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ABSTRACT

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Abstract

Previous studies from the U.S. show, that markets tend to react more to negative news than to the positive ones. This theory applies to credit rating downgrade announcements, which have typically caused negative abnormal returns both on the short and the long-term after the announcement. The stock returns after credit rating downgrades however have not been widely tested in smaller markets, such as in the Nordic countries. Therefore, the aim of this study is to examine the stock returns reaction of companies listed in the Nordic countries around the time when the credit rating downgrade is announced.

A typical method to study whether credit rating downgrades have an impact to stock returns is the event study method, followed by a regression analysis. The results of the event study suggests that the credit rating downgrades are connected with abnormal stock returns in the Nordic markets. However, the statistically significant negative abnormal returns occur mostly prior to the actual event date indicating that the negative abnormal returns are not caused by the credit rating downgrades. This can be due to the deteriorated financial conditions of the rated company being noted by markets before the actual credit rating actions take place and the downgrade announcement is published. Also, other announcements on the markers can cause negative abnormal returns in the event window before the downgrade.

Based on the results of this study the investors react more negatively to the downgrades of companies in the investment grade than in the speculative grade. Also, the negative reaction is stronger, when a downgrade causes the rated company to fall from the investment grade to the speculative grade. Negative credit watch listings and negative outlooks announced prior to the credit rating downgrade however effect positively to the abnormal returns around the event date.

Key words	credit rating, credit rating downgrade, abnormal return, credit watch listing
Further information	

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ABNORMAL RETURNS RELATED TO CREDIT RATING DOWNGRADES

Empirical Evidence from the Nordic Markets 2001–2018

Master´s Thesis
in Accounting and Finance

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1 INTRODUCTION

1.1 Motivation

When buying a house, one would like to see the documents prior to your decision. The documents show the burdens and possible risks attached to the property and help to you land to a decision whether or not to buy the house. Leaking pipes and old heaters are risks that can become expensive in the future and are good to recognize in the early stages. Proper background checks reduce the risk also when investing your money somewhere else than housing. Recognizing the risks helps to assess the profitability of any investment from share purchases to buying complex financial instruments. Usually the challenge is that especially small investors, suppliers and lenders do not have the ability or access to estimate all the risks associated with a certain financial instrument, country or company. This task is not easy for larger actors either. Credit rating agencies therefore exists to provide comparable third party analysis regarding creditworthiness of rated companies and financial instruments.

The major credit rating agencies (CRAs) — Standard & Poor's (later S&P), Moody's Investors Service (later Moody's) and Fitch Ratings (later Fitch) — offer various credit ratings to bond issuers. They rate countries, financial institutions and companies to provide impartial opinions about the creditworthiness of the issuers of securities. (OECD 2010; Dreibelbis & Breazeale 2012.) Since ratings are scaled third-party opinions about the creditworthiness of issuers and their liabilities, credit ratings are of interest to investors subscribing to a bond, lenders granting a loan and suppliers selling material on credit. Every creditor is interested in the risk they are taking and how likely they are to suffer loss. Ratings from Moody's, S&P and Fitch are internationally comparable, which provides important information for investors worldwide. Many investors rely to the announcements by the three big credit rating agencies — S&P, Moody's and Fitch whenever making investment decisions. As a result, the responsibility of credit rating agencies has emphasized, and the public interest has increased towards the services they offer. (European Parliament 2011.)

Companies purchase credit ratings to be able to issue bonds with inexpensive terms. Good credibility means the issuer has a high probability to repay on time its interests and principals of the bond it has issued over the instrument's entire lifetime. Therefore, highly rated companies gain lower interest rates. (S&P 2006.) In Nordic countries the credit ratings have not been as widely utilized as for example in the United States. However, many firms among listed companies in the Nordic countries, which formerly had no ratings by S&P, Moody's or Fitch have purchased a credit rating from a CRA during the past two years according to Thomson One database. Consequently, nearly all the largest companies listed in the Nordic countries now have a rating from at least one of the CRAs.

The credit rating agencies quide investors seeking to minimize risk and maximize return by offering comparable, standardized measures of risk connected to the investment (Moon & Stotsky 1993; Moody's: Ratings definitions 2018). Since global capital markets have expanded exponentially, investors need non-traditional information about the developing nations and their sovereignty as well as possible issues with foreign currencies. (Levich, Majnoni & Reinhart 2002.)

However, rating more complex financial instruments can be challenging also for credit rating agencies, which was shown by the financial crisis in 2008. The credit rating sector faced hard criticism after the rating agencies failed to issue downgrades of prominent US companies on time, some of which eventually went bankrupt. Excessively optimistic ratings helped in creating the global financial crisis, by causing billions of dollars in losses to investors. (Manso 2011.) Since then, credit rating agencies have been under stricter surveillance.

Credit ratings have a relatively long history. Back in the early nineteenth century Henry Varnum Poor started by publishing information about railroad industry in the American Railroad Journal and soon founded his own company — Poor's Publishing. Poor's Publishing released information about the holdings of the railroads as well as assets, liabilities and earnings of the railroads by obtaining the information given by the observed companies. In 1916 Poor's company began bond rating businesses by publishing daily an U.S. focused ninety-stock united price index. This later became S&P 500 — a market value weighted index focusing on the 500 most widely held companies in the U.S. In the Great Depression Poor's Publishing went bankrupt and eventually merged with Standard Statistics in 1941. (Dreibelbis & Breazeale 2012.)

Moody's was also born as a response to the needs of railroad business when John Moody started assessing the operations, finance and management of the railroads. In 1914 the operation expanded into bonds issued by municipalities, for example U.S. cities, and by 1924 Moody's ratings covered almost 100 percentage of the US bond market. In 1970 commercial papers and bank deposits came under analysis and the year also became pivotal since Moody's alongside with other major credit rating agencies started to charge issuers and investors for rating services, which before had been free of charge. The billing change was made due to the increased complexity of the financial markets, which demanded more effort from the credit rating agencies, and selling published outlooks no longer covered the costs. (Moody's History 2018.)

Financial markets change continuously due to global investing environment, economic and political changes. The changing environment is challenging both for investors and credit rating agencies, as the financial crisis in 2008 showed. Despite the role of credit rating agencies in the financial crisis, the credit rating agencies still are the most likely more qualified in evaluating the risk of complex financial instruments than an average investor, since most investors do not have the information needed to evaluate the risk of the investments properly.

However, even before the financial crisis, there were a lot of studies about the credit ratings and what effects the credit rating changes have. Numerous studies document that announcements of credit rating changes have price effects on equity markets (Holthausen & Leftwich 1986; Glascock, Davidson & Henderson 1987; Hand, Holthausen & Leftwich 1992; Dichev & Piotroski 2001). The most interesting finding has been, that in most cases only credit rating downgrades have created significant abnormal returns around the event day, unlike credit rating upgrades. Therefore, this study only concentrates on credit rating downgrades as well as negative outlooks and negative watches given before the downgrade announcements with the expectation, that the credit rating downgrades are associated to statistically significant negative abnormal returns.

1.2 Aim and restrictions

The purpose of this study is to examine if there are negative abnormal stock returns in the Nordic markets caused by the credit rating downgrades. The method used for studying this effect is the event study method and the research sample consists of listed companies.

Several researchers have studied both credit rating upgrades and downgrades. Most of the studies show, that abnormal returns are statistically significantly negative after credit rating downgrades, but usually statistically significant positive results are not detected after credit rating upgrades. For example, Dichev and Piotroski (2001) analyzed the long-term price effects following credit rating upgrades and downgrades and found that only downgrades caused significant abnormal returns and underperformance during the following years. The results of previous studies indicated that a credit rating downgrade is a much more significant event for a firm than a credit rating upgrade can be, since downgrade decreases the value of the company.

Thus, the evidence suggest that investors react more to negative news and are rather indifferent for positive credit rating announcements. Since majority of the previous studies have found only credit rating downgrades to cause abnormal returns, I have chosen to focus solely on the downgrades and possible negative watches and negative outlooks given before them. In this study, my aim is to examine the following research questions:

1. Do the credit rating downgrades cause negative abnormal stock returns in the Nordic markets?

2. Are the possible abnormal returns smaller, if a negative watch or a negative outlook has been given before the downgrade?

Based on previous studies, a credit rating downgrade from investment grade to speculative grade can cause larger abnormal returns. Companies react differently depending on which credit classification they belong to when the credit rating downgrade approaches. Khieu and Pyles (2012) found, that the cash hoarding effect was greater when the company was downgraded from investment grade to speculative grade. Regarding capital structure adjustments, Kisgen (2009) pointed out that firms downgraded to speculative grade reduce their debt twice as likely as other firms in the year following the downgrade. By comparison, upgraded firms did not subsequently change their capital structure.

Also, Hung, Banerjee and Meng (2016) found that companies in speculative grade adjust their debt more than companies in the investment grade to benefit from the information gap and exploit their better rating prior the credit rating downgrade. Reasons for this are for example that less bond portfolio managers and fewer analyst tend to follow lower-rated firms. Therefore, the credit rating downgrade means loss of visibility and investors for the company.

The credit rating agencies have an institutional feature due to their monitoring role of the markets. Since their opinions about the risk associated with certain financial instruments are standardized and widely recognized, for example pension funds use ratings in their guidelines. In many cases they are only allowed to invest in highly-rated companies, usually signifying companies in investment grade. Then when the firm's rating falls from the investment grade to the speculative grade the firm loses investors, which could cause abnormal returns around the downgrade. (Boot, Milbourn & Schmeits 2006.) Therefore, my third research question is as follows.

3. Do firms downgraded into speculative grade have larger abnormal stock returns at Nordic markets than firms, which have not been downgraded from a main category to another?

Firms take similar actions to adjust their capital structure before and after the credit rating downgrade is published. Hung et al. (2016) found, that firms reduce their leverage by 1.5% – 2.0% by issuing less net debt compared to net equity during the year after the credit rating downgrade and typically adjust their level of leverage before publishing the downgrade announcement. This is most likely due to the increased costs caused by the credit rating downgrade, since lower credit rating typically increases the costs of debt financing. Therefore, my final research question addresses the leverage level of a firm and its possible impact to the abnormal returns.

4. Does the leverage explain the abnormal returns of downgraded firms?

This research focuses on downgrades and given negative outlooks and negative watches to long-term credit ratings given by Moody's, S&P and Fitch for listed companies in Nordic markets. Unfortunately, the previous data from negative outlooks and negative watches is only available free of charge by Moody's and Standard & Poor's, meaning that the possible previous announcements before the credit rating downgrades by Fitch are not obtainable in this study. Since Fitch is the smallest of these credit rating agencies and has only 13 observation in the sample of this study, the lack of Fitch previous announcement to credit rating downgrades does not likely have a significant impact on the results. The same applies to the 15 observations from S&P which for some reason did not include previous actions in S&P's Rating Actions webpage.

Mostly the biggest listed companies in Nordic countries have credit ratings by Moody's, Standard & Poor's or Fitch, which signifies that the companies included in this study are large and well-known. The lack of ratings given by Moody's, S&P and Fitch will exclude many small companies from the study, signifying that the results may not be applicable to small companies.

1.3 Structure

Chapter 2 introduces the basic finance theories and concepts related to event study methodology. The chapter presents theories about market efficiency and asymmetric information and attaches them into the credit rating downgrades. Chapter 2 also presents the most notable previous studies from the U.S. and the non U.S. areas.

Chapter 3 focuses solely on credit ratings. The chapter starts with the introduction of the credit rating markets and the purpose of public credit ratings. This chapter also presents the credit rating process and the credit rating scale from AAA to D. Also, credit rating actions prior to the actual credit rating downgrade are discussed alongside with the basic legislation and possible conflict of interest with credit ratings.

Data, hypotheses and the research methodology are introduced in Chapter 4. The data collection process and data exclusions are briefly described and the reasonings for the hypotheses are provided. The chapter also introduces the event study method, which is a basic method used when studying stock reactions during an external event. In this study, the event study method is used to determine the cumulative abnormal returns in the event window. After the event study, regression analyses are made to test the variables causing the cumulative abnormal returns.

The results, starting from descriptive statistics, are presented in Chapter 5. The chapter introduces the concrete findings of the event study and the regression analysis. In Chapter

5 possible explanations for these results are analyzed. Finally, Chapter 6 summarizes the study and gathers the key findings.

2 THEORETICAL BACKGROUND

2.1 Market efficiency

In efficient markets all information is directly transformed into the prices of securities. All information is consistent, clear and available (Fama 1970). Also according to most definitions, information is transparent and accurate. When markets are efficient, any market beating strategies should theoretically not exist, since all information is already adapted into current market prices. Past stock prices cannot be used in predicting the following price development either, since the stock prices follow the random walk model. The assumptions behind the random walk model are that the price changes are independent and subsequent changes are usually equally distributed. In the random walk literature, the expected return is stationary during all times. (Fama 1970.)

The efficiency of the markets can be divided into three different categories, each of them describing the level of market efficiency. If the market fulfils the weak-forms of market efficiency, all past price information is adapted into current market prices. When the market fulfils the semi-strong conditions of market efficiency, the prices contain all the financial information publicly shared and the historical information. The financial information contains for example the annual reports and other public announcements such as credit rating announcements. In markets that fulfil the strong-form condition, all the public and non-public information is directly adapted into the market prices of securities, including the insider information. Hence any participant cannot have a monopolistic access to information relevant for the current price forming.

Alternatively, the markets are not efficient. Fama (1970) states that the market price should react immediately and accordingly to the new information. If the markets are inefficient, the price change appears as too large or not large enough, after which the possible price correction can cause more inefficiency at the markets. The inefficiency of markets can be exploited by investors and if the market reactions are easily anticipated, profits can be made from them. Usually this means markets are not truly efficient.

Sufficient conditions for market efficiency are easily determined, but usually they not exist at the factual markets. The conditions require that there are no transaction costs at the market and all information is available for all participants. Also all participant must agree on how the information effects on the stock price if it has an effect at all and all participants must have an agreement about the future prices. If these conditions are fulfilled, the stock price fully reflects all information available. Although, frictionless markets do not happen in practice.

Through transaction costs information is not freely available for all participants and the first one to know about the new information can benefit from it since stock prices adapt new information with a lag. Also, investors may disagree on the price effect of the new information. Investors can interpret the information differently and therefore have different valuations for stock prices. On the other hand, stock market prices do not only contain price information, but also feelings and assumptions of the market participants'. These aspects are reasons why the efficient markets may not fully exist. Hence, it has been proven that market return can be exceeded with certain strategies, for example by some anomaly-based investment strategies. As Fama (1970) notes the sole way to get higher returns is through higher risk. According to the efficient market hypothesis, investors should invest only on low-cost index funds or ETFs and therefore maximize returns by cutting expenses.

Investors have studied if former price development would anticipate future profits for a long time. *Technical analysis* tries to forecast the future prices and profits by exploiting market inefficiency but does not work if markets can be classified even to the weak-form of efficiency. However, technical analysis can occasionally notice inefficiencies at the markets and exploiting them enhances the market efficiency since noticed inefficiencies will thereby disappear.

An event study studies the market efficiency by testing how the markets react to new information and thereby the event study methodology assumes the market is semi-strong form efficient. Typically, the event study method is used when the effect of a certain exogenous event on stock price is examined, for example a merger announcement. An event study begins by defining the exact event date, which is the announcement date of a merger, acquisition or a credit rating downgrade, to mention a few. After this the abnormal returns, which are the actual returns around the event date minus the expected normal returns on those days, tell if the exogenous event had an effect on the returns and thereby if the event caused a market reaction.

Previous studies (e.g. Holthausen & Leftwich 1986) state that rating agencies handle confidential data and therefore rating announcements reveal new information to the markets. Regarding the efficient market hypothesis, the new information is rapidly converted into prices, which can cause abnormal returns. Stock prices reflect all information publicly available, including the rating announcements. According to Paul Taylor, the president and chief executive officer of Fitch Group, credit ratings have an important role in maintaining the market efficiency. Efficient bond markets are critical for example for industry manufacturing and for the global economy since they are largely used in funding research and development and for investing in infrastructure. The more information is equally shared, the more efficient the markets are and the smaller the information gap between a lender and a borrower will be. (Fitchratings.com 2018.)

2.2 Asymmetric information

Asymmetric information means that the information is unevenly distributed, and certain actors have more information than other participants on the markets. This unbalanced information for example between lenders and borrowers can result in inefficient outcomes at the markets. Akerlof (1970) described the dilemma of asymmetric information with cars sales. He names the bad cars as lemons and only the seller knows if the car he is selling is a lemon. For the buyer the probability to get a good car is q and the probability for a bad one (1-q). At the same time, the buyer cannot identify which cars are lemons and which are not. Therefore, the buyers are only willing to pay the average market price since they pay the same price for a good car and for a lemon. If most of the cars sold in the market are lemons, the good cars may not come to the market at all, since the price paid from them is defined by the majority of bad cars. This theory is based on Gresham's law concerning originally monetary principles. According to Gresham's law "bad money drives out good" (Akerlof 1970), meaning for example that if there are two commodities with the same accepted value, the one which is more expensive to produce or store will disappear.

Separating good quality from bad is necessary in the business world. The CRAs have created their ratings to be able to separate riskier investments from safer ones and therefore credit ratings can address the considerable degree of information asymmetry in financial markets (Elayan, Hsu & Meyer 2003; Abad & Robles 2015).

However, credit rating agencies can also increase the information asymmetry at the markets. Managers can forecast the firm's future better than the investors due to their better knowledge of the firm, which leads to information asymmetry. Hung et al. (2016) noticed that on the periods before the credit rating change the information gap between investors and managers is as its highest. Information asymmetry is shown to be high around credit rating announcements, especially when s firm is downgraded. Since the effect is more significant for downgraded firms, the information value of downgrade announcements is higher (Chung, Elder & Kim 2010).

Hung et al. (2016) pointed out one troubling issue in updating credit ratings - the credit rating agencies are not always able to reflect up-to-date information in their announcements, which does not serve the information asymmetry. The Association for Financial Professionals (AFP) reported based on its survey in 2002 that most company leaders did not think changes in their company's financial situation were promptly reflected in the credit ratings. Generally, the delay was believed to be approximately six months. Therefore Hung et al. (2016) suggest that credit rating agencies increase information asymmetry since credit rating revisions are not always made on time. They base their suggestion on the fact that the changed creditworthiness of a company is first noticed internally, and only after a while published to the audience. This creates increased information asymmetry between the markets and the firm, since the managers have first-hand knowledge about the firm's financial situation, growth opportunities, operating performance and future outlooks. This asymmetry in information is called information gap. The delay on the other hand in announcing credit ratings responding to the changed conditions and expectations the firm is facing, is partly due to credit rating agencies being willing to grant the firms some time to recover from their situation before taking actions which can damage the firm's reputation and worsen its terms when issuing bonds (Boot et al. 2006).

2.3 Role of leverage

The role of debt financing and capital structure in a company varies among industries, the size and age of a company, targets, managements and economical situations. Debt plays numerous roles in capital structure theories (Harris & Raviv 1990, Kim, Chen & Nance 1992). Originally capital structure theories concentrated on the tax benefits of debt (Modigliani & Miller 1963) and then on analyzing the debt level of a company as a signal of its quality (Ross 1977). Later there have also been numerous other theories about the capital structure and role of leverage.

In 1958, Modigliani and Miller presented their famous irrelevance theorem of financial leverage. The idea was that the capital structure does not affect the value of the firm and therefore in an efficient market the dividend policy of a firm and the decisions about issuing stocks or raising debt are irrelevant.

Opposing theories, where the capital structure is relevant for the value of the company, are called relevance theories, which there are plenty of. For example, according to maximum debt theorem, the stock price and therefore the value of a firm increases for two reasons. First, the cost of capital decreases with increased debt amount. Second, willingness to increase debt is seen as a positive signal since it expresses management's confidence about the future (Ross 1977).

Optimal leverage theorem recognizes that the cost of capital decreases with debt but also that the risk of bankruptcy increases. The stock price increases if the level of leverage has been below the optimal amount and decreases if it has been above.

In the bad news theorem (Miller & Rock 1985), unanticipated announcements of new financing indicate that the cash flow has been smaller than expected, which is a negative sign for investors. Managers know more than outside investors about the company's current situation and future opportunities, and announcements reveal new information to the investors. This theory differs from Modigliani and Miller's (1961) theories in which investors and managers have the same information and they share a common understanding about the current and future earnings. Myers and Majluf (1984) stated that new securities are issued when managers believe the security is overvalued, which causes investors to demand discounts. Any change in financial leverage requiring new financing causes the stock price to decline.

Changes in leverage and balance sheet figures launch credit rating changes gradually (Boot et al. 2006; S&P 2006; Chung et al. 2012). Recognizing this, some companies structure their financing to reflect credit rating agencies' criteria to maintain or achieve higher ratings. For example, a large client of S&P had restructured its floating short-term debt by fixing its debt maturity schedule to maintain its short-term rating. In some cases, rating aspects have also been attached on as parts of the company's goals and a good rating or a rating in the investment grade can form a base on company's financial strategy. (S&P 2006.) The leverage level or other balance sheet figures justifying a certain rating are not given by CRAs, but firms can target certain ratings themselves by promoting the company's good financial health and flexibility. A financially strong company will always overcome future obstacles better than a company with short debt maturities and little financial flexibility.

Previous studies show that markets tend to react more to the negative news than to the neutral or positive ones. There is also evidence indicating rated firms themselves tend to react to credit rating downgrades. Khieu and Pyles (2012) reported cash policy changes after credit rating downgrades in the form of increased excess cash holdings by 3 percentage. Excess cash holdings were calculated as the difference between the expected and the actual cash holdings and the similar reaction did not occur in the matched non-downgraded sample companies. The cash hoarding effect was larger in the companies downgraded from investment grade to non-investment grade. The results indicated that firms were preparing for the negative market consequences. While studying information asymmetry between the markets and the firm, Hung et al. (2016) found that firms adjust their financial structure by adding debt by 1.29 percentage before credit rating downgrades. Significant financial actions were not observed before credit rating upgrades. On the other hand, Kisgen's (2009) results revealed that downgraded firms issue 1.5 % – 2.0 % less net debt compared to net equity than other firms within the year after the downgrade. Earlier however, Kisgen (2006) had claimed that in order to avoid the downgrade in the lower ratings and achieve upgrades in the higher ratings, firms reduce their leverage prior to the credit rating announcements. These results are not consisted with the study by Hung et al. (2016), which can be for example effected by the different samples from different years used in their studies.

2.4 Prior literature

2.4.1 U.S researches

Many researchers have examined credit rating downgrades in the U.S. market and found significant abnormal stock returns during and after the event date (e.g. Holthausen & Leftwich 1986; Glascock, Davidson and Henderson 1987; Hand, Holthausen & Leftwich 1992; Dichev & Piotroski 2001). These researchers have typically used stock price data from the U.S. markets of varying lengths of time and studied downgrades and upgrades given by Moody's or S&P. Ratings provided by Fitch are relatively less studied, probably due to its smaller market share compared to its competitors.

Originally the studies examining credit rating changes used monthly stock data (e.g. Pinches & Singleton 1978; Griffin & Sanvicente 1982) instead of daily data, which can effect the results of these previous researches. Lately using the daily data has been more popular since the monthly returns can easily hide the possible abnormal returns around the event date or the monthly data can be widely affected by other events of the same month. To avoid the most evident interferences of other events, for example Holthausen and Leftwich (1986) divided the observations in their sample roughly into "contaminated" and "non-contaminated", since considering all the alternative explanations for the price effect would have been overly burdensome. In their definition, an observation was classified as contaminated when the Wall Street Journal had referred to any other source in their story about the credit rating change or if the magazine had released any firm-specific information between the days –1 and 2 around the event date.

Market efficiency is the key assumption when examining the effect of credit rating changes on the markets, since if the markets are inefficient, there would be no reaction caused by a credit rating change or the reaction would not be proportionate. When a price effect occurs after an announcement of a credit rating change the CRA's have given new information to the markets since if the information had been incorporated to the stock prices beforehand, these price effect would not exists.

Holthausen and Leftwich (1986) examined the information effect of bond credit changes through abnormal daily stock returns after rating announcements. They studied downgrades in ratings given by Moody's and S&P between 1977 and 1982 and discovered negative abnormal stock returns on the event day and the day after the announcement. Primarily they researched if rating agencies do provide new information to the capital markets, which can be examined only through credit rating changes since the rating agencies loss functions are not known and the determination of whether the upgrade or downgrade has been given on time is impossible for an outsider to observe.

Holthausen and Leftwich (1986) questioned some previous studies (e.g. Pinches & Singleton 1978; Griffin & Sanvicente 1982), which had results indicating that the rating changes are announced late and do not provide new information to the market since the information is already incorporated into stock prices. They stated that the price response to the credit rating announcement can be examined solely when the effect occurs. When the effect occurs all the information had not been incorporated to the prices beforehand. Holthausen and Leftwich used the two-day event window in order to decrease the likelihood of other events affecting the measured stock effect. They also excluded events with simultaneous information releases from days −1 to 2.

As a result, they discovered statistically significant abnormal returns with downgrades across rating classes and no significant abnormal returns associated with upgrades. In their study, they used an impressive sample of more than 1,000 credit rating changes. They also included positive and negative credit watch listings, which had a large effect on stock prices both when the contaminated observations were included or excluded. Overall, they find significant negative returns after downgrades but insignificant positive returns after upgrades and their results indicated that credit ratings provide information to the markets.

Also Pinches and Singleton (1978) studied if credit rating changes provide new information to the markets. They used bond rating changes by Moody's and concluded that the credit rating changes were announced with a lag due to the increased or decreased returns before the credit rating change. They expected that the lag would be longer if there had been no company specific events such as an issuance of new debt financing, since these company specific events would have forced the rating agency to re-evaluate the company's financial conditions and therefore the following credit rating changes would have been announced more quickly. For upgrades they discovered the lag to be from one year to a year and a half with and without firm specific events. For downgrades on the other hand the lag was 15 months without the company specific events and only 6 months with them, which proved that the re-evaluation had shortened the lag with credit rating downgrades. Pinches and Singleton concluded that markets anticipate the rating changes and credit rating agencies are slow to change ratings especially without company specific events. Markets are efficient and rating changes do not provide new information. However, Pinches and Singleton's study has since been questioned due to the use of monthly data.

Glascock, Davidson and Henderson (1987) based their study on Pinches' and Singleton's study, but instead of monthly data, they used daily data concentrating on the days 0 and 1. They used Moody's Bond Service rating changes from 1977 to 1981 and found as a result a statistically significant reaction for the downgrades on the announcement date when there was no statistically significant reaction to the upgrades on the day 0, but the residuals however decreased soon after the announcement date. For downgrades the returns on the day 0 drift down only −0.39 percentage but by the day −1 the returns drift −3.56 percentage.

Dichev and Piotroski (2001) examined long-term stock market reaction to rating changes of bonds and find insignificant reactions to upgrades and significant negative reaction to downgrades. The negative reaction was stronger for small firms with low creditworthiness. Dichev and Piotroski concluded in their research that there were no substantial abnormal returns following credit rating upgrades, but there were substantial negative abnormal returns after downgrades. In their study they discovered −10 to −14 percentage a year underperformance during the first year after the downgrade, when the underperformance was at its highest. During the second and third year after the downgrade the returns were at −4 to −6 percent annually.

Credit watch placements are a relatively new aspect to the study of credit rating changes and credit watch listings have been less examined than for example credit rating changes. The reaction to negative credit watch listings is mostly convergent with the reaction to credit rating downgrades. Elayan, Maris and Maris (1996) examined negative credit watch listings with commercial paper ratings and found a significant market response to negative watch listings, when confirmations of the current rating caused no effect and upgrades caused only an insignificant positive reaction. Earlier (1990) they had discovered a negative reaction to negative watch listings preceding rating affirmations, but no reaction when a downgrade followed the negative watch listing. Also, they found no reaction to positive watch listing whether they were followed by an affirmation or an upgrade.

Holthausen and Leftwich (1986) found negative excess returns after negative credit watches but not enough evidence suggesting positive excess returns after positive watches. Few years later Hand, Holthausen and Leftwich (1992) divided credit watches into expected and unexpected announcements and found no excess returns after expected credit watches, but that unexpected negative credit watch placements caused a significant market reaction.

The trend is that in the U.S. the significant reactions are only associated with negative news whether they are negative credit watches or credit rating downgrades. Positive news have rarely caused a significant effect on the U.S. market according to the studies.

2.4.2 Non-U.S. researches

The results from the U.S. market indicated that credit rating downgrades and other negative news cause abnormal stock returns, but that markets are rather indifferent to positive news. Since the U.S. market is a large and liquid market, the results from the U.S. market do not necessarily apply for smaller and less liquid markets.

Elayan, Hsu and Meyer (2003) examined if reaction to credit rating announcements is different between small and large markets due to the limited information at the market and fewer analysts following the firms. They chose to study the market of New Zealand since it is easily qualified as a small market, but also because it is a developed market. They concluded that the stock reaction is greater for firms not cross-listed in the U.S. indicating that CRAs provide information to the smaller markets, which have fewer analysts providing information.

Elayan et al. (2003) found that downgrades and negative credit watch listings are connected to significant negative returns. Also, positive credit watch listings cause a significant positive market reaction, which is consistent with other non-U.S. studies, for example Barron, Clare and Thomas' (1997) at the UK market. However, unlike in many previous studies, a significant positive reaction to credit rating upgrades was also found. Average cumulative abnormal returns were calculated at two-day CAAR period and most of the results were significant at the 0.1 significance level. Overall, they concluded that smaller markets are generally more sensitive also to good news and that CRAs provide new information to the smaller markets decreasing information asymmetry.

Li, Visaltanachoti and Kesayan (2004) wanted to study the effects of credit rating revisions also on small but liquid markets. They chose Sweden due to its high liquidity, which decreases the information asymmetry at the markets. Also due to the liquidity, they expected weaker reaction to the credit rating changes, which they discovered. They found no effect on the event day and the day after (two-day period), but instead significant positive CARs for 10 and 20 days following the downgrade. Li et al. (2004) concluded, that the market had anticipated the news but overreacted causing the stock price slowly to recover after the event date. Even later, at 2 to 6 months, they found statistically significant excess returns denoting that the stock price level balances slowly after the event. Overall, they found significant reaction on short-term to credit rating downgrades and negative outlooks and that the informational value of a downgrade or an upgrade depends of the liquidity of the markets.

3 CREDIT RATINGS

3.1 Credit rating markets

Credit rating agencies offer opinions on the issuers' capability and willingness to meet their financial engagements. The credit rating announcements are not buying or selling recommendations of bonds or shares, but simply opinions about the issuer's creditability. Different credit rating agencies' policies differ from one another — for example S&P's and Fitch's credit ratings evaluate the default risk of the companies whereas Moody's bases its ratings on the estimated loss in case of bankruptcy. The main motive of credit ratings is to evaluate how companies survive from their long-term debts and responsibilities. Fundamentally a credit rating indicates whether a company has a low or high risk of defaulting and therefore determines how attractive the company is as an investment opportunity.

OECD (2010) defined three main functions of credit ratings. First, credit ratings measure the credit risk of the issuer. This action decreases the information asymmetry between issuers and investors and increases the effectiveness of markets. Second, credit ratings create a consistent global rating scale by providing means to compare the credit risk of different issuers in separate countries. Third, ratings give issuers one standardized measure verified by various sources to be used in contracts and regulations. Via a public credit rating the risk analysis of a firm can be summarized in concise form instead of complex description of the firm's financial situation. Ratings standardize the information about businesses, which are alike, which again reduces the asymmetric information between investors and rated companies (Dreibelbis & Breazeale 2012). The three functions above used to be separated but have since been combined into one credit rating announcement to simplify the outcome of the credit rating process. Together these functions offer valuable information to the markets. (OECD 2010.)

Moody's, Standard & Poor's and Fitch are known global actors and they operate around the world. They focus on offering globally comparable ratings to help investors make global investment choices. They follow the same principles in all countries and firms they observe, which makes credit ratings from the same credit rating agency globally comparable. The rating is the same for companies in Asia or in the U.S. when the components defining the credit ratings are similar. (Sinclair 2005.) Therefore, the credit ratings and credit rating changes among Nordic listed companies are considered as equal between the Nordic countries.

Moody's and Standard & Poor's are the largest actors of credit rating markets globally (Sinclair 2005). In 2011, they both had approximately 40% market share, while Fitch had around 15%. Together these major credit rating agencies held 95% of the market share

(European Parliament 2011) and by 2015, the market shares had not changed (Council on Foreign Relations 2015).

The largest credit rating agencies are registered as nationally recognized statistical ratings organizations (NRSROs) under U.S. Securities and Exchange Commission (SEC), which enforces the security and stock exchange industry and proposes rules for securities in the United States. (Sec.gov 2013) SEC originally created the NRSRO status in 1975 and in 2010 there were eleven credit rating agencies with the NRSRO status. Several smaller credit rating agencies, which also were part of the NRSROs, merged with Fitch in 1990s. (OECD 2010.)

After the financial crisis U.S. Securities and Exchange Commission proposed tougher regulations for credit rating agencies (Manso 2011). The financial crisis touched almost the entire world and risky subprime mortgages issued with far too optimistic ratings were one great cause for the crisis. After failing to rate properly structured finance products EU strengthened its surveillance to provide increased protection investors'. After 2009, CRAs needed to be registered and regulated by national competent authorities. CRAs also needed to avoid conflicts of interest, signifying more transparent rating processes and clear rating methodologies. The European Securities and Markets Authority (ESMA) was founded to stabilize financial markets and supervise CRAs registered in EU as an independent EU authority. Other responsibilities of ESMA are investor protection and robust market infrastructure through transparency, integrity and efficiency. (Europe.eu.com 2018.) Credit rating agencies help in reducing fragility of financial markets through their role, which is to watch and take action when the issuer's credit risk has fundamentally changed (Boot, Milbourn & Schmeits 2006).

3.2 Credit rating process

Credit rating agencies are specialized institutions, which offer independent and objective ratings for countries, financial institutions and companies. The issuer requests a public rating from a credit rating agency in order to have a recognized rating from a third party to tell about the issuer's creditworthiness. As seen in Figure 1 the issuer pays to the rating agency and in exchange receives a public opinion of its ability to pay its financial requirements. The rating benefits the investors, subcontractors and other lenders of the company, and the market parties who find the risk to be suitable for their needs, then finance the issuer.

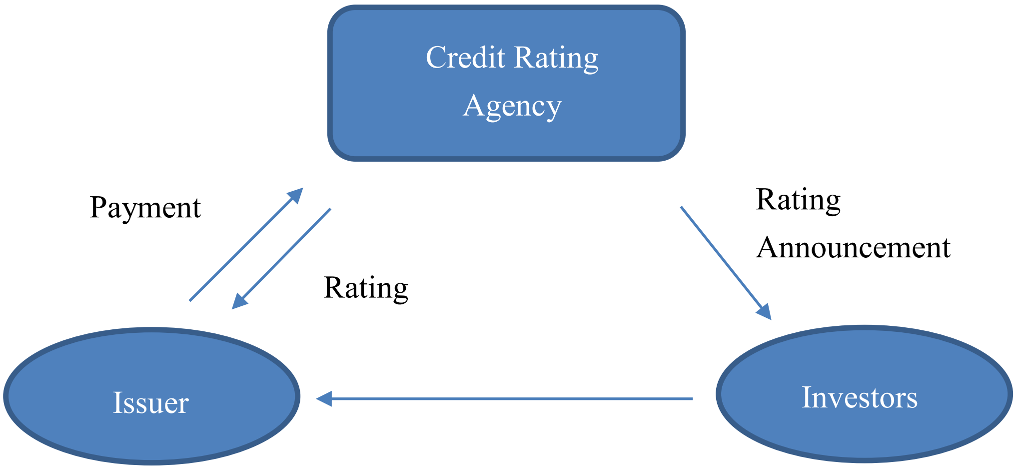

Figure 1: Credit rating system

According to Standard & Poor's principles and rating methodology (S&P: Corporate Methodology 2013), in a rating process they pay attention to a firm's cash flows, competitive position, country and industry risk and on financial instruments when evaluating the firm. Other categories are for example insurance coverage, loan covenants and legal problems. Overall the rating agency is interested in the financial health and sustainability of the rated issuer. Cash flow is probably the most important aspect to be monitored and the credit rating agencies divide the cash flow analysis into four sections: volatility, predictability, strength and limitations. Also, the quality of operational cash flow and the amount and channels of outflow are monitored. Since cash flow is not the only way to finance a company's operational functions, also the company's access to external funds is part of the evaluation.

The cash flow to leverage ratio is under surveillance since higher levels of leverage correlate with higher levels of default. The evaluation of a company's competitive position includes company's overall profitability related to default risk, regulated utilities and regulatory stability. The country risk of the company includes institutional, economic and governance effectiveness as well as the overall financial system and payment culture. It also includes country growth opportunities and political sustainability, alongside with inflation rates. Industry risk refers to the cash flows and earnings of the company, which correlate with the cash flows and earnings volatility of the industry. The credit rating agencies also pay attention to financial instruments issued or supported by the reviewed corporate entity. Other industry risks concern labor availability, infrastructure and corruption levels, taxes, cultural issues and transparency. (S&P: Corporate Methodology 2013.)

Overall industry risk, business risk and financial risk are monitored in all types of rating models. Industry risk is associated with the sector in which the company operates whereas business risk is related only with the specific unit being rated. Business risk includes factors such as technology used, location, market share, inputs for manufacturing, suppliers and customers. Financial risk relates to operating performance, including profitability, gearing, liquidity and business growth and the financial risk factor is more weighted than other risk areas in most rating models. (S&P: Corporate Methodology 2013.)

The rating process according to Standard and Poor's information (S&P: Corporate Methodology 2013; Hung et al. 2016) and the Moody's rating process (Moody's 2018).

1. *Contract* − The client requires a rating and signs an engagement letter
2. *Pre-evaluation* − A team from CRA reviews the provided financial information
3. *Management meeting* – Analysts meet with the management
4. *Analysis* − Information evaluation
5. *Rating committee* − Votes on the credit rating based on the presentation of the lead analyst
6. *Notification* – The client verifies that information presented by the CRA is correct
7. *Publication* – CRA publishes the credit rating announcement
8. *Surveillance* – CRA monitors the client and updates the rating when necessary

The rating processes of S&P and Moody's are mostly identical, starting with a rating application, when an issuer requests a rating and signs the engagement letter. After signing the letter, Moody's' official rating process can start, and the nominated lead analyst will gather information about the issuer or financial instrument from public sources. This phase is mostly similar to S&P's pre-evaluation step where a team reviews the information about the rated unit. Once all the publicly available information is analyzed, CRA asks for substantive financial and non-financial data from the issuer. This requires interaction with the issuer and S&P usually organizes a management meeting, where analysts meet with the company management. After meeting the client and gathering the essential information, starts the analysis, during which all the information is considered in the light of credit rating methodologies and both quantitative and qualitative components. A rating committee then votes about the credit rating based on the presentation of the lead analyst. All recommendations require a majority of the votes of the rating committee and a single analyst has only limited possibility to affect to the rating. (Moody's 2018.)

When the rating committee has voted, a notification will be given to the client to make sure the information is correct. Thus, the client is informed about the decision of the rating committee. After informing the client, the credit rating is published and disseminated by financial news agencies. The client does not know for sure when the announcement is published and the timing depends on the rating agencies. (Moody's 2018.)

Hung et al. (2016) state that shared information is especially important at the phases 5 — rating committee actions and 6 — notification to the client. Once the rating is publicly issued, the rating agency maintains surveillance, which is considered to be the most important part of the whole process. By monitoring the company closely after issuing a credit rating, the rating agency is invariably up to date with the company's situation and can inform investors, when they suspect a possible credit rating upgrade or downgrade. (Sinclair 2005.) Credit rating agencies follow the performance of a firm and report the changed conditions harming or improving the credit worthiness as credit rating downgrades or upgrades.

Hickman (1958) pointed out in the earlier stage of credit rating industry that the credit rating agencies tended to follow the cyclical behavior of stock markets by upgrading companies in good times and downgrading them during bad times, rather than evaluating the actual creditworthiness of the companies.

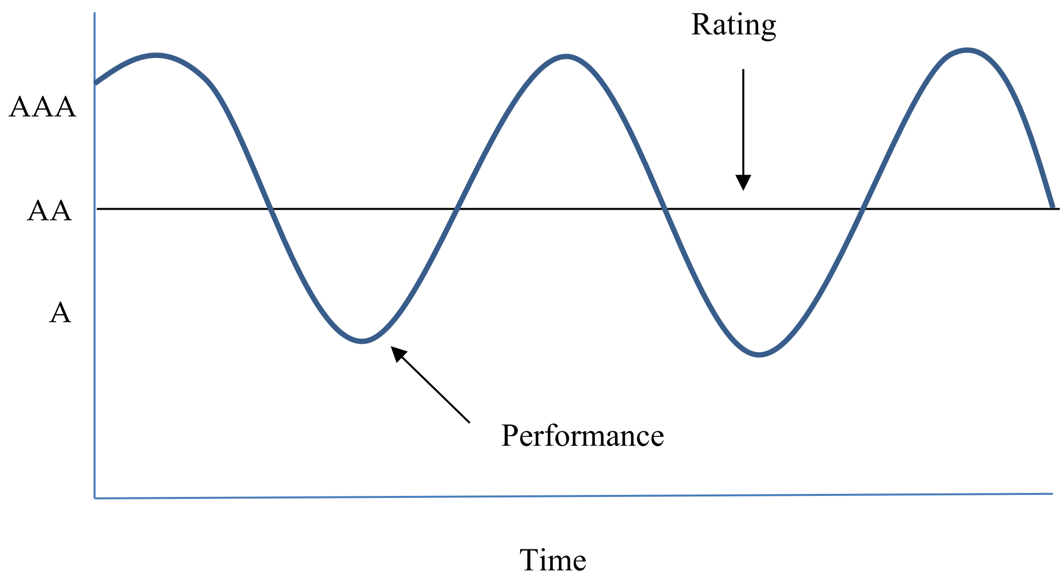

Figure 2: Ratings over time in an ideal world (after S&P 2006)

Ideally, credit ratings are forward-looking and consider all aspects of the future that can be predicted. Natural rises and falls during business cycles are anticipated and do not affect credit ratings as demonstrated in Figure 2, and therefore ratings will remain stable through this natural variation. Cyclicality is a part of business risk and when knowingly favorable times are ahead, there is no reason to lower the rating. If company's performance varies between the AAA and A ratings, an AA rating is suitable for rated issue through the fluctuation. (S&P 2006.)

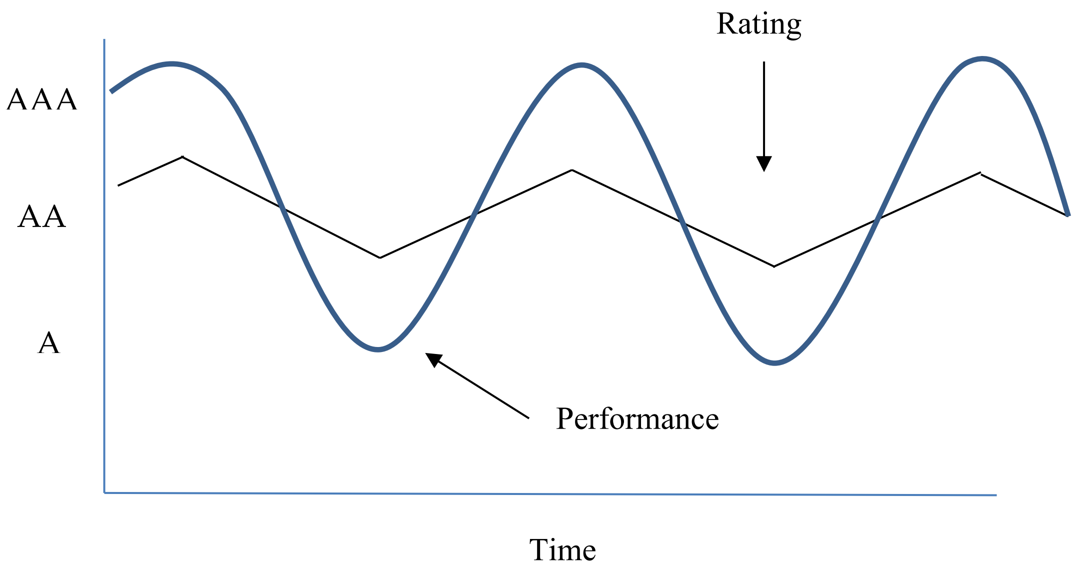

Figure 3: Rating over time in realistic world (after S&P 2006)

However, anticipating seasonal patterns varying from time to time can be a difficult undertaking even for credit rating agencies. The phase length or magnitude can change and even predicted cycles can harm a company's creditworthiness when it has a lasting impact. Therefore, ratings are usually adjusted to shift towards the current phase of a cycle as seen in Figure 3. Credit ratings do not fully match the ongoing phase of business cycles, but the ratings do change because of them. (S&P 2006.) For example, an AA rating can therefore in fact vary between AA− and AA+.

3.2.1 Credit rating downgrade

Ratings reflect the credit quality of a rated company. When a firm's credit rating is downgraded, the credit rating agency have a reason to suspect the company's ability to meet its debt obligations. For example, when a firm with an A credit rating is downgraded to the BBB rating, the credit rating agency has decided the credit quality of the firm has deteriorated and the increased risk requires greater caution. The credit rating downgrade decreases the investors' confidence in the company and a probability of default can create stress in the markets. It becomes harder and more expensive for the company to raise funds. A credit rating downgrade could also lead to costly contract negotiations with suppliers and borrowers and even when the rating would later be restored, losses would nonetheless occur (Chung et al. 2012). Hand et al. (1992) stated that changes in ratings often lead to adjustments to existing credit and loan agreements.

Rating agencies face a dual problem when they lower a company into a new credit category. The new rating must reflect the credit quality of the borrower, while considering the effects the new rating could have on the borrower's credit quality in the future. A lowered rating can increase the company's expenses, which will cause company to do worse during the following quarter years. Therefore, rating companies must be careful when evaluating the company's creditworthiness and consider the continued existence of the company. Since a downgrade can become a self-fulfilling prophecy, an optimal credit rating relationship is achieved when the rating agency is concerned about the survival of the rated company. (Manso 2011.)

Stress tests are used in the evaluations of the company's creditworthiness in different situations. Mostly these are economic worst-case scenarios, which are used to reveal the possible vulnerabilities of the company. In the stress tests the company needs to survive from the depicted situations or otherwise it will most likely to be downgraded. Failing the stress tests does not necessarily mean an automatic downgrade, since the company might not have survived the triggers set for the test, but in real life the company is stable enough to survive the economic scenarios. (Manso 2011.)

3.2.2 Possible conflict of interest

The credit rating process causes a possible conflict of interest, since issuers pay the credit rating agencies for their credit ratings themselves. Credit rating agencies have close relations with some rated companies, which has worried regulators, for example the European Parliament (2011). When a credit rating agency and the rated company have a common interest or go back a long way, the market and the regulators must know that the ratings are trustworthy. The actions of the shareholders of the credit rating agencies should be followed and betting on ratings should be forbidden. (European Parliament 2011.)

The model in which the issuer pays to the credit rating agency for the rating of a security has caused criticism. The model is free for investors, unlike back in 1970s when investors paid for the ratings in the *subscriber pays* model. The change was justified since issuers benefit from the ratings more than investors, since the transparency lowers their cost of financing. Also, issuers need a rating when they are offering their obligations to regulated financial institutions, such as pension funds which can have guidelines stipulating the pension fund only to invest on issuers with low credit risk. (Council on Foreign Regulations 2015.)

The criticism of the payment system arises from the fact that also the credit rating agencies are companies aiming at profit and increased shareholder wealth. Their goal is to increase their own stock price and they do not provide ratings for the greater good. Hence, the rated companies pay directly to the credit rating agencies, which could create incentive to affect to the grade of rated security. Still, likelihood for abuse is fairly low since it is not worth it for credit rating agencies to damage their reputation. The fee paid to the credit ratings agencies would not either rise due to a higher rating. (Sinclair 2005.) For a rating agency, a potential reputation loss followed by inaccurate credit ratings is predicted to be more important than the fees received from any individual company (Manso 2011).

Moody's has been extremely profitable between the years 1995–2000, which was discovered by the initial public offering materials in 2000. The accusation has been made that credit rating agencies can take advantage through pricing power due to the regulated entry of the credit rating industry. (Levich et al. 2002.) Sinclair (2005) also stated that credit rating agencies are increasingly integrated into regulatory arrangements and into the operations of global markets in general. Attention should be paid not only to the visible operations of the credit rating agencies, but also to the political and structural effects of their actions. In the rating process the expertise and knowledge of the CRAs is present. Rating agencies are noticed by markets and governments not because they are always right but because they possess authority and judgement at the capital markets and therefore they are one of the key organizations controlling the financial markets.

3.3 Rating scales

An issuer of a bond is typically a company, government or a financial institution and by issuing bonds they borrow money from investors (Fitchrating.com 2018). Long-term ratings portray the issuer's ability to manage obligations with a maturity of one year or more. According to Moody's, long-term debts are paid with fixed-income and the given credit rating describes the cash flow sufficiency to finance the issuers financial obligations. Therefore, the given credit rating is an opinion about the issuer's relative risk, meaning the issuer's likelihood of default and the amount of financial loss if default occurs.

Credit ratings turn the issuer's risk complexity into a letter-based review. This letter scale gives creditors a simple overview about the issuer's level of risk and is nowadays the most utilized way to estimate credit risk. (Fitchsolutions.com 2018.) Credit ratings can be divided into investment grade and non-investment grade. Investment grade refers to credit ratings above BBB− or Baa. Companies in this category have high capacity to repay their interests and principals and ratings with AAA rating have the highest capacity to repay. In Nordic countries, typically only banks have had Aaa ratings from Moody's, and Nordea and Danske Bank fell from the first grade in 2007. Companies with AAA and AA ratings are considered to have a high credit quality while companies with A and BBB have a medium credit quality. Companies with credit ratings from AAA to BBB are considered to have better credit quality than "junk bonds" with credit ratings from BB+ to the lowest grades. A downgrade from BBB− or Baa3 to BB+ or Ba1 makes a company's bond drop from the investment grade to non-investment grade, also called the speculative grade. This point is an interesting event for firms, since its credibility is now remarkably weakened. (S&P: Corporate Methodology 2013; Fitchratings.com 2018)

Table 1: Credit rating scale

Standard & Poor's	Moody's	Fitch	Explanation
AAA	Aaa	AAA	Issuer's obligations have minimal risk. The obligations with Aaa rating have the highest quality.
AA+	Aa1	AA+	
AA	Aa2	AA	Issuer's obligations are high quality with an especially low credit risk.
AA-	Aa3	AA-	
A+	A1	A+	
A	A2	A	Issuer's obligations belong to the upper-medium-grade and have a low credit rating risk.
A-	A3	A-	
BBB+	Baa1	BBB+	
BBB	Baa2	BBB	The obligations have a moderate credit rating risk. Some speculative characteristics.
BBB-	Baa3	BBB-	
BB+	Ba1	BB+	
BB	Ba2	BB	Notable credit risk, obligations have more speculative characteristics.
BB-	Ba3	BB-	
B+	B1	B+	
B	B2	B	Obligations are subject to high credit risk.
B-	B3	B-	
CCC	Caa	CCC	Obligations are fairly standing and are considered to have rather high credit risk.
CC	Ca	CC	Obligations are highly speculative and are likely to default. Some potential to recover.
C		C	
D	C	D	The issuer has not been able to pay one or more of its expired obligations. Poor change to recover.

Below the credit rating categories from table 1 are explained after S&P (2006) and Moody's (Moody's: Ratings definitions 2018) descriptions.

- *AAA/Aaa* is the highest grade an issuer can receive, and it means that the obligations have a minimal risk. The obligations with Aaa rating have the highest ability to meet their financial engagements.
- *AA/Aa* rated issuers' obligations have a high quality with an especially low credit risk. These issuers have a strong capacity to meet their financial responsibilities.
- *A* rated obligations belong to the upper-medium-grade and have a low credit rating risk. Capacity to meet the financial responsibilities is rather strong.
- *BBB/Baa* rated obligations have a moderate credit rating risk. As being the last grade before the speculative grade, the obligations can have some speculative characteristics. Changes in economic conditions can weaken the capacity of an issuer to meet its financial responsibilities and gradually shift the rating towards non-investment grade.
- *BB/Ba* rated obligations have enough speculative characteristics to belong into the speculative grade, and they are subject to a notable credit risk. Ba rated

obligations are still less likely for nonpayment than other speculative graded obligations.

- *B* rated obligations are subject to high credit risk as belonging into speculative grade. Currently the issuer can meet its financial responsibilities but chance for nonpayment exists in the future.
- *CCC/Caa* rated obligations are fairly standing and are considered to have a rather high credit risk. Currently the issuer is vulnerable for nonpayment. In adverse conditions the issuer is not likely to meet its financial responsibilities.
- *CC/Ca* rated obligations are highly speculative and are likely to default in the near future. These obligations still have some potential to recover, but they are highly non-likely to meet their financial responsibilities.
- *C* rated obligations have typically filed a bankruptcy petition, but payments are currently continued.
- *D/C* rating is the lowest grade an issuer can receive. C rated bonds by Moody's' have poor potential to recover and are typically in default. D rated bonds receive their rating when default has already occurred.

All issuers sharing the same credit rating should not be considered fully equal, since there are many more companies than there are credit rating classes. Credit ratings are meant for investment purposes, but they are not designed for forecasting the future trends. Even though credit ratings do regard the visible future, the credit ratings represent the worst-case scenarios. In addition to statistical information, ratings include many non-statistical factors such as visible changes in the market. (Moody's: Ratings definitions 2018.)

On top of the basic letters from A to D defining credit risk, credit ratings can also be other letter combinations. The letter combination WR stands for withdrawn, and that indicates the issuer does not currently have a valid rating since it has been withdrawn usually due to new information or the lack of information. The letter combination NR means not rated. There are many reasons why a certain issuer does not have a valid credit rating. For example, the issuer's security can belong to a group of securities, which are not rated as a matter of policy. It is also possible that there is not enough information about the issuer and therefore the bonds cannot be rated. Also, the issuance might have been private and therefore the rating is not published. Given credit ratings can also be withdrawn if new material comes into credit rating agency's knowledge. The bond can for example be called for redemption or there may no longer be up-to-date data available. (Moody's: Ratings definitions 2018.)

Credit rating agencies provide diverse ratings for different types of companies. Long-term issuer ratings, as described above, are opinions about the issuer's ability to repay long-term obligation principals and interests with the issuer's fixed-income. These ratings are provided for various types of companies and they portray the likelihood of default and the possible financial losses if the default occurs. Short-term ratings in turn are opinions of the issuer's ability to honor financial obligations on the short-term and this rating type is also widely used. Corporate family ratings are typically given to corporations with a speculative grade credit rating and they are opinions about the corporate family's probabilities to honor all the financial obligations attached to it. These ratings are typically given with a long-term prospect. Bank ratings are usually given with the bank financial strength ratings and they are created to describe a bank's creditworthiness and safety. Then again bank deposit ratings are opinions about the bank's ability to repay its foreign or domestic currency deposit obligations. According to Moody's they surveil especially the prospective payment performance of the banks. In addition, there are some specified ratings given to shares in mutual funds, given to insurance companies and ratings for issuer's creditworthiness within a country. (Moody's Rating Scale and Definitions 2018.)

3.4 Credit watches and outlooks

Credit watches are listed by credit rating agencies, denoting the prospective direction of a rating change that might occur due to a trend or a specific event. A credit watch means the rated unit is under special surveillance and that its credit rating may change in the future due to increased or decreased credibility, usually within the next 90 days. Credit watches can be positive or negative, prognosticating the direction of the possible rating change. Credit watches react faster to publicly known events, such as mergers and acquisitions, than credit rating actions. They are triggered by specific events, which could potentially lead to a change in credit rating, and therefore being set on credit watch transmits the information to the markets. The triggering events can also be different challenges facing the industry or regulatory reforms connected to the issuer's future plans or other current or expected conditions affecting credit quality. The challenges affecting financial performance, usually concerning earnings and cash flow, are also an important reason for being set on a credit watch. (S&P 2006; Chung et al. 2012.)

However, being listed on credit watch does not mean that the rating will certainly change to the direction pointed by the down or up watch or even that the rating will be changed at all. Once the credibility of the company is confirmed or the rating has been upgraded or downgraded, the company will be deleted from the watch list. Also, credit ratings can change without a preceding credit watch action. When all the needed information is available for the CRA, a credit rating change is made immediately. (S&P 2006.)

According to S&P (2006), rating outlooks and CreditWatch listings are tools, which the rating agency uses when the future performance of the rated unit will potentially differ from the initial expectations. The special surveillance attached to CreditWatch typically ends with a review within 90 days unless the outcome of a triggering event starting the special surveillance is unclear. Outlooks have typically a longer time frame than credit watch listings, since they are usually valid for 2 years tracking less certain factors which affect to the ratings. An outlook can be *positive* (when indicating a possible upgrade) *negative* (when indicating a possible downgrade) or *stable* (when the rating is not expected to be changed).

Negative credit watches inform markets about increased default risk. When occasional shocks have little weight in credit rating analysis, credit watch listings make markets aware of the direction of surveillance of a certain issuer. Chung et al. (2012) find that credit watches were caused by changes in financial performance, whereas actual rating changes were associated with deterioration or improvement in leverage and/or balance sheet figures. Also, their study indicated, that credit watches are more likely to be initiated by separate events and more likely to be related to uncertainties with mergers, acquisitions and restructuring developments or financial performance than rating changes. As many as 59.1% of credit watch actions were triggered by publicly known specific events such as mergers and acquisitions but only 21.4% of rating changes were prompted by similar events. Results were consistent with S&P (2006) guidelines about credit watches meaning that credit watches are less likely to be triggered by leverage changes and uncertainties regarding the balance sheet.

The previous studies show that credit watch announcements are linked to abnormal stock returns, denoting that the watches are significant events providing information about the company's credibility. Positive and negative credit watches are associated with mean cumulative abnormal returns (CARs) of 4% and −1.1% in a sample of 10,790 rating actions and 4,539 credit watches issued by Moody's between 1992 and 2010 indicating credit watches to be significant information events themselves (Chang et al. 2012).

Credit watches respond more to a deterioration in a firm's credit quality. Boot et. al. (2006) suggest that firms respond differently to up and down watches. Firms take actions after a down watch to prevent a possible downgrade, but do not take significant actions after up watches. Due to this reaction companies set on a down watch are less likely to be downgraded than companies with an up watch being upgraded. The firm's own actions affect the outcome. Boot et al. (2006) claimed that credit watches can be seen as indirect contracts between the CRA and the issuer, where the issuer is informed about the necessary actions to be made in order to maintain its current rating. After the down watch has been issued, managers and the CRA can discuss, which are the necessary actions to take in order to prevent the possible credit rating downgrade. Chung et al. (2012) supplemented this by noting that down watches occur especially before *fallen angel* downgrades, referring to credit rating changes from investment grade to non-investment grade. Therefore, CRA allows a company to avoid a costly downgrade if certain improvements are made, while giving the information about lowered credit quality to the investors.

Chung et al. (2012) also expected that CRAs would issue more down watches than up watches, since it would be more harmful to their reputation if a downgrade hadn't been preceded by a down watch than an upgrade preceded by an up watch. Therefore, issuing more down watches prevents them from public criticism and possible lawsuits. Chung et al. (2012) find that 63.6% of the downgrades and 69.1% of the upgrades by Moody's were not preceded by any watch action indicating that there were slightly more down watch listings. Their sample consisted of 5,594 downgrades and 2,295 upgrades. The results were also consistent with the previous assumption that a majority of the watches indicated correctly the direction of following rating action. In total 67.3% of the down watches and 68.6% of the up watches were followed by credit rating changes in the same direction. The duration of a down watch is shorter for downgrades with mean duration of 96 days whereas the duration of up watches is 120 days on average.

However, even though negative watches could have a significant effect on the price formation prior to the actual credit rating downgrade, Boot et al. (2006) argued that the issuance of credit watch does not convey new information to the market since the watch is typically caused by publicly known event or trend and therefore the watch listing has been expected. Consequently there should not be significant price reactions following the negative watches, regardless of the warning element, which previous negative outlooks and especially negative watch listings have.

3.5 Discussion about minor credit rating agencies

In Europe, the reliance on "big three" has disquieted MEPs and European Parliament Committee on Economic and Monetary Affair stated in 2011 that more competition should appear on credit rating industry. They also suggested limiting the impact of CRAs to countries' borrowing costs and demanded more transparent standards when rating national debt.

Since there are over one hundred regional rating agencies, the competing agencies could issue ratings after meeting the requirements of European Securities and Markets Authority (ESMA) and thereby receive trustworthiness (European Parliament 2011). ESMA was created in 2011 to supervise credit rating agencies and to order CRAs to reveal their detailed methodologies (Deutche Welle 2011). The European Parliament Committee on Economic and Monetary Affair suggested that the data of International Monetary Fund and European Central Bank could also be used when building analyses and therefore Europe could be more open to competition (European Parliament 2011).

The major market share of the CRAs has been accused of playing a role in causing the financial crisis in 2008. Standard & Poor's paid 1.37 billion worth of settlement after the financial crisis and Moody's was investigated by the U.S. Justice Department. The core business model of the CRAs has still mostly remained untouched. (Council on Foreign Regulations 2015.)

The position of the ”big three” was originally enshrined by the Securities and Exchange Commission (SEC) in 1975 (Council on Foreign Regulations 2015). However, the credit rating industry is a quite natural oligopoly, since investors value comparability, which could not be offered by numerous independent actors on the industry. Also, from the rated companies’ point of view it would require time and money to ask ratings from various agencies. Therefore, it is more convenient for the companies to buy a rating from one or two of the three CRAs, whose ratings are comparable for investors globally. As a result, investors do not have to spend time trying to compare ratings of separate local credit rating agencies. (OECD 2010.)

4 DATA, HYPOTHESES AND RESEARCH METHOD

4.1 Downgrade data

The research sample consists of the listed companies at Nordic markets with credit rating downgrades by Standard & Poor’s, Fitch or Moody’s . The earliest observations are from the year 2001 and the latest ones from the beginning of 2018. Together there were 140 observations in the full sample of this study. These observations are presented in Appendix 1.

The listed companies in Denmark, Finland and Sweden are gathered from the NASDAQ’s website and the listed companies in Norway from Oslo Børs’s website. Together there were 840 listed companies within the Nordic countries, of which 143 are from Denmark, 139 from Finland, 363 from Sweden and 195 from Norway. Oslo Stock Exchange is the only independent stock exchange within the Nordic markets, while other stock exchanges are owned by NASDAQ OMX Group. These companies were searched from the Thomson One database to see if they had credit rating downgrades during the time range of this study. All the gathered credit rating downgrades were made to the long-term foreign ratings by Moody’s, Standard & Poor’s and Fitch. After collecting the downgrading data from Thomson One the information about the prior events to the credit rating downgrades was gathered from the webpages of Moody’s and S&P. The reason for this was, that Thomson One does not record historical actions such as *negative outlooks* or *negative watches* before the actual downgrade. Unfortunately, Fitch declined to provide this information free of charge, and hence only the previous events of downgrades from S&P and Moody’s are obtainable. However, for some reason fifteen of the observed downgrades could not be found from the S&P’s webpage and therefore also these fifteen observations lack prior events.

Usually only publicly listed companies have purchased credit ratings, since having a third-party opinion about the firm’s credibility comforts certain types of investors and would not cover the costs for smaller non-listed companies. Some larger companies have purchased credit ratings from several CRAs and all downgrades made by Moody’s, S&P or Fitch are included in the data if they have not been given excessively close to each other. Since the previous downgrade would interfere the estimation window of the latter event, the estimation period is narrowed or the latter event excluded in these situations.

In total there are 100 observations with a clear 250-day wide estimation window. The observations with less than 110 days between the recent and the prior downgrade have been removed from the sample. Controlling contaminated observations by deleting them has been used for example by Chung et al. (2012) in their study about credit rating watches and rating actions. The 110 days between the recent and the prior downgrade is based on the study of Brown's and Warner's (1985), since they used a 90-day estimation period. The 10 days after the previous event and the 10 days before the following event create a half of the event windows of those observations and therefore it is reasonable precaution to exclude also these event window days from the estimation window. Together there are 40 observations with adjusted estimation windows.

Also, if there were two credit rating announcements given on a same day from different CRA's, only the one with more information about the prior events was included in the sample. For example when Moody's and Fitch had downgraded their rating on the same day, Fitch was excluded due to its lack of prior negative outlooks and credit watch listings. The companies, which are listed in more than one Nordic market were included only in their home market's credit rating announcements due to the fact that otherwise the impact of one downgrade would be measured at maximum three times from three different markets, which would have happened with Nordea as it is listed in Sweden, Denmark and Finland. As a result, there are 140 observations in the research sample.

Table 2 represents the 140 events listed according to year. As the Table shows, the year 2009 following the finance crisis in 2008 had the most credit rating downgrades. During the year 2009 the global effects of the financial crisis have started to show causing financial distress among the companies listed at Nordic markets. This financial distress and worsening balance sheet figures and future cash flows lead to the busiest year of credit rating downgrades.

Table 2: Distribution of observations according to year

Year	Observations	Percentage	Cumulative Percentage
2001	3	2 %	2 %
2002	3	2 %	4 %
2003	8	6 %	10 %
2004	3	2 %	12 %
2005	3	2 %	14 %
2006	9	6 %	21 %
2007	14	10 %	31 %
2008	9	6 %	37 %
2009	22	16 %	53 %
2010	6	4 %	57 %
2011	10	7 %	64 %
2012	16	11 %	76 %
2013	6	4 %	80 %
2014	8	6 %	86 %
2015	7	5 %	91 %
2016	9	6 %	97 %
2017	2	1 %	99 %
2018	2	1 %	100 %
TOTAL	**140**	**100 %**	**100 %**

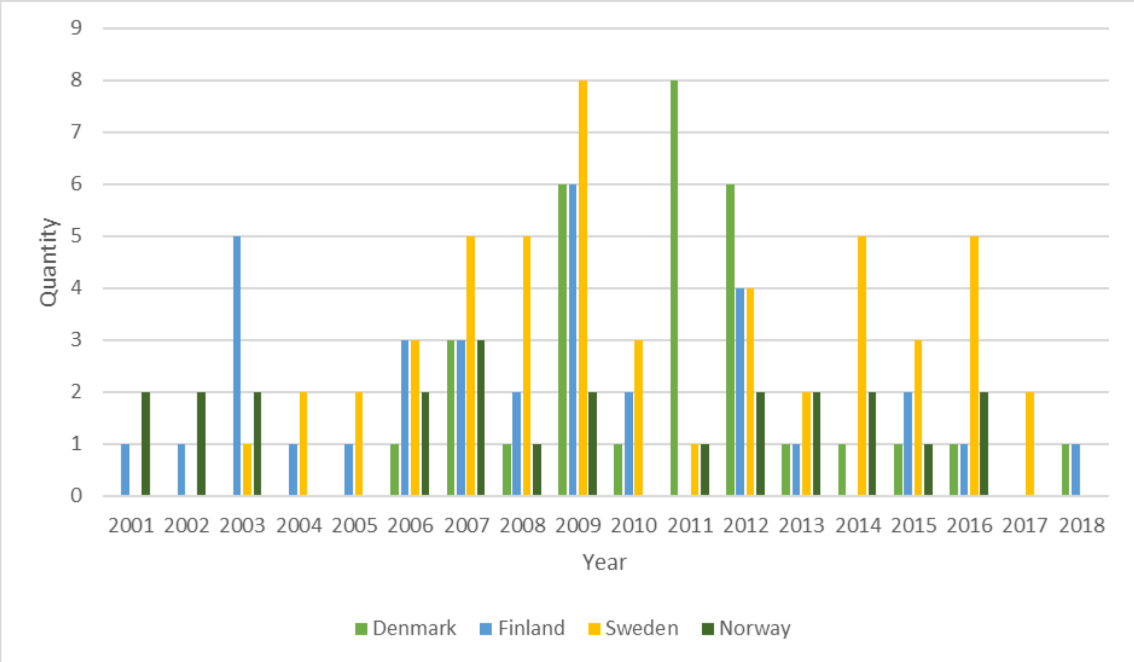

Figure 4: Distribution of credit rating downgrades by year and country

The distribution of the credit rating downgrade observations varies between the years and countries. The year 2009 shows as the highest peak of all the years having in total 22 credit rating downgrades. From those companies 8 are listed at Stockholm Stock Exchange: SEB, Volvo, Sandvik, SSAB, Nordea, Svenska Handelsbanken, SAS and Holmen. None of them were downgraded from the investment grade, but SAS belonged to the speculative grade already before the downgrade. The year 2009 was also the busiest downgrading year to companies listed at Helsinki Stock Exchange, when Metsä Board, Sampo, UPM-Kymmene, Stora Enso, Nokia and Fortum were downgraded. UPM-Kymmene was downgraded from investment grade to non-investment grade and Stora Enso and Metsä Board already belonged to the speculative grade.

The highest peak for Norway occurred a year earlier in 2007 when Sparebank, Norsk Hydro and Yara International were downgraded. Yet they all still belonged to the investment grade. For Denmark the largest amount of downgrades, 8 in total occurred in 2011, when 6 banks were downgraded, Jyske Bank and Danske Banks twice. However, they all still belonged to the investment grade.

In 2017 there are only observations from one of the Nordic countries — Sweden. This indicates that the situation and future prospects in Nordic countries were hopeful. The situation differed largely from the year before when there were in total 9 credit rating downgrades and they included all the Nordic countries. In 2016, Sweden had 5 credit rating downgrades, and the next year's number of 2 was again a bright number for the markets. Also, since 2016 until the beginning of 2018, no company listed in Oslo Børs has been downgraded.

4.2 Return Data

4.2.1 Normal and abnormal returns

The daily total return indexes of the stock prices are collected from Thomson Reuters Datastream. The total return indexes are used instead of a regular price indexes because the total returns indexes describe the performance better than a price index. These daily returns indexes are converted into logarithm returns, because otherwise the cumulative abnormal return would not be the sum of abnormal returns. To convert the stock and later represented index returns I used the following formula, used for example by Elad & Bongbee (2017), to calculate the logarithm returns.

$$R_t = LN\left(\frac{P_t + D_t}{P_{t-1}}\right),$$

where the P_t is the observed price of a day and P_{t-1} is the observed price one trading day prior to the day t. R_t represents the log returns of the day t.

Sharpe (1963) introduced the market model as the simplified model for portfolio analysis, in which the model with fewer parameters led to almost the same results as more complicated models with more variables and relationships among them.

The market model for any security i is (MacKinlay 1997)

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it},$$

where R_{it} describes the returns of the security over a time t and R_{mt} the market portfolio. The component ε_{it} expresses the zero mean disturbance term and α_i and β_i form the parameters for the market model.

After calculating the R_{it} by using the market model, the abnormal return of a sample can be calculated as

$$AR_{it} = R_{it} - \hat{\alpha}_i - \hat{\beta}_i R_{mt},$$

where $\hat{\alpha}_i$ and $\hat{\beta}_i R_{mt}$ are the estimated parameters for the model. Among multi-country event-study methods, Campbell, Cowan and Salotti (2010) describe $\hat{\alpha}_i$ and $\hat{\beta}_i$ as an ordinary least square estimates of market model parameters and R_{mt} as a national total return market-index return. The cumulative abnormal return over the event window is

$$CAR_i(t_1, t_2) = \sum_{t}^{t_2} AR_{it}$$

where t_1 and t_2 define first and last day of the even window. The distribution of the accumulated abnormal returns is

$$CAR_i, (t_1, t_2) \sim N(0, \sigma_i^2(t_1, t_2))$$

where $\sigma_i^2(t_1, t_2)$ is the variance of the observation i from the time t_1 to t_2. The advantage of using the market models depends on the R^2 of the market model regression. Higher R^2 means the greater variance reduction of the abnormal return, which means more benefit from using the model. Two common economic models which provide restrictions on the statistical models are the Arbitrage Pricing Theory (APT) and the Capital Asset Pricing Model (CAPM). The restrictions create more confined models for defining normal returns, and the market model has mostly replaced CAPM. (MacKinlay 1997.)

4.2.2 Index-returns

In order to define the market returns for calculating the normal and abnormal returns, I have gathered the daily stock index data of Oslo Børs, Copenhagen Stock Exchange, Stockholm Stock Exchange and Helsinki Stock Exchange from the past 20 years. I used Thomson Reuters Datastream for the data collection, but unfortunately Datastream provided daily data from OMX Stockholm only since 30.12.2002 and from OMX Copenhagen since 14.12.2001. The rating downgrades preceding and overly close to 30.12.2002 of listed companies in Stockholm Stock Exchange were excluded from this study. No credit rating downgrades of Copenhagen Stock Exchange listed companies were excluded since there were none collected before or overly close to the date of 14.12.2001.

Table 3: Nordic indexes

The Nordic Indexes			
OMX Copenhagen since 14.12.2001	OMX Stockholm since 30.12.2002	OMX Helsinki	Oslo Exchange All

The indexes used as market returns are all share indexes of the Nordic capitals: OMX Helsinki (OMXH), OMX Stockholm (OMXS), OMX Copenhagen (OMXC) and Oslo Exchange All Share. These indexes are selected since they contain all the firms listed at the represented market and therefore represent the market returns. Total return indexes describe the stock performance better than the price indexes and therefore the total return indexes are selected.

Stockholm Stock Exchange is the largest of the Nordic exchange markets. Sweden has been the leading equity market, and the size of the Swedish markets explains the high amount of credit ratings compared to the other Nordic countries. The size of the Swedish stock markets and amount of purchased credit ratings also explain the amount of credit ratings downgrades compared to other Nordic countries.

4.2.3 Risk-free rate of returns

The risk-free rate of return represents the returns of the instrument with the lowest risk on the markets. Any addition in risk increases the return demand by investors, and theoretically the risk-free return then describes the minimum return an investor expects from an investment. In this study the interbank 1 month country specific offered rates, which banks use when they are willing to borrow for other banks in short-term, were used as the risk-free returns of each of the Nordic countries. The daily data for these one-month interbank rates was collected from Datastream and since there are no risk-free returns for one day time period, the risk-free returns are calculated with the help of monthly risk-free returns with the following formula (Vaihekoski 2004):

$$ln\ i_{1m}^{perday} = \ln \frac{360 + i_{1m}^{pa}\ x\ 30}{360 + i_{1m}^{pa}\ x\ 29}$$

where the i_{1m}^{pa} describes the daily total return index price given for the one-month interbank rate.

4.3 Hypotheses

The previous studies have not agreed on the existence of a market reaction after credit rating downgrades and in some studies (e.g. Li et al. 2004) the market reaction has occurred a few days or even a few months after the rating change. If the latter option would be the case now, the price effect would not be seen during the 21-day long event window of which 10 days are post event days. However, in this study the markets are expected to be efficient and a lack in reaction longer than 10 days does not fulfill the description of efficient markets.

The study by Li et al. (2004) is also an interesting example for another reason than just the late market reaction. The abnormal returns after a credit rating downgrade in this study were positive, not negative as expected. This result clearly differed from many of the previous studies made in the U.S. market. Therefore, it is not certain, that the studies about abnormal returns of companies listed in smaller markets would share the results from the U.S. markets. Since not all previous studies have reported significant negative abnormal returns appearing around credit rating announcements, the first hypothesis is as follows:

H1: *Credit rating downgrades cause negative abnormal stock returns at Nordic markets on the event date and shortly after.*

For the hypothesis 1 to be fulfilled, markets need to react to the new information released by the credit rating agencies. The market reaction is measured by monitoring the abnormal returns on the event window days +10 to –10 around the event date. In efficient markets the abnormal returns would not occur if the markets had anticipated the downgrade well beforehand since all the information would already be converted into the share prices.

However, if credit rating agencies have given a negative outlook or a negative watch listing, the possible market reaction should be smaller since markets have been warned that the firm could be facing a downgrade in the near future. In these cases, markets have had time to prepare for the possible downgrade. Outlooks are more common to give to companies under surveillance, but credit watch listings usually mean, that there is a greater chance for the downgrade to occur. Therefore, it is assumed that the negative abnormal returns are smaller in cases where the previous negative watch has been released.

H2: *Abnormal returns are less negative when a negative watch has been given prior to the rating change.*

Since firms belonging to the investment grade are widely recognized to be safe investment opportunities, downgrading from the investment grade into the "junk bonds" harms the company's reputation and credibility. There are also concrete effects, besides the classification change and the mental image attached to the name junk bonds. Some institutional investors and pension funds have strict rules on which type of company they can invest and junk bond meaning bonds under the credit rating level of BBB– are counted inconveniently risky. This means that in some situations, brokers are forced to sell the securities by the downgraded issuer at the latest when the issuer's rating decreases under BBB–, which assumably effects on the stock returns around the event day. Therefore, abnormal returns of firms downgraded from investment grade to non-investment grade should be negative.

H3: *A downgrade to the speculative grade from investment grade has a negative effect to the abnormal returns.*

Among investment grade, the companies are remarkably safe and contain a relatively low level of risk. Also, the companies with higher ratings are usually large, wealthy and widely followed meaning that the credit rating downgrade among them would capture the investors' attention. According to Moody's (Moody's: Ratings definitions 2018) changes in credit ratings are more expected among lower-ratings than among bonds with higher ratings and therefore it can be expected that the abnormal returns differ among investment grade and non-investment grade firms.

H4: *The negative abnormal returns are greater, when the downgraded firm belongs to the investment grade than when it belongs to the non-investment grade.*

And finally, since firms adjust their capital structure before and after the publication of the credit rating downgrade (e.g. Hung et al. 2016), it is natural to test if the level of leverage has an impact to the abnormal returns.

H5: *Increase in the level of leverage effects negatively to the abnormal returns.*

Companies with larger amount of debt could experience larger negative abnormal returns after a credit rating downgrade, since after the downgrade their funding will be more costly. The more debt the company has, the more expensive it will be to receive a new loan. Also, the terms of previous loans can include a statement, whereby the rates will increase since the company's future is riskier than before. Because of these negative effects the returns should have a negative tone after a company with larger amount of leverage is downgraded.

4.4 Event study method

In this study, the abnormal returns caused by credit rating announcements are examined with the event study method. The event study method is widely used in examining the effects of credit rating changes. Originally Fama, Fisher, Jensen and Roll (1969) represented the cornerstone thought that price changes in stock markets are mostly independent, and therefore firm specific events can cause changes is stock prices. The idea was, that market prices change rapidly when they adapt to new information. This rapid price chance was seen as an efficient reaction to the new information on the markets. Until the research by Fama et al. (1969) there had been very little testing on how well and fast the markets actually react to new information.

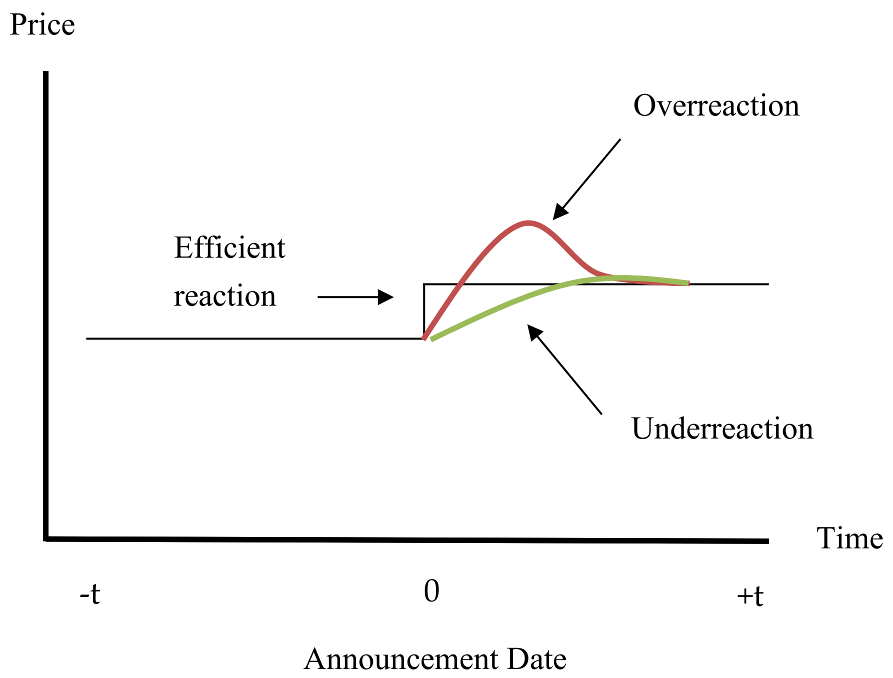

Figure 5: Price effect according to the efficient market hypothesis

In an efficient market reaction, the price adapts quickly to the new information on the markets. The reaction occurs in an accurate amount without overreacting or underreacting to the information. In an overreaction the price raise is excessively high after the information is released and in an underreaction the price change is lower than the normal reaction would be. On the other hand, after an overreaction or underreaction the price usually balances to the normal level the published information originally should have caused.

An event study is a statistical method to determine the impact of an event on the value of the firm. When using the event study method we assume that the event will have an immediate effect on the stock price. The amount of impact can be constructed using the security prices observed before the event (MacKinlay 1997.)

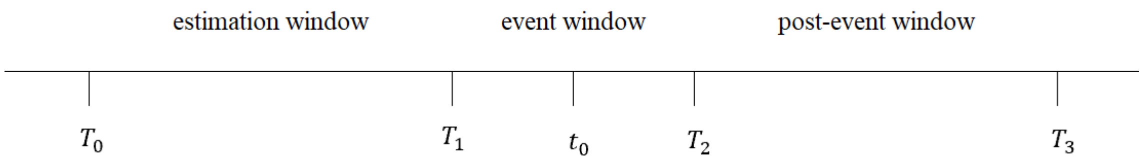

Figure 6: Event study timeline

In event studies, the day 0 represents the actual date of the event (t=0), which in this case is the announcement date of a credit rating downgrade. These event dates are the announced days for credit rating changes from Thomson One. *Event window* covers usually days (–10, 10) around the event day, and estimation window covers typically the days (–260, –11) prior the event window. Estimation window provides the information needed to specify the normal returns of the stock and the market index. After calculating the abnormal returns for the days (–10, 10) based on the returns of the estimation period, the cumulative abnormal returns can be calculated usually starting from the even date. The post-event window is usually defined as the days (11, 260) after the event window and it can be used to define whether there are significant price effects occurring later than 10 days after the event.

Typically, the length of the event window is 10 to 20 days before and after the event date, so that the event window will capture the previous or lagged price impact if it exists. In most of the previous studies about credit rating changes, the used event window is from –10 to 10 days around the event date. Therefore, I chose the same event window length for this study.

Then, there are many ways to calculate the normal returns from the estimation window days (–260, –11) prior to the event. The market model is the most popular and this statistical model relates the return of a given security to the return of the common market portfolio. In the market model, used for example by Kim, Chen and Nance (1992), it is expected that the relation between the market and the security is linear and stable.

Altogether 100 observations in this study had an uncontaminated estimation window from the event date to the date of –260. The estimation period of 40 observations is adjusted and events with shorter than –90 day estimation windows were excluded from the study. The limit of 90 days is based on the study of Brown and Warner (1985). However, the true length between the remaining observations in this very study is 110 days, since 10 days after the first event and 10 days prior the latter event belong to the event window of an observation and could disturb the normal return calculations if included.

For the observations with adjusted estimation periods, as many days as possible without interfering with other events were included in the estimation period. As a result, all the observations with adjusted estimation periods have estimation periods with varying lengths.

In this study, the event study results for each day of the event window are measured by using two methods: the cross-sectional standard deviation test and the sigma-based test. The cross-sectional standard deviation test, later referred to as method I, is a non-standardized test to measure the daily cross-sectional standard deviation of the time-series data. The test statistics for cumulative average abnormal returns ($CAAR_{T1,T2}$) are measured by using the following formula. (Eventstudy.com – Eventus Guide.)

$$\hat{\sigma}_{CAAR_{T1,T2}} = \left(\frac{1}{N} - 1\right) \sum_{i=1}^{N} (CAR_{1,T1,T2} - \frac{1}{N} \sum_{j=1}^{N} CAR_{j,T1,T2})^2$$

$$t_{CAAR} = (CAAR_{T1,T2}) / (\hat{\sigma}_{CAAR_{T1,T2}} / \sqrt{N})$$

The method II is based on Lim's (2011) test statistics and can be utilized when observations are not clustered. This sigma-based test is calculated as follows

$$AAR_T = \frac{1}{N} \sum_{i=1}^{N} AR_{iT}$$

and used for each day T of the event window by

$$\frac{AAR_{iT}}{\sqrt{\frac{1}{N} \sum_{i=1}^{N} \hat{\sigma}_i^2}} \sim N(0,1)$$

The results later show, that the statistically significant cumulative abnormal returns vary depending on the used method.

4.5 Regression analysis

The regression analysis is calculated for three cumulative average abnormal return (CAAR) periods. CAAR(0,1) consists of the cumulative abnormal returns on the event day and the day after. CAAR(0,10) consist of the CAAR's starting from the event day until the day 10 and CAAR(–10,10) starts 10 days before the event day and sums the returns until the day 10. These CAAR(0,1), CAR(0,10) and CAAR(–10,10) periods are the dependent variables of this study and they are investigated using the following regression formula:

$$g_i = b_0 + b_1 PRE_{LEHMAN} + b_2 FALLEN_{ANGEL} + b_3 GRADES_{DOWN} + b_4 INV_{ORIG} + b_5 NEG_{OUTLOOK} + b_6 NEG_{WATCH} + b_7 LEV + b_8 LN_{SIZE} + b_9 NORWAY + b_{10} DENMARD + b_{11} FINLAND + \varepsilon_i,$$

where $g_i$is either $CAAR_i(0,1), CAAR_i(0,10)$ or $CAAR_i(-10,10)$ and b_0 is constant.

Together there are 11 independent variables in this study, including 9 dummy variables. The first of these dummy variables is FALLEN_ANGEL. The FALLEN_ANGEL variable has a value of 1 when the downgrade has caused the company's credit rating to fall from investment grade to non-investment grade. When the downgrade does not change the rating category, the observation has a value of 0. Together there are 9 observations with the FALLEN_ANGEL value of 1.

The dummy variable INV_ORIG has a value of 1 when the rating prior the downgrade has belonged to the investment grade and a value of 0 when it has belonged to the non-investment grade. The dummy variable GRADES_DOWN has a value of 1 when the downgrade has been larger than one step down, for example from AA+ to AA–. Otherwise the value is 0. Together there are fourteen observations, which have been downgraded for two steps and one with a downgrade of three steps. The largest downgrade faced Petroleum Geo Services in 2002, a company listen is Oslo Børs. Each downgrade has the value 1 in the regression analysis, regardless of whether it was a downgrade of one grade or more.

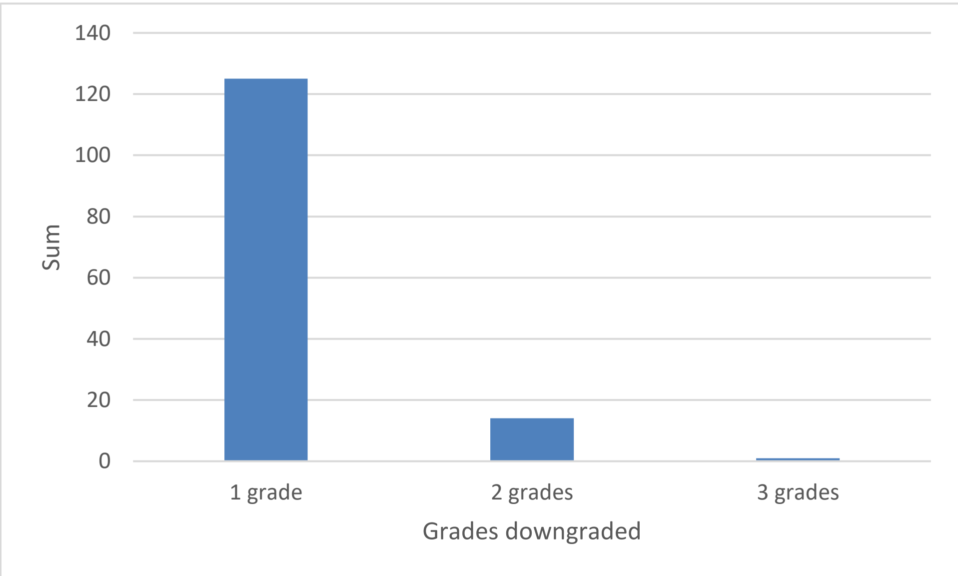

Figure 7: Distribution of observations by grades downgraded

The dummy variables NEG_OUTLOOK and NEG_WATCH are attached to prior events to the credit rating downgrade and they have a value of 1 if a negative outlook or a negative watch listing has preceded the downgrade. Together there are 39 observations with the prior negative outlook and 41 with a negative watch listing. From the observations with obtainable prior events, 28 had no negative outlook or negative watch listings preceding the credit rating downgrade.

The country dummies FINLAND, DENMARK and NORWAY describe the impact the listing place of shares has to the abnormal returns. Sweden has been selected to the basic level of impact and therefore the country dummy variables represent the effect compared to companies listed in Sweden.

The last dummy variable PRE_LEHMAN divides the sample by the date when the credit rating downgrade has been announced. All observations before the September of 2008 have the value of 1 and the observations after September 2008 the value 0. In the sample, 48 of the 140 observations have occurred before the bankruptcy of Lehman Brothers.

The two variables which are not dummy variables are LEV and LN_SIZE. The variable LEV describes the leverage level of a company. The level of leverage is calculated based on Berger's, Ofek's and Yermac's (1997) and Kim's, Chen's and Nance's (1992) studies with the following formula and the required figures are gathered from the balance sheet of the companies gathered from Thomson One.

$$Leverage(book\ value) = \frac{total\ debt(book\ value)}{total\ assets(book\ value)}$$

Market capitalization represents the size of the downgraded firm in this study and LN_SIZE is used as a control variable. The data for the market capitalizations has been gathered from Thomson One and I used the market capitalization value of the year when the downgrade had occurred. If the downgrade occurred at the beginning of 2018, the latest value from the financial statement of 2017 was used. The variable LN_SIZE is expressed as a logarithm of the market capitalization.

5 RESULTS

5.1 Descriptive statistics

The descriptive statistics of the sample provide an overview of how the returns have varied in different lengths of CAAR periods. CAAR(0,10) contains the returns of CAAR(0,1) and CAAR(–10,10) contains the returns of both of the other periods. By comparing the figures of these CAAR lengths, we can determine when the returns have reached the highest and lowest points in this study. Descriptive statistics also show the mean and median of the observations, the shape of the distribution of the observations and also if the distribution of the observations leans to the right or to the left.

As Table 4 shows, each cumulative abnormal return period has minimums more divergent from zero than these periods' maximums are referring that the negative cumulative average abnormal returns are larger than the positive ones. The means and medians however are close to zero in all CAAR periods, and negative only in CAAR(–10,10). This denotes that adding the prior days to the event date when calculating the CAAR captures more negative returns than examining the event window during and after the event only. CAAR(–10,10) also has the largest maximum (0.49) and minimum (–1.87) values compared to shorter CAAR periods, which also indicates that the return fluctuation is larger prior to the actual event date. Especially the minimum value is large compared to CAAR(0,1) and CAAR(0,10).

Table 4: Descriptive statistics of cumulative abnormal returns

	CAAR(0,1)	CAAR(0,10)	CAAR(–10,10)
Mean	0.002	0.007	–0.014
Median	0.004	0.004	–0.003
Maximum	0.173	0.240	0.488
Minimum	–0.291	–0.501	–1.869
Std.Dev.	0.039	0.080	0.197
Skewness	–2.393	–1.531	–5.861
Kurtosis	26.951	14.957	57.500
Observations	140	140	140

The histogram analysis in Figure 8 shows that most of the observations are within a close range from the value 0.0. However, the histograms from each of the periods have at least one separable negative observation from the rest of the group. From the Figure 8 we can also see, that CAAR(–10,10) has the smallest return observed, but also that the observation is separate from the other observations in CAAR(–10,10). The maximum values on the other hand have values much closer to 0.0 and CAAR(–10,10) has a maximum of 0.488 and minimum of –1.869 backing this figure.

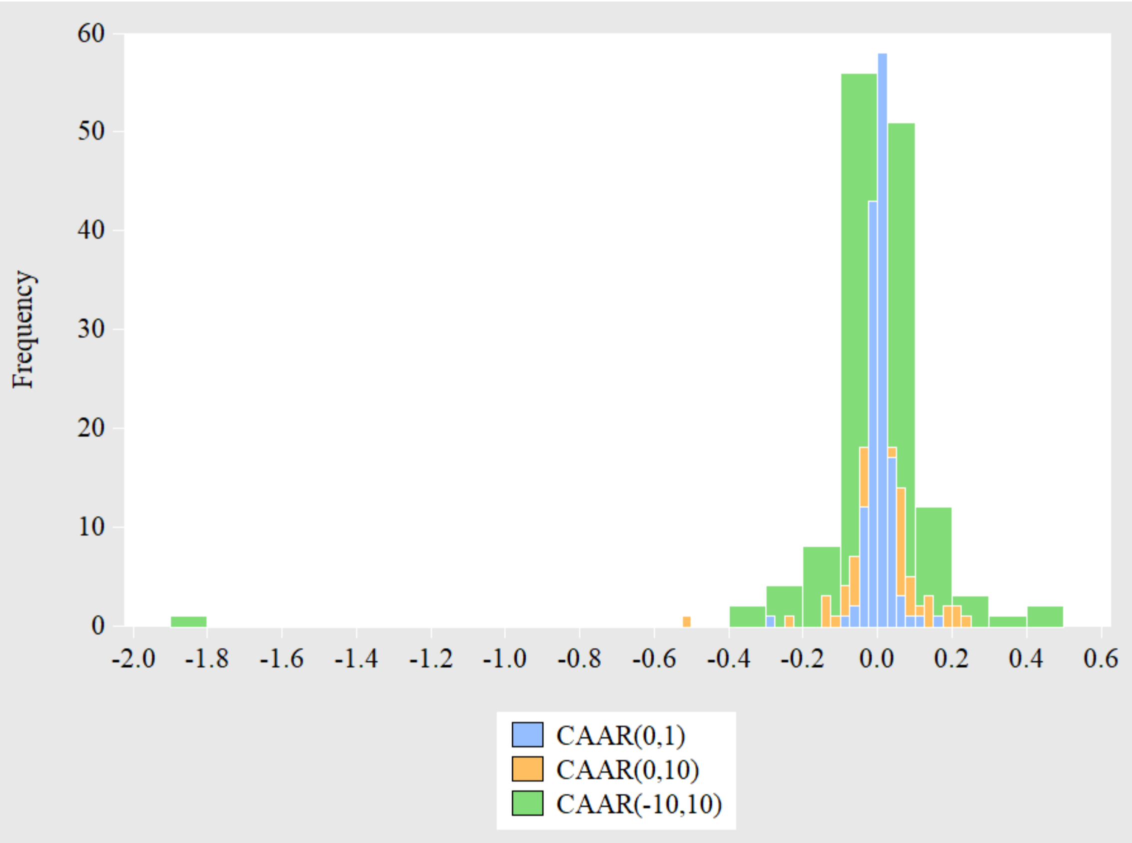

Figure 8: Histogram of distributions

Logically, CAAR(–10,10) has the highest standard deviation, since it also has the most observations. On the contrary, CAAR(0,1) has the lowest standard deviation since it has the least observations.

Skewness g measures if the distribution of observations leans towards the negative values or the positive values. When skewness g is above 0, a positive skew leaning to the right occurs and if the skewness g is under 0, the distribution has a negative skew and it leans to the left. With all the CAAR periods, the skewness is negative meaning that the distributions lean towards the negative values. However, CAAR(0,10) has the smallest negative skew meaning that its observations lean the least to the left.

When kurtosis g_2 has a value greater than 3, the distribution is leptokurtic. If the kurtosis g_2 is lower than 3, the distribution is platykurtic or “flat-topped”. All the CAAR periods have g_2 significantly greater than 3 indicating that they are all leptokurtic. This means that the distributions have high peaks.

The descriptive statistics can also provide short overviews about the variables used in this study. Most of the variables are dummy variables, which can only have values of 0 or 1. Therefore these variables will also have minimums and maximums of 0 and 1 and the median will be defined by the value appearing more than the other among the observations. Therefore, also the median can only have the value of 0 or 1.

As seen from Table 5, most of the variables are dummy variables with the minimum value of 0 and the maximum value of 1. Excluding the variable INV_ORIG, all the dummy variables have a median of 0. The variable INV_ORIG has a median value of 1 since most of the observed companies belong to the investment grade.

Among the variables, LN_SIZE has the largest standard deviation 1.50 since the logarithm of the market capitalization of the examined companies varies the most. The standard deviation of the variable LEV is much smaller 0.19 even though the companies have relatively different amounts of debt. The used formula total debt/total assets of leverage however evens the leverage differences between companies, which explains the small standard deviation.

Table 5: Descriptive statistics of independent variables

	Mean	Median	Maximum	Minimum	Std.Dev.	Skewness	Kurtosis	Observations
PRE_LEHMAN	0.343	0.000	1.000	0.000	0.476	0.662	1.438	140
FALLEN_ANGEL	0.064	0.000	1.000	0.000	0.246	3.553	13.624	140
GRADES_DOWN	0.107	0.000	1.000	0.000	0.310	2.540	7.453	140
INV_ORIG	0.814	1.000	1.000	0.000	0.390	-1.616	3.613	140
LEV	0.705	0.681	1.011	0.173	0.192	-0.134	2.281	140
LN_SIZE	8.250	8.288	11.288	3.598	1.501	-0.128	2.694	140
NEG_OUTLOOK	0.348	0.000	1.000	0.000	0.479	0.637	1.406	112
NEG_WATCH	0.366	0.000	1.000	0.000	0.484	0.556	1.309	112
NORWAY	0.171	0.000	1.000	0.000	0.378	1.745	4.040	140
DENMARK	0.221	0.000	1.000	0.000	0.417	1.342	2.801	140
FINLAND	0.243	0.000	1.000	0.000	0.430	1.199	2.438	140

Most of the variables in Table 5 have a positive skew and therefore the observations are leaning to the right. Only INV_ORIG, LEV and LN_SIZE lean to the left as all the CAR periods. INV_ORIG has the most negative skewness of –1.62 and FALLEN_ANGEL the most positive 3.55.

There are a couple variables close to representing normal distribution. These variables are LN_SIZE 2.69 and DENMARK 2.80, but nonetheless they are slightly platykurtic. In total, 4 independent variables have a kurtosis greater than 3 meaning that they have a leptokurtic distribution. The variable FALLEN_ANGEL has the most leptokurtic distribution at 13.62, which is most likely affected by the fact that it has the least observations. This explanation applies also to the variable GRADES_DOWN since it also has a small amount of observations and a second largest kurtosis value of 7.45.

To see if some of the dependent variables have an influence to each other, the correlations are calculated between each of the dependent variables and presented in Table 6. Correlation measures statistical relationship between two variables and can vary between –1 and 1.

Table 6: Correlations between the independent variables

	PRE_LEH	FALLEN_	GRADES_	INV_ORIG	LEV	LN_SIZE	NEG_OUT	NEG_WAT	NORWAY	DENMARK	FINLAND
PRE_LEHMAN	1.000000	0.043552	0.027688	-0.168977	-0.070545	-0.126930	-0.022831	0.028137	0.130071	-0.280501	0.238304
FALLEN_ANGEL	0.043552	1.000000	0.021592	0.116705	-0.019510	-0.210105	-0.033873	0.033499	0.105409	-0.059286	0.127336
GRADES_DOWN	0.027688	0.021592	1.000000	0.089521	0.138332	-0.186986	-0.264865	0.129677	0.091038	0.121609	0.006575
INV_ORIG	-0.168977	0.116705	0.089521	1.000000	0.198360	0.216940	-0.218912	0.096562	0.048560	0.254746	-0.214751
LEV	-0.070545	-0.019510	0.138332	0.198360	1.000000	-0.260686	-0.065517	-0.271926	0.046522	0.476410	-0.251729
LN_SIZE	-0.126930	-0.210105	-0.186986	0.216940	-0.260686	1.000000	0.082789	0.088124	-0.105603	-0.212711	-0.063702
NEG_OUTLOOK	-0.022831	-0.033873	-0.264865	-0.218912	-0.065517	0.082789	1.000000	-0.555435	0.076512	-0.192869	0.103278
NEG_WATCH	0.028137	0.033499	0.129677	0.096562	-0.271926	0.088124	-0.555435	1.000000	-0.098366	-0.124965	0.037755
NORWAY	0.130071	0.105409	0.091038	0.048560	0.046522	-0.105603	0.076512	-0.098366	1.000000	-0.230089	-0.218844
DENMARK	-0.280501	-0.059286	0.121609	0.254746	0.476410	-0.212711	-0.192869	-0.124965	-0.230089	1.000000	-0.302122
FINLAND	0.238304	0.127336	0.006575	-0.214751	-0.251729	-0.063702	0.103278	0.037755	-0.218844	-0.302122	1.000000

As we can see from Table 6, no notable correlation between the independent variables is detected. The correlations have both negative and positive values, and they mainly vary close to zero. The greatest correlation of –0.55 can be found between NEG_WATCH and NEG_OUTLOOK meaning that these variables are to some degree associated with each other, but not enough to disturb the results of this study.

5.2 Event study results

The event study results are examined using two different methods – the cross-sectional standard deviation test and the sigma-based test. The first method, the cross-sectional standard deviation test, shows no statistically significant abnormal returns on any of the event window days of the full sample. Neither are the cumulative average abnormal returns significant for any of the tested CAAR periods. However, the sigma test, which is later referred to as method II, gives different results.

When there are no significant abnormal returns on specific event days when calculated with the method I, the event window day –1 shows statistically significant negative abnormal returns with method II. The result is significant with the significance level of 0.01 and with the *t*-statistics of –7.33. As we can see from the Table 6, also days –4 and –7 have significant *t*-statistics with the significance levels of 0.05 and 0.10. Also, the cumulative average abnormal returns are significant with the level 0.10 on the CAAR(–10,10) period.

Table 7: Abnormal returns of the full sample

Table 7 presents the daily average abnormal returns and their t-statistics with the cross sectional standard deviation test (method I) and the sigma-based test (method II). The statistically significant p-values are denoted as follows: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

	Sample n=140		
Event window day	AAR	t–statistic method I	t–statistic method II
(–10)	0.00	–1.45	–1.41
(–9)	0.00	–0.44	–0.53
(–8)	0.00	0.79	0.70
(–7)	0.00	1.42	1.70*
(–6)	0.00	0.46	0.52
(–5)	0.00	–1.15	–1.27
(–4)	0.00	–1.14	–2.37**
(–3)	0.00	–0.66	–0.90
(–2)	0.00	–0.65	–0.79
(–1)	–0.01	–1.50	–7.33***
(0)	0.00	1.06	1.16
(1)	0.00	–0.11	–0.13
(2)	0.00	1.32	1.40
(3)	0.00	1.53	1.48
(4)	0.00	0.00	0.00
(5)	0.00	–0.72	–0.78
(6)	0.00	–1.08	–1.19
(7)	0.00	–0.71	–0.60
(8)	0.00	1.17	1.27
(9)	0.00	1.44	1.12
(10)	0.00	0.09	0.09
	CAAR	t–statistic method I	t–statistic method II
CAAR(0,1)	0.00	0.57	0.78
CAAR(0,10)	0.01	1.04	1.24
CAAR(–10,10)	–0.01	–0.86	–1.84*

We can now say that only method II shows statistically significant abnormal returns in the full sample. Since the only statistically significant event window days are –7 (with t-statistic of 1.70*), –4 (with t-statistic of –2.37**) and –1 (with t-statistic of –7.33***), the cumulative average abnormal returns were also statistically significant solely in CAAR(–10,10), with t-statistic of –1.84*. Therefore, the credit rating downgrades cause statistically significant cumulative average abnormal returns only when the event window days prior to the event date are included. Since average abnormal returns are negative starting from day –5 until the day –1, this indicates that the information about the deteriorated financial conditions of the rated company is acknowledged by the markets before the actual downgrade is announced. Given that average abnormal returns are positive on the actual event day also in all subsamples, there is a reason to believe, that the markets have reacted to the negative information before the downgrade announcement. Therefore, there is no negative reaction on the event date because the event had not been surprising but instead the stock price reacts slightly positively, when the expected downgrade is finally announced.

The anticipation of the following downgrade is possibly due to the preceding negative watches and outlooks as well as other publications concerning the company's financial stability and creditworthiness. The negative stock returns can be effected simply the fact that the rated company has worsened future prospects, which are brought to the knowledge of the markets. Highly negative abnormal returns during CAAR(–10,10) and positive returns during CAAR(0,1) and CAAR(0,10) periods indicate, that the markets had first overreacted to the anticipated negative event but started to recover already on the event date. After this, the returns are more positive on the CAAR(0,10) than to CAAR(0,1) indicating that the positive abnormal returns continued to grow after the event day and day 1. These results have similarities with Li et al. (2004) study, where they discovered no statistically significant abnormal returns on the event days 0 and 1, but statistically significant positive abnormal returns on 10 and 20 days after the event. The abnormal returns in the full sample in this study are positive but not statistically significantly positive.

The cumulative average abnormal returns, statistically significant event days and significance levels vary among the Nordic countries and none of the countries fully represents the full sample results by themselves. Therefore, for comparison, the average abnormal returns for each day in the event window and their t- and p-values for each Nordic country are presented in the Table 8.

Table 8: Abnormal returns by country

Table 8 presents the daily average abnormal returns and their *t*-statistics by country. The methods used are the cross-sectional standard deviation test and the sigma test. The statistically significant *p*-values are denoted as follows: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

	FINLAND			DENMARK			NORWAY			SWEDEN		
Event window		Method I	Method II		Method I	Method II		Method I	Method II		Method I	Method II
day	AAR	*t*–statistic	*t*–statistic	AAR	*t*–statistic	*t*–statistic	AAR	*t*–statistic	*t*–statistic	AAR	*t*–statistic	*t*–statistic
(–10)	0.00	(0.37)	(0.29)	–0.01	(–2.09)**	(–1.65)*	–0.00	(–1.00)	(–0.75)	–0.00	(–0.31)	(–0.28)
(–9)	–0.00	(–0.35)	(–0.25)	0.00	(0.39)	(0.28)	–0.00	(–0.28)	(–0.44)	0.00	(0.98)	(0.86)
(–8)	0.00	(1.66)*	(1.28)	–0.00	(–1.00)	(–0.67)	0.00	(0.55)	(0.45)	0.00	(0.11)	(0.12)
(–7)	–0.00	(–0.68)	(–0.73)	0.00	(0.79)	(0.82)	0.01	(1.65)*	(1.31)	0.00	(1.11)	(1.30)
(–6)	–0.00	(–0.61)	(–0.67)	0.00	(0.81)	(0.97)	–0.01	(–2.30)**	(–1.25)	0.00	(0.54)	(0.62)
(–5)	–0.00	(–1.03)	(–1.15)	–0.00	(–0.72)	(–0.88)	–0.00	(–0.05)	(–0.04)	–0.00	(–0.50)	(–0.68)
(–4)	–0.00	(–0.22)	(–0.23)	–0.00	(–1.39)	(–1.08)	0.00	(0.76)	(0.58)	–0.00	(–0.56)	(–1.08)
(–3)	–0.01	(–1.46)	(–1.97)	–0.00	(–0.30)	(–0.31)	–0.00	(–0.08)	(–0.11)	–0.00	(–1.05)	(–1.62)
(–2)	–0.00	(–0.75)	(–0.76)	–0.00	(–1.76)*	(–1.08)	0.00	(0.96)	(0.81)	–0.00	(–0.14)	(–0.27)
(–1)	–0.00	(–1.06)	(–1.03)	–0.01	(–2.49)**	(–3.40)***	–0.06	(–1.21)	(–10.23)***	0.01	(1.15)	(2.16)**
(0)	–0.00	(–1.42)	(–1.20)	0.00	(0.44)	(0.40)	–0.00	(–0.67)	(–0.64)	0.01	(2.54)**	(3.65)***
(1)	0.00	(0.45)	(0.41)	0.00	(0.37)	(0.26)	–0.02	(–1.60)	(–2.65)**	0.00	(1.25)	(1.10)
(2)	0.00	(0.55)	(0.55)	–0.00	(–0.99)	(–0.72)	0.01	(1.52)	(1.86)*	0.00	(0.86)	(0.93)
(3)	0.00	(0.78)	(0.77)	0.00	(0.14)	(0.10)	0.00	(0.69)	(0.58)	0.00	(0.08)	(0.08)
(4)	–0.00	(–0.91)	(–0.81)	–0.00	(–2.03)**	(–1.33)	0.00	(0.67)	(0.42)	0.00	(0.84)	(0.75)
(5)	0.00	(0.25)	(0.22)	0.00	(0.73)	(0.76)	–0.01	(–1.60)	(–1.10)	–0.00	(–0.86)	(–0.64)
(6)	–0.00	(–0.54)	(–0.41)	–0.00	(–0.07)	(–0.05)	–0.00	(–0.77)	(–0.65)	0.00	(0.25)	(0.25)
(7)	–0.00	(–0.09)	(–0.06)	–0.01	(–3.30)***	(–1.91)*	0.00	(0.52)	(0.26)	–0.00	(–0.56)	(–0.54)
(8)	0.01	(1.18)	(1.69)*	–0.00	(–1.45)	(–0.67)	0.01	(1.93)*	(2.07)**	–0.00	(–0.54)	(–0.54)
(9)	0.01	(2.08)**	(2.08)**	–0.00	(–0.58)	(–0.39)	0.00	(0.46)	(0.35)	0.00	(1.13)	(0.86)
(10)	–0.00	(–0.01)	(–0.01)	–0.00	(–0.43)	(–0.32)	–0.00	(–0.27)	(–0.32)	0.00	(1.02)	(0.92)
	CAAR	*t*–statistic	*t*–statistic	CAAR	*t*–statistic	*t*–statistic	CAAR	*t*–statistic	*t*–statistic	CAAR	*t*–statistic	*t*–statistic
CAAR(0,1)	–0.00	(–0.68)	(–0.56)	0.00	(0.55)	(0.47)	–0.02	(–1.47)	(–2.33)**	0.01	(2.64)**	(3.36)***
CAAR(0,10)	0.01	(1.05)	(0.97)	–0.01	(–1.24)	(–1.17)	0.00	(0.04)	(0.05)	0.02	(2.16)**	(2.06)**
CAAR(–10,10)	–0.01	(–0.42)	(–0.43)	–0.04	(–2.54)**	(–2.37)**	–0.06	(–0.69)	(–2.07)**	0.02	(1.40)	(1.74)*

As we can see from Table 8, the statistically significant cumulative abnormal returns differ between countries and the CAAR periods. CAAR(0,1), CAAR(0,10) and CAAR(–10, 10) periods are all statistically significant in method II when solely Swedish observations are noted, and in conjunction also the two shorter CAAR periods are statistically significant with method I at the significance level of 0.05.

On the contrary, none of the Finnish observations are statistically significant with either of the methods. Denmark has statistically significant cumulative average abnormal returns at days –10 to 10 in both methods and Norway in method II on CAAR periods of 0 to 1 days and –10 to 10 days. The actual event date has statistically significant abnormal returns only in Swedish markets but the prior day to the event is statistically significant also in Denmark and Norway.

In Swedish markets the market reacts the most accurate to the downgrades compared to other Nordic markets. There are no statistically significant event window days after the event date and the event date is statistically significant in both methods. This can be effected by the fact that the most observations are from rated companies listen in the Stockholm Stock Exchange and therefore single abnormal returns of one observations do not disturb the sample as much as they could in other country samples with less observations.

Timely the most accurate downgrade announcements of companies listed in Sweden can also be affected by the fact that CRAs all have an office in Stockholm and that these offices are the only ones in the Nordic countries. Due to this CRAs a likely to have better, local knowledge about Swedish stock markets and therefore they are able to take credit rating actions faster.

However, in Sweden also the day preceding the event date is statistically significant, but with smaller significance level than in Denmark and in Norway. This indicates than whatever triggered the credit rating change to be published, is known by the markets or at least by some of its parties a day before the publication is made. This raises a question whether or not the credit rating change is announced though some channels before the public announcement. Other possibility is also that the credit ratings are truly triggered by other publicly known events more than the credit rating agencies admit them to be.

Now, the differences in the returns of each Nordic country are described in the Figure 9 and later the differences in cumulative average abnormal returns in the Figure 10.

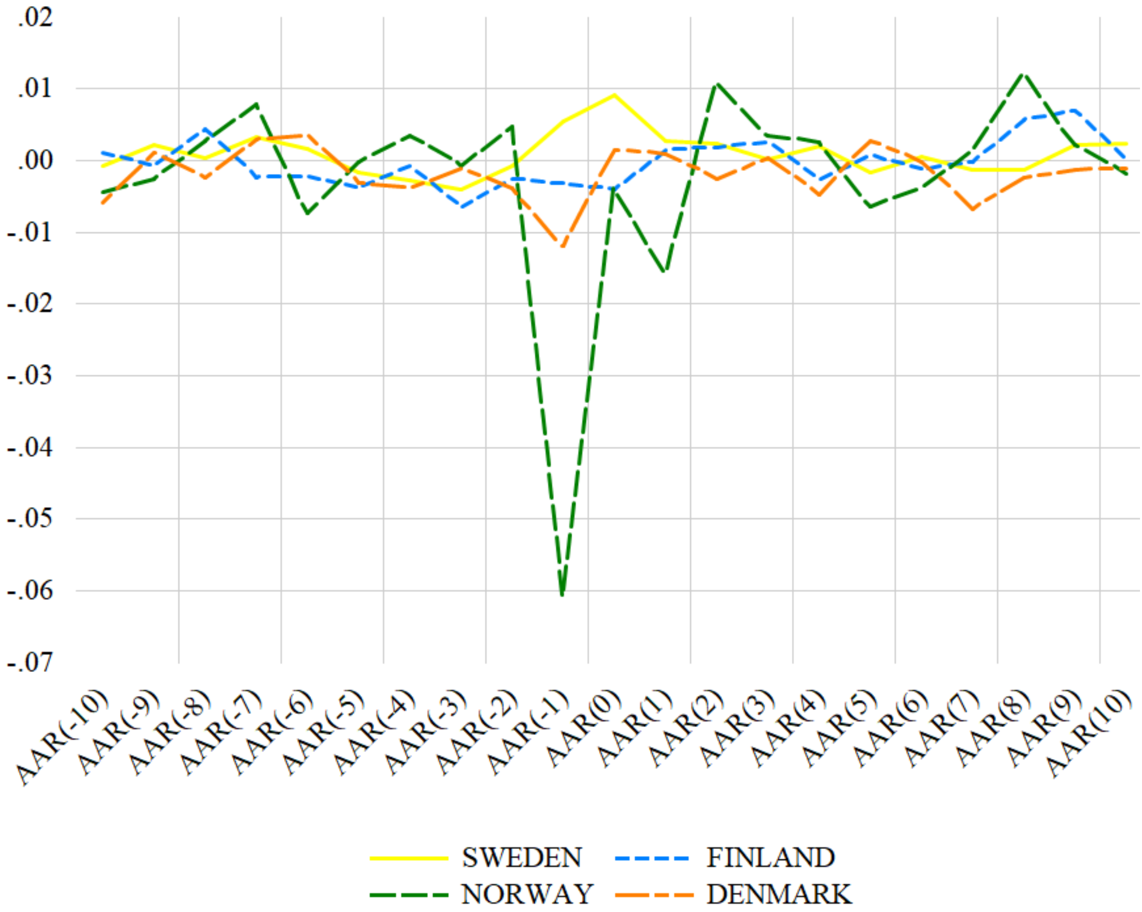

Figure 9: Daily average abnormal returns of each Nordic country

The Figure 9 shows that the returns of companies listed in different Nordic countries do not react in the same manner in all countries. However, the overall return variation is rather small abnormal returns being between 0.01% and –0.01% during most days of the event window. These abnormal returns can be either positive or negative depending on the country where the company is listed, and which event window day is considered. Norway differs from other countries and the largest difference is the great dive in the returns on the day –1 prior to the event date when the returns are around –0.06%. On the same time, other countries have values around or less than –0.01%. Norway has more negative returns also on the day 1, but the difference between Norway and other countries is smaller at that point. Norway also has a couple of spikes on days 2 and 8, which do not occur in other countries. However, these large abnormal returns of Norway can be traced back to one observation from 2002, when Petroleum Geo-Services ASA had the abnormal returns of –1.17% on the day –1 and –0.23% on the day 1. Also, the spikes on days 2 and 8 are caused by this single observation with exceptionally large abnormal returns.

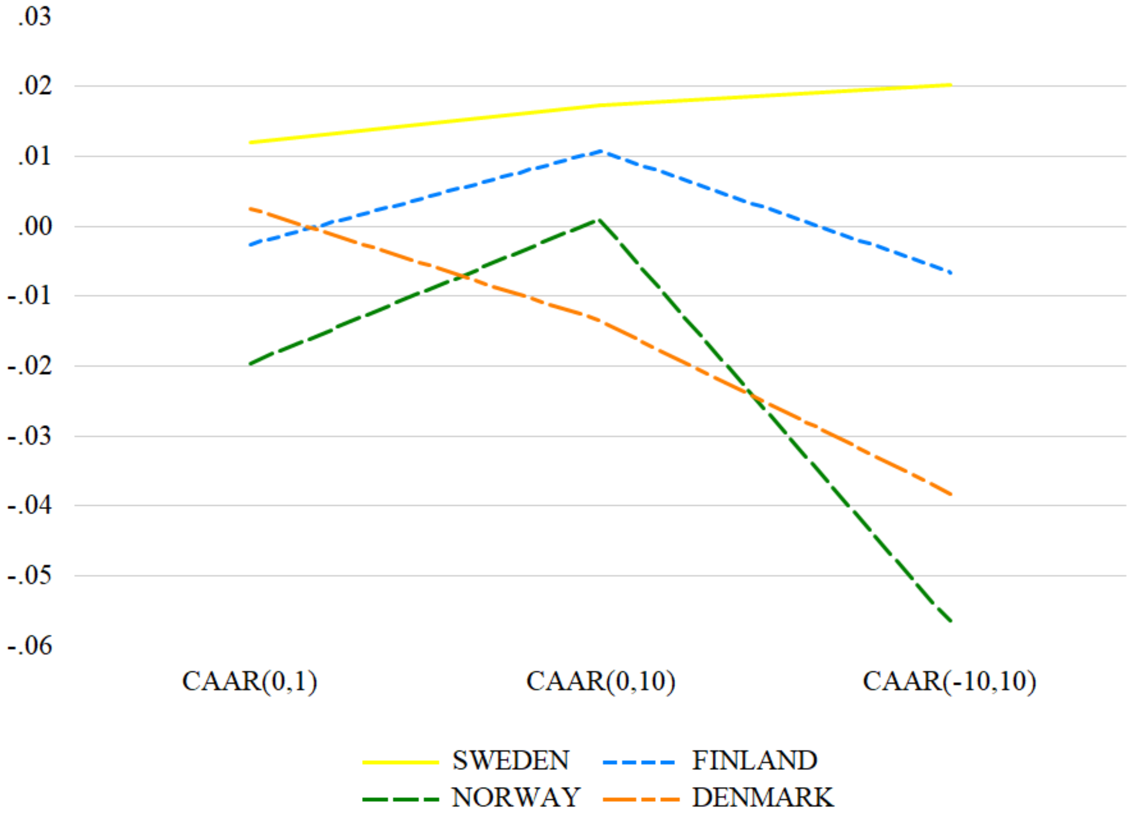

Figure 10: Cumulative abnormal returns by country

As seen in Figure 10, stocks listed in Stockholm Stock Exchange have positive cumulative average abnormal returns on all CAAR periods unlike any of the other countries observed. The returns vary between 0.01% and 0.02% and rise as the length of the CAAR period rises. Companies listed in Oslo Børs have the largest reaction to the credit rating downgrades in periods CAAR(0,1) and CAAR(–10,10). The cumulative average abnormal returns are negative in CAAR(0,1) by –0.02% and in CAAR(–10,10) by almost –0.06%. Only in CAAR(0,10) the average abnormal returns are around 0.00% and Denmark has more negative reaction in the CAAR period. Companies listed in Stockholm

Stock Exchange on the other hand react the most to the downgrades in CAAR(0,10) period, but the reaction is positive.

As presented earlier, the results from the full sample and results from each observed country differ. To receive more information about the stock return reaction during the credit rating downgrades, three subsamples are formed. These subsamples are non-banks and other financial institutions (also called non-banks), post Lehman Brothers bankruptcy (also called post Lehman) and investment origin observations.

The subsample of non-banks and other financial institutions consists of 95 event study observations and excludes observations especially from Denmark. In Denmark, 6 banks altogether have faced 24 downgrades between 2007 and the beginning of 2018 when for example only two banks in Finland have faced in total of three downgrades between 2009 and 2016. In some previous studies banks and other financial institutions have been excluded from the observations for example due to their different relationship with leverage, but since banks form the majority of observations from Denmark, excluding the banks and financial institutions would have overly narrowed the observations in this study. However, knowing this possible issue the subsample of non-banks and other financial institutions was formed to see how the exclusion of banks and financial institutions effects to the results.

When the banks and other financial institutions are excluded, the abnormal returns are statistically significant on the days –8 (with t-statistic of 2.09**) and 8 (with t-statistic of 1.92*) with the cross-sectional standard deviation method and statistically significant in the days –9 (with t-statistic of –1.89*), –8 (with t-statistic of 1.72*), –4 (with t-statistic of –3.16***), –1 (with t-statistic of –6.93***) and 8 (with t-statistic of 2.30**) with the sigma-based method. Cumulative abnormal returns are not statistically significant in any of the tested CAAR periods. With method I there were no statistically significant event window days in the full sample of 140. Without banks and other financial institutions, there are statistically significant abnormal returns also in the cross-sectional standard deviation method. In method II the only statistically significant days in common are days –4 and –1. The t-statistic is greater and more negative in the non-banks and other financial institutions sample for the day –4 with the higher significance level of 0.01. The significance level of 0.01 for the day –1 is common with the full sample.

The subsample named Post Lehman is formed from observations after the bankruptcy of Lehman Brothers and therefore consists of 92 event study observations after September 2009. This sample enables the examination of temporal differences in the stock return reaction between the full period and this subperiod. Dividing observations based of the Lehman Brothers bankruptcy has been used for example by Fieberg, Körner, Prokop and Varmaz (2015) and due to the financial crisis the credit rating agencies were forced to improve their own rating performance in order to regain reliability. Therefore, it is reasonable to divide the sample by this crisis, which caused strict demands for CRAs.

Using method I days –10, 0 and 3 are statistically significant with the 0.10 significance level. Using method II, the statistically significant days are –10, –6, –5 and –4. Regardless of the fact that most of the statistically significant days are prior to the event date, in both methods the only statistically significant period of cumulative abnormal returns is the CAAR(0,1) which does not include the days preceding the event date. In CAAR(0,1) the cumulative average abnormal returns are significant with the level 0.05.

The last subsample consists of the observations belonging to the investment grade before the downgrade. These 114 event study observations form a sample called investment origin. In this sample the cumulative average abnormal returns of the investment grade companies can be compared to the full sample and through these results the return effect of credit rating changes in higher ratings can be further examined. This sample has observations between the years 2001 and 2018, from the full time range of this study.

Using method I the day 7 is statistically significant with t-statistic of –1.92*. With method II days –3 (with t-statistic of –1.82*), –2 (with t-statistic of –2.00**), –1 (with t-statistic of –8.90***), 3 (with t-statistic of 1.66*) and 7 (with t-statistic of –1.64*) are statistically significant. In the full sample, only the day –1 with t-statistic of –7.33*** is commonly statistically significant than in the investment origin sample. Also, the subsample investment grade has the same statistically significant CAAR period of CAAR(–10,10) than the full sample.

The average abnormal returns of each sample are represented in the Figure 11.

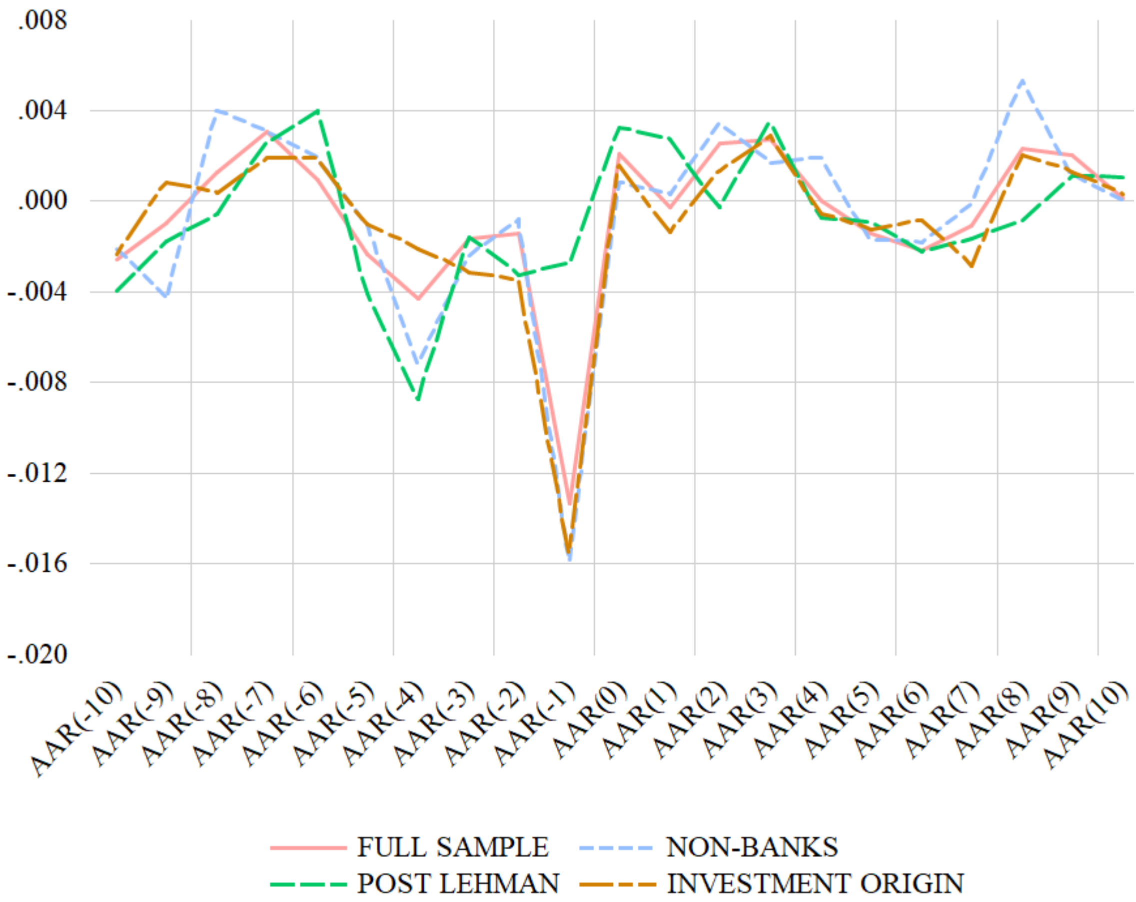

Figure 11: Average abnormal returns of each sample

Figure 11 gathers together the average abnormal returns of four samples: the full sample (n=140), the sample without banks and financial institutions (n=95), the post Lehman sample (n=92) and the sample with only investment grade observations (n=114).

As seen in Figure 11, the subsample of investment origin mainly matches the returns of the full sample, which is not surprising since a large part of the observations of the full sample are also represented in the investment origin sample. One remarkable finding in the Figure 11 is the dive in returns on the day –1 in all of the samples except in the post Lehman sample. This dive in the other samples is around –0.015%, when the average abnormal returns of the Post Lehman sample are –0.003%. After the bankruptcy of Lehman Brothers, the abnormal returns have not dived as they used to on the day –1. This can mean, that the information value of credit rating downgrades have increased after the Lehman Brothers' bankruptcy, since the statistically significant market reaction is linked to the downgrade.

A common feature is that in all samples the average abnormal returns are positive on the actual event date, but prior the event date there had been more negative average abnormal returns than after the event date. This negative trend in average abnormal returns on the days preceding the event date can also be detected from Figure 12.

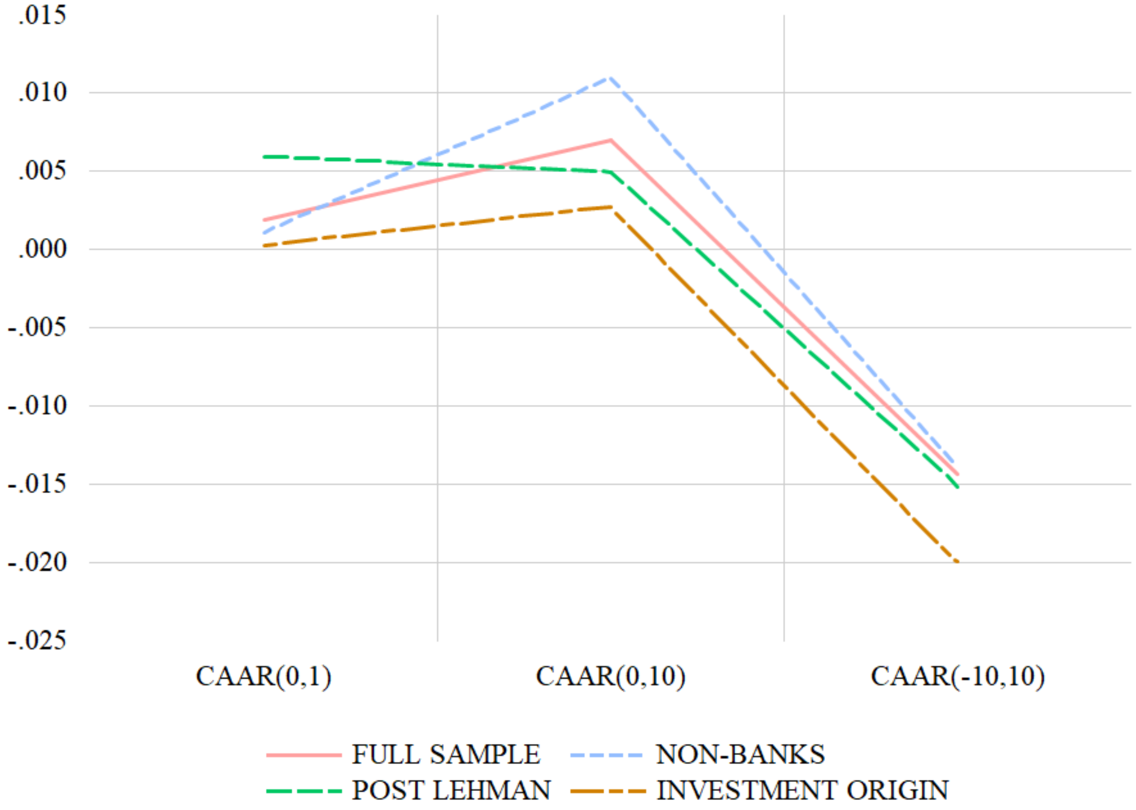

Figure 12: Cumulative average abnormal returns of the samples

Figure 12 presents the cumulative average abnormal returns of the full sample, the sample without banks and other financial institutions, the post Lehman sample and the sample with only investment grade origin observations.

In periods CAAR(0,1) and CAAR(0,10) the average abnormal returns are positive in all samples. In CAAR(0,1) post Lehman sample has the most positive cumulative average abnormal returns (0.006%), while the other samples have values close to 0.000%. In period CAAR(0,10) all other samples except Post Lehman have their largest positive values, and the sample with non-banks and financial institutions has the highest value of 0.011%. All the cumulative average abnormal returns are negative in period CAAR(–10,10) with values between –0.014% to –0.020%. The sample with only investment grade observations has the most negative cumulative average abnormal returns in all CAAR periods.

Table 9: Event study results of all samples

Table 9 presents the daily average abnormal returns and the t-statistics of the full sample, the sample of non-banks and financial institutions, the post Lehman sample and the investment grade sample. The methods used are a cross-sectional standard deviation test and a sigma test. The statistically significant p-values are denoted as follows: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

	Full Sample n=140			W/O Banks n=95			Post Lehman n=92			Investment Grade n=114		
Event window day	AAR	t–statistic (method I)	t–statistic (method II)	AAR	t–statistic (method I)	t–statistic (method II)	AAR	t–statistic (method I)	t–statistic (method II)	AAR	t–statistic (method I)	t–statistic (method II)
(–10)	–0.00	–1.45	–1.41	–0.00	–0.91	–0.90	–0.00	–1.77*	–1.85*	–0.00	–1.37	–1.34
(–9)	–0.00	–0.44	–0.53	–0.00	–1.50	–1.89*	–0.00	–0.77	–0.82	0.00	0.36	0.48
(–8)	0.00	0.79	0.70	0.00	2.09**	1.73*	–0.00	–0.27	–0.25	0.00	0.20	0.21
(–7)	0.00	1.42	1.70*	0.00	1.34	1.36	0.00	0.86	1.19	0.00	0.81	1.10
(–6)	0.00	0.46	0.52	0.00	0.81	0.83	0.00	1.37	1.85*	0.00	0.77	1.08
(–5)	–0.00	–1.15	–1.27	–0.00	–0.40	–0.44	–0.00	–1.48	–1.91*	–0.00	–0.52	–0.58
(–4)	–0.00	–1.14	–2.37**	–0.01	–1.38	–3.16***	–0.01	–1.58	–4.08***	–0.00	–0.73	–1.19
(–3)	–0.00	–0.66	–0.90	–0.00	–0.69	–1.05	–0.00	–0.64	–0.74	–0.00	–1.26	–1.82*
(–2)	–0.00	–0.65	–0.79	–0.00	–0.27	–0.36	–0.00	–1.17	–1.52	–0.00	–1.58	–2.00**
(–1)	–0.01	–1.50	–7.33***	–0.02	–1.21	–6.93***	–0.00	–0.82	–1.28	–0.02	–1.45	–8.90***
(0)	0.00	1.06	1.16	0.00	0.31	0.34	0.00	1.68*	1.51	0.00	0.92	0.91
(1)	–0.00	–0.11	–0.13	0.00	0.10	0.13	0.00	1.49	1.26	–0.00	–0.53	–0.77
(2)	0.00	1.32	1.40	0.00	1.33	1.50	–0.00	–0.13	–0.12	0.00	0.78	0.79
(3)	0.00	1.53	1.48	–0.00	0.79	0.76	0.00	1.65*	1.64	0.00	1.58	1.66*
(4)	0.00	0.00	0.00	–0.00	1.12	0.82	–0.00	–0.39	–0.34	–0.00	–0.32	–0.31
(5)	–0.00	–0.72	–0.78	–0.00	–0.62	–0.73	–0.00	–0.38	–0.46	–0.00	–0.76	–0.70
(6)	–0.00	–1.08	–1.19	–0.00	–0.63	–0.77	–0.00	–0.83	–1.04	–0.00	–0.49	–0.47
(7)	–0.00	–0.71	–0.60	–0.00	–0.07	–0.05	–0.00	–0.78	–0.76	–0.00	–1.92*	–1.64*
(8)	0.00	1.17	1.27	–0.01	1.92*	2.30**	–0.00	–0.41	–0.39	0.00	1.02	1.16
(9)	0.00	1.44	1.12	–0.00	0.66	0.51	0.00	0.73	0.52	0.00	0.83	0.74
(10)	0.00	0.09	0.09	–0.00	–0.01	–0.01	0.00	0.58	0.49	0.00	0.16	0.18
	CAAR	t–statistic (method I)	t–statistic (method II)	CAAR	t–statistic (method I)	t–statistic (method II)	CAAR	t–statistic (method I)	t–statistic (method II)	CAAR	t–statistic (method I)	t–statistic (method II)
CAAR(0,1)	0.00	0.57	0.78	0.00	0.25	0.34	0.01	2.35**	1.96**	0.00	0.07	0.10
CAAR(0,10)	0.01	1.04	1.24	0.01	1.29	1.45	0.00	0.70	0.69	0.00	0.38	0.47
CAAR(–10,10)	–0.01	–0.86	–1.84*	–0.01	–0.59	–1.31	–0.02	–1.35	–1.55	–0.02	–1.05	–2.51**

Table 9 gathers together all the average abnormal returns and cumulative average abnormal returns of the samples presented. From Table 9 we can observe that day –1 is statistically significant at the 0.01 level in the full sample, in the sample of non-banks and financial institutions and in the investment origin sample. Only in the post Lehman sample the day –1 is not statistically significant in either of the methods. However, the event day 0 is statistically significant only in the Post Lehman sample. From this reaction we can conclude, that after the bankruptcy of Lehman Brothers the statistically significant stock return reaction actually occurs on the event date, not the day or several days before as in the other samples. However, the abnormal returns are negative on the days prior the event date and since the reaction is positive on the actual event date, can be concluded that the market has still anticipated the coming downgrade, but have not known when the downgrade will occur. This resulted no significant negative returns on the day –1 but significant positive returns on the event day 0 when the anticipated downgrade had occurred.

5.3 Regression results

To estimate the model $g_i = b_0 + b_1 PRE_{LEHMAN} + b_2 FALLEN_{ANGEL} + b_3 GRADES_{DOWN} + b_4 INV_{ORIG} + b_5 NEG_{OUTLOOK} + b_6 NEG_{WATCH} + b_7 LEV + b_8 LN_{SIZE} + b_9 NORWAY + b_{10} DENMARD + b_{11} FINLAND + \varepsilon_i$, the OSL regressions of each CAAR period were run with eViews using Huber-White errors. The regression results are presented in Table 10 where the Ordinary Least Square (OLS) coefficients and t-statistics of the parameters are gathered.

Table 10: Coefficients and t-statistics of the CAAR periods

Table 10 presents the coefficients and *t*-statistics of each CAAR period. The statistically significant *p*-values are denoted as follows: **p* < 0.10, ***p* <0.05, ****p* <0.01. Sample size *N* is 112 in all periods.

	CAAR(0,1)		CAAR(0,10)		CAAR(−10,10)	
	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic
PRE_LEHMAN	-0.01	-0.57	-0.00	-0.19	-0.03	-0.68
FALLEN_ANGEL	-0.04	-1.06	-0.03	-0.48	-0.24	-1.08
GRADES_DOWN	-0.02	-1.16	-0.04	-1.01	-0.15	-1.26
INV_ORIG	-0.01	-0.85	-0.04	-1.59	-0.08	-1.78*
LEV	0.02	1.45	0.01	0.44	0.06	1.03
LN_SIZE	0.00	0.36	0.00	0.70	0.00	0.57
NEG_OUTLOOK	0.00	0.33	0.01	0.46	0.01	0.20
NEG_WATCH	0.01	-1.23	0.04	2.17*	0.08	1.82*
NORWAY	-0.02	-1.38	0.01	0.52	-0.01	-0.17
DENMARK	-0.01	-1.12	-0.02	-1.04	-0.03	-0.93
FINLAND	-0.01	-1.24	-0.01	-0.49	-0.00	-0.01
Adjusted R-squared	0.08		0.05		0.13	

Overall, very few variables are statistically significant. Few exceptions are variables INV_ORIG and NEG_WATCH. Within investment grade a downgrade has a statistically significant negative impact to the cumulative abnormal returns on CAAR(–10,10). In all the CAAR periods this effect of the variable INV_ORIG is negative, although significant only on the longest CAAR calculated from the days –10 to 10. This effect is significant with the level 0.10 and its *t*-statistic is –1.69. This signifies, that among investment grade, the downgrade announcements are more significant events than within the non-investment grade, and the markets react more negatively (–0.08 in CAAR(–10,10)) to the downgrades made to investment grade companies than to non-investment grade companies.

The variable NEG_WATCH has a positive effect to the cumulative abnormal returns in all CAAR periods and statistically significant this positive effect is in CAAR(0,10) and CAAR(–10,10). The reaction is significant in both CAAR periods with the level 0.10 and *t*-statistics are 2.17 and 1.82 meaning that the cumulative abnormal returns (0.04 in

CAAR(0,10) and 0.08 in CAAR(–10,10)) are higher when the negative watch listing has preceded the downgrade.

Overall, the variables PRE_LEHMAN, FALLEN_ANGEL, GRADES_DOWN and INV_ORIG have a negative impact to the cumulative average abnormal returns. Since the variable PRE_LEHMAN has a negative coefficient, it signifies that credit rating downgrades caused greater negative stock returns before the bankruptcy of Lehman Brothers than after the bankruptcy. This result can be interpreted as improved market efficiency. Since the reaction at the markets is later smaller, it means that the markets had more information about the deterioration of the financial conditions of the rated company prior to the downgrade. Later this conclusion is supported by the results of the Post Lehman sample.

The regression results also suggested that a downgrade larger than one step causes greater negative abnormal returns compared to downgrades of one step. In these cases, the reaction is stronger due to the magnitude of the negative news. If investors have anticipated the negative news, the volume of the rating change may still surprise them, which causes a larger negative reaction to the downgrades of more than one step.

Falling from the investment grade to the non-investment grade can be considered to be a greater negative information than a regular downgrade and therefore it causes greater negative abnormal returns. Also, stock returns of companies in the investment grade face greater negative abnormal returns in cases of downgrades than companies in the non-investment grade. This step from investment grade to speculative grade can also be seen as a "larger downgrade" than a regular fall and therefore stock return reaction is also larger.

Variables LEV, LN_SIZE, NEG_WATCH and NEG_OUTLOOK have a positive impact to the cumulative abnormal returns. The positive stock returns effect of NEG_WATCH and NEG_OUTLOOK can be explained by the warning effect these announcements have. When a downgrade occurs, the returns turn positive when the expected event finally happens. A larger market capitalization expressed with the variable LN_SIZE effects positively to the returns, indicating that the larger the rated company is, the more unlikely it is to face a bankruptcy. Therefore, the reaction to downgrades is positive towards companies with a smaller market capitalization. Also, the level of leverage effects positively to the returns, which is rather surprising but can be explained for example by the signaling theory or the decreasing overall costs of capital, when the amount of debt financing increases.

Then, regression results of the subsamples have some similarities but also differences compared the results of the full sample of 112 observations. When banks and other financial institutions are excluded, also the statistically significant independent variables change as seen in Table 11.

Table 11: Regression results without banks and other financial institutions

Table 11 presents the coefficients and *t*-statistics for each CAAR period without banks and other financial institutions. The statistically significant *p*-values are denoted as follows: *p < 0.10, **p <0.05, ***p <0.01. The sample size is 67 observations.

	CAAR(0,1)		CAAR(0,10)		CAAR(−10,10)	
	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic
PRE_LEHMAN	0.00	0.15	0.01	0.84	0.02	0.79
FALLEN_ANGEL	-0.00	-0.03	0.05	1.27	0.04	0.89
GRADES_DOWN	-0.02	-1.86*	0.02	0.77	-0.03	-1.18
INV_ORIG	-0.01	-0.84	-0.04	-2.02**	-0.07	-1.81*
LEV	0.03	1.94*	-0.02	-0.57	0.03	0.48
LN_SIZE	0.00	0.09	0.00	1.01	0.00	0.24
NEG_OUTLOOK	-0.01	-1.22	0.01	0.53	0.00	0.13
NEG_WATCH	0.01	0.86	0.04	1.77*	0.07	-1.62
NORWAY	0.00	0.04	0.01	0.38	0.03	0.81
DENMARK	-0.00	-0.37	-0.00	-0.05	-0.05	-1.41
FINLAND	-0.02	-1.92*	-0.03	-1.45	-0.06	-1.68*
Adjusted R-squared	0.05		0.08		0.10	

In the non-banks and other financial institutions sample there are numerous statistically significant variables of which two are significant in more than one CAAR period. Being listed in Helsinki Stock Exchange has a negative impact between –0.02 and –0.06 to cumulative abnormal returns when the listed company is downgraded compared to companies listed in Stockholm Stock Exchange. This negative effect is significant at the level 0.10 in CAAR(0,1) and CAAR(–10,10). Also the variable INV_ORIG is statistically significant in CAAR(0,10) and CAAR(–10,10) periods with *t*-statistics of –2.02** and –1.81*. In all periods the belonging originally to the investment grade has a negative impact to the cumulative abnormal returns.

INV_ORIG and NEG_WATCH are statistically significant variables common with the full sample. NEG_WATCH is statistically significant in CAAR(0,10) on the significance level 0.10 and *t*-statistics of 1.77. The impacts also point to the same directions. In the sample of non-banks and other financial institutions, also LEV and GRADES_DOWN have a statistically significant values 1.94* and –1.86* in CAAR(0,1). Leverage effect positively to the cumulative abnormal returns in CAAR(0,1) and CAAR(–10,10) but negatively in the mid-CAAR. Also GRADES_DOWN effects differently in the mid-CAAR period, where the effect is positive when it otherwise has been negative.

This denotes, that after the day 1, markets react differently to the level of leverage and to the larger downgrades than right before, during and after the event date. This could be explained for example through the behavior of smaller investors, who do not follow the markets on daily basis and take investing actions with a lack. Therefore, for example many sudden selling bids can cause a negative effect on the returns of some indebted company few days later than when the downgrade has been announced. However, the returns of the asset can also be more positive few days after the event date, if for example the returns have decreased before or during the event date and start to recover few days later. This could explain why downgraded companies with more than one step have positive returns in mid-CAAR.

The regression results of the post Lehman sample are presented in Table 12.

Table 12: Regression results of the post Lehman sample

Table 12 presents the coefficients and *t*-statistics for each CAAR period of the Post Lehman sample. The statistically significant *p*-values are denoted as follows: $*p < 0.10$, $**p < 0.05$, $***p < 0.01$. The sample size is 73 in all periods.

	CAAR(0,1)		CAAR(0,10)		CAAR(−10,10)	
	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic
FALLEN_ANGEL	0.02	1.40	0.07	1.76*	0.05	0.79
GRADES_DOWN	0.01	1.51	0.01	0.74	0.03	0.81
INV_ORIG	0.01	0.95	-0.03	-1.00	-0.07	-1.51
LEV	0.01	0.54	-0.02	-0.64	0.05	0.85
LN_SIZE	-0.00	-0.34	0.00	0.97	0.00	0.68
NEG_OUTLOOK	0.00	0.42	-0.00	-0.03	-0.03	-1.04
NEG_WATCH	-0.01	-1.04	0.01	0.50	0.01	0.49
NORWAY	-0.00	-0.39	0.07	2.04**	0.08	1.67*
DENMARK	-0.01	-1.31	-0.02	-0.80	-0.06	-2.13**
FINLAND	-0.00	-0.69	-0.02	-0.85	-0.03	-0.82
Adjusted R-squared	-0.04		0.14		0.11	

In the post Lehman sample there are more statistically significant variables than in the full sample. In CAAR(0,10) there are two statistically significant variables, FALLEN_ANGEL (with the *t*-statistic of 1.76*) and NORWAY (with the *t*-statistic of 2.04**). In CAAR(–10,10) period, NORWAY (with the *t*-statistic of 1.67*) and DENMARK (with the *t*-statistic of –2.13**) are statistically significant variables. However, none of these statistically significant variables are common with the full sample regression results. The fact that the country dummies become statistically significant, can largely be effected by the smaller size of the sample. According to these results, the market where the rated company is listed affects to the average abnormal returns especially before and after the event date. Being listed in Danish or Finnish markets effects negatively to the returns compared to the Swedish market and being listed in Norwegian market effects mostly positively to the returns. These differences become statistically significant on the longer CAAR periods. Sweden in event study results had no statistically significant event window days after the event day but for example Norway and Denmark had. This can explain why the differences between listing places are more visible in the longer CAAR periods and also why the country dummies turn significant in some samples.

Interesting feature in this sample is, that the sample is the only one where GRADES_DOWN effects positively to the results in all CAAR periods unlike in any other samples. This can be interpret that after the bankruptcy of the Lehman Brothers, the downgrades greater than one step are seen as a positive sign. Investors are still interested about the downgraded company, possible due to the higher premiums the higher riskiness requires.

On top of the positive attitude towards larger downgrades, the post Lehman sample is also the only sample where the variable NEG_WATCH has a negative effect to the cumulative abnormal returns, even though the negative reaction occurs only in the CAAR(0,1) period. Here, the preceding negative watch listing has possibly not functioned as a warning sign for the possible downgrade, and the negative watch listing increases momentarily the negative effect of the downgrade announcement.

The regression results of the investment origin sample are represented in Table 13.

Table 13: Regression results of the investment origin sample

Table 13 presents the coefficients and *t*-statistics for each CAAR period of the investment origin sample. The statistically significant *p*-values are denoted as follows: **p* < 0.10, ***p* <0.05, ****p* <0.01. The sample size is 93 in all periods.

	CAAR(0,1)		CAAR(0,10)		CAAR(−10,10)	
	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic	Coefficient	*t*-Statistic
PRE_LEHMAN	-0.01	-1.13	-0.01	-0.59	-0.05	-0.99
FALLEN_ANGEL	-0.04	-1.11	-0.05	-0.65	-0.27	-1.18
GRADES_DOWN	-0.02	-0.99	-0.05	-1.17	-0.17	-1.33
LEV	0.02	1.21	0.01	0.18	0.05	0.89
LN_SIZE	-0.00	-0.29	-0.00	-0.51	-0.00	-0.77
NEG_OUTLOOK	0.01	0.90	0.02	1.04	0.02	0.62
NEG_WATCH	0.01	1.17	0.03	1.82*	0.07	1.50
NORWAY	-0.02	-1.57	0.01	0.49	-0.02	-0.26
DENMARK	-0.01	-1.16	-0.02	-0.91	-0.04	-1.06
FINLAND	-0.00	-0.25	0.02	1.02	0.06	0.99
Adjusted R-squared	0.10		0.03		0.13	

From all the CAAR periods only the variable NEG_WATCH in statistically significant on the level 0.10 at CAAR(0,10) period. Overall the results are similar to the full sample. As in the full sample, the variables PRE_LEHMAN, FALLEN_ANGEL and GRADES_DOWN have a negative impact to the cumulative abnormal returns in all CAAR periods. The variables LN_SIZE, NEG_OUTLOOK and NEG_WATCH have a positive impact to the cumulative abnormal returns at all CAAR periods. Among country variables the impact to the cumulative average abnormal returns is more negative in CAAR(0,1) than the reaction is with listed companies in Sweden, but on longer CAAR periods the impact can be either negative or positive compared to Sweden.

5.4 Robustness analysis

The robustness of this study is tested with different subsamples. As seen from the event study and the regression analysis results, the results vary between the samples. For example, the results in the Post Lehman sample differ from the full sample results indicating that the results change over time. Also, the results vary between the full sample and the sample of non-banks and financial institutions meaning that there is no robustness between the business sectors.

Table 9 compared the event study results of the different samples and it demonstrates well that there are statistically significant days such as –4 and 8, which are most likely affected by single observations with huge abnormal returns. These unusually large returns on some days in event window can be caused by numerous reasons, most likely other events and announcements on the markets. For example, financial statement releases and interim reports can affect to the market returns of this study if the releases are published near the credit rating announcements. These news can cause abnormal returns in the event window not provoked by the credit rating change. Also profit warnings, merger announcements, splits and other announcements can increase or decrease the abnormal returns in the event window on other days than on the event date.

Large possible long-lasting events on the markets can also disturb the values in the estimation window, of which the normal returns are counted. If the normal returns are corrupted, it automatically effects to the abnormal returns on the event window, which can also lead to disturbed cumulative abnormal returns. The possible disturbed normal and abnormal returns in this study has not been prevented, but the CAAR periods of different lengths allow the examination of different parts of the event window. The shorter the CAAR period is, the smaller change there is for other events to occur simultaneously to the credit rating downgrade.

6 SUMMARY AND CONCLUSIONS

6.1 Research summary and conclusions

In this study the role of credit rating agencies was examined focusing on new information they provide to the markets and more specifically, does this information cause abnormal returns in the Nordic markets. The information to the markets is provided in the form of credit rating announcements and since markets tend to react more to the negative news, the credit rating downgrades were examined due to negative information the downgrade announcements provide.

The results show that in the Nordic countries credit rating downgrades are associated with abnormal returns. However, the negative abnormal returns cannot be declared to be caused by the credit rating downgrades, since they mostly occur before the downgrade announcements. The full sample showed statistically significant abnormal returns on days prior to the event date and also the cumulative abnormal returns are statistically significant only in the longest CAAR period, which includes the previous event window days. These cumulative average abnormal returns were –0.01%, when the cumulative average abnormal returns after the event day were positive. Therefore, the most significant abnormal returns occur prior to the actual event date indicating that the negative information begins to incorporate to the stock returns before the actual downgrade announcement. This denotes that in the most Nordic countries there is still a lag between the occurrence of the deteriorated financial conditions of a rated company and the publication of a credit rating downgrade announcement.

The credit rating downgrades are especially associated with the abnormal returns in Sweden, where the abnormal returns are however unexpectedly positive on days –1 and 0. Companies listed in Stockholm Stock Exchange show statistically significant abnormal returns on day –1 and on the event day and also all the CAAR periods are statistically significant. Also, when excluding the days –1 and 0, no other statistically significant event window days occur. This shows that the market reaction around credit rating downgrades is the strongest in Sweden when compared to the other Nordic countries. Sweden is also the only one of the studied countries, where the event day shows statistically significant positive abnormal returns, but also with companies listed in Sweden, the significant reaction started a day earlier, on day –1. In Sweden, Norway and Denmark statistically significant abnormal returns occur on day –1 and excluding Sweden, not on the actual event day 0. This could mean, that the knowledge about the upcoming downgrade has leaked to the markets or at least some of its participants a day earlier, or that the credit rating downgrades are actually triggered by the other events on the markets more than the credit rating agencies admit them to be.

However, the average abnormal returns of the day –1 were not statistically significant in the post Lehman sample. The sample showed slightly negative average abnormal returns on the days –5 to –1 before the event date and on the event date the returns then turned statistically significantly positive. This indices, that since the bankruptcy of Lehman Brothers the significant market effect has occurred on the actual event day even though the upcoming negative information has been anticipated by the markets beforehand. Solely the timing of the downgrade has been unclear, which indicates that the downgrades have not leaked or been provoked by other events as clearly as they possibly were before the bankruptcy of Lehman Brothers.

A remarkable finding in the regression results is that preceding negative outlooks and negative watches affect the abnormal returns positively. The reaction is strong enough for the variable describing preceding negative watch listings to be the only variable significant in two CAAR periods in the full sample regression results. The possible explanation for why this independent variable is associated with positive abnormal returns can be found from the previous studies (e.g. Li et al. 2004). When a negative watch listing is announced, the markets at some level prepare to the credit rating downgrade and the negative impact is already converted into to stock prices before the downgrade. When the downgrade later occurs, the cumulative abnormal returns turn positive since the returns no longer “wait” for the bad news to be released.

The other interesting finding is that the firms in the investment grade face more negative abnormal returns during downgrades. The difference is the greatest in the longest CAAR period but also the regression results of the full sample show that the variable describing firms in the investment grade is statistically significant with a negative impact to the cumulative abnormal returns.

The key findings of this study in the form of conclusions for hypotheses are gathered in Table 14.

Table 14: Summary of key findings

	Hypothesis	Empirical Evidence	Conclusion
H1	Credit rating downgrades cause negative abnormal stock returns at Nordic markets on the event date and shortly after.	Since CAAR(0,1) is zero and CAAR(0,10) is positive, can be said that the credit rating downgrades do not have a negative effect to the abnormal returns during and after the event date.	Rejected
H2	Abnormal returns are less negative when a negative watch has been given prior to the rating change.	Regression analysis shows that NEG_WATCH effects positively to the cumulative abnormal returns and statistically significant this reaction is in CAAR(0,10) and CAAR(–10,10) periods.	Accepted
H3	A downgrade to the speculative grade from investment grade has a negative effect to the abnormal returns.	Regression analysis of all samples shows the variable FALLEN_ANGEL to have a negative impact to the cumulative abnormal returns.	Accepted
H4	The negative abnormal returns are greater, when the downgraded firm belongs to the investment grade than when it belongs to the non-investment grade.	The investment grade sample has more negative cumulative average abnormal returns than the full sample indicating that the downgrade among investment grade causes larger negative abnormal returns.	Accepted
H5	Increase in the level of leverage effects negatively to the abnormal returns.	Regression analysis shows that the increse in debt effect positively to the abnormal returns.	Rejected

The event study results show statistically significant abnormal returns around the announcement of a credit rating downgrade and therefore hypothesis 1 is accepted. However, the negative cumulative abnormal returns occur on days prior to the event day, and therefore are not caused by a credit rating downgrade. The negative cumulative average abnormal returns are significant when calculated from the event window days –10 to 10.

The regression analysis results show, that abnormal returns are less negative when a negative watch or negative outlook has been listed prior to the credit rating downgrade. In fact, the impact of the previous negative watch listing is positive to the cumulative abnormal returns and hence hypothesis 2 is accepted. Also, hypotheses 3 and 4 are accepted since downgrading from investment grade as well as downgrading among the investment grade are associated with a negative impact to the cumulative abnormal returns. Also, the sample including only investment origin observations has more negative cumulative abnormal returns than the full sample.

The hypothesis 5 is rejected since unlike expected, the increase in leverage did not affect the cumulative abnormal returns negatively, instead the impact was positive. The larger amount of debt was seen as a positive sign at markets during the downgrade, which could be explained by Ross' (1977) theories. A larger level of leverage decreases the overall cost of capital, which increases the stock price. Adding debt when financing is available with better terms can also inspire investors' confidence, since it signals that the management of the rated firm feels confident about the future enough to add to the level of leverage despite the downgrade.

6.2 Limitations for the thesis

The major limitations concerning this study mostly relates to the limited observations. Purchasing credit ratings from CRAs is a rather new trend in Nordic listed countries, and therefore not all rated companies have yet faced a downgrade. Limited amount of downgrade observations for example distorts the results of the event study by country. Norway has only 24 credit rating downgrade observations and a single exceptionally abnormal observation can distort the cumulative average abnormal returns calculated from companies listed is Oslo Børs as can be seen from the event study results.

The overall research sample consist of 140 observations, however not all of the observations could not be used in the regression analysis. Lack of prior events from Fitch and some S&P's downgrades, limited the data in regression analysis, thus limiting the observations in all the samples. On top of the lack of the prior events, for example only 9 observations included a fall from the investment grade to the speculative grade and therefore the results of the these *fallen angels* can hardly be generalized.

6.3 Suggestions for further research

Since more and more Nordic listed firms have purchased credit ratings recently, after a few years there will be a larger amount of credit rating downgrades obtainable in the Nordic markets. With a greater amount of credit rating downgrades, the results can be more precise and will better represent the stock market reaction to credit rating announcements. With the current results, single observations seem to have too much weight, because of some unexplained statistically significant event window days and the fact that the results largely differ between the samples and countries.

Also, the other external events possibly affecting the price formation have not been examined in this research. By removing or otherwise controlling the contaminated events, the results could capture the abnormal returns better and possible avoid unexplained statistically significant event window days.

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APPENDIX

Appendix 1: List of observations

Issuer	Country	Date	CAAR (0,1)	CAAR (0,10)	CAAR (−10,10)	CRA	Original rating	Followed rating
PETROLEUM GEO SERVICES ASA	Norway	19.1.2001	-0,06	0,02	-0,36	S&P	BBB	BBB-
METSA BOARD OYJ	Finland	27.6.2001	0,02	0,01	-0,07	S&P	BBB	BBB-
TELENOR ASA	Norway	25.9.2001	-0,04	0,02	0,40	S&P	A	A-
PETROLEUM GEO SERVICES ASA	Norway	31.7.2002	-0,29	-0,50	-1,87	S&P	BBB-	BB-
STOREBRAND ASA	Norway	21.8.2002	0,03	0,05	0,18	S&P	BBB	BBB-
METSO OYJ	Finland	26.11.2002	0,03	0,05	0,16	S&P	BBB+	BBB
ELISA OYJ	Finland	13.3.2003	-0,04	0,09	-0,06	Moody's	A3	Baa2
STOREBRAND ASA	Norway	2.5.2003	-0,01	-0,03	-0,10	Moody's	Baa1	Baa3
UPM-KYMMENE OYJ	Finland	16.5.2003	0,00	-0,01	-0,07	S&P	BBB+	BBB
METSO OYJ	Finland	23.6.2003	-0,02	0,07	0,05	Moody's	Baa2	Baa3
SAS AB	Sweden	23.6.2003	-0,01	0,10	0,13	Moody's	Ba2	B1
PETROLEUM GEO SERVICES ASA	Norway	30.7.2003	-0,10	-0,14	-0,09	S&P	CC	D
METSA BOARD OYJ	Finland	17.12.2003	-0,03	0,05	-0,05	S&P	BBB-	BB+
ELISA OYJ	Finland	22.12.2003	-0,01	-0,05	-0,05	S&P	A-	BBB+
METSO OYJ	Finland	17.2.2004	-0,02	-0,07	-0,06	Moody's	Baa3	Ba1
SAS AB	Sweden	27.5.2004	0,02	0,01	-0,01	Moody's	B1	B2
SECURITAS AB	Sweden	3.8.2004	0,06	0,12	0,12	Moody's	Baa1	Baa2
METSA BOARD OYJ	Finland	4.3.2005	-0,04	-0,03	0,02	S&P	BB+	BB
SAS AB	Sweden	25.5.2005	0,01	0,03	0,01	Moody's	B2	B3
TELIA COMPANY AB	Sweden	28.10.2005	-0,03	-0,01	0,05	S&P	A	A-
METSA BOARD OYJ	Finland	8.2.2006	0,01	0,06	0,05	S&P	BB	BB-
STORA ENSO OYJ	Finland	23.2.2006	0,01	0,06	0,11	S&P	BBB+	BBB
COPENHAGEN AIRPORTS A/S	Denmark	4.4.2006	0,01	0,02	0,05	S&P	A	BBB+
NORSK HYDRO ASA	Norway	2.6.2006	0,01	0,01	0,01	S&P	A	A-
TELENOR ASA	Norway	1.8.2006	0,02	0,01	0,04	S&P	NR / A-	BBB+
METSA BOARD OYJ	Finland	4.8.2006	-0,02	-0,02	-0,13	S&P	BB-	B+
SWEDISH MATCH AB	Sweden	9.10.2006	0,00	-0,08	-0,08	S&P	A-	BBB+
SVENSKA CELLULOSA SCA AB	Sweden	17.10.2006	0,01	-0,01	-0,05	S&P	A-	BBB+
ELECTROLUX AB	Sweden	27.10.2006	0,03	0,06	0,08	Fitch	BBB+	BBB
METSA BOARD OYJ	Finland	21.3.2007	-0,02	-0,05	-0,01	S&P	B+	B
DANSKE BANK A/S	Denmark	10.4.2007	0,00	0,00	-0,05	Moody's	Aaa	Aa1
JYSKE BANK A/S	Denmark	10.4.2007	-0,02	-0,03	-0,01	Moody's	Aa1	Aa2
NORDEA BANK AB	Sweden	10.4.2007	0,00	0,02	0,02	Moody's	Aaa	Aa1
SKANDINAVISKA ENSKILDA BANKEN AB	Sweden	10.4.2007	0,00	0,03	0,01	Moody's	Aa1	Aa2
SPAREBANK 1 SR BANK ASA	Norway	10.4.2007	-0,02	-0,04	0,01	Moody's	Aa2	Aa3
SYDBANK A/S	Denmark	10.4.2007	0,01	0,00	-0,04	Moody's	Aa2	Aa3
ASTRAZENECA PLC	Sweden	24.4.2007	-0,03	-0,02	-0,01	Fitch	AA+	AA
SSAB AB	Sweden	19.7.2007	0,04	0,03	-0,05	S&P	BBB+	BBB
NORSK HYDRO ASA	Norway	3.8.2007	0,00	0,02	0,03	S&P	A-	BBB
YARA INTERNATIONAL ASA	Norway	4.10.2007	0,02	0,09	0,17	S&P	BBB+	BBB
METSA BOARD OYJ	Finland	22.10.2007	0,02	0,02	0,01	S&P	B	B-
STORA ENSO OYJ	Finland	22.10.2007	0,01	0,01	-0,06	S&P	BBB	BBB-
SWEDISH MATCH AB	Sweden	25.10.2007	0,01	0,03	0,12	S&P	BBB+	BBB
UPM-KYMMENE OYJ	Finland	21.4.2008	-0,05	0,03	0,09	S&P	BBB	BBB-
SANDVIK AB	Sweden	20.5.2008	0,02	-0,02	0,03	S&P	A+	A
SWEDBANK AB	Sweden	27.6.2008	0,04	0,07	-0,01	Moody's	Aa1	Aa2
SAS AB	Sweden	22.7.2008	0,17	0,24	0,49	S&P	BB	BB-
STORA ENSO OYJ	Finland	28.7.2008	-0,04	0,20	0,27	Fitch	BBB-	BB+
INDUSTRIVARDEN AB	Sweden	21.11.2008	0,00	0,03	-0,05	S&P	A+	A
COPENHAGEN AIRPORTS A/S	Denmark	4.12.2008	0,02	0,07	0,11	S&P	BBB+	BBB
STOREBRAND ASA	Norway	15.12.2008	-0,02	0,22	0,33	S&P	BBB+	BBB
ELECTROLUX AB	Sweden	17.12.2008	0,02	-0,06	-0,08	S&P	BBB+	BBB
METSA BOARD OYJ	Finland	16.1.2009	-0,01	-0,13	-0,25	S&P	B-	CCC+
DANSKE BANK A/S	Denmark	5.2.2009	-0,07	-0,24	-0,30	S&P	AA-	A+
SKANDINAVISKA ENSKILDA BANKEN AB	Sweden	5.2.2009	0,11	-0,04	-0,01	S&P	A+	A

SAMPO OYJ	Finland	12.2.2009	-0,02	-0,04	-0,07	Moody's	Baa1	Baa2
VOLVO AB	Sweden	13.2.2009	0,00	-0,01	0,12	Moody's	A3	Baa1
JYSKE BANK A/S	Denmank	20.2.2009	-0,01	-0,10	-0,13	S&P	A+	A
SANDVIK AB	Sweden	2.3.2009	0,05	-0,03	-0,04	S&P	A	A-
SPAREBANK 1 SR BANK ASA	Norway	17.3.2009	0,02	0,20	0,15	Moody's	Aa3	A1
NORSK HYDRO ASA	Norway	18.3.2009	0,01	0,03	0,05	Moody's	Baa1	Baa2
UPM-KYMMENE OYJ	Finland	1.4.2009	0,05	0,13	0,07	S&P	BBB-	BB+
STORA ENSO OYJ	Finland	14.5.2009	0,02	0,00	0,01	S&P	BB+	BB
NOKIA OYJ	Finland	24.7.2009	0,00	-0,04	-0,19	Fitch	A+	A
SSAB AB	Sweden	30.7.2009	0,04	0,05	-0,04	S&P	BBB	BBB-
NORDEA BANK AB	Sweden	8.9.2009	0,00	-0,04	-0,04	Moody's	Aa1	Aa2
SPAR NORD BANK A/S	Denmank	8.9.2009	-0,01	-0,01	0,01	Moody's	A1	A2
SVENSKA HANDELSBANKEN AB	Sweden	8.9.2009	-0,01	-0,03	-0,03	Moody's	Aa1	Aa2
SYDBANK A/S	Denmank	8.9.2009	-0,02	-0,09	-0,14	Moody's	Aa3	A1
JYSKE BANK A/S	Denmank	8.9.2009	-0,04	-0,09	-0,12	Moody's	Aa2	A1
FORTUM OYJ	Finland	5.10.2009	0,01	-0,01	0,01	Fitch	A	A-
SAS AB	Sweden	6.11.2009	0,02	0,02	0,01	S&P	B	B-
HOLMEN AB	Sweden	9.12.2009	0,01	0,00	0,03	S&P	BBB+	BBB
DANSKE BANK A/S	Denmank	18.12.2009	0,03	-0,01	-0,08	S&P	A+	A
VOLVO AB	Sweden	8.2.2010	0,02	-0,03	0,00	Fitch	BBB	BBB-
UPM-KYMMENE OYJ	Finland	17.2.2010	-0,02	0,05	0,07	S&P	BB+	BB
COPENHAGEN AIRPORTS A/S	Denmank	25.2.2010	0,01	0,04	-0,02	S&P	BBB	BBB-
SANDVIK AB	Sweden	9.3.2010	0,01	0,04	0,03	S&P	A-	BBB
NOKIA OYJ	Finland	18.11.2010	-0,01	0,00	0,02	Fitch	A-	BBB+
SSAB AB	Sweden	6.12.2010	0,01	0,10	0,16	S&P	BBB-	BB+
BANKNORDIK P/F	Denmank	16.2.2011	0,01	0,07	-0,05	Moody's	A3	Baa1
DANSKE BANK A/S	Denmank	16.2.2011	-0,03	0,00	-0,15	Moody's	Aa3	A1
RINGKJOEBING LANDBOBANK A/S	Denmank	16.2.2011	0,01	-0,06	-0,07	Moody's	A1	A2
SPAR NORD BANK A/S	Denmank	16.2.2011	0,02	-0,08	-0,13	Moody's	A2	Baa1
JYSKE BANK A/S	Denmank	19.5.2011	-0,01	-0,04	-0,03	Moody's	A1	A2
SYDBANK A/S	Denmank	19.5.2011	0,00	-0,01	-0,05	Moody's	A1	A2
INDUSTRIVARDEN AB	Sweden	11.11.2011	0,00	0,03	0,04	S&P	A	A-
JYSKE BANK A/S	Denmank	1.12.2011	0,03	0,01	0,06	S&P	A	A-
AKASTOR ASA	Norway	14.12.2011	-0,03	-0,05	-0,09	Fitch	BBB-	BB+
DANSKE BANK A/S	Denmank	14.12.2011	0,03	0,05	-0,03	Fitch	A+	A
AKTIA BANK ABP	Finland	29.2.2012	0,03	-0,01	0,03	Moody's	A1	A3
NOKIA OYJ	Finland	2.3.2012	0,01	0,04	0,00	S&P	BBB	BBB-
NORDEA BANK AB	Sweden	24.5.2012	-0,01	0,03	0,03	Moody's	Aa2	Aa3
SVENSKA HANDELSBANKEN AB	Sweden	24.5.2012	-0,01	0,02	-0,01	Moody's	Aa2	Aa3
RINGKJOEBING LANDBOBANK A/S	Denmank	30.5.2012	0,00	-0,01	-0,02	Moody's	A3	Baa1
SPAR NORD BANK A/S	Denmank	30.5.2012	0,00	-0,01	0,01	Moody's	Baa2	Baa3
DANSKE BANK A/S	Denmank	30.5.2012	0,00	0,03	0,02	Moody's	A2	Baa1
JYSKE BANK A/S	Denmank	30.5.2012	0,03	0,00	0,06	Moody's	A2	Baa1
SYDBANK A/S	Denmank	30.5.2012	0,04	0,03	0,09	Moody's	A2	Baa1
STORA ENSO OYJ	Finland	26.7.2012	0,01	0,00	-0,08	Fitch	BB	BB-
SECURITAS AB	Sweden	17.8.2012	-0,01	-0,02	-0,07	S&P	BBB+	BBB
G4S PLC	Denmank	5.11.2012	0,04	-0,07	-0,06	S&P	BBB	BBB-
SONGA OFFSHORE SE	Norway	6.11.2012	0,01	-0,14	-0,40	S&P	B+	B
SAS AB	Sweden	19.11.2012	0,01	0,02	0,13	S&P	B-	CCC+
FORTUM OYJ	Finland	27.11.2012	0,01	0,02	0,01	S&P	A	A-
SPAREBANK 1 SR BANK ASA	Norway	6.12.2012	-0,02	-0,03	-0,05	Moody's	A1	A2
SPAR NORD BANK A/S	Denmank	6.3.2013	0,01	0,06	0,04	Moody's	Baa3	Ba1
NOKIA OYJ	Finland	5.7.2013	0,01	-0,07	-0,05	S&P	BB-	B+
AKASTOR ASA	Norway	22.7.2013	-0,01	0,00	0,06	Fitch	BB+	BB
SSAB AB	Sweden	27.9.2013	0,00	0,08	0,02	S&P	BB+	BB
AB SKF	Sweden	16.10.2013	-0,02	-0,03	-0,07	S&P	A-	BBB+
SONGA OFFSHORE SE	Norway	28.11.2013	0,00	0,06	-0,29	S&P	B-	CC
SANDVIK AB	Sweden	17.3.2014	-0,01	0,00	0,04	S&P	BBB+	BBB
SSAB AB	Sweden	19.5.2014	0,00	0,06	0,08	S&P	BB	BB-
ALFA LAVAL AB	Sweden	26.5.2014	0,00	0,00	0,00	S&P	A-	BBB+
TDC	Denmank	16.9.2014	0,00	0,02	-0,13	Moody's	Baa2	Baa3
PETROLEUM GEO SERVICES ASA	Norway	4.11.2014	0,08	0,18	0,04	S&P	BB	BB-
ELECTROLUX AB	Sweden	6.11.2014	0,00	-0,01	-0,01	S&P	BBB+	BBB
ASTRAZENECA PLC	Sweden	21.11.2014	-0,03	-0,03	-0,03	Fitch	AA-	A+
STOREBRAND ASA	Norway	17.12.2014	0,00	0,00	-0,10	Moody's	Baa3	Ba1
ASTRAZENECA PLC	Sweden	1.5.2015	0,01	0,00	-0,06	S&P	AA-	A+

AB SKF	Sweden	5.5.2015	0,01	-0,01	0,00	S&P	BBB+	BBB
FORTUM OYJ	Finland	28.5.2015	0,00	-0,01	-0,05	Moody's	A2	Baa1
STOREBRAND ASA	Norway	10.7.2015	0,03	0,02	0,05	S&P	BBB	BBB-
ASTRAZENECA PLC	Sweden	10.11.2015	-0,01	0,08	0,09	S&P	A+	A
FORTUM OYJ	Finland	17.11.2015	0,03	0,04	0,04	Fitch	A-	BBB+
TDC	Denmank	27.11.2015	-0,01	0,00	0,00	S&P	BBB	BBB-
EQUINOR ASA/STATOIL	Norway	22.2.2016	-0,02	0,00	0,00	S&P	AA-	A+
SSAB AB	Sweden	22.2.2016	0,00	0,15	0,22	S&P	BB-	B+
SAMPO OYJ	Finland	20.4.2016	-0,01	-0,01	-0,01	S&P	A	A-
ERICSSON	Sweden	17.10.2016	-0,01	-0,07	-0,28	S&P	BBB+	BBB
AB SKF	Sweden	27.10.2016	0,03	0,07	0,10	S&P	BBB	BBB-
A.P. MØLLER MÆRSK	Denmank	14.11.2016	-0,01	0,02	-0,06	S&P	BBB+	BBB
PETROLEUM GEO SERVICES ASA	Norway	25.11.2016	0,04	0,15	0,20	Moody's	Caa1	Caa2
ELECTROLUX AB	Sweden	20.12.2016	0,00	-0,02	0,04	S&P	A-	BBB+
SVENSKA CELLULOSA SCA AB	Sweden	20.12.2016	0,00	-0,01	0,04	S&P	A-	BBB+
ERICSSON	Sweden	31.3.2017	-0,01	-0,05	-0,05	S&P	BBB	BBB-
ASTRAZENECA PLC	Sweden	28.7.2017	0,01	0,00	-0,10	S&P	A-	BBB+
FORTUM OYJ	Finland	18.1.2018	-0,01	-0,01	0,03	S&P	BBB+	BBB
DANSKE BANK A/S	Denmank	2.2.2018	-0,01	0,00	0,05	Moody's	Aa3	A1