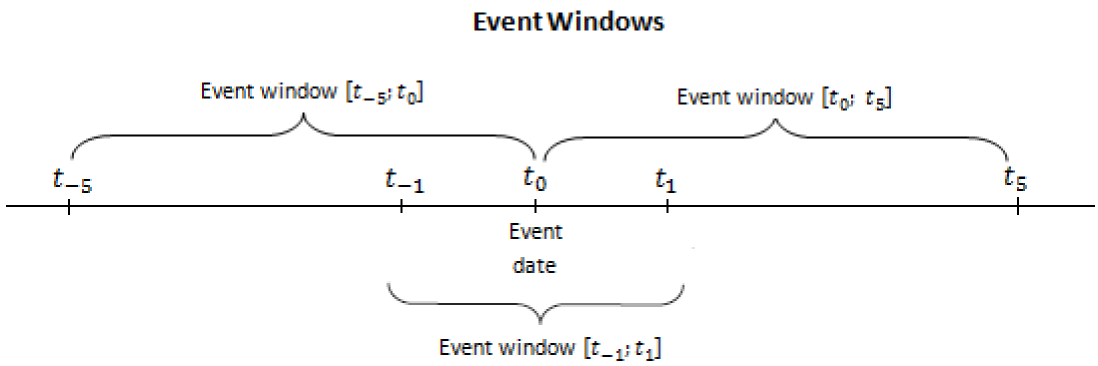
An event study examines the effect of some (unanticipated) event, X, on a dependent variable, Y. Y is often the value of an asset, e.g. stock prices (returns), exchange rates, volatility or bond prices. Examples of X are earnings announcements, stock splits, mergers or takeover announcements, or a regular change (Benninga, 2008). In this thesis, Y is the (log) stock return of the issuing company, and X is a change in credit rating. Event studies are widely used in corporate finance and other areas like accounting, industrial organization and macroeconomics, and the literature is extensive. Event studies serve an important purpose in corporate finance research and the cleanest evidence on market-efficiency comes from event studies (Fama, 1991).

The time-line of an event study can be illustrated as followe:



Source: (Benninga, 2008)

I have defined the estimation window (control period) to be 252 trading days prior to the event date, and the return frequency is daily. Daily data is favourable because it allows precise measurement of the stock-price's reaction to credit rating announcements, the central issue for testing market efficiency (Fama, 1991). It is a trade-off between improved estimation accuracy and relevance (potential parameter shifts) in choosing the estimation window. It is necessary with some length on the estimation window (number of observations) in order to capture the "normal" stock price behaviour prior to the announcement and the expected return of the stock. On the other hand, using a too wide estimation window increases the probability of including non-representative data, i.e. old data that is obsolete (Benninga, 2008). 252 days is often used in event studies however, the choice is arbitrary and other estimation periods could be just as good. I have chosen three different event windows in addition to abnormal return on the event day, t_0.



I defined the following event windows: $[t_{-5}; t_0]$, $[t_{-1}; t_1]$ and $[t_0;\ t_5]$. The event window $[t_{-5}; t_0]$ consists of five trading days plus the event day and has been chosen because I assume it captures most of the pre-announcement effect. Previous studies (Holthausen and Leftwich (1986), Goh and Ederington (1993)) observe significant returns prior to announcements, indicating some anticipation. This is often used as evidence of information leakage by insiders. In this study, such a stock price pattern would indicate that the CRAs, the company itself or someone else with inside information reveals this to the market prior the credit rating announcement.

The event window $[t_{-1}; t_1]$ is chosen for two reasons. I assume that the closer one is to the announcement day, i.e. the day the decision is made to upgrade/downgrade a firm, the more likely it is that inside information is leaked to the market and utilized. Furthermore, the post event day (t_1) takes into account that the announcement may be released after the stock exchange has closed and/or that the stock is not traded on the day t_0. A wide window is more likely to capture the entire effect of the credit rating announcement. On the other hand, a narrow event window minimizes the likelihood that the announcement effect is contaminated with other "noisy" news (Holthausen & Leftwich, 1986). Event studies on daily data typically show that stock prices, on average, seem to adjust within a day to the event announcement (Fama, 1991). Consequently, I expect this event window, in addition to t_0 itself, to be the most significant window.

The post-event windows are normally used to investigate the long term effect of the event, which is not a subject of this thesis. Moreover, long-horizon event studies suffer from serious limitations, thus making it difficult to draw inference. They are, for example, often poorly specified and have limited power to detect abnormal performance. In contrast, short-horizon methods are much more reliable and are less sensitive to assumptions about the return generating process (Eckbo, 2007). Consequently, I have constructed a narrow post-event window, $[t_0;\ t_5]$. It is meant to capture that all investors might not rebalance their portfolios on the announcement day. For example, some large institutional investors may avoid selling all their stocks immediately in order not to affect the stock price unnecessarily. Thus, I allow for some days succeeding the announcement day, so investors can adjust to the new information. The lengths of the event windows are arbitrary, and I recognize that other lengths could be just as reasonable.

4.2 Data Overview and Processing

The data sample consists of 23 different Scandinavian public companies rated by Standard and Poor's during a ten year period from 2001–2011 (Table 1a). Thirteen industries are represented in the sample. The majority of observations are in the following industries: telecom services (17%), capital goods (12%), energy (12%), paper & forest products (12%) and information technology (11%) (Table 1b). No single industry seems to dominate the sample, which could have been a potential source of bias. The frequency of upgrades and downgrades are unevenly distributed across time (Figure.1a and b). The table does not provide any clear picture and the imbalance is probably due to the time period chosen.

There are a total of 93 observations i.e. changes in issuer credit rating, from which 64 are downgrades, 29 are upgrades, and two are defaults (Table 2). Descriptive statistics for the sample are provided in Table 3.The initial sample was about twice that size, but many observations were deleted either because there was no change in rating (initial rating or reconfirmation of rating) or the firm was delisted and stock price data was unavailable. The limited number of observations is a weakness of the study because the results become more influenced by large positive or negative observations, which may not be representative for the true population.

4.2.1 Methodological Issues

In order to draw inference, the sample has to be representative for the population. There are different sampling methods used in empirical research. Random sampling is necessary to avoid bias in the sample selection. It is also one of the criteria for satisfying parametric statistical test. The only way to fully avoid the possible bias in sampling is to have data of the entire population. In most cases, that is neither possible nor feasible. My sample from S&P comprises the majority of Scandinavian corporations that have an issuer credit rating. If the firms rated by S&P share some underlying characteristics that are not shared by firms rated by other CRAs, it would introduce selection bias to the sample. It has, however, not come to my attention that such a bias exists. Most companies have ratings issued by more than just one CRA. Hence, the sample from S&P is likely to represent most firms that are being rated.

A more serious concern in the empirical research is non-sampling errors. Non-sampling errors are due to mistakes made in the acquisition of data or in the processing of the data. I gathered information on stock prices from Thomson Datastream, Macrobond and Yahoo! Finance. The frequency of the data is daily, and I used the adjusted closing price, which has been amended to include any corporate actions such as stock splits, dividends and rights offerings. Balance sheets were gathered from the two former ones or directly from the company's homepage. Non-sampling errors could have occurred during this process and consequently affected the results.

Non-response errors are another potential pitfall in the research. Non-response errors arise when observations are not obtained for some of the firms in the sample. Firstly, the variables for leverage (see section 4.2.3) are based on interim reports. I was not able to obtain interim balance sheets for some of the observations, in which case I used the latest annual report. Secondly, I did not manage to gather information on the variable for CreditWatch (see section 4.2.4 A) for all observations. The consequence of this is a reduction in the response rate which decreases the validity of the research.

4.2.2 Confounding Effects

Calculations of abnormal returns can be distorted if the rating agency announcement is accompanied by a concurrent disclosure. Concurrent disclosures will act as "noise" in the calculation of excess returns, making it difficult to isolate the partial effect of the rating announcement. Early research on the stock price effect of rating announcements did not control for confounding events, although the problem was recognized (Holthausen & Leftwich, 1986). Holthausen and Leftwich (1986) identify possible "noisy information" by examining all the stories in the Wall Street Journal Index for potential new stories in the event window. If the stories contained any other information than the rating agency announcement, the observation was classified as contaminated and deleted from the sample. Goh and Ederington (1993) also searched the Wall Street Journal Index for other firm-specific information releases in the event window. By adjusting for this "noise", they found that the negative cumulative abnormal returns (CAR) of downgrades became less negative, and the negative pre-announcement CARs became insignificant.

A manual inspection of all news regarding the issuing company might seem favourable. However, such an inspection would be very comprehensive and almost impossible to implement. Firstly, most large public companies are covered by the media every single day, and the vast stream of news today is incomparable to those 20 to 30 years ago. Secondly, it would introduce possible biases in the research, namely with respect to which news to regard as “noise” and which are not. Instead, I apply a statistical approach to reduce the effect of observations which appear to be inconsistent with the rest of the data set. These extreme observations are often called outliers and could be caused by other information than the credit rating announcement itself. Outliers could in most cases be detected visually in a scatter plot or by inspecting a frequency chart. The effect of including an outlier is that the average for the sample becomes unrepresentative, the standard deviation[1] increases and the power of statistical tests goes down (Foster, 1986). Almost all quantitative studies are based on normality or models that assume a normal distribution. Hence, adjusting for outliers makes the data better satisfy the basic assumptions necessary to run most statistical test. Other types of news (“noise”) could be correlated with both the dependent and independent variable and therefore need to be accounted for. This is also referred to as omitted variable bias[2]. Failing to control for noise could give rise to type I errors, i.e. reject the null hypothesis when it is in fact true (Wooldridge, 2008). Such spurious regression is a threat to internal validity and may result in erroneous conclusions about the effect of credit rating changes on stock returns.

I decided to take an operationally active approach towards outliers. Two widely used methods are trimming and winsorizing the sample. The former entails sorting the observations in ascending order and removing a given percentile of the extreme observations in both ends. The drawback with this method is that you lose observations. Hence, this method is not favourable as the sample size is rather limited. In the latter method, the data is also sorted in ascending order, and all outliers are set equal to a specified percentile of the

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[1] Std.dev = σ = $\sqrt{\sigma^2}$

[2] Omitted variable bias can be summarized mathematically by a formula for this bias: $\hat{\beta}_1 \rightarrow \beta_1 + \rho_{X,\varepsilon}\frac{\sigma_\varepsilon}{\sigma_X}$, where the correlation between ε_i and X_i is corr(X_i, ε_i) = $\rho_{X,\varepsilon}$. Then, as the sample size increases, $\hat{\beta}_1$ is close to $\beta_1 + \rho_{X,\varepsilon}\frac{\sigma_\varepsilon}{\sigma_X}$ with increasing probability (Stock & Watson, 2007)

data. I decided to use a 90% winsorizing, in that all data above the 95th percentile is set to the 95th percentile, and all data below the 5th percentile is set to the 5th percentile. The cut off point is, however, arbitrary. This method avoids losing observations. On the other hand, the substituted numbers are really not observed observations but constructed ones. I experienced that the mean, standard deviation, skewness and kurtosis[3] improved for all event windows (Table 4). The most significant results apply to credit rating downgrades. The change in the mean value for downgrades is much more significant than for upgrades, indicating that the initial sample was highly influenced by large negative stock returns.

4.2.3 Capital Structure

Having observations that vary in size introduces biases in all parametric tests, and hence, it is feasible to work with ratios. The theory of how capital structure may affect stock returns is operationalized through the dummy variables *Lev1* and *Lev2*. These two variables are defined as:

Lev1 = Net Debt / Total Assets

Lev2 = Current Assets / Current Liabilities

Lev1 is a proxy for solvency. Issuer credit ratings express forward looking opinions regarding the creditworthiness of issuers and affect the terms on which firms are able to refinance their debt in the future. Consequently, I expect a measure of solvency to be the most important variable in explaining the hypothesised larger impact of credit rating announcements for highly leveraged firms. *Lev2* is a proxy for liquidity and is presumably less significant. However, as debt is about to become due, it is classified as a current liability and firms with significant long term debt will tend to have a great deal of short term debt. It captures in essence much of the same as *Lev1*, but it also recognizes that firms with much current assets not reflected in net debt, e.g. accounts receivable, increases the firm's ability to repay interests in a timely manner. In addition, it disentangles firms that are financed with much short-term debt from those which are financed with more long-term debt.

Investors use accounting information in order to assess *Lev1* and *Lev2*. Hence, I have used the latest quarter report for all observations. If a change in credit rating occurs in April, for

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[3] Skewness = $\frac{E[(Y-\mu_Y)^3]}{\sigma_Y^3}$ Kurtosis = $\frac{E[(Y-\mu_Y)^4]}{\sigma_Y^4}$

example, it is crucial to use the latest quarterly report (Q1). Using the Q2 report would invoke hindsight bias. It means that investors need to have access to the information (on Lev1 and Lev2) at the time that the credit rating occurs (t_0). Using information that is not yet available to investors would obviously be erroneous.

Not all companies release their information to stakeholders simultaneously. Non-synchronous accounting periods make it difficult to use standardised dates for releases of accounting information to the stock exchange. I did, however, with lack of other information, assume that Q1 reports were released on April 1st, Q2 on July 1st etc. One potential problem with cross-sectional and time-series analysis is that structural changes may occur over the sample period or event window due to e.g. mergers, acquisitions or divestures. Another possible problem is changes in accounting methods (e.g., mandatory adoption of IFRS) and other firms may have changed their individual reporting format. Quarterly information could be subject to seasonal components and unadjusted information. For example, many firms have seasonal variations in sales, which affect accounts receivable, accounts payable, cash, inventory etc. This would make *Lev2* cyclical as well. Furthermore, about 70% of impairments are made in the last quarter, and hence affect *Lev1* (Foster, 1986). All these possible pitfalls are assumed not to be significant. However, it would be feasible to try to correct for these factors in more comprehensive research.

4.2.4 Dummy Variables

A. Market Anticipation

Hsueh and Liu (1992) suggest that the conflicting empirical results in previous studies are due to failure to controll for anticipation, and ignoring market anticipation will bias the results. Holthausen and Leftwich (1986) suggest that an expectations model of rating changes could provide more powerful tests of the effect of rating change announcements by concentrating on those which are least expected. I try to operationalize expectations in the market by taking account for warnings of possible rating changes via additions to the S&P CreditWatch List. I do a separate examination of credit rating upgrades preceded by positive outlooks and neutral or negative outlooks. My expectation is that upgrades preceded by positive outlooks are more anticipated in the market than upgrades preceded by neutral or negative outlooks. I do a similar examination of downgrades, and the dummy variable is denoted *Watch*.

One problem with this approach was access to information of additions to CreditWatch List. From a total of 93 observations I found that 11 observations were not obtainable, and only 13 of the observations were assigned to the category neutral or developing. Only twice did the credit rating occur in the opposite direction as indicated by the review. Historically have 66%-76% of all ratings have been changed in the same direction as indicated by the review and rarely in the opposite direction (Moody`s Investors Service, 2002).

B. Rating Re-classification

Hypothesis five suggests that a change from investment grade to non-investment grade, or vice versa, is incrementally significant. There are ten observations that involve a reclassification, from which three are upgrades from non-investment grade to investments grade, and seven observations are downgrades from investment grade to non-investment grade. The dummy variable for re-classification is denoted *Reclass*.

C. Rating Category

I have pooled the sample based on credit rating into rating categories (Table 5). This has been done to facilitate the fact that the default rate is non-linear in rating category, i.e. the default rate over consecutive years rises more steeply for low levels of credit rating than high levels of credit rating (Moody`s Investors Service, 2002). Hence, it makes sense to evaluate credit rating announcements conditional on the given rating class, as suggested in hypothesis five. The categories follow industry analogy and are used by, among others, Morgan Stanley. For example, A+, A and A- have been pooled together into the rating category *upper medium grade,* BBB+, BBB and BBB- have been pooled together into the rating category *lower medium grade* etc. The categories are donated *Grade* and are used later in the analysis. I also discriminate firms based on whether they are classified as investment grade or not. The dummy is named *Invest.grade* and takes on the value 0 for investment grade firms and 1 for non-investment grade firms. I expect the coefficient on this variable to be positive for upgrades and negative for downgrades, as a change in credit rating presumably has greater effect for firms which already have a low credit rating.

The majority of upgrades are in the rating class *lower medium grade* (53%), while the majority of downgrades are in the *lower medium grade* (40%) and *speculative grade* (23%). The picture is that upgrades seem to tilt towards the upper range of the rating scale, while downgrades seem to tilt towards the lower range of the rating scale (Table 6). This comes as no surprise and is probably due to rating transition, i.e. emission risk. Issuers that came to have a certain rating are not equally likely to observe a rating in the opposite direction of the previous change in credit rating. In other words, an upgrade is more likely to be followed by an upgrade than a downgrade and vice versa (Moody`s Investors Service, 2002). This is also referred to as rating momentum. Consequently, by including a dummy for rating class I allow for a conditional treatment of ratings and emission risk.

4.3 Calculating Abnormal Returns

An event study seeks to establish whether the cross-sectional distribution of returns at time zero is abnormal, that is, systematically different from expected (Eckbo, 2007). Abnormal return (*AR)* for an individual stock is calculated as the difference between the actual return of firm *i* on time *t*, $R_{i,t}$, and the expected return of the stock, $E(R_{i,t})$.

$$AR_{i,t} = R_{i,t} - E(R_{i,t})$$
$$AR_{i,t} \sim N(0, \sigma_{i,t}^2)$$

In the event study literature, the focus almost always is on the mean of the distribution of abnormal returns i.e. the first moment of the return distribution. Exact statistics depends on $\mathrm{AR}_{\mathrm{i,t}}$ being independent and identically distributed across time (i.i.d). According to Eckbo (2007), cross-correlation in abnormal returns is almost irrelevant in short-window event studies. Under the null hypothesis, $\mathrm{AR}_{\mathrm{i,t}}$ is normally distributed with zero mean and unit variance[4].

In a sample of N stocks, the cross-sectional average abnormal return (AAR) at time t is:

$$\overline{AR}_t = \frac{1}{N}\sum_{i=1}^{N} AR_{it}$$

The variance is defined as:

$$var(\overline{AR}_t) = \frac{1}{N}\sum_{i=1}^{N} \sigma_{AR_i}^2$$

The expected return is given by a particular model and the abnormal return is a direct measure of the unanticipated change in the stockholders wealth associated with a credit rating announcement. The expected return model serves as a proxy for the “normal” return

[4] The variance of a discrete random variable *Y*, donated σ_Y^2 , is σ_Y^2 = var(*Y*) = E$[(\mathrm{Y} - \mu_Y)^2]$

of stock i, and must be specified in order to calculate excess returns. Each method has its advantages and disadvantages, and both the bias and precision of the expected return measure can differ, affecting the properties of abnormal return measures (Eckbo, 2007). There are, in general, two approaches for measuring expected returns, that is, statistical models and economic models (MacKinely, 1997). The former ones follow statistical assumptions about the behaviour of stock returns and do not depend on any economic theory. The latter ones are based on assumptions regarding investor's behaviour and are not based solely on statistical assumptions. The potential advantage of economic models is not the absence of statistical assumptions, but the opportunity to calculate more precise measures of expected return using economic restrictions (MacKinely, 1997).

4.3.1 Expected Return Models

A. Mean Adjusted Return

The constant mean return model is a statistical model. It is the simplest model and requires no underlying theory of asset prices (MacKinely, 1997). The model can be expressed as:

$$E(R_{i,t}) = \bar{R}_{i,t} + \varepsilon_{i,t}$$
$$E(\varepsilon_{i,t}) = 0,\ var(\varepsilon_{i,t}) = \sigma^2$$

where $R_{i,t}$ is the period t return of asset i, and $\varepsilon_{i,t}$ is an error term with zero mean and unit variance. $R_{i,t}$ is assumed to be normally distributed and i.i.d. Despite the model's simple design, it often yields results similar to those of more sophisticated models (MacKinely, 1997). However, the method would produce upwardly or downwardly biased abnormal returns in bull and bear markets, respectively.

B. Market Adjusted Return

The market adjusted return is the return of the market ($R_{m,t}$) in the event window. The model assumes that all stocks, on average, generate the same rate of return. Thus, the differences in return between stock i and the market represent excess or abnormal return.

$$E(R_{i,t}) = R_{m,t} + \varepsilon_{i,t}$$
$$E(\varepsilon_{i,t}) = 0,\ var(\varepsilon_{i,t}) = \sigma^2$$

The model can be viewed as a restricted market model (see below) with α_i equal to zero and β_i constrained to one. Because the model parameters are prespecified, it requires no estimation period. It does, however, require a choice of which benchmark to use. The benchmark is a proxy for the market portfolio which includes all traded assets. No index fully satisfies this criterion, but a broad-based, value-weighted index or a float weighted index like the S&P500 or MSCI World Index is often used (Benninga, 2008). I have deviated a bit from theory in my choice of benchmark. I believe it is favourable to use national indexes because the samples of stocks are more likely to be correlated with their national stock market than with e.g. S&P500. Hence, I use the OSEBX for the Norwegian stocks, OMXS30 for Swedish stocks and OMXC20 for Danish stocks. Stockholm Stock Exchange and Copenhagen Stock Exchange have been acquired by OMX, which is now part of the NASDAQ OMX Group.

C. The Market Model

The market model is the most common model for estimating the stock's behaviour under "normal" circumstances (MacKinely, 1997). It is a statistical approach, and theory does not impose any constraints on the model. The market model for stock *i* is computed based on a single factor market model and can be expressed as

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t}$$

$$E(\varepsilon_{i,t}) = 0, var(\varepsilon_{i,t}) = \sigma^2$$

$R_{i,t}$ and $R_{m,t}$ are the period *t* return of stock *i* and the market respectively. In this model, as for the market adjusted return model, OSEBX, OMXC20 and OMXS30 serve as proxies for the market return in the respective countries. The coefficients, $\hat{\alpha}_i$ and $\hat{\beta}_i$, are estimated running an ordinary least-square (OLS)[5] regression over the estimation period and the expected return is:

$$E(R_{i,t}) = \hat{\alpha}_i + \hat{\beta}_i R_{m,t}$$

By substituting $E(R_{i,t})$ in the formula for *AR* we get the following expression:

$$AR_{i,t} = R_{i,t} - (\hat{\alpha}_i + \hat{\beta}_i R_{m,t})$$

The R^2 is a measure of how well the OLS regression fits the data[6].

[5] The OLS estimator chooses $\hat{\alpha}_0$ and $\hat{\beta}_1$ to minimize: $\sum_{i=0}^{n} \hat{\varepsilon}_i^2 = \sum_{i=0}^{n} (Y_i - \hat{\alpha}_0 - \hat{\beta}_1 X_i)^2$

where $\hat{\varepsilon}_i = Y_i - \hat{Y}_i = Y_i - \hat{\alpha}_0 - \hat{\beta}_1 X_i$ and $Y_i = \alpha_0 + \beta_1 X_i + \varepsilon_i$

[6] The regression R^2 is the fraction of the sample variance of Y_i explained by the regressors: $R^2 = \frac{ERR}{TSS} = 1 - \frac{SSR}{TSS}$

D. CAPM Adjusted Return

The Capital Asset Pricing Model, CAPM, was originally developed by Sharpe (1964), Lintner (1965) and Mossin (1966). The CAPM generalize the relationship between expected returns on assets and their exposure to market risk. It states that an asset is expected to earn the risk-free rate plus a premium for bearing risk, measures by the asset's beta (Bodie, Kane, & Marcus, 2008). It is formally expressed as:

$$\mathrm{E}(R_i) = R_f + \beta_i(E(R_m) - R_f)$$

R_f is the risk free rate and $(E(R_m) - R_f)$ is the expected market risk premium, and the beta, β_i[7] measures the co-movement between the stock i and the market. This model, in contrast to the market model, imposes constraints on the constant term. Despite its appealing construction, the CAPM has received considerable criticism due to its underlying assumptions (e.g. about investor's behaviour and only one common risk factor). Because the validity of the restrictions imposed by the model is highly questionable, the use of CAPM has almost ceased in event studies (MacKinely, 1997).

E. Multifactor Models

A one-factor model assumes that the return on the stock is driven solely by the market index. A multi-factor model appreciates that there could be other factors, which helps explain the return of the stock. Fama and French have done extensive research on alternative factors, besides market risks, for explaining the realized return of stocks. They found "value" and "size" to be the most important factors. To address these risks, they constructed two factors: SMB (small minus big market capitalization) to address size and HML (high minus low book-to-market ratio) to address value (Womack & Zhang, 2003). Analogous to the CAPM, this model describes the expected return of stock *i* as a result of three risk factors:

$$R_i = R_f + \beta_i(R_m - R_f) + \beta_i SMB + \beta_i HML$$

where the explained sum of squares is, $ESS = \sum_{i=1}^{n}(\hat{Y}_i - \bar{Y})^2$ and the total sum of squares is, $\mathrm{TSS} = \sum_{\mathrm{i=1}}^{\mathrm{n}}(\mathrm{Y_i} - \bar{\mathrm{Y}})^2$

[7] $\beta_i = \frac{Cov(r_i,r_m)}{Var(r_m)}$ and $\mathrm{cov}(X,Y) = \sigma_{XY} = \mathrm{E}[(X - \mu_X)(Y - \mu_Y)]$

Other multifactor models include industry returns (matched firm approach), to account for industry-specific information in addition to the market-specific information (Benninga, 2008):

$$R_{i,t} = \alpha_i + \beta_{i,market}R_{market,t} + \beta_{i,industry}R_{industry,t}$$

The method is very similar to the reference portfolio method.

F. Reference Portfolios

In this model, the expected return is assumed equal to the return on a reference portfolio. The reference portfolio should comprise companies with similar characteristics as stock *i*, usually based on the criteria of size and the book-to-market ratio (B/M). Researchers often rank firms into deciles portfolios based on size and/or the B/M ratio. The average return of the portfolio is used as a proxy for the expected return. This approach, and the industry average method is often used on US data, e.g. by Kliger and Sarig (2000). This method is, in my opinion, less feasible on the Scandinavian stock market, due to the limited number of public companies and the lack of peer group companies.

Generally, the gain from employing multifactor models for event studies is limited. This is because of the marginal explanatory power of additional factors and little reduction in the variance of abnormal returns (MacKinely, 1997).

Short horizon models, like in this thesis, are generally not very sensitive to the choice of return model, nor are they with respect to cross-sectional or time-series dependence of abnormal returns (Eckbo, 2007). Choosing a model of expected returns poses a significant challenge because event study tests are joint tests. However, one advantage of using daily data is that one can circumvent the joint-hypothesis problem that market efficiency must be tested jointly with an asset pricing model (Fama, 1991). Consequently, the way one estimates expected returns in calculating abnormal returns may have little effect on inference. By acknowledging this, I decided to calculate abnormal returns relative to two commonly used return models: (i) the *market adjusted return* model and (ii) the *market model*. The latter one is estimated by running an OLS regression of stock *i* on the benchmark over the estimation period. The former one simply assumes α_i equal to zero and β_i constrained to one.

4.3.2 Aggregation of Abnormal Returns

The abnormal return observations must be aggregated in order to draw overall inference. The aggregation is across two dimensions: a cross sectional dimension, N, and a time-series dimension, T. This is referred to as panel data or longitudinal data. The advantages of panel data are the ability to increase the sample size, reduce multicollinearity problems[8], and are able to build more dynamic models and enable better control of unobserved effects (Wooldridge, 2008).

A. Time-Series Aggregation

When estimating returns over multiple days, there are a number of methods for time-series aggregation over the event windows (Eckbo, 2007). One method is to calculate the cumulative abnormal return (CAR) in the pre-event window and post-event window. The CAR for an individual stock is the abnormal return of the stock over the event window (t, T):

$$CAR_{i(t,T)} = \sum_{t=1}^{T} AR_{i,t}$$

Under the null hypothesis of no abnormal return, the CAR is zero and the test statistics $\frac{CAR_i}{\hat{\sigma}_{CAR,i}}$ is Student's t distributed with *N-1* degrees of freedom.

The buy-and-hold abnormal return (BHAR)[9] is another method for time-series aggregation. CAR and BHAR measure the return to an investor who follows a simple trading strategy that buys/sells the stock at the time of a credit rating announcement (t_0) and holds the stock through the end of the post-event window $[t_0;\ t_5]$. CAR and BHAR is of interest when applied to the post-event window, as these measures provide information about market efficiency, in that nonzero abnormal returns following a credit rating announcement are inconsistent with efficiency and imply a profitable trading strategy (ignoring trading costs) (Eckbo, 2007).

[8] Perfect multicollinearity arises when one of the regressors is a perfect linear combination of the other regressors and is a violation of the OLS assumptions. Panel data reduces the likelihood of perfect multicollinearity because of variation between cross-sections and variation over time (Wooldridge, 2008).

[9] $\mathrm{BHAR}_{\mathrm{i},(\mathrm{t}=1,\mathrm{T})} = \prod_{\mathrm{t}=1}^{\mathrm{T}}(1 + \mathrm{R}_{\mathrm{it}}) - \prod_{\mathrm{t}=1}^{\mathrm{T}}(1 + \mathrm{E}(\mathrm{R}_{\mathrm{it}}))$

B. Cross-Sectional Aggregation

Cross-sectional tests provide a more complete picture of the effect of credit rating announcements. These tests appreciate that the stock price effect is related to firm characteristics. This allows us to discriminate among various economic hypotheses (Eckbo, 2007). The cumulative average abnormal return (CAAR) is:

$$\overline{CAR}_{t,T} = \sum_{t=1}^{T} \overline{AR}_t$$

and the variance is defined as:

$$\text{var}(\overline{CAR}_{t,T}) = \sum_{t=1}^{T} var(\overline{AR}_t)$$

For a cross-section of firms, (cumulative) abnormal returns are regressed against firm characteristics, e.g. leverage (*Lev1* and *Lev2*), whether or not the firm is reclassified (*Reclass*), is put on CreditWatch list (*Watch*), in which rating category (*Grade*) the firm is and whether it is classified as investment grade or non-investment grade (*Invest.grade).*

4.4 Testing for Significance

The effect of a credit rating announcement is assessed by a t-test, which utilizes the excess increase/decrease in the stock price over the event window, relative to the standard deviation of the stock's return over the estimation window. In the event study literature, the focus almost always is on the mean of the distribution of abnormal returns. This allows one to establish whether the event is, on average, associated with a change in the stock price and predict the sign of the average effect. To test for significance of abnormal returns, I use parametric tests of t-statistics[10]. Finally, I make use of linear (multiple) regression analysis.

4.4.1 The t-statistics

The t-statistics is used to test whether the AAR/CAARs are significantly different from zero. A t-test is a parametric test, which follows a Student t distribution. The Student t distribution has a bell shape similar to that of the normal distribution, but when the number of observations is small (N < 20), it has more mass in the tails (excess kurtosis). When N is 30 or more, the Student t distribution is well approximated by the standard normal distribution.

[10] Parametric tests could also be complemented with non-parametric tests, like the sign test and the rank test.

$$t_{AAR} = \frac{\overline{AR}_{i,t}}{\frac{\sigma(AR_{i,t})}{\sqrt{N}}}$$

$$t_{CAAR} = \frac{\overline{CAR}_{i,t}}{\frac{\sigma(CAR_{i,t})}{\sqrt{N}}}$$

Across N firms, the t_{AAR} is the relevant statistics for testing the abnormal return on the event day (t_0). The t_{CAAR} is the appropriate test statistics for the respective event windows. The degrees of freedom used in this test are *n*-1 and the *p*-value which can be calculated by using:

$$p\text{-value} = 2\Phi(-|t|)$$

I also make use of the two-sample t-test in order to assess whether there are any differences between abnormal returns based on certain criteria, e.g. market anticipation, re-classification and rating category:

$$t_{AAR} = \frac{(\overline{AR}_1 - \overline{AR}_2)}{\sigma(\overline{AR}_1 - \overline{AR}_2)}$$

$$t_{CAAR} = \frac{(\overline{CAR}_1 - \overline{CAR}_2)}{\sigma(\overline{CAR}_1 - \overline{CAR}_2)}$$

The *p*-value is calculated exactly as in the case of a single population. If the alternative hypothesis is one-sided rather than two sided, the *p*-value is calculated as:

$$p\text{-value} = Pr_{H_0}(\mathrm{Z} > \mathrm{t}) = 1 - \Phi(t)$$

4.4.2 Regression Analysis

The t-statistics is useful in that it provides a statistical measure of the AAR/CAAR and the sign of the effect. It does, however, not provide any explanation for the observed stock return associated with credit ratings. In order to discriminate among the various economic hypotheses set forth, I make use of regression analysis. The explanatory variables which I expect to be related to abnormal stock returns are: leverage (*Lev1* and *Lev2)*, anticipation *(Watch)*, reclassification *(Reclass)*, and rating classification (*Invest.grade)*. The simple linear regression with one independent variable is:

$$Y_i = \alpha_0 + \beta_1 X_1 + \varepsilon_i, \quad i = 1,\ldots,\mathrm{N}$$

where Y_i is abnormal returns, α_0 is the intercept, β_1 is the slope of the regression line, X_1 is the independent variable and ε_i is the error term. Multiple regression analysis is used to model the relationship between (cumulative) abnormal returns and independent variables which may explain the effect of credit ratings on stock returns. The advantage of multiple regressions is that we can estimate the (partial) effect of one regressor while holding constant the other variables. In multiple regressions, the F-statistics is used to test joint hypothesis about the regression coefficients.

The multiple regression model with two regressors is:

$$Y_i = \alpha_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \varepsilon_i, \quad i = 1,...,\mathrm{N}$$

Where subscript *i* indicates the i^{th} of the *n* observations in the sample. Y_i is abnormal returns, α_0 is the intercept, β_1 and β_2 are the coefficients on $X_{1,i}$ and $X_{2,i}$ respectively, and ε_i is the error term.

5. Results

The t-statistics for credit rating downgrades and upgrades for all event windows are summarized in the following table:

Table. 7

Mean (Cumulative) Abnormal Returns for Credit Rating Downgrades and Upgrades

The cumulative average abnormal return (CAAR) and the average abnormal return (AAR) is calculated relative to two expected return models: The market model and the market adjusted return model. CAAR and AAR is reported for all event windows. T-statistics is given in parentheses below the mean values.

Event window	Market Model Downgrades	Market adj.Model Downgrades	Market Model Upgrades	Market adj.Model Upgrades
AAR(t=0)	-1,47 %	-1,58 %	0,65 %	0,42 %
	(-1,98)**	(-2,05)**	(2,92)***	(2,27)**
CAAR(t=-1,1)	-2,17 %	-2,40 %	0,96 %	0,94 %
	(-1,76)**	(-1,90)**	(2,22)**	(2,06)**
CAAR(t=-5,0)	-2,89 %	-2,83 %	0,87 %	0,32 %
	(-2,34)**	(-2,29)**	(1,16)	(0,42)
CAAR(t=0,5)	-3,23 %	-2,34 %	0,40 %	0,39 %
	(-2,07)**	(-1,97)**	(0,94)	(0,92)

[1] T-statistics are in parantheses

[2] * p < 0.10, ** p < 0.05, *** p < 0.01

5.1 Credit Rating Downgrades

First I test hypothesis 1: *Credit rating downgrades have a negative effect on stock returns.*

$$H_0: \overline{CAR} \geq 0$$

$$H_A: \overline{CAR} < 0$$

This is a one-sided test with a 5% significance level and the critical value is 1,671. By using the market adjusted return model, the AAR/CAAR is negative for all event windows and highly significant at all reasonable levels. Hence, I can reject the null hypothesis and claim that credit rating downgrades have a negative effect on stock prices. The t-statistics from using the market model expected return yields the same results. We can see that the risk-adjustment has almost no effect on the estimates. This confirms that the choice of expected return model has virtually no effect on the results. It does, however, add a certain element of robustness to the statistics.

5.1.1 Capital Structure

In order to assess whether highly leveraged firms experience more significant stock price reactions to credit rating announcements (hypothesis 3), I ran a regression of CAR/AR on *Lev1* and *Le*v2.

Table. 8

Regression of (Cumulative) Abnormal Returns on Lev1 and Lev2

Lev1 and Lev2 are proxies for net-debt-to-asset (D/A) and the current ratio (CA/CL), respectively.

$$CAR_{i(t,T)} = \alpha_0 + \beta_1 Lev1_{i,t} + \beta_2 Lev2_{i,t} + \varepsilon_{i,t}$$

$$\underset{}{\mathrm{AR}_{\mathrm{i(t=0)}}} = \underset{(-1.02)}{-0.0187} + \underset{(0.19)}{0.0048}\mathrm{Lev1}_{i,t} + \underset{(2.11^{**})}{0.0130}\mathrm{Lev2}_{i,t} + \varepsilon_{\mathrm{i,t}} \quad \mathrm{R}^2 = 0.08, \mathrm{SER} = 0.0262$$

[1] T-statistics are in parentheses [2] *p < 0.10, **p < 0.05, ***p < 0.01 [3]SER = Standard Error of the Regression
[4]Only event windows with significant estimates are reported

From the regression on AR, we see that the coefficient β_2 is positive and significant on the 5% level. The sign on β_2 is as expected, that is, a higher current ratio (CA/CL) is associated with positive abnormal returns. *Lev2* is a proxy for liquidity and captures that firms that are financed with much short-term debt (low current ratio) experience more significant negative abnormal returns than less leveraged firms in the case of downloads. The magnitude of the coefficients is important in order to determine whether they have economic or practical significance. Increasing the current ratio, e.g. from 1 to 2, will hamper the effect of a downgrade by 1.30%, measured by abnormal returns. 1.30% of the market value is obviously of economic interest. On the other hand, it is questionable how feasible it is to increase the current ratio by a factor of two. The positive sign on β_1 is counterintuitive, as a higher debt-to-asset (D/A) ratio is associated with negative abnormal returns. However, the coefficient is not significant and the regression suggests that only *Lev2* is important in explaining abnormal returns. Consequently, only variations in short term debt seem to explain abnormal returns for firms being downgraded. The R^2 is 0.08, thus the variation in *Lev1* and *Lev2* does not explain much of the variation in AR.

5.1.2 Reclassification

Hypothesis 4 suggests that credit ratings that result in a reclassification from investment grade to non-investment grade have a greater effect on stock returns than credit announcements that do not invoke such a reclassification. I did a separate examination of downgrades which resulted in a reclassification ($\overline{CAR}_{\text{reclass}}$) and downgrades which did not result in a reclassification ($\overline{CAR}_{\text{not}}$). Out of the 64 downgrades, only nine observations resulted in a reclassification. A two-sample t-test was used to assess the difference between the abnormal returns:

$$t_{CAAR} = \frac{(\overline{CAR}_{\text{reclass}} - \overline{CAR}_{\text{not}})}{\sigma(\overline{CAR}_{\text{reclass}} - \overline{CAR}_{\text{not}})}$$

The null hypothesis and the one-sided alternative hypothesis are:

$$H_0: (\overline{CAR}_{\text{reclass}} - \overline{CAR}_{\text{not}}) = 0$$

$$H_1: (\overline{CAR}_{\text{reclass}} - \overline{CAR}_{\text{not}}) < 0$$

Table 9 summarizes the results.

Table. 9

Downgrades resulting in a reclassification vs. No-reclassification

The table shows the difference in cumulative average abnormal return (CAAR) and the average abnormal return (AAR) for firms being reclassified from investment grade to non-investment grade vs. firms for which a downgrade does not result in a reclassification

	df	Mean diff.	S.E.	t-value	p-value
AAR (t=0)	62	-0,0351	0,0218	-1,6090	0,0564
CAAR(t=-1.1)	62	-0,0363	0,0284	-1,2764	0,1033
CAAR(t=-5.0)	62	-0,0274	0,0321	-0,8531	0,1984
CAAR(t=0.5)	62	-0,0649	0,0335	-1,9405	0,0284

The table above shows that the mean difference in abnormal return is more negative for firms being reclassified than for firms which are not reclassified. The AAR on the announcement day is -0.0351 and almost significant on the 5% level. However, it is more interesting to notice the highly significant negative CAAR (-0.0649) in the post-event window. This gives support to hypothesis 4, namely that firms for which a downgrade result in a reclassification have greater effect on abnormal returns than downgrades which do not result in a reclassification.

5.1.3 Market Anticipation

Anticipation may be a determinant in explaining abnormal returns. A separate examination of credit rating downgrades, contingent on the outlook being negative ($\overline{CAR}_{\mathrm{neg}}$) or not ($\overline{CAR}_{\mathrm{not}}$) could give an answer to this question. Unfortunately, it was not possible to analyse statistically as only two observations out of 64 were non-negative (one positive and one neutral).

5.1.4 Rating Category

Hypothesis 5 suggests that changes in credit rating have a more significant effect on stock returns for firms with low credit rating compared to firms with high credit rating. First, I examined whether there are any differences in abnormal returns for firms classified as investment grade ($\overline{CAR}_{\mathrm{inv}}$) or non-investment grade ($\overline{CAR}_{\mathrm{not}}$). I pooled all firms above BBB- and all firms below BBB-. Out of 64 observations, 37 were downgrades within the investment grade classification, while 27 were within the non-investment grade classification.

A two-sample t-test is used to assess the difference between the two groups:

$$t_{CAAR} = \frac{(\overline{CAR}_{\mathrm{inv}} - \overline{CAR}_{\mathrm{not}})}{\sigma(\overline{CAR}_{\mathrm{inv}} - \overline{CAR}_{\mathrm{not}})}$$

The null hypothesis and the two-sided alternative hypothesis are:

$$H_0: (\overline{CAR}_{\mathrm{inv}} - \overline{CAR}_{\mathrm{not}}) = 0$$

$$H_1: (\overline{CAR}_{\mathrm{pos}} - \overline{CAR}_{\mathrm{not}}) \neq 0$$

The t-test yields the following results for the different event windows:

Table. 10

Downgrades for Investment grade firms vs. Non-investment grade firms

The table shows the mean difference in cumulative average abnormal return (CAAR) and the average abnormal return (AAR) for firms being downgraded within the investment grade classification vs. firms being downgraded within the non-investment grade classification.

	df	Mean diff.	S.E.	t-value	p-value
AAR (t=0)	62	0,0435	0,0147	2,9620	0,0043
CAAR(t=-1.1)	62	0,0470	0,0155	3,0266	0,0055
CAAR(t=-5.0)	62	0,0461	0,0219	2,1027	0,0396
CAAR(t=0.5)	62	0,0420	0,0237	1,7765	0,0807

It is evident from the table that the difference in AAR/CAAR is significantly different between investment grade firms and non-investment grade firms. The results are highly significant for all event windows except the post-event window. The result indicates that firms within different rating classes cannot be treated similarly and yields for a conditional treatment of ratings and emission risk.

The regression in Table 11 allows for a finer rating partition by dividing the downgrades into groups based on the rating category in which a firm is classified after a change in credit rating. I ran the following regression:

Table. 11

Regression of Cumulative Abnormal Returns on Rating Category

Firms are pooled into rating categories in order to allow for a conditional treatment of rating category and the effect of credit rating changes. The categories are named Grade1, Grade2 etc.

$$CAR_{i(t,T)} = \alpha_0 + \beta_1 Grade4_{i,t} + \beta_2 Grade5_{i,t} + \beta_3 Grade6_{i,t} + \beta_4 Grade7_{i,t} + \beta_5 Grade8_{i,t} + \varepsilon_{i,t}$$

$$\underset{(0.42)}{\mathrm{CAR}_{i(-1,1)} = 0.0063} - \underset{(-0.30)}{0.0053\mathrm{Grade4}_{i,t}} - \underset{(-1.37)}{0.0281\mathrm{Grade5}_{i,t}} - \underset{(-0.60)}{0.0139\mathrm{Grade6}_{i,t}}$$

$$- \underset{(-3.83^{***})}{0.1999\mathrm{Grade7}_{i,t}} - \underset{(-4.44^{***})}{0.1199\mathrm{Grade8}_{i,t}} + \varepsilon_{i,t}$$

$$R^2 = 0.39, \mathrm{SER} = 0.0500$$

[1] T-statistics are in parentheses [2] *p < 0.10, **p < 0.05, ***p < 0.01 [3]SER = Standard Error of the Regression
[4] See Table 5 for description of the rating categories. There were no downgrades in the others categories.

All the coefficients are negative, as expected (they are all downgrades). *Grade7* and *Grade8* are significant on all reasonable levels, while the remaining coefficients are non-significant. *Grade7* and *Grade8* are the lowest rating categories hence it is not surprising that downgrades in these rating categories yield significant negative abnormal returns. These

categories are, as the names indicate, extremely speculative and with little prospects for recovery. Controlling for downgrades of more than one notch did not affect the results.
I was initially expecting the coefficient on *Grade5* (β_2) to be significant. This rating category comprises firms which have been reclassified from investment grade to non-investment grade. Moreover, section 5.1.2 found reclassifications to be significant in the post-event window and almost significant on the announcement day. A plausible explanation for why *Grade5* is not significant could be that it does not solely comprise firms that were reclassified. It does, for example, also include firms that were downgraded from BB+ to BB or from BB to BB-. These changes in credit rating are possibly not as important as the change from BBB- to BB+, and thus render *Grade5* insignificant. This indicates that the categories could be too wide and that more refined categories would yield different results. However, this was not feasible due to the limited number of observations in the sample.

5.2 Credit Rating Upgrades

I now move on to testing hypothesis 2: *Credit rating upgrades have no effect on stockl returns.*

$$H_0: \overline{CAR} = 0$$

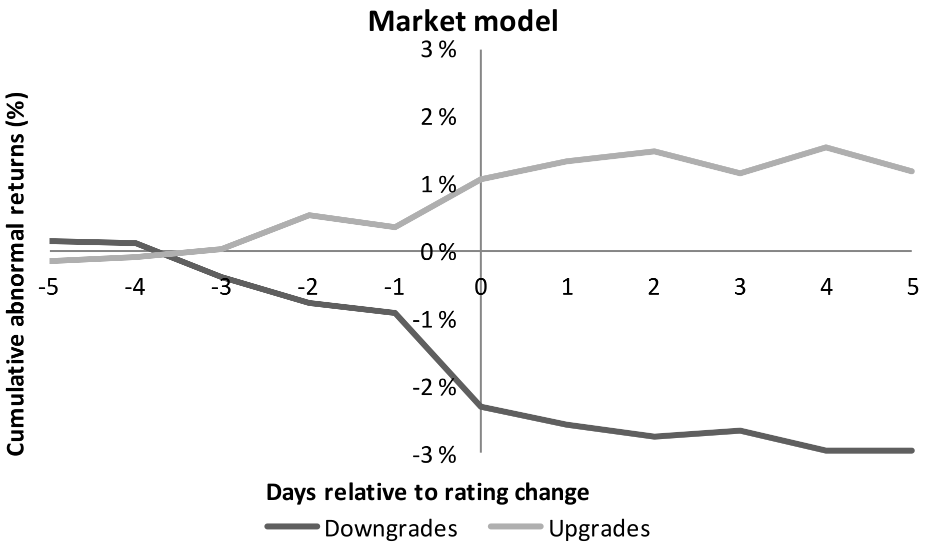
$$H_A: \overline{CAR} \neq 0$$

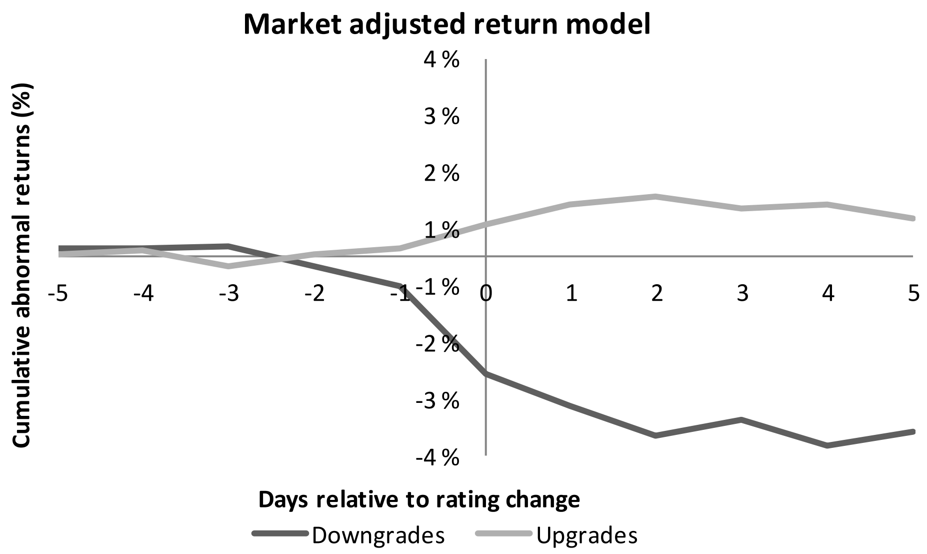
The mean (cumulative) abnormal returns for upgrades are reported in Table 7 (p. 36). The significance level of the test is 5% and the critical value for the two-sided test is 2.048. The AAR/CAAR is positive for all event windows. By using the market adjusted return model, $AAR_{t=0}$ is 0.0042 and significant on the 5% level. The $CAAR_{t(-1,1)}$) is 0.0094 and also significant on the 5% level. Hence, I can reject the null hypothesis that credit rating upgrades have no effect on stock returns. However, I cannot reject the null hypothesis for $CAAR_{t(-5,0)}$ and $CAAR_{t(0,5)}$ that credit rating upgrades have no effect on stock returns in the pre-event window or the post-event window. The t-statistics from using the market model expected return yields similar results and the effect of credit rating upgrades is not altered by the choice expected return model.

It is evident from Table 7 that credit ratings do indeed convey information to the market. The information content of credit ratings, however, seems to be most significant for downgrades. Credit rating downgrades yield significant negative abnormal returns at the announcement day and in all the event windows. Credit rating upgrades yield significant positive stock returns on the day of the announcement and plus/minus one day $[-1;1]$ but not in the pre-event window or post-event window.

The cumulative abnormal returns for each day are illustrated in the figures below for the market model and the market adjusted return model respectively:

Figure 2 Stock market reactions to rating change announcement





It is evident from Figure 2 that there is a substantial stock price reaction on the announcement day (t_0) and plus/minus one day$[-1;1]$, which we know from the t-tests to be statistically significant. It is also possible to depict that the cumulative abnormal return is more significant for downgrades than for upgrades in both the pre-event window and the port-event window. The market model and the market adjusted return model gives the same picture and the choice of expected return model does not seem to alter the results.

5.2.1 Capital Structure

In order to assess whether highly leveraged firms experience more significant stock returns to credit rating announcements (hypothesis 3), I ran a regression of CAR/AR on *Lev1* and *Lev2*.

Table. 12

Regression of cumulative abnormal returns on Lev1 and Lev2

Lev1 and Lev2 are proxies for net-debt-to-asset (D/A) and the current ratio (CA/CL), respectively.

$$CAR_{i(t,T)} = \alpha_0 + \beta_1 Lev1_{i,t} + \beta_2 Lev2_{i,t} + \varepsilon_{i,t}$$

$$\underset{}{\mathrm{AR}_{i(t=0)}} = \underset{(2.67^{**})}{0.0214} - \underset{(-2.13^{**})}{0.0234\mathrm{Lev1}_{i,t}} - \underset{(-1.26)}{0.0038\mathrm{Lev2}_{i,t}} + \varepsilon_{i,t} \quad R^2 = 0.16, \mathrm{SER} = 0.0095$$

$$\mathrm{CAR}_{i(-1,1)} = \underset{(1.36)}{0.0272} - \underset{(-1.73^{*})}{0.0475\mathrm{Lev1}_{i,t}} + \underset{(0.47)}{0.0036\mathrm{Lev2}_{i,t}} + \varepsilon_{i,t} \quad R^2 = 0.13, \mathrm{SER} = 0.0237$$

[1] T-statistics are in parentheses [2] *p < 0.10, **p < 0.05, ***p < 0.01 [3]SER = Standard Error of the Regression
[4]Only event windows with significant estimates are reported

We see that the coefficient β_1 is negative and significant both on the announcement day (5% level) and in the event window $[-1;1]$ (10% level). The sign on β_1 is as expected that is, a higher debt-to-asset ratio is associated with less positive abnormal returns. Hence, the regression indicates a relationship between abnormal returns and capital structure. The magnitude of the coefficients is –0.0234 on the announcement day but has little economic significance. For example, a firm with an initial D/A ratio of 0.5 would only experience 0.234%[11] higher abnormal returns by reducing the D/A ratio to 0.4. The corresponding change in AR is 0,475%[12] for $CAR_{(-1,1)}$. β_2 is not significant and the sign is counterintuitive on the announcement day. One would expect β_2 to be positive i.e. that firms with a high current ratio experience more significant abnormal returns in the case of upgrades. The regression indicates that only *Lev1* is important in explaining abnormal returns for upgrades.

[11] $\Delta Y = \beta_1 \Delta X_1 \rightarrow \Delta Y = 0.0234*0.1 = 0.00234$ (0.234%)

[12] $\Delta Y = \beta_1 \Delta X_1 \rightarrow \Delta Y = 0.0475*0.1 = 0.0475$ (0.475%)

This is an interesting result, as it is opposite from credit rating downgrades. Evidently, liquidity (*Lev2)* has more explanatory power than solvency (*Lev1)* for downgrades, while the opposite seems to be true for upgrades. The R^2 is 0.16 for $AR_{t=0}$ and 0.13 for $CAR_{t(-1.1)}$. Thus, the explanatory power of the regression is low.

5.2.2 Reclassification

Out of the 29 firms that were upgraded, only three experienced a reclassification from non-investment grade to investment grade. Hence, the sample is too small for an analysis on reclassification to make sense.

5.2.3 Market Anticipation

As suggested earlier, anticipation may be a determinant in explaining abnormal returns. I did a separate examination of credit rating upgrades, contingent on the outlook being positive ($\overline{CAR}_{\mathrm{pos}}$) or not ($\overline{CAR}_{\mathrm{not}}$). Out of the 29 upgrades, 15 observations were preceded by positive outlooks, 13 neutral outlooks and only one of the upgrade was preceded by a negative outlook. A two-sample t-test is used to assess the difference between the two groups:

$$t_{CAAR} = \frac{(\overline{CAR}_{\mathrm{pos}} - \overline{CAR}_{\mathrm{not}})}{\sigma(\overline{CAR}_{\mathrm{pos}} - \overline{CAR}_{\mathrm{not}})}$$

The null hypothesis and the two-sided alternative hypothesis are:

$$H_0: (\overline{CAR}_{\mathrm{pos}} - \overline{CAR}_{\mathrm{not}}) = 0$$

$$H_1: (\overline{CAR}_{\mathrm{pos}} - \overline{CAR}_{\mathrm{not}}) \neq 0$$

The t-test did not yield any significant results for any of the event windows. Hence, I cannot say that there is any difference between upgrades preceded by positive outlooks and upgrades preceded by neutral or negative outlooks. One explanation for this could be that addition to S&P CreditWatch simply is not a suitable proxy for market anticipation. For example, the effect of being put on watch list could already be reflected in the stock price at the time of the credit rating announcement. Furthermore, one must take into account the availability of other sources of information in the market prior to the rating announcement which may render the dummy *Watch* useless. A more comprehensive study might want to disentangle the effect of *Watch* for different firms and time-periods. As shown by Hsueh and

Liu (1992), the effect of a rating change is more pronounced during periods of high market uncertainty and the information content of credit ratings is more significant for firms in which information is relatively limited.

5.2.4 Rating Category

First, I examined whether there was any difference in abnormal returns for firms classified as investment grade or non-investment grade. I pooled all firms above BBB- and all firms below BBB-. A two sample t-test for the difference in abnormal returns did not yield any significant results for any of the event windows.

Secondly, I assessed whether changes in credit rating have a more significant effect on stock returns for firms with low credit rating, compared to firms with high credit rating (hypothesis 5). I ran the following regression:

Table. 13

Regression of Cumulative Abnormal Returns on Rating Category

Firms are pooled into rating categories in order to allow for a conditional treatment of rating category and the effect of credit rating changes. The pooling across rating notches was done to increase the number of observations in each rating class.

$$CAR_{i(t,T)} = \alpha_0 + \beta_1 Grade2_{i,t} + \beta_2 Grade3_{i,t} + \beta_3 Grade4_{i,t} + \beta_4 Grade5_{i,t} + \varepsilon_{i,t}$$

$$\mathrm{CAR}_{i(-1,1)} = \underset{(-1.18)}{-0.0284} + \underset{(0.52)}{0.0179 Grade2_{i,t}} + \underset{(1.36)}{0.0350 Grade3_{i,t}} + \underset{(1.81^{*})}{0.0451 Grade4_{i,t}} + \underset{(1.19)}{0.0315 Grade5_{i,t}} + \varepsilon_{i,t}$$

$$\mathrm{R}^2 = 0.17, \mathrm{SER} = 0.0241$$

[1] T-statistics are in parentheses [2] *p < 0.10, **p < 0.05, ***p < 0.01 [3]SER = Standard Error of the Regression
[4] See Table 5 for description of the rating categories. There were no downgrades in the others categories.

All the coefficients are positive, as expected (they are all upgrades). β_3 is significant on the 10% level, the remaining coefficients are not significant. β_3 is the coefficient on *Grade4*, which is the lowest rating category within the investment grade classification. It sounds reasonable that this is where we are most likely to find significant results. It indicates that upgrades have a more significant effect on firms with low credit rating, compared to firms with high credit rating, thus giving some support to hypotheses 5. Moreover, the rating category *Grade4* also entails firms that have been reclassified from non-investment grade to investment grade, indicating that reclassification could have an effect on abnormal returns.

5.3 Regression Analysis

Simple linear regressions give answers to whether the explanatory variables each have an individual effect on abnormal returns. However, simple regressions could produce misleading results, in that they do not recognize other potential important determinants of abnormal returns. Leaving out other potentially important variables could make the OLS estimator biased. This is referred to as omitted variable bias. Omitted variable bias occurs when (i) the omitted variable is correlated with the included regressor, and (ii) the omitted variable is a determinant of the dependent variable (Wooldridge, 2008). For example, *Grade* may very likely be correlated with *Lev*, and *Grade* is also a possible determinant of abnormal returns. Consequently, the OLS estimator from running a simple regression would be biased.

Multiple regression analysis is used to model the relationship between (cumulative) abnormal returns and different independent variables. The advantage of multiple regressions is that we can estimate the (partial) effect of one variable while holding constant the other variables. In multiple regressions, the F-statistics is used to test joint hypothesis about the regression coefficients.

Based on the aforementioned hypotheses, I formulate the following multiple regression model:

$$(1)\quad CAR_{i,(t,T)} = \alpha_0 + \beta_1 Lev1_{i,t} + \beta_2 Lev2_{i,t} + \beta_3 Reclass_{i,t} + \beta_4 Watch_{i,t} + \beta_5 Invest.grade_{i,t} + \varepsilon_{i,t}$$

Here $CAR_{i,(t,T)}$ is the sample cumulative abnormal return from period *t* to T. *Lev1* and *Lev2* are proxies for capital structure and β_1 and β_2 are the important parameters in assessing hypothesis 3. *Reclass* is a dummy variable which takes on the value 1 for yes and 0 otherwise. The variable is meant to gauge the impact of being reclassified, either from investment grade to non-investments grade or vice versa. Thus β_3 is the important parameter for assessing hypothesis 4. *Watch* is also a dummy variable, which captures (un)anticipation. For upgrades, it takes on the value 1 if the event is not anticipated (non-positive outlook) and 0 otherwise. For downgrades, it is 1 if the event is not anticipated (non-negative outlook), and 0 otherwise. Thus the coefficient β_4 tells whether a change in credit rating, not preceded by outlook in the same direction, yields abnormal returns. *Invest.grade* is a variable that indicates level, i.e. what classification the firm gets after a change in credit rating, that is, either investment grade or non-investment grade. It allows for a conditional treatment of ratings and emission risk, as suggested by hypothesis 5. It is 0 for investment grade and 1 for non-investment grade.

5.3.1 Credit Rating Downgrades

The results from running regression (1) on downgrades are reported below:

Table. 14

Results from Ordinary Least Squares Estimation of (Cumulative) Abnormal Returns for Credit Rating Downgrades.

Lev1 and Lev2 are proxies for capital structure. Reclass is meant to gauge the impact of being reclassified, either from investment grade to non-investments grade, or vice versa. Watch is a variable which captures (un)anticipation and Invest.grade is a variable which indicates level, i.e. what classification the firm gets after a change in credit rating.

$$CAR_{i(t,T)} = \alpha_0 + \beta_1 Lev1_{i,t} + \beta_2 Lev2_{i,t} + \beta_3 Reclass_{i,t} + \beta_4 Watch_{i,t} + \beta_5 Invest.grade_{i,t} + \varepsilon_{i,t}$$

	Market adjusted return model		*Market model*	
	$AR_{t=0}$	$CAR_{t(-1.1)}$	$AR_{t=0}$	$CAR_{t(-1.1)}$
α_0	-0,0132 (-0,57)	0,0032 (0,06)	-0,0104 (-0,48)	-0,0087 (-0,18)
β_1	-0,0088 (-0,25)	-0,0292 (-0,36)	-0,0039 (-0,12)	-0,0142 (-0,19)
β_2	0,0175 (2,64)**	0,0109 (0,72)	0,0136 (2,23)**	0,0132 (0,97)
β_3	0,0120 (0,92)	-0,0200 (-0,66)	0,0078 (0,65)	-0,0138 (-0,52)
β_4	0,0144 (0,51)	-0,1290 (-1,99)**	0,0391 (1,51)	-0,1066 (-1,84)*
β_5	-0,0212 (-2,18)**	0,0170 (0,75)	-0,0168 (-1,92)*	0,0187 (0,96)
R^2	0,20	0,12	0,17	0,12
SER	0,0264	0,0611	0,0245	0,1254
F(5, 41)	2,02	0,35	1,67	0,33
p-value	0,09	0,35	0,16	0,34

[1] T-statistics are in parentheses, *p < 0,10, **p < 0,05, ***p < 0,01

[2] p-value of regression is reported below the F-statistics

[3] R^2 is the fraction of the sample variance of Y_i explained by the regressors.

[4] The standard error of the regression (SER) estimates the standard deviation of the error term ε_i.

We see from the regression on $AR_{(t=0)}$ that the coefficient on *Lev1* has changed sign from positive to negative compared to the simple regression in Table 8. This is intuitive, as a higher debt-to-assets ratio is associated with negative abnormal returns. However, the coefficient is still not significant. β_2 tells the same story as Table 8, namely that firms with a high current ratio (CA/CL) experience less negative AR after being downgraded. The coefficient is significant on the 5% level for $AR_{(t=0)}$, but not significant in the event window $CAR_{(-1,1)}$. There are no differences between the two expectation models when it comes to capital structure. The coefficient is also economically significant. Increasing the current ratio, e.g. from 1 to 2, will hamper the effect of a downgrade by 1.75 %, measured by abnormal returns. 1.75 % of the market value is obviously of economic interest. On the other hand, it is questionable how feasible it is to increase the current ratio by a factor of two.

The two-sample t-test (Table 9) showed that a reclassification from investment grade to non-investment grade yields negative abnormal returns for all event windows. After controlling for other explanatory factors, this is only evident for $CAR_{(-1,1)}$. Moreover, the coefficient is not significant in any of the two models.

The coefficient β_4 is highly negative and significant in the event window $CAR_{(-1,1)}$. This indicates that firms that are not placed on a negative outlook prior to a downgrade, experience significantly negative abnormal returns. The magnitude of the coefficient is huge, indicating a 12.9 % decline in equity value. Hence, additions to S&P CreditWatch give valuable information to investors and have both economic and statistical significant. The result is also evident from the market model, although only significant on the 10% level.

The coefficient β_5 is negative and significant in the announcement day. This is consistent with the two-sample t-test in Table 10. It indicates that credit rating downgrades within the non-investment grade classification yield negative abnormal returns and supports the argument for a conditional treatment of credit ratings. The coefficient is -0.0212 which is economically significant. The market model indicates the same results however, only on the 10% level.

In order to test joint hypotheses on multiple regression coefficients we use the F-statistics. Under the null hypothesis, all the coefficients $\sum_{i=1}^{5}\beta_i$ are zero, while the alternative hypothesis is that at least one of the coefficients are non-zero. Under the null hypothesis, the

F-statistics has a sampling distribution that is given by the $F_{q,\infty}$ distribution[13]. The F-statistics have very different values for the different event windows and depends on the expectation's model. Based in the market adjusted return model, the F-statistics is 2.02 on the announcement day and significant on the 10% level. However, for the remaining windows, the F-statistics is not significant regardless of expectation model.

R^2 in a multiple regression model measures the proportion of variation in abnormal returns that is explained by the independent variables. The R^2 varies between 0.12 and 0.20 and is highest on the announcement day. However, it is not meaningful to compare R^2 between regression models in which the dependent variable is not the same or use different sets of observations as the estimation period. In general, the explanatory power of the model seems low. The R^2 is an ambiguous measure and must be interpreted with caution. It does not, for example, tell whether the variables are significant, it says nothing about inference, if there are omitted variable bias or whether I have included the most appropriate variables.

5.3.2 Credit Rating Upgrades

The results from running regression (1) on upgrades are reported below:

[13] q-restrictions

Table. 15

Results from Ordinary Least Squares Estimation of (Cumulative) Abnormal Returns for Credit Rating Upgrades.

Lev1 and Lev2 are proxies for capital structure. Reclass is meant to gauge the impact of being reclassified, either from investment grade to non-investments grade, or vice versa. Watch is a variable which captures (un)anticipation and Invest.grade is a variable which indicates level, i.e. what classification the firm gets after a change in credit rating.

$$CAR_{i(t,T)} = \alpha_0 + \beta_1 Lev1_{i,t} + \beta_2 Lev2_{i,t} + \beta_3 Reclass_{i,t} + \beta_4 Watch_{i,t} + \beta_5 Invest.grade_{i,t} + \varepsilon_{i,t}$$

	Market adjusted return model		*Market model*	
	$AR_{t=0}$	$CAR_{t(-1.1)}$	$AR_{t=0}$	$CAR_{t(-1.1)}$
α_0	0,0215 (1,82)*	0,0155 (0,56)	0,0325 (2,40)**	0,0305 (1,06)
β_1	-0,0245 (-1,76)*	-0,0391 (-1,19)	-0,0174 (-1,13)	-0,0101 (-0,31)
β_2	-0,0030 (-0,71)	0,0086 (0,87)	-0,0116 (-2,22)**	-0,0087 (-0,79)
β_3	-0,0033 (-0,46)	0,0121 (0,73)	-0,0023 (-0,30)	0,0015 (0,09)
β_4	0,0013 (0,26)	-0,0005 (-0,05)	-0,0029 (-0,60)	-0,0044 (-0,42)
β_5	-0,0012 (-0,29)	-0,0069 (-0,57)	0,0101 (1,76)*	-0,0069 (-0,57)
R^2	0,15	0,20	0,30	0,05
SER	0,0102	0,0241	0,0112	0,0238
F(5, 21)	0,82	1,18	1,84	0,95
p-value	0,55	0,34	0,15	0,22

[1] T-statistics are in parentheses, *p < 0,10, **p < 0,05, ***p < 0,01

[2] p-value of regression is reported below the F-statistics

[3] R^2 is the fraction of the sample variance of Y_i explained by the regressors.

[4] The standard error of the regression (SER) estimates the standard deviation of the error term ε_i.

We see from the regression that the coefficient β_1 is negative on the announcement day and in the event window $t_{(-1,1)}$. However, it is only weakly significant (10% level) for $AR_{t=0}$. This confirms the finding in Table 12, namely that firms with a high D/A ratio experience less significant abnormal returns in the case of upgrades. The magnitude of the coefficient is –0.0245, but has little economic significance. For example, a firm with an initial D/A ratio of 0.5 would only experience 0.245%[14] higher abnormal returns by reducing the D/A ratio to 0.4. The market model gives the same sign on the coefficients, but yields no significant results.

β_2 gives ambiguous results, with both negative and positive sign. The only significant coefficient is for $AR_{t=0}$ according to the market model. The coefficient is -0.0116 and highly significant. This is counterintuitive, as one would expect firms with a high current ratio to experience positive AR in the case of upgrades. Hence, it is not meaningful to interpret any economic significance of the coefficient as it has no ground in economic theory.

Furthermore, the coefficient β_3 also gives vague results. The sign is negative for $AR_{t=0}$ in both models, and positive for $CAR_{t(-1.1)}$ in both models. However, none of the results are significant. The sample of upgrades is only comprised of three reclassifications. The contradicting results are probably due to the small number of observations.

The coefficient β_4 yields about as inconclusive and nonsignificant results as β_3. The signs are both positive and negative for $AR_{t=0}$ in both models and negative for $CAR_{t(-1.1)}$. The two-sample t-test in section 5.2.3 did not give any significant results between upgrades preceded by positive outlooks and those which did not. Hence, the multiple regression confirm that credit rating outlooks do not seem to convey any information in the case of upgrades.

The coefficient β_5 is negative and insignificant for all event windows except for $AR_{t=0}$ according to the market model. This confirms the two-sample t-test (5.2.4) that there is no difference in abnormal returns for firms classified as investment grade or non-investment

[14] $\Delta Y = \beta_1 \Delta X_1 \rightarrow \Delta Y = 0.0245*0.1 = 0.00245$ (0.245%)

grade. However, the coefficient on $AR_{t=0}$ is 0.0101 and only significant on the 10% level according to the market model.

The F-statistics have very different values for the different event windows and depend on the expectation's model. The market model yields the highest F-statistics (1.84) on the announcement day but it is not significant. In general, the multiple regressions models seem to perform poorly when it comes to upgrades. The R^2 varies between 0.05 and 0.30, and is highest on the announcement day. As mentioned earlier, one should not put too much emphasis on this measure, especially considering the diverging results and insignificant coefficients.

6. Conclusion

This thesis investigates the effect of credit rating announcements on stock returns. I found that credit rating downgrades have a negative effect on stock returns, and upgrades have a positive effect, measured by cumulative abnormal returns. Hence, credit rating announcements convey new information. However, the information content of credit ratings seems to be most significant for downgrades. This is consistent with previous research, e.g. by Holthausen and Leftwich (1986), Hand, Holthausen and Leftwich (1992), Goh and Ederington (1993) and Hsueh and Liu (1992). The choice of expected return model did not alter the results.

A simple regression analysis showed that firms that have a high current ratio prior do a downgrade experience less negative abnormal returns compared to firms with a low current ratio. In the case of upgrades, firms with a high net debt-to-assets ratio experience less positive excess returns compared to firms with a low net debt-to-assets ratio prior to an upgrade. Downgrades that result in a reclassification from investment grade to non-investment grade yield significant negative abnormal returns in the post event window. Hence, a downgrade that affects the access to commercial papers and bond liquidity issues is incrementally significant. It was not possible to run the same test on upgrades due to the small sample size.

I tried to gauge the market's anticipation of a change in credit rating by examining downgrades (upgrades) preceded by negative (positive) credit rating outlooks and those which were not preceded by a negative (positive) outlook but did not get any significant results for upgrades. Plausible explanations could be that the proxy for anticipation is not suitable or that failing to account for other sources of information prior to the announcement renders the dummy variable useless. The sample of downgrades was too small to analyze. Moreover, I found that that downgrades for firms with non-investment grade rating yield more negative excess returns compared to downgrades for firms with investment grade rating. Hence, firms within different rating classes cannot be treated similarly and calls for a conditional treatment of ratings and emission risk. Similar results were obtained for upgrades, however only weakly significant.

A multiple regression was used to model the relationship between cumulative abnormal returns and different independent variables. After controlling for other explanatory variables, it is still evident that firms with a high current ratio prior to a downgrade experience less negative abnormal returns on the announcement day. In addition, downgrades that are not anticipated by the market experience negative abnormal returns. The results are both statistical and economically significant. The multiples regression on upgrades did not produce any significant results. Moreover, the regression produces ambiguous results and their interpretation is often counterintuitive. In general, the multiple regression model seems to perform poorly when it comes to upgrades and the explanatory power of the model is low. It would be desirable to perform the analysis on a larger sample, in order to obtain more robust results. Furthermore, in a more comprehensive study, it would be favourable to do a manual inspection of confounding effects to reduce the effect of outliers/noise in the sample. An interesting suggestion for further research could be to do a separate analysis of the results in bull and bear markets, that is, to investigate whether upgrades/downgrades and the explanatory variables are contingent on the general market conditions.

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8. Appendix - Tables

Table1a List of Issuers

Issuer	Domicile	Industry
Alfa Laval	Sweden	Capital Goods
Autoliv	Sweden	Automobiles & Components
Copenhagen Airports	Denmark	Transportation
Electrolux	Sweden	Consumer Products
Enitel	Norway	Telecom Services
Ericsson	Sweden	Information Technology
ISS	Denmark	Commercial & Professional Svc
L E Lundbergforetagen	Sweden	Finance
Norsk Hydro	Norway	Metals & Mining
Norske Skogindustrier	Norway	Paper & Forest Products
Novo Nordisk	Denmark	Health Care
Petroleum Geo-Services	Norway	Energy
Sandvik	Sweden	Capital Goods
SAS	Sweden	Transportation
SSAB	Sweden	Metals & Mining
Statoil	Norway	Energy
Stora Enso	Sweden	Paper & Forest Products
Swedish Match	Sweden	Consumer Products
TDC	Denmark	Telecom Services
Telenor	Norway	Telecom Services
TeliaSonera	Sweden	Telecom Services
Volvo	Sweden	Capital Goods
Yara International	Norway	Chemicals

Table 1b List of Sample Industries

Industry	Observations	
Telecom Services	16	17 %
Capital Goods	11	12 %
Energy	11	12 %
Paper & Forest Products	11	12 %
Information Technology	10	11 %
Metals & Mining	7	8 %
Transportation	6	7 %
Automobiles & Components	5	5 %
Commercial & Professional Svc	4	4 %
Consumer Products	4	4 %
Chemicals	3	3 %
Health Care	3	3 %
Finance	1	1 %

Table 2 List of Issuers and Credit Rating Announcements

Firm	Date	Action	Rating	Classification
Alfa Laval	28.04.08	Upgrade	BBB+	Lower medium grade
Alfa Laval	28.11.03	Upgrade	BBB	Lower medium grade
Alfa Laval	11.06.02	Upgrade	BBB-	Lower medium grade
Autoliv	27.07.10	Upgrade	BBB+	Lower medium grade
Autoliv	26.11.09	Upgrade	BBB	Lower medium grade
Autoliv	19.02.09	Downgrade*	BBB-	Lower medium grade
Autoliv	21.11.08	Downgrade	BBB+	Lower medium grade
Autoliv	12.08.05	Upgrade	A-	Upper medium grade
Copenhagen Airports	25.02.10	Downgrade	BBB-	Lower medium grade
Copenhagen Airports	04.12.08	Downgrade	BBB	Lower medium grade
Copenhagen Airports	04.04.06	Downgrade	BBB+	Lower medium grade
Electrolux	09.11.10	Upgrade	BBB+	Lower medium grade
Electrolux	17.12.08	Downgrade	BBB	Lower medium grade
Enitel	27.08.01	Downgrade	CCC-	In default with little prospects for recovery
Enitel	29.08.01	Selective default	SD	Default
Enitel	11.07.01	Downgrade	CCC	Extremely speculative
Ericsson	15.06.07	Upgrade*	BBB+	Lower medium grade
Ericsson	28.02.05	Upgrade**	BBB-	Lower medium grade
Ericsson	10.11.04	Upgrade	BB+	Speculative
Ericsson	07.11.02	Downgrade	BB	Speculative
Ericsson	01.08.02	Downgrade**	BB+	Speculative
Ericsson	22.07.02	Downgrade	BBB-	Lower medium grade
Ericsson	16.05.02	Downgrade	BBB	Lower medium grade
Ericsson	13.11.01	Downgrade	BBB+	Lower medium grade
Ericsson	14.05.01	Downgrade	A-	Upper medium grade
Ericsson	30.01.01	Downgrade	A	Upper medium grade
ISS	30.05.08	Upgrade	BB-	Speculative
ISS	17.05.05	Downgrade*	B+	Highly speculative
ISS	12.05.05	Downgrade***	BB+	Speculative
ISS	09.04.03	Upgrade	BBB+	Lower medium grade
L E Lundbergforetagen	08.06.07	Upgrade	A+	Upper medium grade
Norsk Hydro	19.11.10	Upgrade	BBB	Lower medium grade
Norsk Hydro	20.03.09	Downgrade	BBB-	Lower medium grade
Norsk Hydro	03.08.07	Downgrade**	BBB	Lower medium grade
Norsk Hydro	02.06.06	Downgrade	A-	Upper medium grade
Norske Skogindustrier	12.08.10	Downgrade	B-	Highly speculative
Norske Skogindustrier	17.02.10	Downgrade	B	Highly speculative
Norske Skogindustrier	19.05.09	Downgrade	B+	Highly speculative
Norske Skogindustrier	21.04.08	Downgrade	BB-	Speculative
Norske Skogindustrier	28.01.08	Downgrade	BB	Speculative
Norske Skogindustrier	14.11.06	Downgrade**	BB+	Speculative
Norske Skogindustrier	08.04.04	Downgrade	BBB-	Lower medium grade
Novo Nordisk	24.06.11	Upgrade	A+	Upper medium grade
Novo Nordisk	13.06.07	Upgrade	A	Upper medium grade
Novo Nordisk	29.04.04	Upgrade	A-	Upper medium grade
Petroleum Geo-Services	02.12.10	Upgrade	BB	Speculative
Petroleum Geo-Services	10.07.06	Upgrade	BB-	Speculative
Petroleum Geo-Services	06.05.05	Upgrade	B+	Highly speculative
Petroleum Geo-Services	30.07.03	Downgrade	D	Default

Table 2 List of Issuers and Credit Rating Announcements (cont.)

Petroleum Geo-Services	31.12.02	Downgrade*	CC	In default with little prospects for recovery
Petroleum Geo-Services	20.11.02	Downgrade*	CCC+	Substantial risks
Petroleum Geo-Services	29.10.02	Downgrade*	B	Highly speculative
Petroleum Geo-Services	31.07.02	Downgrade***	BB-	Speculative
Petroleum Geo-Services	19.01.01	Downgrade	BBB-	Lower medium grade
Sandvik	24.05.11	Upgrade	BBB+	Lower medium grade
Sandvik	09.03.10	Downgrade*	BBB	Lower medium grade
Sandvik	02.03.09	Downgrade	A-	Upper medium grade
Sandvik	20.05.08	Downgrade	A	Upper medium grade
SAS	06.11.09	Downgrade	B-	Highly speculative
SAS	06.11.08	Downgrade*	B	Speculative
SAS	22.07.08	Downgrade	BB-	Speculative
SSAB	06.12.10	Downgrade**	BB+	Speculative
SSAB	30.07.09	Downgrade	BBB-	Lower medium grade
SSAB	19.07.07	Upgrade	BBB	Lower medium grade
Statoil	03.08.07	Upgrade	AA-	High grade
Statoil	08.11.06	Upgrade	A+	Upper medium grade
Stora Enso	14.05.09	Downgrade	BB	Speculative
Stora Enso	11.11.08	Downgrade**	BB+	Speculative
Stora Enso	22.10.07	Downgrade	BBB-	Lower medium grade
Stora Enso	23.02.06	Downgrade	BBB	Lower medium grade
Swedish Match	25.10.07	Downgrade	BBB	Lower medium grade
Swedish Match	09.10.06	Downgrade	BBB+	Lower medium grade
TDC	15.12.10	Upgrade***	BBB	Lower medium grade
TDC	14.06.10	Upgrade	BB	Speculative
TDC	11.04.06	Downgrade	BB-	Speculative
TDC	26.01.06	Downgrade***	BB	Speculative
TDC	13.03.03	Downgrade	BBB+	Lower medium grade
TDC	19.03.02	Downgrade	A-	Upper medium grade
Telenor	30.06.09	Upgrade	A-	Upper medium grade
Telenor	01.08.06	Downgrade	BBB+	Lower medium grade
Telenor	23.01.02	Downgrade	A-	Upper medium grade
Telenor	16.01.01	Downgrade	A	Upper medium grade
TeliaSonera	28.10.05	Downgrade	A-	Upper medium grade
TeliaSonera	05.02.03	Downgrade	A	Upper medium grade
TeliaSonera	18.04.02	Downgrade	A+	Upper medium grade
Volvo	15.04.11	Upgrade	BBB	Lower medium grade
Volvo	15.03.10	Downgrade	BBB-	Lower medium grade
Volvo	06.08.09	Downgrade	BBB	Lower medium grade
Volvo	29.04.09	Downgrade	BBB+	Lower medium grade
Yara International	04.10.07	Downgrade	BBB	Lower medium grade
Yara International	20.12.05	Upgrade	BBB+	Lower medium grade
Yara International	30.11.04	Upgrade	BBB	Lower medium grade

* More than one notch
** Reclassification
*** More than one notch and reclassification

Table 3 Descriptive Statistics for Upgrades and Downgrades

	Upgrades				Downgrades			
	AAR (t=0)	CAAR(t=-1,1)	CAAR(t=0,5)	CAAR(t=-5,0)	AAR (t=0)	CAAR(t=-1,1)	CAAR(t=0,5)	CAAR(t=-5,0)
Mean	0,0042	0,0094	0,0039	0,0032	-0,0158	-0,0164	-0,0234	-0,0245
Median	0,0029	0,0062	0,0056	-0,0021	0,0000	-0,0023	-0,0073	-0,0050
Std.dev	0,0100	0,0245	0,0227	0,0418	0,0615	0,0795	0,0951	0,0890
Kurstosis	0,38	-1,08	-0,94	0,16	3,53	1,13	1,38	0,42
Skewness	0,84	0,27	0,01	-0,38	-1,99	-0,97	-1,30	-0,97
Min	-0,0092	-0,0285	-0,0348	-0,0909	-0,1951	-0,2092	-0,2681	-0,2273
Max	0,0269	0,0525	0,0420	0,0674	0,0471	0,1178	0,1038	0,1052

Table 4 The Effects of Winsorizing on Statistical Properties

Upgrades								
	Mean		**Std.dev**		**Skewness**		**Kurtosis**	
	before	*after*	*before*	*after*	*before*	*after*	*before*	*after*
R(t=0)	0,0066	0,0055	0,0169	0,0127	2,0191	0,8419	8,1518	3,0455
AR(t=0)	0,0048	0,0042	0,0126	0,0100	1,6029	0,7997	6,4883	3,1194
CAR(t=-1,1)	0,0093	0,0094	0,0246	0,0245	0,2461	0,2513	1,9113	1,8947
CAR(t=0,5)	0,0021	0,0039	0,0276	0,0227	-1,0097	0,0094	4,9883	2,0168
CAR(t=-5,0)	0,0039	0,0032	0,0437	0,0418	-0,2336	-0,3598	3,0840	2,9371

Downgrades								
	Mean		**Std.dev**		**Skewness**		**Kurtosis**	
	before	*after*	*before*	*after*	*before*	*after*	*before*	*after*
R(t=0)	-0,0418	-0,0208	0,1679	0,0655	-5,0674	-1,8252	29,5432	2,9164
AR(t=0)	-0,0380	-0,0158	0,1685	0,0615	-5,2441	-1,9941	31,1490	3,5337
CAR(t=-1,1)	-0,0573	-0,0240	0,2405	0,1010	-3,7441	-1,7707	14,3111	3,5703
CAR(t=0,5)	-0,0533	-0,0234	0,2393	0,0951	-4,1850	-1,2959	20,1311	1,3787
CAR(t=-5,0)	-0,0523	-0,0283	0,1987	0,0987	-3,7631	-1,2857	16,2482	1,3478

Table 5 Rating Categories

Rating	Category	Grade
AAA	Prime	1
AA+ AA AA-	High grade	2
A+ A A-	Upper medium grade	3
BBB+ BBB BBB-	Lower medium grade	4
BB+ BB BB-	Speculative	5
B+ B B-	Highly speculative	6
CCC+ CCC	Substantial risks Extremely speculative	7
CCC- CC SD	In default with little prospects for recovery Default	8

Table 6 Distribution of Up/Downgrades across Rating Classification

Rating Class	Upgrades		Downgrades	
Prime	0	0 %	0	0 %
High grade	1	3 %	0	0 %
Upper medium grade	7	23 %	11	18 %
Lower medium grade	16	53 %	25	40 %
Speculative	5	17 %	14	23 %
Highly speculative	1	3 %	6	10 %
Substantial risks	0	0 %	1	2 %
Extremely speculative	0	0 %	1	2 %
In default with little prospects for recovery	0	0 %	2	3 %
(Selective)Default	0	0 %	2	3 %

9. Appendix – Figures

Figure 1a Frequency of Sample Upgrades and Downgrades over Time

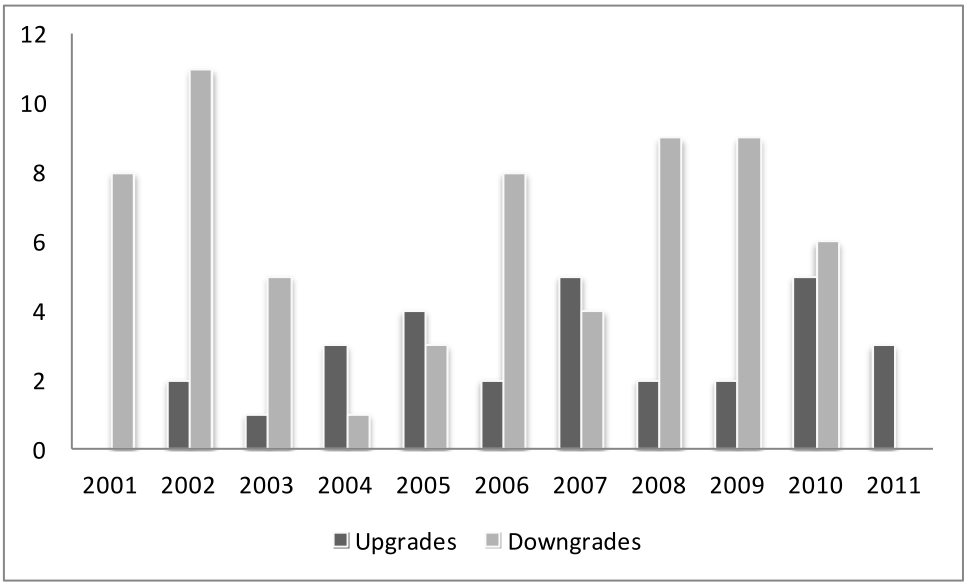

Figure 1b Frequency of Sample Upgrades and Downgrades over Time