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The Effect of Credit Rating Announcements

A comparative study between the US and European market about credit rating
changes and stock prices

Students:

Elisabeth Ekstedt

Hampus Hammarstrand

Supervisor: Jens Forssbaeck

ABSTRACT

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Authors: Elisabeth Ekstedt & Hampus Hammarstrand

Supervisor: Jens Forssbaeck

Keywords: Credit ratings, Abnormal returns, Event study, Financial crisis, Market comparison

Purpose: The purpose of this study is to further deepen the knowledge surrounding credit rating announcements and their impact on companies' stock prices. Furthermore, the authors want to investigate whether the potential impacts differ between the US market and the European market, as well as previous to the financial crisis compared to post the financial crisis of 2007-2009

Methodology: Event study and multivariate regression analysis

Theoretical perspectives: Information content hypothesis, Efficient market hypothesis, Incentive signalling approach, Economic rationality theory

Empirical foundation: The sample consists of 3691 credit rating changes between 2003-2019 for the European market and the US market.

Conclusions: The US market reacts stronger to downgrades compared to the European market, while there is no difference for upgrades. The market also reacts stronger to downgrades after the financial crisis compared to before, with no correlation for upgrades before and after the crisis.

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Elisabeth Ekstedt

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Hampus Hammarstrand

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1. INTRODUCTION

In 1909, John Moody began selling detailed information and manuals to prospective lenders. At the same time, he also published the first bond rating. Moody's business started to grow in the early 20th century when railroad building required external financing in the US. The demand for third-party assessment of the creditworthiness from the borrowers increased and shortly after, the concept of credit rating agencies arose (Partnoy, 1999). Over the next decade, Standard & Poor's and Fitch started providing their first ratings, which was the beginning of what would turn in to a multi-billion dollar industry (Güttler & Wahrenburg, 2007).

Several years later, credit ratings played a significant role in what would be one of the biggest financial crises in modern history. In the middle of September 2008, Lehman Brothers filed for bankruptcy protection, which was the largest filing in US history. The filing was the start of the financial crisis of 2007-2009, which could partly be explained by the high ratings provided for subprime loans with low quality. The agencies failed to provide the investors with an accurate representation of security prices, and several parties accused the agencies of bearing the main responsibility for the financial crisis (Council of Foreign Relations, 2015). They got particularly criticised for using a complex and unreliable model when calculating the risk of default for securitised products and individual mortgages (McLean & Nocera, 2010).

Since the agencies failed to portray default risk accurately, criticism against them emerged. Many firms received inaccurate high ratings, which later led to a mass downgrade from the rating agencies. As a result of the financial crisis, stronger regulations got implemented towards the agencies and they were forced to be more transparent during the rating process (G20 Information Centre, 2015).

Credit ratings are a frequent variable in analysis and assessment by pension funds, debtholders, banks and investors. Even though the credit rating agencies lost much credibility after the financial crisis, they still play an essential role in the financial markets. This is since debt is used as a capital source of financing, with a reported market value of approximately 92 000 billion USD in 2016, compared to equity offerings of 60 000 billion USD (SIFMA, 2018). Since credit ratings have this vital function in the financial market, credit rating announcements would probably have an impact on stock prices as new information gets released to the market.

There are several reasons why credit rating changes might affect stock returns differently depending on which market they occur in. One of them is related to what type of financing each market prefers. US companies primarily fund their operations with bonds, whereas European companies lean more towards traditional bank loan financing. According to AFME (2014), the distribution in US companies between bond financing and loan financing is 70% bonds and 30% bank loans. In European companies, the distribution is the opposite. Thus, credit ratings might play a more substantial role in the US market compared to the European market. As a result, one might wonder if the rating changes have a more significant impact on US companies' stock returns.

The purpose of this study is to further deepen the knowledge surrounding credit rating announcements and their impact on companies' stock prices. Rating announcements have been frequently analysed previously, but not across larger samples. Furthermore, the authors want to investigate whether the potential impacts differ between the US market and the European market, as well as previous to the financial crisis compared to post the financial crisis of 2007-2009. Since the debt market between these geographical areas differs, credit rating changes might also be of varying nature. The method used is an event study, covering company credit rating changes from 2003-2019, which makes it possible to find out how stock prices adjust to new information and how the effect of a credit rating change is absorbed.

There have been several studies examining the relationship between credit ratings and stock performance, with the conclusion that credit rating changes impact stock prices (Avramov et al. 2012; Creighton, Gower & Richards, 2007; Halek & Eckles; 2010; Poon & Chan, 2008). Researchers have also examined specific industries and countries, but no studies comparing different markets have been found. The time period examined also differs from most of the previous research, since the sample includes rating pre, during and post financial crisis.

Following the introduction, an empirical and theoretical framework of this study will be presented. This section is the foundation on which the analysis of the empirical data is based on. It is presented in four subsections: empirical foundation, theory, literature review and hypothesis development. The initial two are needed to understand both the previous research conducted and the research presented in this study, as well as why the topic is of interest. Based on the first three subsections, hypotheses development is presented in subsection four. A

discussion regarding choice of method, criticism and self-reflection is presented here as well. In section three, the methodology used to test the hypotheses is presented, included subsections of the empirical data analysed and a thorough description of how event studies are carried out, followed by a description of statistical methods used and a presentation of the variables. Section four contains the results combined with the analysis of the presented figures. Lastly, discussion and proposals for further research are found in section five.

2. EMPIRICAL AND THEORETICAL FRAMEWORK

The following section will include the empirical foundation and chosen theories for the thesis, followed by a literature review of previous research. Based on this, three hypotheses were developed which is presented at the section end.

2.1 EMPIRICAL FOUNDATION

A more detailed description of credit rating agencies will be explained in the following section. It will include the concept of credit ratings, the credit rating process and information regarding how the financial markets differ between Europe and the US.

2.1.1 CREDIT RATING AGENCIES AND THE RATING PROCESS

Credit ratings for companies tell the willingness and ability of an issuer to meet its financial obligations. The reason why companies use ratings is that they can raise money from investors when issuing rated bonds. Credit ratings also provide investors and banks with useful information as well as giving companies access to debt markets. As a result of their major use, they play an essential role in the financial markets. Credit ratings are being issued for states as well as corporations and are provided by the credit rating agencies. The biggest ones are Standard & Poor's, Moody's and Fitch, also referred to as “the big three”. They have approximately 96% of the market share, where S&P has 49%. Moody’s 34% and Fitch has 13% of the market share (SIFMA, 2017).

The credit rating agencies provide two different types of credit ratings: issuer-specific ratings, which is the overall quality of the obligor (like a government, municipality or corporation), and an issue-specific rating which refers to a specific financial instrument, e.g. a bond. The different ratings are illustrated in *Table 1*. Another important use of credit ratings is that BASEL uses them to determine minimum capital requirement (Basel Committee on Banking Supervision, 2017).

Rating	Definition	Rating Description	
AAA	Prime	Extremely strong capacity to meet its financial commitments	
AA+ to AA-	High Grade	Very strong capacity to meet its financial commitments	
A+ to A-	Upper Medium Grade	Strong capacity to meet its financial commitments	
BBB+ to BBB-	Lower Medium Grade	Adequate capacity to meet its financial commitments	Investment-grade
BB+ to BB-	Non-investment Grade Speculative	Less vulnerable in the near term than other lower-rated obligors	Non-investment grade
B+ to B-	Highly Speculative	More vulnerable in the near term than other lower-rated obligors, but still has the capacity to meet its financial commitments	
CCC+ to CCC-	Substantial Risks	Vulnerable to non-payment and is dependent upon favourable business, economic and financial conditions for the obligor to meet its financial commitments	
CC	Extremely Speculative	Highly vulnerable in the near term than other lower-rated obligors	
C	Default Imminent	Highly vulnerable to non-payment, and it is expected that the obligation will have low relative seniority or lower ultimate recover	
RD/SD/D	In Default	S&P believes that the obligor will fail to pay all or a majority of its obligations	

Table 1. S&P long-term issuer credit ratings (Standard & Poor’s Ratings Services, 2014)

Just as rating agencies can rate companies, individual bonds get evaluated by the agencies. Bond ratings measure the financial ability of the issuers to fulfil its financial commitments. It also tells how it affects the yield for investors and bonds, where lower ratings often have a higher yield to compensate for the additional risk. (Fidelity, 2019)

All rating agencies use different methodologies to measure creditworthiness and they are typically expressed as a grade to communicate the level of risk (Standard & Poor’s Ratings Services, 2014). The process of how a company receives a new rating is divided into several steps. First of all, the company (issuer) requests a rating from an agency. After that, the agency makes an initial evaluation and then meets with issuer management. Then they conduct an

analysis of the company, which is later provided to a rating committee that reviews the analysis and assesses its accuracy. If it is deemed to be accurate, the new rating is then notified to the issuer and later made public. When the rating is published, there is surveillance of rated issuers and issues. A summary of the process is presented in *Figure 1*.

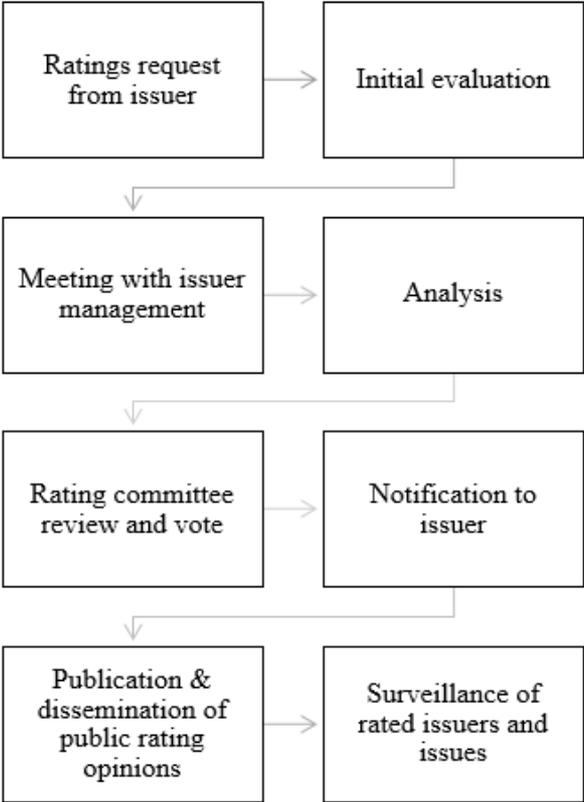


Figure 1. The credit rating process (Standard & Poor’s Ratings Services, 2014)

Most of the information analysed by the agencies to determine the creditworthiness of companies is already public information. However, it can be a very complex and time-consuming process to analyse all this information due to its magnitude, especially for private investors. During the process, more non-public information from the issuer can be available to the agencies, giving them access to inside information. (Technical Committee of the International Organization of Securities Commission, 2008)

Later on, ratings can be adjusted if overall shifts in the worldwide economy or changes in the business environment occur. New technology or competition can damage a company’s expected earnings and therefore lead to a downgrade. Other factors that can trigger credit rating changes are capital spending requirements and varying debt burdens. When a rating change occurs, the

market's perception of the company's risk might change, which can lead to a change in the price of the security. According to Standard & Poor's (2014), ratings do not tell anything about asset value; neither does it provide a buy or sell recommendation. Therefore, a credit rating should only partly be a factor in an investment decision as a rating only tells the investor the quality of the credit and what they can expect to get back in the event of default. (Standard & Poor's Ratings Services, 2014)

2.1.2 BOND VERSUS BANK FINANCING

Debt financing consists of both traditional bank lending and issuing of bonds. Depending on which country or industry the company is operating in, it uses different sources of capital. La Porta et al. (2012) examined why some countries have better access to capital markets compared to others. They concluded that countries with a better legal environment and with better protection against investors often had easier access to capital markets. The correlation found between weak investor protection and the least developed capital markets might explain why some countries prefer using bonds instead of traditional bank lending.

The bond market in the US developed due to deregulations of the bank market in the early 1980s. Previous regulations were established in conjunction with the Great Depression. Issued loans from the banks were based on insufficient information and led to the first real financial crisis for the US. The crisis caused regulations for the banks regarding financing and hampered conventional banks from developing. This led to US companies starting to search for financing in other places, like the bond market which favoured the companies with a larger need for capital. After this, the corporate bond market started to develop. (Gambacorta & van Rixtel, 2013)

There are both benefits and drawbacks for companies regarding the usage of bank loans compared to bonds. Rajan (1992) discussed the sharing of information required for the different types of financing and highlights the costs associated with bank lending. A bank obtains private information which the firm cannot communicate to the public market, like information generated during the lending process about the firm's prior projections, the competence of personnel and the ability to meet prior targets. Bondholders on the other hand only receive public information, making the information asymmetry between the issuer and the creditors larger compared to the firm and the bank. Hence, there are discussions regarding the bargaining

power banks have against the firm when a project has begun. The bargaining power arises due to informed banks having more control over whether they want to keep on financing the current project for the firm or not. (Rajan, 1992)

2.2 THEORY

This section will present the theories which are the underlying ideas to understand the impact of stock prices due to credit rating changes. These theories will then be the foundation for the final hypothesis development.

2.2.1 INFORMATION CONTENT HYPOTHESIS

Information asymmetry is a recurring concept on the stock market. The idea is based on that the actors on the market possessing different levels of information, leading to a lack of market economic equilibrium. The theory argues that one part in a transaction has more information than the other. Akerlof (1970) used an example with old cars when describing the information asymmetry. He argued that the buyer often has an information disadvantage in a car transaction compared to the seller, making it difficult for the buyer to see any difference between a bad car and a good car. Because of this, the seller cannot sell good cars for better than average market prices. The same thing occurs on the financial markets, e.g. due to the issuers of bonds having more information regarding the ability to repay compared to what the lender has. According to this theory, an information asymmetry can be assumed between credit rating agencies and the market. Since rating agencies possess public as well as private information, a rating change should have a surprising effect on stock prices when announced.

Most of the rated companies are listed, making their financial data available for the public. As a result, credit rating agencies have been questioned regarding how much private information they really have access to. Jones, Johnstone and Wilson (2015) showed that ratings with a high degree of accuracy could be predicted, making rating agencies less useful. On the other hand, several studies have shown that there is an effect on the stock market after a rating announcement, showing that the credit rating agencies have access to private information.

This asymmetry can be reduced by signals to the market. The incentive-signalling approach explains how the market observes and interpret the information they receive in order to value

the company (Ross, 1977). Even though the main purpose of credit ratings does not include sending signals to the market in terms of “Buy”, “Sell” or “Hold”, they still contain useful information for investors. A credit rating change sends signals containing information about the company’s financial status. This can also lead to rivaling firms gaining an advantage on the market, since the signal may indicate that a competitor has a weakening financial status. A downgrade can also affect a whole industry by signalling that there are adjustments about general operational environment conditions.

Depending on the change, the market reacts in different ways and may affect the stock price either short-term or long-term. This is because credit rating agencies might provide insider information regarding current management policies, credit factors and financial and operating plans received during meetings with the management (Ederington, Yawitz & Roberts, 1987). Credit ratings are therefore useful for mitigating the information asymmetry between the issuer and the market.

2.2.2 EFFICIENT MARKETS

The efficient market theory is based on the assumption that all investors act rationally. There are several economic theories and studies which indicates that there is symmetry between economic expectations and market outcome. One of those is called the rational expectations theory and is initially conveyed by John Muth (1961). The theory tries, similar to the incentive signalling approach, to explain how people interpret and process the information they gather by continually adjusting their decisions based on new information.

A common way of describing the term “efficient market” is derived from the definition made by Eugene F. Fama (1970). According to this definition, markets are efficient if stock prices fully reflect all information publicly available at any time. In other words, investors cannot predict stock prices based on public information as it should already be reflected in the stock price. For this to be true there are a few underlying assumptions: investors are expected to make rational decisions, have homogeneous expectations and costs related to transactions do not exist. There are three different levels of market efficiency:

Weak form

If a market is a weak form efficient, it means that past price histories of stock performance are being reflected in the stock price. In other words, investors cannot consistently outperform the market by using historical data to predict future performance (e.g. through technical analysis).

Semi-strong

If a market is efficient on a semi-strong level, the stock prices reflect all publicly available information. Compared to the weak form, this means that potential future events are reflected in stock prices as well. Hence, investors should not be able to consistently outperform the market by using historical data and publicly available information.

Strong form

If a market is strong form efficient, it means that all private information is reflected in the stock prices on top of historical data and publicly available information.

In the case of credit ratings and event studies, the market is assumed to be semi-strong in order. If the market were to be strong form efficient, the information announced by credit rating agencies would already be reflected in the stock prices.

Several researchers and investors have disputed the efficient market hypothesis. Since people have become very affluent by buying and selling, it contradicts that the market would be efficient. Some observed anomalies are overreactions on the market when new information is being published with abnormal high stock returns. The expected overreaction contradicts the efficient market theory since it creates an imbalance in the pricing of the assets (De Bondt & Thaler, 1987). Later, the overreactions adjust over time. Earlier research has shown that it takes up to 6 months for a stock to adjust to its true value, due to the first reaction after a positive or negative announcement often being exaggerated (Bernard, 1993).

Another aspect that contradicts the efficient market hypothesis is the excessive volatility on the stock market. Shiller (1981) compared changes related to the specific company and the estimated size of the future net surplus, finding that stock price movements have been stronger compared to the changes in the fundamental corporate value. Volatility tests indicate that movements in stock prices can not only be explained by the rational expectations from investors

but by their irrational reasoning. His conclusion is therefore that stock prices are too volatile to be dependable with efficient markets. Ackert (1994) conducted a study based on these assumptions saying that individuals overreact to new information and reaching the conclusion that uncertainty on the market explains the stock price volatility. The study failed to explain why the market overreacts to new information.

2.2.3 WEALTH REDISTRIBUTION HYPOTHESIS

One theory that contradicts the previously mentioned theories is the wealth redistribution hypothesis, initially developed by Zaima and McCarthy (1988). The hypothesis is based on a conflict of interest between equity investors and bond investors, where shareholders seek higher returns at the expense of bondholders. Since a downgrade gives information about the issuer's credit quality, the value of the bond should decrease. However, this does not mean that the value of the firm decreases with an equal amount. Instead, the wealth redistribution claims that some of the value is transferred to the shareholders from the bondholders. The reason for this is that if a downgrade is motivated with riskier investments, the bond value should decrease, making shareholders benefit from a downgrade. In other words, a higher variance of cash flow and investments might lead to a downgrade, causing an increase in stock prices. From a short-term perspective, shareholders should benefit from a downgrade as long as the company does not raise any new debt.

The information content hypothesis, economic rationality theory and the signalling hypothesis all suggest that an upgrade (downgrade) should lead to positive (negative) stock returns. Since the wealth redistribution hypothesis predicts opposite results compared to the previously mentioned theories, it might offset the signalling effects and the information content hypothesis.

2.3 LITERATURE REVIEW

There is a lot of previous research about credit ratings and stock performance. Below, a selection of the most relevant studies is presented for the purpose of this study. At the end of the literature review, a summary of all previous empirical findings can be found in *Table 2*.

2.3.1 THE EUROPEAN MARKET

Barron, Clare and Thomas (1997) research the UK bond market to find a correlation between ratings and stock returns. If the company is rated for the first time, there is no significant effect

on stock prices. A downgrade on the other hand leads to a decrease in stock prices and an upgrade leads to an increase in stock prices. Hence, they concluded that the market only reacts to a rating change, and not when a company is rated for the first time.

Li, Visaltanachoti and Kesayan (2004) study the Swedish stock market with the purpose to see how the market reacts to rating changes, both in the short-term and long-term perspective for rating assignments and positive rating outlooks. They find that downgrades and negative outlooks impact stock prices negatively long-term, but not short-term. The authors explain the results by arguing that the Swedish stock market is a highly liquid market with low asymmetric information, leading to weak effects on the market. The results indicate that the Swedish stock market is slow to absorb new information. Variables they used were firm size, book-to-market value and leverage, with no significant results for any of them.

Pacheco (2012) research the Portuguese market during 2006-2011 to study the impact on stock prices when a credit rating change occurs. The method used is an event study, and he finds a significant effect on stock prices in relation to credit rating changes, for which upgrades causes positive stock performance and downgrades causes negative stock performance. The author ties the result to the then bearish market and previous sovereign rating changes. He also notes a stronger effect after 2010, which he assumes is because of the traces from the financial crisis.

2.3.2 THE US MARKET

Hand, Holthausen and Leftwich (1992) conducts a study with the purpose to examine the relationship between stock prices and bond ratings. The results show that a downgrade causes negative stock returns, whereas no significant correlation is found between upgrades and positive stock returns. The authors also measure if the bond is below investment grade or above it, with the conclusion that a change in credit rating below investment grade is more significant compared to if it is investment graded.

The year after, Goh and Ederington (1993) argue that only some downgrades lead to negative implications and explore whether all downgrades are bad for equity holders. Since credit rating agencies give a reason for the credit change, difference reasons should affect equity holders in different ways. If the rating is triggered by a change in the firm's financial performance in terms of cash flow and profitability, the stock price should react differently compared to if the rating

is triggered by changes in solidity or liquidity. In conclusion, downgrades cause by the former change impact stock prices heavier than downgrades caused by the latter change. Their study goes in line with the wealth redistribution hypothesis, claiming that changes in credit ratings that are motivated by decreased or increased cash flow volatility has a different implication for shareholders and bondholders.

Halek and Eckles (2010) study the eventual asymmetric reaction of rating changes to stock prices of insurance companies. The result shows that a downgrade cut stock prices up to 7 % and that upgrades only have a small significant effect. One thing they control for is whether it matters which agency makes the rating announcement, with the result that the market reacts stronger to S&P's downgrades compared to Moody's. The stock market also falls dramatically when two agencies give a downgrade close by to each other, or when losing a threshold rating (e.g. goes from A- to BBB+). These asymmetric reactions between upgrades and downgrades are explained by the information asymmetry in the capital markets.

Later on, Avramov et al. (2012) publish a study showing that high-risk firms with lower credit ratings experience higher negative returns compared to firms with higher ratings. In line with previous research, a downgrade has a more significant effect on the stock price compared to an upgrade.

Reddy, Bosman and Mirza (2019) conduct an event study on all firms listed on S&P 500 between 2006 and 2015, with the purpose to investigate how the global financial crisis affected the effect of credit ratings. They divide the sample using three sub-periods: before, during and after the global financial crisis. Their conclusion is that the market is more sensitive to credit ratings after the financial crisis compared to before and that the market reacts stronger to downgrades than to upgrades. According to the authors, the difference between the effect of upgrades and downgrade can be explained by companies being more prone to releasing optimistic information compared to pessimistic information. The positive information is therefore not new to the investors. Also, rating changes from non-investment grade to investment grade significantly impact equity prices.

Mutual findings for the US studies are that all the authors find that a downgrade affects stock prices in a negative way, and that the correlation between upgrades and positive stock performance is weak or non-existing.

2.3.3 OTHER MARKETS

Two other authors who research downgrades in bond ratings and stock returns are Joo and Pruitt (2006). The time period they measure is before and after the Asian financial crisis in 1997. Before 1997, a downgrade led to approximately a 2% decrease in stock price. After the crisis, the stock price instead dropped approximately 30%, showing that the market is 15 times more reactive to credit rating changes after the financial crisis compared to before. Poon and Chan (2008) also examine the Asian market and conducts a study on the Chinese stock market. The result is similar; a downgrade leads to negative stock performance. Joo and Pruitt (2006) conclude that the underlying uncertainty in the economic climate explains the reaction and the market, while Poon and Chan (2008) discusses whether the Chinese credit ratings contain useful information or not. Earlier, the Chinese credit rating agencies have been criticised for giving too optimistic credit ratings and not containing any useful information. From the results of their study, they conclude that ratings convey useful information and therefore affect the market when released. Two variables that Poon and Chan (2008) use are the firm size and industry, with the conclusion that both of them contribute to negative stock return.

The Australian market is researched by both Creighton, Gower and Richards (2007) and Choy, Gray and Rangunathan (2006). All of the authors use the market model and present similar results; downgrades have a more significant effect on the stock return compared to upgrades. Creighton, Gower and Richard's (2007) research also shows that firm size mattered as announcement effects have a larger effect on small firms compared to large firms. The reaction is also stronger when a rating goes from investment grade to non-investment grade. The reason that the stock price is affected when going from investment grade to non-investment grade is that some portfolio managers have restrictions regarding which companies they can hold. Psychological effects from investors might matter as well due to movements below the investment grade. Another variable they used is the firm size, with the assumption that large firms might be less impacted by ratings since they are subject to more market scrutiny.

The most significant results for Choy, Gray and Rangunathan (2006) are when the firm's rating drop more than one category (e.g. goes from A- to BBB+), or when the firm is unregulated. The authors explain their result with the signal that credit ratings send to the market regarding financial strength, creditworthiness and quality, changing the firm's financial fortunes. As previous studies concluded, there is an asymmetry between upgrades and downgrades, since companies are more willing to release positive information. The authors also research the effect of a company going from investment grade to non-investment grade, with the result that the stock prices experience negative abnormal returns. For upgrades, they did not find any significant evidence when being upgraded to investment grade. They explain that a company losing investment grade status might lead to a higher cost of capital or borrowing constraints since some financial regulators might prevent financial institutions from using securities with a rating that is below investment grade.

2.3.4 SUMMARY

As shown, there is a lot of research regarding credit ratings and stock return, with a vast spread regarding geographic markets and time periods. Almost all the authors used an event study to calculate the abnormal returns, but only a few made a regression analysis to control for which factors that actually impact the stock returns. When looking back at previous empirical studies, there is an apparent asymmetry between upgrades and downgrades, where almost all studies find a causality from downgrades to negative stock performance, and only a few find that upgrades affect the stock price in a positive way. The asymmetry is several times explained by the assumption that companies are more prone to release positive information rather than bad news. Positive news that might be associated with the upgrade is probably already out on the market and is therefore not seen as new information to the investors. The most commonly used variable is whether the rating goes from investment grade to non-investment grade since it is perceived as a strong signal to investors. Industry and the firm size of the company are also two commonly used variables, with the assumption that there should be a larger information asymmetry depending on which industry the company is operating in or how large the company is.

Author	Year	Data	Sample	Method	Time period	Market	Findings
Hand, Holthausen & Leftwich	1992	Bond ratings from S&P Credit Watch List. Variables: investment grade	1 133	Multivariate regression analysis	1977-1982	US	Downgrades leads to negative returns. No correlation between upgrades and positive returns
Goh & Ederington	1993	Bond ratings from Moody's	1 078	Event study	1984-1986	US	Downgrades can lead to both positive and negative abnormal return depending on what the reason is for the credit change
Barron, Clare & Thomas	1997	New bond ratings and credit rating changes	23	Event study	1984-1992	UK	Significant results for rating downgrades and positive CreditWatch announcements
Li, Visaltanachoti & Kesayan	2004	Credit ratings from S&P and Moody's. Variables: Size, leverage, book value, credit outlook	83	Event study and multivariate regression analysis	1992-2003	Sweden	Downgrades leads to negative returns for long term but not for short term. No correlation between upgrades and positive stock performance
Choy, Gray & Raganathan	2006	Credit ratings by S&P and Moody's. Variables: number of grades, investment grade	127	Event study and multivariate regression analysis	1989-2003	Australia	Only significant market reaction for downgrades. Bigger market reaction for firms in an industry that is not regulated
Joo & Pruitt	2006	Bond ratings from the three biggest Korean rating firms before and after the financial crisis. Variable: rating level	2 302	Multivariate regression analysis	1995-2002	Asia	The market was 15 times more reactive after the financial crisis
Creighton, Gower & Richards	2007	Bond ratings from Moody's and S&P. Variables: firm size, investment grade	33	Event study	1990-2003	Australia	Downgrades leads to negative returns and upgrades leads to positive returns
Poon & Chan	2008	Credit ratings on the Shanghai Stock Exchange. Variables: state legal shares, listing years, firm size, industry	170	Event study	2002-2006	Asia	Downgrades leads to negative return
Halek & Eckles	2010	Credit ratings. Variables: year, number of level changes, industry & rating agency	1 240	Event study	1992-2005	US	Downgrades leads to negative returns and the effect is stronger compared to upgrades and positive returns
Pacheco	2012	Credit ratings from Moody's.	49	Event study	2006-2011	Portugal	Downgrades leads to negative return and upgrades leads to positive returns. Extra vulnerable after the financial crisis
Avramov et al.	2012	Credit ratings on firms listed on NYSE. Variables: asset growth, accruals, firm size	4 953	Multivariate regression analysis	1985-2008	US	Downgrades leads to negative return and the effect is stronger compared to between upgrades and positive returns
Reddy, Bosman & Mirza	2019	Ratings from S&P's 500. Variables: Investment grade	1427	Event study	2006-2015	US	Downgrades leads to negative return. No correlation between upgrades and positive returns. Extra vulnerable after the financial crisis

Table 2: Literature review

2.4 HYPOTHESIS DEVELOPMENT

According to the information content hypothesis, the stock price should be affected when a company receives a new credit rating. The reason for this is that agencies provide the market with new information, which reduces the information asymmetry. According to Fama (1970), financial markets are supposed to be efficient, saying that it is impossible for investors to “beat the market” since the stock price should reflect all the available information to its fullest. If the stock market would be affected by the new information that credit ratings provide, it is shown that the market is semi-strong. The information credit rating agencies provide should be valuable for stakeholders, making downgrades and upgrades associated with abnormal stock performance. Muth (1961) proposed that investors base their decisions on rational thinking in terms of experience, the available information on the market and their rational outlook. The theory explains the relationship between future expectations and outcomes, saying that an upgrade in credit rating would lead to a positive return while a downgrade would lead to a negative stock return. The decision behind this is the economic mechanism that a downgrade might indicate that the company might suffer from financial distress leading to a less profitable firm and a negative stock return.

Based on previous findings and existing theories, rating changes announcements should bring new and valuable information to the market which investors will react on. Hence, the first hypotheses for this thesis will be the following:

H₁ = There is a statistically significant increase (decrease) on a company's stock price when it receives an upgrade (downgrade) in credit rating.

When establishing whether credit ratings add any valuable information in *Hypothesis 1*, the authors further want to investigate if the market reaction after a credit rating change is stronger in the US market compared to the European market. The hypothesis is based on the fact that financing differs between these markets, where bonds are more established in the US. Hence, the second hypothesis is the following:

H₂ = The stock price of US companies is more heavily impacted by credit rating changes compared to European companies.

To further analyse which factors might contribute to the impact on stock prices upon rating changes, it needs to be examined how the financial crisis impacts the different markets. After the financial crisis of 2007-2009, the uncertainty in the global economy increased. The following hypothesis is based on previous research concluding that the market has been more reactive to credit ratings after a financial crisis compared to before (Joo & Pruitt, 2006; Pacheco, 2012; Reddy, Bosman & Mirza, 2019). In line with previous empirical findings together with a general uncertainty in the global economy, the authors expect announcements post-financial crisis to have a stronger impact on stock performance compared to pre-financial crisis. Hence, the third hypothesis is the following:

H₃ = The stock price of companies where credit rating changes occurred post the financial crisis is more heavily impacted compared to companies experiencing a rating change previous to the financial crisis.

3. METHODOLOGY

The following section will describe the final sample and the data analysed. The method used for analysis is an event study along with multivariate regressions. Additionally, potential issues with the event study method and the robustness of the regression model is discussed.

3.1 DATA

Data for S&P credit rating changes, announcement dates, industries, leverage ratios and firm market cap has been obtained from Bloomberg and Thomson Reuters Eikon, while daily stock prices have been obtained from Datastream.

The sample consists of 3691 credit rating changes during the time-period 2003-2019; 2791 US changes and 900 European. Out of these, 1987 changes were upgrades and 1704 downgrades. The observations for Europe include companies from the 13 biggest European countries in terms of GDP 2018 (IMF, 2018; *Appendix A*). The index used to estimate beta values for each particular stock (which is further explained in section 3.2.3) was MSCI World Index which is also obtained from Bloomberg. The reason for using the same index for both markets was partly due to convenience with setting up the model, but also to get a fair comparison between all observations. As for the choice of credit rating agencies, Standard & Poor's was chosen since they have the biggest market share of "The Big Three" (SIFMA, 2017). Additional summary statistics are presented in *Appendix B*, showing specific data for the US market and the European market separately. In order to enable a proper execution of the event study, all observations in the sample had to fulfil the following criteria:

- ❖ The company has experienced at least one credit rating change by Standard & Poor's during 2003-2019.
- ❖ The company needs to be listed during the time of the rating change.
- ❖ The company needs to have had a credit rating from S&P prior to the new rating (e.g. a company's first rating is not counted as a change).
- ❖ The company needs to have daily stock prices available within the test period (see *section 3.2.2, Figure 2*).
- ❖ The exact announcement date of the rating change needs to be available.
- ❖ The company needs to have available data for all chosen control variables in this study at the time of the event.

	Europe		US			
	Upgrade	Downgrade	Upgrade	Downgrade	Total	Downgrade/total
2003	11	16	48	43	118	50%
2004	19	6	57	28	110	31%
2005	26	8	61	36	131	34%
2006	29	15	60	32	136	35%
2007	33	8	58	45	144	37%
2008	19	37	65	84	205	59%
2009	5	48	60	114	227	71%
2010	10	22	118	41	191	33%
2011	46	47	137	56	286	36%
2012	27	34	100	52	213	40%
2013	26	37	112	46	221	38%
2014	30	36	143	61	270	36%
2015	36	47	116	141	340	55%
2016	37	25	109	230	401	64%
2017	44	22	116	102	284	44%
2018	61	14	137	112	324	39%
2019	8	11	23	48	90	66%
Total	467	433	1520	1271	3691	46%

Table 3. Sample distribution

Sample for each respective market and rating change is presented in *Table 3*. The rightmost column shows the percentage of downgrades to the total number of ratings. As seen, the ratio was relatively low before the financial crisis of 2007-2009, high during the crisis and then quite volatile in the remaining period. As a consequence of credit ratings being more extensively covered in the US, the distribution between US and EU observations is not ideal. However, due to the size of the total sample in comparison over both market and years, this is not considered an issue of substantial magnitude.

3.2 CHOICE OF METHOD

The authors choice of method has been selected by looking at previous studies, and the common method used is an event study (Creighton, Gower & Richards, 2007; Goh & Ederington, 1993; Halek & Eckles, 2010; Pacheco, 2012; Poon & Chan, 2008; Reddy, Bosman & Mirza, 2019). The purpose of an event study is to compare the performance before and after a specific event, in this case, a credit rating change.

When conducting an event study, the event needs to be unexpected and one needs to be able to pinpoint when it occurred (Campbell, Lo & MacKinlay, 1997). According to MacKinlay (1997), the theory about event studies says that since the market is rational, the effect of the event is immediately reflected in the stock price. The approach in an event study is first to identify the event that should be examined. Therefore, an estimation window and event window are decided. The estimation window is used to estimate the parameters of the study and the event window is the time period being examined. In the event window, the abnormal return is being calculated by subtracting the expected return from the actual return. The cumulative abnormal return (CAR) is being calculated by accumulating the abnormal return. Calculations for these are explained and presented in *section 3.2.3*.

3.2.1 DEFINITION OF AN EVENT AND EVENT WINDOW

The event that will be examined is the day when a company either is experiencing a downgrade or an upgrade in credit rating. Therefore, the event day will be the day the rating agency publishes the new credit rating.

When deciding on an event window, several considerations are made. The event window needs to be big enough to capture eventual abnormal returns, but not too big that it will capture ratings issued by other rating agencies or outlook changes that can affect the stock performance. Furthermore, the windows need to capture any potential leaks prior to the announcement as well as recoil effects after the announcement. Previous studies use narrow windows in order to reduce the possibility of capturing other rating changes or events that might affect the returns. Several of these claim that the ideal event window should be 11 days (Choy, Gray & Rangunathan, 2006; Poon & Chan, 2008; Reddy, Bosman & Mirza, 2019). Poon and Chan (2008) used various event windows in order to capture when the credit rating changes begin to give effect on the stock market. They used $t-1$ to $t+1$, $t-3$ to $t+3$ and $t-5$ to $t+5$ as event windows, which this thesis also will use. The use of narrow windows reduces the risk of other occurring impactful events being included, which could bias the results.

3.2.2 ESTIMATION WINDOW

When measuring daily stock returns, MacKinlay (1997) suggest an estimation window of 120 days. The event window should be excluded from the estimation window, to prevent any impact on the normal performance parameter estimation (MacKinlay, 1997).

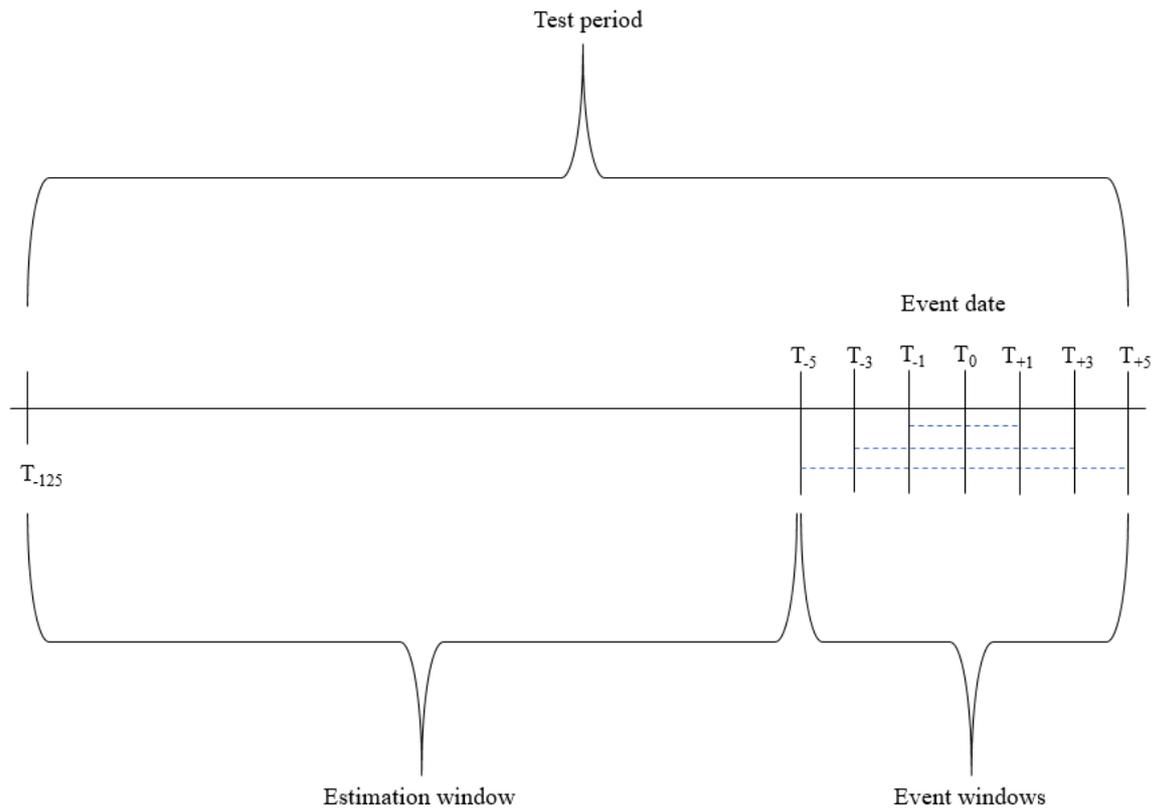


Figure 2. Event window and estimation window

3.2.3 MEASUREMENT OF ABNORMAL RETURNS

In order to retrieve abnormal returns, both actual and expected returns must be calculated. The actual return is given by *Equation 1*

$$R_{i,t} = \left[\frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \right]$$

Equation 1. Calculation of actual return

where $P_{i,t}$ is the stock price at time t and $P_{i,t-1}$ is the stock price one day prior to t .

To estimate the expected returns, the market model has been applied. This model is frequently used in studies that examine abnormal returns. According to MacKinlay (1997), one of the benefits with the market model is that it only includes the return which is not affected by the variation of the market. The model requires a reference index to measure the abnormal return.

MacKinlay (1997) suggests a broad-based stock index, and the chosen one is the MSCI World Index for both the European market and the US market.

The parameters in the market model are given by *Equation 2*

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

Equation 2. Calculation of the market model

where $R_{i,t}$ is the return of the stock i at the time period t , $R_{m,t}$ is the return of the market at the time period t , and ε is the residual for the stock with an expected value of 0. The alfa value and the beta value are being estimated in the model. The expected return, also defined as the normal return, assumes a linear relationship between the return of the market and the return of the asset. *Equation 3* and *Equation 4* are used to calculate the alfa and beta values respectively in the market model:

$$\hat{\alpha} = \frac{\sum R_{i,t}}{n} - \beta * \frac{\sum R_{m,t}}{n}$$

Equation 3. Calculation of alfa-value

$$\hat{\beta} = \frac{n * \sum (R_{m,t} * R_{i,t}) - \sum R_{m,t} * \sum R_{i,t}}{n * \sum R_{m,t}^2 - \sum R_{m,t}}$$

Equation 4. Calculation of beta-value

Abnormal returns for each observation at day t is then calculated by subtracting the expected return from the actual return, illustrated below in *Equation 5*.

$$AR_{i,t} = R_{i,t} - E[R_{i,t}]$$

Equation 5. Calculation of abnormal return

Since the authors are interested in testing abnormal returns for the whole sample rather than single observations, average abnormal return (AAR) is then calculated by

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

Equation 6. Calculation of average abnormal return

In order to retrieve cumulative abnormal returns (CAR), the sum of abnormal returns for each respective observation and event window is estimated. The equation is given by

$$CAR_{i,t} = \sum_{t=T_1}^{T_2} AR_{i,t}$$

Equation 7. Calculation of CAR

Similar to AAR, cumulative average abnormal returns (CAAR) is calculated by aggregating the cumulative abnormal returns and dividing the sum by the number of observations as shown in *Equation 8*. Again, this enables the testing of the whole sample rather than single observations.

$$CAAR_t = \frac{1}{N} \sum_{i=1}^N AAR_{i,t}$$

Equation 8. Calculation of CAAR

In order to enable an analysis of the abnormal returns, t-tests are performed. In this study, two forms of t-tests are applied: one-sample t-tests and two-sample t-tests with unequal variances. In the one-sample t-tests, the null hypothesis is $CAAR(t) = 0$. The test statistic is given by

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

Equation 9. One-sample t-test

Where SCAAR is the standard deviation of CARs across the sample, which is given by

$$S^2_{CAAR} = \frac{1}{N-1} \sum_{i=1}^N (CAR_i - CAAR)^2$$

Equation 10. SCAAR

In the two-sample t-tests, the null hypothesis is $CAAR(x) - CAAR(y) = 0$, i.e. the mean difference between the samples is equal to zero. The test statistic is given by

$$t = \frac{CAAR_x - CAAR_y}{\sqrt{\frac{SCAAR_x}{N_x} + \frac{SCAAR_y}{N_y}}}$$

Equation 11. Two-sample t-test

Both the one sample t-test and two-sample t-tests have been performed in Stata. A low p-value would indicate that the null hypothesis is rejected, meaning that the mean difference in both types of tests is significantly different from zero. The one-sample tests are conducted on all the upgrades and the downgrades for each event window respectively, resulting in six different tests. This is done to establish if there is an overall effect on credit rating changes in general. Afterwards, the two-sample t-tests are applied to subsamples comparing EU versus US rating changes and pre versus post-financial crisis rating changes in order to detect any potential significant differences.

3.2.4 METHODOLOGY DISCUSSION

The authors have chosen a well-established method in the form of an event study (MacKinlay, 1997), and since it is an accepted and widely used method to measure abnormal returns, it increases the reliability of the study. As other methods, event studies also have their pitfalls. Even though the date of the event is most certainly known, the authors have not been able to find data for whether the rating change is announced nearby (or after) the closing time of the

market, giving the market less time to interpret the information. If this is the case, the next day could be classified as the event day since that is the day the market absorbs the information and react on it. To deal with this issue, the event window is expanded and does not only include the event day. However, a potential problem with this solution is that the window captures other happenings like credit outlooks, credit ratings issued by other agencies, press releases or other macroeconomic events which can affect the movements on the stock price (Wells, 2004). In this study, this risk is reduced due to the number of observations that this study is examining.

3.3 REGRESSION MODEL AND ROBUSTNESS

To further analyse eventual correlations and causality between rating changes and stock prices, several multivariate OLS-regression analyses are performed. As with the t-tests, these are also done in Stata. In total, there are 24 regressions (four per event window) run on two subsamples where one consists of all upgrades and the other of all downgrades. The regression analyses add additional value to the t-tests as it allows for controlling other factors outside the hypotheses which might affect the observed reactions in stock prices. This is conducted by adding and including several control variables on top of the dependent variable and main explanatory variables.

3.3.1 DEPENDENT VARIABLE

The chosen dependent variable is Cumulative Abnormal Return (CAR) which is calculated from the event study, separately for upgrades and downgrades. This variable is used in previous researches that used an event study together with multivariate regressions (Joo & Pruitt, 2006; Li, Visaltanachoti & Kesayan, 2004).

3.3.2 MAIN EXPLANATORY VARIABLES

Since the purpose of the study is to examine the reactions in stock prices between the two markets, a dummy variable is used to compare rating changes occurred on a company that is listed on the European market with the US market. In the regression, the variable is named “US” and takes the value 1 if the rating change happened to a US company and 0 if European.

A dummy variable for the financial crisis (FC in the regression) is also included and takes the value 1 if the rating change occurred after the financial crisis and 0 if it occurred before. The

stock prices after the financial crisis are expected to be more sensitive to rating changes before the financial crisis compared to before. Halek and Eckles (2010) also used specific time periods as an explanatory variable, and Joo and Pruitt (2006) found that the market was more reactive to credit ratings after a financial crisis compared to before. The date of the Lehman Brothers bankruptcy (15th of September 2008) has been chosen to separate the different time periods (Williams, 2010).

3.3.3 CONTROL VARIABLES

Standard & Poor's has two categories in their rating scale called "Investment grade" and "Non-investment grade", which refers to the quality of the company's credit. Everything under BBB- is in the category "Non-investment grade". Choy, Gray and Raguathan (2006) argue that there is a strong signal to the market of a company losing its investment grade status since it might signal significant economic losses due to the higher cost of capital or financial constraints. Creighton, Gower and Richard (2007) used the investment grade variable as well, explaining that some portfolio managers might remove companies that are losing their investment grade status leading to negative stock return. The psychological effects from investors not willing to hold stock without an investment grade status might matter as well. Hence, the variable "IGChange" has been included in the regressions and takes the value 1 if the rating change caused a change in investment grade. This means that the regression for all upgrades only show rating changes from non-investment grade to investment grade, and vice versa for the downgrade regressions.

Another dummy variable used as a control in the regressions takes the value 1 if the rating change has occurred within the investment grade ratings and 0 if it occurred within non-investment grade. Hand, Holthausen and Leftwich (1992) uses investment grade as a control variable in their research about bond ratings and their result concluded that bonds below the investment grade experienced a more significant effect on the stock price compared to bonds over the investment grade. The reason for choosing this variable is to see whether it matters if the rating goes below investment grade. It could be argued that these changes are more substantial than changes occurring below investment grade, as the general interest for investing is higher for investment-grade firms than for non-investment grade. The variable is written as "IG" in the regressions.

According to Kliger and Sarig (2000), firms with higher leverage react stronger to credit rating changes compared to firms with lower leverage. The variable total debt to total asset ratio is therefore added, with the expectation that firms with lower ratio are less sensitive to credit ratings compared to firms with a higher leverage ratio. In the regressions, the variable is written as “DebtAssets”.

A commonly used variable in earlier studies is controlling for industry (Poon & Chan, 2008). The reason is that some industries might be more volatile than others. Depending on which industry the company is operating in the information available may also differ. The different categories are classified according to the two-digit SIC code (Government of the United Kingdom, 2019). All industries are presented in *Appendix C*. Similar to industries the size of the company can have an impact on the volatility of the stock, and therefore also be more sensitive to rating changes. Several earlier types of research have used firm size as a control variable (Avramov et al., 2012; Creighton, Gower & Richards, 2007; Poon & Chan, 2008). In the regressions market cap is logged to improve the accuracy of the model and is written as “logMarketCap”. As with industries the size of the company may matter depending on how much information is available.

Halek and Eckles (2010) and Poon and Chan (2008) used specific years as dummy variables. The reason for choosing this dummy is to see if there is any cyclicalities on the market or to detect if any years are extra volatile. The years after the financial crisis are expected to have a stronger impact on CAR.

The final regression including all variables is given by the following equation:

$$CAR_i = B_0 + B_1US_i + B_2FC_i + B_3IGChange_i + B_4IG_i + B_5logMarketCap_i + B_6DebtToAssets_i + B_7Industry_i + B_8Year_i + u$$

Equation 12. Final regression

3.3.4 ROBUSTNESS

In order to produce as accurate of a result as possible by using multivariate OLS regression, it is desirable for the coefficients in the model to be the Best Linear Unbiased Estimates (BLUE). Another way of phrasing this is that the model should have the lowest variance possible. The model is BLUE if it satisfies the following multiple linear regression (MLR) assumptions:

MLR.1: Linearity in parameters

MLR.2: Random sampling from the population

MLR.3: No multicollinearity in the sample

MLR.4: Exogenous independent variables

MLR.5: Homoscedastic independent variables

A sixth assumption regarding normal distribution of the dependent variable is often included as well. Samples are virtually never perfectly normally distributed. However, the sample in this study is large enough that the central limit theorem can be applied, which says that the mean value of a sample will be close to the mean value of the population (which is desired) when samples are sufficiently large. As for linearity in parameters, none of the regressions includes squared or other similar non-linear variables. Furthermore, no selective bias has been present other than the meeting of criteria as mentioned in section 3.1. A correlation matrix including the independent variables can be found in *Appendix D*, where no alarmingly high levels of correlation can be found; thus, meeting the criteria of no multicollinearity. To test for exogeneity in variables, a Ramsey RESET test has been applied to all regressions (see *Appendix E*). In all the tests, the null hypotheses of no omitted variables can be rejected meaning that the model lacks explanatory variables. This is basically inevitable, and the most important control variables have been included to deal with this issue to the best of the author's ability. Lastly, Breusch-Pagan tests were applied to (see *Appendix E*) detect any signs of heteroscedasticity. As can be seen, the data is heteroscedastic since the null-hypothesis of constant variance is rejected in all tests. Hence, all regressions are run with robust standard errors to deal with this problem.

4. RESULTS AND ANALYSIS

The following section consists of results from the event study and the regressions. Firstly, abnormal returns from rating changes announcements in general are presented. Secondly, a comparison between the US and European market follows. Thirdly, the differences between pre and post the financial crisis are presented. Lastly, the event study results are complemented by multivariate regression analyses.

4.1 DEVELOPMENT OF ABNORMAL RETURNS

The average abnormal returns and the cumulative average abnormal return have been plotted over the 11-day period from t-5 to t+5 around the event date, illustrated in *Figure 3* and *Figure 4*. For upgrades, the graph shows a positive drift a few days before the announcement with the highest abnormal returns showing on the announcement day. Later a slightly volatile development can be seen the days after the announcement. The effect for downgrades is significantly higher compared to the one for upgrades, with a negative trend starting at t-4 with the highest negative abnormal return on the announcement day and t-1. Two days after, the returns are less volatile and no abnormal return is identified.

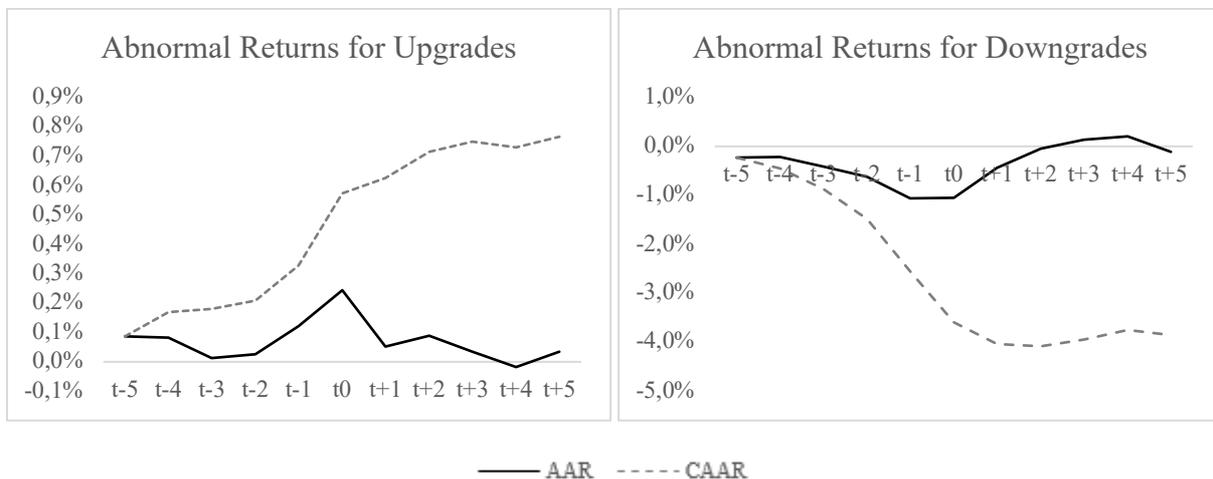


Figure 3. Abnormal returns for upgrades

Figure 4. Abnormal returns downgrades

Table 4 includes all the upgrades and downgrades in the sample and illustrates the results of CAAR and one sample t-tests for each event window respectively. The results for all upgrades show statistical significance on a 1% level for upgrades for all the different event windows. The t-1 to t+1 event window shows a CAAR of 0,43%, the t-3 to t+3 window shows a CAAR of 0,59% while the t-5 to t+5 window shows a CAAR of 0,77%.

As well as for upgrades, the t-tests for downgrades are significant on a 1% level for all the different event windows. This shows that there is a strong correlation between downgrades and abnormal returns. The t-1 to t+1 window shows CAAR of -2,55%, the t-3 to t+3 window shows CAAR of -3,52% and the t-5 to t+5 shows CAAR of -3,88%. Overall, downgrades show a bigger CAAR compared to upgrades despite all the results being statistically significant on a 1% level, indicating a clear asymmetry between the effect on upgrades and downgrades.

Window	Total Upgrades				Total Downgrades			
	CAAR	VAR (CAAR)	t-dist	p-value	CAAR	VAR (CAAR)	t-dist	p-value
-1 to +1	0.0043	0.0010	4.2693	0.0000***	-0.0255	0.0039	-6.5222	0.0000***
-3 to +3	0.0059	0.0014	4.2361	0.0000***	-0.0352	0.0051	-6.8786	0.0000***
-5 to +5	0.0077	0.0017	4.6769	0.0000***	-0.0388	0.0060	-6.4758	0.0000***
	<i>1987 observations</i>				<i>1704 observations</i>			

Table 4. One-sample t-test for abnormal returns

The results confirm that there is an information asymmetry between the credit rating agencies and the market, which shows that the agencies contain non-public information. According to the economic rationality theory, as well as for the signalling hypothesis, investors react to new information rationally. In other words, an upgrade should cause an increase in stock prices and vice versa for downgrades.

For upgrades, the results go in line with previous findings which states that it causes positive abnormal return (Barron, Clare and Thomas, 1997; Creighton, Gower & Richards, 2007; Halek & Eckles, 2010). The strong reaction on the market can be explained by investors overreacting, the first days after a credit rating announcement. Similar to upgrades, downgrades cause abnormal returns, but in a negative way. This result goes in line with a majority of previous findings (Avramov et al, 2012; Barron, Clare and Thomas (1997); Creighton, Gower & Richards, 2007; Halek & Eckles, 2010; Hand, Holthausen & Leftwich, 1992; Li, Visaltanachot & Kesayan, 2004; Pacheco, 2012; Poon & Chan, 2008; Reddy, Bosman & Mirza, 2019)

Like previous empirical findings (Avramov et al.; 2012; Halek & Eckles, 2010; Pacheco, 2012; Reddy, 2019), the stock market reacts stronger to downgrades than it does to upgrades. The reason for the asymmetry could be that people are generally risk-averse; they are more afraid of losing money than they are eager to earn money.

On the other hand, the wealth redistribution hypothesis contradicts the presented results since the theory proposes that a downgrade should lead to positive abnormal returns, depending on what information the credit rating contain. The results also contradict the study of Goh and Ederington (1993), saying that a downgrade in some cases should lead to an increase in stock prices. Since there is no data regarding the reason for the rating changes, it is difficult to tell how this theory explains the results. Either way, the results find stronger support from the information content hypothesis and incentive-signalling approach.

Moreover, the results show that the market is semi-strong and new information provided by the credit ratings are incorporated in the price upon rating change announcements. As Reddy, Bosman and Mirza (2019) concluded, the reason that the market reacts stronger to downgrades compared to upgrades is that companies have an incentive to release positive information, unlike negative information. With this said, most of the positive information is already known to the public and incorporated in the stock price. Hence, a downgrade should lead to stronger reactions on the market since more previously unknown information is released.

Strong support for *Hypothesis 1* is shown in the results, saying there is a significant increase (decrease) on a company's stock price when it receives an upgrade (downgrade) in credit rating. The stock price is affected by a rating change regardless of it being a downgrade or an upgrade, but with a stronger effect for downgrades. This shows that there is information asymmetry between credit rating agencies and the market, as well as a reaction asymmetry between upgrades and downgrades.

4.2 ABNORMAL RETURNS US AND EU

As can be seen in *Figure 5*, positive abnormal returns for upgrades in both markets is already present at t-5, but the strongest reaction occurs on the announcement day, t0. After that, the abnormal returns decrease. The graph shows quite similar development for both markets over the whole period.

For downgrades, the same pattern cannot be found as for upgrades. When comparing CAAR between the US and Europe, both markets have a slightly negative trend over the whole period, which can be seen in *Figure 6*. However, from t-2 and onwards, the negative AAR for US

companies are significantly bigger, causing the US CAAR line to significantly decrease compared to the EU CAAR line.

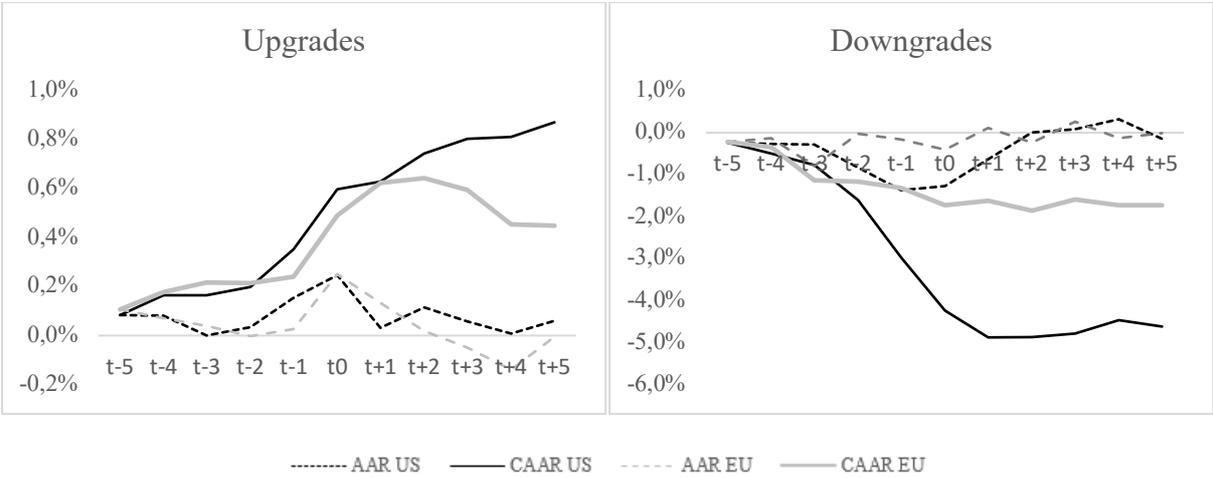


Figure 5. Abnormal returns for upgrades for US and Europe

Figure 6. Abnormal returns for downgrades for US and Europe

The two-sample t-tests in *Table 5* show no statistically significant differences between the two markets reactions to upgrades. Downgrades, on the other hand show a strongly significant difference on a 1% level for all the event windows, where the negative CAAR is bigger for the US companies. In the t-1 to t+1 window, the CAAR for US is 2,81 percentage points higher than for Europe. For the t-3 to t+3 window, CAAR is 3,04 percentage points higher for the US, and the t-5 to t+5 window is 2,88 percentage points higher for the US.

Window	Upgrades					Downgrades				
	EU	US	Δ CAAR	t-dist	p-value	EU	US	Δ CAAR	t-dist	p-value
-1 to +1	0.0041	0.0043	-0.0002	-0.1046	0.9167	-0.0046	-0.0327	0.0281	4.0722	0.0000***
-3 to +3	0.0042	0.0064	-0.0022	-0.7887	0.4305	-0.0125	-0.0429	0.0304	3.1231	0.0018***
-5 to +5	0.0045	0.0087	-0.0042	-1.2496	0.2117	-0.0173	-0.0462	0.0288	2.7155	0.0007***
Observations	467	1520				433	1271			

Table 5. Two-sample t-tests for upgrades and downgrades between Europe and the USA

The authors have not been able to find any previous studies specifically comparing credit rating changes between the US and European market, making it hard to compare it with any previous research. A reason explaining the difference between the markets could be, as discussed earlier, that the debt financing distribution differs between the markets.

As Rajan (1992) discussed, the benefits of using bonds are that the companies do not need to release as much private information compared to when applying for a bank loan. Since bonds are more used in the US compared to Europe, theoretically there would be a bigger information asymmetry on the US market. Even though banks act under bank secrecy, there is a risk that insider information may leak out to other units in the bank, or in the worst case to the market, eventually incorporating that information into the stock price.

As seen in *Appendix B*, the average debt to assets ratio is significantly bigger for the US companies compared to the European companies. As Kliger and Sarig (2000) concluded, firms with higher leverage are more sensitive to credit ratings than firms with lower credit ratings resulting in more volatile stock performance. Looking separately at upgrades, the average debt to asset ratio is 26% for European companies and 37% for US companies. The difference in leverage ratio for companies experiencing a downgrade is an average of 29% for European companies while the average for US companies is 46%. Compared to upgrades, the difference in leverage ratio is bigger for downgrades. The difference in leverage might explain the significant difference in stock returns between the two markets and could also describe why the market reacts stronger to downgrades than it does to upgrades.

There is partial support for Hypothesis 2 saying that the stock price of US companies is more heavily impacted by credit rating changes compared to European companies. The results present evidence for this to be true for downgrades, but not for upgrades.

4.3 ABNORMAL RETURNS BEFORE AND AFTER THE FINANCIAL CRISIS

Illustrated in *Figure 7* and *8* is the development of AARs and CAARs for upgrades and downgrades respectively, pre and post-financial crisis over the 11-day period. Upgrades have experienced a decrease in CAAR after the financial crisis, albeit subtle. A clear upward spike can be seen on the event day. There is also a clear drift for both periods with positive AARs during nearly all days surrounding the event.

The downgrades show a reversed pattern compared to upgrades where the CAARs are significantly more negative after the financial crisis than before. A downwards spike can be

seen during the event day, but also one day prior (t-1) for AARs after the financial crisis. A clear negative trend of CAAR is evident, indicating that the AARs are negative for most of the days surrounding the event.

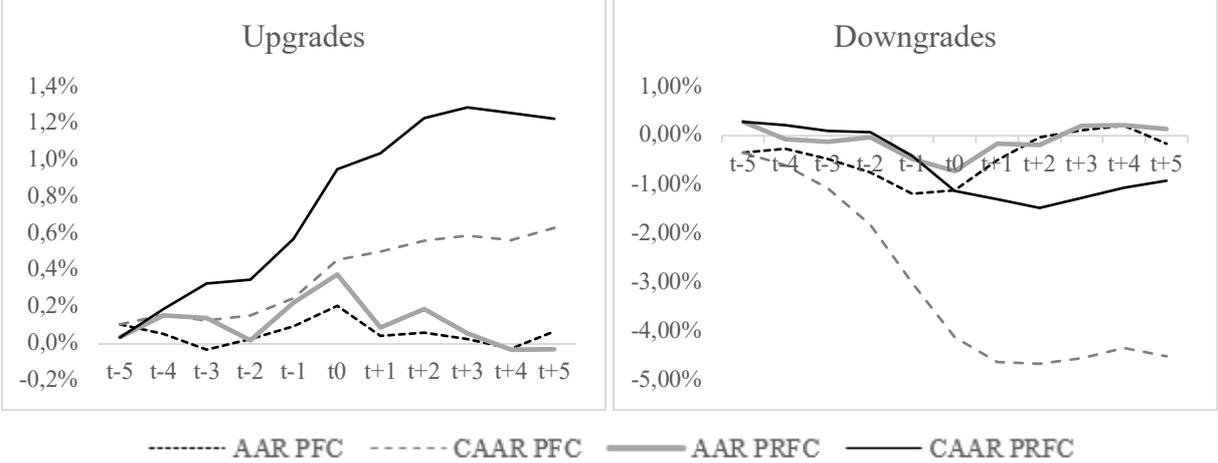


Figure 7. Abnormal returns pre and post-financial crisis for upgrades

Figure 8. Abnormal returns pre and post-financial crisis for downgrades

In *Table 6*, the results from the two-sample t-tests for upgrades and downgrades respectively, pre and post-financial crisis can be found. For upgrades, there is a statistically significant difference for CAAR between the two time periods on event window t-3 to t+3 and t-5 to t+5. In the former window, CAAR is 0,67 percentage points higher from upgrades occurring previous to the financial crisis compared to afterwards and the p-value shows a statistical significance on the 5% level. The difference in the latter event window shows weaker statistical significance on the 10% level, where CAAR is 0,59 percentage points higher from upgrades occurring previous to the financial crisis compared to afterwards. For downgrades, the differences show stronger statistical significance compared to upgrades on all event windows. Over the t-1 to t+1 event window, the difference in CAAR post-financial crisis is 1,45 percentage points compared to pre-financial crisis, with a statistical significance on a 5% level. The t-3 to t+3 window shows a difference of 2,45 percentage points post-financial crisis, with a statistical significance on a 1% level. Lastly, the most stretched event window of t-5 to t+5 shows a difference of 3,58 percentage points, also significant on a 1% level. Overall, the differences between the two time-periods are more substantial for downgrades compared to upgrades. The downgrades show statistically significant differences on all event windows at the

second decimal, whereas upgrades only experience a difference at the third decimal with weaker to no statistical significance across the event windows.

Window	Upgrades					Downgrades				
	Pre CAAR	Post CAAR	Δ CAAR	t-dist	p-value	Pre CAAR	Post CAAR	Δ CAAR	t-dist	p-value
-1 to +1	0.0069	0.0034	0.0034	1.509	0.1317	-0.0136	-0.0280	0.0145	2.2991	0.0217**
-3 to +3	0.0110	0.0043	0.0067	2.2421	0.0252**	-0.0149	-0.0394	0.0245	2.8776	0.0041***
-5 to +5	0.0122	0.0063	0.0059	1.6687	0.0955*	-0.0092	-0.0450	0.0358	3.7354	0.0002***
Observations	469	1518				295	1409			

Table 6. Two-sample t-test for downgrades between pre and post financial crisis

It is clear that there has been a shift downwards for both upgrades and downgrades after the financial crisis; upgrades experience less positive abnormal returns and downgrades experience more negative abnormal returns. Again, there is an apparent asymmetry between upgrades and downgrades as shown in the previous samples of this study and in earlier research (Avramov, 2012; Choy, 2006; Hand, 1992; Halek & Eckles, 2010; Li, Visaltanachot & Kesayan, 2004; Reddy, Bosman & Mirza 2019). The heavier impact of downgrades goes in line with previous research which indicates a more reactive market in regards to credit rating changes after a financial crisis compared to before (Joo & Pruitt, 2006; Pacheco, 2012; Reddy, Bosman & Mirza 2019), but the results for upgrades contradicts previous results from Reddy (2019) which indicated stronger reactions.

The lower abnormal returns for upgrades post-financial crisis could be explained by damaged credibility regarding credit rating agencies' optimistic ratings. As mentioned previously, the rating agencies were accused of handing out undeservedly high ratings and thus being one of the central factors to the crisis. Hence, an increased scepticism towards upgrades specifically could be expected from investors. However, the statistical significance of the results in this study is relatively weak and the differences might merely be derived from happenstance.

The same analysis cannot be applied to downgrades; rating changes occurring after the financial crisis experienced increased abnormal returns with strong statistical significance. Aside from general explanations regarding the asymmetry between upgrades and downgrades, a possible explanation could be an increased risk aversion and fear from investors ever since the financial crisis occurred. Since the credit rating agencies are still around producing a growing multi-

billion-dollar industry, it can be argued that they have learned from the mistake causing the crisis, while also improving and further developing the rating process. Rating changes occurring today would then be deemed more accurate, leading to an increased trust in ratings provided and therefore impacting stock prices to a larger extent than before. Under the assumption that the market is semi-strong, this could also be seen as the rating agencies possessing more valuable information than previously, which upon rating change announcements reduces the existing information asymmetry. Further support for volatile markets during uncertain times can be found in Ackert's (1994) study where he concludes that uncertainty on the market is a primary reason for excessive volatile stock prices. Because of the uncertainty in the global economy after the financial crisis, the market probably reacts stronger to a negative outlook or a CreditWatch announcement. Even though Ackert (1994) could not find a further explanation of why the market overreacts, it might be explained that people are naturally risk-averse, preferring lower risk compared to high.

Partial support for Hypothesis 3 is found saying that the stock price of companies where credit rating changes occurred post the financial crisis is more heavily impacted compared to companies experiencing a rating change previous to the financial crisis. The results present evidence for this to be true for downgrades, but not for upgrades.

4.4 REGRESSIONS

Results of the regressions for CAR on all observations are presented in *Table 7* and *8*. The leftmost column in each respective event window includes only the main explanatory variables. Moving further to the right, control variables are included and adding explanatory value to the model which can be seen in the increasing R-squared value. The dummy "FC" is deliberately left out in regressions (4) as it controls for eventual cyclicity in specific years over the whole sample period which would conflict with this variable. Results from the "Year" dummy can be found in *Appendix G*.

4.4.1 UPGRADES

The results in *Table 7* show no statistically significant correlation between rating changes occurring in the US and CAR. For changes occurring post FC, a majority of the regressions show a statistically significant negative correlation, indicating that these upgrades on average experience less abnormal returns surrounding the event. Next to no significant correlations were

found when controlling for specific years. The coefficient for “IGUpgrade” show statistical significance at the 10% level in regressions (2) but this is diminished when controls for Industries and Year are added in event window t-3 to t+3 and t-5 to t+5. For the control variable IG, a significant negative correlation on the 1% level was found on all regressions in which it was included, meaning that companies rated within the investment grade category experience less abnormal returns surrounding the event. No significance was found on “logMarketCap” or “DebtAssets”.

Upgrades												
VARIABLES	t-1 to t+1				t-3 to t+3				t-5 to t+5			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
US	0.000 (0.002)	-0.001 (0.002)	-0.000 (0.002)	-0.001 (0.002)	0.003 (0.003)	-0.000 (0.003)	0.002 (0.003)	0.001 (0.003)	0.005 (0.003)	0.002 (0.003)	0.004 (0.004)	0.003 (0.004)
FC	-0.003 (0.002)	-0.005** (0.002)	-0.004* (0.002)		-0.007** (0.003)	-0.009*** (0.003)	-0.009*** (0.003)		-0.006* (0.004)	-0.008** (0.003)	-0.009*** (0.004)	
IGUpgrade		-0.007* (0.004)	-0.008* (0.004)	-0.008* (0.004)		-0.010* (0.006)	-0.010 (0.006)	-0.009 (0.006)		-0.012* (0.007)	-0.011 (0.007)	-0.010 (0.007)
IG		-0.011*** (0.003)	-0.011*** (0.004)	-0.011*** (0.004)		-0.013*** (0.005)	-0.012** (0.006)	-0.012** (0.006)		-0.017*** (0.006)	-0.015** (0.006)	-0.014** (0.006)
logMarketCap		0.001 (0.001)	0.001 (0.001)	0.001 (0.001)		0.000 (0.001)	0.001 (0.001)	0.000 (0.001)		0.001 (0.002)	0.001 (0.002)	0.001 (0.002)
DebtAssets		0.004 (0.006)	0.003 (0.007)	0.001 (0.007)		0.013 (0.009)	0.016 (0.010)	0.014 (0.010)		0.010 (0.011)	0.015 (0.012)	0.014 (0.012)
Controls												
Industries	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Year	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
Constant	0.007*** (0.002)	0.009 (0.011)	0.015 (0.012)	0.011 (0.013)	0.009*** (0.003)	0.016 (0.013)	0.024 (0.022)	0.017 (0.023)	0.009** (0.004)	0.014 (0.015)	0.027 (0.021)	0.021 (0.022)
Observations	1,987	1,987	1,987	1,987	1,987	1,987	1,987	1,987	1,987	1,987	1,987	1,987
R-squared	0.001	0.009	0.051	0.058	0.002	0.014	0.054	0.063	0.002	0.011	0.045	0.053

Robust standard errors in parentheses

Table 7. Regressions for upgrades

The results of the dummy variable US confirm that there is no significant difference in abnormal returns depending on whether the company is located in the US or EU, which goes in line with the previously conducted two sample t-tests in *Table 5*. As previously mentioned, no studies investigating abnormal returns with this specific angle of approach was found by the authors. Hence, it is difficult to draw any conclusions regarding the results in comparative ability with previous research. The results of the dummy variable FC also go in line with previous t-tests in *Table 6* indicating lower abnormal returns for companies experiencing an upgrade post the financial crisis. Since no significance was found on the variables for Year (see Appendix G), the results suggest that the different periods pre and post the crisis has a significant impact on cumulative abnormal returns rather than specific cyclicalities of years. As for the results regarding companies experiencing an upgrade in investment grade, the findings contradict the results of Reddy, Bosman and Mirza (2019) who instead find significant positive impacts on stock prices, but go in line with Choy, Gray and Ragunathan (2006) and Halek and Eckles

(2010) which do not find any significant results. The significance found on changes occurring within investment grade contradicts the results from Reddy, Bosman and Mirza (2019) who finds significant positive impacts on abnormal returns instead. Finding no significant results on companies' market cap or leverage ratio was unexpected since previous studies have found significant results for both leverage and firm size (Kliger & Sarig, 2000; Creighton, Gower & Richards, 2007)

4.7.2 DOWNGRADES

The results from *Table 8* show a statistically significant negative correlation on a 1% level in the leftmost regressions between downgrades occurring in the US and CAR, indicating that these observations on average experience 2.8%, 3.1% and 3% more negative abnormal returns respectively for each event window. However, no significant results are found between these variables when controlling for other factors. For downgrades occurring post FC, the same pattern as with the US variable can be identified with the exception of a significant coefficient of -2,1% in regression (2) on the t-5 to t+5 window and a significant coefficient of -1,5% at the 5% level in regression (1) on the t-1 to t+5 window. When years are controlled for, Appendix G shows several years post FC with a significant negative coefficient on the 5% level for the t-1 to t+1 window, but no specific cyclicity is identified across all windows.

The control variables "IG" and "logMarketCap" show strong statistically significant coefficients across all regressions with the exception of "IG" in the event window t-5 to t+5. For "IG" the coefficients are negative, indicating that downgrades where the company has a rating categorised as investment grade on average experience more abnormal negative returns. For "logMarketCap" the coefficients are positive, indicating that companies with higher market cap on average experience less negative abnormal returns and vice versa for companies with lower market caps. No significant results were found for "DebtAssets".

Downgrades												
VARIABLES	t-1 to t+1				t-3 to t-3				t-5 to t+5			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
US	-0.028*** (0.007)	-0.008 (0.007)	-0.007 (0.008)	-0.006 (0.007)	-0.031*** (0.010)	-0.003 (0.010)	0.005 (0.012)	0.004 (0.011)	-0.030*** (0.011)	-0.000 (0.010)	0.010 (0.012)	0.008 (0.012)
FC	-0.015** (0.006)	-0.006 (0.006)	-0.004 (0.006)		-0.025*** (0.009)	-0.011 (0.008)	-0.006 (0.009)		-0.037*** (0.010)	-0.021** (0.009)	-0.014 (0.010)	
IGDowngrade		0.014 (0.010)	0.013 (0.010)	0.009 (0.010)		0.013 (0.013)	0.006 (0.014)	0.003 (0.014)		0.010 (0.016)	-0.002 (0.016)	-0.006 (0.016)
IG		-0.033*** (0.009)	-0.030*** (0.010)	-0.035*** (0.011)		-0.026** (0.013)	-0.032** (0.014)	-0.038*** (0.014)		-0.017 (0.016)	-0.024 (0.016)	-0.032** (0.016)
logMarketCap		0.022*** (0.004)	0.023*** (0.004)	0.024*** (0.004)		0.022*** (0.005)	0.022*** (0.005)	0.024*** (0.005)		0.022*** (0.006)	0.022*** (0.006)	0.024*** (0.006)
DebtAssets		0.018 (0.021)	0.010 (0.023)	0.016 (0.023)		-0.013 (0.026)	-0.033 (0.029)	-0.028 (0.029)		0.004 (0.034)	-0.023 (0.037)	-0.018 (0.037)
Controls												
Industries	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Year	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
Constant	0.008 (0.007)	-0.160*** (0.029)	-0.151*** (0.037)	-0.143*** (0.036)	0.009 (0.009)	-0.160*** (0.036)	-0.142*** (0.047)	-0.144*** (0.046)	0.013 (0.010)	-0.173*** (0.043)	-0.102* (0.057)	-0.095* (0.056)
Observations	1,704	1,704	1,704	1,704	1,704	1,704	1,704	1,704	1,704	1,704	1,704	1,704
R-squared	0.007	0.057	0.081	0.091	0.006	0.042	0.067	0.077	0.006	0.034	0.067	0.080

Robust standard errors in parentheses

Table 8. Regressions for downgrades

Since no significant results are found for the US variable when adding control variables, this indicates that there are other factors than the mere geographical location which explain the significant differences found in the t-tests (see *Table 5*). The significant results of “IG” and market cap suggest that these characteristics are correlated with CAR, which might indicate that this is where the effect derives from instead. For the financial crisis results, no significant results were found when controlling for other variables. However, looking at Appendix G, investors seem to react stronger closer to the event day (window t-1 to t+1) post-financial crisis for most of the years. Thus, the initial reaction is significantly more impactful close to the event day post- financial crisis but evened out over longer periods like the t-3 and t+3 and t-5 to t+5 windows.

Reddy, Bosman and Mirza (2019) also find a significant impact of changes occurring within the investment grade in line with this study, whereas Choy, Gray and Raganathan (2006) and Halek and Eckles (2010) finds no significant results with this variable. For market cap, the results contradict previous research by Li, Visaltanachoti and Kesayan (2004) who find no significant impact, and Poon and Chan (2008) who find significant impacts but in the opposite direction. On the other hand, the results regarding market cap go in line with Creighton, Gower and Richards (2007). The insignificant results from downgrades in investment grade category contradicts previous findings from Reddy, Bosman and Mirza (2019) but go in line with findings from Choy, Gray and Raganathan (2006) and Halek and Eckles (2010). Finding no

significant results related to companies leverage ratio was unexpected and contradicts the results of Kliger and Sarig (2000).

5. DISCUSSION AND CONCLUSIONS

The purpose of this thesis was to research whether the stock prices of US companies react stronger to a credit rating announcement compared to the stock prices of European companies. In conclusion, the reaction on the US market is significantly stronger compared to the European market when a company receives a downgrade, but there is no difference between the two markets when a company receives an upgrade. Several factors might explain the difference in abnormal returns for the two markets. One reason could be that the information asymmetry differs between the European and US market due its differentiations in financing when it comes to bonds and bank loans, where the latter forces companies to expose private information to a larger extent. Another reason could be that the general uncertainty regarding credit ratings is bigger on the US market compared to the European market since the financial crisis actually had its starting point there. The authors believe that the purpose has been fulfilled, and the new information regarding credit rating changes on a global scale has been provided for investors and researchers.

In order to determine whether credit ratings affect the stock prices, t-tests were executed to find an eventual difference. The conclusion is that credit rating changes impact stock prices due to the information asymmetry that exists between the credit rating agencies and the market, and the way of investors to act rationally. As with upgrades, the reaction on the market after a downgrade shows that there is an information asymmetry between the credit rating agencies and the market. The negative trend for downgrades, which starts a few days before the announcement day suggests that investors might anticipate this rating change a few days prior to the event day. A number of underlying reasons could explain this anticipation, but an example would be a negative CreditWatch announcement or other speculations from the market.

When comparing the results before and after the financial crisis of 2007-2009, it is concluded that the stock market reacts stronger to a downgrade after the financial crisis, but not for an upgrade. This might be because of the raised economic uncertainty on the market due to the financial crisis, and a lot of investors might still associate inaccurate credit ratings with the financial crisis. The chosen date that separates the different time periods might be criticised since the bankruptcy of Lehman Brothers, which also in many cases refers to the start of the financial crisis, leads to the post sample including several massive downgrades during the

financial crisis. The downgrades probably lead to several outliers for the sample, but as seen in *Appendix F*, it would not matter whether to put it at the beginning of 2007 or at the end of 2009 since the cumulative average abnormal returns are bigger several years after the financial crisis.

As mentioned earlier, Standard & Poor's (2014) states that credit ratings do not tell anything about the asset value, neither if it is a buy or a sell recommendation. The results on the other hand show clearly that the market reacts on credit rating changes. What is interesting is whether it is the rating change per se that investors react to, or what might happen to the company after the rating change. A new rating might experience a consequent change in capital structure or that investors might face several restrictions. Even a rating that can be seen as unrelated to any changes in credit risk may still send a signal to the market. That might confirm to the market that the company still is financially stable and therefore making investors feel secure.

5.1 LIMITATIONS AND FURTHER RESEARCH

The focus in this thesis was to examine credit ratings for companies because the authors expected that the market reacts stronger to a company credit rating change compared to one of their bond ratings. Further research could be examined between the markets, but instead looking at bond rating changes to determine any eventual effects on stock prices.

It would also be interesting to replicate this study, but instead examine the abnormal return for stock prices over a long-term perspective. As mentioned earlier, previous studies show that an overreaction can explain the abnormal return on the market, which after around 6 months adjusts to its true value.

Another area that is less researched is sovereign ratings, and one specific topic for that would be how credit ratings for companies are affected when the sovereign ratings have had an upgrade or a downgrade recently. Are some industries more affected by the sovereign rating change than others, or does the market size matter whether they are affected or not?

Other variables that could be added is controlling for specific stock exchanges since some exchanges are more volatile than others. The size of the companies can also be measured in different ways, like the book to market value.

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APPENDICES

Appendix A. The 13 biggest economies in Europe

Country	Nominal GDP 2018 (billion \$)	Observations
Germany	4,029,140	107
UK	2,808,899	157
France	2,794,696	159
Italy	2,086,911	90
Russia	1,576,488	97
Spain	1,437,047	85
Netherlands	909,887	33
Switzerland	709,118	51
Sweden	554,659	52
Poland	549,478	24
Belgium	536,055	22
Austria	459,401	9
Norway	441,439	14
USA	20,890,000	2791

(IMF, 2018)

Appendix B. Summary statistics

EU

Upgrades	Obs	Mean	Std. Dev.	Min	Max
CAR t-1 to t+1	467	0,41%	3,49%	-22,15%	26,41%
CAR t-3 to t+3	467	0,42%	4,92%	-25,67%	29,70%
CAR t-5 to t+5	467	0,45%	5,89%	-37,29%	30,01%
Market Cap (mUSD \$)	467	21 731,15	35 386,86	10,85	263 508,80
Debt to Assets	467	25,74%	17,42%	0,00%	104,17%
Downgrades					
CAR t-1 to t+1	433	-0,46%	9,95%	-67,29%	103,59%
CAR t-3 to t+3	433	-1,25%	15,27%	-125,37%	113,48%
CAR t-5 to t+5	433	-1,73%	15,44%	-124,31%	89,79%
Market Cap (mUSD \$)	433	17 452,63	31 969,38	14,33	276 823,70
Debt to Assets	433	29,36%	18,36%	0,00%	98,47%

US

Upgrades	Obs	Mean	Std. Dev.	Min	Max
CAR t-1 to t+1	1520	0,43%	4,72%	-36,67%	54,25%
CAR t-3 to t+3	1520	0,64%	6,51%	-47,97%	66,51%
CAR t-5 to t+5	1520	0,87%	7,75%	-53,44%	67,69%
Market Cap (mUSD \$)	1520	10 935,77	27 600,27	7,86	581 012,90
Debt to Assets	1520	37,15%	23,65%	0,00%	202,71%
Downgrades					
CAR t-1 to t+1	1271	-3,27%	17,74%	-113,56%	289,94%
CAR t-3 to t+3	1271	-4,29%	22,71%	-139,17%	263,71%
CAR t-5 to t+5	1271	-4,62%	27,16%	-173,20%	276,10%
Market Cap (mUSD \$)	1271	5 772,44	20 134,13	0,18	283 342,00
Debt to Assets	1271	45,80%	27,38%	0,00%	197,84%

Appendix C. Industries, Two-digit SIC Code

Industries	
Apparel and Accessory Stores	Tobacco Products
Communications	Coal Mining
Apparel, Finished Products from Fabrics & Similar Materials	Petroleum Refining and Related Industries
Holding and Other Investment Offices	Building Materials, Hardware, Garden Supplies & Mobile Homes
Printing, Publishing and Allied Industries	Furniture and Fixtures
Oil and Gas Extraction	Railroad Transportation
Industrial and Commercial Machinery and Computer Equipment	Construction - General Contractors & Operative Builders
Health Services	Lumber and Wood Products, Except Furniture
Wholesale Trade - Nondurable Goods	Security & Commodity Brokers, Dealers, Exchanges & Services
Chemicals and Allied Products	Motion Pictures
Fabricated Metal Products	Metal Mining
Business Services	Motor Freight Transportation
Transportation by Air	Transportation Services
General Merchandise Stores	Primary Metal Industries
Electronic & Other Electrical Equipment & Components	Mining and Quarrying of Nonmetallic Minerals, Except Fuels
Electric, Gas and Sanitary Services	Automotive Dealers and Gasoline Service Stations
Engineering, Accounting, Research, and Management Services	Stone, Clay, Glass, and Concrete Products
Eating and Drinking Places	Miscellaneous Manufacturing Industries
Paper and Allied Products	Leather and Leather Products
Transportation Equipment	Educational Services
Measuring, Photographic, Medical, & Optical Goods, & Clocks	Hotels, Rooming Houses, Camps, and Other Lodging Places
Real Estate	Food Stores
Personal Services	Insurance Carriers
Nondepository Credit Institutions	Automotive Repair, Services and Parking
Water Transportation	Textile Mill Products
Pipelines, Except Natural Gas	Amusement and Recreation Services
Miscellaneous Retail	Heavy Construction, Except Building Construction, Contractor
Rubber and Miscellaneous Plastic Products	Membership Organizations
Depository Institutions	Social Services
Food and Kindred Products	Construction - Special Trade Contractors
Wholesale Trade - Durable Goods	Local & Suburban Transit & Interurban Highway Transportation
Home Furniture, Furnishings and Equipment Stores	Insurance Agents, Brokers and Service

Appendix D. Correlation Matrices

UPGRADES

	US	FC	IGUpgrade	IG	MarketCap	DebtAssets
US	1.0000					
FC	0.0636	1.0000				
IGUpgrade	0.0985	-0.0176	1.0000			
IG	-0.1859	-0.0906	-0.5389	1.0000		
MarketCap	-0.1528	-0.0370	-0.1121	0.2429	1.0000	
DebtAssets	0.2116	0.1476	0.0991	-0.4158	-0.1740	1.0000

DOWNGRADES

	US	FC	IGDowngrade	IG	MarketCap	DebtAssets
US	1.0000					
FC	-0.0212	1.0000				
IGDowngrade	0.0748	0.0040	1.0000			
IG	-0.2994	-0.1991	-0.2999	1.0000		
MarketCap	-0.2099	-0.0405	-0.1000	0.3595	1.0000	
DebtAssets	0.2715	0.1449	-0.0018	-0.4344	-0.1940	1.0000

Appendix E. Ramsey Reset and Breusch-Pagan test

Ramsey RESET for Upgrades	Ramsey RESET for Downgrades
----------------------------------	------------------------------------

Ho: model has no omitted variables

Ho: model has no omitted variables

CAR t-1 to t+1

F(3, 1899) = 7.58

Prob > F = 0.0000

CAR t-3 to t+3

F(3, 1899) = 14.89

Prob > F = 0.0000

CAR t-5 to t+5

F(3, 1899) = 15.32

Prob > F = 0.0000

CAR t-1 to t+1

F(3, 1619) = 47.87

Prob > F = 0.0000

CAR t-3 to t+3

F(3, 1619) = 25.05

Prob > F = 0.0000

CAR t-5 to t+5

F(3, 1619) = 21.22

Prob > F = 0.0000

Upgrades

Downgrades

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

H0: Constant variance

H0: Constant variance

Variables: fitted values of CAR t-1 to t+1

chi2(1) = 536.52

Prob > chi2 = 0.0000

Variables: fitted values of CAR t-1 to t+1

chi2(1) = 1142.60

Prob > chi2 = 0.0000

Variables: fitted values of CAR t-3 to t+3

chi2(1) = 469.87

Prob > chi2 = 0.0000

Variables: fitted values of CAR t-3 to t+3

chi2(1) = 691.65

Prob > chi2 = 0.0000

Variables: fitted values of CAR t-5 to t+5

chi2(1) = 318.36

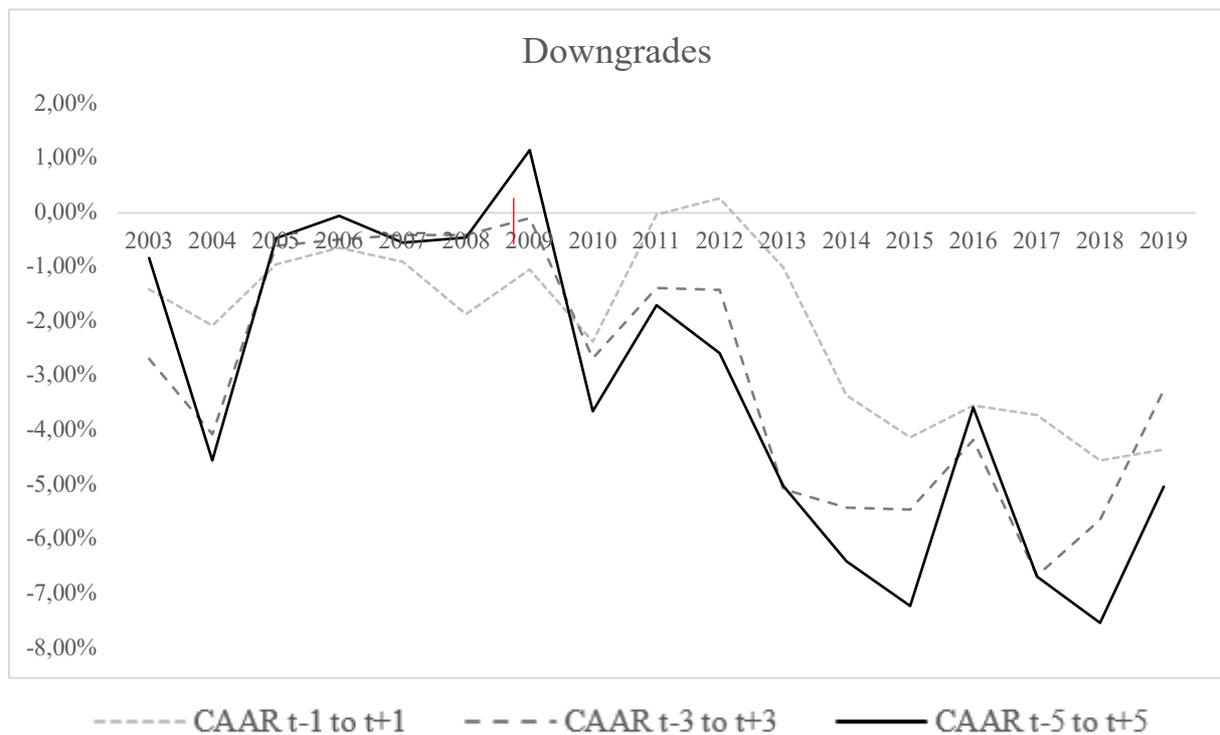
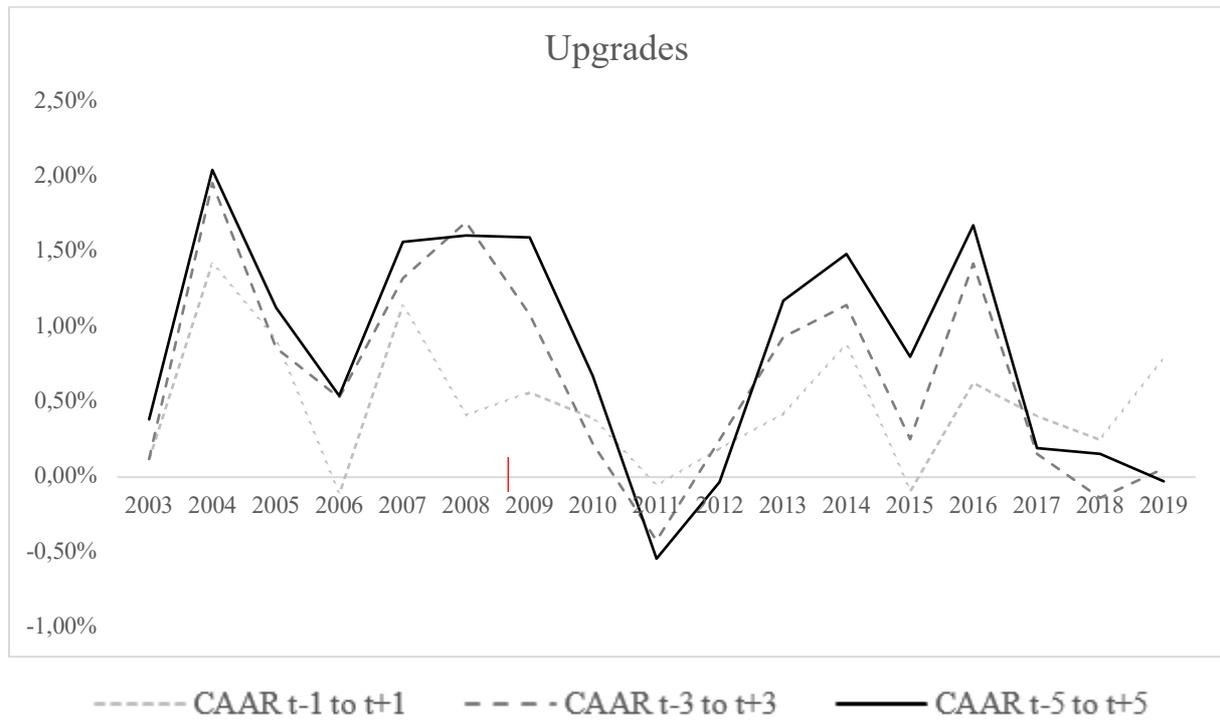
Prob > chi2 = 0.0000

Variables: fitted values of CAR t-5 to t+5

chi2(1) = 449.45

Prob > chi2 = 0.0000

Appendix F. Timeline for the different event windows



The red line shows the date of the Lehman Brothers bankruptcy (September 15th 2008)

Appendix G. Regressions with year as a dummy

Upgrades				Downgrades			
Year	t-1 to t+1	t-3 to t+3	t-5 to t+5	Year	t-1 to t+1	t-3 to t+3	t-5 to t+5
2004	0.011* (0.006)	0.016 (0.010)	0.013 (0.012)	2004	-0.012 (0.021)	-0.019 (0.029)	-0.031 (0.029)
2005	0.007 (0.007)	0.006 (0.009)	0.006 (0.011)	2005	-0.003 (0.011)	0.012 (0.015)	-0.006 (0.021)
2006	-0.003 (0.005)	0.004 (0.009)	-0.000 (0.011)	2006	-0.010 (0.014)	0.007 (0.016)	-0.008 (0.021)
2007	0.009 (0.005)	0.009 (0.009)	0.008 (0.011)	2007	-0.018 (0.015)	0.008 (0.020)	-0.015 (0.026)
2008	0.006 (0.007)	0.017 (0.011)	0.011 (0.014)	2008	-0.038** (0.016)	-0.010 (0.024)	-0.022 (0.027)
2009	0.002 (0.025)	0.001 (0.032)	0.002 (0.045)	2009	-0.021 (0.028)	-0.004 (0.041)	0.003 (0.051)
2010	0.003 (0.023)	-0.007 (0.030)	-0.008 (0.043)	2010	-0.055** (0.028)	-0.046 (0.039)	-0.058 (0.048)
2011	-0.000 (0.023)	-0.011 (0.029)	-0.018 (0.043)	2011	-0.024 (0.029)	-0.027 (0.040)	-0.033 (0.050)
2012	0.003 (0.023)	-0.003 (0.029)	-0.012 (0.042)	2012	-0.021 (0.028)	-0.020 (0.040)	-0.029 (0.048)
2013	0.004 (0.023)	0.002 (0.029)	-0.002 (0.042)	2013	-0.048 (0.031)	-0.077* (0.043)	-0.077 (0.050)
2014	0.010 (0.023)	0.006 (0.029)	0.002 (0.042)	2014	-0.059** (0.029)	-0.065 (0.041)	-0.071 (0.051)
2015	-0.001 (0.023)	-0.003 (0.029)	-0.002 (0.043)	2015	-0.060** (0.030)	-0.052 (0.042)	-0.063 (0.051)
2016	0.007 (0.023)	0.007 (0.030)	0.004 (0.043)	2016	-0.045 (0.030)	-0.030 (0.044)	-0.015 (0.053)
2017	0.005 (0.023)	-0.006 (0.029)	-0.012 (0.043)	2017	-0.061** (0.029)	-0.069* (0.040)	-0.067 (0.050)
2018	0.005 (0.023)	-0.004 (0.029)	-0.008 (0.043)	2018	-0.069** (0.030)	-0.054 (0.042)	-0.078 (0.051)
2019	0.009 (0.024)	-0.006 (0.031)	-0.013 (0.044)	2019	-0.086** (0.038)	-0.091* (0.054)	-0.133* (0.068)
Constant	0.011 (0.013)	0.017 (0.023)	0.021 (0.022)	Constant	-0.143*** (0.036)	-0.144*** (0.046)	-0.095* (0.056)
Observations	1,987	1,987	1,987	Observations	1,704	1,704	1,704
R-squared	0.058	0.063	0.053	R-squared	0.091	0.077	0.080

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Data for sample will be provided upon request